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European Naturalistic Driving Study

Interactions with vulnerable road users

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Executive Summary

Within UDRIVE there has been a specific focus on pedestrians, cyclists and Powered Two Wheelers (PTWs). These groups of road users are particularly vulnerable in traffic because they lack the protective shell that helps preventing serious injury once involved in a collision. In addition, these transport modes have several features that make them more prone to getting involved in a crash, e.g. related to reduced conspicuity and for the two-wheelers the difficulty to remain in balance, either or not in combination with high speeds. This type of factors make that pedestrians, cyclists and PTWs have a high risk of getting fatally or seriously injured in traffic.

Within UDRIVE, a large amount of 'naturalistic' data was collected to get more in-depth insight in the interactions of these groups with passenger cars and trucks. The aim was to identify and understand the everyday behavioural patterns in these interactions as well as the circumstances of conflicts or safety critical events in these interactions. The current Deliverable reported on the analyses and results of a number of specific interaction types.

Method

Data were collected by a naturalistic driving approach. In a naturalistic driving study data is collected by equipping people's own vehicle with various sensors and cameras and unobtrusively registering characteristics of the vehicle, the driver/rider and the environment over longer periods of time and during normal, everyday trips. The analysis of the interactions of car and truck drivers with pedestrians and cyclists was based on data collected from the participating cars and trucks. The analysis of the safety critical events and interactions of PTWs was also based on data from equipped, naturalistic riding PTWs. Data were collected between October 2015 and May 2017.

Starting point for the analyses of the pedestrian and cyclist interactions was the UDRIVE database with data from 186 car drivers in Great Britain, France, Germany, Poland, and the Netherlands, and from 48 truck drivers based in the Netherlands. By April 2017, the database consisted of a total of 42724 hours of car data, and 41397 hours of truck data. The results related to PTWs stem from 47 motorscooter (125CC) riders in Spain, resulting in a database 859 hours of PTW data (Note that these numbers may be slightly different from other UDRIVE deliverables as the dataset was still growing at the time of writing the deliverables.) Depending on the exact research question, the analyses were conducted on a part of the database that fulfilled the selection criteria, e.g. right turning manoeuvres, straight sections, urban areas, et cetera. The next three sections briefly summarize the main findings with respect to pedestrians, cyclists and PTWs as based on the UDRIVE database analyses.

Interactions with cyclists

The analyses of the cyclist data looked at interactions between cyclists and both passenger cars and trucks.

Safety critical events in interaction

First, we investigated which behavioural and situational factors contributed to the occurrence of what was called Safety Critical Events (SCEs) in these interactions, i.e. to real or near-crashes. A near-crash was defined as a situation which was not planned and required an immediate, urgent evasive manoeuvre by at least one of the conflict partners to avoid a crash. The analysis was based on just over 13,200 hours of car data from 125 drivers collected in Germany, Great Britain, France, Poland, and the Netherlands, and on around 6,000 hours of truck data from 41 drivers collected in the Netherlands.

The analysis of the car/truck-cyclist interactions revealed very few SCEs. Overall 11 SCEs were identified: three in interactions with a car, and eight in interaction with a truck. All were near crashes; no actual crashes have been found in the database. All SCEs took place on urban roads with a speed limit of 50 km/h or less. An explanation could be that there are less encounters between cyclists and motorised vehicles on higher speed roads. Given the small number of SCEs only a qualitative analysis was conducted. That indicated that the identified SCEs were caused by a combination of features of the infrastructure (a curve or a too narrow road), features of the manoeuvre (often overtaking), the presence of other traffic, and an error or unexpected behaviour of the cyclist (slowing down). Drivers didn't seem to make any judgment or performance errors in the observed SCEs. None of the drivers were involved in a secondary task or exceeded the speed limit when they started their evasive manoeuvre and nearly all drivers avoided a collision by further decreasing their speed.

Interactions at intersections and roundabouts

We then zoomed in on a specific type of interaction between vehicle drivers and cyclists, notably interactions on intersections and roundabouts. A first analysis looked at the looking behaviour of car drivers who turned right (left in the UK) passing the path of a (potential) cyclist who wants to go straight through the intersection. This is the typical scenario of a blind-spot crash. The final dataset consisted of 961 intersection manoeuvres by 69 drivers from France, the Netherlands, Poland, and United Kingdom. Furthermore, there were 826 roundabout manoeuvres by 46 drivers from France, the Netherlands, and United Kingdom. Approximately half of the data stem from the United Kingdom, due to it being available early in the project. The results show that on average car drivers actively check the blind spot, i.e. by looking over their shoulder, in around 8% of the cases at intersections and around 4.5% of the cases at roundabouts. Car drivers mostly (between 65 and 95% of the cases) looked in the direction of the road into which they intended to turn, followed by the directions 'elsewhere' and 'sidewalk'. Checking the 'blind spot' was done least often. There was a large difference between the investigated countries. On average, at intersections, Dutch car drivers checked their blind spot 6 times more often than drivers in the other three countries (in 27% of the cases), and at roundabouts they did so 21 times more often (in 19% of the cases). The most logical explanation for this difference is that in the Netherlands the prevalence of cyclists and bicycle lanes is higher.

A second analysis of the interactions at intersections and roundabouts focused on the looking behaviour of truck drivers. For this analysis the final dataset consisted of 159 right turn manoeuvres by 10 truck drivers and 209 roundabout manoeuvres by largely the same 10 truck drivers. All of the drivers were Dutch, driving in the Netherlands. On average, truck drivers were observed to check the blind spot in 19% of the cases at intersections and in 27% of the cases at roundabouts. Compared to Dutch car drivers, these Dutch truck drivers checked their blind spot somewhat less often at intersections, and somewhat more often at roundabouts. It should be noted, however, that some of the trucks may have had in-vehicle camera information about the situation in the blind spot, and hence they had no need to turn their head or make large eye movements.

Overtaking manoeuvres

Finally, we had a look at car-cyclist interactions during overtaking manoeuvres. A total of 147 overtaking manoeuvres were analysed. These were manoeuvres by 41 car drivers from France, Germany, Poland and United Kingdom, and concerned rural roads only. It was found that on average overtaking manoeuvres took 9.3s (± 3.5s) and the car speed during overtaking was 61km/h (± 15km/h).

A distinction was made between 'flying' overtaking and 'accelerating' overtaking. It is called a flying overtaking manoeuvre when the speed of the overtaking vehicle speed remains more or less constant before and during the overtaking. It is called an accelerating overtaking manoeuvre when the overtaking vehicle first stays behind the cyclist and then starts overtaking by increasing its speed. Around 70% of the overtaking manoeuvres was found to be 'flying', apart from Poland, where around 50% of the overtaking manoeuvres was 'flying'.

The main variable of interest in this analysis was the lateral distance between the car and the bicycle, during the actual overtaking manoeuvre. On average the lateral distance was 1.65m (± 0.64m). This is close to the lateral distance of 1.5m that most European countries require by law for overtaking. There were several factors, however, that affected the actual lateral distance. Lateral distances were larger when the speed of the car was higher, when the speed of the cyclist was higher, and when the overtaking vehicle was following another vehicle. Lateral distances were found to be smaller when the cyclist was positioned further away from the edge of the road (towards the centre of the road), when (in case of a flying overtaking manoeuvre) the car driver was a woman, and (in case of accelerative overtaking manoeuvres) when there was an oncoming vehicles.

Interactions with pedestrians

For detecting interactions between cars and pedestrians, the cars were equipped with a Mobileye system. This system provides continuous measures of the distance of the car to 'objects' around the car, including pedestrians, calculating, for example, the expected time-to-collision. A detailed analysis of the car-pedestrians interactions was based on car data from Great Britain and France. It could be concluded that the real dangerous interactions (real or expected conflicts) were associated with higher car speeds than less dangerous interactions, and required more severe braking. Just over 400 conflicts were identified using a collision warning signal that was switched off for participants, but available to the researchers. The conflicts could be clustered into four subgroups linked to the car's speed profile.

1. Conflicts that involved the highest speed group mainly concerned a situation in which the pedestrian (still) was on the pavement.
2. Conflicts that involved a group of car drivers that had just increased their speed before the conflict occurred; again generally a conflict conflicts in which with a pedestrian was who (still) was on the pavement.
3. Conflicts in which the high speed drivers probably had noticed the potential conflict well in advance, and had reduced speed to avoid a collision.
4. Conflicts in which the car driver had not reduced speed until very late, seemingly because he had not at all noticed the pedestrian. This group of potential conflicts contained the highest percentage of real conflicts (SCEs).

As indicated, the current study used the Mobileye system as a means to identify interactions with pedestrians. Originally, however, this system is meant to be an in-vehicle system that warns drivers when they approach a pedestrian. Based on the UDRIVE data it was investigated whether this system, if used as a warning device, would indeed be able to provide the correct and relevant information to the driver. It was concluded that in some cases an early alert as provided by Mobileye may be potentially beneficial for preventing a conflict to turn into a real collision. Analysis of the videos showed that the large majority of (expected) conflicts as identified by the system were indeed (potential) conflicts. Hence, the system is good and relevant for detecting potential conflicts with pedestrians. In around three quarters of these situations, the driver him/herself had spotted the pedestrian in time. In the still substantial share of remaining situations, a warning system could have been of help. A warning system can be expected less useful in conditions with relativly many pedestrians. In those cases car drivers appeared to be already more alert to pedestrians' presence and potential conflicts.

Interactions with PTWs

Where information about pedestrians and cyclists was inferred from the data collected by the instrumented cars and trucks, the information about the powered two-wheelers (PTWs) also comes from instrumenting the PTWs themselves, i.e. from Naturalistic Riding. The work on PTWs looked at the possibilities and challenges of identifying conflicts or safety critical events. Furthermore, it looked at characteristics of everyday riding with a special focus on speed choice and acceleration at urban intersections, and on the distance (time headway) between cars and PTWs on straight road sections.

The identification of safety critical events

Obviously, PTWs have their own very specific dynamics, posing specific requirements to the data collection equipment and to the interpretation of the collected data. Some of the previous attempts with Naturalistic Riding showed that one of the challenges is the identification of safety critical events (SCEs). In our study SCEs were identified by looking at a set of kinematics-related variables (including longitudinal acceleration, lateral acceleration, vertical acceleration, rotation speed) and identifying the extremes or outliers: the high-g events. For these events, the video material was studied to assess if there had actually been an SCE and in case it had, to identify the circumstances related to rider, other traffic and infrastructure.

Analyses were based on 497 hours of data (equalling 13.654 kilometres driven) from 39 riders in Spain. A total of almost 1,300 potentially relevant events were identified based on the motion-related variables. Because only around 70% of the video registrations were usable, around 500 events could be checked based on video registration. The vast majority of the identified events appeared to be related to a non-safety relevant manoeuvre, such as a speed bump, a tight curve, starting from or braking to a stand-still, entering or leaving a parking lot, etc. In other words there were a large amount of ‘false alarms’. Only two safety relevant events were identified based on these high-g events. One was based on an extreme longitudinal acceleration (harsh braking) in a one directional dual lane situation where the view off a pedestrian who started to cross at a zebra crossing was blocked by vehicles in the other lane. The other was based on extreme lateral acceleration (swerving) due to a passenger car entering from a side road into the path of the motor rider. Obviously, based on this approach it is unknown how many SCEs were missed. Situations in which it is the other road user who takes evasive actions rather than the motor rider who might not even have perceived the potential hazard, will never be identified based on g-forces from the motor cycle.

Characteristics of everyday riding behaviour

This analysis focused on speed choice and acceleration by PTW riders in four common urban intersection scenarios: free flow followed by a right turn, free flow followed by a left turn, full stop followed by a left turn, and full stop followed by a right turn. The analysis was based on 7350 manoeuvres by 32 riders, where each rider featured at least 10 manoeuvres in at least one of the above scenarios.

There are two main findings in this study. First, significant differences have been found between the scenarios. Pair-wise comparisons showed that most scenarios were significantly different from each other on all measures, these being speed at the manoeuvre onset, speed at the manoeuvre offset, average speed, maximum speed, minimum speed, acceleration at the manoeuvre onset, average positive and negative acceleration, and maximum positive and negative acceleration.

The second main finding concerns a comparison between riders. Across riders significant differences have been found in speed choice and acceleration during manoeuvres, as well as in the time window surrounding full stops prior to the manoeuvres. Furthermore, riders appear to use a constant deceleration in the five seconds preceeding a full stop, but the magnitude of this deceleration varies across riders. These findings suggest that riders have different preferences (i.e., riding styles) regarding speed choice and acceleration.

If such preferences indeed exist, they may inform the development of intelligent warning systems on what is ‘normal’ and ‘abnormal’ riding behaviour. Furthermore, the existence of preferences warrants further research on whether groups of riders share similar preferences. This could be done with a bottom-up, or data-driven, approach (e.g., cluster analysis), or through a top-down approach (e.g., with behavioural questionnaires).

Time headway between cars and PTWs

This analysis focused on the time headway, i.e. the following distance expressed in seconds, on straight sections of roads between cars and PTWs in comparison to the time headway between two cars and between cars and trucks. For this analysis the starting point was the car. Data came from 140 car drivers from France, Germany, Netherlands, Poland and the United Kingdom who together had driven almost 650,000 km and waswhich were searched to identify relevant interactions. Final analyses included over one hundred million situations where the car was behind another car, over 6 million situations where the car was behind a truck and almost 370,000 situations where the car was behind a PTW. Different road types with different speed profiles were included in the analysis.

Overall, the time headways for following another car, a truck or a PTW were very similar. At lower driving speeds (< 50km/h) the average time headways were around 1.7s, at medium speeds (60 - 80km/h) the average time headways varied somewhat between 1.4 and 1.6s. At speed over 80km/h the time headway in car-car situations remained around 1.4s, but the time headway in car-truck situations tended to increase again to around 1.7s. Whereas the general picture showed very similar time headways for the different vehicle combinations there are two exceptions worth mentioning: cars followed trucks slightly closer than they followed other cars and PTWs, and at medium speed cars followed PTWs at a slightly longer distance than cars or trucks. There were hardly any differences between the five countries in the choice of time headway. We just saw that the German car drivers seemed to keep somewhat more distance behind trucks at medium speed, and the French car drivers seemed to keep somewhat less distance to other cars. Distances to PTWs were very comparable between countries. All together the data did not show that car drivers tend to follow PTWs closer than cars or trucks. There was even an indication that car drivers followed at some larger distance.

Conclusion

Overall it can be concluded that Naturalistic Driving is a very interesting method to collect in-depth and valid insights in road user behaviour. Compared to previous large Naturalistic Driving studies (e.g., 100 Cars, SHRP2), UDRIVE has a unique focus by including interactions with vulnerable road users, both from the perspective of car and truck drivers, as well as from the perspective of powered two-wheelers. Rather than focusing exclusively on crashes, the interactions with vulnerable road users have been studied at varying levels of criticality, ranging from Safety Critical Events and blind spot checks to overtaking manoeuvres and everyday riding. The findings have given rise to recommendations on vehicle safety, for awareness campaigns and training, and on the design of road infrastructure. It is our hope that the recommendations, once implemented, will improve the safety of vulnerable road users, and in this way contribute to the EU target of halving the number of road deaths by 2020.

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1 Introduction

1.1 This work in the UDRIVE project

This technical report (public deliverable) from the UDRIVE project presents the analysis performed in that project with respect to *Vulnerable Road Users* (VRU). UDRIVE is a naturalistic driving study (NDS) – the largest to date in Europe. An NDS is a study where data are collected unobtrusively in drivers' vehicles as they go about their everyday lives over longer periods of time (Bärgman, 2016). UDRIVE is a 4.5 year project (ending June 2017) funded by the European Commission (FP7), and the individual partners in the project. This report has been written as part of work package 4.4 (*WP4.4 Vulnerable road users* - hereafter vulnerable road user will be called VRU) in the sub-project called *SP4 Data analysis*, and is the main deliverable and dissemination of WP4.4 from the UDRIVE project. WP4.4 is further divided into two main analysis tasks: 4.4.2 Analysis of drivers interacting with cyclists and pedestrians and 4.4.3 Analysis of PTWs behaviour and interactions with other vehicles. The studies in WP4.4 have been performed in relation to different levels of criticality (see Figure 1.1), from everyday driving to the study of critical events. This report describes those studies, grouped in terms of interactions with cyclists, interactions with pedestrians, and interactions with PTWs.

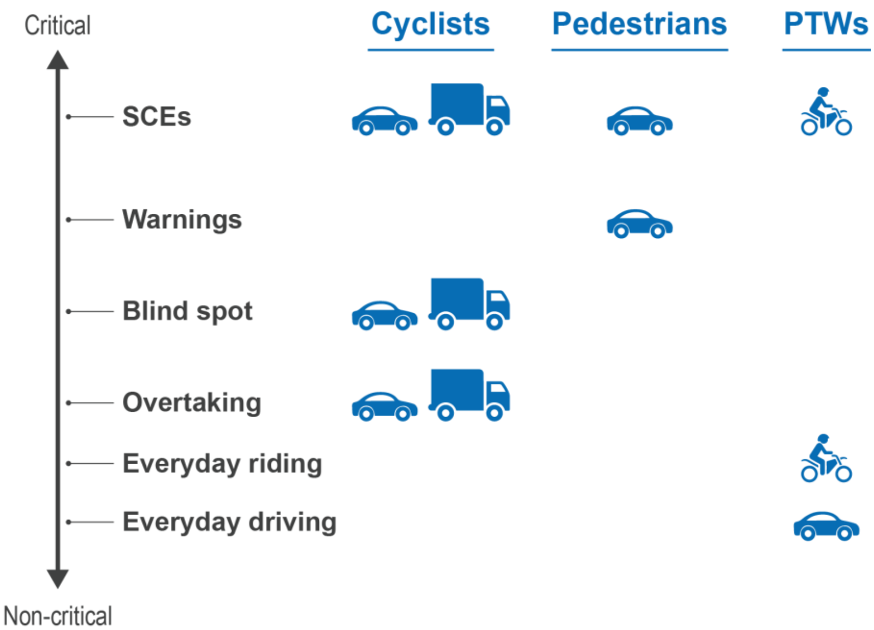

Figure 1.1: Studies on interactions with cyclists, pedestrians, and powered two-wheelers (PTWs), ordered according to criticality of the interaction. Icons correspond with the perspective from which the data have been obtained (i.e., instrumented cars, trucks, or PTWs).

1.2 Background

In today's Europe the number of road fatalities is steadily decreasing (European Commission, 2016. For vulnerable road users, however, the trend is not the same (European Commission, 2017). While traffic safety for pedestrians, and riders of bicyclists and PTW are important to the society, designers of infrastructure, legislation, and policies, as well as designers of safety systems in vehicles are lacking detailed information (e.g., due to lack of registrations, Methorst et al., 2016) about the interactions between cars/trucks and VRUs from the real worlds. With the advent of naturalistic driving studies (Dingus et al., 2006; Campbell, 2012), the behaviours of both drivers and VRUs can be studied in detail, and even the detailed unfolding of critical events can be studied to provide additional information for designers of measures to reduce injuries and fatalities on our roads, and meet the EU target (European Commission, 2010). In UDRIVE we have studied bicyclists, pedestrians and PTWs.

1.2.1 Bicyclists

Using a bicycle is a relatively risky mode of transportation, given that you as a rider do not enjoy the level of protection that the modern restraint and protective systems in for example cars and trucks experience, while bicyclists travel on roads where interactions occur with metal beasts (cars and trucks) at relatively high speed. Across Europe, 10-15 % of all urban fatalities are bicyclists – a relative increase in recent years (Dozza, Schwab, and Wegman, 2017). The registration of traffic fatalities has generally been better than the registration of serious traffic injuries, but both types of registrations are flawed, especially when bicyclists are not registered as a separate category in some EU countries (Methorst et al., 2016). In the Netherlands – where the registration of serious injuries has not been very reliable since 2009 – the total number of serious road injuries has increased by 3% each year between 2006 and 2015. However, serious injuries among bicyclists have increased yearly by 5% (for crashes involving motor vehicles) and 7% (for crashes not involving motor vehicles) over the same period, while serious injuries among car occupants showed a yearly decrease of 2,5% (Korving et al., 2016). The aforementioned figures illustrate the worrisome position of cyclists on European roads.

Analysing bicyclist safety with naturalistic driving studies is relatively new, and rare. Some studies have investigated the interaction between cars/trucks and bicyclist in a naturalistic setting, but from the bicyclists perspective (Dozza & Werneke, 2014). Studies of bicyclists in NDD collected from cars and trucks is even rarer, partially due to the lack of information on when interactions occur in the vast datasets collected in NDS, such as SHRP2 (Campbell, 2012). One form of naturalistic studies that have been performed to target bicyclist and car interactions is the use of site-based data collection (Van Nes et al., 2013). However, such studies partly lack the information about the drivers' behaviour. An advantage of naturalistic driving studies is the possibility to measure behaviour in more detail. In UDRIVE we have aimed at studying the interaction between bicyclists and car/trucks, with particular focus on vehicle/bike interactions in case the vehicle turns right, and with the behaviour of the driver at the forefront.

1.2.2 Pedestrians

Similar to bicyclists, pedestrians do not have a protective shield like car and truck occupants have. Due to their vulnerability, pedestrians face a high risk of injury or even death when in a crash (Shinar, 2007). There are few naturalistic driving studies that study the safety of pedestrians. Those that exist typically study event-based NDD (Habibovic et al., 2013). In UDRIVE we focus on the interaction between pedestrians and cars/trucks, from descriptive statistics of driver behaviour in everyday driving, to qualitative analysis of safety critical events.

1.2.3 Powered two-wheelers (PTWs)

Powered Two-Wheelers (PTW) are an extremely diverse group of vehicles. Shortly after World-War Two, there were many transport vehicles built based on motorcycles. At that time, the PTW was the most common means of individual motorised traffic. Not surprisingly, Europeans were keen of having safer and weather-protected vehicles. PTW manufacturers tried to keep their customers satisfied and started with building car-like vehicles derived from motorcycles. Therefore, today PTW designs include cruisers, choppers, enduros, super-motos, tourings, sports and super-sports bikes, and manufacturers keep on creating new categories. Except for a small minority of motorcycles (e.g. Honda Gold Wing with an airbag), there are no passive safety systems on PTWs. Passive safety is limited to the personal protective equipment of the rider.

Naturalistic driving studies that study PTW are more numerous than such studies performed to investigate bicyclist and cyclists, but it is still a rare type of study. Recent NDS on PTWs include the 100 Motorcyclists Naturalistic Study (Williams et al., 2015). PTW-related research always has to consider the particularities of both riders and vehicles. In some regions a large share of riding is done just for the sake of it (e.g. Austria: 75% according to Winkelbauer & Schwaighofer, 2012), while PTWs are a natural means of transportation in some regions. In UDRIVE we have studied the PTW type classified as scooter used in an area (Spain) where it is primarily used as a means of transport (Marquet & Miralles-Guasch, 2016). The analysis of PTWs in UDRIVE included descriptive statistics and identifying safety critical events.

1.3 General methodology

Each analysis has a specific sample, of a specific type of instrumented vehicle type (car, truck, PTW), in specific situations. These specifics are described in the corresponding sections. However, there are also some commonalities across the analyses, which are described here.

1.3.1 Global sample characteristics

The acquisition of data started (the first instrumented vehicle on-road with a study participant) in October 2015. By April 2017, 42724 hours of Naturalistic Driving Data (NDD) were collected from 186 car drivers in France (N=43), Germany (N=27), Poland (N=31), the Netherlands (N=33), and Great Britain (N=52). Furthermore, 41397 hours of NDD were collected from 48 Dutch truck drivers, and 859 hours of NDD were collected from 47 riders of Powered Two-Wheelers (PTW) in Spain. The last de-installation of data acquisition systems in the UDRIVE study-vehicle is planned for May 2017. For more information on the sample, see deliverable UDRIVE D33.1 - Overview of OS preparation, sample characteristics and piloting. Note that these sample statistics may differ slightly from other deliverables as, at the time of writing this report and generating these statistics, data are still being added to the UDRIVE database.

For practical reasons, some of the analyses were conducted on just a part of the database. For example, the UK data became available earlier in the central database than the NL and GER data. In each of the analyses the corresponding sample will be further described.

1.3.2 Vehicles

Three types of instrumented vehicles have been used. Instrumented cars have been used in France, Germany, the Netherlands, Poland, and Great Britain. The participants drove either in a Renault Clio III, a Renault Clio IV, or a Renault Mégane III. All vehicles were owned by the participants, except in the Netherlands. Dutch drivers drove in a leased Renault Clio IV which was provided to them free-of-charge while they participated in the study. Instrumented trucks have been used in the Netherlands. Truck drivers were recruited at four Dutch transport companies. Volvo FL and Volvo FM trucks were used, which are small and medium size delivery trucks. Finally, instrumented powered two-wheelers, 125 CC motorscooters, have been used in Spain.

1.3.3 Data Acquisition System

This section provides a brief overview of the Data Acquisition System (DAS) with which the UDRIVE data have been collected (for more information, consult UDRIVE deliverable "D21.1: Technical DAS requirements").

Cars

A DAS was installed, which registered, amongst others, seven camera views (i.e., front left, front center, front right, cabin view, cockpit view, driver face, pedals), CAN bus data (e.g., vehicle speed), and GPS position information. The GPS data were enriched with a map matching procedure, yielding information on the presence of intersections and roundabouts, local speed limits, locality type (e.g., urban, rural), as well as heading direction (i.e., a value between 0 and 360 degrees).

Furthermore, the DAS recorded continuous signals from a Mobileye smart camera, including the presence of other road users (cyclists, cars and pedestrians) and the distance between the car and the other road users. This camera offers the opportunity to find events wherein a cyclist is present, as an efficient alternative to observing all video data. Furthermore, the 'pedestrian collision warning' (PCW) given by the Mobileye serves as an indication of an imminent conflict with a pedestrian or cyclist. Within UDRIVE, this warning is only visible to the researchers, not to the drivers themselves. The Mobileye version that was implemented in UDRIVE is operational only in day-light.

Recording started and ended when the car key was switched. Only trips in which the driver was known to have signed informed consent have been included in the project database.

Trucks

The truck DAS was identical to the Car DAS, except for the number and type of camera views. Eight camera views were used, these being front left, front center, front right, blind spot left, blind spot right, cabin view, driver face, and a pedal view.

Powered Two-Wheelers

The PTW DAS featured 5 camera views: front left, front center, front right, driver face, and a rear view. No CAN data were collected, nor was a Mobileye installed. Other than that, the PTW DAS was identical to the Car DAS.

1.3.4 Data analysis

The analyses in this report are related to parts of trips in which specific VRU interactions occurred. To obtain these parts, often referred to as 'data segments' or 'segments', a Matlab-based tool named 'Salsa' has been developed (see UDRIVE deliverable "D24.1: Description of the analysis tools framework"). The tool synchronizes and visualizes sensor and video data signals, thereby facilitating analysts in programming Matlab scripts to identify segments. These scripts will be described in more detail in the subsequent chapters.

1.3.5 The role of manual annotation of video

Much of the analyses documented in this report have required manual annotations of videos to provide information about both the driver behaviour and the traffic context. Such annotations have been performed at four annotation sites, and been divided into separate types of annotations. For example, three of the sites (UDRIVE partners: TUC, SAFER and Leeds) have jointly worked on the identification and verification of which driver was driving in each individual record of data. The main annotation site (TUC) further performed manual annotations of video related to pedestrian interactions. The fourth annotation site (SWOV) did all video annotations related to the interaction of cars and trucks with bicyclists. The descriptions of annotations related to the pedestrians and bicyclists are provided in each section of this deliverables, and the actual annotation schemas are provided as appendices.

1.4 Report structure

The objective of this work package (WP4.4) has been to investigate some key research questions relating to VRUs (i.e. pedestrians, cyclists and Powered Two Wheelers (PTWs)). The key research questions are outlined in Table 1.1. Further information on the background of these questions can be found in the corresponding sections.

Table 1.1: The main research questions across this technical report/deliverable.

Chapter	Related to task #	Lead partner	Research questions	Interaction with Cyc.	Interaction with Ped.	Interaction with PTWs
2	4.4.2	SWOV	What are the contributory factors to critical events and accidents involving cars and trucks versus bicycles?	X		
3	4.4.2	SWOV	Which factors influence whether car drivers perform a shoulder check before a right turn (UK: left turn) on an urban intersection, or before an exit manoeuvre at an urban roundabout?	X		
4	4.4.2	SAFER	When do car drivers cast their last sideway glance towards a potential cyclist to the right before they enter the encroachment zone in a right turn (UK: left turn) manoeuvre in an urban intersection? Which factors influence the timing of such glance behaviour?	X		
5	4.4.2	SWOV	Which factors influence whether truck drivers perform a shoulder check before a right turn on an urban intersection, or before an exit manoeuvre at an urban roundabout?	X		
6	4.4.2	SAFER	Which factors influence the lateral distance when a car starts to overtake and passes a cyclist?	X		
7	4.4.2	Or Yarok	What characterises conflicts involving motorised traffic and pedestrians?		X	
7	4.4.2	Or Yarok	How do car drivers behave in the presence of pedestrians?		X	
8	4.4.2	Or Yarok	Does an ADAS with pedestrian detection capabilities have the potential to reduce the risk associated with driver-pedestrian conflicts?		X	
9	4.4.3	KFV	Which circumstances related to rider, infrastructure and trip have an impact on the occurrence of safety critical events?			X
10	4.4.3	SWOV	What characterises riding speed and g-forces of motorscooter riders in common traffic scenarios at urban intersections?			X
11	4.4.3	KFV	Do car drivers keep PTW riders at a different distance then other motorized traffic on straight road sections, and does rider conspicuity play a role in this difference?			X

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Part I: Interactions with cyclists

2 Safety critical events involving cyclists

2.1 Introduction

Cyclists are vulnerable road users because of their high risk for injury when they are involved in a crash (ETSC, 2012). When they collide with a motorised vehicle this likely has severe consequences for the cyclist. In 2014 in Europe 2.112 people riding a bicycle were killed in road accidents (European Commission, 2016). The Netherlands has the highest percentage of cyclist fatalities, 25% of all road fatalities were cyclists in 2014, followed by Denmark with 16% and Hungary with 16%. Even though the number of cyclist fatalities in Europe has decreased over the years, the overall percentage of cyclist fatalities of all road fatalities increased from 7% in 2005 to 8% in 2014. The following findings on cyclist fatalities in 2014 in Europe give some insight into the environmental characteristics of the fatal event:

- Although there are large differences between countries, on average 55% of cyclist fatalities occurred in urban areas. On average 27% fatalities occurred at intersections or roundabouts.
- Most fatalities occur during the day, between 8:00 and 20:00. On average 26% of cyclist fatalities occurred when it was dark or twilight.
- The incidence of cyclist fatalities is higher in summer than in winter. This is likely due to a higher number of cyclists in summer compared to winter.

In a study by Safetynet (2008) 91 cyclist crashes, involving all injury severities, were analysed in order to identify the cause of the accident. These events consisted of crashes with other cyclists and drivers in Germany, Italy, the Netherlands, Finland, Sweden and the UK between 2005 and 2008. Their analysis showed that either the cyclist and/or the driver initiated a manoeuvre too early or initiated no action Cyclists often cycled in an incorrect direction. Other critical factors that happened before the collision was that the anticipated manoeuvre wasn't taken in time or continued for too long, an action wasn't taken or too late, the driven speed was too fast or a drive exhibited excess acceleration or braking. A different study (Habibovic & Davidsson, 2011) analysed 9702 crashes between cars and vulnerable road users. This study showed that the most frequent contributing factor to crashes was the driver not noticing the vulnerable road user because of reduced visibility (due to physical obstructions, weather, and/or light conditions), reduced awareness, and/or insufficient comprehension. In these studies databases based on police reports on crashes have been analysed. Naturalistic driving studies into safety critical events (i.e. crashes or near-crashes) with cyclists would provide additional insight into what factors contribute to crashes. The naturalistic driving method wherein the actual behaviour of drivers and cyclists can be observed, because the behaviour is recorded on video, presents the opportunity to actually see what happens before a crash.

A naturalistic cycling study by Schleintz et al. (2015), using instrumented bicycles, recorded more than 1600 trips, 400 hours of cycling by 32 cyclists in Germany. The goal of their study was to identify and describe safety critical events between cyclists and other road users, with a specific interest into conflict partners and the type of infrastructure. Safety critical events were defined as "situations (including crashes) that require a sudden, evasive manoeuvre to avoid a crash or to correct for unsafe acts performed by the driver himself/herself or by other road users". 77 safety critical events were found. Safety incident rate (SIR) was calculated as the number of safety critical events per 100 kilometres cycled for the different infrastructure types. For roads without bicycle infrastructure the SIR was 0.89, for roads with bicycle infrastructure the SIR was 2.06 and for cycling on the pavement SIR was 2.29. Participant cycled most of the time on roads without bicycle infrastructure (53.6%) compared to roads with bicycle infrastructure (24.3%) and the pavement (10.4%). Motorised vehicles were the most frequent conflict partners, in 43% of the events (21 % other cyclists, 29% pedestrians). Their findings based on the video data show that SCEs with motorised vehicles are most often caused by drivers not giving right of way to the cyclist, for example by turning right and not checking for cyclists.

A large naturalistic driving study in the United States (SHRP2) has investigated driver crash risk factors and the prevalence of these factors (Dingus et al., 2016). This study captured naturalistic driving data from 3500 participants, resulting into more than 56 million kilometres of driving data. They analysed a dataset including 905 injurious and property damaging crash events for factors contributing to crash causation. Their focus was on observable impairment of the driver, driver performance error, driver judgement error and observable driver distraction. Prevalence of behaviour was determined by baseline driving to get insight into how often behaviour generally occurs. The results show that driver-related factors are present in almost 90% of the crashes. The study shows the following results:

- Drug/alcohol impairment and drivers being emotional increases crash risk, though occurrence is low. Drowsiness and fatigue only increased crash risk for certain drivers, but not in general. Driver performance error like failing to signal, driving too slowly or making an improper turn increases crash risk greatly but most errors are not occurring often.
- Driver judgment error includes speeding well above the speed limit or inappropriately for the situation, aggressive driving like following too closely. Prevalence of occurrence is relatively high and judgment errors increases crash risk.
- Distraction is detrimental to driver safety; in 68% of the crashes a driver was visibly distracted. Drivers being engaged in potentially distracting activities during 52% of their baseline driving, indicates that distraction is occurring often. These findings suggest that distraction is the most important contributing factor to crashes.

2.1.1 Objective of the present study

The described studies give insight into cyclist fatalities in Europe, the cause of cyclist fatalities, safety critical events from a cyclist's perspective and the causation of crashes by car drivers. Since cyclists are so vulnerable in traffic and car-cyclist crashes are occurring often and result in serious injury or fatality for the cyclist, cyclist safety is an important issue to investigate.

Therefore, the objective of this study is to investigate the contributing factors to safety critical events (crashes and near crashes) between car and truck drivers with cyclists in Europe. Possible contributing factors are investigated; these consist drivers' behavior, cyclists' behavior, weather, distraction and impairment, infrastructure, visual obstruction, precipitating event, speed and reaction time and driver error.

This study is the first European study wherein safety critical events between drivers and cyclists in a naturalistic driving setting from the perspective of the driver are investigated. A naturalistic driving approach offers the opportunity to get additional insights in the causation of crashes since real life driving behaviour can be analysed. These insights can be used for improving policy, education and awareness, vehicle design and road infrastructure regarding cyclist safety.

2.2 Method

2.2.1 Database and instrumentation

Participants were car and truck drivers recruited for the UDRIVE-project. A selection of these drivers was included for this study, as not all driver data were available for analysis yet in March 2017. At this time 6000 hours of truck data by 41 drivers from the Netherlands was present in the database, and 13200 hours of car data by 125 drivers from Germany, Great Britain, France, Poland, and the Netherlands.

2.2.2 Event selection

The aim in this study was to select events in the data wherein a safety critical event (i.e. crash or near-crash) with a cyclist had happened. To do so the triggers time to collision (TTC), headway time, pedestrian collision warning (PCW), and lateral and longitudinal acceleration were looked at (for specifications of the trigger values, see UDRIVE deliverable D42.1: "Everyday and risky driving". Except for the PCWs, these triggers are often used in instrumented-vehicle studies to identify safety-relevant events (Guo et al., 2010). The first three triggers were generated by or based on data from the Mobileye, and acceleration triggers was based on CAN bus data. The triggers were augmented with a label that specified the type of the closest road user (e.g., car, pedestrian, cyclist) at the onset of the trigger Only triggers where the road user type was 'cyclist' were considered for further examination. .

At the time of retrieving the segments no time to collision events were found in which a cyclist was present. Further explorative analysis, by checking segments that were selected based on a trigger, showed that pedestrian collision warnings provided the highest chance for finding safety critical events. The other triggers may not be a good predictor for safety critical events in this study since the focus is on safety critical events between drivers and cyclists, instead of safety critical events between two cars.

All of the PCW warnings were used as a trigger to look at the video data. Annotators were instructed to search for safety critical events in close temporal proximity to the onset of the PCW. The PCW was used as an initial search area. When a safety critical event was found, annotators analysed the event within a time window of -15 sec to +5 sec relative to observed/perceptual onset of the safety critical event.

2.2.3 Data sample

The data set based on the PCW triggers included 64 triggers for the truck data and 41 triggers for the car data. In Table 2.1 information is given about the data sample.

Table 2.1 Data sample based on the Pedestrian Collision Warning (PCW) trigger

	Cars	Trucks
Number of PCW triggers	41	64
Maximum speed at onset PCW	47.0 km/h	48.1 km/h
Minimum speed at onset PCW	3.1 km/h	11.2 km/h
Maximum distance cyclist	22.9 m	36.0 m

2.2.4 Annotation

Four trained annotators viewed and annotated the data. They were given training on how to determine whether a SCE was present and on the variables that had to be annotated. A codebook defined the variables that annotators had to record. This was based on the general codebook used for UDRIVE. A list of the variables used for this analysis can be found in appendix A. Some adjustments were made to the codebook, these adjustments are described in appendix A as well.

The training for the annotation consisted of an explanation of the project and of the codebook used for annotation. To train the annotators thoroughly they were all given PCW triggers for cars and for trucks and were asked to annotate all interactions in the video with the subject vehicle within the specified time frame. All annotators were given the same triggers, so inter-rater reliability could be calculated using Krippendorf's alpha and percent agreement. Based on the inter-rater reliability results a plenary discussion was held with the annotators about their views on how to annotate interactions and safety critical events to make sure everybody interpreted safety critical events in the same way.

SALSA (i.e. analysis and visualization tool developed within UDRIVE) was used for viewing video clips and selecting and showing triggers. Annotators would select a predefined PCW trigger and see the video belonging to that trip. They could see the trigger in the data and analyse the video images, speed and braking behaviour in the selected time window. Results were recorded in spread sheets.

2.2.5 Definition of a safety critical event

The focus of this study was on safety critical events between the subject driver and a cyclist. In this study safety critical events include crashes and near-crashes. Annotators identified whether a situation was a safety critical event, using the definitions as formulated in the central project codebook (see deliverable D41.1: “UDRIVE Synthesis of results”).

The definition of a crash is as follows:

> A crash is any contact that the subject vehicle has with another conflict partner, either moving or fixed, at any speed that is observable or in which kinetic energy is measurably transferred or dissipated. This excludes roadway features meant to be driven over such as speed bumps. Crashes must meet the following two criteria:
>
> 1. Impact. The vehicle must make contact with another conflict partner and/or the manoeuvre must result in some degree of road departure.
>
> 2. Not premeditated (i.e., not planned). The manoeuvre(s) performed by at least one conflict partner must not be premeditated (planned). This criterion does not rule out crashes caused by unexpected events experienced during a premeditated manoeuvre (e.g., a premeditated aggressive lane change resulting in a crash with an unseen or faster-than-expected vehicle in the adjacent lane).

The definition of a near-crash is as follows:

> A near-crash is any circumstance that requires a rapid evasive manoeuvre by at least one conflict partner to avoid a crash. Near-crashes must meet the following four criteria:
>
> 1. No impact. The subject vehicle must not make contact with any other conflict partner, and the manoeuvre must not result in a road departure.
>
> 2. Not premeditated (i.e., not planned). The manoeuvre(s) performed by at least one conflict partner must not be premeditated (planned). This criterion does not rule out near-crashes caused by unexpected events experienced during a premeditated manoeuvre (e.g., a premeditated aggressive lane change resulting in a conflict with an unseen vehicle in the adjacent lane that requires a rapid evasive manoeuvre by one of the vehicles).
>
> 3. Evasive manoeuvre is required. An evasive manoeuvre to avoid a crash was required by at least one conflict partner. An evasive manoeuvre is any action performed to avoid a potential collision by changing the trajectory or speed, such as steering, braking, accelerating, running, or stopping.
>
> 4. Urgent response required. The required evasive manoeuvre must also require an urgent response given the amount of time from the beginning of the subject’s reaction and the potential time of impact. A manoeuvre has to be performed differently than usually.

2.3 Results

Due to the limited amount of safety critical events results are qualitatively analysed. Results are therefore explorative and haven’t been subjected to statistical tests.

2.3.1 Participant sample

Pedestrian Collision Warnings (PCW) were used to look through the video data to identify safety critical events (crashes and near-crashes). 57 out of 64 trips that had a PCW trigger were valid for annotation for truck drivers, meaning that they had a cyclist present around the onset of the PCW trigger and had sufficient video quality for annotation. For car drivers this was 36 video’s out of 41. In Table 3.2 an overview is given of the participant/data sample.

Table 2.2: An overview of participants and data sample

	Cars	Trucks
Valid video's	36	57
Number of SCE's	3	8
Number of participants	27	13
% Dutch drivers	19	100
% UK drivers	37	-
% French drivers	37	-
% Polish drivers	7	-

2.3.2 Safety critical events for cyclists and cars

Three safety critical events with cyclists were identified between the subject vehicle, a car driver and a cyclist. All of these events were labelled as near-crashes by the annotators according to the definition stated in 2.2.5. No crashes were found in this data selection. All three conflicts involved a cyclist and the subject vehicle on a collision course. An urgent evasive manoeuvre was required by the subject vehicle to avoid a collision.

A qualitative description per safety critical event is given in Table 2.3. In Table 2.4 the findings are summarised and an overview is given of the qualitative results.

Table 2.3: Qualitative description of all safety critical events between cyclists and car drivers

Event	Description
Cyclist-car SCE 1	The subject vehicle is starting his overtaking manoeuvre just before a curve in the road. He has to abort this manoeuvre by braking and steering to the right, because there is a cyclist approaching from the opposite direction. The driver of the subject vehicle is alert the entire time. 2 seconds pass between starting an evasive manoeuvre and the begin time of the safety critical event. Speed was 35 km/h at the start of the evasive manoeuvre and 18 km/h at the time of the safety critical event.
Cyclist-car SCE 2	The subject vehicle is driving just before a curve in the road, when he has to brake and steer to the right because there is a vehicle approaching from the opposite direction making it impossible to overtake the cyclist in front of him. 4 seconds pass between starting an evasive manoeuvre and the begin time of the safety critical event. Speed was 50 km/h at the start of the evasive manoeuvre and 24 km/h at the time of the safety critical event.
Cyclist-car SCE 3	A cyclist approaching from opposite direction suddenly changes sides of the road, resulting in the cyclist coming straight onto the path of the subject vehicle. The driver needs to brake and deviates from the trajectory direction. The driver is visibly surprised and seems to be cursing. The SCE happened on a school campus terrain, on a one-way lane. 1 second passes between starting an evasive manoeuvre and the begin time of the safety critical event. Speed was 13 km/h at the start of the evasive manoeuvre and 9 km/h at the time of the safety critical event.

Table 2.4: Findings on the characteristics of safety critical events between a car driver and a cyclist for selected variables

Variable	Results
Drivers	Two out of three drivers are from the Netherlands, the third driver is from the UK.
Cyclists	Two cyclists were adults between 19 and 69 years old (gender is unknown), one was an elderly man (older than 70 years).
Weather	The weather was clear and the events occurred during daylight. For one event direct bright sunlight could have decreased visibility for the driver.
Infrastructure	The events didn't take place at an intersection. For two out of three events a bicycle lane was present. In the UK no bicycle lane was present. Two out of three events didn't take place in an urban area, though the speed limit for all events was below 50 km/h.
Visual obstructions	In all three safety critical events a curve or hill in the field of view decreased visibility. In two out of three events the presence of trees, crops or vegetation could have limited the view of the driver.
Precipitating event	In two out of three events the subject driver changes lane to overtake the cyclist, both the cyclist as the car are moving in the same direction. In one event the cyclist moves in the opposite direction, head-on to the driver.
Speed and reaction time	As an evasive manoeuvre drivers decrease their speed and steer in the opposite direction of the cyclist in all events. The drivers start their evasive manoeuvre 4 to 1 second before the safety critical event.
Distraction and impairment	Neither the drivers nor the cyclists were performing secondary tasks. Driver's didn't seem drowsy or in another way impaired. One of the drivers showed a surprise reaction in regard to the event, the other two didn't.
Driver error	The drivers don't seem to make any judgment or performance errors . In one event a cyclist suddenly changes side of the road.

2.3.3 Safety critical events for cyclists and trucks

Eight safety critical events with cyclists were identified between the subject vehicle, a truck driver and a cyclist. All of these events were near-crashes. No crashes were identified in this data selection. All eight conflicts involved a cyclist and the subject vehicle on a collision course. In most events an urgent evasive manoeuvre was required by the subject vehicle to avoid a collision.

A qualitative description per safety critical event is given in Table 2.5. In Table 2.6 the findings are summarised and the qualitative results are described.

Table 2.5: Qualitative description of all safety critical events between cyclists and truck drivers

Event	Description
Cyclist-truck SCE 1	The cyclist is cycling on an adjacent cycle lane with a broken line, but is swaying towards the road. Therefore the truck driver has to make an urgent and evasive manoeuvre to the left to avoid a crash with the cyclist. The driver was smoking before and during the manoeuvre and was exhaling smoke out of the left side window. When the driver had overtaken the cyclist the driver checked his blind spot to see were the cyclist was. 1 second passes between starting an evasive manoeuvre and the begin time of the safety critical event. Speed was 36 km/h at the start of the evasive manoeuvre and 35 km/h at the time of the safety critical event.

Table 2.5 (continued): Qualitative description of all safety critical events between cyclists and truck drivers

Event	Description
Cyclist-truck SCE2	The driver wants to overtake a cyclist on the right side in a curve, though when he has begun his manoeuvre there's an oncoming car approaching. The driver has to make an urgent manoeuvre (braking) to avoid a crash. Due to trees and because of the curve, the driver couldn't see the oncoming vehicle earlier. The driver is smoking before and during the manoeuvre. Less than 1 second passesbetween starting an evasive manoeuvre and the begin time of the safety critical event. Speed was 32 km/h at the start of the evasive manoeuvre and 23 km/h at the time of the safety critical event.
Cyclist-truck SCE3	The truck driver was overtaking a cyclist just before a curve in the road (to the right), but he had to brake for an oncoming vulnerable road user (a scoot mobile). 1,5 seconds pass between starting an evasive manoeuvre and the begin time of the safety critical event. Speed was 27 km/h at the start of the evasive manoeuvre and 25 km/h at the time of the safety critical event.
Cyclist-truck SCE4	The driver is making a left turn on a T-intersection when a cyclist is coming from his right side and going straight. They are so near to each other that as a result when the truck driver is turning they are nearly colliding. The driver is decelerating to make sure he doesn't crash with the cyclist coming from his right. 1 second passes between starting an evasive manoeuvre and the begin time of the safety critical event. Speed was 10 km/h at the start of the evasive manoeuvre and 11 km/h at the time of the safety critical event.
Cyclist-truck SCE5	Two cyclists make a sideway manoeuvre to avoid collision with the truck by going onto the pavement due to the truck driver whom is steering to the left side of the road because of a curve in the road. The road is not wide enough for the truck driver and the two cyclists. Speed was 15 km/h at the time of the safety critical event.
Cyclist-truck SCE6	Cyclist in front of the truck had to cross a bridge and suddenly lowered speed. This forces the truck to decelerate. 3 seconds pass between starting an evasive manoeuvre and the begin time of the safety critical event. Speed was 17 km/h at the start of the evasive manoeuvre and 9 km/h at the time of the safety critical event.
Cyclist-truck SCE7	The cyclist stops on the road to step off his bicycle and leave the road. The truck driver has to stop to avoid a crash with the cyclist, because there is another car approaching in the opposite direction. The road is not wide enough for the cyclist, the truck and the car. 2 seconds pass between starting an evasive manoeuvre and the begin time of the safety critical event. Speed was 15 km/h at the start of the evasive manoeuvre and 5 km/h at the time of the safety critical event.
Cyclist-truck SCE8	The truck driver has to break and abort his manoeuvre to overtake the cyclist for an oncoming automobile. The driver seems to be a little bit impaired by sunlight, but alert the whole time. 4 seconds pass between starting an evasive manoeuvre and the begin time of the safety critical event. Speed was 21 km/h at the start of the evasive manoeuvre and 12 km/h at the time of the safety critical event.

Table 2.6: Qualitative descriptions of the safety critical events for selected variables for safety critical events between a truck driver and a cyclist

Variable	Results
Drivers	Out of the 13 drivers, for 5 drivers a safety critical event was identified. Out of these 5, for 2 drivers two safety critical events were identified, for the other 3 drivers 1 safety critical event was identified.
Cyclists	Most cyclists were adults between 19 and 69 years old (63%). Most of the cyclists were men (75%).
Weather	The weather was clear and the events occurred during daylight. For one event direct bright sunlight could have decreased visibility for the driver
Infrastructure	All events occurred in an urban area with a speed limit of 50 km/h, and often in moderate residential areas (75%). One safety critical event occurred at an intersection. In 50% of the events a bicycle lane was present at the right side of the driver.
Visual obstructions	In 50% of the events the sight of the driver was not obstructed. In the other events glaring sunlight, a curve in the road or a parked vehicle obstructed the sight of the drivers.
Precipitating event	Drivers either steer away from the cyclist and/or brake. In one safety critical event the evasive manoeuvre is made by the cyclists. 50% of the safety critical events are related to the truck driver overtaking the cyclist.
Speed and reaction time	In 75% of the events the driver decreases speed at the start of the evasive manoeuvre until the safety critical event. The drivers start their evasive manoeuvre 4 to 1 seconds before the safety critical event.
Distraction and impairment	In two of the events drivers were smoking, no other secondary task behaviour was identified during the events. In one event the cyclist is engaging in a secondary task as well, though the nature of the task couldn't be determined. Drivers didn't seem drowsy or impaired and they were paying attention to the driving task. One driver showed a surprise reaction in regard to the SCE.
Driver error	The drivers don't seem to make any judgment or performance errors. In one of the SCE's a driver is forced to take a curve more to the left side, since the road is too small. In two SCE events the cause of the SCE seems to be caused by an error by the cyclist; swaying to the left side, and stopping and stepping of the bicycle.

2.4 Discussion

The objective of this study was to investigate the contributing factors to crashes and near crashes between car and truck drivers with cyclists. Because of the small amount of near crashes found in the data, and no crashes, the results were analysed qualitatively. The results in this study give an indication to the contributing factors of crashes.

The results indicate that in this study the safety critical events seem to be caused by a combination of:

- infrastructure (a curve or a road being too narrow);
- the drivers' manoeuvre (often overtaking);
- other oncoming traffic;
- an error by the cyclist;
- or a manoeuvre by the cyclist (slowing down).

Other characteristics of the safety critical events were:

- All 11 safety critical events take place on a road with a speed limit of 50 km/h or less;
- none of the drivers are driving too fast at the start of their evasive manoeuvre;
- all of the drivers decrease their speed or decelerate as an evasive manoeuvre;

- the drivers don't seem to make any judgment errors, aren't engaged in secondary task behaviour and seem alert;
- overall in 3 events out of 11 safety critical events the cyclist seems to be at fault.

2.4.1 Findings of the current study in relation to other studies

The SHRP2 naturalistic driving study shows that distraction is the largest contributing factor to crashes in general and driver-related factors are present in almost 90% of the crashes (Dingus et al., 2016). Other studies specifically aimed at crashes between cyclists and motorised vehicles (Safetynet, 2008; European Commission, 2016; Habibovic & Davidsson, 2011) based on fatality databases identify contributing factors that could be related to distraction. Factors that are identified are manoeuvres being initiated to early or not in time or no action being taken by a driver, a driver not noticing a cyclist because of reduced visibility, reduced awareness or insufficient comprehension and cyclists cycling in an incorrect direction.

In this qualitative naturalistic driving study into near crashes between car drivers and cyclists and truck drivers and cyclists drivers didn't seem to be distracted when the safety critical event occurred. As research shows that inattention is a large contributing factor to crashes, this could be an explanation why these near-crashes did not develop into crashes. Drivers overall seemed to be alert and not impaired.

Also cyclists are being noticed in time by the drivers, resulting in the driver performing an evasive manoeuvre in time (at least 1 second before the SCE) before a crash could happen.

2.4.2 Limitations and future research

A naturalistic driving approach into analysing safety critical events offers the advantage of being able to see in detail what happens before the event. A limitation to this study still is that the behaviour of the driver can be analysed better than the behaviour of the cyclist. Naturalistic cycling studies offer additional insights on cycling behaviour and safety critical events.

In this study no crashes were identified in the data. Even though crashes and near crashes are not the same, near crashes have similar elements as a near crash by definition. Guo et al. (2010) conclude that near crashes can be used as a 'surrogate crash' for the analysis of factors contributing to crashes. Their study indicates that a positive relation exists between the frequencies of contributing factors for crashes and near crashes.

Another limitation to this study is that we can't draw firm conclusions because of the small number of safety critical events identified in the data. Moreover the way the data are sampled might not represent general driver behaviour. The Pedestrian Collision Warning was used to find safety critical events, though the smart camera probably will not have detected all near-crashes with cyclists. If it would be possible to look at all UDRIVE data, potentially more safety critical events would be identified.

Using the technique of a smart camera like the Mobileye presents possibilities in addition to other triggers to find safety critical events in an efficient way. Possibly using the technique in combination with often used measures like headway time and lateral and longitudinal acceleration. For this study only safety critical events with cyclists have been analysed, though the smart camera also registers pedestrians and cars. .

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3 Blind spot shoulder checks of car drivers toward cyclists on urban intersections

3.1 Introduction

Vision is the number one sense needed while driving. Visual search was identified by Ranney (1994) as 'an aspect of driving that must be central to a complete description of the cognitive abilities necessary for a skilled driver' (p. 745). Analysis of the driving task have shown that 95% of the information is identified with vision (McKnight & Adams, 1970; Shinar & Schieber, 1991). When the road environment becomes increasingly complex, a driver must shift visual attention constantly, while simultaneously performing other tasks (Chun et al., 2013). When the visual work-load increases, for example while making a lane change or a turn on an intersection, critical information may be missed or misidentified (Herslund & Jørgensen, 2003).

Failure to effectively search the roadway will likely result in a collision, or at the least cause a neglect in route information (Underwood, Crundall, & Chapman, 2002). Svenson, Gawron, and Brown (2005) have estimated that 5% of reported car accidents occur during lane changes, and a further 10% may occur while making a turn (SWOV, 2017). According to Levulyté et al. (2016), a typical crash scenario is when a car turns right across the path of a cyclist riding straight through the intersection. This scenario was listed as the most frequent accident type between cyclists and cars at bicycle crossings in an in-depth study on car-bicycle collisions in Finland (Räsänen & Summala, 1998). An earlier study by Summala et al. (1996) suggests that such accidents occur because drivers focus their attention to traffic coming from the left, thus missing the presence of cyclists from the right.

Rear-quarter blind spots are areas on the road which cannot be seen while looking forward or through either the rear-view or side mirrors. However, these areas are observable by looking backwards over one's shoulder. A failure of the driver to perform a shoulder check before making a turn on an intersection can lead to serious accidents with cyclists.

The number of blind spot fatalities may be reduced if there is a better understanding of blind spot checking behavior. Previous studies on the attention drivers have for their blind spots have mostly focused on lane changes (Kiefer & Hankey, 2008; Lavallière, Simoneau, Tremblay, Laurendeau, & Teasdale, 2012; McLaughlin, Hankey, & Dingus, 2008; Svenson et al., 2005). However, little is known regarding blind spot checks prior to making turns on intersections. Romoser and Fisher (2009) conducted a simulation study and found that most notably, failure to take a secondary look in blind spot occurred in 10-20% of turns on intersections. To our knowledge there are no studies on blind spot checks at roundabouts.

Therefore, our objective is to use naturalistic driving data to investigate which factors influence whether drivers perform a shoulder check before making a right turn (UK: left turn) on an urban intersection, or an exit manoeuvre at a roundabout. The factors under consideration consist of infrastructural, situational, and behavioural characteristics. Data have been collected from four countries: France, the Netherlands, Poland, and United Kingdom. We expect to find more blind spot checks in the Netherlands, because of its higher prevalance of cyclists and cyclist facilities compared to the other countries.

3.2 Method

The UDRIVE database features more than 41.000 hours of naturalistic driving data with instrumented cars. The present study focuses on the UDRIVE car data that were available after driver identification by February 2017 (note: a study on gaze behaviour by truck drivers is presented in Chapter 5). Right turn maneuvers (UK: left turn, henceforth 'right turn') have been automatically extracted, and the resulting data segments have been annotated. The sample population, data extraction process, and annotation process will be described next.

3.2.1 Driver demographics

A sample of seventy-two drivers from four countries (i.e., France, the Netherlands, Poland, United Kingdom) resulted from the data reduction process described in paragraph 3.2.5. The distributions of gender and age across these countries are described in Table 3.1.

Table 3.1: Car driver sample demographics across countries.

Nationality	Drivers	Gender		Age (years)			
		M	F	Min.	Max.	*M*	*SD*
Total	72	34	38	21	70	43.8	12.4
France	19	10	9	23	64	44.7	12.1
the Netherlands	9	4	5	26	70	44.2	14.7
Poland	11	5	6	27	43	36.0	4.9
United Kingdom	33	15	18	21	66	45.8	13.1

3.2.2 Manoeuvre identification

A Matlab-based tool has been developed for the UDRIVE project to synchronize, visualize, and analyze sensor and video data signals (i.e., see UDRIVE deliverable “D24.1: Description of the analysis tools framework”). This tool was used to obtain data segments (i.e., parts of a trip) containing right turn maneuvers on urban intersections and roundabouts with a maximum speed limit of 50km/h, see Figure 3.1.

A sequence of data points was tagged as candidate maneuver when the derivative of map heading (i.e., yaw rate) exceeded 5 deg/sec, and when this sequence covered a total map heading change between 50 and 160 degrees. The latter threshold was chosen to avoid selecting U-turns. The yaw rate threshold was found empirically (i.e., by comparing threshold values with video data). Next, a time window was drawn six seconds before the onset of the maneuver, and three seconds following the maneuver offset. Candidate maneuvers were only considered if the locality type in their time window was exclusively urban (i.e., not rural), if the speed limit was not above 50 km/h, and if there was an overlap with an intersection or roundabout. In case of a roundabout, only the exit maneuver was selected (i.e., when the driver would cross the trajectory of a cyclist in its blind spot). Note that one trip may contain multiple maneuvers, of which the corresponding time windows may overlap. This study focuses on isolated maneuvers. Therefore, maneuvers with overlapping time windows have been excluded.

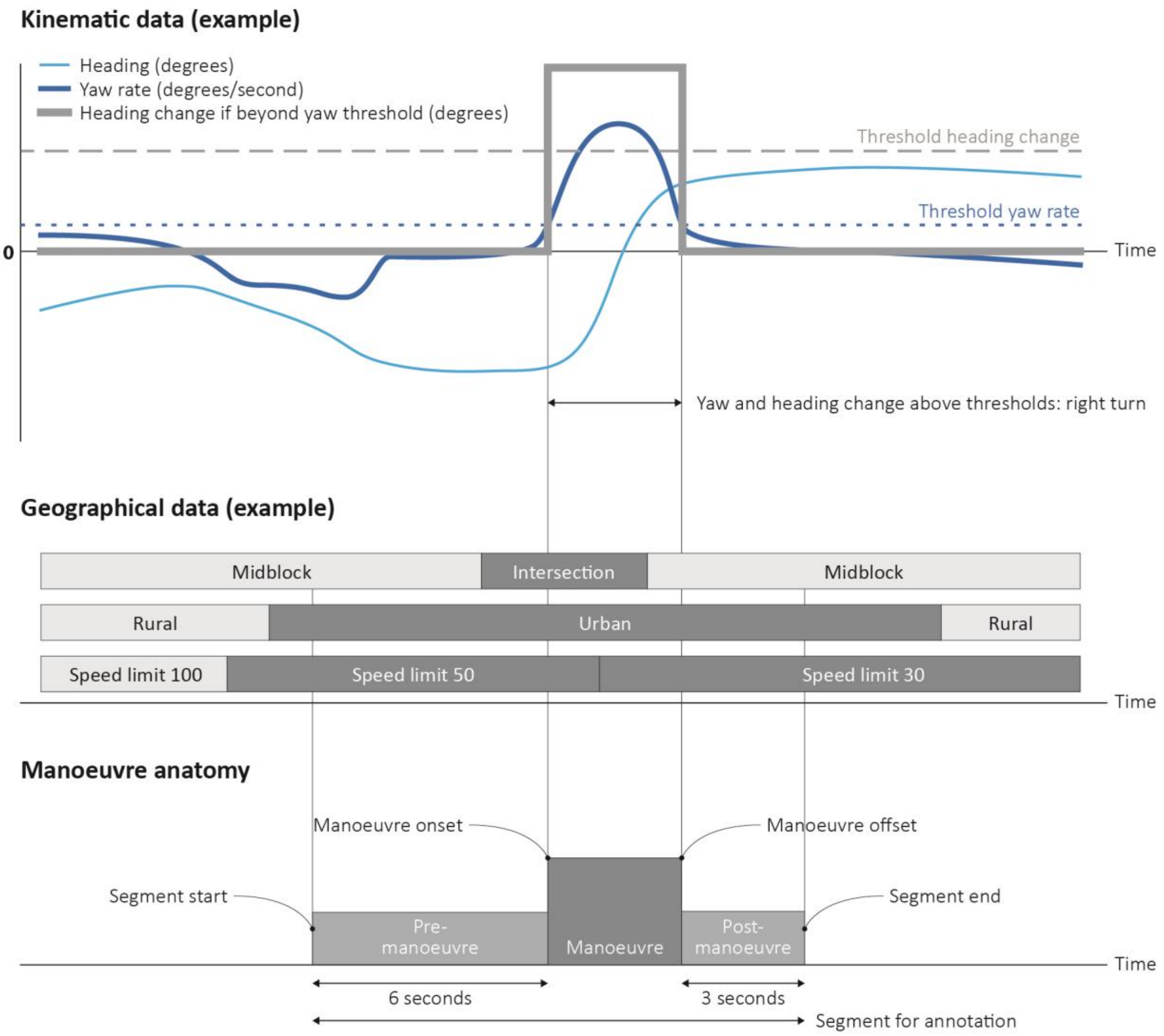

Figure 3.1: Extraction of manoeuvres based on kinematic data of the car and geographical data.

3.2.3 Data reduction

A three-stage data reduction procedure was used. Stage 1 excluded segments without speed data, segments recorded between sunset and sunrise (i.e., to ensure visibility in the camera views), and segments belonging to trips with a distance below 1 km. Furthermore, if a trip contained more than one intersection or roundabout segment, then one of each type was randomly selected. For each driver, an initial 50 segments were selected, if available. Stage 2 concerned a manual quality check of the selected segments. Annotators (see below) excluded cases in which the main road of an intersection concerned a right turning curve, and cases where the roundabout was avoided by means of a bypass lane. Furthermore, annotators validated if the video quality was appropriate (e.g., driver face visible, cameras connected), and if the video data were synchronized with the numerical data. In the third stage only drivers with at least 10 valid segments were selected.

3.2.4 Annotation

Five annotators were trained to validate and annotate the selected segments. The annotators were supported by a dedicated codebook (see Appendix B), with a subset of the variables in the central UDRIVE codebook. Infrastructural variables included intersection type, road type, priority regulation, and facilities for cyclists. Situational variables included traffic flow, and presence of vulnerable road users. Finally, behavioral

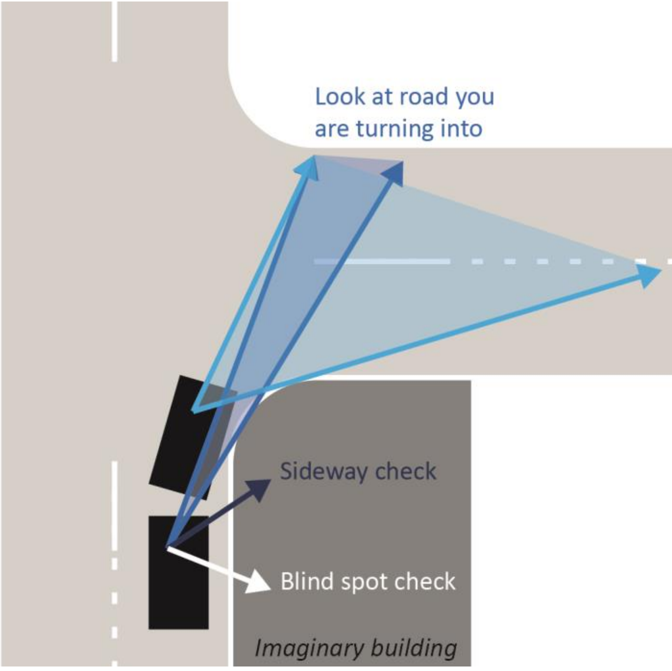

Figure 3.2: Operationalization of gaze categories.

variables included timestamps for the start and end of the maneuver, entering the encroachment zone, secondary task engagement, and gaze direction over time.

Gaze direction was coded from the start of the segment until the end of the maneuver. Gaze categories consisted of: 'Blind spot check on right side' (with or without cyclist presence, or unknown presence), 'Sideway glance on right side' (with or without cyclist presence, or unknown presence), 'Glance towards the road the driver is turning into', 'Elsewhere' (e.g., forward, interior, sideway in other direction), 'Unsure', and 'Impossible to determine'.

For blind spot checks it was required that the driver turned his or her head over the shoulder. The distinction between sideway checks and future road checks changes over the course of the manoeuvre, as illustrated in Figure 3.2. Annotators were instructed to imagine an infinitely high building at the border of the road. When a driver was looking 'through' this building, the gaze direction was classified as sideway check. When a driver was looking 'past' this building, the gaze direction was classified as looking towards the future road.

After a few days of annotating, interrater reliability was calculated through percentage agreement and Krippendorf's alpha. A second training session was held to increase interrater agreement, based on which the annotators revised their work.

3.2.5 Data analysis

The annotated data were processed with Matlab version R2015b. For each segment a flag was raised when the blind spot was checked at least once prior to the offset of the maneuver. Separate flags were created for blind spot checks prior to the manoeuvre, and during the manoeuvre. For descriptive data, proportional scores were calculated for each driver by dividing the number of flags by the number of segments on each factor of interest (i.e., infrastructural, situational, and behavioural).

Furthermore, a series of Generalized Linear Mixed Models (GLMM, SPSS version 24) with a binomial distribution were constructed to test twelve individual main effects of the infrastructural, situational, and behavioural factors. Thus, each GLMM featured one repeated measure as independent variable. In addition, Country was introduced as between-subjects fixed effect. The results of the statistical tests were compared against an alpha level of α = .00417 (i.e., .05/12) to reduce chance-capitalization. While the default link type is typically logit, the descriptives (see section 3.3) showed that the majority of the proportional scores were zero, or close to zero. For this reason, a complementary log-log link was chosen, in line with recommendations by Stroup (2013, p.317). The Netherlands has been chosen as reference in the contrast analysis across countries, because cyclists and cyclist facilities are more prevalent than in the other countries.

3.3 Results

The initial segment selection consisted of 30230 intersections and 14261 roundabouts. After data reduction, the final dataset consisted of 961 intersection maneuvers by 69 drivers, and 826 roundabout maneuvers by 46 drivers, see Table 3.2. The UK data feature a relatively high share in the total dataset. The cause for this over-representation is that the UK data were available earlier than the data of the other countries. Furthermore, the Polish roundabout data featured only four drivers with at least ten valid segments after data reduction stage 2. For this reason, the Polish roundabout data were not considered in subsequent analysis.

Table 3.2: Distribution of segments across drivers and countries.

Country	Intersections		Roundabouts	
	Segments	Drivers	Segments	Drivers
Total	961	69	826	46
France	236	19	186	14
the Netherlands	132	8	179	8
Poland	150	11	-	-
United Kingdom	443	31	461	24

We first provide an overview of blind spot checks in both maneuvers, followed by an examination of infrastructural, situational, and behavioral factors. As it turns out, drivers do not often perform a shoulder check. Therefore, we finish the results section by exploring where drivers look instead.

3.3.1 Overview blind spot checks

In general, drivers did not often check their blind spot. At intersections, 37 of the 69 drivers never looked. All Dutch drivers checked their blind spot at least once, with a maximum proportion of 70% (i.e., one drivers checked the blind spot in 70% of the intersections observed with that driver). At roundabouts, 31 of the 46 drivers never checked their blind spot (maximum: 46%).

Table 3.3 shows the proportion of blind spot checks, averaged over all drivers. Prior to the manoeuvre drivers have checked their blind spot in approximately 4% of the cases, both at intersections and roundabouts. The figures suggest that drivers check their blind spot more often during intersection manoeuvres, but not during roundabout manoeuvres. An increase is found when the 'pre-maneuver' and 'during maneuver' sections are combined. The result is not additive, because some drivers occasionally checked their blind spot in both sections. The combined score will be used throughout the remainder of the analysis.

A Generalized Linear Mixed Model was used on the combined blind spot results, with Country as fixed effect (i.e., omitting the factors used in the analyses of the subsequent paragraphs). At intersections, a significant main effect was found for Country, $F(3,65) = 13.78$, $p < .001$. Simple contrasts revealed that, compared to the Netherlands, the percentage was significantly lower in France, $t(65) = -4.77$, $p < .001$, in Poland, $t(65) = -3.38$, $p = .001$, and in the UK, $t(65) = -4.44$, $p < .001$. At roundabouts, too, a significant main effect was found for Country, $F(2,43) = 12.82$, $p < .001$. Simple contrasts with the Netherlands as reference revealed that the percentage in the UK was significantly smaller than that of the Netherlands, $t(43) = -4.01$, $p < .001$. Likewise, the percentage in France was significantly smaller than that of the Netherlands, $t(43) = -4.55$, $p < .001$.

Table 3.3: Overview of blind spot checks across countries.

Time window	Country	Intersections (*N* = 69)			Roundabouts (*N* = 46)		
		X (*n*)	*M* (%)	*SD*	*X* (*n*)	*M* (%)	*SD*
Pre-maneuver	Total	961 (69)	3.71	8.24	826 (46)	3.97	8.71
	FR	236 (19)	1.39	3.50	186 (14)	.55	2.06
	NL	132 (8)	19.91	14.59	179 (8)	16.14	15.28
	PL	150 (11)	2.48	4.96	-	-	-
	UK	443 (31)	1.40	3.05	461 (24)	1.90	3.44
During maneuver	Total	961 (69)	6.37	10.88	826 (46)	2.41	6.63
	FR	236 (19)	2.28	4.61	186 (14)	0	-
	NL	132 (8)	24.65	19.87	179 (8)	9.62	12.99
	PL	150 (11)	6.60	8.50	-	-	-
	UK	443 (31)	4.07	5.84	461 (24)	1.40	3.45
Combined	Total	961 (69)	7.29	11.84	826 (46)	4.77	10.60
	FR	236 (19)	3.01	4.77	186 (14)	.55	2.06
	NL	132 (8)	27.26	21.67	179 (8)	19.21	19.04
	PL	150 (11)	7.30	9.55	-	-	-
	UK	443 (31)	4.77	6.28	461 (24)	2.42	4.25

NOTE: Gaze has been evaluated from 6 sec. pre-maneuver to the end of the maneuver. *X* = number of segments across all drivers. *n* = number of drivers with at least one data point on the corresponding factor. *M* = Average proportion of blind spot checks per driver.

3.3.2 Infrastructural factors

Table 3.4 shows the average proportion of blind spot checks on six infrastructural factors. The annotators have frequently used the comments field to report the absence of an encroachment zone at intersections. Consequently, no timestamp for entering the encroachment zone was entered. In most of the cases an infrastructural characteristic was reported to explain the absence of an encroachment zone (e.g., pre-sorting lanes, “cyclist cannot go straight on this intersection”, “It is highly unlikely that a cyclist is making use of this road”). Based on these comments, the factor ‘Encroachment Zone’ has been included in Table 3.4. Note, however, that the absence of an encroachment zone does not necessarily imply an absence of cyclists: several examples with a cyclist have been recorded. This may explain why the proportion of blind spot checks in the Netherlands is higher than in the other countries, even in absence of an encroachment zone. As a related finding, Table 3.4 supports the notion that the prevalence of cyclist facilities is the highest in the Netherlands. The average prevalence of cyclist facilities (i.e., adjacent lanes and separated tracks) across all manoeuvres is 10% at intersections, and 29% at roundabouts. However, in the Netherlands, these proportions are 37% at intersections and 67% at roundabouts.

On intersections, the GLMMs yielded three significant main effects (see Table 3.5). First, a significant main effect of Road transition was found. Simple contrasts with ‘Equal size roads’ as reference showed that the blind spot was checked significantly more often when the driver approached an intersection from the primary road, $t(135) = 3.71$, $p < .001$. No significant effect was found between ‘Equal size roads’ and ‘Start secondary road’.

The second significant main effect on intersections was found with Priority regulation. Regulation by law was chosen as reference category. Simple contrasts revealed that significantly less blind spot checks were performed in the category ‘Lights without partial conflicts’, $t(188) = -4.20$, $p < .001$. Comparisons with the other categories were non-significant.

Finally, the third significant main effect of Encroachment zone showed that drivers checked their blind spot more often when an encroachment zone was present.

Table 3.4: Blind spot checks as function of infrastructure

Factor	Country	Category	Intersections			Roundabouts		
			X (*n*)	*M* (%)	*SD*	*X* (*n*)	*M* (%)	*SD*
Intersection type	Total	T by-road	215 (59)	5.98	16.39	-	-	-
		T main road	420 (66)	11.96	17.36	-	-	-
		X	307 (61)	5.03	14.51	-	-	-
		Y	13 (7)	4.76	12.60	-	-	-
		5 or more legs	6 (5)	0	-			
	FR	T by-road	47 (16)	2.08	8.33	-	-	-
		T main road	101 (18)	7.59	15.50	-	-	-
		X	78 (17)	2.02	5.78	-	-	-
		Y	7 (3)	0	-	-	-	-
		5 or more legs	3 (3)	0	-			
	NL	T by-road	31 (8)	23.96	34.34	-	-	-
		T main road	57 (8)	32.25	17.97	-	-	-
		X	40 (7)	29.52	32.88	-	-	-
		Y	4 (2)	16.67	23.57	-	-	-
		5 or more legs	0 (0)	-	-			
	PL	T by-road	20 (8)	4.17	11.79	-	-	-
		T main road	45 (10)	17.33	22.87	-	-	-
		X	83 (11)	2.05	5.16	-	-	-
		Y	1 (1)	0	-	-	-	-
		5 or more legs	1 (1)	0	-			
	UK	T by-road	117 (27)	3.50	9.39	-	-	-
		T main road	217 (30)	7.39	11.74	-	-	-
		X	106 (26)	1.67	4.96	-	-	-
		Y	1 (1)	0	-	-	-	-
		5 or more legs	2 (1)	0	-			
Roundabout type	Total	Single lane	-	-	-	525 (46)	5.69	13.58
		Multiple lanes	-	-	-	261 (35)	4.63	17.28
		Mini	-	-	-	22 (9)	0	-
		Turbo	-	-	-	18 (6)	0	-
	FR	Single lane	-	-	-	167 (14)	.55	2.06
		Multiple lanes	-	-	-	17 (7)	0	-
		Mini	-	-	-	1 (1)	0	-
		Turbo	-	-	-	1 (1)	0	-
	NL	Single lane	-	-	-	125 (8)	27.05	22.53
		Multiple lanes	-	-	-	38 (6)	20.34	39.41
		Mini	-	-	-	0 (0)	-	-
		Turbo	-	-	-	16 (4)	0	-
	PL	Single lane	-	-	-	-	-	-
		Multiple lanes	-	-	-	-	-	-
		Mini	-	-	-	-	-	-
		Turbo	-	-	-	-	-	-
	UK	Single lane	-	-	-	233 (24)	1.57	3.37
		Multiple lanes	-	-	-	206 (22)	1.82	5.26
		Mini	-	-	-	21 (8)	0	-
		Turbo	-	-	-	1 (1)	0	-

Table 3.4 (continued): Blind spot checks as function of infrastructure

Factor	Country	Category	Intersections			Roundabouts		
			X (*n*)	*M* (%)	*SD*	*X* (*n*)	*M* (%)	*SD*
Road transition	Total	Equal size roads	271 (65)	4.08	12.37	735 (46)	3.83	9.41
		Start primary road	423 (66)	11.22	19.20	60 (26)	8.65	23.39
		Start secondary road	267 (63)	4.02	11.21	31 (20)	12.50	31.93
	FR	Equal size roads	119 (17)	.84	3.46	138 (14)	0	-
		Start primary road	60 (17)	6.86	14.20	37 (13)	1.92	6.93
		Start secondary road	57 (18)	1.39	5.89	11 (9)	0	-
	NL	Equal size roads	46 (8)	16.80	24.64	155 (8)	14.21	18.58
		Start primary road	53 (8)	38.26	36.10	9 (5)	40.00	41.83
		Start secondary road	33 (7)	18.37	25.85	15 (7)	35.71	47.56
	PL	Equal size roads	25 (11)	9.09	17.26	-	-	-
		Start primary road	78 (10)	10.56	14.11	-	-	-
		Start secondary road	47 (9)	1.23	3.70	-	-	-
	UK	Equal size roads	81 (29)	.57	3.09	442 (24)	2.60	4.50
		Start primary road	232 (31)	6.84	10.07	14 (8)	0	-
		Start secondary road	130 (29)	3.05	7.10	5 (4)	0	-
Priority regulation	Total	Law	202 (56)	10.61	21.14	20 (10)	0	-
		Signs	512 (69)	8.25	18.25	696 (46)	5.03	11.04
		Lights (conflict)	112 (43)	11.05	27.98	26 (13)	0	-
		Lights (no conflict)	135 (49)	2.96	12.36	84 (20)	11.31	30.60
	FR	Law	63 (16)	6.10	14.65	0 (0)	-	-
		Signs	103 (19)	1.90	6.15	185 (14)	.55	2.06
		Lights (conflict)	35 (13)	11.54	29.96	1 (1)	0	0
		Lights (no conflict)	35 (14)	0	-	0 (0)	-	-
	NL	Law	59 (8)	34.38	37.54	0 (0)	-	-
		Signs	32 (8)	33.23	38.94	147 (8)	21.72	18.46
		Lights (conflict)	7 (4)	62.50	47.87	1 (1)	0	-
		Lights (no conflict)	34 (7)	13.61	25.71	31 (5)	22.40	43.69
	PL	Law	29 (11)	9.39	17.44	-	-	-
		Signs	60 (11)	8.96	19.06	-	-	-
		Lights (conflict)	44 (9)	2.78	8.33	-	-	-
		Lights (no conflict)	17 (8)	6.25	17.68	-	-	-
	UK	Law	51 (21)	5.63	12.39	20 (10)	0	-
		Signs	317 (31)	5.44	7.56	364 (24)	2.08	3.77
		Lights (conflict)	26 (17)	2.94	12.13	24 (11)	0	-
		Lights (no conflict)	49 (20)	0	-	53 (15)	7.62	25.82

Table 3.4 (continued): Blind spot checks as function of infrastructure

Factor	Country	Category	Intersections			Roundabouts		
			X (*n*)	*M* (%)	*SD*	*X* (*n*)	*M* (%)	*SD*
Cyclist facilities	Total	None	863 (69)	6.66	12.89	589 (44)	1.95	4.03
		Adjacent lane	35 (22)	9.09	19.74	63 (20)	4.06	11.91
		Separated track	63 (20)	21.75	34.85	174 (22)	9.10	18.41
	FR	None	216 (19)	2.24	4.67	146 (14)	0	-
		Adjacent lane	14 (9)	5.56	16.67	39 (12)	1.67	5.77
		Separated track	6 (5)	20.00	44.72	1 (1)	0	-
	NL	None	83 (8)	23.30	28.83	59 (6)	3.61	5.81
		Adjacent lane	12 (5)	30.00	27.39	11 (4)	12.50	25.00
		Separated track	37 (7)	40.71	40.16	109 (8)	25.02	23.70
	PL	None	132 (11)	7.06	10.76	-	-	-
		Adjacent lane	0 (0)	-	-	-	-	-
		Separated track	18 (7)	7.14	12.20	-	-	-
	UK	None	432 (31)	4.94	6.44	384 (24)	2.49	4.44
		Adjacent lane	9 (8)	0	-	13 (4)	2.78	5.56
		Separated track	2 (1)	0	-	64 (13)	0	-
Encroachment Zone	Total	Yes	841 (69)	7.81	12.16	-	-	-
		No	120 (42)	5.22	17.70	-	-	-
	FR	Yes	215 (19)	3.22	5.18	-	-	-
		No	21 (8)	0	-	-	-	-
	NL	Yes	103 (8)	28.99	19.65	-	-	-
		No	29 (7)	20.63	38.72	-	-	-
	PL	Yes	130 (11)	8.14	10.74	-	-	-
		No	20 (9)	2.78	8.33	-	-	-
	UK	Yes	393 (31)	5.05	7.06	-	-	-
		No	50 (18)	2.78	8.57	-	-	-

NOTE: Gaze has been evaluated from 6 sec. pre-maneuver to the end of the maneuver. *X* = number of segments across all drivers. *n* = number of drivers with at least one data point on the corresponding factor. *M* = Average proportion of blind spot checks per driver.

Table 3.5: GLMM main effect results on infrastructural factors

Factor	Intersections			Roundabouts		
	df	*F*	*p*	*df*	*F*	*p*
Intersection type	4,156	2.15	.077	-	-	-
Roundabout type	-	-	-	3,53	2.33	.084
Road transition	2,152	7.78	.001	2,46	.009	.99
Priority regulation	3,183	15.12	< .001	3,48	.39	.76
Cyclist facilities	2,98	.006	.99	2,47	1.34	.27
Encroachment zone	1,77	706.29	< .001	-	-	-

NOTE: Each main effect was tested with a separate GLMM. The main effect of Country was significant at Roundabout type, Road transition (intersections), Priority regulation (intersections), and Encroachment zone. Encroachment zone was not annotated for roundabouts.

Regarding the roundabouts, the GLMMs have yielded awkward results when including the French data. For example, the estimated means showed a decrease in blind spot checks when a visual obstacle was present, whereas the descriptive data clearly show an increase (see paragraph 3.3.3). A possible explanation could be that with one exception, all percentages of blind spot checks for the French drivers are zero. Therefore, the French roundabout data have been excluded from further statistical analysis in paragraphs 3.3.2 to 3.3.4. No significant main effects have been found for infrastructural factors on the remaining countries (see Table 3.5). However, a significant interaction between Country and Roundabout type was found, $F(1,66) = 4158.97$, $p < .001$. From single lane roundabouts to multiple lane roundabouts, the decreasing proportion appears to be larger the Netherlands than in the UK. This interaction also appears to be true from single lane roundabouts to turbo roundabouts.

3.3.3 Situational factors

Sight conditions based on weather and lighting were rated as good in 97% of the intersection manoeuvres, and 98% of the roundabout manoeuvres. Furthermore, the prevalence of cyclists coming from the opposite direction is very low (intersections: .5% with 4 drivers, roundabouts: .9% with 6 drivers). Therefore, the factors ‘Sight condition’ and ‘Cyclist from opposite direction’ have been excluded from further analysis. Table 3.6 displays the average proportion of blind spot checks as function of the remaining situational factors.

One significant main effect have been found at roundabouts, see Table 3.7. The factor ‘Early VRU right side’ concerns the presence of Vulnerable Road Users (VRUs, i.e., cyclists, pedestrians) in the first three seconds of the six second time window prior to the maneuver. Significantly more blind spot checks were observed when an early VRU was present. The presence of an early VRU resulted in a neglegible difference at intersections. Hence, the effect was non-significant.

The effect of Encroachment zone at roundabouts yielded a p value of .013, which is normally considered a significant effect. However, we have compared against a lower alpha value to redcuce chance-capitalization. Therefore, we do not regard the effect Encroachment zone as significant.

Furthermore, table 3.6 suggests that drivers check their blind spot more often at roundabouts if their trajectory included a full stop (i.e., waiting then free, waiting then restricted). This would be a logical finding, because drivers would have to update their situational awareness when a cyclist could overtake them while standing still. However, the effect of traffic flow was non-significant.

Table 3.6: Blind spot checks as function of traffic situation.

Factor	Country	Category	Intersections			Roundabouts		
			X (*n*)	*M* (%)	*SD*	*X* (*n*)	*M* (%)	*SD*
Traffic flow	Total	Free flow	513 (69)	7.78	15.05	338 (46)	3.39	8.60
		Restricted flow	289 (68)	7.08	16.25	442 (46)	4.66	11.06
		Waiting then free	74 (42)	6.75	21.80	24 (14)	21.43	42.58
		Waiting then restricted	85 (41)	8.74	25.68	22 (18)	16.67	38.35
	FR	Free flow	111 (19)	2.22	6.67	57 (14)	0	-
		Restricted flow	86 (19)	1.05	4.59	125 (14)	.79	2.97
		Waiting then free	18 (10)	5.00	15.81	1 (1)	0	-
		Waiting then restricted	21 (10)	12.50	31.73	3 (3)	0	-
	NL	Free flow	85 (8)	27.68	21.88	84 (8)	13.44	15.92
		Restricted flow	27 (8)	27.83	28.65	83 (8)	16.90	20.92
		Waiting then free	8 (5)	13.33	29.81	6 (4)	75.00	50.00
		Waiting then restricted	12 (4)	58.33	41.94	6 (5)	60.00	54.77
	PL	Free flow	71 (11)	12.76	18.53	-	-	-
		Restricted flow	63 (11)	3.86	10.15	-	-	-
		Waiting then free	8 (6)	0	-	-	-	-
		Waiting then restricted	8 (5)	0	-	-	-	-
	UK	Free flow	246 (31)	4.29	10.67	197 (24)	2.03	4.86
		Restricted flow	113 (30)	6.55	14.73	234 (24)	2.84	6.04
		Waiting then free	40 (21)	7.94	25.61	17 (9)	0	-
		Waiting then restricted	44 (22)	0	-	13 (10)	0	-
Early VRU right side	Total	Yes	151 (57)	7.04	17.17	59 (29)	18.39	36.01
		No	810 (69)	7.25	12.63	767 (46)	3.15	7.97
	FR	Yes	33 (16)	0	-	16 (9)	0	-
		No	203 (19)	3.60	5.86	170 (14)	.65	2.43
	NL	Yes	23 (8)	23.33	28.00	31 (8)	41.67	41.79
		No	109 (8)	28.97	23.01	148 (8)	11.18	15.82
	PL	Yes	56 (11)	14.22	23.52	-	-	-
		No	94 (11)	4.74	9.21	-	-	-
	UK	Yes	39 (22)	2.65	8.68	12 (12)	16.67	38.92
		No	404 (31)	4.76	6.79	449 (24)	1.94	4.13

Table 3.6 (continued): Blind spot checks as function of traffic situation.

Factor	Country	Category	Intersections			Roundabouts		
			X (*n*)	*M* (%)	*SD*	*X* (*n*)	*M* (%)	*SD*
Cyclist from driver direction	Total	Yes	20 (16)	28.13	44.60	20 (13)	16.67	33.33
		No	941 (69)	7.22	12.13	806 (46)	4.37	9.53
	FR	Yes	0 (0)	-	-	1 (1)	0	-
		No	236 (19)	3.01	4.77	185 (14)	.55	2.06
	NL	Yes	12 (8)	31.25	45.81	12 (5)	43.33	43.46
		No	120 (8)	28.00	22.67	167 (8)	16.81	17.24
	PL	Yes	1 (1)	100.00	-	-	-	-
		No	149 (11)	6.72	8.64	-	-	-
	UK	Yes	7 (7)	14.29	37.80	7 (7)	0	-
		No	436 (41)	4.62	6.44	454 (24)	2.46	4.29
Visual obstruction	Total	Yes	252 (66)	10.17	21.86	157 (40)	11.68	26.27
		No	709 (69)	6.73	12.67	669 (46)	3.80	10.13
	FR	Yes	48 (17)	6.86	24.34	18 (10)	0	-
		No	188 (19)	3.07	5.74	168 (14)	.65	2.43
	NL	Yes	30 (8)	28.75	27.89	31 (7)	32.79	42.96
		No	102 (8)	28.14	22.87	148 (8)	17.17	18.16
	PL	Yes	37 (10)	14.32	31.46	-	-	-
		No	113 (11)	6.76	10.65	-	-	-
	UK	Yes	137 (31)	5.84	10.87	108 (23)	10.33	22.68
		No	306 (31)	3.43	6.51	353 (24)	1.17	4.64

NOTE: Gaze has been evaluated from 6 sec. pre-maneuver to the end of the maneuver. *X* = number of segments across all drivers. *n* = number of drivers with at least one data point on the corresponding factor. *M* = Average proportion of blind spot checks per driver.

Table 3.7: GLMM main effect results on situational factors

Factor	Intersections			Roundabouts		
	df	*F*	*p*	*df*	*F*	*p*
Traffic flow *	3,181	.30	.83	3,52	1.15	.34
Early VRU right side	1,118	.014	.91	1,29	10.74	.003
Cyclist from driver direction **	1,62	.63	.43	1,31	.013	.91
Visual obstruction	1,77	1.69	.20	1,35	6.86	.013

NOTE: Each main effect was tested with a separate GLMM. The main effect of Country was significant at Traffic flow (intersections), Early VRU right side, Cyclist from driver direction (intersections), and Visual obstruction. * SPSS: The validity of the model fit was uncertain at roundabouts. ** SPSS: The intersection model was calculated without PL data, because the model did not yield an output with PL data.

3.3.4 Behavioural factors

Secondary task involvement was rated in terms of manual, visual, and auditory non-driving tasks (e.g., making phone calls, inspecting documents). Separate ratings were recorded for the time window prior to the maneuver, and the maneuver itself. Almost all drivers were at some point involved in a secondary task. Table 3.8 shows the average proportion of secondary task involvement when a visual component was included (e.g., visual, audio-visual, manual-visual). It is interesting to note that about two-third of the drivers were involved in a secondary task with a visual component during at least one manoeuvre (i.e., second factor in Table 3.8). The absence of significant effects (see Table 3.9) suggests that drivers did not compensate their gaze behaviour when they were involved in such tasks, or that there was not enough statistical power to find a significant effect.

Table 3.8: Blind spot checks as function of secondary task involvement with a visual component.

Factor	Country	Category	Intersections			Roundabouts		
			X (*n*)	*M* (%)	*SD*	*X* (*n*)	*M* (%)	*SD*
Secondary task with visual component (pre-manoeuvre)	Total	Yes	27 (18)	16.67	38.35	18 (14)	14.29	36.31
		No	934 (69)	7.16	11.55	808 (46)	4.58	10.47
	FR	Yes	10 (6)	16.67	40.82	4 (4)	0	-
		No	226 (19)	2.70	4.76	182 (14)	.55	2.06
	NL	Yes	4 (3)	66.67	57.74	2 (2)	50.00	70.71
		No	128 (8)	26.43	20.75	177 (8)	19.01	18.66
	PL	Yes	5 (4)	0	-	-	-	-
		No	145 (11)	7.39	9.57	-	-	-
	UK	Yes	8 (5)	0	-	12 (8)	12.50	35.36
		No	435 (31)	4.84	6.37	449 (24)	2.11	4.16
Secondary task with visual component (during manoeuvre)	Total	Yes	41 (31)	8.06	26.13	31 (21)	9.52	30.08
		No	920 (69)	7.24	11.77	795 (46)	4.67	10.78
	FR	Yes	13 (9)	0	-	13 (8)	0	-
		No	223 (19)	3.11	4.88	173 (14)	.60	2.23
	NL	Yes	6 (3)	50.00	50.00	5 (5)	20.00	44.72
		No	126 (8)	26.50	21.36	174 (8)	19.61	19.27
	PL	Yes	7 (7)	0	-	-	-	-
		No	143 (11)	7.74	10.21	-	-	-
	UK	Yes	15 (12)	8.33	28.87	13 (8)	12.50	35.36
		No	428 (31)	4.63	6.46	448 (24)	2.07	4.08

NOTE: Gaze has been evaluated from 6 sec. pre-maneuver to the end of the maneuver. *X* = number of segments across all drivers. *n* = number of drivers with at least one data point on the corresponding factor. *M* = Average proportion of blind spot checks per driver.

Table 3.9: GLMM main effect results on behavioural factors

Factor	Intersections			Roundabouts		
	df	*F*	*p*	*df*	*F*	*p*
Visual secondary task (pre-manoeuvre)	1,79	.001	.98	1,22	.93	.35
Visual secondary task (during manoeuvre)	1,91	.018	.89	1,34	.15	.70

NOTE: Each main effect was tested with a separate GLMM. The main effect of Country was significant on both factors for intersections.

3.3.5 Exploration other gaze behaviour

If drivers rarely check their blind spot, then where do they look instead? The gaze categories ‘Unsure’ and ‘Cannot be determined’ have rarely been used by the annotators. Therefore, drivers must have looked either sideway, towards the future road, or elsewhere (i.e., the remaining gaze categories).

Area graphs have been created to visualize the relative proportion of each gaze category over time. Figures 3.3 and 3.4 display the results of all intersection and roundabout manoeuvres, distributed across country. The onsets of the manoeuvres in each of the panels have been aligned at t=0. We have chosen to use the kinematic data described in Figure 3.1, rather than the manually annotated timestamp, because this ensures that all manoeuvres contain annotated gaze data at t=-6 (i.e., the start of the time window). Synchronicity between the manually annotated timestamp and the kinematic timestamp was checked by subtracting the timestamp values for each manoeuvre. The mean difference was .14 sec (*SD* = 1.08), which means that the onset according to the automatic extraction can be interpreted as the onset according to manual annotation.

Comparison across countries

The most striking finding in Figure 3.3 and 3.4 is the relative proportion of the gaze categories. At any given time, drivers were mostly looking at the future road towards the manoeuvre was being made. The share of this gaze category varied between approximately 65% and 95%. Prior to the manoeuvre onset, the second most occurring category was generally ‘Elsewhere’, followed by ‘Sideway’. During manoeuvres (i.e., t>0) the proportion of ‘Sideway’ increased, but it rarely surpassed the proportion of ‘Elsewhere’. As expected, ‘Blind spot’ was the least prevalent gaze category.

Figures 3.3 and 3.4 show that if the blind spot is checked prior to the manoeuvre onset, this happens mostly in the last second prior to the manoeuvre onset (i.e., -1<t<0). Furthermore, the top panels show an increased proportion of sideway glances at intersections as the manoeuvre onset is approached. This increase appears to start earlier in the Netherlands (i.e., approximately at t = -3) than in France and United Kingdom (both at approximately t = -1).

Another striking finding is that hardly any sideway checks have been observed at roundabouts in France and United Kingdom (see bottom panels in Figures 3.3 and 3.4). In the Netherlands, on the other hand, drivers appear to frequently perform sideway checks and blind spot checks, with an increase of such behaviour one second prior to the manoeuvre onset.

We continue by juxtaposing the charts of gaze behaviour over time for three variables that seem to significantly affect gaze behaviour. These area charts contain data from all countries, which means that the observations from the United Kingdom have a relatively large share in the gaze proportions, compared to the other countries (i.e., see Table 3.2).

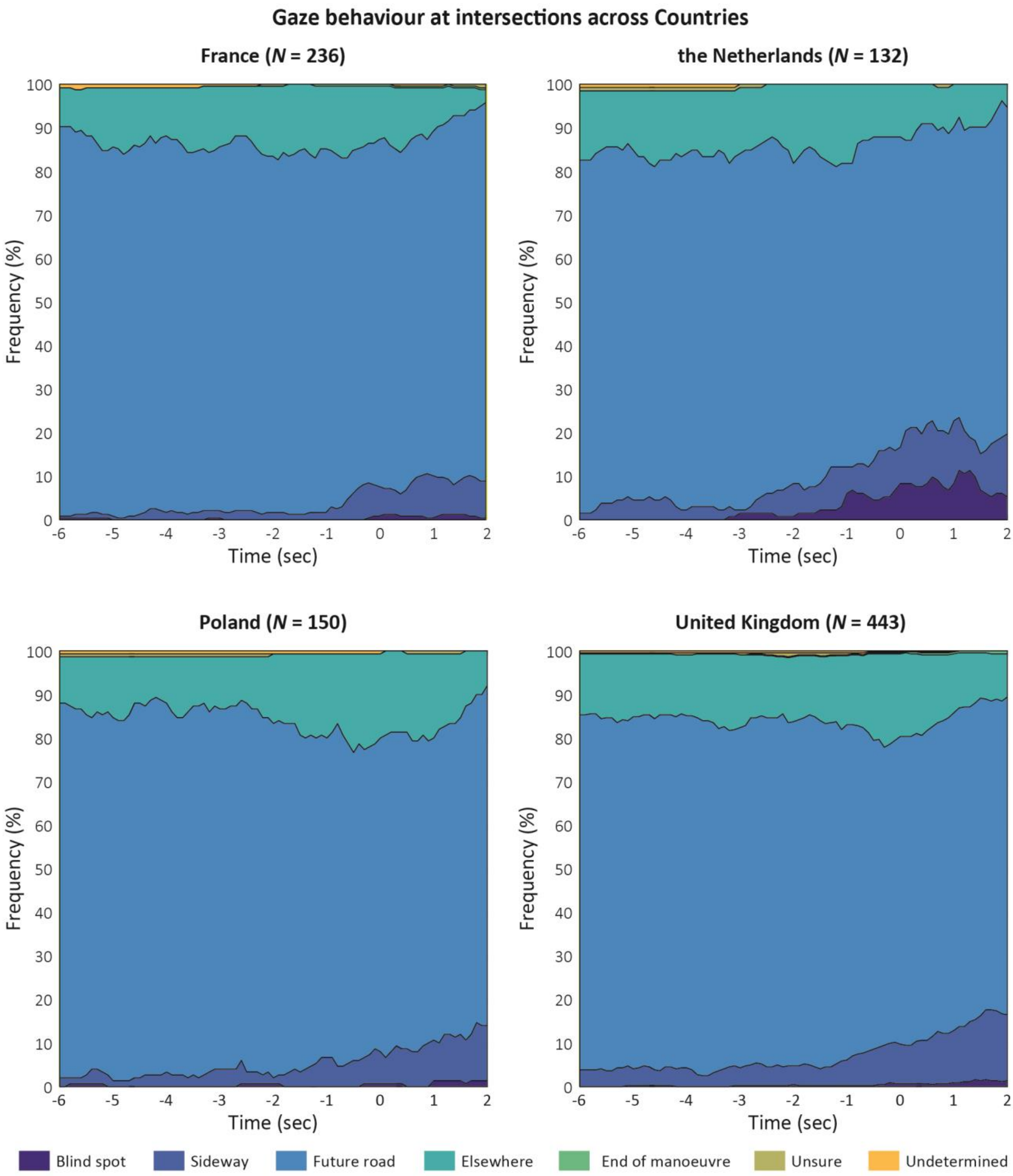

Figure 3.3: Comparison of gaze behaviour over time at intersections for each country. NOTE: t0 corresponds with the manoeuvre onset. *N* represents the number of manoeuvres.

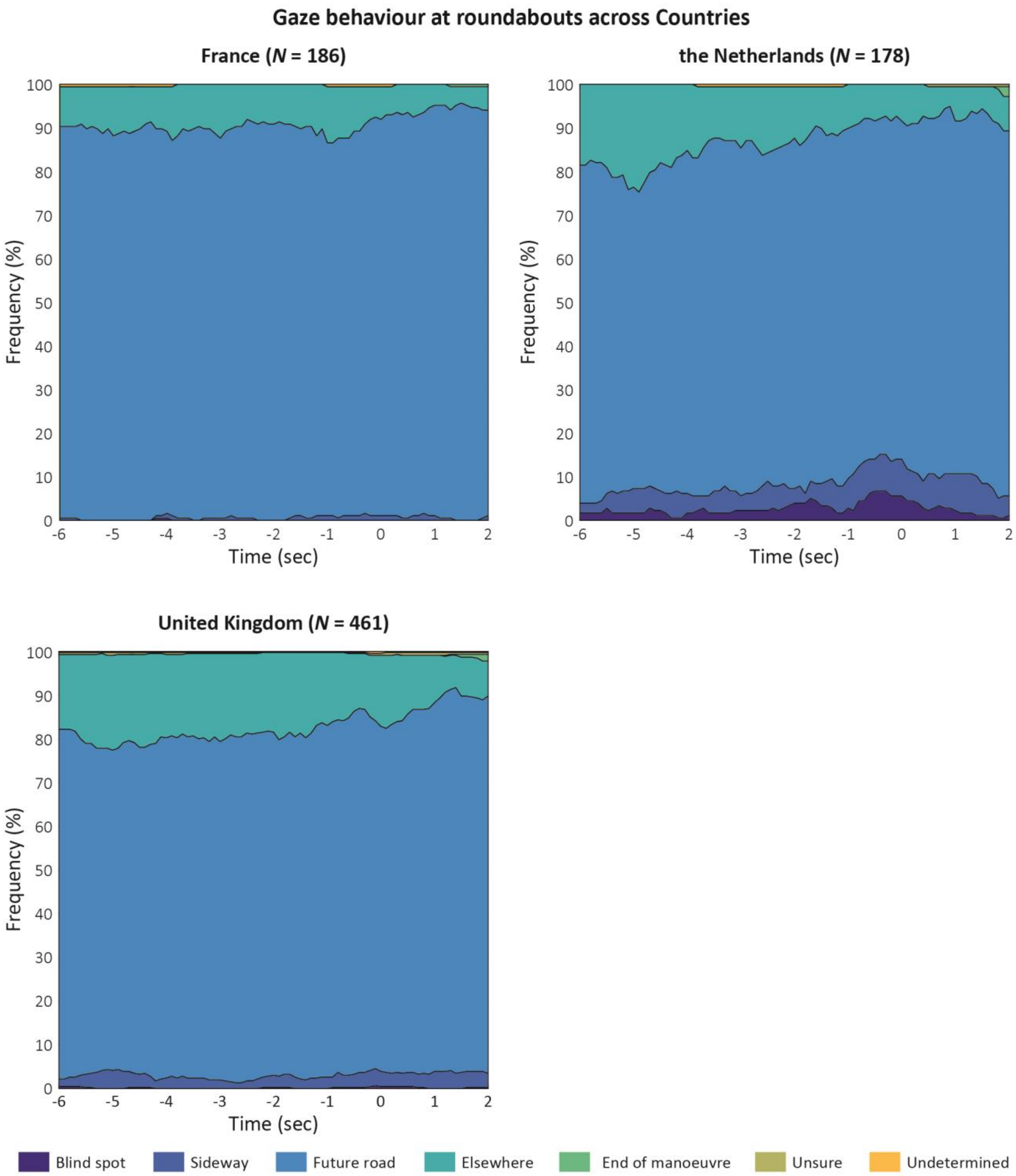

Figure 3.4: Comparison of gaze behaviour over time at roundabouts as function of country. NOTE: t0 corresponds with the manoeuvre onset. *N* represents the number of manoeuvres.

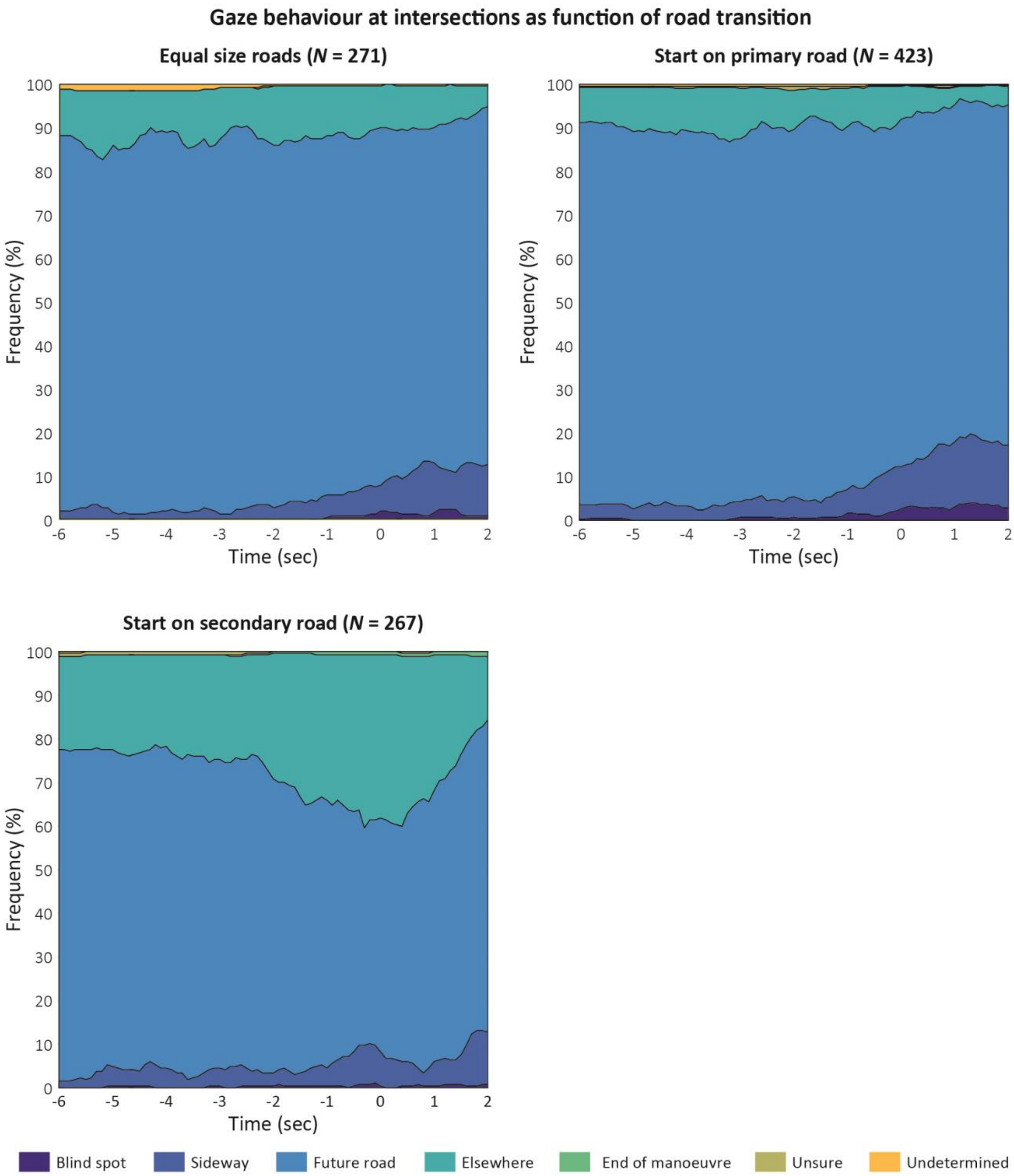

Figure 3.5: Comparison of gaze behaviour over time at intersections as function of road transition. NOTE: t0 corresponds with the manoeuvre onset. *N* represents the number of manoeuvres.

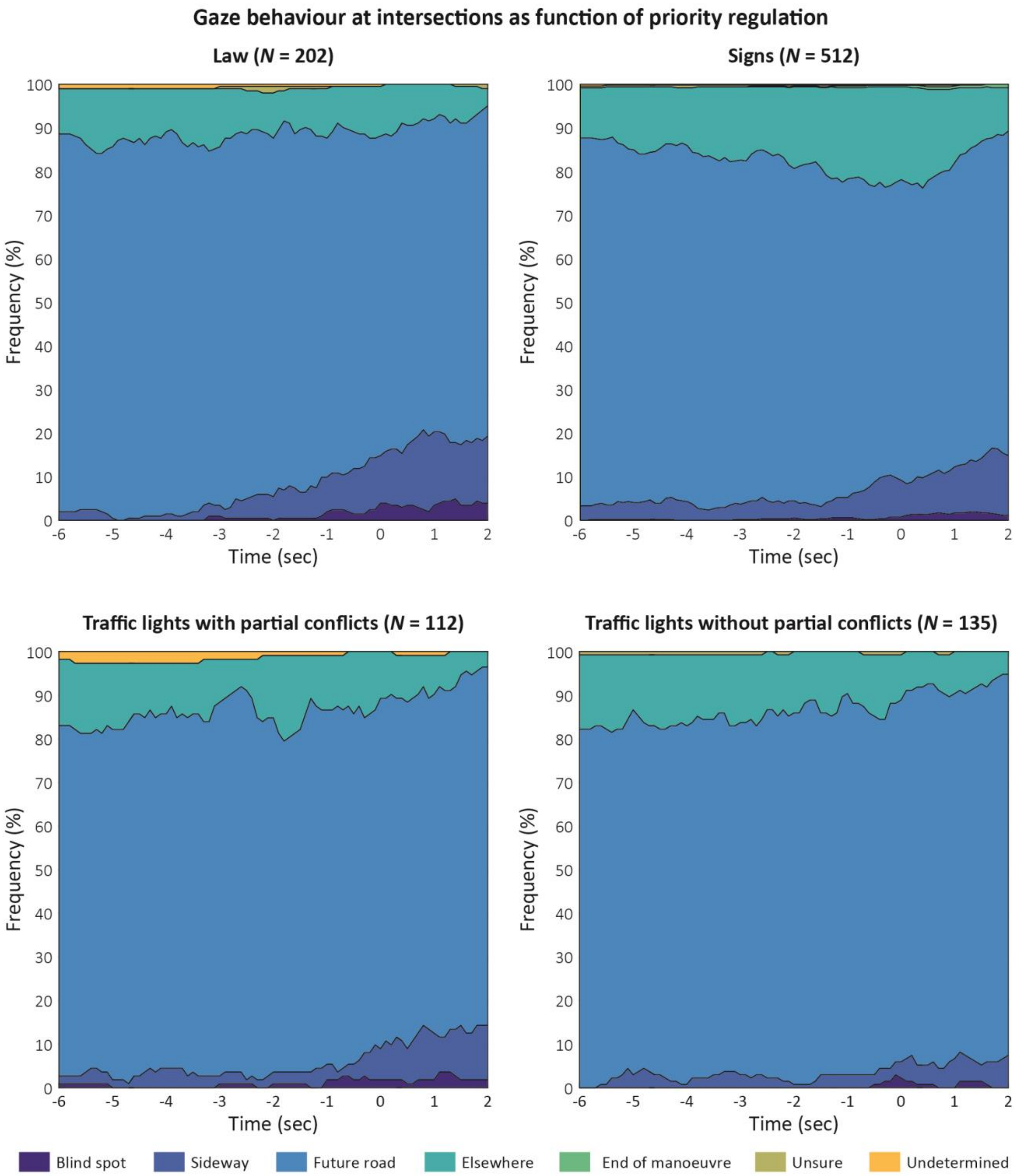

Figure 3.6: Comparison of gaze behaviour over time at intersections as function of priority regulation. NOTE: t0 corresponds with the manoeuvre onset. *N* represents the number of manoeuvres.

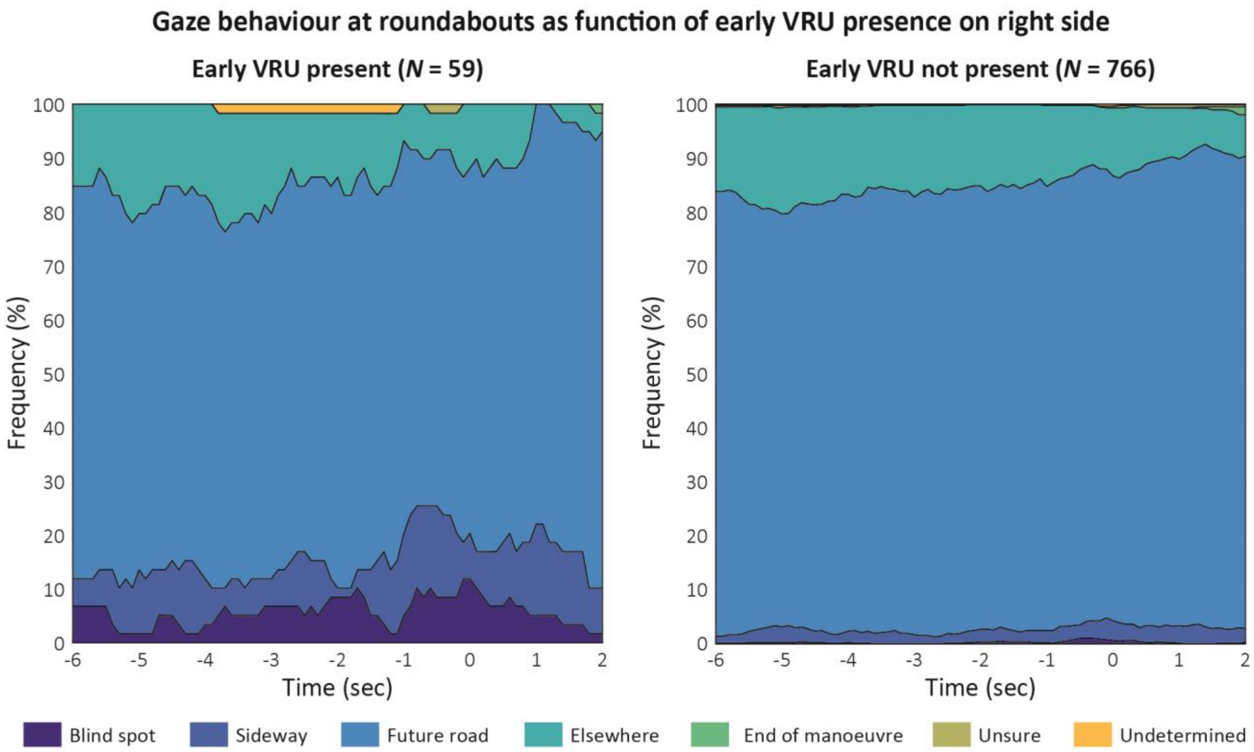

Figure 3.7: Comparison gaze behaviour over time at roundabouts as function of presence early VRU. NOTE: t0 corresponds with the manoeuvre onset. *N* represents the number of manoeuvres.

Comparison road transition types at intersections

Figure 3.5 displays the area charts of segments at transitions between two equal roads (left) and segments where the driver started on the primary road (right). Throughout the whole time frame (i.e., 6 sec before the start of the manoeuvre until 3 sec after) there were more sideway glances at Primary than at Equal, predominantly between t=-1sec and t=2 sec. This difference appears to be at the cost of glances in the 'Elsewhere' category. Furthermore, when starting at the primary road, blind spot appear earlier (from t=-3sec) than at equal road transitions (from t=-1sec).

Comparison priority regulation at intersections

The area charts of Figure 3.6 show that the blind spot was checked at various moments ranging between t=-3sec and the manoeuvre onset at t=0sec, except in case of 'Lights without partial conflicts' (note: the proportion in that range is very low, but still present, at 'Signs'). Furthermore, the pattern of increasing sideway glances appears to vary across the priority regulation types. At 'Law' and 'Signs', the increase starts around t=-3sec and t=-1.5sec, respectively. In both categories with traffic lights, however, sideway glances only start to increase at the manoeuvre onset.

Comparison of presence early VRU at roundabouts

Figure 3.7 displays the area charts of segments where a vulnerable road user was present in the first three seconds of the time frame (left), and when this was not the case (right). It appears as if drivers continuously check their blind spot at roundabouts when a VRU was present in the first few seconds of the time frame. In contrast, when no early VRU was observed, drivers appear to typically check their blind spot only in the second prior to the start of the manoeuvre. In addition, the proportion of sideway glances is higher when an early VRU was present, in particular at the second prior to the start of the manoeuvre.

3.4 Discussion

This chapter examined how often car drivers check their blind spot, which factors influence such behavior, and when blind spot checks occur. Data from four countries have been examined: France, the Netherlands, Poland, and United Kingdom. The main finding is that drivers only check their blind spot prior to the maneuver in approximately 4% of the cases, both for intersections and roundabouts. When the manoeuvre is included, the frequency of blind spot checks marginally increases to 7% at intersections, and 5% at roundabouts. These figures are lower than what has been found in experimental studies on right lane changes (e.g., 15% in Kiefer & Hanckey, 2008).

3.4.1 Low average frequency of blind spot checks

The low average frequency of blind spot checks raises the question if this is problematic, and in which circumstances. Perhaps drivers felt that the traffic did not necessitate blind spot checks in the majority of the manoeuvres. However, there are situations in which blind spot checks should definitely be performed. One of those situations concerns stop and go traffic. When drivers have to wait, cyclists may overtake the car in the meanwhile. Drivers should then check the blind spot to update their situation awareness. A previous pilot study (Christoph et al., 2010; Van Nes et al., 2013) showed that drivers waiting at a traffic light cast more sideway glances (i.e., including blind spot checks) before making a turn. In our study, however, no significant effects have been found on the factor Traffic flow. Possibly, the difference with the pilot study can be attributed to the fact that our study focused only on blind spot checks, whereas the former included both blind spot checks and sideway glances. Therefore, Chapter 4, which investigates the timing of gaze behaviour, also includes sideway glances.

Another potential explanation for the low average frequency of blind spot could be that the infrastructure did not necessitate blind spot checks. An example would be where a separate cycle track does not go straight where the driver takes a right turn. In such situations, low blind spot check scores may not be an issue. At intersections we have found significantly more blind spot checks when an encroachment zone was present. However, the average proportion with an encroachment zone is 7.81%, which is not much higher than the overall average at intersections.

Finally, the low blind spot scores may be explained by a technological factor that was not part of our dataset. Some vehicles are equiped with wide-view room mirrors, multifocal mirrors, or convex mirrors attached to the side mirrors, to make the visual search of the blind spot easier for drivers (e.g., Svenson et al., 2005). It is unclear whether the vehicles used in this study were equiped with such specialty mirrors. Furthermore, no dedicated category for mirror checking has been used during annotation. Therefore, if such mirrors were present, then the proportional scores presented in this study should be viewed as the minimum observed blind spot checks.

3.4.2 Intersections versus roundabouts

A potential explanation for the difference in blind spot checks between intersections and roundabouts is their physical layout. The complexity of monitoring merging traffic lanes at a roundabout is inherently higher than those at a right turn on an intersection (except if the driver leaves a roundabout at the first arm). Could such increased complexity cause competition between gaze directions, in which case the blind spot is overlooked? Tentative support for this hypothesis is found in the area charts on gaze behaviour. Compared to intersections, drivers not only perform less blind spot checks on roundabouts, but also less sideway checks. Instead, they mostly look forwards.

3.4.3 Differences across countries

A large difference has been found across the investigated countries. On average, the frequency of blind spot checks in the Netherlands was 9.1 times as high as in France, 5.7 times as high as in the UK, and 3.7 times as high as in Poland. At roundabouts, Dutch drivers performed blind spot checks 7.9 times more often as in the UK, and 35 times more often than in France. The most logical explanation for this difference is that in the

Netherlands the prevalence of cyclists and cyclist facilities is higher, the latter of which has been confirmed by our data. Nonetheless, our finding raises the question to what extent the extreme neglect of blind spot checks in the UK, France, and Poland have contributed to cyclist fatalities, especially seeing that the number of cyclist fatalities in Europe is decreasing slow compared to motorised traffic (Levulyté et al., 2016).

3.4.4 Limitations and recommendations

The tables with descriptive data show many differences within countries on individual factors. On some factors, such as the presence of cyclist facilities, the categories appear to yield opposite effects on blind spot checks across countries. Yet, no significant interaction effects have been found. The samples size on distinct categories may have been too low. For example, there were no observations on the category 'Adjacent lane' in Poland, and no complex intersections with five or more legs in the Netherlands. This raises the question if it is reasonable to use the same analysis model (i.e., using the same factors and categories) to compare across countries. Alternatively, a large proportion of the variance in each GLMM may have been claimed by the factor Country, thereby limiting the possibility to detect potential subtle effects on other factors. Thus, further research at the level of invidivual countries is warranted.

This study focused on main effects, as opposed to interaction effects. The latter effect type could have helped in understanding some of our findings. For example, we have not found a significant effect of traffic flow, whereas one could reasonably expect that more blind spot checks would be performed when the manoeuvre is preceeded by a full stop (i.e., this situation warrants checks for being overtaken by cyclists). We did, however, find a significant effect on the presence of an early VRU at roundabouts. Tests on interaction such as between traffic flow and early VRU presence may refine our understanding of the situations that influence blind spot check behaviour. At the moment of writing, however, we do not have a sample size large enough to test such effects.

A large sample may also improve the generalizability of the findings. While the current sample features a similar distribution of gender and age across countries, no young (i.e., age <21 years) or elderly (i.e., age >70 years) are included. It is known from previous studies that younger drivers are overrepresented in crashes (Foss et al., 2011; McCartt et al., 2009). Therefore, additional data collection with younger drivers is warranted.

Acknowledgments

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4 Timing of gaze behaviour by car drivers towards cyclists at intersections

This Chapter stands by itself, except for compulsory reading of the general introduction of this report (Chapter **Fout! Verwijzingsbron niet gevonden.**). There are some references to other sections of the report, but those are not necessary for the understanding of this section.

4.1 Introduction

The fact that drivers rarely check their blind spot is intriguing (see Chapter 3). The glance area charts presented in section 3.3.5 sheds some more light on what drivers actually look at. However, there are still open questions with respect to drivers' threat/hazard assessment and timing of glances in relation to the actual conflict zone – in this case, where the right turning car and a potential bicyclist from the right would be encroaching into each other's paths (Figure 4.1).

One aspect of drivers' interaction with bicyclist is related to when drivers stop considering road-users from a specific area on the road or other part of the traffic scene as potential threats/hazards. For example, when a driver is about to turn right in an intersection he/she can have many different predictions about movements of other road users (Engström et al., 2017). For example, as a driver approaches an intersection to turn right (left in the UK) he/she is likely to make predictions about the likelihood of a specific type of road users (e.g., bicyclists) entering into the future path of his/her vehicle – a threat/hazard prediction of the traffic scene. The basis of such predictions would, for example, include prior experience of driving in general, driving in intersections, making right turns in intersections, making right turns in "this" specific intersection, (potentially) being a bicyclist (in the specific intersection or generally), as well as the information gathered from the drivers (human) senses about the specific situation as a drivers approaches the intersection. Literature (Senders et al., 1967; Zwahlen et al., 1988; Engström et al., 2017) argues that drivers "sample" the traffic environment by directing the eyes (gaze) to areas to reduce the uncertainty of predictions. Building on this, hypotheses can be formulated on <u>in case</u> drivers stop looking in a specific area of the roadway (the last time they looked – in hindsight) he/she is predicting that there are <u>no more threats/hazards</u> (potential future surprises; Engström et al., 2017) in that area, or, at least, that there is a very low probability that there may be a future threat. With this reasoning, it should be possible to increase the understanding of driver threat/hazard assessment (including predictions of the presence and state of potential threats/hazards) by studying when drivers stop looking in an area of potential threats/hazards. Intersections are particularly suitable traffic situations to perform such studies as drivers' typically need to perform large changes in the direction of the driver gaze (smaller gaze-angle changes are hard to capture in naturalistic driving data; Victor et al., 2015). In UDRIVE we studied when drivers stop looking towards the near-side (right side in right-hand driving countries and left in e.g. the UK) when turning right. We study the time point when drivers take their last look towards the near-side before having completed the turn in relation to when the drivers' vehicle enters into the encroachment zone (EZ). The EZ is defined as the zone where two vehicles trajectories overlap (see the grey rhomb in Figure 4.1 where the cars future path (outer edges of the car) overlaps with a potential bicyclist trajectory (that crosses the street that the driver is turning into) from the right). When there was no physical infrastructure that allowed a bicycle to enter from the right, the EZ was set as undefined and discarded from the analysis.

Specifically, analyses in this Chapter aimed at answering the following research questions:

- When do car drivers cast their last sideway glance towards a potential cyclist to the right before they enter the encroachment zone in a right turn (UK: left turn) manoeuvre in an urban intersection? (Figure 4.6)
- How often are such glances never casted? (Figure 4.2 and 4.4)
- Which factors influence the timing of such glance behaviour? (Figure 4.8)

The rationale behind these research questions with respect to traffic safety in UDRIVE are: If drivers fail to check their right side for potential bicyclist when they turn right, or they look to the right early in the intersection approach, they may not perceive a bicyclist about to encroach into their future path. More precise information about these aspects of right turns can help designers of policies and training schemas, as well as designers of infrastructure and in-vehicle safety systems in developing safety measures which are most needed to reach the EC safety target.

This study complements the analysis of blind-spot-check prevalence by extending the blind-spot checks to overall (right side Poland, Netherlands, and France; left side UK) threat assessment and analysis of the timing of such assessment (glances towards the right/left). This analysis relates to drivers' assessments of bicyclists potentially encroaching the drivers future path by entering the drivers roadway from the same direction as the driver originally came from (see Figure 3.2) – on the same roadway or on bike lanes or other bike-specific infrastructure. The analyses in this section contain the same definitions and annotations with respect to categorical variables in the analysis as in section 3.2.

To address the research questions outlined above with respect to driver threat assessment and threat prediction, UDRIVE uses an analysis method which applies a metric called intersection gaze release time (IGRT) is applied. IGRT is defined as the time from when a driver looks towards an area of interest (e.g., an area of potential threat) the last time before he/she enters into the encroachment zone, until the driver enters into the EZ. This method was introduced in a Swedish study of driver behaviours in intersections (Smith et al., 2009), and further explored by (Bärgman, Werneke and Smith, 2013). This method has, however, not previously been employed to study driver/bicyclist interactions in right turns – which we have done in UDRIVE. Smith et al. (2009) studied drivers' timing of the last glance towards an intersecting secondary road when passing at high speed on a rural highway. Bärgman, Werneke and Smith (2013) instead studied the timing of the drivers' last glance towards oncoming traffic when turning left (right hand traffic) in an intersection, relative to the entering of the EZ (of the two vehicles). The latter study used the EuroFOT naturalistic driving field operational test (http://www.eurofot-ip.eu/) while the former was a pilot study performing a controlled on-road experiment.

4.2 Method

The same dataset as was used for the blind-spot analysis (section 3.2) was also used for the analyses of IGRT and right-side checks in general (if drivers looked to the right at all between six seconds before the start of the right turn until they entered into the EZ). That is, 961 manually in-depth annotated right-turns were used. To enable the calculation (and subsequent analysis) of IGRT, manual annotation of driver glance behaviour during the time when drivers approached each intersection right turn was needed (also used to create glance area charts; see section 3.2), as well as annotation of the point in time when the driver enters in what we call the encroachment zone (EZ) (see description of annotation procedures in section 3.2.6), was performed.

The IGRT value was calculated by subtracting the time at the end of the last glance towards the right (see Figure 4.1) from the time of the vehicle entering into the EZ (see Figure 4.1).

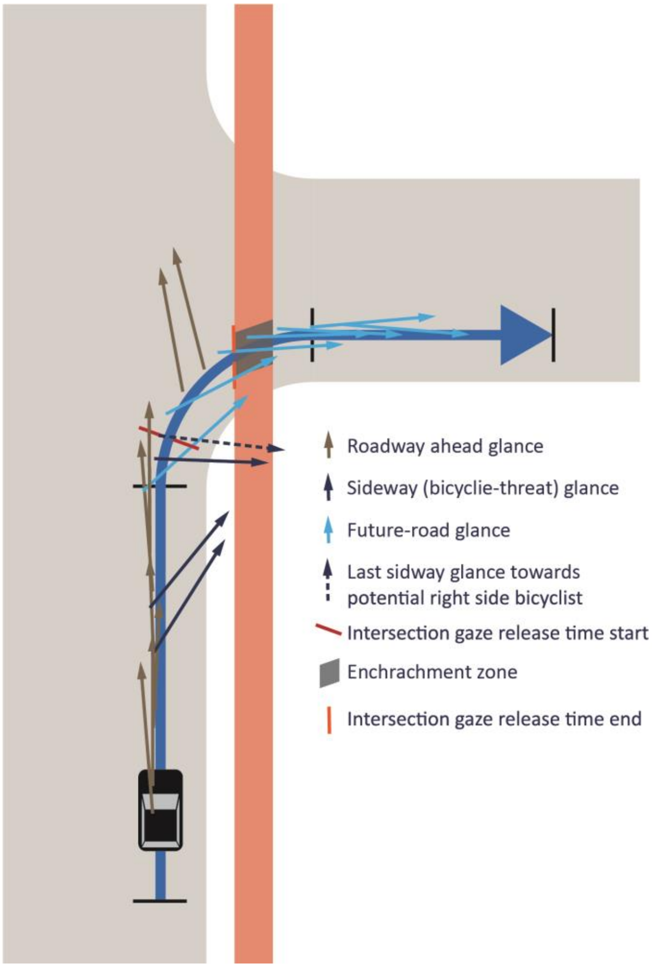

Figure 4.1: Schematic overview of elements required in the calculation of Intersection Gaze Release Time (IGRT). All but the large blue arrow (the vehicle path) represents glances (fixations) of the driver in the vehicle turning right over time – during the approach and through the turn. The encroachment zone (EZ) is defined as the rhomb defined by the overlapping trajectories. IGRT is defined as the time from the last glance towards the right (red 20 degree line) until the vehicle enters the EZ (orange vertical line).

4.2.1 Analysis

Six different types of analyses were performed with respect to IGRT and drivers (not) glancing towards the right during the approach until entering the EZ. First the number of right turns where a) the EZ was not defined, b) the drivers actually looked to the right at all (given the annotation definition), and c) there was a valid IGRT value (there was a right-side check) were compared. A pie chart was used to illustrate the number and percentage of these three sets of data in relation to the total set of (annotated) right turns used in the analysis. This was further broken down, into the number of right-turns that had calculable IGRTs (where there was an EZ), and the proportion of those that actually had a right-side check at all (and thus a valid IGRT was calculated). In addition, the proportion (percentage) of right-turns with a right-side glance out of the total calculable IGRT was calculated per driver. All of these analyses were done to understand the prevalence of drivers checking the right-side at all during the approach (and when there was no EZ, such a check would not be necessary, hence excluding it from analysis), and the distribution of such checks across drivers – as a complement to the blind-spot check analysis in section 3.2.

Second, the IGRT values were analysed (using only those right-turns that had valid IGRTs). Two distributions of the 262 valid IGRT values were created; one for the IGRT values themselves, and one where the natural logarithm (log) was applied to each IGRT sample. The natural logarithm was used to transform the zero-bounded IRGT to a more normally distributed dataset. Normal probability plots were created to verify the normality assumption. The IGRT and log(IGRT) distributions provide insight into the glance timing of right-turning vehicles and can be compared with a) IGRT in other scenarios, and b) the time available for coming to a complete stop before reaching the encroachment zone. This provides insight into what are (potentially) safe and unsafe glance behaviours in right turns (in addition to those not performing a right-side check at all). The latter (b) requires analyses of time-series kinematics and is not within the scope of this deliverable.

The third analysis studied the regional/international differences with respect to a) valid (a right-side glance and an EZ present) versus calculable (no right-side glance but an EZ present) IGRTs in the dataset across countries, and b) the values of IGRT across countries. The former was done through comparing the proportions of valid IGRTs across countries using chi^2 tests. Note that the chi^2 tests do not handle the unbalance in number of valid IGRTs across drivers and thus results should be used with that caveat. To handle this unbalance (but then intrinsically using a reduced sample size) a complementary analysis was performed using a generalized linear model (GLM) to compare the proportion of valid IGRT values (right-side checks in right-turns with an EZ) for the individual drivers, in the right-turns where IGRT was calculable (right-turns with an EZ), across countries. The GLM used an identity (normal) link function. Four models were created, each with one of the four countries as the reference category (France, the Netherlands, Poland and Great Britain); their Beta, t-statistics, and p-values are reported. Further, the comparison of the values of IGRT was done in two ways: Modelling, and visualizing the IGRT values using box-plots. As for the former, a GLM was used to predict IGRT (response variable) with the country (nominal predictor, with France, the Netherlands, Poland and Great Britain, as categories) as the independent variable (predictor/fixed effect). A log link function was used to perform the analysis on a “more normal distribution” than IGRT (which is bounded by zero and thus intrinsically not normal; see the results section analysis of normality). Here and in the following, the main reason for using a GLM instead of an ANOVA has been the unbalance in number of observations across drivers. That is, some drivers had many more IGRT values than others (see Result section). To handle this unbalance, weighing was used. Weighting was performed in the following way: each individual observation (each right turn) got the weight of one over the total number of observations that a driver had (in this dataset). The specific analyses of the influence of country were performed due to the European focus of UDRIVE and the rich dataset collected in UDRIVE facilitating such analysis. Understanding regional differences can help EU policy makers and legislator in their task to balance needs and requirements across countries.

The fourth analysis investigates which factors may influence the IGRT values. A univariate analysis using a generalized linear model (GLMM) approach was used to predict IGRT (response variable). That is, a separate GLM was used for each of a set of factors/predictor (gender, secondary task pre-manoeuvre, early VRU right-side, cyclist from driver direction, visual obstruction, secondary task during manoeuvre, cyclist facilities, road transitions, traffic flow, priority regulation, and intersection type). For details on these factors, see section 3.2. Again, the reason for using a GLM instead of an ANOVA was the unbalance in number of observations across drivers (see above), but also that, if multiple (univariately analysed) factors would significantly influence IGRT values, a multi-variate model could be constructed, and interaction effects studied. The reason for this analysis was to identify which factors influence IGRT (or, actually log(IGRT), as a log link-function was used). Separate factors/predictors (univariate analysis) were used only as a first selection of predictors. Predictors with a p, compared to a constant model, of less than 0.01 were kept for further analysis. In addition, an analysis of the Akaike information criterion (AIC) was done across the predictors. AIC is a measure of quality of modelling approaches such as GLM (Burnham et al., 2010). However, AIC is only a relative measure (for a set of data) and the absolute values should not be compared. Instead analysis should be done (and has so in this report) in relation to a chosen reference model. In the modelling in this section the model with the lowest AIC was used as a reference. Different from studying p-values AIC addresses the trade-off between model complexity and goodness of fit of a model. Low AIC values are better (higher quality) models. A figure showing the predictors sorted by increasing-AIC was created.

Fifth, the predictors that had a $p<0.01$ and lowest AIC in the univariate GLM analysis was further studied, and compared with the AIC criterion. Box plots and comparison of distributions was performed for these predictors. Note, however, that the box plots does not take the unbalance in the number of observations across drivers into account (drivers with many observations will be overrepresented). However, as general information about the values of IGRTs for the investigated significant factors (predictors), the inclusion of box-plots was deemed appropriate.

The sixth analysis was the study of the effect of drivers' traits – as captured by self-report questionnaires (UDRIVE D33.1 - Overview of OS preparation, sample characteristics and piloting) – on the IGRT values, and the choice to perform a right-side check glance at (during the 6 s before the manoeuvre until entering the EZ). Three types of analysis were performed: a median split analysis, a univariate analysis using GLM, and a multi-variate GLM analysis. All three types of analysis analysed five standard driver behaviour scores. Two of the scores were from the Arnett Inventory of Sensation Seeking (AISS; Arnett, 1994): novelty and intensity. The AISS aims to assess personality traits of sensation seeking (which is thought to affect risk taking), and to capture this through the two sub-scales (novelty and intensity). The remaining three standard driver behaviour scores were the mean of errors, aggressive violations, and ordinary violations, respectively, from analysis of the driver behaviour questionnaire (DBQ) proposed first by Reason et al. (1990). A more recent meta-analysis of the DBQ showed these scales to be predictive of self-reported accidents (de Winter and Dodou, 2010). In the median split analysis the drivers were split in two groups for each of the five scale – below or above (or equal to) the median of the score across the drivers. A t-test was then conducted to identify significant differences between the two (low and high scores, respectively). In the univariate GLM analysis each score was used as separate independent variable (one model for each variable), predicting IGRT (response variable). Here an identity (normal) link function was used as the scores were assumed to be normally distributed. In the multivariate analysis, all five variables were used as independent variables in one GLM model, predicting IGRT (again with the identity link function). Results

4.2.2 Right-side checks during intersection approach

In 255 right turns (26.53%; Figure 4.2) there was no EZ annotated. The reason for there not being an EZ was that the infrastructure did not permit a bicyclist to enter the road from the right during the subject vehicle's turn. In 444 events (46.2%; Figure 4.2) of the remaining 706 right there were no glances to the right during the six seconds before the start of the right turn, until the entering of the EZ (i.e. time section in which glances were manually annotated and IGRT was defined). As a result, in only 262 right turns (27.26%; Figure 4.2) there were valid IGRT values available. Sixty-five of the original 69 drivers in the dataset (generating the 961 right turns) had at least one right turn with a right side check when there was an EZ. The four remaining drivers never made a right side check, even if there was an EZ. Figure 4.4 illustrates in what percentage of calculable right turns (i.e., with an EZ) each drivers had an actual right-side check-glance. Figure 4.3 further shows the number of right-turns with calculable IGTRs that each of the 65 drivers (with at least one side-check glance) had, sorted by increasing number of calculable IGRTs. The IGRT analysis focused on both the 262 right turns where there were an IGRT value (EZ available and a right-side check), and how many of the 706 right turns that had an EZ where there was a right-side check during the intersection approach.

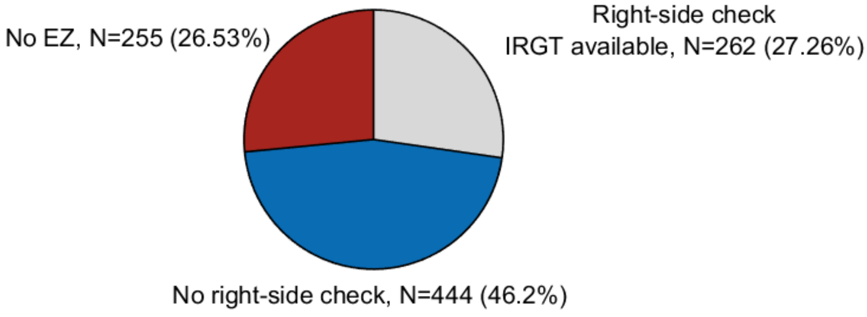

Figure 4.2: A visualization of the portion of events with no EZ, where IGRT was calculable, and the proportion of actual IGRTs.

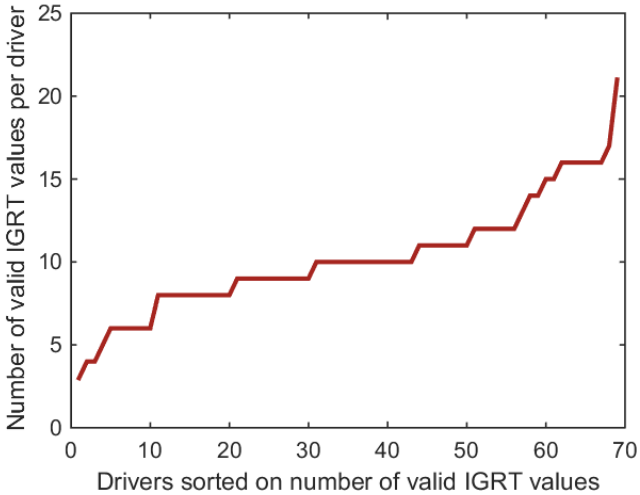

Figure 4.3: Drivers sorted on the number of IGRT values

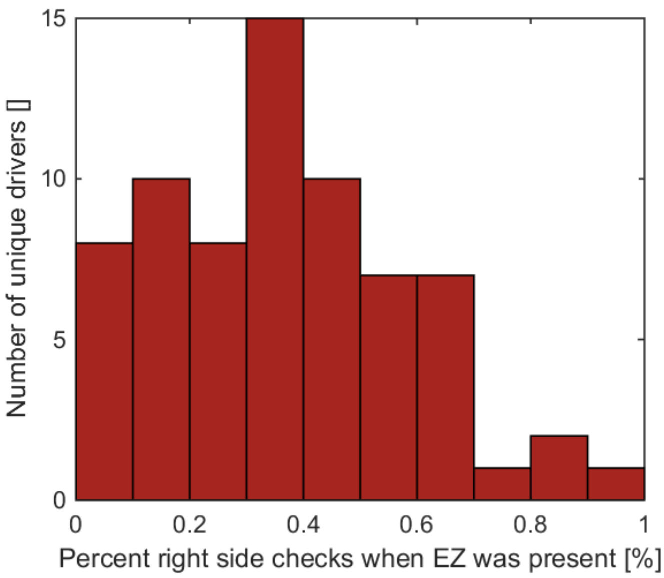

Figure 4.4: The percent right-side checks across drivers between six seconds before the starts of the right (UK left) turn and when the subject's vehicle entered into the encroachment zone (EZ). Only for the proportion of right-turns that had an IGRT (See figure 4.2).

4.2.3 IGRT distribution

The average number of IGRTs across the drivers with an IGRT was 10.2. The median and standard deviation was 10, and 3.42, respectively. See Figure 4.3 for a visualization of the number of IGRT values across drivers. Note that neither IGRT nor the natural logarithm of IGRT (log(IGRT)) conveys information about some drivers performing more or less threat assessment to the right, as exposure information (how many right turn they conducted in relation to the number of actually annotated right turns) was not considered in this analysis. Figure 4.5 shows the normality-check plot for IGTR and log(IGRT), indicating a somewhat right-skewed distribution with more variance than for a normally distributed metric. Figure 4.6 shows the distributions of the IGRT and log(IGRT), respectively. The right skew is likely due to the window of analysis applied in UDRIVE, bounding IGRTs to be no earlier than 6 s before the start of the right-turn manoeuvre.

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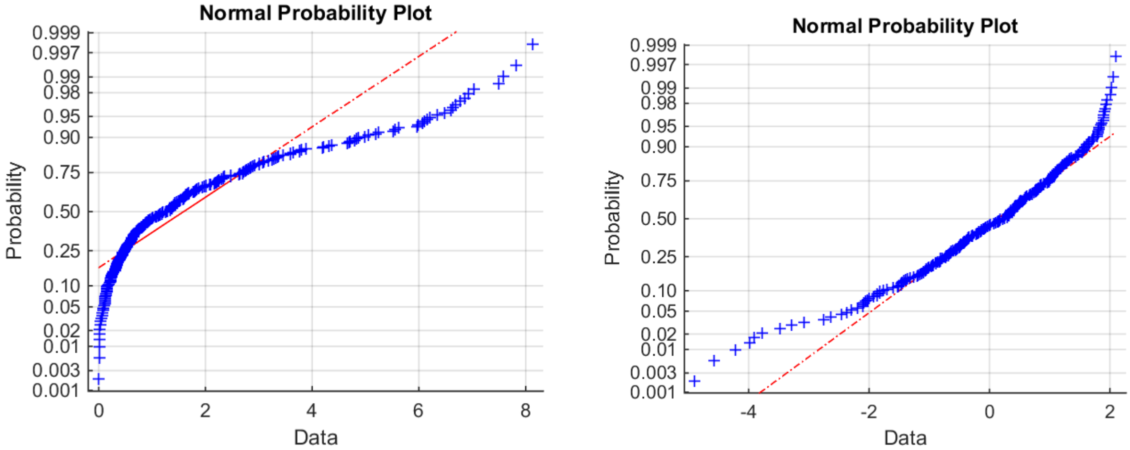

Figure 4.5: Normal probability plot for IGRT (left) and log(IGRT) (right).

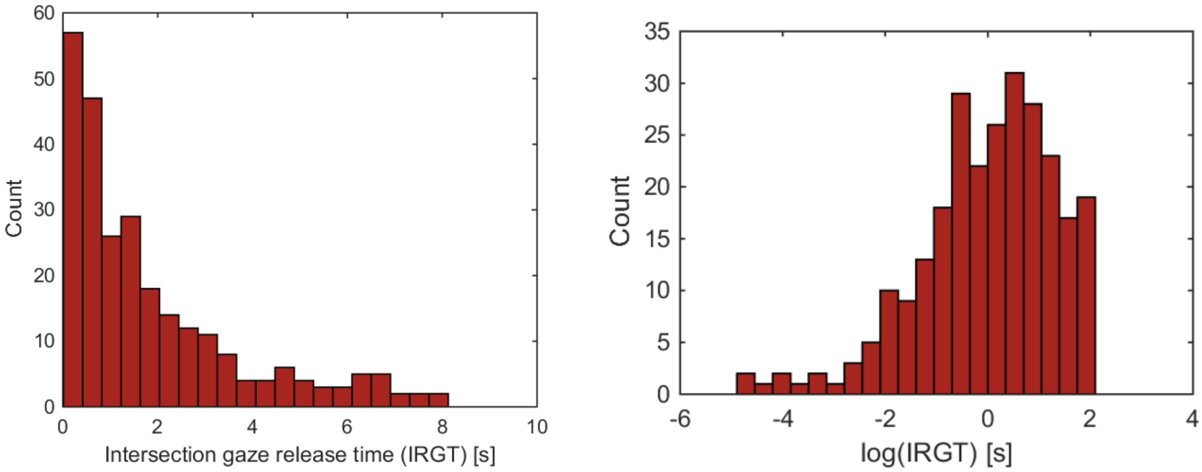

Figure 4.6: The distribution of IGRT values (left) and log(IGRT) (right)

4.2.4 Analysis of country/region influence on IGRT

A breakdown of Figure 4.2 (number/percent of no EZ, calculable, and valid IGRTs) across countries are shown in Table 1. United Kingdom had by far the largest proportion of both calculable (49.0%) and valid IGRTs (50.8%), but that is due to most right-turns being selected from drivers in the United Kingdom (as they were available earliest in UDRIVE). Chi^2 tests were performed to evaluate difference between pairs of countries. With an alpha of 0.01 (additional corrections for multiple tests in this analyses are up to the author) there was a significantly (much) lower proportion of right-side checks (valid IGRTs) in France compared to the Netherlands (chi^2=24.0, p<0.0001), and compared to the United Kingdom (chi^2=8.4, p=0.0038). The proportion of right-side checks in the Netherlands was higher than in Poland (chi^2=7.2, p=0.0072) and the United Kingdom (chi^2=9.7, p=0.0019). There was no significant difference between France and Poland, and Poland and the United Kingdom (see Table 4.2 for clarification). Note that this analysis treats each observation as independent, and does not take into account the unbalance in observations (calculable IGRTs) across drivers illustrated in Figure 4.3.

Table 4.1: Distribution of right turns with IGRT values across drivers and countries.

Country	Right turns where IGRT was calculable (had an encroachment zone)		Right turns where IGRT had a value (had a glance to the right)	
	Number of right-turns	% of total	Number of right-turns	% of total
Total	706	100	262	100
France	185	26.2	48	18.3
the Netherlands	74	10.5	43	16.4
Poland	101	14.3	38	14.5
United Kingdom	346	49.0	133	50.8

Table 4.2: For easier cross-referencing to Table 4.1 for a reader: The p-values from the comparisons of proposition of calculable and valid IGRT values across countries using Chi^2. Bold values are significant with alpha=0.01.

	Chi^2 crosstab p-values		
	The Netherlands	Poland	United Kingdom
France	**<0.0001**	0.040	**0.0038**
the Netherlands		**0.0073**	**0.0019**
Poland			0.88

The results of the complementary GLM modelling of the proportion of valid IGRT values out of the calculable IGRT right-turns for each driver and across countries are shown in Table 4.3. The overall model statistics (compared with a constant model) was ($F_{1,65}$=3.0, p=0.034). Only the proportions between France and the Netherlands were significantly different with alpha=0.01. Note, however, that the number of observations used in this modelling was then number of drivers for each country, while the individual right-turns are use in the in the Chi^2 analysis above. This difference in samples size is likely the main reason for the difference in levels of significance between the Chi^2 analysis and the GLM analysis. Taking the sample size difference into account, the results between the two types of analysis are reasonably consistent.

Table 4.3: The results (Beta, t-statistics, and p-values) for GLM models predicting the proportion of valid IGRTs of the calculable IGRTs for each individual driver, across all combinations of countries. Bold values are significant with alpha=0.01.

	The Netherlands	Poland	United Kingdom
France	**Beta=0.30** **t=3.0** **p=0.0035**	Beta=0.09 t=1.14 p=0.26	Beta=0.08 t=1.32 p=0.19
The Netherlands		Beta=-0.18 t=-1.82 p=0.073	Beta=-0.19 t=-2.25 p=0.028
Poland			Beta=-0.0092 t=-0.13 p=0.90

To handle the unbalance in observations across drivers a generalized linear model (GLM) was also used to evaluate if there was a difference in the IGRT values across countries. The model was not significant compared to a constant model at alpha=0.01 (or even at alpha=0.05).

Figure 4.7 shows a box-plot of the IGRT and log(IGRT) values, respectively, for the reader to get as complete picture as possible of IGRT. Note, that the observations (individual right-turns) are again considered independent and the unbalance in the number of valid IGRTs across drivers is not handled in the box-plot representation.

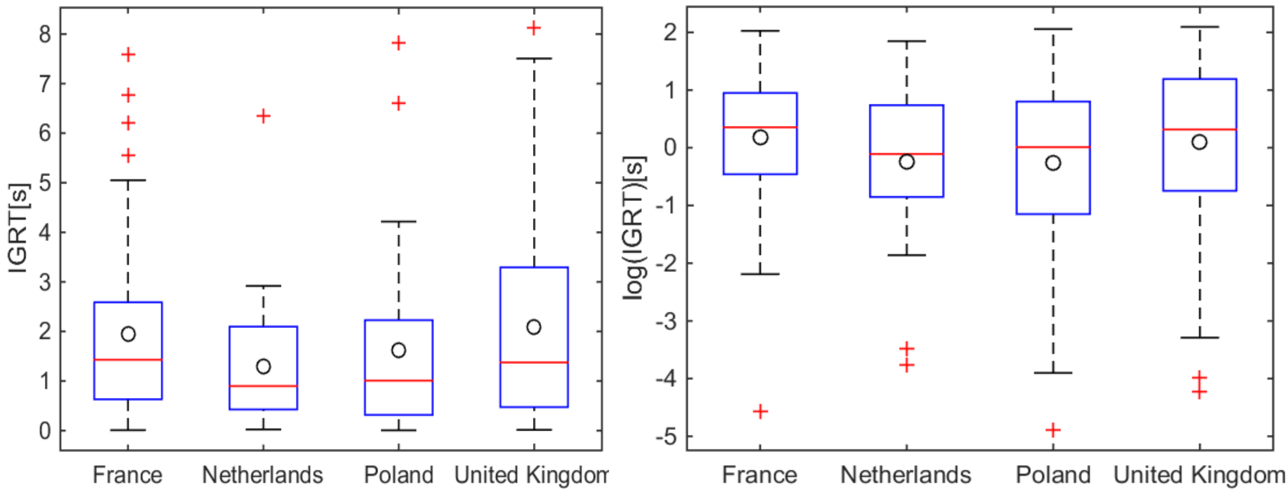

Figure 4.7: Box-plot of the IGRT values across countries.

4.2.5 Analysing which factors influence IGRT values

The univariate (each predictor individually) generalized linear modelling approach using a log link-function and was analysed in two ways. First, the model fits were evaluated with respect to significant differences compared to a constant model (F-statistics) with an alpha of 0.01. The results showed only gender to be significantly different (F(); p=0.0048), while all other predictors were not significant (other than gender, only Cyclist facilities had a p<0.1; p=0.033). The second analysis was the comparison of the Akaike information criterion (AIC) across the univariate models. Figure 4.8 shows the AIC for the 11 evaluated predictors sorted by increasing AIC (offsetting all to the AIC of the lowest AIC). Not surprisingly, as gender was the only significant model, gender also had the lowest AIC. As no other factor then gender gave a significant model fit, further multi-variate analysis of combinations of factors are not reported here (such analysis was performed in different ways, but not reported here as it did not provide additional insights, to reduce clutter, and to improve clarity). Further analysis was, however, performed to understand how gender affected the IGRT values.

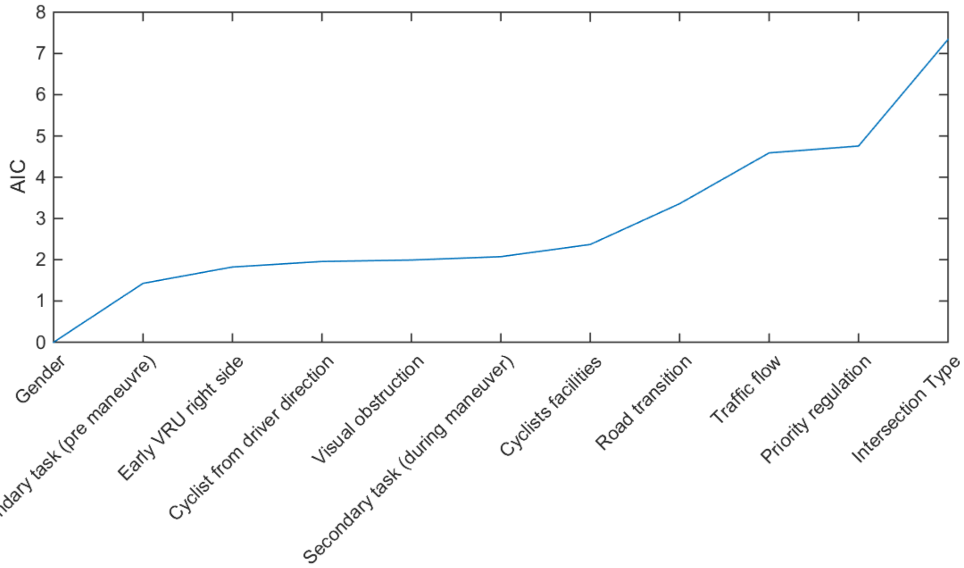

Figure 4.8: The Akaike information criterion (AIC) for the 11 predictors (see section 3.2), sorted by increasing AIC relative to the lowest AIC (gender).

4.2.6 Further analysis of gender

As gender both resulted in a significant GLM model prediction and had the lowest AIC, IGRT values for this predictor was further studied. Figure 4.9 shows the box-plots, with means included, for both IGRT and log(IGRT). Figure 4.10 also shows the actual distributions of IGRT for males and females, respectively. Males, on average, have a larger IGRT than females. That is, they made their last glance towards the right-side earlier (less safe?) than females. Figure 4.10 indicates that males have a somewhat "thicker tail" in the IGRT distribution.

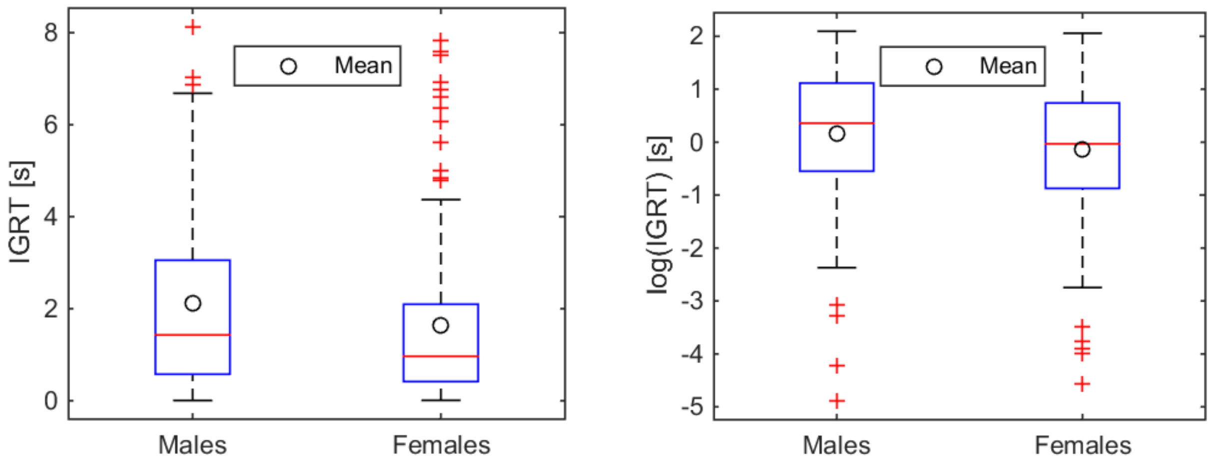

Figure 4.9: Box plots of the difference between males and females with respect to IGRT (left) and log(IGRT) (right).

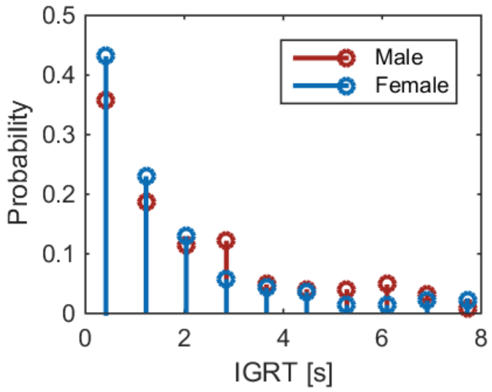

Figure 4.10: Distributions (stem plot) of IGRT for males and females, respectively, across the entire dataset.

To investigate any interaction effect by country, a GLM with both gender and country, and its interaction effect, was fitted to the data. The results showed a clear interaction effect and the F-statistics of the model increased ($F_{1,254}$=5.6; p=<0.00001). Only when UK drivers were used as the reference category in the GLM gender still showed a statistically significant main effect (t(254)=4.47, p<0.00001). In the same model, the interaction between country and gender was marginally significant with males in the UK having a higher log(IGRT) values than females in France (t(254)=2.0,p=0.041) and Poland (t(254)=-2.6, p=0.025). When other countries were used as the reference category in the model, only the same two interaction effects were even marginally different. Beta (the coefficient) for gender was 0.67 for log(IGRT) as the response variable, indicating male drivers in the UK having a higher IGRT (log(IGRT)) values – an earlier last-glance to the right – than others. Note, that the number of male drivers in this analysis for the UK was only 13 (and 17 were females). Figure 4.11 shows an example distribution of IGRT for the interaction effect between gender and country – males-in-UK compared to females-in-France. The figure shows longer IGRTs (earlier right-side glances) for male UK drivers.

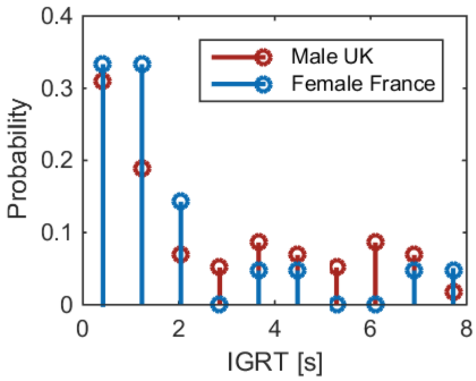

Figure 4.11: Distributions (stem plot) of IGRT for males-in-UK and females-in-France, respectively, across the entire dataset (no care taken to unbalance in number of observations/right-turns between drivers).

4.2.7 Evaluation of the influence of driver self-reports

In addition to the modelling aiming to identify which external factors influence the IGRT, analyses were conducted to evaluate if driver traits – as captured through self-report questionnaires – could be identified that influence driver IGRT.

The median split analysis did not show any significant difference between the two groups of drivers (split by the median score of the respective measures across all drivers) for any of the five scores of the questionnaire. Univariate GLM models for each of the five factors also showed no significant effects. The third, and final analysis, a GLM with all five standard scores as factors in the model was constructed. That is, a model investigating if the combination of self-report standard scores predicted log(IGRT). This analysis did not show the combinations of the driver traits (as captured by the self-report questionnaires) to significantly predict log(IGRT) values.

4.3 Discussion

This part of the study of car/bicyclist interaction in UDRIVE aimed to study the timing of right-side checks while drivers approach an intersection to turn right, as well as to identify how often drivers fail to perform such right-side check during the approach. To study timing a metric called intersection gaze release time (IGRT) was analysed. This metric quantifies the time from the last glance towards an area where a threat/hazard may appear (i.e., in this study, a bicyclist coming from the right), until the subject vehicle enters into the encroachment (conflict) zone of the (ego) vehicle and a potential bicyclist from the right. The larger the IGRT, the earlier the driver stops considering any right-side threat/hazard (e.g., a bicycle).

Similar to the blind-spot analysis, the fact that drivers only perform a right-side check in 37.1% of the right-turns where there is an encroachment zone is striking. This likely means that the drivers in the majority of right turns predicted that there would not be any encroaching bicyclists (or that no cyclist could appear due to lack of infrastructure) from the right. This was true for the right turns in our dataset (and for most right turns in general). However, for the bicyclists across Europe that die or are severely injured every year after being struck by a right turning vehicle, this is no consolation. Our results show that drivers seem to be putting very much trust in their prediction model of the probability of bicyclists (not) encroaching while the drivers turn right; for intersection right turns in general, and for the individual right turns in our study in particular. It also likely means that the drivers trusted the information they acquired from their senses (particularly the eyes) early in the intersection approach, about potentially encroaching road-users from the direction of their own traveling. With the method used in UDRIVE for acquiring time-series of drivers glance behaviours in the right turn approach, the small angles that early right-side checks (see Figure 4.1) would produce are not captured (to narrow angles compared to a look-ahead). We can thus not rule out that drivers make early (in the approach) right side checks. However, bicyclists approaching the intersection from the right side road turning right (crossing the side street) before entering into the (see Figure 4.1) would typically not be identified early in the approach. Also, when the right side is occluded right-side checks would not be possible early, and at least for those right-turns we should see a significant increase in the number of right-side checks later on (valid IGRTs). However, occlusion did not show significant effects – there was no significant difference when occlusion was evaluated as an independent variable predicting IGRT. From the perspective of driver behaviour and measures to improve safety one important aspect is drivers' variability. Figure 4.4 shows the, somewhat unexpected, large variability in drivers' proportion of right-side checks out of the total number of right-turns. Some drivers are relatively good at checking their right, but the vast majority checks the right less than half of the time.

An obvious reason for drivers not checking can be that they assume that the more vulnerable road-users would take care and not encroach even if they would approach the intersection to produce a potential encroachment. Future studies should investigate if this is the case.

The comparison of the proportion of valid IGRTs (right-turns with a glance and an EZ) versus calculable IGRT right turns (when an EZ was present) showed significant differences between primarily France and the Netherlands. This may be a question of exposure (many more bicyclist in the Netherlands), a matter of cultural/regional traits between the two countries (ref something?), or even (but possibly less likely) a matter of the differences in infrastructure. Future studies should compare the risks of bicyclist being killed or injured in the car-right-turn scenario with a bicyclist coming from the right, controlled by exposure and infrastructure.

The analysis of factors/predictors of IGRT values resulted in only gender as a significant predictor. Further analyses revealed an interaction effect between gender and country (specifically related to the UK). This is an unexpected and not very intuitive result. It is unclear why males in the UK would make their last glance to their left (other countries in the study, right) earlier than, for example, females in France. This may be an effect of left vs. right side driving, but that is also not obvious (then there would have been an overall country difference which there was not). Although results show this interaction effect, we are currently reluctant to claim that the significant interaction effect in IGRT is related to driver threat/hazard assessment (which could be interpreted as more risk taking by UK males). Instead we suppose some confounding bias that we have yet to identify.

No correlation was found with the two driver trait analysis tools to assess risky behaviours through self-report. That is, neither the Arnett Inventory of Sensation Seeking (AISS), nor the Driver Behaviour Questionnaire showed any predictive power with respect to IGRT (or log(IGRT)) values.

4.3.1 Method

This method and associated analysis is only a complement to the blind spot and gaze area chart analysis presented previously. As previously stated, the main aim of this analysis was to understand the timing of drivers' threat/hazard assessment towards the right when turning right in addition to understanding how often drivers fail to perform check-glances to their right at all. That is, the result of the blind-spot analysis (section 3.3.1-3.3.4) and the area charts (section 3.3.5) gave limited insight into the timing of drivers' threat assessment, and the blind-spot analysis investigated a subset of right-side checks. The area charts provide a great overview of the time spent looking in different areas, but as a glance can be short and initiated at different timings, threat/hazard assessment strategies cannot be derived from the area charts – that is where studying IGRT helps. Further, the blind-spot checks are a crucial part of negotiating intersections, but by studying all right-side glances (checks) a commentary picture about drivers right-turn manoeuvres is gained. It should be noted that IGRT is a post-hoc analysis to provide understanding of threat/hazard assessment, and it is not suited for direct implementations in advanced driver assistance systems – you would not know if the driver would look towards the right in the future (closer to the encroachment zone).

4.3.2 Future research

This analysis has only scratched the surface of the use of IGRT for intersection negotiations. By analysis gaze area charts (e.g., Figure 3.7) and intersection gaze release time (IGRT), it is possible to better understand drivers glance scanning behaviours in intersections, as well as their threat assessment strategies. Future research would benefit should use such tools to study interactions with vulnerable road users in other intersection manoeuvres, as well as in relation to other areas of potential threats in the traffic scene. In addition to modelling IGRT timing (as done here), further understanding of which contextual and behavioural factors that influence the decision to check an area for threats (e.g., through studying IGRT in relation to that area), could further inform in particular infrastructure designers, driver training specialists, and policy makers/legislators in their pursuit of reducing traffic injuries and fatalities.

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5 Gaze behaviour of truck drivers toward cyclists on urban intersections

5.1 Introduction

One of the most dangerous collision opponents cyclists can encounter is a truck at an intersection (Niewoehner & Berg, 2005). Between 5 and 10 cyclists lose their lives in a blind spot accident with a truck every year in the Netherlands (SWOV, 2015). This number is about equal in larger countries, such as Germany, where there are less cyclists on the road (Niewoehner & Berg, 2005).

Several measures have been proposed to minimize blind spot accidents (Schoon, 2012). From an infrastructural perspective, the greater the separation between a cycle lane (if present) and the main road, the better the truck driver's view on the presence of cyclists. From a behavioural perspective, cyclists are advised not to stop next to a truck, e.g., when waiting for a traffic light. Finally, truck drivers have been advised to use their blind spot mirrors as final check just before entering the zone where the truck crosses the trajectory of potential cyclists. The presence of blind spot mirrors has been a requirement for new trucks since 2007, and it has been advised to also enforce installment on older models.

Note, however, that there is a tradeoff between increased separation between the main road and the cycle lane, and the use of blind spot mirrors. The greater the separation, the greater the angle of the truck's trajectory with the trajectory of the cyclist. Consequently, the direction of the blind spot mirror, which is alongside the truck, will no longer be aligned with the cycle lane. Hence, no cyclist presence can be observed. This means the blind spot mirrors should be used in the time window before initiating the manoeuvre.

Failure of a truck driver to spot a cyclist alongside the truck could have various reasons. For example, the truck driver could have been looking in the blind spot location, but not identify the cyclist as such (Talbot et al., 2014). When a truck and a cyclist are both moving, the moment of visibility is very short, so the opportunity to spot the cyclist is reduced. Furthermore, truck drivers may be inclined to scan for other traffic coming from the left at the cost of blind spot checks, in line with a car study by Summala et al. (1996). However, a study by Olsen, Lee, and Wierwille (2005) showed that the blind spot was one of the most prevalent glance locations for drivers making a lane change to the left. These mixed findings warrant additional research on blind spot checks at right turn manoeuvres. Schoon (2012) recommends research on the actual use of blind spot mirrors using naturalistic driving data.

Therefore, the objective of this study is to investigate if truck drivers check their blind spot for cyclists before making a right turn on an urban intersection or roundabout, and which factors influence such behavior. The UDRIVE naturalistic driving dataset provides an opportunity to study these maneuvers in an everyday, real-life driving context.

5.2 Method

The UDRIVE database features more than 41.000 hours of naturalistic driving data with instrumented trucks. The present study focuses on the data that were available after driver identification by February 2017. Right turn maneuvers have been automatically extracted using the same procedure as described in section 3.2.2. Furthermore, the data reduction process described in section 3.2.3 has been used. The resulting data segments have been annotated with regard to infrastructural, situational, and behavioral factors. The sample population and annotation process will be described next.

5.2.1 Truck drivers and vehicles

Truck drivers were recruited at four Dutch transport companies. Forty-Two Dutch truck drivers (41 males, 1 female) participated in the study, with ages between 21 and 70 years (M = 47.51, SD = 11.27). Volvo FL and Volvo FM trucks were used. Both models are equipped with a blind spot mirror mounted in the top right corner of the front windshield. Thus, the position of the blind spot mirror requires the driver to turn his/her head sideways and look upwards.

5.2.2 Annotation

Five annotators were trained to validate and annotate the selected segments. The annotators were supported by a dedicated codebook (see Appendix B), with a subset of the variables in the central UDRIVE codebook. Infrastructural variables included intersection type, road type, priority regulation, and facilities for cyclists. Situational variables included traffic flow, and presence of vulnerable road users. Finally, behavioral variables included timestamps for the start and end of the maneuver, secondary task engagement, and gaze direction over time. Gaze direction was coded from the start of the segment until the end of the maneuver. Gaze categories consisted of: 'Blind spot check on right side' (with or without cyclist presence, or unknown presence), 'Sideway glance on right side' (with or without cyclist presence, or unknown presence), 'Glance towards the road the driver is turning into', 'Elsewhere', 'Unsure', and 'Impossible to determine'. After a few days of annotating interrater reliability was calculated through percentage agreement and Krippendorf's alpha. A second training session was held to increase interrater agreement, based on which the annotators revised their work.

5.2.3 Data analysis

The annotated data were processed and analyzed using Matlab version R2015b. For each segment a flag was raised when the blind spot was checked at least once prior to the onset of the maneuver. A separate flag was created for blind spot checks during the maneuver. Proportional scores for each driver were calculated by dividing the number of flags by the number of segments on each factor of interest.

5.3 Results

The initial selection of right turn maneuvers featured 10.122 intersections and 4.374 roundabouts. Many candidate maneuvers had to be excluded from further analysis because of asynchrony between the video data and the numerical data, or because the driver face was not visible. The latter issue may have been caused by non-participant colleagues, who may have moved or disconnected the cameras to avoid being recorded (even though such data would have been removed anyway during driving identification). After data reduction, the final dataset consisted of 159 right turn maneuvers by 10 truck drivers (range: 10-34 maneuvers) and 209 roundabout maneuvers by 10 truck drivers (range: 11-34 maneuvers), with an overlap of 8 truck drivers between the maneuver types. We first provide an overview of blind spot checks in both maneuvers, followed by an examination of infrastructural, situational, and behavioral factors. Due to the low number of drivers and observations, no inferential statistical analyses have been performed. Instead, descriptive data will be presented.

5.3.1 Overview blind spot checks

Table 5.1 shows the proportion of blind spot checks, averaged over all drivers. Prior to the maneuver drivers check their blind spot in approximately 5% of the intersections, and 13% of the roundabouts. The figures suggest that truck drivers check their blind spot more often during the maneuver. Another increase is found when the 'pre-maneuver' and 'during maneuver' sections are combined. The result is not additive, because some drivers occasionally checked their blind spot in both sections. The maximum combined score was 50% for one driver at intersections, but on average, only 19% of the intersections and 27% of the roundabouts have been checked. The combined score will be used throughout the remainder of the analysis.

Table 5.1: Overview of blind spot checks.

Time window	Intersections (N = 10)		Roundabouts (N = 10)	
	M (%)	SD	M (%)	SD
Pre-maneuver	5.25	4.02	12.80	8.45
During maneuver	17.54	8.96	21.58	12.24
Combined	19.45	9.00	27.40	12.78

NOTE: M = Average proportion of blind spot checks per driver.

5.3.2 Infrastructural factors

All manoeuvres took place in an urban environment. Table 5.2 shows the average proportion of blind spot checks on five infrastructural factors. Blind spots are most often checked on X-intersections, followed by T-intersections approached from the main road, and then from the by-road. This order is logical, because cycle lanes typically do not extend towards the opposite side of the road in the latter category, thus limiting the possibility of crossing a cyclist's trajectory. The differences, however, are small. At roundabouts, the turbo category and the single lane category yielded a similar proportion of blind spot checks. Less blind spot checks were observed at roundabouts with multiple lanes. This absence may be explained by the fact that the separated cycle tracks of these relatively large roundabouts are approached perpendicular, which reduces the necessity to perform a blind spot check.

When the road drivers turn into is of equal size as the one they leave, the blind spot was checked less often than at unequal road transitions. This finding is observed at both intersections and roundabouts.

With regard to priority regulation on intersections, drivers most often checked their blind spot when priority was regulated by law. Regulation by lights with partial conflicts (i.e., when two crossing trajectories both receive green light) yields the lowest blind spot score, but it should be noted that the total number of observations on that factor is limited (i.e., 9 cases across 6 drivers). The vast majority of roundabouts were regulated with signs, at which the average proportion of blind spot checks mirrored the overall average in Table 5.1.

Table 5.2: Blind spot checks as function of infrastructure

Factor	Category	Intersections			Roundabouts		
		X (*n*)	*M* (%)	*SD*	*X* (*n*)	*M* (%)	*SD*
Intersection type	T by-road	35 (10)	15.33	18.41	-	-	-
	T main road	50 (10)	19.00	20.49	-	-	-
	X	70 (10)	22.82	19.76	-	-	-
	Y	4 (3)	0	-	-	-	-
Roundabout type	Single lane	-	-	-	178 (10)	28.06	12.55
	Multiple lanes	-	-	-	9 (6)	16.67	40.82
	Mini	-	-	-	1 (1)	100	-
	Turbo	-	-	-	21 (8)	27.50	36.55
Road transition *	Equal size roads	34 (10)	12.67	23.03	164 (10)	20.33	14.97
	Start primary road	67 (10)	20.55	15.93	35 (9)	56.77	38.96
	Start secondary road	58 (10)	24.76	31.75	8 (6)	16.67	40.82
Priority regulation *	Law	45 (10)	22.00	13.72	2 (2)	0	-
	Signs	45 (10)	16.60	16.45	203 (10)	27.79	12.77
	Lights (conflict)	9 (6)	8.33	20.41	0 (0)	-	-
	Lights (no conflict)	60 (9)	15.73	21.07	4 (2)	16.67	23.57
Cyclist facilities **	None	72 (10)	19.40	8.97	37 (10)	16.43	20.42
	Adjacent lane	21 (8)	18.13	23.76	9 (6)	61.11	49.07
	Separated track	62 (10)	14.75	18.87	162 (10)	28.19	15.40

NOTE: Gaze has been evaluated from 6 sec. pre-maneuver to the end of the maneuver. *X* = number of segments across all drivers. *n* = number of drivers with at least one data point on the corresponding factor. *M* = Average proportion of blind spot checks per driver. Drivers without data points in a category have been omitted from calculations on that category. *SD* = Standard Deviation. * Two 'Unknown' road transitions and priority regulations have been omitted from the roundabouts. ** Four 'Unknown' cyclist facilities have been omitted from the intersections, and one from the roundabouts.

Finally, the presence of cyclist facilities at roundabouts (i.c., adjacent lane, separate track) has resulted in a large increase of blind spot checks, particularly with adjacent lanes. However, this is not the case with intersections, where separate tracks resulted in a marginally lower score.

5.3.3 Situational factors

Sight conditions based on weather and lighting were rated as good in 97.5% of the right turn segments, and 99.5% of the roundabout segments. Therefore, the factor 'sight condition' has been excluded from further analysis. Table 5.3 displays the average proportion of blind spot checks as function of the traffic situation.

Looking at traffic flow, intersections featured more blind spot checks after 'waiting then free' (i.e., where 'waiting' concerns a full stop) compared to 'free flow' and 'restricted flow'. No large differences have been found at roundabouts, but this could be due to the low number of observed cases that involved waiting. In both maneuvers, no blind spot checks were performed in the 'waiting then restricted' category.

The factor 'Early VRU right side' concerns the presence of Vulnerable Road Users (VRUs, i.e., cyclists, pedestrians) in the first three seconds of the six second time window prior to the maneuver. Table 5.3 shows that early VRU presence resulted in less blind spot checks at intersections. Furthermore, drivers did not check their blind spot when a cyclist was coming from the driver's own direction, and neither coming from the opposite direction. At roundabouts, the influence of early VRU presence and a cyclist coming from the opposite direction appears to be marginal. A cyclist coming from the driver's direction resulted in a lower proportion of blind spot checks.

Table 5.3: Blind spot checks as function of traffic situation.

Factor	Category	Intersections			Roundabouts		
		X (*n*)	*M* (%)	*SD*	*X* (*n*)	*M* (%)	*SD*
Traffic flow	Free flow	91 (10)	13.68	11.39	152 (10)	24.68	9.58
	Restricted flow	33 (10)	14.58	18.50	49 (10)	33.62	32.21
	Waiting then free	27 (8)	37.92	38.00	5 (3)	33.33	57.74
	Waiting then restricted	8 (6)	0	-	3 (3)	33.33	57.74
Early VRU right side *	Yes	44 (8)	11.19	13.72	51 (10)	23.45	27.32
	No	113 (10)	19.91	14.45	158 (10)	27.27	11.89
Cyclist from driver direction	Yes	10 (6)	0	-	25 (9)	18.52	25.61
	No	149 (10)	20.67	9.55	184 (10)	28.16	12.96
Cyclist from opposite direction	Yes	5 (3)	0	-	4 (4)	25.00	50.00
	No	154 (10)	20.08	9.35	205 (10)	27.41	12.61
Visual obstruction	Yes	30 (9)	13.62	18.60	26 (9)	2.78	8.33
	No	129 (10)	21.23	10.76	183 (10)	30.12	13.75

NOTE: Gaze has been evaluated from 6 sec. pre-maneuver to the end of the maneuver. *X* = number of segments across all drivers. *n* = number of drivers with at least one data point on the corresponding factor. *M* = Average proportion of blind spot checks per driver. Drivers without data points in a category have been omitted from calculations on that category. *SD* = Standard Deviation. * VRU = Vulnerable Road User. Two 'Unknown' ratings have been omitted from the intersections.

5.3.4 Behavioural factors

Secondary task involvement was rated in terms of manual, visual, and auditory non-driving tasks (e.g., making phone calls, inspecting documents). Separate ratings were recorded for the time window prior to the maneuver, and the maneuver itself. Table 5.4 shows the average proportion of secondary task involvement when at least one of the above cases was true. Almost all drivers were at some time involved in a secondary task.

The frequency of blind spot checks increased when secondary task involvement was observed prior to intersection maneuvers. The reverse pattern was found during intersection maneuvers, where secondary task involvement was accompanied with a decrease in blind spot checks. A similar pattern was found at roundabouts, except that the overall proportions were higher than at intersections, in line with Table 5.1.

Table 5.4: Blind spot checks as function of secondary task involvement.

Factor	Category	Intersections			Roundabouts		
		X (*n*)	*M* (%)	*SD*	*X* (*n*)	*M* (%)	*SD*
Secondary task	Yes	23 (9)	30.56	42.90	28 (8)	34.79	32.63
(pre-maneuver) *	No	133 (10)	19.31	11.06	181 (10)	26.13	15.98
Secondary task	Yes	28 (9)	13.27	18.62	35 (9)	21.45	33.30
(during maneuver) *	No	127 (10)	20.29	11.34	174 (10)	27.48	14.93

NOTE: Gaze has been evaluated from 6 sec. pre-maneuver to the end of the maneuver. *X* = number of segments across all drivers. *n* = number of drivers with at least one data point on the corresponding factor. *M* = Average proportion of blind spot checks per driver. Drivers without data points in a category have been omitted from calculations on that category. *SD* = Standard Deviation. * Three 'Unknown' ratings have been omitted from the intersections at 'pre-maneuver', and four ratings at 'during maneuver'.

5.4 Discussion

This chapter examined how often truck drivers check their blind spot, and which factors influence such behavior. The main finding is that drivers check their blind spot prior to the maneuver in approximately 5% of the intersections, and 13% of the roundabouts. When the maneuver is included, the frequency of blind spot checks increases to 19% at intersections, and 27% at roundabouts.

5.4.1 Infrastructural factors

Observations concerning traffic lights that allow conflicts with other road users' trajectories yielded an average blind spot check frequency of only 8% at intersections. Additional research is required to verify if the truck driver could have had a green light simultaneously with cyclists in the blind spot. If this was not the case, then the traffic lights appear to have ensured the truck drivers that no blind spot checks were necessary. If, on the other hand, there was a potential collision course with cyclists, then the necessity to check traffic from many directions apparently comes at the cost of checking the blind spot.

At transitions from a secondary road to a primary road the blind spot was checked more than twice as often than at transitions between equal roads. An explanation is that the approach from a secondary road typically does not give right of way. Consequently, there is a higher necessity to scan the environment for other road users. Moreover, there is an increased opportunity, because one often has to wait before making a maneuver towards the primary road. These factors may have contributed to an increase in blind spot checks.

5.4.2 Situational factors

A striking finding is that the presence of a cyclist coming from the truck driver's direction did not result in any blind spot checks. Even though the number of observations is small (i.e., 10 cases across 6 drivers), the consequence of such behavior is potentially fatal.

The highest frequency of blind spot checks was found when truck drivers had to wait at an intersection, followed by a free flow situation (i.e., category 'waiting then free' in factor 'traffic flow'). With 38% in that situation, blind spots were checked almost twice as often as the overall frequency, and more than twice as often as the situation in which drivers did not have to wait before starting their maneuver. This difference could be explained by the possibility of cyclists overtaking the truck from the right while the latter is waiting. Such possibility requires from the truck driver a re-evaluation of the scene before making the intended maneuver. In a situation without a full stop re-evaluation may have been judged as unnecessary. However, the above explanation does not hold true for the situation where a full stop is followed by restricted flow (i.e., category 'waiting then restricted), in which no blind spot checks were observed at all.

Could, perhaps, the presence of other road users in front of the truck distract the driver such that blind spot checks are forgotten, or considered inappropriate? In line with this hypothesis is the influence of cyclists coming from the opposite direction, whose presence was returned by the absence of any blind spot checks. The number of observations in the latter factor is too limited, however, to truly substantiate the hypothesis.

5.4.3 Behavioural factors

The profession of truck drivers gives rise to frequent secondary task involvement, such as checking an order status, and phone calls with the dispatcher. Therefore, it is not surprising to find that 9 out of 10 truck drivers were involved in secondary tasks at intersections, and at roundabouts.

Secondary task involvement is associated with an increased blind spot check frequency prior to making a maneuver. Possibly, drivers resolved their lost pre-maneuver situation awareness by performing additional scans of the environment. The only opportunity to do so would then be during the maneuver, in line with the overall figures in Table 5.1.

It is reasonable to expect pre-maneuver secondary task involvement when drivers have to wait in front of a traffic light, but not during the actual maneuver itself. Therefore, it is striking to find that secondary task involvement was more prevalent during maneuvers than before maneuvers, especially combined with the finding that the blind spot was checked less often compared to when no secondary task involvement was observed. Apparently, secondary task involvement during a maneuver obstructs last-minute blind spot checks.

5.4.4 Limitations and recommendations

If truck drivers so rarely check their blind spot, then where do they look instead? The annotators had the option to select among ten gaze categories, of which three were dedicated to the blind spot (i.e., with or without cyclist presence, or presence unknown). The annotators pointed out that the 'unknown' and 'impossible to determine' categories were rarely used. Thus, using the remaining categories, the truck drivers must have casted either sideway glances, or towards the future road, or elsewhere. Sideway glances prior to the maneuver could explain the low prevalence of blind spot checks, especially in a free flow situation where potential cyclists are long overtaken when the maneuver is performed. This should be investigated in a future analysis.

The main limitation of the present study is the low number of truck drivers that ended up having enough manoeuvres after data reduction. The UDRIVE database is growing still, so that additional maneuvers may be selected in the future. Furthermore, many candidate maneuvers have been excluded from further analysis because of asynchrony between the video data and the numerical data. Once these signal types have been aligned, an additional batch of annotation can be performed to update our figures. When additional drivers are included in the data, it may also be possible to run inferential statistics. Until that time, the figures presented in this chapter should be interpreted as an initial indication for gaze behaviour by Dutch truck drivers. Furthermore, the results should not be generalized to other European countries, seeing that the prevalence of cyclists is relatively high in the Netherlands, as is the prevalence of cyclist facilities (also see chapter 3).

Another limitation is that we have no full specification of the assistive technologies in each of the instrumented trucks. Some trucks may have had a blind spot camera, which the driver could assess through a video screen on the dashboard. If this technology has indeed been installed, we cannot identify such gaze behaviour with the current gaze annotation categories. Therefore, the figures presented in this chapter should be interpreted as a minimum proportion of blind spot checks.

5.5 Conclusions

Truck drivers' failure to check the rear-quarter blind spot in a right turn manoeuvre can lead to fatal incidents with cyclists. This study has shown a striking absence of blind spot mirror checks at intersections and roundabouts, in particular before the maneuver is started.

Lives could be saved by technology that supports the truck driver in detecting potential blind spot collisions (Fletcher et al., 2003). Furthermore, much can be gained by awareness training for cyclists and truck drivers. From the perspective of the cyclist, this study supports the recommendation from a previous study (Talbot et al., 2014) that cyclists should be made aware of the blind spots of large vehicles, and that they should not undertake large vehicles on the approach to a junction.

In The Netherlands truck drivers are required to attend a training, which includes cyclist awareness, and in Canada and the USA the Automobile Association (AAA) and the Cyclist League (LAC) manage a campaign together, that promotes shared responsibility for traffic safety by showing common courtesy and respect (Pattinson & Thompson, 2014). The time window during which each traffic situation is assessed may change with the increasing number of high speed electric bicycles. Therefore, our findings, and especially with regard to secondary task involvement and traffic flow, may inform awareness training on blind spot incidents.

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6 Cyclist overtaking manoeuvres by car drivers

6.1 Introduction

While the total number of road crashes in Europe is decreasing, the number of cyclists in traffic increase, and crashes involving bicycles are not significantly decreasing. Crashes between cars and bicycles often result in severe injuries or even fatalities. Latest information on car-to-cyclist crashes, recently compiled in Europe, includes details on the related crash configurations, driving directions, outcome in terms of injury severity, accident location, other environmental aspects and driver responsibilities (Wisch, 2017). The authors found that car-to-cyclist crashes in which the vehicle was traveling straight and the cyclist is moving in line with the traffic result in the greatest number of fatalities. When cars and bicycles share the same lane in traffic, cars typically need to overtake, creating dangerous conflicts. In rural roads, overtaking manoeuvres occur with the car moving significantly faster than the bicycle. Crashes with large speed differences often result in severe injuries or even death. By understanding the behaviours of car drivers overtaking bicyclists, and the differences of such behaviours between countries, guidelines and policies, as well as in-vehicle technologies (e.g. different levels of automated interventions), can be designed to increase safety on our roads. Previous studies that have investigated such overtaking behaviour have done so through controlled experiments (Dozza, 2015), or simulator studies (Bianchi, 2017). The aim of this study is to extend previous research by answering the questions: 1) Is there a difference in the lateral distance, both when the car starts to overtake and passes the cyclist, in different countries? and 2) what factors influence the lateral distance when the car starts to overtake and passes the cyclist?

6.2 Method

UDRIVE naturalistic driving data are used from cars driving over a period of months in Great Britain, France, Poland, Germany and the Netherlands. Events where a bicyclist was present in the driver's lane were automatically extracted and then manually coded with respect to overtaking—preserving only true bicycle overtaking events on straight roads for the analysis. The present analysis – inspired by work by Dozza et al. (2015) – included quantification of the driver comfort zone, such as the lateral distance between the car and the bicycle during the overtaking event. The lateral distance in this work was defined as the perpendicular distance between right edge of the car and left extremity of the bicycle (Mehta, 2015). Other studies quantify four phases of an overtaking event (see Dozza et al., 2015) with respect to distance, speed and timing. Similarly, in this work, the start of each phase is defined as: 1) the cyclist is visible in the front video (see **Fout! Verwijzingsbron niet gevonden.** and **Fout! Verwijzingsbron niet gevonden.** for details on camera sensors); 2) the vehicle starts to steer (starts overtaking); 3) the vehicle is three meters behind the cyclist; 4) the vehicle is three meters in front of the cyclist, see Figure 6.1. The starts of the first two phases are manually annotated while the last are calculated from the vehicle sensor data. In comparison to the work in Deliverable 4.2, overtaking other motorized vehicles on rural roads, there are two more phases (after 2 and 3) and do not apply in the overtaking of cyclist since the car might not necessary perform a lane change after steering away and hence after passing the cyclist. From the vehicle sensor data the overtaking segments were automatically identified when the cyclist is first cycling in the same direction as the vehicle and then disappears within 50 m from the vehicle and the vehicle speed is above 20 km/h. These conditions make sure that the VRU is not disappearing far ahead, e.g. a motorbike overtaking the vehicle, or a VRU disappearing when travelling slow, e.g. while the vehicle stands still at an intersection. After these automatic segment detections, extensions of ten seconds before and after the segments were annotated. The measures/variable for each overtaking segment are shown in Table 6.1. An example of a true overtaking segment with each of the four phases is shown in Figure 6.2.

The overtaking segments can be differentiated by how they are performed. The flying overtaking is performed when the overtaking vehicle's speed remains constant or near constant during the overtaking. The accelerating overtaking is performed when the overtaking vehicle follows behind the soon-to-be-overtaken road user and by increase in its speed. In comparison to car overtaking other vehicles, see D24, the flying manoeuvre is similarly defined and the accelerative manoeuver is referred as normal. There is one more manoeuvre type i.e. piggy backing. The piggy backing means following another vehicle during overtaking manoeuvre and does rarely apply for bicyclists because overtaking is much faster here and there usually is no cue behind a cyclist. Mixed effect model is used for the analysis (Bates, 2012).

6.2.1 Annotated data

Several attributes of the overtaking-manoeuvres were annotated, mainly due to limitations of the performance of the automatic signal-processing. If an overtaking occurred the attributes annotated were:

- What type of VRU was overtaken, i.e. bicyclist or pedestrian.
- How many VRUs were overtaken, i.e. one or several VRUs were overtaken.
- What type of overtaking-manoeuvre was performed, i.e. flying or accelerative.
- What type of lane-markings were visible at the site of the overtaking, i.e. a central marking dividing the two adjacent lanes and markings separating the lane from the lane-shoulder (central, edge, none or both).
- Was there a vehicle in front of the ego-vehicle with a THW less than three seconds.
- Was there oncoming traffic present in the adjacent lane during any of the phases of the overtaking-manoeuvre.

A complete list of what was annotated can be found in Table 6.2. Gender of the cyclist and use of helmet were considered to be annotated but showed to be difficult due to the video quality and blurring of parts of video recordings in some countries.

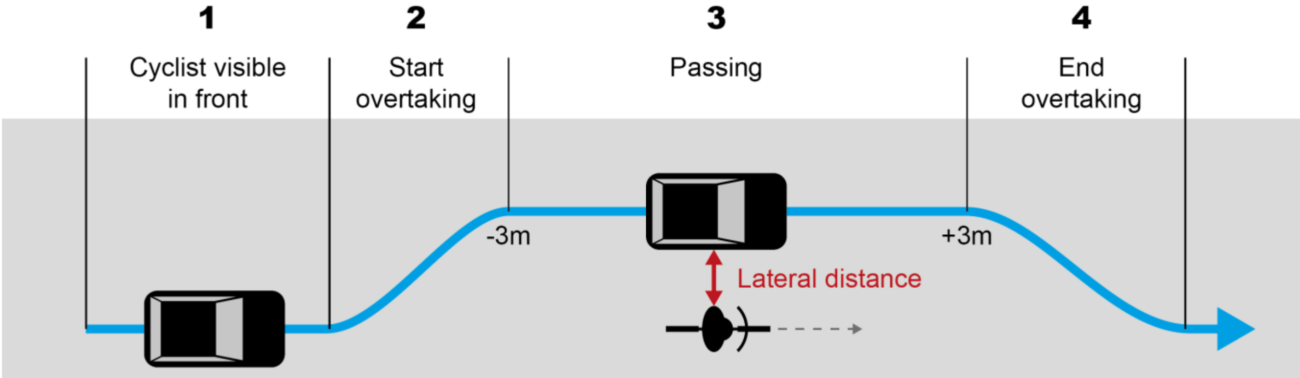


Figure 6.1: Four overtaking phases of a car overtaking a cyclist.

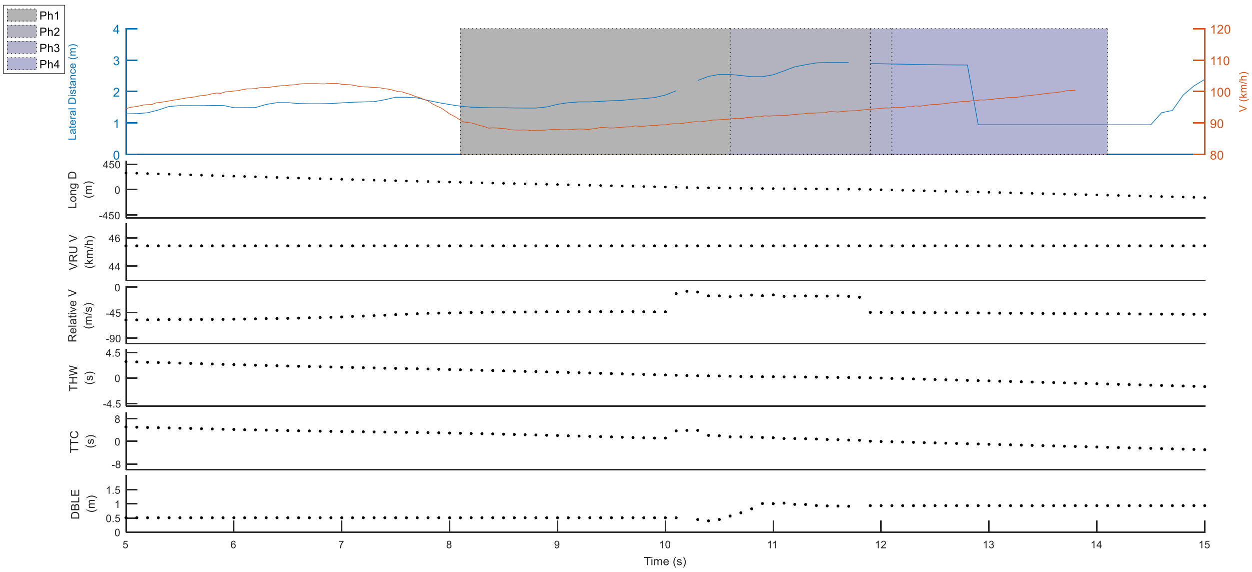


Figure 6.2: Four phases in car-to-cyclist overtaking segments. Example is accelerative manoeuvre. The X-axes shows the time; the left y-axes, the lateral distance of the vehicle to the cyclist; right y-axes, the vehicle speed.

Table 6.1: Available variables per segment

Variables	Description	Mean (Standard Deviation)
Time	The time resolution is 0.1 s	
LateralDistanceToVRU*	The lateral distance to the closest VRU from the ego vehicle	1.64 (0.40)
LongitudinalDistanceToVRU	The longitudinal distance to the closest VRU from the ego vehicle.	64.29 (46.06)
Speed*	Vehicle speed of the ego vehicle	60.26 (5.14)
RelativeVelocityToVRU	Relative velocity between the closest VRU and the ego vehicle	1.21 (0.48)
DistanceToLaneEdge	Distance between the ego vehicle and the lane edge (laneshoulder if travelling in the outmost lane)	1.68 (0.24)
DistanceToAdjacentLane	Distance between the ego vehicle and the adjacent edge	1.27 (0.29)
LateralAcceleration	Lateral acceleration of the ego vehicle	-0.01 (0.02)
LongitudinalAcceleration	Longitudinal acceleration of the ego vehicle	0.01 (0.02)
DistanceBetweenLaneEdgeAndVRU*	Distance between the VRU closest to the vehicle and the lane edge	0.01 (0.45)
THW*	Time headway to the closest VRU based on the longitudinal distance to the closest VRU	1.21 (0.48)
TTC*	Time to collision to the closest VRU based on the longitudinal distance to the closest VRU	2.54 (1.30)
YawRate	Vehicle Yaw Rate	3242 (599)
SteeringWheel	Vehicle Steering Wheel Angle	-271.99 (848.34)

THW_To_Vehicle	Time headway to the closest vehicle	2.24 (0.71)
Radius	Road curvature (from MAP data)	9.73 (95.68)
SpeedLimit	Road speed limit (from MAP data)	88.46 (4.40)
Inclination	Road inclination (from MAP data)	-29.63 (53.04)
Driver ID *	Individual identification number for drivers within the UDRIVE database	Categorical
Speed of VRU*	The speed of the VRU	20.90 (8.66)
Lane width*	The width of the lane in which the ego vehicle is located	2.87 (0.70)
Turn indicator	Turn indicator lights status, either on or off.	Categorical
Day Type	If the trip was recorded during dawn, day, dusk or night	Categorical
AbsDistance	Pythagorean distance	23.10 (5.26)
Time of Day	The time of day expressed as a MATLAB date-string	
Country Info	Operation site; In which country the trip was recorded	

Table 6.2: Annotated variables per segment

Variables	**Description**
IsOvertaking	Boolean verifying that the ego vehicle performed an overtaking of VRU during the segment
Maneuver Type	Accelerating and Flying,
MultipleVRU*	Boolean indicating that the ego vehicle overtook more than one VRU during the segment
TypeOfVRU	Categorical: bicyclist, pedestrian, motorbike or other VRU
StraigthRoad	Boolean indicating whether the ego vehicle performed the overtaking on a straight road
Rural Road	Boolean
Driving in most right lane	Boolean
Lane visibility	No lane visible, Side lane visible, Central Lane visible, Both lanes visible
VRU in same direction of EGO vehicle	Boolean
VRU type	Bicycle, Pedestrian, Motorbike, Other
VRU relative position	Between EGO and side lane, Outside side lane, Other
LeadingVehiclePresent*	Boolean indicating whether the ego vehicle performed the overtaking while piggybacking (THW < 3s)
OncomingTrafficPresent*	Boolean indicating whether there was traffic in the adjacent lane while performing the overtaking
AnnotatedPhase1Index	Index where the to-be-overtaken VRU is distinguishable in the video-feed
AnnotatedPhase2Index	Index where the ego vehicle can be seen to adjust its trajectory due to the VRU in the video-feed
AnnotatedPhase3Index	Index where the Long D-signal first reaches below 3 meters
AnnotatedPhase4Index	Index where the Long D-signal first reaches below -3 meters
EndPhase4Index	Index where the distance travelled since phase 4 began reaches above 50 meters.
SyncError	How much time the signal comes before the video-feed.
Comment	Comment of the annotator

6.3 Results

A total of 5000 overtaking manoeuvres were automatically detected in the UDRIVE data set. The researchers visually examined the video recording of 550 segments to select the true overtaking manoeuvres on straight rural roads and the cyclist was cycling on the same lane as the car. Within the sample of manually identified overtaking segments, the segments with all phases annotated and no missing data were analysed (N=147, Ndrivers = 41), see Table 6.3. Within the visually reviewed segments, all overtaking manoeuvres in The Netherlands occurred while the cyclist was riding on a separate cyclist lane. Therefore after the initial annotation process they were not considered for the context annotation. Most of the overtaking segments occurred in daylight (138 of 147), with an average duration of 9.3±3.5s and an average vehicle speed of 61±15km/h. The average lateral distance in the passing phase was 1.65±0.64m. The lateral distance at the start of the overtaking and at the passing) are presented in this section and compared across countries for both accelerative and flying manoeuvres.

Table 6.3: Annotated true overtaking segments (*N* = 147)

Overtaking type	GE	FR	PL	UK
Accelerative	7	18	15	9
Flying	19	39	17	23
Total	26	57	32	32

The duration of the all phases is shown in Figure 6.3, where the shortest is the passing phase. The lateral distance per overtaking type at the start of the overtaking and per country is shown in Figure 6.4.

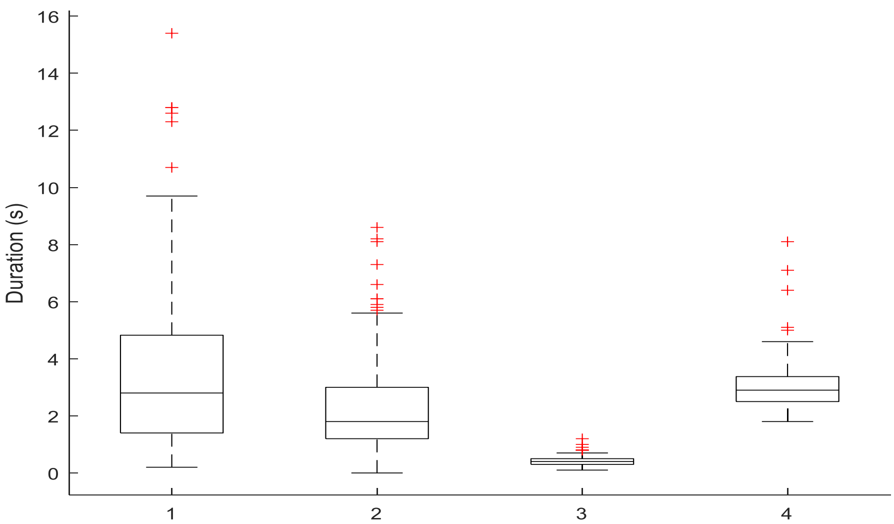


Figure 6.3: Duration of the four phases. Average duration per phase 3.5s, 2.3s, 0.4s and 3.0s respectively.

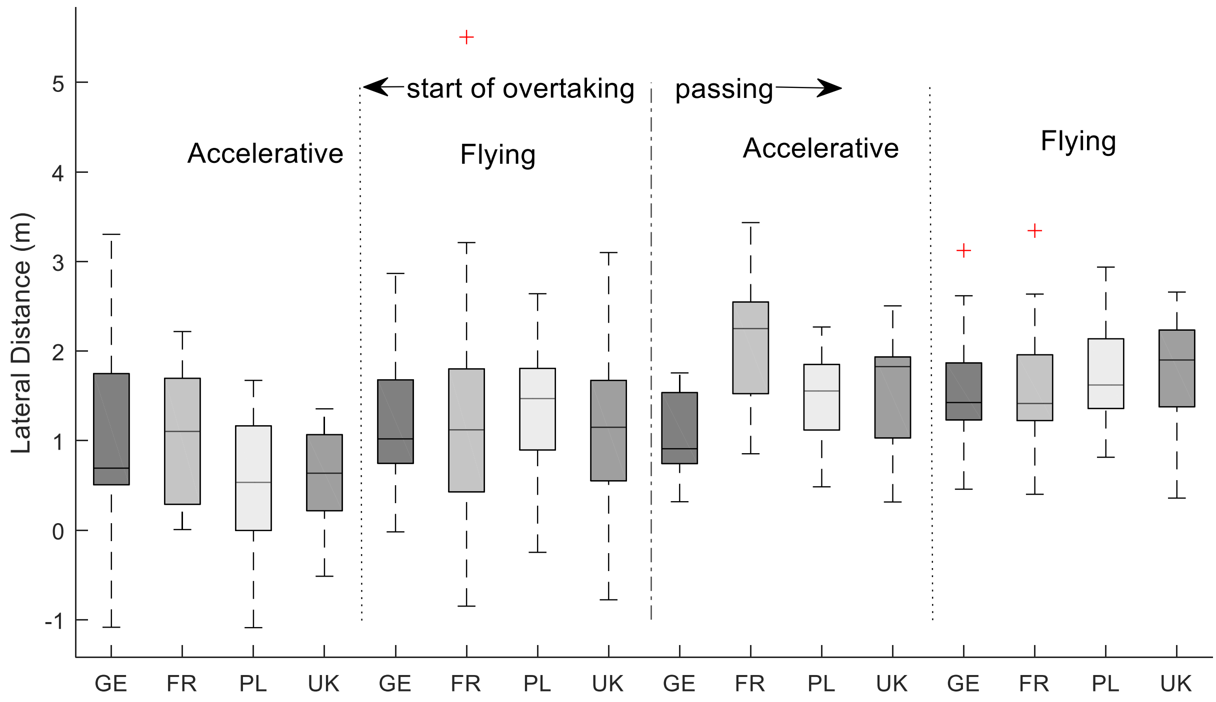


Figure 6.4: Lateral distance at the start of the overtaking and at the passing per country and per manoeuvre type. The country abbreviations are used for Germany, France, Poland and UK (GE, FR, PL, UK). The shades of grey for the different boxes show the lateral distance distribution for different country.

In order to understand which factors potentially affect the lateral distance between the car and cyclist in overtaking manoeuvres in real world, first a factor analysis is performed. Then the output from the factor analysis is used to investigate the relationship between the factors and the lateral distance both descriptively and statistically.

Choice of predictors

Factor analysis was used to identify latent variables in the data sets that are represented by highly correlated input variables. A covariance matrix produce a set of eigenvectors and eigenvalues. The most commonly used criterion for factor retention is the Guttman-Kaiser criterion, which only retains eigenvalues greater than 1, see Figure 6.5.

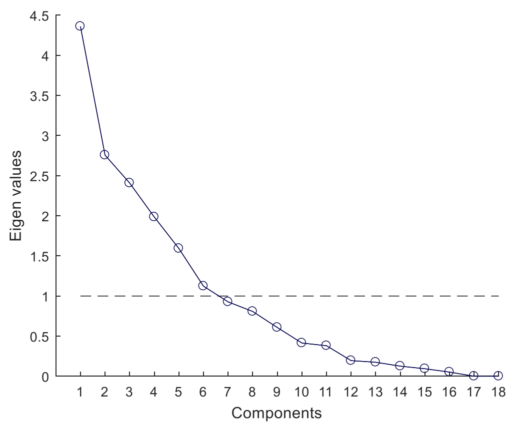


Figure 6.5: Initial Eigen values.

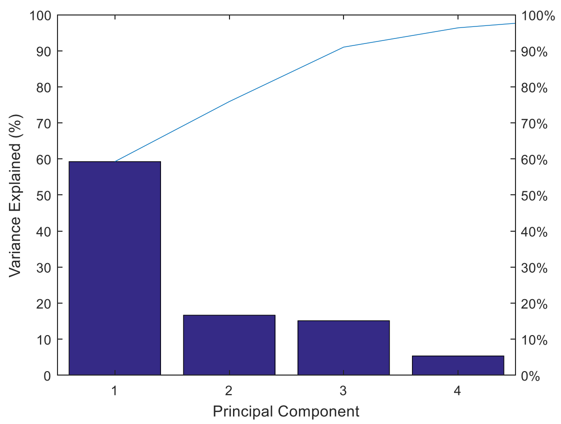


Figure 6.6: A scree plot of the percent variability explained by each principal component.

This, Figure 6.6 only shows the first four (instead of the total 18) components that explain 95% of the total variance. The only clear break in the amount of variance accounted for by each component is between the first and second components. However, the first component by itself explains less than 70% of the variance, so more components might be needed. It can been seen that the first two principal components explain 75% of the total variability in the observations, so that might be a reasonable way to reduce the dimensions. Instead of taking 18 different predictor variables, by using the rotated loadings matrix, 6 predictors that are continuous variables (vehicle speed, distance between lane edge and VRU, TTC, THW, lane width, speed of the VRU) are chosen.

Linear Mixed Effects Model

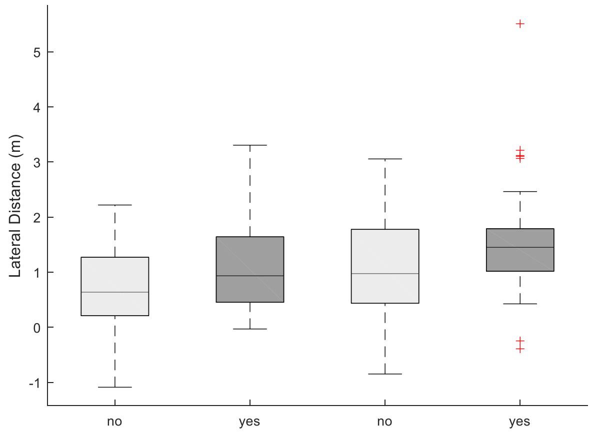
The models analysed in this section are built with R (R Core Team, 2012) and package lme4 (Bates, Maechler & Bolker, 2012). The analysis considers a linear mixed effects analysis of the relationship between lateral distance and the predictor variables. The continuous variables chosen based on the factor analysis(vehicle **speed**, **distance** between lane edge and VRU, **TTC**, **THW**, **lane width**, **speed** of the VRU) are considered in the model as fixed effects without interaction term. Furthermore, the categorical variables presence of **oncoming** and **leading** traffic, **multiple** VRUs overtaken and **country are also considered as** fixed effects without interaction term. Driver, the identifier of the car driver which performed the overtaking manoeuvre, is added as random effect with intercept.

A series of models starting with all predictors and all combinations of them are fitted to the data. The models were assessed using the Akaike information criterion (AIC). Lower values of AIC indicate better models, and differences of less than 2 suggest the models do not differ substantially (Burnham et al. 2010).

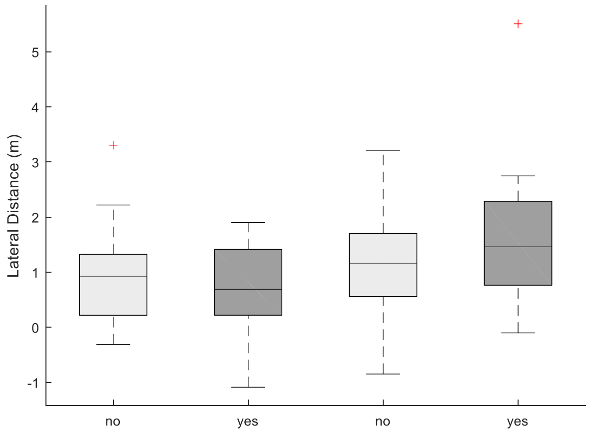
The following four sections show the results for the accelerative and flying manoeuvres at the start of the overtaking and at the passing. The sections have the same structure i.e. first graphical exploration of the relationship between the predictor variables and the outcome is presented and second the results of the linear mixed effects analysis.

6.3.1 Start of overtaking

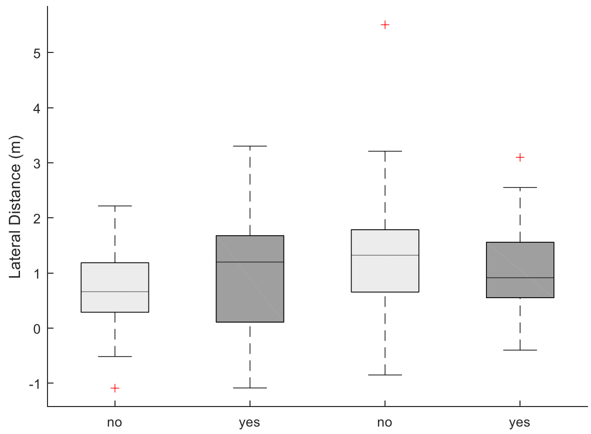
The lateral distance between the vehicle and the cyclist at the start of overtaking , for two manoeuvre types, is shown in Figure 6.7 (a-f). The continuous variables such as vehicle speed, relative velocity and distance between lane edge and VRU per country and for the two manoeuvre types are shown in appendix (see Appendix C).



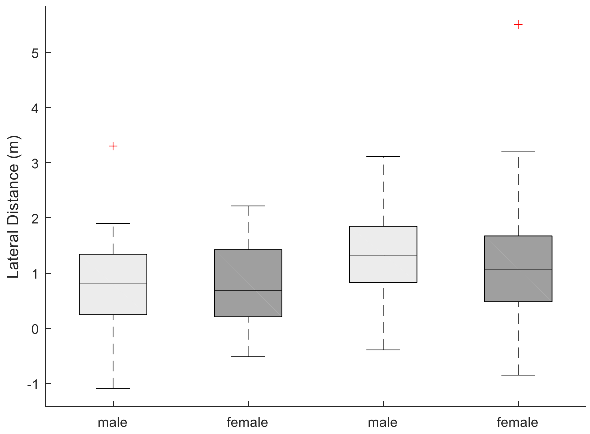
a. Presence of leading vehicle



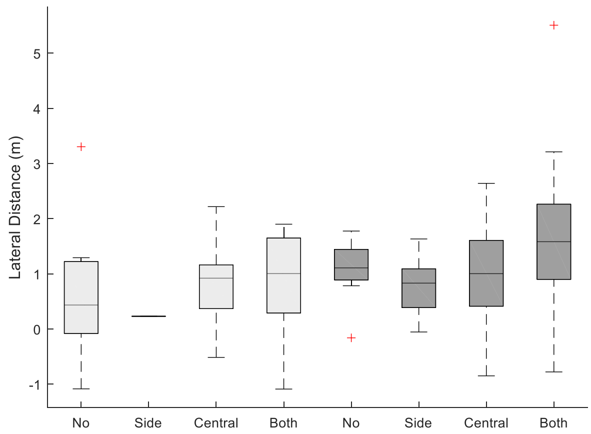
b. Presence of oncoming vehicle



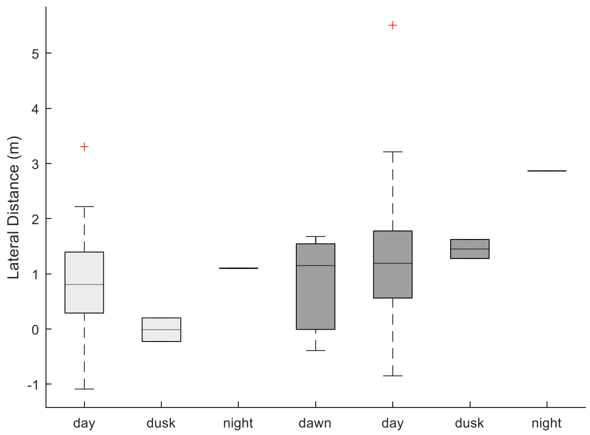
c. Multiple VRU overtaken



d. Gender



e. Lane visibility



f. Day type

Figure 6.7: Lateral distance with respect to presence of leading and oncoming vehicle, multiple VRU, gender, lane visibility, and day type at the start of overtaking for accelerating (light grey) and flying manoeuvres (dark grey).

The continuous variables are approximately normally distributed and do not have extreme outliers The relationship between the *lateral distance* and the *speed* and the *lateral distance* and the *distance between lane edge and VRU* are shown in Figure 6.8 and Figure 6.9 respectively, along with a simple linear regression line fit to the data in that figure. Each point in these figures shows one measure from one overtaking segment. The *lateral distance* increases with the increase in the vehicle *speed* (, Figure 6.8) and decreases with increase of the *distance between lane edge and VRU (*Figure 6.9). The negative *distance between lane edge and VRU* indicates that the cyclist has crossed the lane edge.

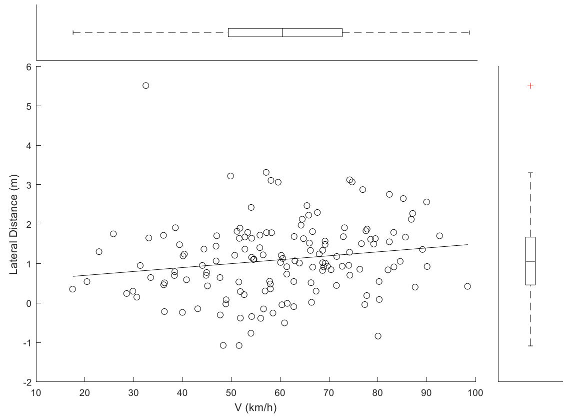


Figure 6.8: Speed vs lateral distance at start of overtaking.

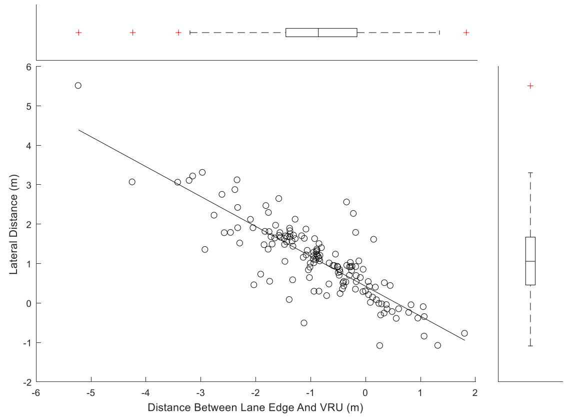


Figure 6.9: Distance between lane edge and VRU vs lateral distance at start of overtaking.

Accelerative manoeuvres

For the accelerative manoeuvre, several models were built and summarized in Table 6.4. The model description, in the first column, indicates the combination of the fixed effects used in the liner mixed model. The second column shows the AIC, the third shows the difference from the model with the lowest AIC and the final shows the model likelihood. A lower AIC indicates the model fits the data better, but a difference of less than 2 is typically required to justify including another variable based on statistical significance. The best model, according to the AIC criterion, is the first model in the Table 6.4 with the following predictors: lane width and distance between lane edge and VRU. In the fixed effects, lateral distance is 0.34m greater for every 1m increase in lane width. The lateral distance decreases by 0.84m when distance between land edge and VRU increases by 1m. Significant estimates are for both predictors: lane width, and distance between land edge and VRU, Table 6.5.

Table 6.4: Summary of AIC results for models relating the lateral distance and predictor variables, at start of overtaking for the accelerative manoeuvre.

Model	AIC	ΔAIC	Model likelihood
laneW + dble_vru	74.27	0.00	-32.10
gender + laneW + dble_vru	75.43	1.16	-31.71
laneW + dble_vru + mulVRU	75.74	1.47	-31.87
laneW + oncV + dble_vru	75.75	1.48	-31.87
speed + laneW + leadV + dble_vru	77.90	3.63	-32.00

Table 6.5: Summary of estimates for the fitted model ('*' p<0.001, '**'p<0.01, '*' p<0.05)**

	Lane width	**Distance between land edge and VRU**
Coefficient Estimate (Standard Error)	0.34(0.11)**	-0.84(0.08)***

Flying manoeuvres

For the flying manoeuvre at the start of the overtaking several models were built, summarized in Table 6.6. The model description, in the first column, indicates the combination of the fixed effects used in the liner mixed model. The second column shows the AIC, the third shows the difference from the model with the lowest AIC. A lower AIC indicates the model fits the data better, but a difference of less than 2 is typically required to justify including another variable based on statistical significance. The best model, according to the AIC criterion, is the first model in the table with the following predictors: country, lane width, presence of lead vehicle, distance between lane edge and VRU and VRU speed.

The fixed effects showed that the lateral distance is higher by 0.02 m for every unit of VRU speed (1km/h), see Table 6.7. The lateral distance increases by 0.14m also for increase of 1m in lane width. The presence of leadvehicle increases the lateral disctance by 0.21m. The lateral distance decreases by 0.74m when distance between land edge and VRU increases by 1m. The Wald test, which tells how confident are the estimates of the effect of these predictors on the lateral distance, indicated that the predictors: lane width, lead vehicle present, and distance between land edge and VRU and VRU speed are significant. Females kept lower lateral distance than males, but this was not significant.

Table 6.6: Summary of AIC results for models relating the lateral distance and predictor variables, at start of overtaking for flying manoeuvre.

Model description	AIC	ΔAIC	Model likelihood
laneW + leadV + dble_vru + speedVRU + gender	142.61	0.00	-63.30
laneW + leadV + dble_vru + speedVRU	142.86	0.25	-64.43

Table 6.7: Summary of estimates for the fitted model ('*' p<0.001, '**'p<0.01, '*' p<0.05)**

	Lane width	**Lead vehicle**	**Distance between land edge and VRU**	**VRU speed**	**Gender**
Coefficient Estimate (Standard Error)	0.14 (0.06)*	0.21(010)*	-0.74 (0.04)***	0.02 (0.00)***	-0.14(0.09)

6.3.2 Passing phase

The results for the passing phase are showing the lateral distance in the time point when the longitudinal distance between the vehicle and VRU is zero i.e. they are parallel.

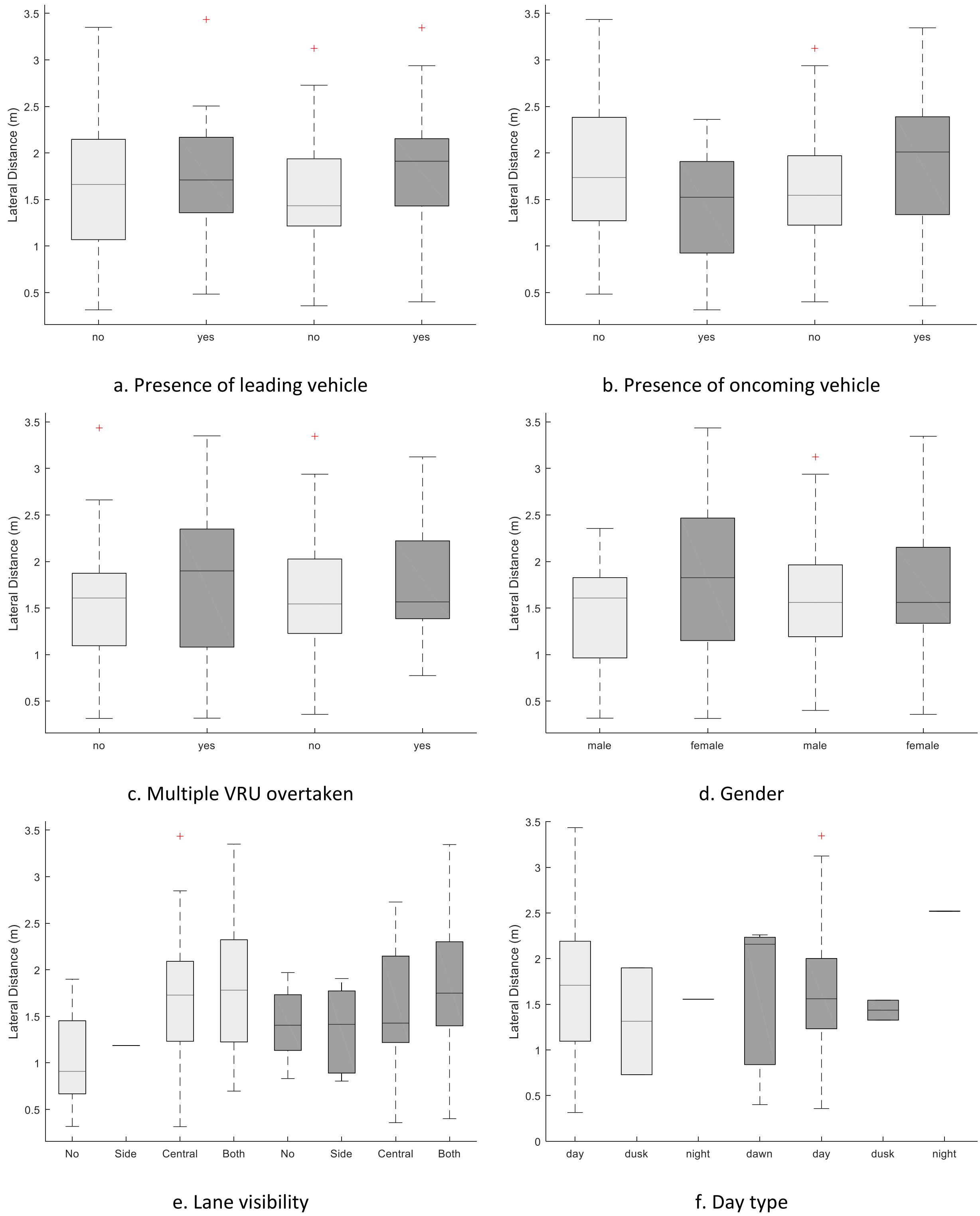


Figure6.10: Lateral distance with respect to presence of leading and oncoming vehicle, multiple VRU, gender, lane visibility and day type in the passing phase for the both accelerating (lighter grey) and flying manoeuvres (darker grey).

The lateral distance between the vehicle and the cyclist in the passing phase , for the two manoeuvre types, is shown in Figure 6.10 (a-f).. The continuous variables such as speed, relative velocity and distance between lane edge and VRU per country and for the two manoeuvre types are shown in appendix (see Appendix C).

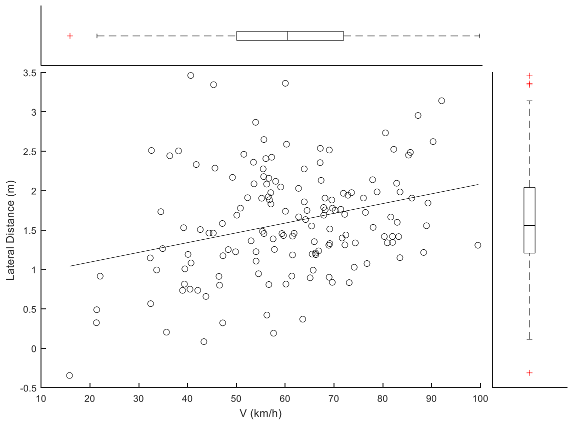


Figure 6.11: Speed vs lateral distance in passing phase.

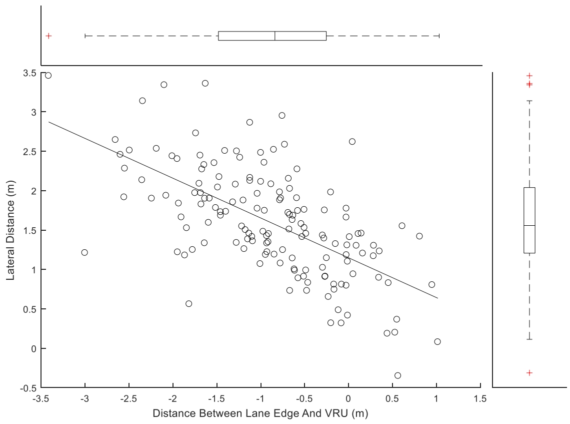


Figure 6.12: Distance between lane edge and VRU vs lateral distance in passing phase.

(Note: Lane width is the same for all the phases and is shown only for phase 2. THW and TTC are not shown for phase 3 since they decrease to zero in the beginning of phase 3). The relationship between the *lateral distance* and the *speed* and the *lateral distance* and the *distance between lane edge and VRU* are shown in Figure 6.11 and Figure 6.12 respectively, along with a simple linear regression line fit to the data in that figure. Each point in these figures shows one measure from one overtaking segment. The *lateral distance* increases with the increase in the vehicle *speed* (Figure 6.11) and decreases with increase of the *distance between lane edge and VRU (*Figure 6.12).

Flying manoeuvre

Similar to the analysis at the start of the overtaking, an analysis was conducted for time when the vehicle and cyclist are parallel to each other (longitudinal distance between the vehicle and cyclist is zero) in the passing phase . The best model is with the following fixed predictors: speed, country, lane width, lead vehicle, TTC and distance between land edge and VRU, see Table 6.8. The adding of fixed effects country and TTC improved the null model, see Table 6.9. Overall, in the model for the flying manoeuvre, car speed, lane width, lead vehicle and distance between lane edge and cyclist were all significant, see Table 6.9.

The lateral distance is higher by 0.01 m for every unit 1km/h in speed of the VRU. The lateral distance increases also for increase in lane width of 1m (0.13m) and lead vehicle present (0.34m). The lateral distance decreases by 0.44m for 1m increase in distance between land edge and VRU . The countries France and Poland have lower lateral distance than Germany.

Table 6.8: Summary of AIC results for models relating the lateral distance and predictor variables, in passing phase for flying overtaking manoeuvre.

Model	AIC	ΔAIC	Model likelihood
speed + country + laneW + leadV + ttc + dble_vru	146.03	0.00	-62.01
speed + laneW + leadV + dble_vru	148.11	2.08	-67.29

Table 6.9: Summary of estimates for the fitted model ('*' p<0.001, '**'p<0.01, '*' p<0.05)**

	Speed	Country	Lane width	Lead vehicle	Distance between land edge and VRU	TTC
Coefficient Estimate (Standard Error)	0.01 (0.00)**	FR:-0.28(0.13) PL:-0.30(0.17) UK:-0.00(0.14) *	0.13(0.06)*	0.34(0.10)**	-0.44(0.05)***	0.04(0.03)

Accelerative manoeuvre

The best model is the model with the following fixed predictors: speed, gender, lane width, lead vehicle, TTC, distance between land edge and VRU and multiple VRUs being overtaken, see Table 6.10. The lateral distance is higher by 0.03m for every unit 1km/h in speed of the VRU. The lateral distance increases also for lane width (0.17m) and TTC (0.09m). The lateral distance decreases for distance between land edge and VRU (0.37), lead vehicle present (0.33m) and multiple VRU overtaken (0.34m). The female drivers keep higher lateral distance (0.22m) than males. Significant estimates are for predictors: speed, lead vehicle, TTC, distance between land edge and VRU and multiple VRUs. Gender and lane width are not significant, see Table 6.11.

Table 6.10: Summary of AIC results for models relating the lateral distance and predictor variables, in passing phase for the accelerative overtaking manoeuvre.

Model	AIC	ΔAIC	Model likelihood
speed + country + laneW + leadV + oncV + dble_vru	60.69	0.00	-19.34
speed + laneW + leadV + dble_vru	68.97	8.28	-27.48

Table 6.11: Summary of estimates for the fitted model ('*' p<0.001, '**'p<0.01, '*' p<0.05)**

	Speed	Country	Lane width	Lead vehicle	Distance between land edge and VRU	Oncoming vehicle
Coefficient Estimate (Standard Error)	0.01(0.00)***	FR:0.58(0.16) PL:0.11(0.17) UK:0.25(0.20) ***	0.13(0.11)	-0.32(0.13)**	-0.61(0.08)***	-0.23(0.11)*

6.4 Discussion

This work analysed how cars overtake cyclists on rural roads in four European countries. The objective was to answer the questions: 1) Is there a difference in the lateral distance, both when the car starts to overtake and passes the cyclist, in different countries? And 2) what factors influence the lateral distance when the car starts to overtake and passes the cyclist?

First, this study showed that there is a difference between countries with respect to lateral distance in the passing phase. Specifically, for the accelerative manoeuvre the drivers from France, Poland and UK kept greater lateral distance than the drivers in Germany, while opposite was found for the flying manoeuvres. Within the visually reviewed segments, all overtaking manoeuvres in Netherlands occurred while the cyclist was riding on a separate cyclist lane. Therefore after the initial annotation process they were not considered for the context annotation and thus for the analysis.

Second, the analysis showed which factors influence the lateral distance for both flying and accelerative manoeuvres. Overall, for the flying and accelerative manoeuvre in the passing phase, car speed, lead vehicle present and distance between lane edge and cyclist were all significant. The lateral distance increased with wider lane width although this was significant only for the flying manoeuvre. The lateral distance was found to increase with TTC in the flying manoeuvres, but was not significant. The presence of oncoming vehicles significantly decreased the lateral distance in the accelerative manoeuvres.

The average lateral distance in the passing phase was 1.65±0.64m. Most European countries have a legislation of 1.5m for overtaking. This work shows that drivers do not always leave appropriate distance when passing cyclist, even though the average is close to these recommendations, in line with previous studies (Llorca 2017, Dozza 2015).

Additionally, in the passing phase for both manoeuvres, the increase in vehicle speed increased the lateral distance. This was opposite of the previous studies which did not found significant influence of vehicle speed to lateral distance (Dozza 2016, Mehta 2015). However, the cyclists expect that higher speeds require larger lateral distance (Llorca, 2017).

Furthermore, only in at start of the overtaking of the flying manoeuvre gender had an effect on the lateral distance. In this case, overtaking drivers pass closer to a cyclist when the driver is female. In addition, only at the start of the overtaking of the flying manoeuvres the VRU speed influenced the variability of the lateral distance. The drivers passed further from the cyclist if the VRU speed was higher.

The further out into the road the cyclist was positioned, the less space the cyclist received from overtaking cars. This could be due to the driver following the same path when overtaking a bicycle no matter where the cyclist is. Hence the further out the cyclists are, the less space will be between them and an overtaking vehicle. This finding is in line with the findings of the study by Walker, 2007. However, this does not mean that the cyclist are safer if they are cycling closer to the road edge. When they are cycling closer to the road edge they have less possibility to move away if a car gets too close. There are also other risks closer to the road edge, such as uneven road surface or dirt (Walker, 2007).

If overtaking vehicles were following another vehicle, in the flying manoeuvres for both phases, larger lateral distances were observed. The analysis showed that the presence of oncoming vehicles influences the lateral distance only in the accelerative manoeuvres, as found in previous study (Dozza, 2016).

Overall, lateral distance was influenced by road infrastructure factors, and tended to be greater with wider lane widths. A wider road, may help increase the lateral distance between the overtaking vehicles and cyclists, but the speeds may also increase with lane width. Appropriate measures to keep the vehicle speeds lower through proper speed limit may need to be taken into account (Chapman, 2012; Shackel 2014). Furthermore, the provision of adequate shoulders could be an appropriate mechanism to ensure safe overtaking manoeuvres.

In addition, to increase safety for all road users driver training to stimulate better overtaking techniques and cyclist training in appropriate on-road positioning may be needed. Driver comfort zone during overtaking manoeuvres from naturalistic driving data could provide information for legislators and policy makers in Europe, as well as support safety system designers in the automotive industry.

Trucks

The same data preparation method and annotation procedure was applied to the truck data, however after reviewing 100 overtaking segments it was found that all the overtaking manoeuvres occurred while the cyclist was riding on a separate cyclist lane and in city traffic. This could be due the developed cyclist infrastructure in different countries, specifically in the Netherlands, where the trucks were driven. Therefore after the initial annotation process the analysis was not carried out for the truck data.

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Part II: Interactions with pedestrians

7 Interactions between drivers and pedestrians

7.1 Introduction

Many research questions (RQs) regarding interactions between drivers and pedestrians can be addressed using the UDRIVE database. In this chapter, we address two major questions:

RQN1: What characterises conflicts involving motorised traffic and pedestrians?

RQN2: How do car drivers behave in the presence of pedestrians?

These two RQs are clearly very general and are highly dependent on how conflicts between drivers and pedestrians are defined and detected, and how presence of pedestrians is defined.

Driver-pedestrian interactions are complex and can be manifested in many forms. The next section provides a literature review on this topic, with an emphasison factors contributing and characterizing those interactions, namely: situational factors, pedestrians' behaviour and characteristics as well as drivers' behaviour and characteristics. The literature review also provides a survey of different methodologies used to detect and model driver-pedestrian interactions with emphasise on naturalistic studies (such as UDRIVE). The last section of the literature review concentrates on advanced driver assistance systems and in particular pedestrians protection systems. The Mobileye system, which is part of the UDRIVE data acquisition system (DAS) is mentioned in that context, and specifically its ability to detect presence of pedestrians and identify potential conflicts with pedestrians.

7.2 Literature review

7.2.1 Introduction

Walking is the most traditional mode of transportation and is particularly important for children below the age of 12 and adults aged 75 and above (Sucha, 2014). Survey data from seven European countries show that in 12-30 percent of all trips, walking was used as the main mode of transport. Since pedestrians have no shield to protect them in case of a collision, they are often labelled as vulnerable road users (VRU)(Shinar, 2007).

According to the World Health Organisation (WHO), every year approximately 1.25 million people die as a result of a road traffic crash. Between 20 and 50 million more people suffer non-fatal injuries, with many incurring a disability as a result of their injury. Unable to defend themselves against the speed and mass of the motor-vehicle, pedestrians' safety depends, to a large extent, on the vehicle's speed. For instance, at a collision speed of 50km/h the risk of fatal injury for a pedestrian is almost eight times higher compared to a speed of 30 km/h (Pasanen, 1992).

Statistically, motor-vehicle crashes with pedestrians constitute a relatively small proportion of all crashes, however, as above mentioned, due to their vulnerability, pedestrians face a high risk of injury or even death (Shinar, 2007). Pedestrians are more at risk to be involved in a fatal crash in the less developed countries. More specifically, in very poor countries, pedestrians constitute more than 35 percent of all fatalities as opposed to 15 percent or less in the richer countries (Shinar, 2007). Accident statistics in Sweden show that 36 percent of all the police reported accidents, which involve an injury between pedestrians and drivers, occur at pedestrian crossings (OECD, 2009). Encounters between drivers and pedestrians at pedestrian crossings are critical situations, in which there is a need for better speed adaptation on the driver's behalf. In an encounter with a pedestrian, the driver has to be influenced before he or she reaches the “decision zone”, 50 to 40 meters before the pedestrian crossing (Varhelyi, 1998).

7.2.2 Contributing factors to driver-pedestrian interactions

Many factors affect driver-pedestrian interactions. These factors are next described.

<u>Encounters between pedestrians and drivers – General Information</u>

The purpose of the current section is to shed light on driver-pedestrian interactions with focus on crash risk and safety. One of the main topics that needs to be addressed is how drivers and pedestrians interact and how drivers react to pedestrians' crossing attempts. In a controlled experiment by Katz et al. (1975), the researchers found that drivers slowed down or stopped more often for pedestrians who were crossing under the following conditions:

1. The approach speed of the vehicle was low;
2. The pedestrian did not look at the approaching vehicle;
3. There was a relatively long distance between the vehicle and the pedestrian's point of entry into the road, and
4. A group of pedestrians, rather than a single pedestrian, attempted to cross.

This suggests that there are several factors influencing drivers' behaviour at crosswalks (Katz et al., 1975). Himanen and Kulmala (1988) found that the most important explanatory variables influencing drivers' behaviour included pedestrians' distance from the curb, the size of the city, the number of pedestrians crossing simultaneously, vehicle speed, and vehicle platoon size.

Persson (1998) found that the likelihood of a driver yielding to the pedestrian increases if information about the pedestrian's intention is increased by the combination of various forms of cues. According to Persson (1998), while almost none of the drivers gave precedence at a zebra crossing when the pedestrian just stopped at the curb and looked at the approaching drivers, 31 percent stopped or slowed down when the pedestrian looked at the driver and signalised with a hand gesture that he or she was about to cross. According to Varhelyi (1998), situations in which the pedestrian crosses first can be divided into three categories:

1. Crossing before the arrival of the car without influencing its speed;
2. Situations when the approaching car is provoked to brake by the pedestrian who does not stop before crossing;
3. Ideal situations, when the approaching car brakes on the driver's own initiative in order to give way to the pedestrian.

In driver-pedestrian encounters, three out of four drivers maintain the same speed or accelerate and only one out of four slows down or brakes (Varhelyi, 1998). Moreover, Varhelyi (1998) stated that the driver's decision to stop is already made 40 to 50 meters before the crosswalk. However, according to Schweizer et al. (2009), a distance of 50 meters to the crosswalk is not enough for the driver to react compliantly to a suddenly emerging pedestrian. Drivers can only react compliantly to the pedestrian if they are aware of the pedestrian's crossing intention. Interestingly, the profile of mean speeds reaches its highest value at a distance of 40-50 meters before the zebra crossing, where it is statistically significantly higher than in non-encounters. As described by Sucha (2014), this may be an indication of "competitive behaviour" on the driver's behalf, which signalises his or her intentions to the pedestrian by speed. In other words, the driver signalises that he or she does not intend to give way to the pedestrian. In most incidences, drivers expect pedestrians to stop and place the responsibility for avoiding a collision on the pedestrian. Drivers do not lower their speeds sufficiently in order to be prepared to stop in an unexpected dangerous situation (Sucha, 2014).

On the basis of observations of car-pedestrian encounters at pedestrian crossings at non-signalised intersections in four European countries, Westra and Rothengatter (1993) found that the probability of a conflict was greater if the speed of the approaching vehicle was higher. The willingness of drivers to give way to pedestrians at zebra crossings is relatively low and varies within different studies. Danielsson et al. (1993) showed that only 30 percent of drivers gave priority to pedestrians at zebra crossings, putting pedestrians at risk for injury. Alternatively, Sucha (2014) found that only 12-20 percent of drivers gave priority to pedestrians at crosswalks. Additionally, it seems that there is a discrepancy between what drivers claim to do and what they actually do. When Swedish drivers were asked “How often do you give way to a pedestrian at pedestrian crossings?” 67 percent answered “very often” or “always” (Dahlstedt, 1994). However, the presence of pedestrians at a zebra crossing has little or no speed-reducing influence on approaching vehicles. Hydén et al. (1995) found that when vehicular speeds at zebra crossings are brought down to 30 km/h and below, the interaction between vehicles and pedestrians changes, so that drivers are more willing to give way to pedestrians.

The situational factors, which contribute to the risk of collision between drivers and pedestrians are discussed below.

<u>Situational factors</u>

Darkness is the condition associated with most pedestrian fatalities: 51 percent of pedestrian fatalities in the EU (based on 24 countries) occurred in darkness. According to data derived from Mobility & Transport ERSO (2013), pedestrian fatalities are more seasonal than all fatalities, i.e. the number increases during the autumn and decreases in the spring, with highest fatality rates between October and December. The increase in pedestrian fatalities during the winter is probably caused by the higher danger for pedestrians in darkness. The time of darkness/twilight is longer than in other seasons and pedestrians are much less visible in the dark. Respectively, the lowest pedestrian fatality rates occur in April, May and June.

Another important factor influencing pedestrian-driver interactions is the **location of the encounter**. Whereas the encounter with pedestrians may occur on various roads, in or outside the city, it is most common in urban areas where the densities of both pedestrians and vehicles are highest. Accordingly, pedestrians are at a greater risk for injury due to a car crash in urban areas. Crashes involving pedestrians are most likely to occur when the pedestrian is crossing the road. The crossing situation at crosswalks and intersections was previously discussed.

Vehicle characteristics and conditions such as vehicle speed, vehicle type, and vehicle movement were also found to be associated with pedestrian crashes (Lee & Abdel-Aty, 2005). For instance, Anderson et al. (1997) observed that when the speed limit was reduced, the number of fatal pedestrian crashes was reduced as well. Lefler and Gabler (2004) found that pedestrians' fatality rate was two to three times higher when pedestrians were struck by light trucks or vans (LTV) when compared to cars. Furthermore, Preusser et al. (2002) found that turning vehicles were at greater risk for pedestrian crashes, since drivers often fail to give precedence to pedestrians at intersections.

<u>Driver behaviour and characteristics</u>

Evans (1991) showed that severe crash involvement rates are highest for young (late teens to mid-20s) and especially **male drivers**, a phenomenon he suggests can best be explained by behavioural factors and an underlying propensity to take risks. Respectively, Lee & Abdel-Aty (2005) showed that in case of crashes at driver's fault, male drivers aged 25-64 are more involved in crashes as causers than any other driver group.

A study by Borowsky et al. (2010) examined how experienced and young-**inexperienced drivers** respond to and identify pedestrians when they appear in residential roads within populated neighbourhoods and in urban roads, which are less populated. As part of a hazard perception test, participants were connected to an eye tracking system and were asked to observe 58 traffic scene movies. Subsequently, they were asked to press a response button each time they identified a hazardous situation. The major goal was to examine how well drivers perceive and detect pedestrians when they expect and search for pedestrians (i.e. in residential areas) and when they don’t necessarily expect pedestrians (i.e. in sparsely populated urban areas). Analysing all pedestrian-related events revealed that, regardless of driving experience, drivers detect pedestrians less often when they appear in less populated areas and more often when they appear in residential areas (Borowsky et al., 2012).

It is important to identify **high risk drivers**, since it enables researchers to comprehend, which drivers are most prone to be involved in car crashes. Besides the above mentioned variables of age, gender, and experience - driver personality also plays an important role in individual driving risk (Costa and McCrea, 1992). Various studies have shown the association between personality characteristics and risky driving behaviour (Dahlen & White, 2006; Jonah, 1997; Jonah et al., 2001; Machin & Sankey, 2008; Ulleberg & Rundmo, 2003). The tendency to commit driving violations, speeding, and an inadequate decision making process have all been reliably shown to be associated with increased accident risk West et al. (1993). Further driver behaviours, which were linked to an elevated risk for severe crashes and injuries, are alcohol or drug use as well as the lack of seat belt use (Kim et al., 1995). Finally, sleepiness in drivers is widely believed to be an important cause of road traffic injuries.

According to the National Highway Traffic Safety Administration (NHTSA), **driver inattention**, in its various forms, contributes to approximately 25 percent of police reported accidents. More specifically, **driver distraction** is argued to play a significant role in over half of inattention crashes (Stutts et al., 2001). Distraction occurs when drivers attend to other, non-driving related tasks or events to the degree that they fail to allocate sufficient attention to the driving task. As a result, their driving performance is compromised. That is to say, distraction only occurs if the secondary task has a negative effect on the driving behaviour (Young et al., 2007). Researchers tend to concentrate on in-vehicle distraction; that is, distraction caused by activities or objects inside the vehicle rather than those outside the vehicle (Young et al., 2003). Driver distraction may be divided into technology-based distractions such as the use of mobile phones, route navigation and email/internet services as well as non-technology-based distractions such as conversing with passengers, eating/drinking, smoking, etc. (Young & Regan, 2007).

Engaging in a secondary task and its influence on driving behaviour has been one of the most debated topics in recent years, mainly due to the increased use of mobile phones with wireless communication services in the cars. Numerous on-road and simulator studies have showed that drivers tend to decrease their mean speed when engaging in a secondary task. In a simulator study, Haigney et al. (2000) examined how engaging in a mobile phone task effects the driver's driving performance. The researchers compared hand-held versus hands-free use of mobile phones. The results showed that drivers' mean speed decreased during mobile phone use, regardless of study condition.

Pedestrian behaviour and characteristics

Crashes involving pedestrians are most likely to occur when the pedestrian is crossing the road. For example, in the U.S. 63 percent of crashes involving pedestrians between 1995 and 1998 occurred while the pedestrian was crossing (Hatfield & Murphy, 2007). In this section, pedestrian characteristics, which play an important role in the driver-pedestrian interaction, will be reviewed.

Studies have shown that young (5-19 years old) and elderly (65 and above years old) pedestrians are at higher risk to get injured or killed as a result of a car crash. The association between death and age is strongly related to increased fatality in older pedestrians, in agreement with many previous studies (Kim et al., 1995).This association is typically explained by the increased frailty associated with ageing. Additionally, males are overrepresented in pedestrian deaths in most countries. More specifically, male pedestrians are approximately 2.3 times more at risk to die as a result of a car crash when compared to female pedestrians (Evans, 1991).

Other factors, which were found to influence crash risk, include the time the pedestrian is exposed to traffic, the number of roads crossed and crossing speed (Shinar, 2007).

In addition to official rules that govern the flow of traffic, humans often rely on some form of informal rules resulting from non-verbal communication among them and anticipation of the other traffic participants' intentions. For instance, pedestrians intending to cross a street where there is no stop sign or traffic signal, often establish eye contact with the driver to ensure that the approaching car will stop for them. Other forms of non-verbal communication include gazing, hand gesture, nodding or body posture.

Schmidt and Färber (2009) showed that drivers mainly use body language such as leg and head movements or turning of the body to predict pedestrians' intentions. And indeed, in more than 90 percent of the cases, pedestrians use some form of attention to communicate their intention of crossing. The most prominent form of attention is looking in the direction of the approaching vehicles. The importance of visual contact is confirmed by several other studies. For example, (Zito et al., 2015) showed that drivers find it difficult to assess a pedestrian's intention if the pedestrian's head is not turned to traffic, even if the pedestrian is outstretching his arm to signal his crossing intention. The observations of Schweizer et al. (2009) and Schneemann and Gohl (2016) confirm the existence of a mutual gaze behaviour during the interaction process.

In a psychological experiment by Schmidt and Färber (2009), participants were unable to correctly evaluate pedestrians' crossing intentions based only on the course of their motion, strengthening the notion that parameters of body language (posture, leg and head movements) are indispensable cues in the pedesestrian's interaction with the driver.

In more recent works, the pedestrian's body language is used as means of predicting behaviour. In these studies, head orientation is associated with the pedestrian's level of awareness. In a new study by Rasouli et al. (2017), the researchers created a new dataset with over 650 samples of pedestrian behaviours in several street configurations and different weather conditions. The research was conducted in order to study pedestrians' behaviour while crossing.

Rasouli et al. (2017) identified types of non-verbal communication cues pedestrians use at the point of crossing, their responses, and under what circumstances the crossing event takes place. The researchers found that in more than 90 percent of the cases, pedestrians gazed at the approaching cars prior to crossing, in non-signalised crosswalks. The crossing action, however, depends on additional factors such as the structure of the street, time to collision, explicit driver's reaction or structure of the crosswalk.

Up to 15 percent of pedestrian fatalities are suggested to be related to inattentiveness on the part of the pedestrian (Bungum et al., 2005). An observational field survey of 270 females and 276 males was conducted in order to compare the safety of crossing behaviours amongst pedestrians. The researchers compared pedestrians using, versus not using, a mobile phone while crossing. Amongst females, pedestrians who crossed while talking on a mobile phone crossed more slowly, and were less likely to look at the traffic before starting to cross. Additionally, they were less likely to wait for traffic to stop compared to matched controls. For males, pedestrians who crossed while talking on a mobile phone crossed more slowly at unsignalised crossings. These effects suggest that talking on a mobile phone is associated with cognitive distraction that may undermine pedestrian safety (Hatfield & Murphy, 2007). In another study, Bungum et al. (2005) examined distraction amongst pedestrians. Distraction was defined as the engagement in a secondary task while crossing, such as listening to music, talking on a mobile phone, eating, drinking, smoking, etc. as they crossed the street. According to Bungum et al. (2005), only 13.5 percent of pedestrians looked left and right before entering the crosswalk. Moreover, approximately 20 percent of the pedestrians were engaged in a distracting task as they crossed the street. Thompson et al. (2013) showed that compared to other distracting behaviours amongst crossing pedestrians, text messaging was associated with the highest risk for injury.

Research using emergency rooms data shows that pedestrians who are injured or killed, were under some influence of alcohol at the time of the accident (LaScala et al., 2000). Profiles of injured pedestrians manifest that 19-65 percent were drinking alcohol, often heavily, prior to the accident (Bastos & Galante, 1976; Middaugh, 1988). Pedestrians who are under the influence of alcohol also appear to have more severe injuries (Bradbury, 1991) and face higher mortality (Williams et al., 1995) than those who are not under the influence of alcohol. It is important to bear in mind that laws prohibiting alcohol use exist only for drivers, not for pedestrians. Same goes for texting- whereas drivers are prohibited from texting and driving, pedestrians text and walk, a habit, which may put them at risk for injury, since texting diverts their attention from traffic.

7.2.3 Methodology

In order to study pedestrian-driver interactions, it is essential to examine the existing methodological techniques. Traditionally, researchers have focused on the analysis of crash statistics as well as on observational data, the use of driving simulators, instrumented vehicles and self-report measures. These methods have greatly contributed to the understanding of road user behaviour and will be discussed in the following section along with a newer research technique- naturalistic driving.

Observational Studies

Observational research (or field research) is a non-experimental research method, in which a researcher observes ongoing behaviour. This research technique involves the direct observation of phenomena in their natural setting. With regard to driver-pedestrian interactions, this method is often applied to measure pedestrians' crossing behaviour. In a study by Thompson et al. (2013), pedestrians were observed at 20 high-risk intersections. Observers recorded demographic and behavioural information, including use of a mobile phone (talking on the phone, text messaging, or listening to music). Following the observations, the researchers examined the association between distraction and crossing behaviours (Thompson et al., 2013).

A study by Rosenbloom et al. (2016) is a further example for an observational study aimed to study pedestrians' road crossing behaviour. The study was based on observations of 2591 pedestrians in six crosswalks in two different cities. It revealed that pedestrians in the high socio-economic city demonstrated safer road crossing patterns than in the low socio-economic city. Additionally, elderly pedestrians revealed safer crossing patterns than younger pedestrians. Four trained observers were implemented in order to accurately assess the age and crossing behaviour of the pedestrians (Rosenbloom et al., 2016).

Self-Reports

Self-report data are widely used in the field of road safety research. This approach allows for a larger number of crash types to be recorded, as archival data are generally restricted to more severe crashes (Barraclough et al., 2016). Research indicates that approximately 25 percent of all crashes are forgotten each year, with drivers more likely to report crashes that occurred closest to the time of the survey. Furthermore, self-reports are used to study perceptions, attitudes and (declared) behaviour patterns. There are several limitations to the use of self-reports, such as memory recall and method bias. Method bias can reflect a tendency on the part of respondents to answer questions in a standardised manner or giving socially desirable responses - potentially distorting results (Krueger & Kling, 2000).

With regard to pedestrian-driver interactions, self-report measures can be used to measure driver and pedestrian (reported) behaviour. However, it is important to bear in mind that just because a person claims to act a certain way in a given situation, it doesn't necessarily mean that it will be the case in real life. For instance, in a Swedish study, Dahlstedt (1994) asked drivers how often they give way to pedestrians at pedestrian crossings. 67 percent answered "very often" or "always", which is far from what is observed in reality at pedestrian crossings.

Driving Simulators

In the early 1960's, driving simulators were applied in the research field to study driver behaviour and drivers interactions with the vehicle and the road environment (Roberts, 1980).

The benefits of using driving simulators in road safety research are well documented (Bella, 2008) and evidenced by the fact that over 60 research driving simulators exist worldwide, owned and operated by academic institutions, government research establishments and vehicle manufacturers. Driving simulators are used to monitor driver behaviour and performance. Additionally, they may be used to aid researchers in their understanding of theoretical concepts and situation awareness (Gugerty, 2011). The driving simulators range from simple, low cost two-dimensional to more complex, high cost 3 -dimensional simulators (Blana, 1996).

The main advantage of driving simulators is that they can provide an inherently safe environment for driving research, which can be easily and economically configured to investigate a variety of driver related research questions. Additionally, they make it possible to control experimental conditions over a wider range as compared to field tests and can be easily changed from one condition to another. However, driving simulators also have several limitations. For instance, results from driving simulator studies cannot always be easily transferred to real traffic situations, since both the traffic environment and the vehicle characteristics are only approximations of reality (Jamson & Jamson, 2010).

In addition to simulators, which are used to simulate driving behaviour, recently, pedestrian simulators have been implemented. Pedestrian simulators, however relatively scarce, provide essential information on the pedestrian's decision making process, threat perception (e.g. when does the pedestrian consider it safe enough to cross), etc. One advanced Dome projection facility and pedestrian simulator can be found at the Ben Gurion University's Ergonomics complex in Israel. The Dome simulator consists of 180° spherical screen aligned with a highly accurate projection system of three projectors. The participant typically views a scenario on the Dome screen. An eye tracker, which measures eye movement, is attached to the participant's head. When using a head tracker, a technique called Eye-Head integration can be performed, allowing for accurate mapping of line of gaze onto the pre-defined dome screen, which enables faster data analysis (Tapiro et al., 2016).

Controlled Experiments and Field Experiments

A controlled experiment refers to a scientific observation, which was designed to measure the effect of an independent variable on the dependent variable. The independent variable is "manipulated" by the researcher, so that its various effects on the dependent variable can be measured.

Controlled experiments are not common in road safety research. However, there is a valuable controlled experiment by Katz et al (1975), which was conducted in order to determine the relative importance of pedestrian, vehicle, and situational factors in influencing drivers to give precedence to crossing pedestrians. The researchers examined the following variables:

1. Type of crossing;
2. Distance between the oncoming vehicle and the pedestrian;
3. Orientation of the pedestrian;
4. Number of pedestrians;
5. Approach velocity of the vehicle.

Trained pedestrians performed the start of an everyday street crossing attempt and interacted with regular drivers, whose response was measured in terms of changes in car velocity. The experiment was replicated at two sites for a total of 960 crossing trials. The results indicate that drivers slowed down for crossing pedestrians when: (1) the approach speed of the vehicle was low; (2) the crossing took place on a marked crosswalk; (3) there was a relatively long distance between the vehicle and the pedestrian's point of entry into the road; (4) a group of pedestrians, rather than an individual, attempted to cross; and, (5) the pedestrian did not look at the approaching car (Katz et al., 1975).

In a field experiment by Hakkert et al. (2002), the researchers wanted to examine whether the implementation of a pedestrian detecting system near the crosswalk zone would aid drivers to better acknowledge pedestrians' presence at a pedestrian crossing. Flashing lights, which were embedded in the pavement adjacent to a marked crossing, were used to warn drivers of pedestrian presence. The results indicate that under certain conditions, the markings can bring a decrease of about 2–5 kph in average vehicle speeds, near the crosswalk zone. Additionally, it was shown that drivers increased the rate of giving way to pedestrians by approximately 40 percent. Moreover, a significant reduction in vehicle–pedestrian conflicts in the crosswalk zone was achieved. Finally, there was a reduction in the share of pedestrians crossing outside the crosswalk area (Hakkert et al., 2002).

Instrumented car studies

In instrumented vehicle studies, participants drive in real traffic but in a special, highly equipped vehicle with, usually, an experimenter on-board. This makes the drivers aware of the fact that they participate in an experiment, which may affect their driving behaviour. However, not always an experimenter is on-board and the use of instrumented cars represents a step forward from traditional driving simulator studies, where the environment is somewhat artificial.

There are two types of instrumented cars, high Instrumented Cars (HICs) and low instrumented cars (LICs). HICs are specialised vehicles that continuously record a large number of data from the driver, car, and surroundings. HICs provide different sources of data including numerical driving parameters, video data from the driver and the surroundings, the driver's eye movements and geographical data. In summary, HICs record as much information as possible about what happens inside and outside the car. In contrast, low instrumented cars (LICs) typically record a much smaller number of measures and the equipment used can be easily installed in the cars of participants (Valero-Mora et al., 2013).

Naturalistic Driving (ND)

Naturalistic driving is a relatively new approach among applied traffic research methods and refers to studies undertaken using unobtrusive observation when driving in a natural setting. In Naturalistic Driving Studies (NDS) the driver knows, however, gradually becomes unaware of the observation, as the data collection is organised as discreet as possible. Participants' own vehicles are equipped with several small cameras and sensors, which continuously register vehicle manoeuvres (e.g. speed, acceleration and direction), driver behaviour (e.g. eye, head and hand gestures) and external conditions (e.g. road, traffic and weather characteristics). The retrieved data are used to study the relationship between driver-, vehicle-, and/or environmental factors with the intention to study the risks of potential crashes (van Schagen & Sagberg, 2012). Moreover, drivers use their own vehicles and are instructed to drive as they routinely drive, a factor which contributes to the natural behaviour on the driver's part. Furthermore, no feedback on their driving behaviour is given to the drivers. In previous studies both in Europe (PROLOGUE) and in the United States, the approach has proven its potential to contribute substantially to the understanding of the processes resulting in crashes and near crashes. The naturalistic driving method offers two main advantages. First, detailed pre-crash information is gathered and second, information regarding normal traffic behaviour in everyday traffic situations is accumulated.

The first significant naturalistic driving project that investigated pre-crash causal and contributing factors is the 100-Car Naturalistic Driving Study. The study was sponsored by the National Highway Traffic Safety Administration and the Virginia Department of Transportation. Participants were 100 drivers and data were collected in an unobtrusive manner across the time period of one year. A primary goal was to provide vital exposure and pre-crash data necessary for understanding causes of crashes, supporting the development and refinement of crash avoidance countermeasures, and estimating the potential of these countermeasures to reduce crashes and their consequences. The resulting database contains many extreme cases of driving behaviour and performance, including severe drowsiness, judgment error, risk taking, willingness to engage in secondary tasks, aggressive driving, and traffic violations (Dingus et al., 2006).

The largest ND study, which was conducted in order to address the role of driver performance and behaviour in traffic safety is The Strategic Highway Research Program 2 (SHRP2) (Campbell, 2012). The driving of a large sample of drivers was recorded in their personal vehicles, offering project researchers comprehensive behavioural information for researching the interactions between drivers and various pedestrian features at selected signalised intersections through which they drove.

The current UDRIVE study is the first large-scale European naturalistic driving study (www.UDRIVE.eu).

Advanced Driver Assistance Systems (ADASs)

The main reason for the occurrence of crashes is the inability of road users to detect and perceive oncoming dangers before a sufficient amount of time, so that reactions for crash avoidance can be taken. Hence, advanced driver assistance systems (ADASs) and built-in protection systems are developed to detect pedestrians and predict the possibility of collisions using sensors and computer vision techniques.

Advanced driver assistance systems, and particularly pedestrian protection systems (PPSs), have become an active research area aimed at improving traffic safety. These intelligent on-board systems aim to anticipate crashes in order to avoid them or at least, to moderate their severity (Geronimo et al., 2010). Some examples include adaptive cruise control (ACC), which maintains a sufficient gap between vehicles, and lane-keep-assist (LKA) which signalises when the car is driven out of the lane. PPS is a particular type of ADAS and its major challenge is the development of reliable on-board pedestrian detection systems. Basically, the main objective of a PPS is to detect the presence of both standing and moving pedestrians. However, due to the varying appearance of pedestrians (e.g., different clothes, changing size, etc.) and the unstructured environment, it is very difficult to cope with the demanded robustness of this kind of system.

One of the most known and widely used technological developments in this area is the Mobileye system (Shashua et al., 2004). The system is based on a mono-camera, which is inspired by human vision techniques. The driver is alerted when a potentially dangerous situation is detected by the sensor. After the driver is alerted, he or she can take action to avoid or correct the situation- such as reduce driving speed, stop the car, etc. More specifically, if a cyclist or pedestrian is detected by the sensor, the system signalises in real time via a display, "Danger Zone (DZ)" to the driver, so that the latter becomes alert to the situation. The second important signal is "Pedestrian (& Cyclist) Detection and Collision Warning (PCW)". The system alerts the driver that a pedestrian/cyclist is in close proximity of the car. In other words, the system alerts drivers of a forthcoming collision with a pedestrian or cyclist. Two factors, which play an important role in the detection system are the proximity of the pedestrian to the car and driving speed of the car at the time of the pedestrian detection. Clearly, the faster the car is driving, the higher the risk for collision.

Naturally, such sensor based approaches have some limitations. The current Mobileye system, for example, detects pedestrians only in day time, when visibility conditions are not poor, and the pedestrian is within the field of view of the camera.

As described above, naturalistic studies involve studying drivers' behaviours in a natural environment. In order to collect data on the participants' driving behaviour, researchers may choose to use an ADAS. As in the case of the present study, when the system detects a potentially dangerous situation, the feedback alert remains concealed from the driver, however visible to the researcher. In that manner, researchers can evaluate the ADAS and study the system's advantages and disadvantages. In the current research, Mobileye technology was implemented into participants' cars, however, the signals were only visible to the researchers.

7.3 Analysis

7.3.1 The Database used for the analysis

The analysis presented in this chapter is based on data collected in the UK and France, which was available on the UDRIVE database by February 20th, 2017 for the UK data and by March 2nd , 2017 for the French data.

The data used for the analysis is presented in Table 7.1.

Table 7-1: Data used for the analysis

Attribute	UK	France
number of trips	18,452	18,669
hours driven	4,395	4,769
day-time hours driven	3254	3505
dark-time hours driven	1141	1264
hours driven with speed limit < 50kmh	2002	2548
hours driven with speed limit between 50-80kmh	595	300
hours driven with speed limit > 80kmh	1459	1532
km driven	191,174	210,235
number of drivers	48	41

In the following analysis, the combined database was used (of both the UK and the French data). For special cases, a comparison between the UK and the French data was performed, and when interesting – presented.

7.3.2 Detection of Driver-Pedestrian interactions

The big challenge in naturalistic studies, following data collection, is to scan the data for meaningful information. This procedure is still far from automatic, although a lot of effort has been currently devoted to it and some operational and effective procedures have been developed and implemented to facilitate the automatization of this procedure.

The most straightforward approach is to generate triggers that serve as indicators to detect the relevant information and then manually or automatically scan the data around the time-stamps suggested by the triggers. The most common approach implemented in naturalistic studies is to use kinematic vehicle data (such as: longitudinal and lateral accelerations, yaw rate and speed) as triggers for unsafe behaviour. These triggers can be extracted from the vehicle's CAN data. Another group of triggers relies on distance values and hence, requires radar or other distance measurement devices. Once distance is available, it is possible to compute time-to-collision (TTC).

However, detection of pedestrians and driver-pedestrian interactions are much more complex and require dedicated triggers for the analysis. More specifically, it is highly desired to have a system that can detect pedestrians and indicate the distance between the driver and the pedestrians as well as the estimated TTC.

In UDRIVE, the Mobileye system was included and integrated into the DAS. This system enables, in addition to other features, to detect interactions with pedestrians. The Mobileye system provides continuous measures of the distance to pedestrians within the driver's field-of-view (FOV). Additionally, the system categorises the interactions with pedestrians and their expected TTC into two major categories: Danger Zone (DZ) and Pedestrian Collision Warning (PCW). DZ corresponds to pedestrians, who are present in the FOV of the drivers, but not necessarily on a collision course. PCW corresponds to an expected tangible conflict with a pedestrian, which requires an immediate action (either from the driver or the pedestrian) to prevent an actual crash. In that context, it is worth noting that no such indications were available to the drivers participating in UDRIVE. However, in its industrial add-on configuration, the Mobileye system includes a display, which visually and auditory wise displays alerts to drivers. The DZ alert is conveyed via a small green pedestrian image exhibited on the display, while the PCW alert is conveyed by a large red pedestrian image with a loud auditory sound.

The total PCWs and DZ instances detected by the Mobileye system appear in

Table 7-2. Please note that complete data sets were not always available for the figures presented in Table 7.1. Hence, sometimes smaller data sets were used for the analysis. For instance, after cleaning the PCWs for missing location data, a total of 201 PCWs for the UK and 209 for France were available for a more detailed analysis.

Table 7-2: Mobileye alerts

Mobileye detection	**UK**	**France**
PCW	221	249
DZ	4017	6560

It is important to bear in mind that the pedestrian detection Mobileye version, which was implemented in UDRIVE is operational only in day-light. Hence, the analysis presented in this chapter and in chapter **Fout! Verwijzingsbron niet gevonden.** refers only to day-time driving behaviours.

7.3.3 Annotation of driver-pedestrians' interactions

The PCWs identified by the Mobileye system were used as triggers for scanning the data for conflicts. The UDRIVE central annotation team manually viewed and annotated all the PCW instances (n=410) according to the UDRIVE code-book. The annotated categories for PCWs appear in Appendix A.

In Figure 7-1 a division of the categorization of PCWs and DZs according to various categories is detailed. The right branch of the tree in the Figure corresponds to the 410 PCWs detected by Mobileye. These PCWs are classified into: 351 valid PCW (cases in which the vehicle is moving forward and the related pedestrian is seen in a close distance) and 59 not-valid (otherwise). The valid PCWs are further classified into three categories: 81 classical conflicts, 37 proximity instances and 233 non-conflict instances. The definitions of the three categories appear in the Figure next to their boxes. Note that the fact that 68% of the valid PCWs are marked as "non-conflict" does not indicate false-alarms, rather a potential conflict that did not materialize. Further, those three groups are differentiated according to whether an evasive manoeuvre was present in that instance or not. Finally SCEs are determined based on the type of conflict detected, an occurrence of evasive manoeuvre and the event circumstances, resulting in a total of 67 SCEs. Note that the definition of an SCE is in the essence of all naturalistic studies and typically leaves some space for the common-sense of the annotators. For example, in the 100-car study the following definition appears: "*A subjective judgment of any circumstance that requires, but is not limited to, a crash avoidance response on the part of the subject-vehicle driver, any other vehicle, pedestrian, cyclist, or animal that is less severe than a rapid evasive maneuver (as defined in near-crash event), but greater in severity than a normal maneuver to avoid a crash(...)*" (Klauer et al., 2006). Hence, the SCEs in Figure 7-1 contain an "*" to indicate a definition of potential conflict between a driver and a pedestrian in which an action is required to avoid a crash.

The left branch of Figure 7-1 corresponds to DZ instances. These were locally and randomly tested for validity (on a sample of n=344) and approximately 90% were found to be valid (the case in which the vehicle was moving forward and pedestrians were in its FOV).

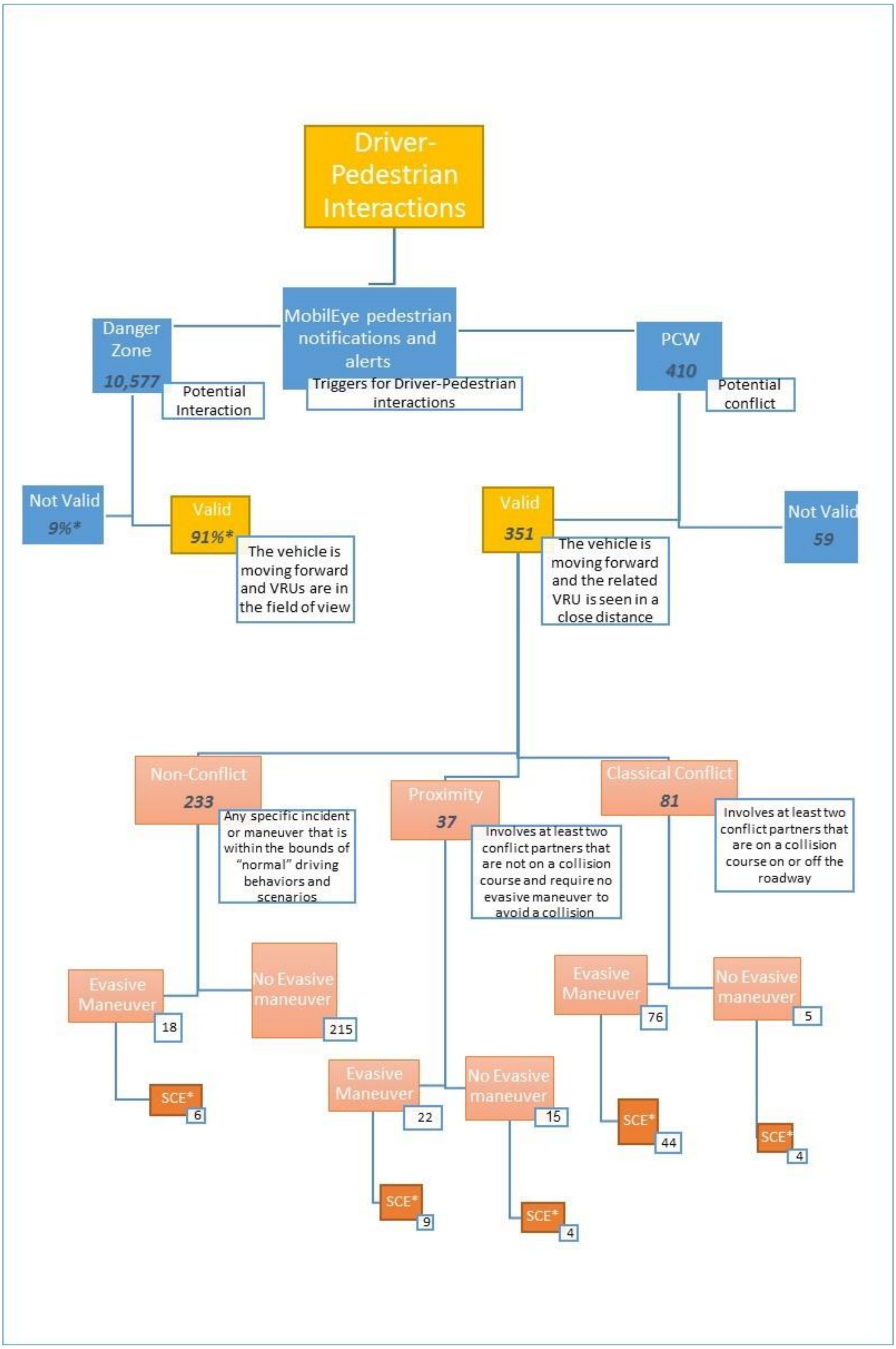

Figure 7-1: Annotation of driver-pedestrians' interactions. NOTE: annotation for validity of DZ was done on a sample of 344 cases.

7.3.4 Controls

In order to understand drivers' behaviour when in conflict with pedestrians, we generated two types of controls. PCW events, as generated by the Mobileye technology and described in the previous section, are used as triggers to driver-pedestrians conflicts. Baseline-controls are intended to look at similar conditions and circumstances characterising the PCWs, but without actual conflicts. As aforementioned, two types of controls are generated: (1) Danger Zone (DZ) based controls, and (2) Location Based (LB) controls. The DZ controls correspond to instances, in which pedestrians are present, but not on a conflict course. The LB controls correspond to instances that occur at the same location of the PCW, but not necessarily when pedestrians are present. The idea of generating two types of controls to PCW is to try to understand the effects of pedestrians' presence, compared to infrastructure characteristics. It is possible that conflicts with pedestrians are prevented, due to the presence of pedestrians (prior to the conflict) and hence, drivers are more aware of potential conflicts with pedestrians and adjust their speed and awareness (DZ controls) accordingly. Alternatively, it is possible that the infrastructure is designed and built to accommodate pedestrians and when drivers drive in this type of environment – they automatically adjust their driving to the possibility of encountering pedestrians, even when no pedestrians are present (LB controls). Note that LB controls do not necessarily have zero pedestrians; however, the average number of pedestrians is much smaller when compared to the DZ controls, which include the presence of pedestrians by definition.

Sampling of controls was carried out using the Propensity Score Matching (PSM) technique, for the selection of controls, which were matched to PCW events. The similarity to PCW events is made with respect to: (1) Driver ID, (2) Intersection type and (3) Speed limit (as an indicator of road type). The sampling is made without return. The sampling was conducted by a factor of four (i.e. 4 instances sampled per 1 PCW).

7.3.5 PCW vs DZ Control and LB Control

PCW, DZ and LB instances all have a point in time, in which they occur. For PCW and DZ this point in time corresponds to the actual occurrence of the event (as determined by the Mobileye system). For LB control instances, this point corresponds to the point in time, in which the LB control was chosen (based on the PSM sampling procedure). Table 7.2 and Figure 7-2 present the descriptive statistics on speed, acceleration and event duration of PCW, DZ and LB controls. Note that for LB controls, event duration is irrelevant.

Table 77.2: Summary statistics for PCW, DZ and LB controls

variable	group	mean	S.D.	median	sample size
speed	DZ control	15.24	10.58	11.79	1640
speed	LB control	29.36	12.37	29.40	1419
speed	PCW	26.17	10.21	25.87	410
acceleration	DZ control	-0.28	1.06	-0.23	1620
acceleration	LB control	-0.13	0.8	-0.11	1404
acceleration	PCW	-0.65	0.92	-0.45	405
event duration	DZ control	1.40	0.98	1.10	1640
event duration	PCW	1.43	0.37	1.60	410

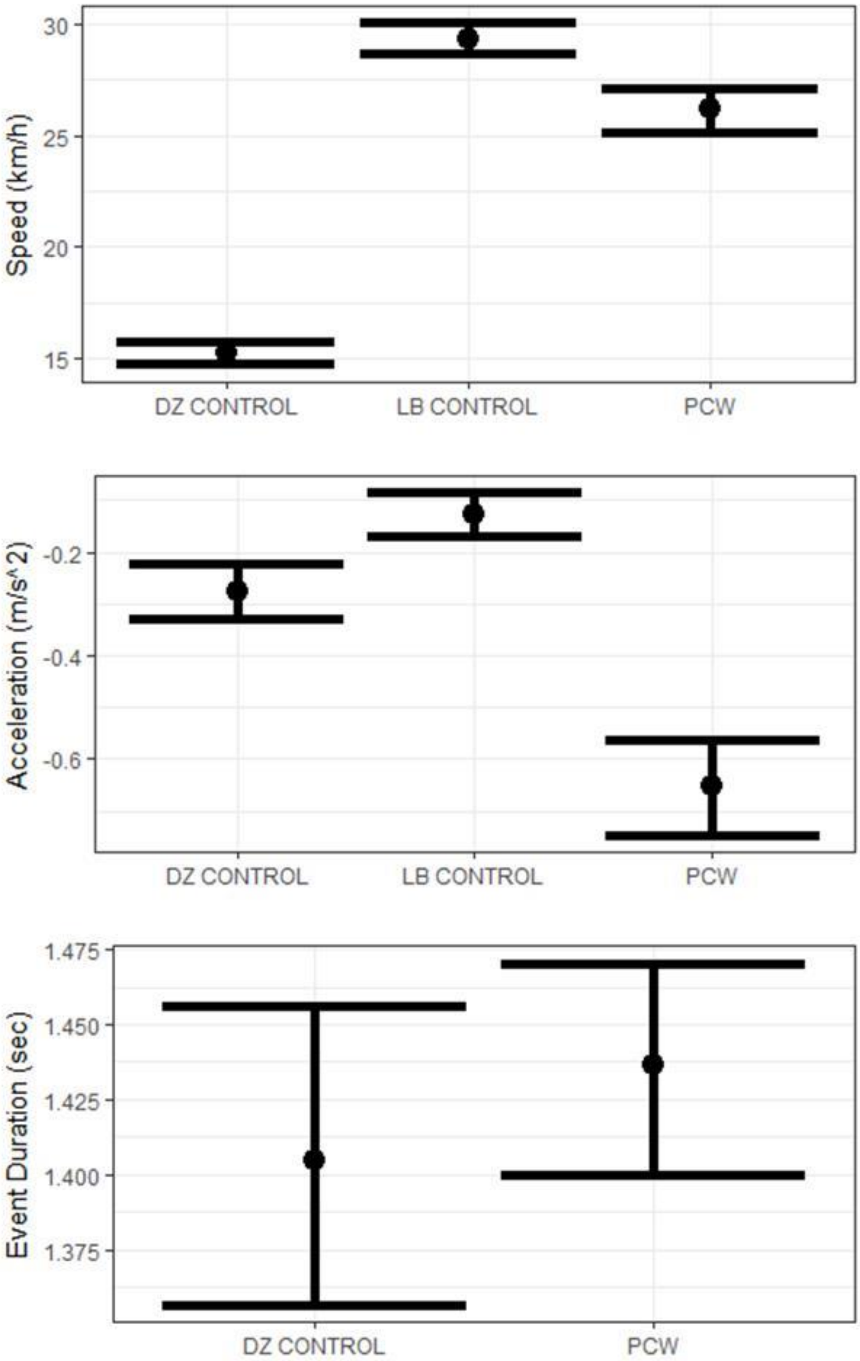

Figure 7-2: Descriptive statistics of PCW, DZ and LB controls (mean and confidence intervals)

It can be easily noticed that the speed of DZ events is significantly lower than the speed of PCW and LB controls. Additionally, the level of deceleration (negative acceleration) in PCW events is more extreme compared to the other types of events and can be regarded by the definition of PCW as an actual conflict, whereas DZ and LB instances do not correspond to actual conflicts.

All confidence intervals were calculated based on a bootstrap technique, which does not assume a normal distribution of the analysed variable.

The data presented in Table 7.2 and Figure 7.1 corresponds to a single point in time – the time of the occurrence of the event. In order to gain a better understanding of those instances – a wider view and perspective are required. This is achieved by looking at the "time window", in which the PCW, DZ and LB instances occurred. This time window was chosen to be 12 seconds before the event and 7 seconds following its occurrence.

Figure 7-3 presents the mean speed distribution during a time window, in which "0" corresponds to the time-point of the event occurrence. It is clear from the Figure that DZ events have consistent lower speeds. Figure 7-3 provides an interesting view to support the suitability of LB controls (to PCW), since the speed distribution prior to the event is very similar between PCW and LB controls and very different from the speed of DZ controls. A possible explanation for this difference may be related to the essence of the DZ controls; DZ events correspond to instances, in which pedestrians are present but not on a collision course. Hence, drivers adjust their speeds to be prepared to potential conflicts with pedestrians. It is also interesting to note the sharp reduction in speed for the PCW sequence, starting approximately one second prior to the event.

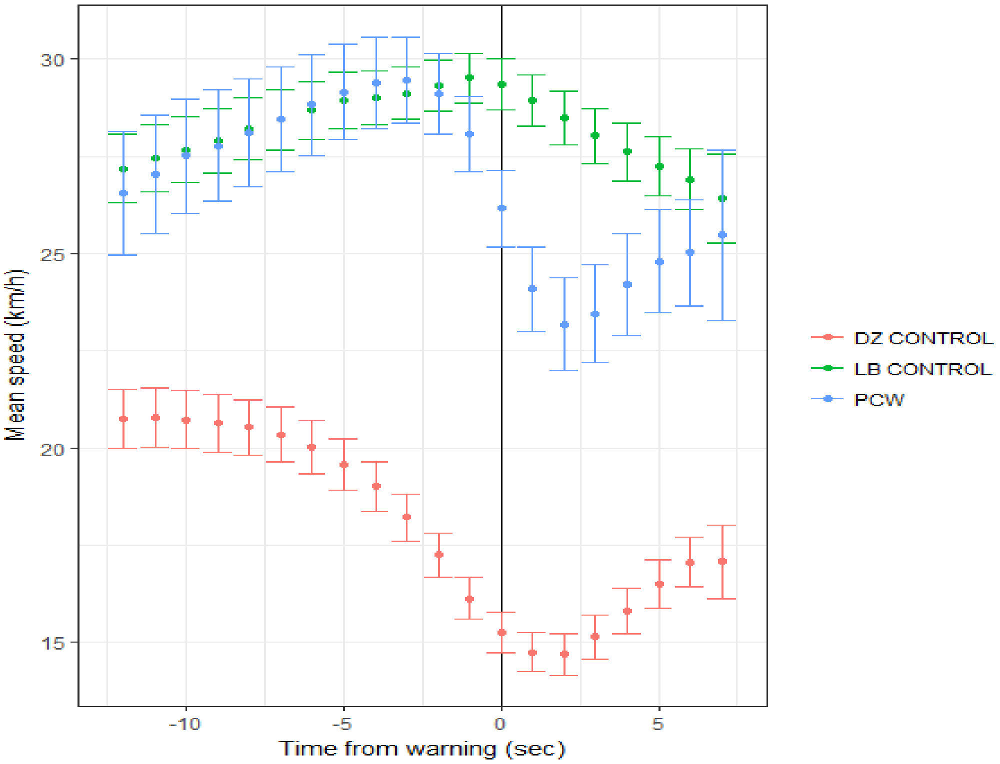

Figure 7-3: speed distribution of PCW, DZ and LB controls

The sharp speed decline for the PCW sequence around time zero is even more evident in Figure 7-4, where the average deceleration for the PCW events reaches -0.53m/s^2. The speed reduction for the DZ events is more modest and for the LB controls events less detectable.

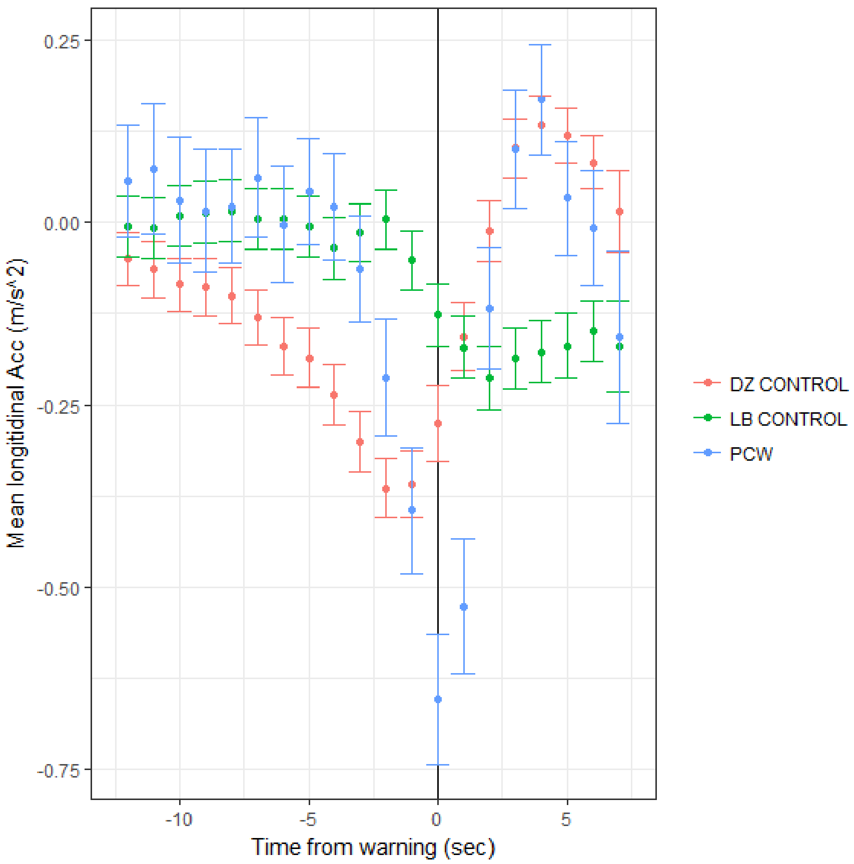

Figure 7-4: Acceleration distribution of PCW, DZ and LB controls

The richness of the data collected in UDRIVE, enables us to look at this interesting time window from a different angle. The Mobileye system provides, when relevant, an indication whether pedestrians (one or more) were in sight (where the distance to the pedestrian is typically less than 30 meters). In Figure 7-5, this distribution is presented over the time window of occurrences of PCW, DZ and LB controls. Clearly, these probabilities reach their peak at time "0" for PCW and DZ events. However, it is interesting to note that LB controls also decline after time "0". This supports the suitability of the LB controls to represent locations in which pedestrians' presence is indeed expected.

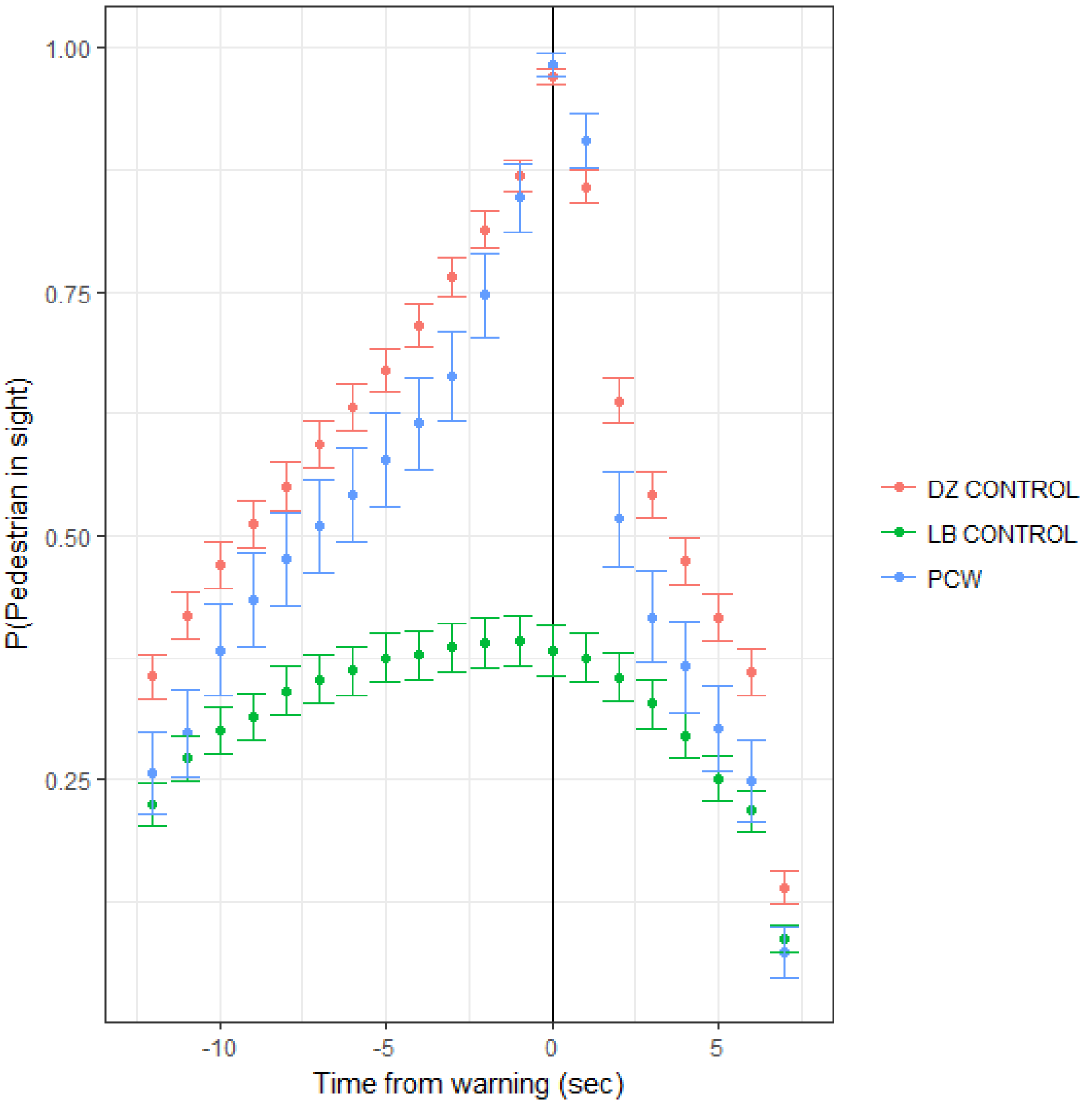

Figure 7-5: Probability of pedestrian detection by time

7.3.6 Cluster analysis of PCW according to patterns of speed behaviour

In our analysis, PCW events correspond to candidate Safety Critical Events (SCE) or to actual conflicts between drivers and pedestrians. Hence, in this section, we take a closer look at the PCW instances and try to better understand them and the circumstances, in which they occurred. Speed choice and speed management are key factors in all conflicts, which occur in road safety and in particular, in conflicts involving pedestrians. Therefore, speed is the most natural choice to cluster PCWs.

In order to cluster PCWs according to speed, we implemented the clustering method described by Genolini and Bruno (2011), which uses an extension of the k-means procedure for longitudinal data. The implementation of this method was adopted from the KML3d package in the R software (Genolini et al., 2015).

Figure 7-6 presents the four clusters, which correspond to the PCWs found in the UK and the French data. These four clusters provide a clear and distinct speed choice behaviour around the occurrence of the PCW (at time "0").

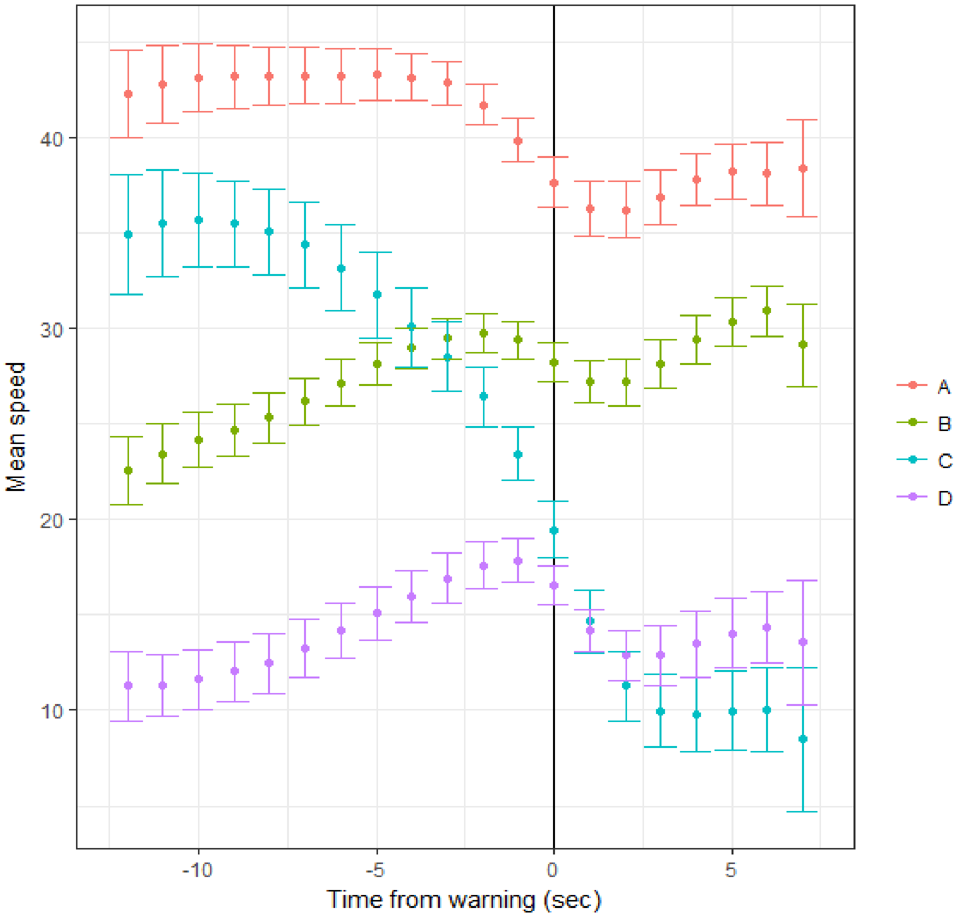

Figure 7-6: Clusters of PCW according to longitudinal speed distribution

The behaviour portrayed through the four clusters is very interesting. Cluster A corresponds to the group of PCWs occurring at (relatively) high speeds, with a decrease in speeds 2-3 seconds prior to the PCW occurrence. Cluster B is somewhat intriguing as drivers increase their speeds prior to the PCW and decrease it at the last second before its occurrence. Cluster C represents a "classic" conflict or SCE pattern, in which starting at a high speed, drivers notice the potential conflict 3-6 seconds prior to its occurrence and significantly reduce their speeds accordingly. Finally, cluster D is probably the most interesting cluster, as drivers do not reduce their speeds until the actual onset of the conflict in time “0”.

A separate clustering for the UK and French data provides quite similar clusters, as presented in Figure 7-7 and Figure 7-8, respectively.

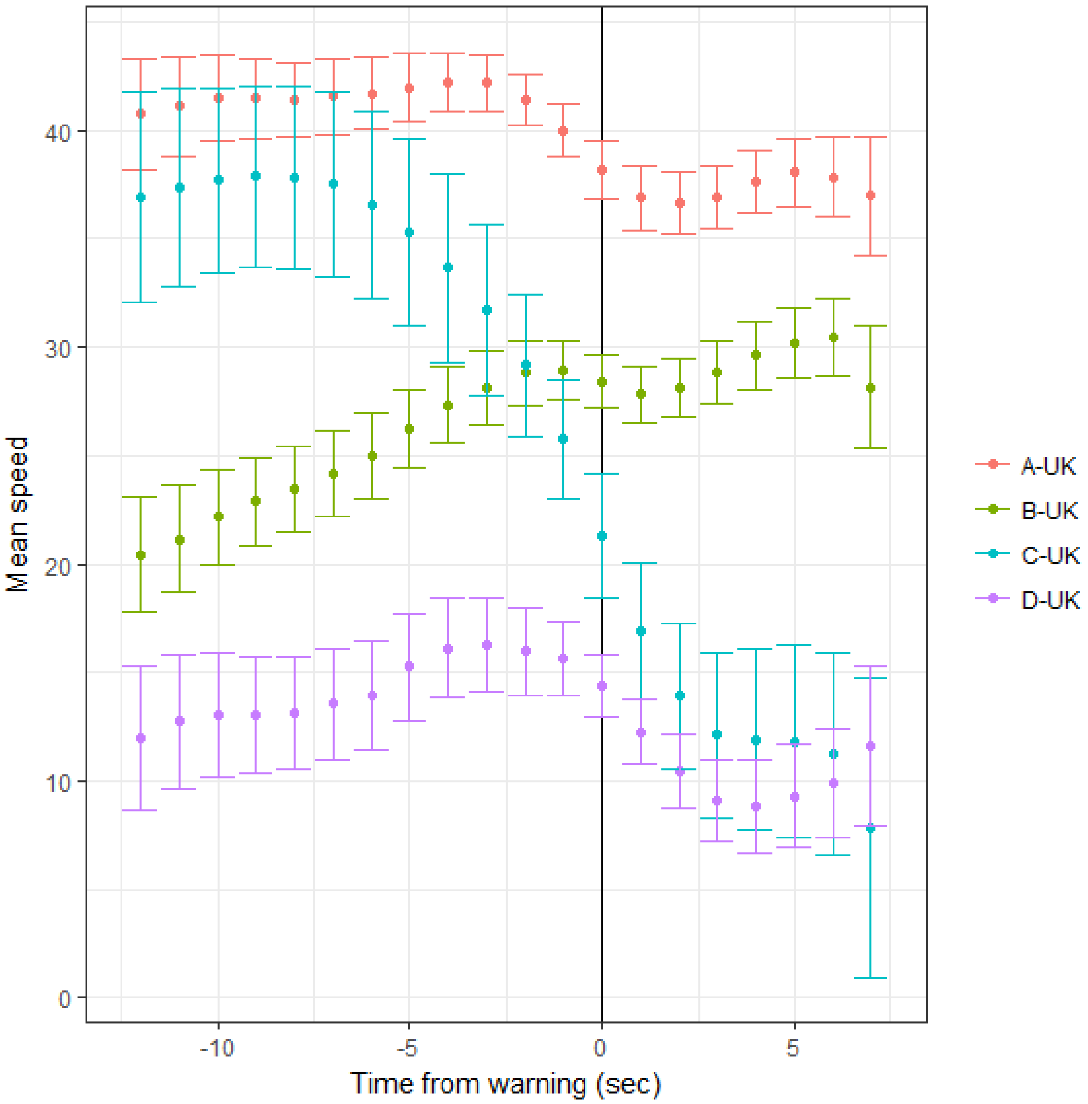

Figure 7-7: Clusters of PCW according to speed for the UK data

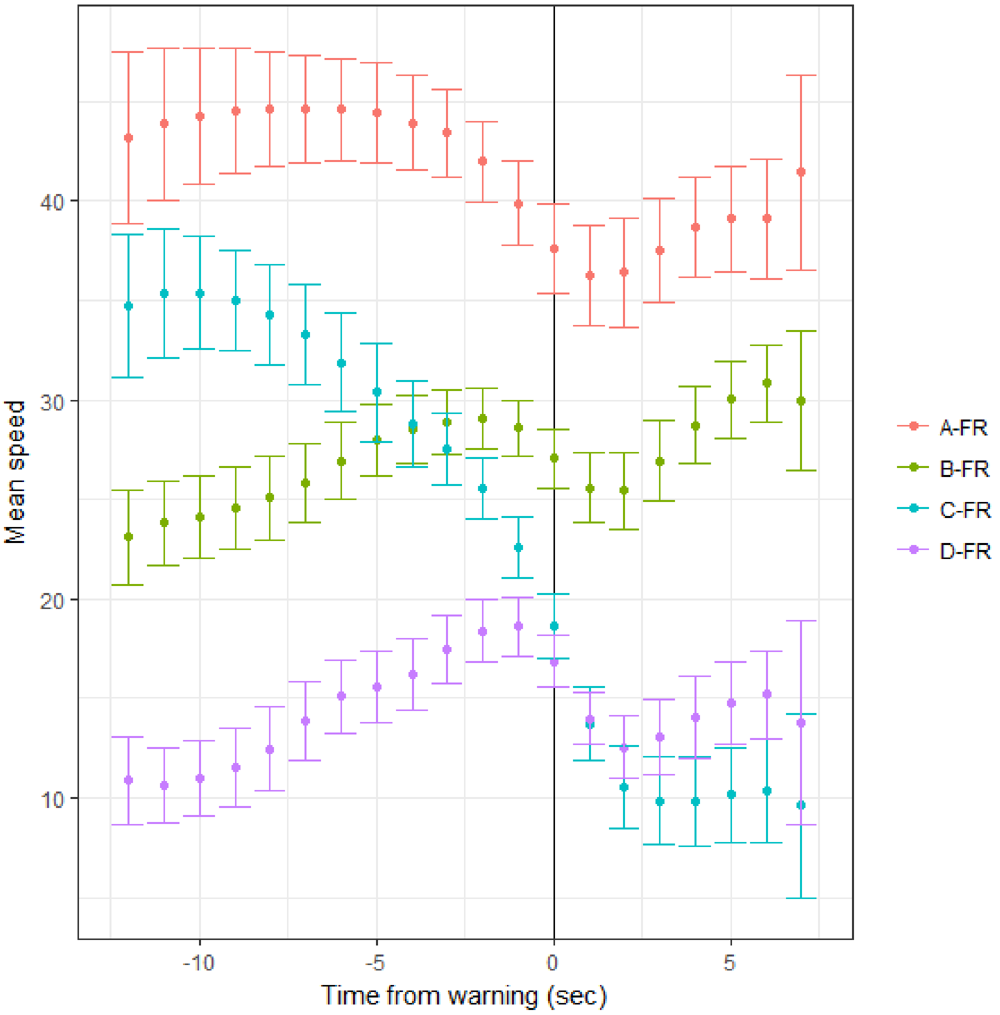

Figure 7-8: Clusters of PCW according to speed for the French data

Table 7-3 presents the clusters' sizes for the three analyses: the entire sample (corresponding to the UK and French data analysed together), the UK data and the French data.

Table 7-3: Cluster sizes for the entire sample and for the UK and French data separately

Cluster	ALL	UK	FR
A	107	67	42
B	128	72	59
C	65	22	44
D	110	40	64
total	410	201	209

In order to compare the cluster distribution between the UK and France, we examined the proportion of PCW events categorised into the 4 clusters in the UK and in France. This is presented in Figure 7-9. It can be noticed that whereas in clusters A and B there are more PCW cases for the UK, the opposite is true for clusters C and D. The differences among the clusters' distribution are statistically significant.

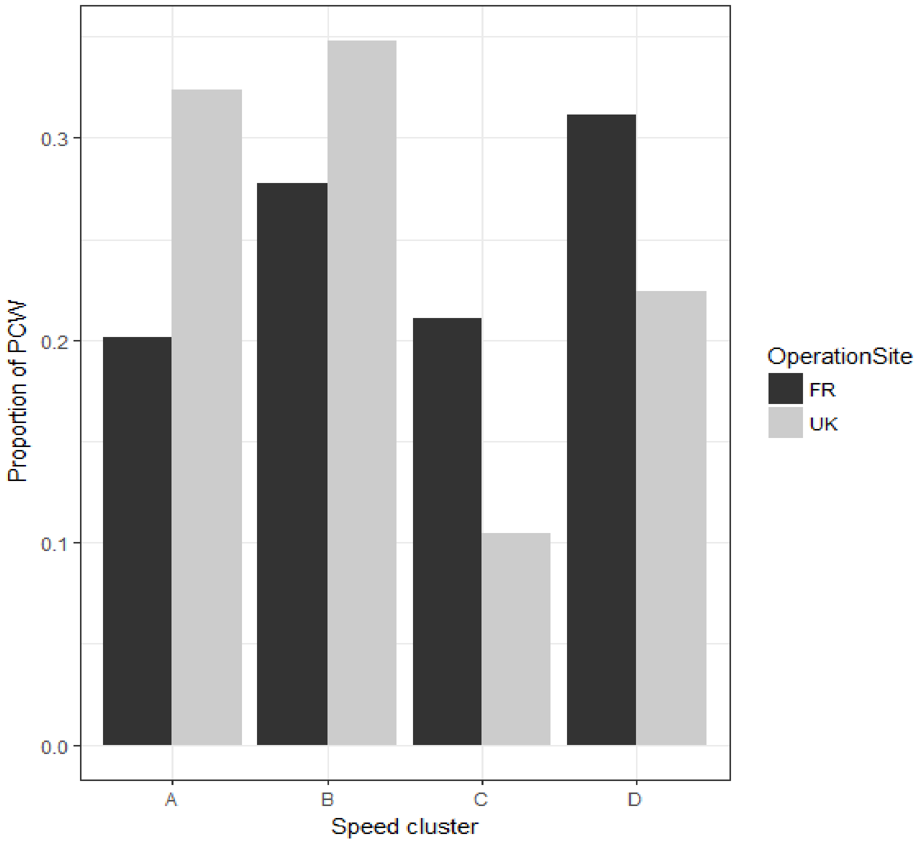

Figure 7-9: Proportion of PCW events by speed cluster and site

Next, we investigated the behaviours underlying the four clusters, according to several important parameters and attributes.

One of the most interesting behaviours for investigation is the occurrence of conflicts, SCEs, or crashes. Fortunately for the public (and unfortunately for researchers…), no crashes occurred in the here analysed data. Hence, SCE candidates were very suitable to investigate and analyse. When looking at SCEs determined by the central annotation teams, a total of 67 SCEs was determined, as illustrated in Figure 7-1. Out of the 67 SCEs, 38 SCE candidates were identified in the French data and 29 SCEs in the UK data. Table 7-4 presents the distribution of the SCEs among the four clusters. The first percentage value corresponds to the share of the SCEs in that particular cluster compared to the cluster size. The second percentage value corresponds to the share of the SCEs in that particular cluster compared to the total number of SCEs (for example: in cluster C of the UK there were 8 SCEs, which make up 35% of the PCWs in that cluster and 28% of the total SCEs found in the UK).

Table 7-4: SCE distribution among clusters

Cluster	ALL	UK	FR
A	12 (11%, 18%)	6 (9%, 21%)	5 (12%, 13%)
B	16 (12%, 24%)	8 (11%, 28%)	10 (17%, 26%)
C	17 (26%, 25%)	8 (35%, 28%)	10 (23%, 26%)
D	22 (20%, 33%)	7 (18%, 24%)	13 (20%, 34%)

As can be viewed from Table 7-4, cluster C, as expected, contains high percentages of SCEs (first percentage value). However, following cluster C, is the interesting D cluster, in which drivers were not aware of the conflict until it actually occurred. When looking at percentages from total number of SCEs (second percentage values) – cluster D seems to have the most, regardless of its size. This verifies the interesting behaviour presented by this cluster as demonstrated in Figure 7-6, Figure 7-7 and Figure 7-8.

In order to further understand the behaviour portrayed by the 4 speed clusters, we cross tabulated the clusters distribution with the annotation regarding the type of infrastructure facility. The results are presented in Table 7-5 for the combined database (UK and France). A detailed analysis of the UK and France separately revealed similar patterns.

Table 7-5: Cluster distribution according to VRU facility type

Cluster	no VRU facility	pavement	zebra-crossing
A	19 (21%)	54 (39%)	13 (14%)
B	22 (24%)	47 (34%)	38 (41%)
C	9 (10%)	19 (14%)	23 (25%)
D	40 (44%)	18 (13%)	19 (20%)

The figures in Table 7-5 correspond to absolute numbers and the figures in parenthesis correspond to the relative proportion of the specific facility type. For example: 40 PCWs were in class D with no VRU facility and they comprised 44% of the PCWswhich had no VRU facility.

The "no VRU facility" represents cases, in which there was no clear separation between vehicles and pedestrians (for example by a clearly marked pavement), corresponding mostly to drivers and pedestrians sharing the same space. It is very interesting to note the largest proportion of "no VRU facility" PCWs in cluster D (marked in red). This can serve, on the one hand, as a good explanation for the low speeds that drivers in this cluster chose, and on the other hand, may account for the unexpected encounters between drivers and pedestrians.

Another interesting observation is the high proportions of PCWs occurring on the pavement, which are common in clusters A and B (marked in blue). This can serve as a good explanation for the relatively high speeds that characterise these clusters, and also for the fact that in cluster B drivers even increased their speeds before the PCW.

An interesting question is why PCWs occurred when the pedestrian was on the pavement. These instances can be associated with several scenarios. Figure 7-10 demonstrates, for example, such PCW. In this case, a pedestrian is walking on the pavement, but very closely to its edge. Other cases are happening, for example, when a car is heading towards a pedestrian that is walking or standing on the pavement, but the car is on a turning course.

Figure 7-10: A pedestrian walking close to the edge of the pavement

7.3.7 Multinomial Model for speed cluster

This section looks at the probabilities for a PCW being in each of the four speed clusters (‘A’,’B’, ‘C’ and ‘D’) given the operation site (FR, UK) and the type of pedestrians' facility available (‘No VRU facility’, ‘Pavement’, ‘Zebra Crossing’). For this analysis, we applied a multinomial logistic regression for the speed clusters. The multinomial logistic regression is an extension of logistic regression designed for cases when the dependent variable is nominal with more than two levels (Hilbe, 2009). A multinomial model for speed cluster ('A','B','C','D') was calibrated according to pedestrians' facility type, the operation site (FR, UK), and the interaction between them. The model is defined as follows:

$$\mathrm{Prob}(Y = \mathrm{Cluster}\ 'A'|f,s) = \frac{1}{1+\sum_{SC=\{'B','C','D'\}} e^{\beta_0^{sc}+\beta_1^{sc}*f+\beta_2^{sc}*s+\beta_3^{sc}*f*s}}$$

$$\mathrm{Prob}(Y = SC|f,s) = \mathrm{Prob}(Y = \mathrm{Cluster}\ A) * e^{\beta_0^{sc}+\beta_1^{sc}*f+\beta_2^{sc}*s+\beta_3^{sc}*f*s}$$

Cluster 'A' was selected as the reference cluster. The terms 'f' and 's' denote the pedestrians' facility and the site, respectively. The SC term is a categorical variable, which takes values of 'B','C' and 'D' according to the speed cluster. Each speed cluster has a different set pf coefficients for the intercept (β_0^{sc}), the pedestrian facility (β_1^{sc}), the site (β_2^{sc}) and the interaction between them (β_3^{sc}).

One way to interpret the results of the multinomial model is to look at the value of the calibrated coefficients (the $\beta_{0..3}^{sc}$). Our approach is different, as we chose to analyse the differences between speed clusters according to the model’s estimated probabilities. The estimated probability for each cluster given the location of the pedestrian are described in Figure 7-11. For statistical inference, we evaluated the confidence intervals using a bootstrap technique.

The estimated speed cluster probabilities and the corresponding confidence intervals reveal some interesting results and insights. First, the difference between the UK and France is quite evident: while in France, the estimated speed clusters' probabilities are not statistically different according to the pedestrian facility, the results for the UK are different. For the UK, the estimated probability for speed cluster D in the case of “No VRU facility” is larger than for the other speed clusters, in agreement with the results presented in Table 7-5. This emphasizes again the possible explanation of drivers choosing to drive slower on one hand, but failing to notice the PCW before its actual occurrence. Similarly, for the case of “Pavement” clusters A and B have higher probability than clusters C and D. Clusters A and B are clearly the clusters of higher speeds. The fact that pedestrians are on the pavement, can encourage this speed choice. In the case of pedestrian on the zebra crossing the most probable cluster is B in which drivers slightly slows down and then speed up again. This pattern of behaviour also exists in cluster A which account for ~13% of PCW events in the UK zebra crossings.

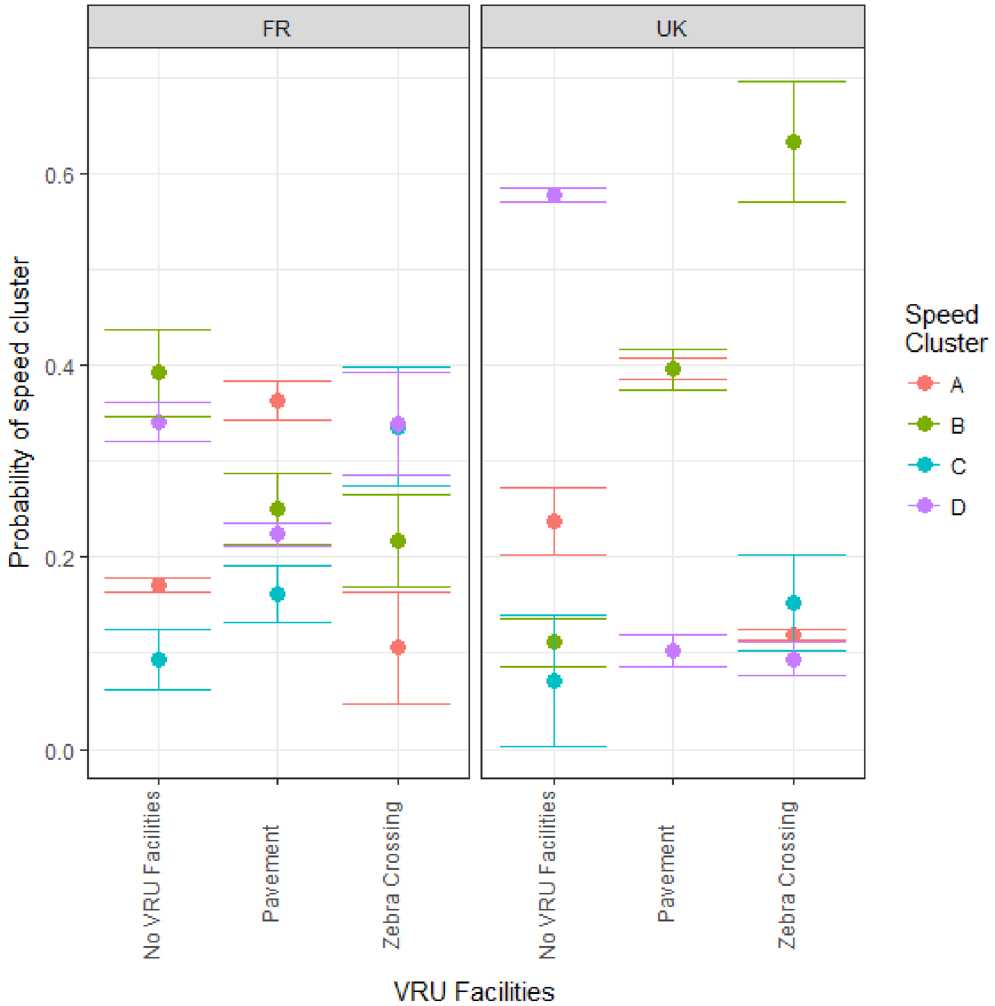

Figure 7-11: binominal model for speed cluster

7.3.8 Surprise vs. Non-Surprise PCW

The notion of "surprise" is important in road safety. Generally speaking, road users should not be surprised by other road users and should not surprise other users. In many crash-investigations drivers admit that they did not see the danger causing the crash, at least not on time to react and prevent it. In the context of driver-pedestrian interactions, clearly drivers should not be surprised by the presence of pedestrians, and should be well prepared to anticipate conflicts with pedestrians. This section categorizes and compares two versions of PCW occurrences. The first case is for PCW events, in which a prior event (PCW or DZ) occurred. Such PCW events (perhaps) could have been prevented, if the prior event was handled correctly, namely, the driver would have been (better) prepared for a conflict with pedestrians. The second case refers to instances, in which PCWs were not preceded by any other (PCW or DZ) event. For the latter, it is possible that drivers were surprised by the presence of pedestrians and hence, a conflict occurred.

In order to discriminate between the previously mentioned two cases, two groups of PCWs were generated: PCWs that were preceded by a PCW or DZ event during the 4 seconds range prior to its occurrence (*N*=191) and PCWs that were not preceded by a PCW or DZ event (*N*=219) during those 4 seconds. The first group is denoted by "non-surprise" and the second by "surprise" PCW events. Hence, the later includes cases such as a pedestrian suddenly jumping into the road and surprises the driver.

Figure 7-12 presents the speed distribution of the PCWs, according to the division into "surprise" and "non-surprise" groups. It can be noticed that whereas the speed is similar at the beginning of the time window (approx. 12 seconds prior to the PCW occurrence), it increases significantly before the PCW occurrence for the "surprise" group. This can be explained by the fact that whereas the "non-surprise" group encountered pedestrians during the 4 seconds prior to the PCW occurrence and hence, maintained a low speed, drivers within the "surprise" group did not encounter pedestrians during that time-window and hence were not anticipating potential conflicts with pedestrians. Consequently, drivers in the “surprise” group even increased their speed. Naturally, both groups reduced their speed a few seconds before the PCW occurrence (at time "0").

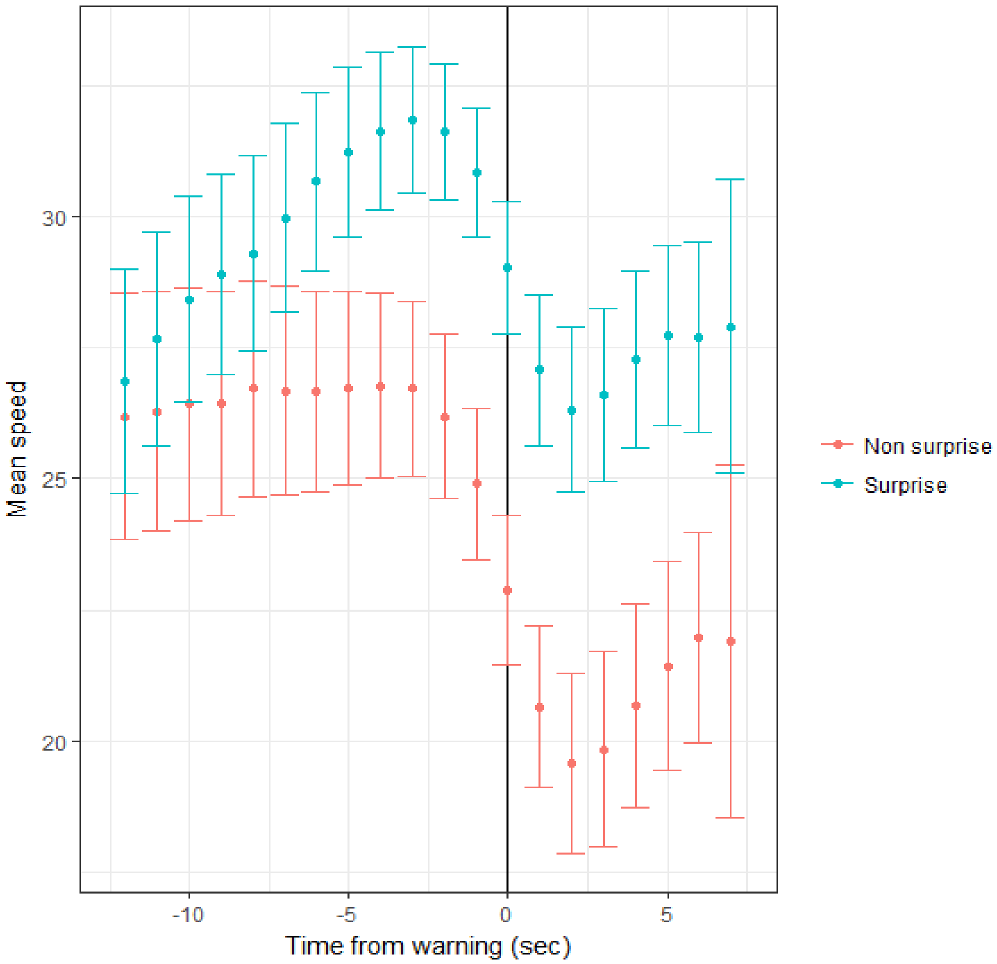

Figure 7-12: Speed distribution of "surprise" and "non-surprise" PCWs

In Figure 7-13, mean event duration of "surprise" and "non-surprise" PCWs are presented. Event duration is calculated using the Mobileye data based on indication of "event-start" and "event-end" for each PCW. Event-start refers to time "0" and event-end relates roughly to the time, in which the conflict dissipates, i.e., when TTC becomes large enough and the potential danger is over. It can be seen that "surprise" PCWs have longer event duration values. As TTC is positively correlated with distance and negatively correlated with speed and since it is clear from Figure 7-12 that speeds are higher for the "surprise" group and the drop in speed is larger for the "non-surprise" group – it could provide an explanation for the longer event duration of the surprise group. That is to say, for the “surprise” group, it takes longer to achieve safety margin from the pedestrian, due to the driver's high speed and slower reduction of speed.

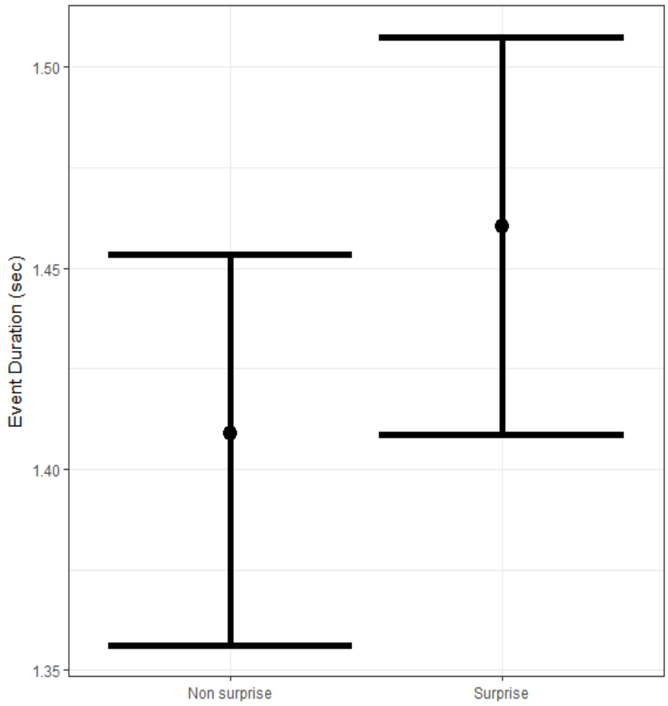

Figure 7-13: Mean event duration of "surprise" and "non-surprise" PCWs

7.4 Summary

In this chapter, we investigated interactions between drivers and pedestrians. The interactions were explored on three main levels: (1) when there was a conflict, or expected conflict between drivers and pedestrians (PCW), (2) when pedestrians were present in the field of view of the drivers but not on a collision course (DZ), and (3) when drivers were driving in locations, in which conflicts occurred earlier on (LB).

The comparison of the three levels was meant to see if and how drivers adjust their behaviour and safety margins when they drive in the presence of pedestrians and/or infrastructure that contains VRU facilities.

It was found that pedestrians’ presence plays an important role in keeping drivers aware and alert towards potential conflicts with pedestrians. Additionally, speed plays a major role in discriminating between PCWs and DZ events: PCWs occur at much higher speeds and the decelerations needed to avoid actual conflicts are much higher for PCWs.

A detailed analysis of the 410 PCWs detected in the database revealed interesting insights. The PCWs were grouped into 4 distinct clusters according to their speed distribution. Cluster A, corresponding to the PCWs with the highest speed is characterized by having most PCWs occurring when pedestrians were on the pavement. Similarly, cluster B, in which drivers even increased their speeds before the PCW, also portrays relatively high speeds, and contains many instances, in which pedestrians were on the pavement. Cluster C is a typical SCE cluster: in the PCWs associated with this cluster, drivers started at high speeds, noticed the potential conflict well in advance of its occurrence (3-6 seconds), and reduced their speeds significantly. Hence, they were able to avoid the conflict. Finally, cluster D, is probably the most interesting cluster. In this cluster, drivers did not reduce their speeds until the actual timing of the conflict, which raise the question whether they even noticed its potential occurrence. Indeed, in cluster D, the highest percentage of SCE candidates occurred.

The analysis of potential conflicts between drivers and pedestrians, as presented in this chapter, is based only on triggers generated by the Mobileye data (PCWs and DZs). Clearly, no system is perfect, and there could be cases in which conflicts occurred but were not detected by the Mobileye system. Furthermore, as noted, the Mobileye pedestrian detection system was operational only in day-light. Still, the large pool of PCWs generated enables us to closely investigate potential conflicts and derive important insights.

The notion of “surprise” is also explored in this chapter: are drivers surprised by the appearance of pedestrians and hence, face a potential conflict? It was found that when PCWs were preceded by other events involving pedestrians (PCW or DZ), drivers significantly reduced their speeds and were better prepared for a potential conflict with pedestrians.

The analysis described in this chapter is clearly limited, in both its dataset and the parameters that were actually analysed and reported. Still, some of the insights gained through this analysis could have valid and straightforward implications. These highlights are summarized below. However, it is highly recommended to apply and strengthen the analysis by considering the full UDRIVE database and more detailed analyses.

The following highlights can summarize the insights gained from the analysis conducted in this chapter:

- ✓ Pedestrians’ presence plays an important role in keeping drivers aware and alert towards potential conflicts with pedestrians.
- ✓ Speed plays a major role in discriminating between PCWs and DZ events: PCWs occur at much higher speeds and the decelerations needed to avoid actual conflicts are much higher for PCWs.
- ✓ VRU facilities and in particular, pavements, play an important role in explaining drivers’ behaviour in the presence of pedestrians. More severe conflicts occur when there are no VRU facilities.
- ✓ The notion of “surprise” plays an important role: when PCWs were preceded by other events involving pedestrians (PCW or DZ), drivers significantly reduced their speeds and were better prepared for a potential conflict with pedestrians.

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8 Can ADAS reduce the conflicts between drivers and pedestrians?

8.1 Introduction

In this chapter, we try to answer a somewhat complex research question:

RQ: *Does an ADAS with pedestrian detection capabilities have the potential to reduce the risk associated with driver-pedestrian conflicts?*

This RQ is complex, as it relates to hypothetical situations, since the Mobileye alerts were not visible to drivers participating in UDRIVE. Furthermore, in the dataset analysed in this chapter (similar to the dataset presented in section 7.3.1), no real crashes occurred. That is to say, drivers were able to avoid crashes without the help of ADAS. Still, the aim in this chapter is to investigate the potential of ADAS to further reduce conflicts between drivers and pedestrians.

In this chapter, we refer to the cluster analysis presented in chapter **Fout! Verwijzingsbron niet gevonden.** and Figure 7-6, which we include here again for the sake of completeness (see Figure 8.1). As demonstrated and discussed in chapter **Fout! Verwijzingsbron niet gevonden.**, the four clusters represent different behaviours. It is hypothesised that cases corresponding to PCWs, which belong to cluster D, have the greatest potential to benefit from an early alert, as braking and decelerating only begins at the onset of the PCW at time “0”.

Additionally, this chapter includes a comprehensive literature review on pedestrians’ protection systems. This review appears next (in section 8.2) and includes three types of systems: traffic engineering measures, passive systems and active systems. The Mobileye system used in UDRIVE is an example of an active system. However, whereas in its industrial version the Mobileye system alerts drivers (both visually and audibly) and can be part of an automatic braking system, in its naturalistic version (as used in UDRIVE) – its in-vehicle alerts to drivers are silenced and no active action takes place.

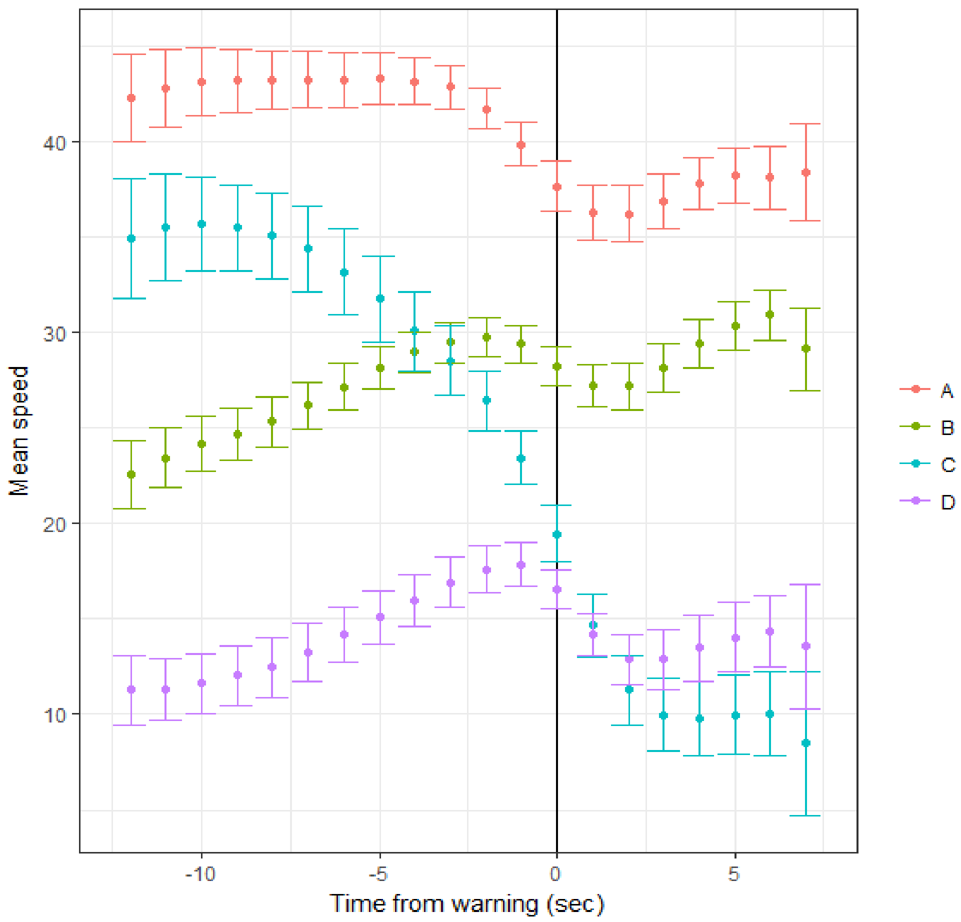

Figure 8-1: Speed clusters of PCWs

8.2 Pedestrian Protection Systems: A literature review

Pedestrian safety is a problem of global dimensions. Traffic accidents are one of the main causes of injuries and death worldwide (Gandhi & Trivedi, 2007). According to the World Bank website, pedestrians account for 65% of the fatalities out of the 1.17 million traffic related deaths around the world. Attempts to reduce pedestrian- motor vehicle conflicts and crashes can be divided into three different categories: Traffic engineering measures, passive vehicle safety systems and active vehicle safety systems. These topics will be next reviewed.

8.2.1 Traffic engineering measures

Pedestrians have been given little consideration in the design of the roadway system. Since pedestrians and vehicles need to share the road safely, engineering modifications can reduce the risk of vehicle-pedestrian crashes and minimize conflict situations (Retting et al., 2003). The engineering modifications to the environment can be classified into three main categories: separation of pedestrians from vehicles by time and space, reduction in vehicle speeds and increase of pedestrians' visibility (Retting et al., 2003).

<u>Separation of pedestrians from vehicles by time and space</u>

The main idea is to decrease conflicts between pedestrians and drivers by separating between them- either by time or space. At intersections with traffic signals, exclusive traffic signal phasing is successful at reducing conflicts between drivers and pedestrians (Houten et al., 2000). Moreover, in order to ensure that drivers have cleared the intersection before the display of pedestrian walk signals, adequately timed yellow and all-red clearance signs are essential at traffic signals. A study by Retting et al. (2002) showed that combined alterations in the duration of yellow and all-red signal timing reduced the risk of pedestrian crashes at intersections by 37 percent when compared to control sites. Another method is the use of automatic pedestrian detection, which can be applied at traffic signals instead of pedestrian push buttons. In that manner, pedestrians are automatically detected and a walking signal is displayed. Moreover, this technique may extent pedestrians' crossing time, so slower or elderly pedestrians can finish crossing safely (Hughes et al., 2000). In addition to the above described time-related separation measures, space-related separation techniques can be applied. For instance, over- and underpasses can significantly reduce conflicts between drivers and pedestrians, minimizing the encounter possibilities between drivers and pedestrians (Retting et al., 2003). However, due to the high cost of such facilities, this is a limited solution. A less expensive but yet simplifying crossing technique refers to refuge islands, which allow pedestrians to cross in two stages. This technique may be particularly beneficial for elderly pedestrians. A further inexpensive intervention at signal-controlled intersections involves repositioning of stop lines further back from crosswalks, thus increasing the separation between pedestrians and vehicles (Retting & Van Houten, 2000).

<u>Reduction in vehicle speed</u>

Vehicle speed management seems to offer the greatest potential for pedestrian injury prevention, especially in residential areas. The connection between speed and risk in case of a crash is particularly strong regarding collisions between vehicles and pedestrians. The general pattern is that speeds below 30km/h rarely result in fatalities, speeds around 50 km/h result in fatalities in 10-15 percent of cases and that speeds higher than 80 km/h almost always result in fatalities (Rosen et al., 2011). Speed calming measures, which are part of the road infrastructure, include amongst others speed humps and roundabouts. In terms of crash reduction, converting conventional intersections to roundabouts can reduce the rate of pedestrian crashes by 75 percent (Schoon & van Minnen, 1994). Particularly, single-lane roundabouts have been reported to successfully lower vehicle speed (Retting et al., 2003).

<u>Increase of pedestrian visibility</u>

There are numerous engineering measures, which are designed to increase the visibility of pedestrians. For instance, increased intensity of roadway lighting can increase pedestrians' visibility at night. This is particularly important, since more than half of all fatal pedestrian crashes occur at night (Zegeer & Bushell, 2012). Another method to increase pedestrian visibility is through parking restrictions. This includes removal of on-street parking and the implementation of diagonal parking, which requires the car to park at a 30 degree angle to the curb in the direction of traffic flow (Retting et al., 2003). This method has been shown to reduce the number of pedestrians entering the roadway in front of a parked vehicle (Retting et al., 2003). Finally, in-pavement flashing lights, which are automatically activated by the presence of pedestrians, may both increase pedestrian visibility as well as prompt drivers to yield to pedestrians (Retting et al., 2003).

8.2.2 Passive Vehicle Safety Systems

Despite the magnitude of the pedestrian injury problem, only little effort has been devoted to vehicle modification as a way to reduce pedestrian injuries resulting from a car crash. However, alterations to the vehicle structure may help reduce the impact of the pedestrian's injury (Crandall et al., 2002). Since most pedestrian-vehicle crashes involve frontal impacts and the vehicle's front structures are responsible for most pedestrian injuries, some alterations to the frontal structure of the car may be particularly recommended to enhance pedestrian safety (Crandall et al., 2002). Pedestrian airbags at the windshield pillar can reduce head injuries by 90 percent and upper body injuries by 50 percent (Gandhi & Trivedi, 2007). This is particularly important, since head trauma is responsible for most serious injury and pedestrian mortality (Crandall et al., 2002). While head injury is the leading cause of fatalities, lower limb trauma is the most common injury, due to the fact that typically, the car bumper is the first vehicle structure that contacts the pedestrian's body (Crandall et al., 2002). One possible approach is to apply an extra layer of energy absorbing material over the bumper. However, this technique is controversial, since the bumper also must protect the vehicle front from damages that can be caused by vehicle-vehicle collisions (Schuster & Staines, 1998). Another approach is to install sensors in the bumper that can sense the pedestrian's impact and instantly lift the bonnet to provide a softer landing place for the pedestrian's upper body. Combined with the aforementioned windshield pillar airbag, the pedestrian's upper body and head will have a better chance to remain protected from serious injury due to the collision.

8.2.3 Active Vehicle Safety Systems

Introducing active safety systems

Worldwide organizations such as the OECD (Organization for Economic Co-operation and Development) and the WHO (World Health Organization) have outlined a set of goals and actions to enhance pedestrian safety. Among these measures, the development of new safety-based vehicle technologies is promoted (Hamdane et al., 2015). Along with the above presented passive systems, active safety systems are developed and introduced, with the aim to prevent crashes. These active systems employ various types of sensors and computer vision algorithms in order to detect pedestrians and to predict the possibility of collisions (Gandhi & Trivedi, 2007). Once a hazard is detected, these systems trigger various countermeasures to avoid or mitigate collisions. More specifically, the system can generate a warning to the driver or proceed with measures such as autonomous emergency braking (AEB) or autonomous steering (Broggi et al., 2009).

Active safety systems are essentially composed of three different components: sensors for detection, a unit for processing and actuators for triggering an emergency manoeuvre. Regarding the first component, in order to detect various obstacles, cameras operating in visible light or infrared radiation (Near, Mid, Far) as well as RADARs and Laser Scanners are used. The different sensor types will be next described.

Sensor Types

One type of sensors, which is used for pedestrian detection are **imaging sensors**, which use visible light. Imaging sensors can capture a high-resolution view of the scene. However, extracting information involves a substantial amount of processing. When compared to "time-of-flight" sensors, such as **RADARs** and **LASER** scanners, the latter give accurate information on the distance to the object- in this case- pedestrians. However, their resolution is often limited. More specifically, the advantage of RADARs and LASER scanners is that they provide accurate depth information by measuring the time it takes for the emitted rays to return to the sensor. It is important to bear that in mind, since imaging sensors lose depth information in the conversion process. This is to say, they provide a 2-Dimensional perspective projection of a 3-Dimensional scene. When comparing the two, RADARs are usually mounted in the vehicle's front, whereas LASER scanners, due to their wide field of view (FOV), may be mounted in front or sides of the vehicle. This may be particularly useful for pedestrian detection in blind spots.

In general, **video sensors** are the common choice for driver support systems. However, separating pedestrians from the background is a difficult task in computer vision, since pedestrians are mostly found in city traffic conditions where the background texture form a highly cluttered environment. More specifically, the system has to identify a pedestrian from other vehicles, poles, trees, etc. (Shashua et al., 2004). Pedestrian detection becomes specifically challenging at night-time and when the weather conditions are bad (Shashua et al., 2004). As visible light becomes less effective during night-time, thermal **infrared**

radiation (IR) sensors can be applied. Thermal IR sensors are sensitive to the radiation emitted by the human body and are hence effective for pedestrian detection at night. However, these sensors are less effective in hot daytime conditions, where there is less temperature difference between pedestrians and the background. Another sensor, which is useful for night-time vision is a **near-IR sensor** accompanied by an illuminator (Gandhi & Trivedi, 2007). These systems are less expensive than thermal IR sensors and they've been used for surveillance applications.

The integration of data from various types of sensors with different characteristics reduces the risk of detecting false targets and increase the confidence and data accuracy of the detected target. In that manner, using sensors that have complementary functions allows for a more accurate pedestrian detection (Coelingh et al., 2010).

Motion as a cue for pedestrian detection

As aforementioned, the active safety systems merge and filter the data collected from the environment in order to distinguish pedestrians from other background obstacles. As soon as pedestrians are detected by the sensors, they are tracked in order to predict any collision.

Motion is an important cue in detecting pedestrians. In case of stationary infrastructure- based cameras, background subtraction is used to separate moving objects from a fixed background (Gandhi & Trivedi, 2007). However, in case of vehicle mounted cameras, both the car and the pedestrian are in motion. This complicates pedestrian tracking and moving analysis (Geronimo et al., 2010).

Mobileye – an example

Advanced Driver Assistance Systems (ADAS) have passive as well as active functions. A passive system alerts the driver of a potentially dangerous situation, so that the driver can take action to correct or avoid it. In contrast, active safety measures such as Automatic Emergency Braking (AEB) identify the imminent collision and brake without the driver's intervention. Other ADASs may also include a function called Evasive steering, which has the ability to decide within a split second whether to perform automatic braking or evasive steering and to execute the manoeuvre reliably, at a relatively high vehicle speed (up to 50km/h) (Keller et al., 2011). However, the latter function isn't part of Mobileye Technology and will hence not be further discussed.

One of the most known and widely used technological developments in this area is the Mobileye system (Shashua et al., 2004). The system is based on a mono-camera, which is inspired by human vision techniques. The driver is alerted when a potentially dangerous situation is detected by the sensor. After the driver is alerted, he or she can take action to avoid or correct the situation- such as reduce driving speed, stop the car, etc. More specifically, if the system detects a pedestrian in close proximity to the car, moving at a certain speed, the system triggers a "Pedestrian Detection and Collision Warning (PCW)" signal. In other words, the system alerts drivers of a forthcoming collision with a pedestrian. Please note that in UDRIVE, being a fully naturalistic study, no alerts were provided to participants. Two factors, which play an important role in the detection system, are the proximity of the pedestrian to the car and driving speed of the car at the time of the pedestrian detection. Clearly, the faster the car is driving, the higher the risk for collision.

Using a single forward facing camera located typically near the rear view mirror, the Mobileye-Advance Warning System (AWS) detects and tracks vehicles on the road ahead- providing range, relative speed and lane position data. One method for Forward Collision Warning (FCW) analysed by Yang et al. (2003) uses *time to contact* (TTC) to trigger the warning. A FCW signal is issued when the *time-to-contact* (TTC) is lower than a certain threshold - typically 2 seconds. Other authors describe this as Time to Collision (TTC). Similarly, with regard to the evaluation of an active safety system, such as AEB, one needs to assume a certain prediction model. Automatic braking has to be applied a certain time before a collision occurs, so one has to estimate how the involved road users will behave during a certain prediction prospect (Coelingh et al., 2010). A common measure for calculating the collision risk is time to collision (also denoted by TTC). Assuming that two objects move in the same direction and assuming constant acceleration, the time to collision can be calculated. Additionally, the time needed to avoid collision by braking can be calculated too and implemented into the system.

A pedestrian safety system's success or failure, from a technical viewpoint, will depend largely on the rate of correct detections versus false alarms that it produces. One of the possible concerns for a safety system, which involves only a warning function, such as PCW, is that if it will display too many warning signals, the driver will eventually either learn to ignore them, or alternatively, turn the system off. On the other hand, for a safety function that involves AEB, one needs to make sure that the driver remains alert at all times and doesn't count solemnly on the automatic safety measure.

8.3 Analysis

8.3.1 Valid and relevant PCWs

In order to evaluate the potential of Mobileye to reduce risks, we first need to know how many of the conflicts identified by the system are indeed valid, i.e. correspond to potential conflicts with pedestrians. An invalid alert refers to a situation, in which no pedestrian was present, or no potential conflict was observed. More specifically, the instruction given to the annotators was: Valid = there is an interaction of a vehicle with VRU, while the vehicle is moving forward and the VRU is seen in a close distance?

Based on the evaluations conducted by the annotation team, 351 out of the total 410 PCWs are valid (i.e. 86%). It is important to mention that many of the valid PCWs (approximately 38%) occurred while the pedestrian was on the pavement. Furthermore, from the 351 valid segments there are 233 (66%) segments marked as no conflict interactions. These segments do not correspond necessarily to "false –alarms", rather to potential conflicts that did not materialize. Categorisation of the PCWs according to the various conflict types according to annotation appears in Figure 7-1.

Another important factor refers to whether the pedestrian was seen by the driver. The annotation team evaluated a variable called: "pedestrian early spotted", corresponding to the evaluation that the driver saw and noticed the pedestrian. If, for example, the driver was engaged in a secondary task and hence, wasn't looking in the direction of the pedestrian, then this variable was labelled as "no". Out of the total of 410 PCWs, 307 (75%) were defined as "early spotted". The distribution of the proportions of "early spotted" among the four speed clusters is presented in Table 8-1 for the UK and French data.

Table 8-1: Distribution of "early spotted pedestrians" among the four clusters

cluster	early spotted UK	early spotted FR
A	56 (83%)	35 (83%)
B	53 (74%)	44 (75%)
C	15 (65%)	33 (75%)
D	27 (69%)	44 (69%)

It can be noticed that cluster A has the highest percentage of early spotted pedestrians, which can explain the high speeds of this cluster. Cluster D has lower proportions of "early spotted" pedestrians, which can be related to the delayed braking in this cluster and to the potential surprises caused by pedestrians' appearance. Clearly, when pedestrians are spotted early on, the risk of collision is reduced and consequently, the need for an ADAS is lower. The important question is **when** are pedestrians spotted and whether the ADAS would have identified the pedestrian earlier on. If so, this would have lowered the risk of collision.

In order to generate potential candidates for cases, in which Mobileye alerts would have been relevant in preventing a conflict, a local annotator was instructed to go over all 410 PCWs and generate a (subjective) opinion on the subject matter. The results are by no means clear-cut. However, they provide some (biased) idea on the extent of those instances. The results of this evaluation appear in Table 8-2.

Table 8-2: Can ADAS (such as Mobileye) reduce the collision risk?

Cluster	UK	FR
A	14 (21%)	18 (43%)
B	13 (18%)	31 (53%)
C	11 (48%)	28 (64%)
D	18 (46%)	46 (72%)
total	**56 (28%)**	**123 (59%)**

The results presented in Table 8-2 present a clear difference between the UK and French drivers. There are significantly more cases in France, for which it was assumed that an ADAS system such as Mobileye could have helped reduce the conflict. Additionally, this proportion is highest for cluster D, strengthening once again the notion that PCWs in that cluster encompass some form of surprise and hence, ADAS would have been beneficial in those cases.

It is important to keep in mind that during the data collection phase, hardly any real conflicts occurred. Hence, most of the conflicts were resolved in this data set without the alerts that would have been generated by Mobileye.

8.3.2 The notion of surprise

In section 7.3.8 we defined the notion of surprise of drivers by pedestrians' presence, based on whether there was a preceding event including pedestrians prior to the conflict or not. Figure 8-2, which is included for completeness again, clearly demonstrates the difference in speed behaviour between the two cases. The "non-surprise" cluster (with N=191) corresponds to cases, in which there was some form of pedestrians' presence during the 4 seconds prior to the onset of the PCW (either DZ or PCW events). The "surprise" cluster (with N=219), on the other hand, corresponds to cases, in which there was no pedestrians' presence during that 4-second time window. The gap between the two clusters corresponds to the potential of speed reduction, which allows drivers to be better prepared for a potential conflict with pedestrians. Hence, alerting drivers 4 seconds or less on potential expected conflicts, or driving in an environment with pedestrians, can clearly help drivers become more aware of potential conflicts and adjust their speeds accordingly.

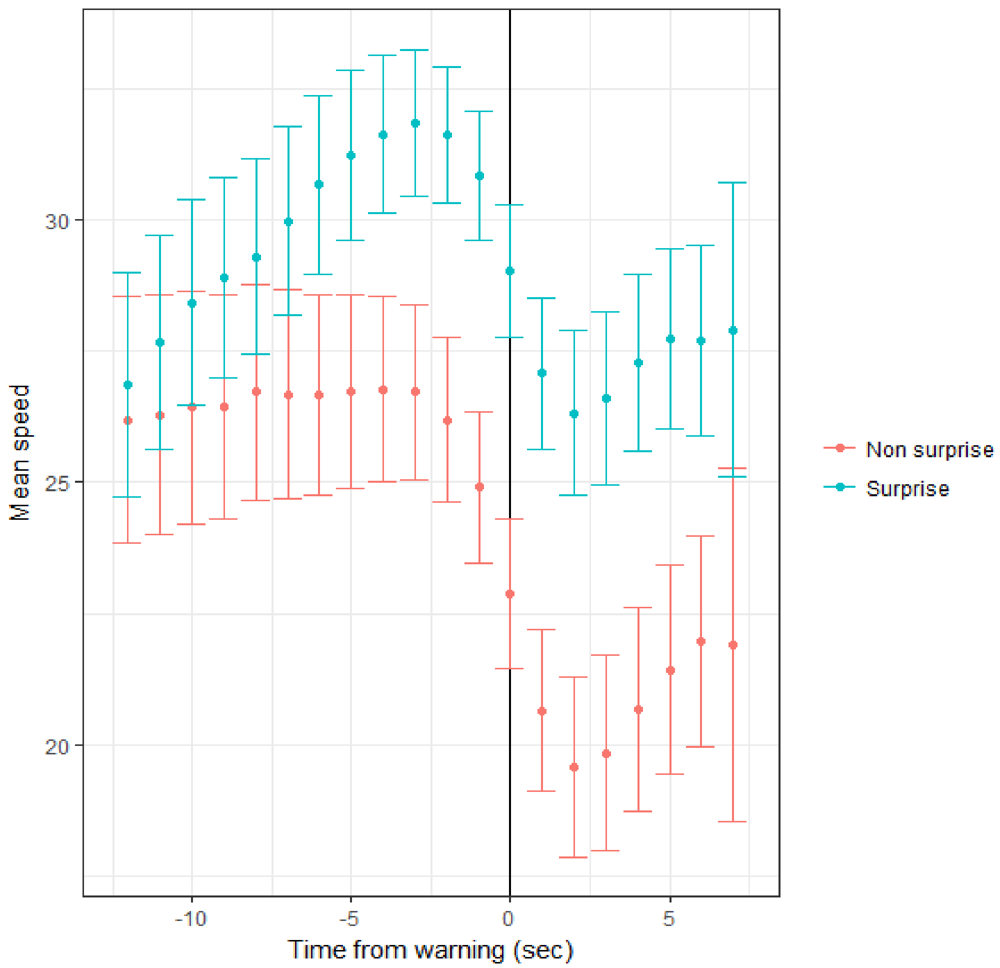

Figure 8-2: Speed distribution of surprise and non-surprise clusters

8.3.3 Braking times compared to start of PCW

In order to try and estimate whether the Mobileye alerts would have been effective in mitigating risk, it is crucial to understand the timing of the PCW alert (had it been provided to drivers) compared to the timing, in which the driver actually saw the pedestrian and took an action (if needed).

The graph in Figure 8-3 presents a good example for cases, in which the Mobileye alert would have preceded the drivers' reaction and hence, would have potentially reduced the risk of collision. In this Figure, the X-axis represents time (in seconds) and the Y-axis speed (in km/h). The PCW onset occurs at time 832.2 however the driver is continuously increasing his speed until time 833.5, and starts the actual braking action (denoted by the green horizontal line in the Figure) only at time 837. Hence, providing an alert to the driver at the onset of the PCW would have given the driver 3-5 seconds to better realise, understand and react to the potential conflict.

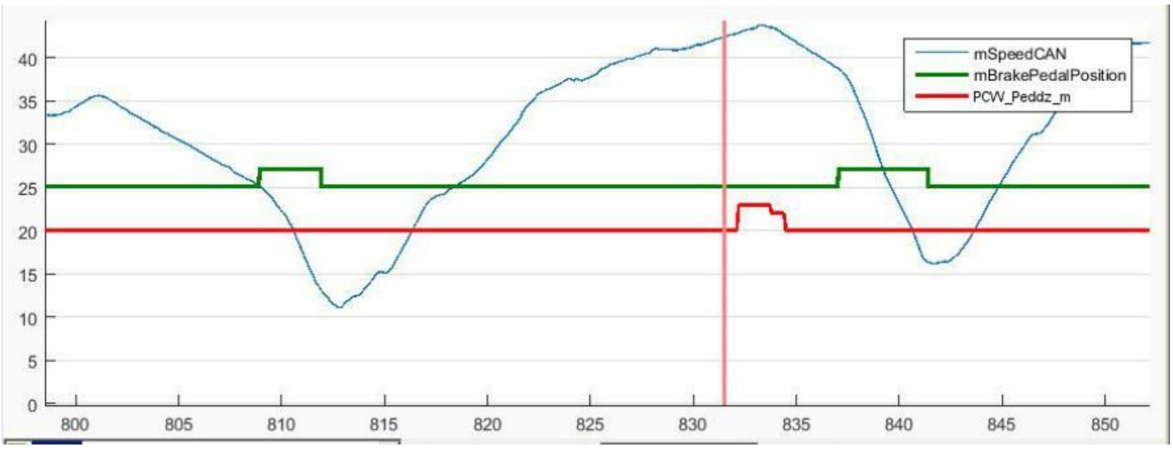

Figure 8-3: Speed, braking and PCW alerts during a time window

It is interesting to see what was actually happening during the time window which appears in Figure 8-3.

In Figure 8-4, the field of view of the driver at time 832.1 (marked by the vertical red line in Figure 8-3) is presented. The situation presented in the Figure depicts a case, in which pedestrians are walking on the side with no VRU facility and at close proximity to the road. At that point in time, the driver is still accelerating, demonstrating a clear unsafe behaviour.

Figure 8-4: Field of view of the driver before PCW onset

Next, we examine braking and acceleration behaviour prior to the onset of PCWs. We categorised the total of 405 PCWs (5 PCWs were omitted from the analysis due to insufficient information) according to the following two categories based on the behaviour of the drivers prior to the PCW:

1. Drivers decelerated prior to the PCW
2. Drivers accelerated prior to the PCW

Table 88-3 presents some summary statistics regarding 6 groups, according to the initial braking time, prior to the PCW onset. Group 1 in the Table belongs to the above mentioned category 2 and contains 22% of the cases, whereas groups 2-6 belong to category 1 and account for 78% of the PCWs.

Table 88-3: Braking behaviour prior to PCW onset

group	initial braking time (sec) compared to PCW onset	Number of PCWs	% of PCWs preceded by DZ	% of PCWs with pedestrian on pavement
1	0	89	37%	45%
2	0.1-1.1	66	44%	35%
3	1.1-2.1	49	41%	35%
4	2.1-3.1	49	47%	33%
5	3.1-5.1	72	57%	24%
6	5.1-13.1	80	50%	31%

Group number 1 in Table 88-3 represents cases, in which no braking at all occurred prior to the PCW onset. This group corresponds, most likely, to cases, which show the potential of the Mobileye system to alert the driver towards risk that the driver was unaware of. In this group, drivers did not slow but rather increased their speed prior to the onset of the PCW. The case presented in Figure 8-3 and Figure 8-4 demonstrates such a case.

One possible explanation for this behaviour is related to the fact that in 45% of the cases, the pedestrian was on the pavement and hence, the potential for actual contact was low. Still, in this group (group 1) 10 cases of classical or proximity conflicts were determined by the annotators, and 24 cases were classified into cluster D, making them potential real candidates for the case in which a prior alert would have reduced the conflict.

In group 2, drivers decelerated on average 0.65 seconds before the onset of the PCW. Additionally, 44% of the PCWs were preceded by a DZ event, which appeared on average 0.54 seconds before the PCW. Hence, it is possible, that for some of the PCWs in this group, the Mobileye would have responded with a DZ alert earlier than the driver, indicating the presence of pedestrians.

8.4 Summary

In this chapter, we tried to answer the question regarding the potential of the ADAS used in UDRIVE, namely, the Mobileye system, to reduce conflicts between drivers and pedestrians. It is not easy to determine whether alerting drivers would have reduced these conflicts, which have been resolved, in any case. Still, we investigated the validity of the alerts (that would have been generated) and their relevance. Additionally, we compared the timing of the potential alert to the timing, in which drivers actually took action (typically by decelerating and braking).

Moreover, we examined preceding events relating to pedestrians' presence and conflicts with pedestrians (that would have been generated by the Mobileye system) as part of a mechanism to draw the driver's attention to potential conflicts with pedestrians.

Certain cases, not too many, showed a clear pattern of potential benefit of an early alert by the Mobileye system. These cases correspond to situations, in which relatively harsh braking has begun after the onset of PCWs.

When evaluating a research question, such as the one addressed in this chapter, not many cases are required in order to demonstrate effectiveness, since the few real potentially life-saving alerts are the ones that matter.

The analysis presented in this chapter is clearly limited as it is based on a relatively small sample of driver-pedestrians' conflicts detected in the UDRIVE data. Furthermore, its focus is on locating the relatively few instances in which the driver did not notice the risk while the ADAS did. Noticing, or being aware of risks is not an easy measure to determine and validate, unless in obvious cases (such as: the driver is visually distracted, or a crash actually occurs). Hence, it is not easy to quantify the extent of the potential for risk reduction. Clearly, for that, much larger samples are needed. Such big samples will probably not be available through naturalistic, however, insurance-related statistics which takes into consideration the availability of different ADASes – can provide a good a reliable macro estimate for this extent. On the micro level - an approach, which validates the risk awareness based on self-reflection of the drivers, can provide a good and valid measure to the effectiveness of pedestrian-detection ADAS in mitigating risk.

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Part III: Interactions with powered two-wheelers

9 Identification of safety critical events with powered two-wheelers

9.1 Introduction

9.1.1 Earlier Naturalistic Studies and Other Relevant Literature

There is not very much experience with naturalistic studies with motorcycles or other powered two-wheelers. There was a pilot study, practically four pilot studies at different places, carried out within the European-Commission-funded project "2 BE SAFE" (Weare&Reed et al, 2011). However, these activities focussed more on assessment of feasibility than on applied research. A study involving twelve motorcycles was carried out at KFV (Pommer et al, 2014), which did not fully succeed in using movement data (accelerations and rotations) to determine safety-critical events. Most of the relevant SCEs in this study had been collected by notification by the subject riders. We had used a simple trigger (negative acceleration of more than 5 m/s², i.e.0.5 g). By this approach, 186 events were identified; for 6 there was no video recorded, for 86, the videos could not be found due to synchronisation errors, 38 were braking manoeuvers by our own staff for calibration (a success finding these!). In 33 cases, the annotation found no reason for harsh braking, another 12 braking manoeuvres were considered a sort of "offensive driving" . Only the ten events left included a sort of conflict, among which 3 were considered severe. Another seven severe conflicts were found though rider feedback.

A study in the USA involving 100 and another one involving 160 motorcycle riders succeeded in detection of SCEs by use of dynamic triggers and only a smaller amount by rider reports.. In the 100-motorcylce-study of the Motorcycle Safety Foundation (Buche, 2016), 45 out of the 100 riders did not experience a single critical event. There were 30 crashes in total, most of them capsize event, i.e. riders dropping the vehicle at low or no speed. From the analysis, it was found that crossing an intersection is the most risky task. The crashes or near crashes in that study were also detected by subject rider reports, but most of them were identified though data mining in the movement data.

Studies on crash causation are another very relevant source for this kind of research. A recent study by KFV (Winkelbauer et al, 2016) identified two scenarios, which strike out all others in terms of crash causation: On the one hand, it is speed-related crashes, which may be considered mainly rural run-off-the-road crashes. On the other, there was "unexpected behaviour by other road user" causing as many crashes. These crashes typically occur at urban intersections and will be most likely be due to perception errors or errors in estimating the powered two-wheelers' speed.

This research aimed at identification of safety-critical events by data mining of movement data of the powered two-wheelers, which were operated at the Spanish operation site.

9.1.2 Research Question

As indicated above, there is little known about effective triggering of safety critical events for motorcycles. The UDRIVE research questions 4.8 reads:

Which circumstances related to rider, infrastructure and trip have an impact on SCE occurrence?

The main purpose of this task is to identify triggers for safety-critical events as a necessary precondition to consecutively analyse any kind of circumstances, which may have had an influence on the occurrence of these safety-critical events.

9.2 Method

The analysis for this task was done twice, first in January of 2017, where only small amounts of data were available. For the second and final analysis, the queries were run in the last week of March and finished by the end of March. Within the same period, the videos of the scenes which had been identified by data mining were observed for assessment of criticality.

The hypothesis, which was followed to identify safety-critical event was very similar to the approach for cars. It was argued that either dangerous situations are caused by extreme situations in terms of vehicle dynamics; or they are followed by avoidance manoeuvres, which also incur peaks of dynamic parameters. Some earlier research, e.g. KFV's naturalistic riding study (Pommer et al, 2014) came to the conclusion that the data did not allow for an accurate triggering of safety-critical events, but they were confident that with more and better data, dangerous situations could easily be identified. As for cars, the idea was more or less to look at the dynamic parameters, select episodes including outliers and finally determine the critical scenarios by video observation.

Additional signals would not be available in UDRIVE, since there is no CAN data for the scooter data, a speed sensor was built in, but the data are not available for analysis due to technical reasons, Mobileye is not built to be used on tilting vehicles and brake light, turn indicator and horn signal were not captured. Hence, there were translator and rotatory parameters of movement available for analysis. It was planned to take the hundred highest and lowest records for each of these parameters.

9.2.1 Data treatment

Due to the experience of KFVs staff in running naturalistic studies, it was decided to limit use of SALSA[1] to a necessary minimum and analyse the data by SQL[2] queries directly on the database. SALSA was initially used to get familiar with the data, to calculate some additional parameters for the car analysis. Later, the data of the episodes which were found were extracted and SALSA was used to watch the videos and look at the acceleration and rotation data.

Six specific variables were calculated and added to UDRIVE's motorcycle database.

- dKFV_acc_x_avg, dKFV_acc_y_avg and dKFV_acc_z_avg (adapted accelerations)
- dKFV_gyro_x, dKFV_gyro_y, dKFV_gyro_z (adapted rotations)

These variables were calculated from the original variables for acceleration and rotation.

- Acceleration x = lateral acceleration (g)
- Acceleration y = longitudinal acceleration (g) {deceleration gives positive values y}
- Acceleration z = vertical acceleration (g)
- Gyroscope x/y/z = rotation speed

The following treatments were implemented by use of Matlab code via SALSA:

  - Each 15 values were averaged to one, i.e. the data rate was reduced from 30 to two Hertz, this is a very simple method, which so far has delivered reasonable results. The original data are extremely noisy (Figure 9.1 and Figure 9.2). Floating averages would have been an option, but they did not work well within pilot analysis if suitable data treatment. Within these pilots, different methods and parameters of noise reduction were tested. On the one hand, the filters

[1] SALSA ist the name of the graphical user interface, which was particularly set up for UDRIVE. It facilitates viewing, annotation and analysis of UDRIVE data.
[2] Structured Query Language, a common computer language for (in particular large) databases

were not to smooth away all outliers, on the other hand, noise artefacts should not trigger critical events. The method described above performed best, also with respect to the size of the database and the available calculation performance of the database and the servers.

- Current speed above 10 km/h, else NULL, in order to make sure that there are “real accidents” and no drops at low or no speed.
- All values were corrected by the offset from zero in order to correct for positioning of the sensor. It has to be noted that the position of a motorcycle strongly depend on the weight and position of the rider. Even luggage can change the initial position.
- Only trips of a length of more than 120 s. It was found that for trips of lower duration the correction for the average does not work out well.
- Round values to two digits behind the comma.
- At a later stage, the analysis was further limited to a speed below 55 km/h since it appeared that the outliers at higher speeds are mainly data artefacts.

All further analysis was done by direct application on the database using MySQL. The variables mentioned above were extracted and frequency tables were set up.

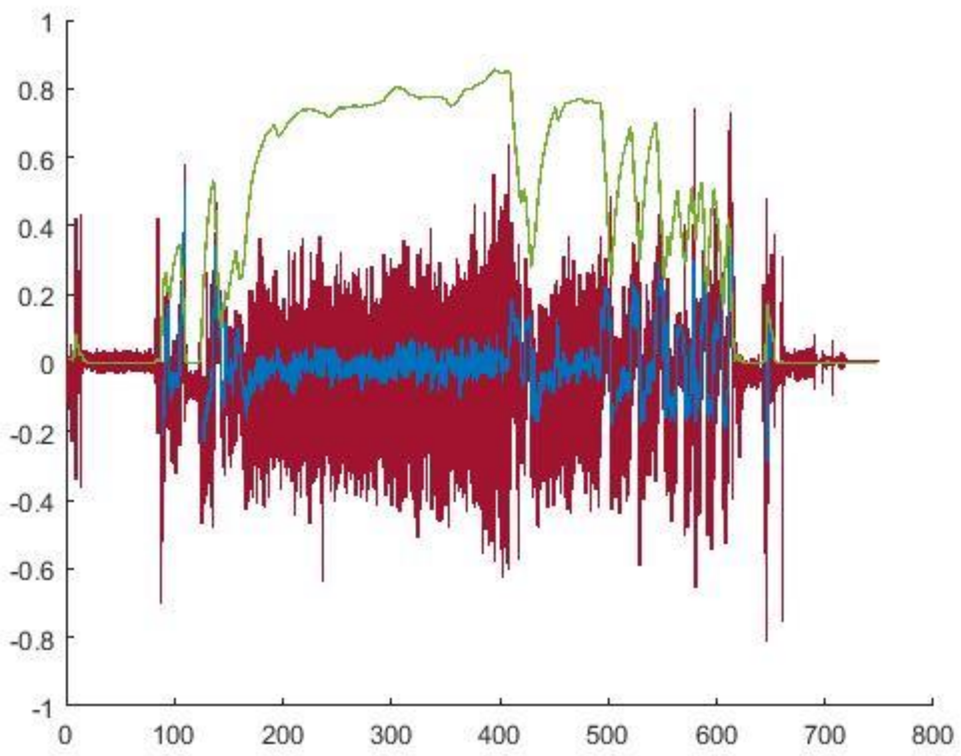

Figure 9.1: Example of speed and acceleration data (green=Speed, red=acceleration data at 30Hz, blue=reduced acceleration data in g)

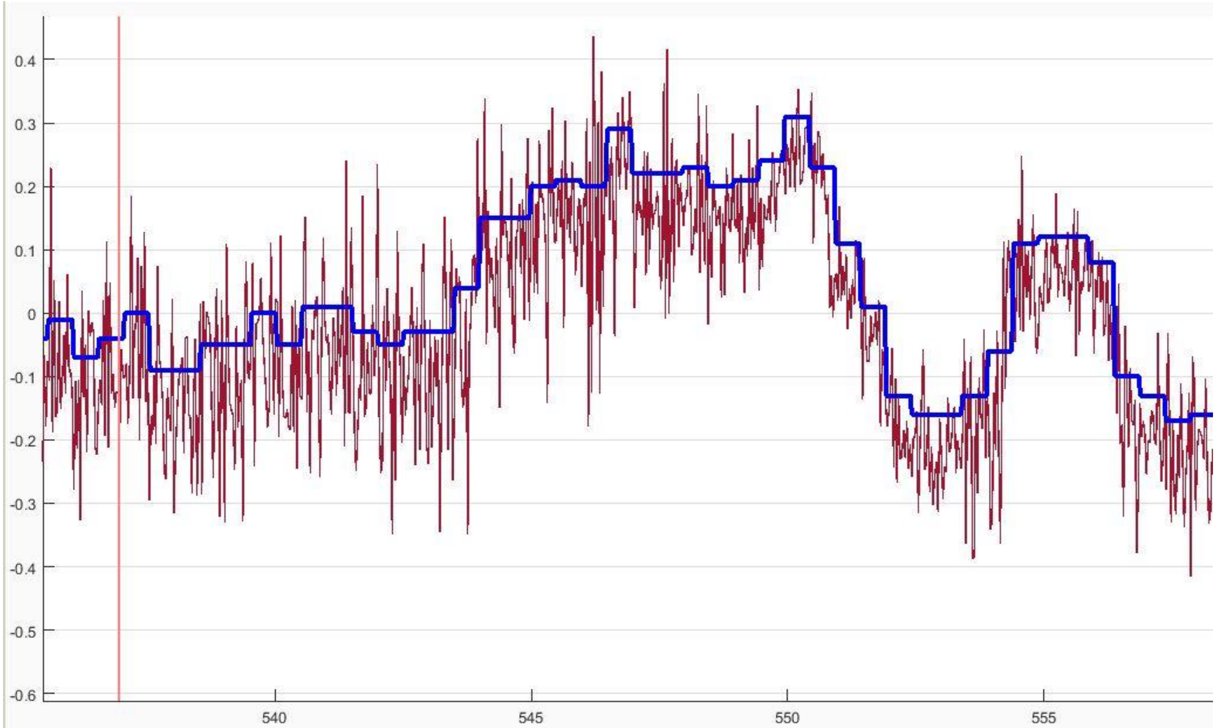

Figure 9.2: Example of acceleration data (red=acceleration data at 30Hz, blue=reduced acceleration data in g)

9.2.2 Identification of SCEs

The identification of safety-critical events (for definition, please see below) was done as follows:

- For the parameters indicated above, frequency tables were set up and, for better understanding, graphs were plotted.
- A threshold for outliers was defined
- For all episodes with an outlier, the videos were analysed (if available). Due to technical problems, the videos were not available for all trips, in particular the front camera videos. Less frequently, all videos had not been stored. For later trips, the front camera was frequently out of position (picture about upside down).

Safety-criticality is a very difficult issue to define for motorcycles. There is one most relevant variable to consider in addition to what has to be considered for other vehicles: riding skills. Studies (e.g. Winkelbauer, 2004) found that braking deceleration of riders on closed track, if they are asked to brake as hard as they can without falling, vary between 3 and 10 m/s². This is also caused by the differences between vehicles, which have very different properties. Hence, it was decided to use expert assessment, in case it would be necessary, of up to five experienced motorcycle riders among KFV staff. However, in the cases mentioned later, the conclusion on criticality was very clear.

The same applies to the other types of incidents (crash, near crash, conflict, etc). In principle, this research follows all the agreements which have been made for UDRIVE in general, but in terms of interpretation, the analysis within this task of UDRIVE has to consider particularly the manoeuvrability of a powered two-wheeler and reasonability in terms of riding skills.

9.3 Results

9.3.1 Frequencies of values and outliers of acceleration

The figures in this chapter show the distributions of records of the six dynamic parameters, which were used to gain an idea of what the data look like (Figure 9 to Figure 9.10). The following tables (Table 9.1 to Table 9.4) include the numbers of outliers. Please take note that this does not reflect the number of events (or something like “episodes”, which include outliers). In most of the cases, there are several of these outliers within one event. That was expected before the analysis, but it was also expected that it is by far more efficient to deal with multiple outliers within the video annotation than to create sophisticated SQL queries, which could have summarised multiple outliers within a short period automatically in order to provide e more convenient access to e.g. “episodes” including one or more outliers.

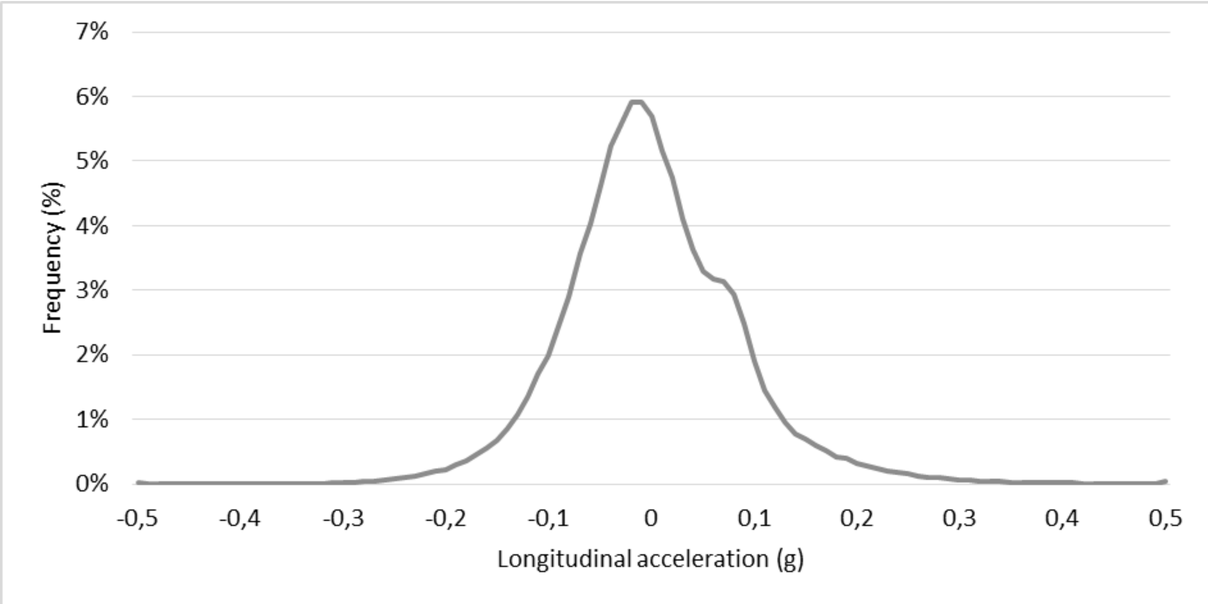

Figure 9.3: Frequency of longitudinal accelerations

Table 9.1: Number of outliers for longitudinal acceleration

Longitudinal acceleration (g)	number of records
< -0.5 g	84
> +0.5 g	131
total outliers	215
Total records	411.466

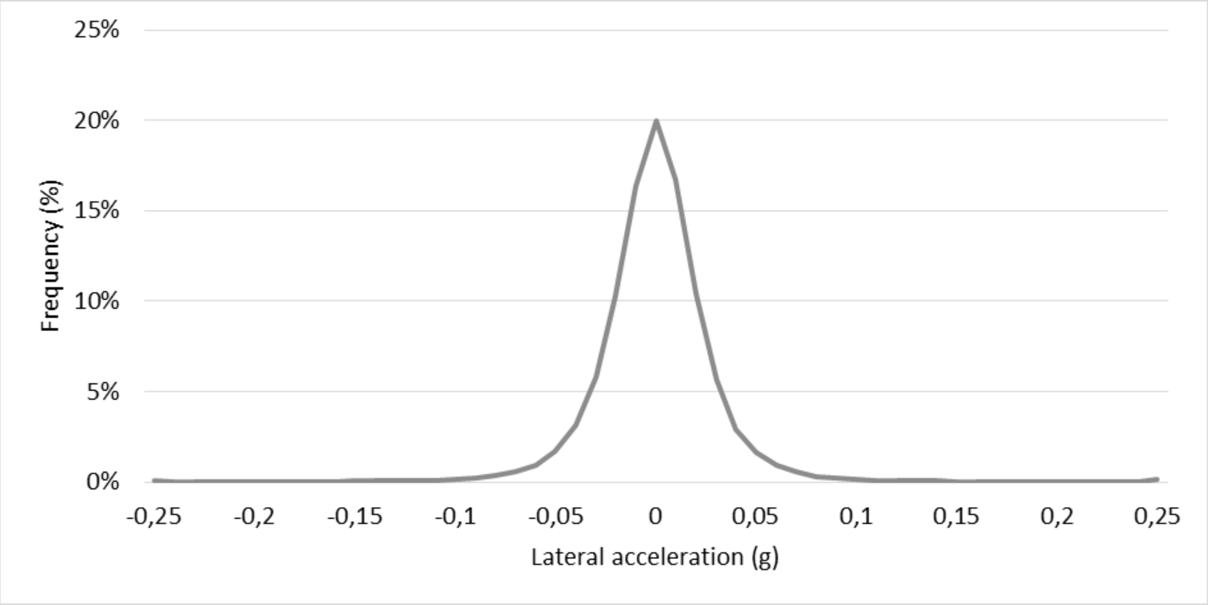

Figure 9.4: Frequency of lateral accelerations

Table 9.2: Number of outliers for lateral acceleration

Lateral acceleration (g)	number of records
<-0,25	286
>+0,25	508
total outliers	794
outliers < 55 km/h	128
Total records	411.466

Most outliers had been caused by vibrations > 55 km/h, even for lateral acceleration (please see 9.4.2): Hence, the analysis was limited to speeds up to 55 km/h, where 128 outliers remain (see Figure 9.5)

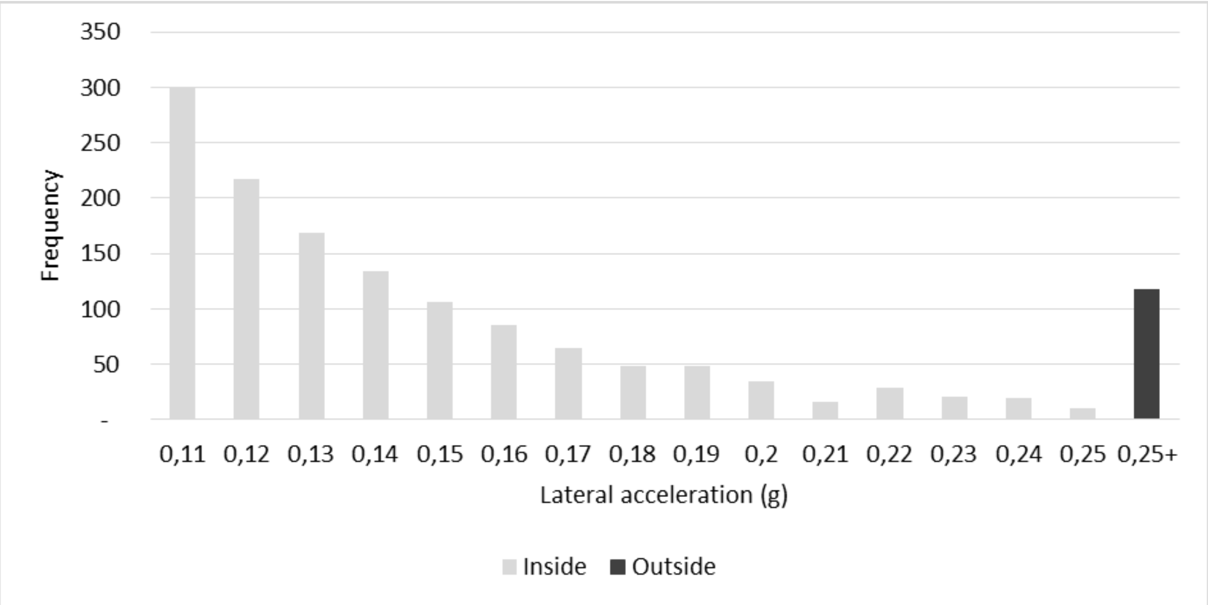

Figure 9.5: Distribution of frequencies of absolute lateral accelerations (g) with restriction to speed < 55 km/h and absolute acceleration > 0.1 g

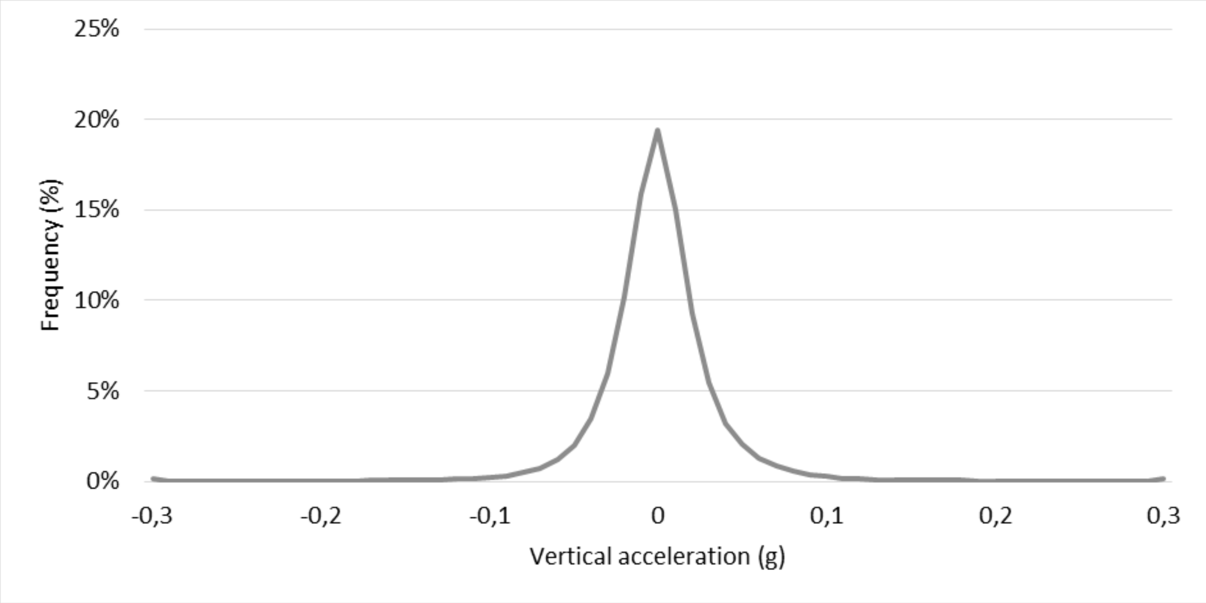

Figure 9.6: Frequency of vertical accelerations, all speeds

Table 9.3: Number of outliers for vertical acceleration

Longitudinal acceleration (g)	number of records
< -0,3	646
> +0,3	676
total outliers	1.322
outliers < 55 km/h	148
Total records	411.466

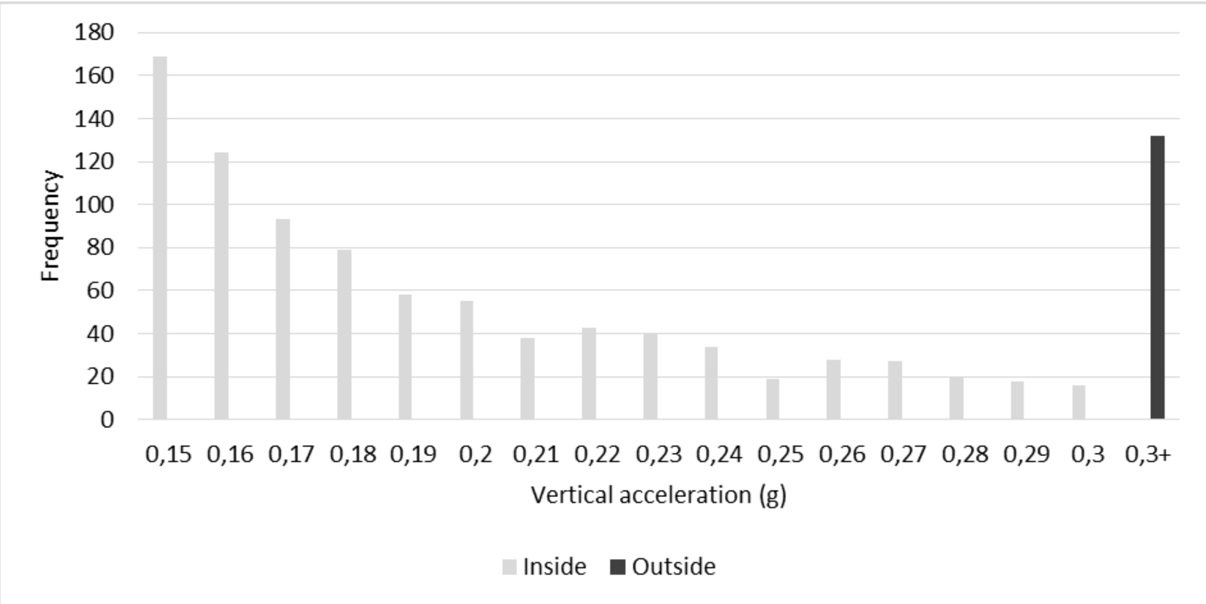

Figure 9.7: Frequency of vertical accelerations, speed < 55 km/h

9.3.2 Frequencies of Values and Outliers of Rotation Speed

In the same way as for accelerations, the available records for rotational movement (rotation speed) were plotted and outliers were analysed later. Figure 9.8, Figure 9.9 and Figure 9.10 show the distributions for pitch, roll and yaw rates.

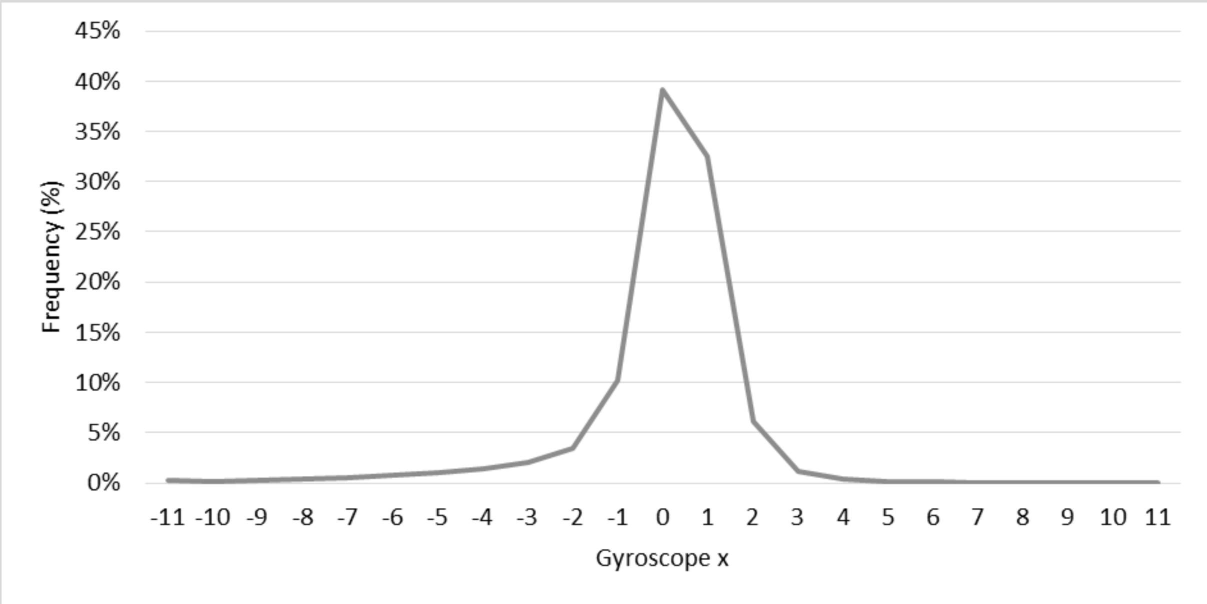

Figure 9.8: Frequency of pitch rate (N=411,420)

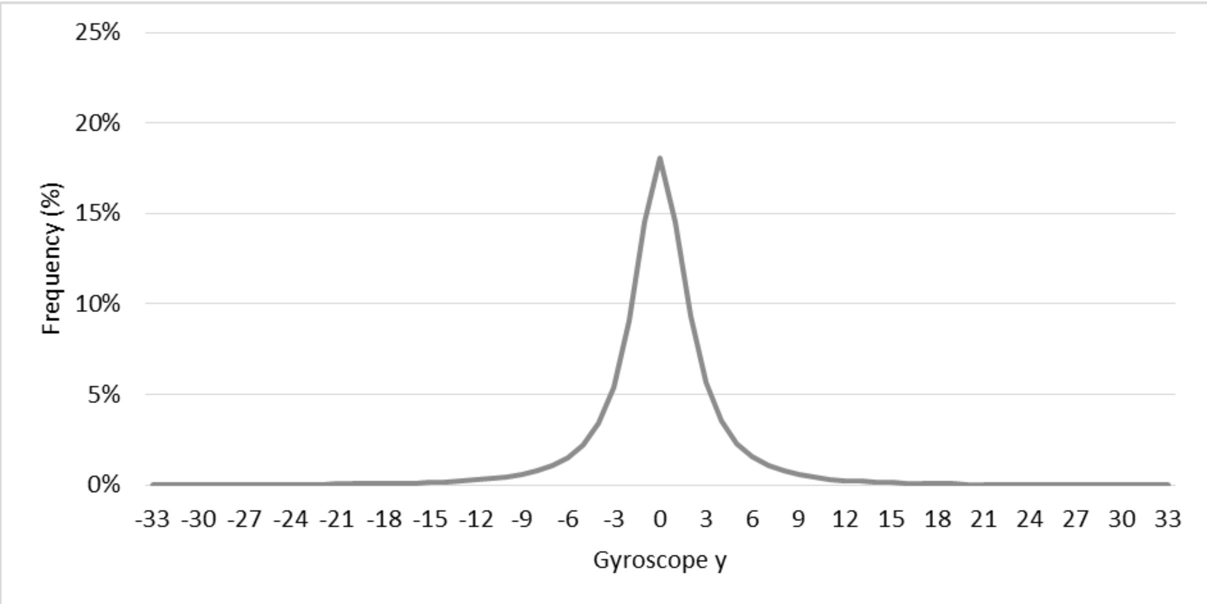

Figure 9.9: Frequency of roll rate (N=411,420)

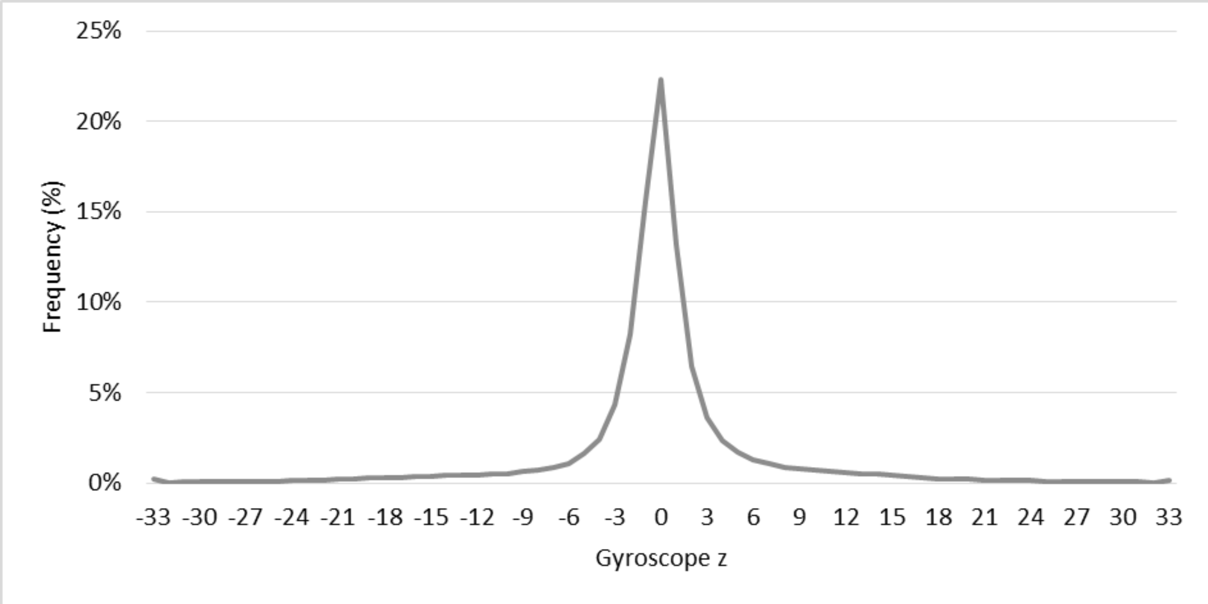

Figure 9.10: Frequency of yaw rate (N=411,420)

Based on this distribution, the threshold for outliers were set as shown in Table 9.3.

Table 9.4: Number of outliers for vertical acceleration

Gyroscope	pitch	roll	yaw
threshold	+/- 10	+/- 33	+/- 33
<	1.104	97	755
>	78	117	575
outside	1.182	214	1.330
Total	411.466	411.466	411.466

9.3.3 Video analysis

The final thresholds for the parameters of motion, respectively at which values a video analysis should be done were set to ("abs" = absolute value, "acc" = acceleration, "avg" = average):

- Abs(acc_y_avg) > 0,50 (braking, accelerating)
- Abs(acc_x_avg) > 0,25 (lateral movement
- Abs(acc_z_avg) > 0,30 (vertical moment)
- Abs(gyro_x_avg) > 10 (pitch)
- Abs(gyro_y_avg) > 33 (roll)
- Abs(gyro_z_avg) > 33 (yaw)

Video analysis was done twice:

- First batch in Feb. 2017: gyro (109 values) and acc (272 values), all speeds
- Second batch on March 21st, 2017, acceleration parameters (1.294 values), at speed < 55 km/h

Table 9.5 gives an overview on the total amount of data that had been considered for Video annotation. Table 9.6 indicates to which extent the videos could be used and

Table 9. shows the results of the annotation.

Table 9.5: Total data to analyse for 2nd batch

4.347	Trips
497	Hours
13.654	Km
27	average speed [km/h]
39	Drivers
1.294	Acceleration values

Table 9.6: Analysis with respect to camera availability

Analysis	Video	N	%	%
Not possible	all video black	668	52%	69%
	front video black	211	16%	
	video file defect	12	1%	
possible	video strongly rotated	205	16%	31%
	ok	198	15%	
	Total	1.294	100%	

Table 9.7: Overview on annotations

Variable	direction	no event	event	Total
acc_x	lateral	359	-	359
acc_y	longitudinal	499	2	501
acc_z	vertical	434	-	434
Total		1.292	2	1.294

The annotation was done based on a list of trips, which was generated by using MySQL code. SALSA was not used for annotation. If available the videos were observed.

Findings of Batch 1:

- With increasing speed, also the share of artefacts increased. Despite the averaging of 15 values to one, the sensors created outliers, where there was no particular movement recognisable on the video. It was found that up to speed of 55 km/h, smoothing worked well, but above, the noise in the signal was so strong that only data artefacts could be detected. Up to 55 km/h, there could be manoeuvres detected in most cases of outliers, however, movements could not be linked to safety-critical events.
- The gyroscopic data could not provide any additional input, since their outliers all occurred together with outliers of acceleration variables.

Findings batch 2:

- Video analysis could not be carried out due to missing video footage for about 70% of the outliers. For another 16%, the front camera was turned about 170 degrees, i.e. almost upside down.[3] In 15% of the cases, the front cam was well installed and the video available, but with most of these cases, the other videos were not available. I.e. that a reasonable assessment of the video was hardly possible for most of the cases.
- Remarkably, more than 50% of the triggered events occurred with one single vehicle. Unfortunately, there was not a single video stream available for this vehicle.
- There were no crashes observed.
- There were no near crashes.
- There were two conflicts, which could have been considered safety-critical events.
- In a vast majority of the cases that could be assessed, the outliers of motion variables are related to a particular manoeuvre, which can be identified, see Table 9..

[3] We did not think of trying to rotate the videos. This would have made sense only, if it would have been possible to detect the out-of-position-angle of all videos and rotate them. However, image proccessing requires very much computer power and expensive software. It was just good enough to turn our heads in case it was necessary.

Table 9.8: Detailed list of annotations

Observed manoeuvre	not relevant		relevant	Total	Video ok	acc_x	acc_y	acc_z
Harsh braking (incl. event 1)	16		1	17	13	0	13	0
Swerving (Event 2)	0		1	1	1	0	1	0
Turning manoeuvres	2		0	2	0	0	0	0
Normal acceleration	13		0	13	2	0	2	0
Bump, pothole	9		0	9	3	1	0	2
Braking	149		0	149	134	70	61	3
Braking in a curve	6		0	6	0	0	0	0
Braking for pedestrian on zebra	5		0	5	3	0	3	0
Moving inside garage	11		0	11	0	0	0	0
Curve	163		0	163	117	61	55	1
Parking lot, entrance or exit	1		0	1	1	0	0	1
Swerving without recognisable reason	5		0	5	1	1	0	0
Normal movement on unpaved road	7		0	7	1	0	0	1
Speed bump	10		0	10	10	5	4	1
Lane change	5		0	5	5	0	0	5
Starting from/braking to stand still	46		0	46	45	10	11	24
Moving in(to) underground parking	43		0	43	43	40	3	0
Overtaking	1		0	1	0	0	0	0
No suitable video or no manoeuver recognised	800		0	800	24	7	7	10
Total	1292		2	1294	403	195	160	48

9.3.4 Safety-critical event One

Figure 9.11 shows an outline of safety-critical event one. A passenger car came from a side-road and cut into the path of the subject vehicle. The subject rider started swerving to the left and strongly applied the brakes. Luckily, the car driver from the right stopped his vehicle, since if she/he would have proceeded, the collision would have been unavoidable to the subject rider. Some remarks on this event:

- The vehicle video did not allow for detection of the road signs. However, use of google street view could solve the problem, where it is very clear that the car driver was give priority to the subject rider due to a stop sign.
- The video does not show whether the car driver had stopped his vehicle at the stop line.
- Swerving to left is a natural reaction, but in case the car driver would not have stopped, swerving to the right would have been the better option.
- The subject rider did not fall. It would have been a natural reaction to pull both brakes as hard as possible, which the rider obviously did not. Otherwise he would have fallen and most likely, this event would have led to a collision and severe injury to the rider.

- Probably this event is partly due to poor visibility conditions at this T-type intersection. The blue passenger car at the right in Figure 9.11 impedes sight of the vehicles coming to the right to the traffic from their left, at least if the stop their vehicles at the stop line.
- Summarising, this was a classic case of an incident between car and a powered two-wheeler. A scenario like this appeared in 27.7% of the injury crashes in the recent study of KFV on accident causation with powered two-wheelers (Winkelbauer et al, 2017).
- Among researchers, these kind of events is called “SMIDSY”-events, where the acronym stands for “Sorry mate, I did not see you”. Sometimes, similar events are called the “Looked but failed to see”-kind of event.

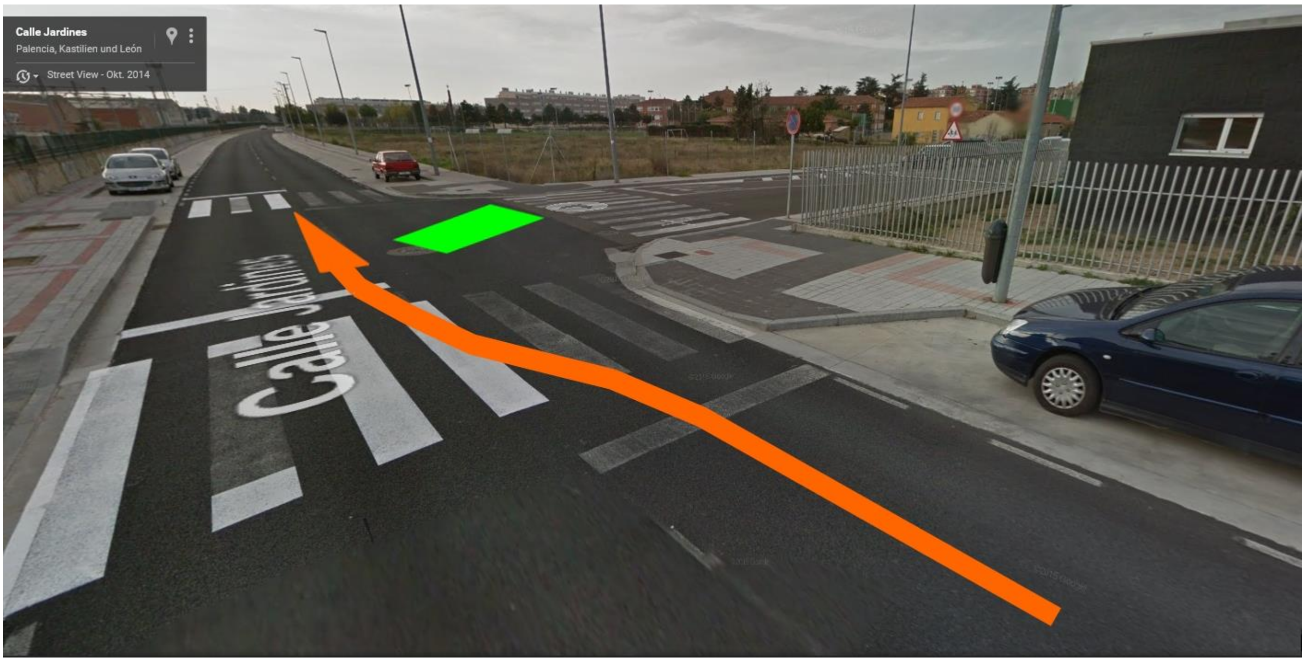

Figure 9.11: Location safety critical event one

9.3.5 Safety-critical event Two

This event took place on an urban trunk road. It was a dual carriageway; there were two lanes for the direction the subject vehicle was moving in. The subject rider was riding at moderate speed of about 45 km/h on the right lane. A car on left lane passed him and cut into the subject rider’s lane at far too low time headway. Some meters ahead, there was a zebra crossing without traffic light. A woman with a baby buggy had started crossing this road at the zebra crossing from left to right. The driver of the lead vehicle could not see this woman; a transporter in front was impeding her/his vision to this pedestrian. **Fout! Verwijzingsbron niet gevonden.** shows the location of this event. **Fout! Verwijzingsbron niet gevonden.** shows two positions of the relevant vehicles at the looming of the event and where the vehicles came to a full stop.

Figure 9.12: Location of safety critical event two (Source: Google Street View)

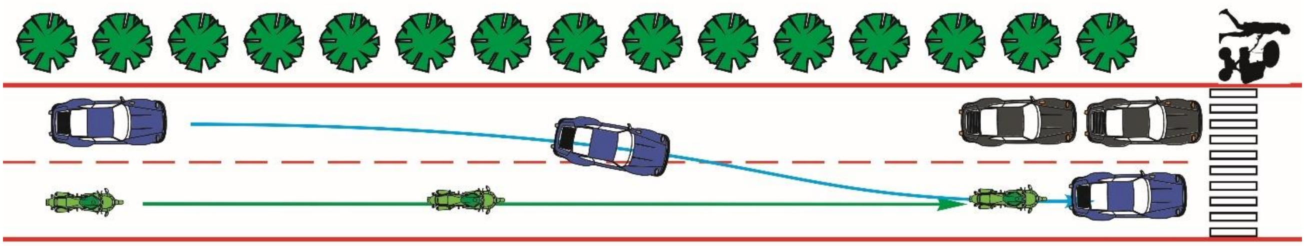

Figure 9.13: Outline of safety critical event two

This is again a classic layout of a collision or critical event, however, this one is not of the SMIDSY type. This one is linked to a failure in prediction of potential hazards. The lead vehicle driver could have expected a pedestrian and could have concluded that her/his behaviour could lead to a dangerous situation for the PTW rider. There may be two mistakes:

- Failure of prediction of the potential appearance of a pedestrian at the zebra crossing. She/he could have known, if she/he would have had better predictive skills, that there might be a pedestrian crossing the road and, consequently, she/he would force the powered two-wheeler rider to strongly decelerate after cutting into her/his lane.
- Wrong or no consideration of reasonable deceleration with a PTW, which is much lower than for a passenger car (Winkelbauer, 2004)

9.4 Discussion

9.4.1 Potential Infrastructure Improvement

Both of the critical events refer to well-known design principles.

Safety-critical event two would never occur in Austria. Austrian principles on road design do not allow a zebra crossing without traffic light on a road with more than one lane into one direction. This event is a striking example of why this rule was implemented.

Safety-critical event one is less clear. In principle, visibility seems to be quite good on this intersection. Pedestrians are made well visible by the “earlobes” on both corners. Probably, there should be some indication where to stop at this intersection. In Austria, a second stop line would have been required one meter ahead of the intersection.

The warning sign on children indicates that there is a school or similar location close to this intersection. This might be the reason why zebra crossings were installed on this intersection. Nevertheless, zebra crossings should not be installed if either frequencies of pedestrians or motor vehicles are too low, which seems to be the case on this road. If that is the case, this intersection and the critical event that occurred there give a good example, why a zebra crossing might turn out to have negative impacts as well.

9.4.2 Methodology with Respect to Triggers

The methodology chosen to identify safety critical-events was successful. Looking at “high-g events”, i.e. situations where either accelerations or rotations speed create outliers is successful in detecting safety-critical events. It does, however, not satisfactory distinguish between routine situations with high accelerations and dangerous events. Like in previous studies, there are many false alarms.

It was found that high-g-events cannot be separated by use of different signals. E.g. moving over a speed hump, through a pothole or from the ramp of an underground parking to the even part creates outliers in two, three or even four variables at a time. This is not unusual. In personal exchange, a researcher at the Technical University of Vienna told the author of this chapter that they were using a 25.000 Euro motorcycle equipped with three data acquisition systems for about 100.000 Euros in total. If this highly instrumented motorcycle moved over tram rails or just over the ruts of a cross road, the respective motion was detected by multiple sensors, and could clearly be seen in the records of various signals, for acceleration as well as rotation. There were no other signals available, which could possibly have been user to discern false positive hits from incidents. Hence, this issue is not a question of the quality of a data acquisition system. It is a fact that stems from the typical dynamic properties of a powered two-wheeler.

The only kind of motion that could clearly be identified was a trip through a roundabout. This event is mainly found in the rotation signal of the longitudinal axis. In particular, the fast rotation from right to left side leaning after the entrance and, the other way round, shortly before the exit, could clearly be identified within the data. One could even say that a roundabout, which does not trigger a rotation event, is not a good roundabout. According to guidelines on road design, a roundabout should require a minimum of deflection from a straight line in passing through; otherwise it could not fulfil the task of reducing driving speed (see Figure 9.14).

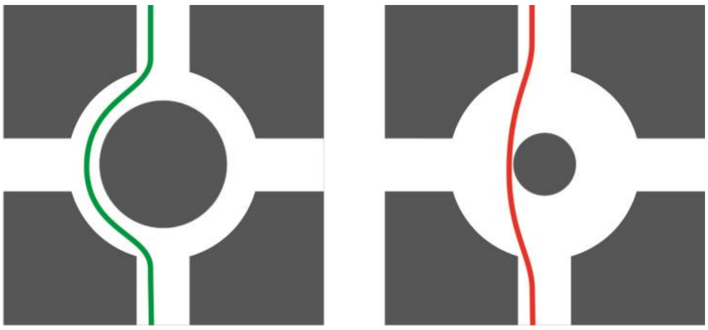

Figure 9.14: Outline of “good” and “bad” roundabout

According to the previously mentioned paper (Winkelbauer, 2004) on decelerations reasonably achievable by riders (6 to 6.5 m/s²), emergency braking cannot be automatically distinguished from a standard braking manoeuver (at about 5 m/s²). Evasive manoeuvres can be and were found, but they show similar patterns to motion in a roundabout.

Vibration turned out to be a problem for the sensors that were used in UDRIVE as well as in previous studies. It would probably be even easier to detect current revolutions per minute of the engine than the current motion of the whole vehicle if the sensor is mounted too close to the engine. Vice versa, if the sensors are mounted too far away from the engine, they are automatically mounted in the periphery, where any movement of the body results in higher amplitudes.

Further, many traffic situations, which would induce low amplitude signals in cars and trucks, create multiple high amplitudes for motorcycles. Where braking for cars is rather easy to detect for cars, harsh braking with motorcycles causes triggering with two, three or even four signals. Finally, motorcycle riders have a rather consistent preference for harsh braking, which is also one of the key results from the "every day riding" research task.

It would therefore be useful for any further naturalistic study involving two-wheel vehicles, to implement an incident button for the subjects to push immediately after a dangerous event. Moreover, it would probably be even more useful to sound an alarm to a rider if signals exceed a threshold and ask the rider for criticality of the respective situation.

To a certain extent, another issue appeared with UDRIVE as it appeared in the KFV naturalistic riding study: For cars, it is difficult enough to assess criticality of a situation. This turns out even more difficult for powered two-wheelers. Where safety-critical event one was quite clear, for the other event, it was discussed for more than an hour by several people whether this could be considered dangerous or not. In most cases, those riding powered two-wheelers themselves have a very different view on criticality than non-riders. Hence, the absence of a powerful sensor for locating other road users like Mobileye is a huge drawback for naturalistic studies on powered two-wheelers and the authors want to encourage Mobileye to develop a device suitable for powered two-wheelers.

A camera mounted to the helmet could be an option, but they strongly interfere with the idea of naturalistic research, for most cameras the battery would have to be replaced at least hourly. A wire connection to the vehicles would be much too dangerous. Lege artis, a riders should always keep the head in an upright position, which would be an advantage; practically, most riders don't and in particular experienced riders frequently move their heads. Research using helmet cams can be done by analysing the numerous crash videos, which are available on YouTube, but for naturalistic research, helmet cams are not an option.

9.4.3 Generalizability

Neither in KFV's naturalistic study nor in UDRIVE, the speed sensor on the front wheel delivered useful data due to technical issues. Hence, none of these two studies could investigate whether this sensor would deliver useful information to trigger high-g-events. There are some advantages: A sensor measuring rotation speed of the front wheel would be less influenced by movement of the full vehicle. Although there is some movement of the front wheel suspension, it would be negligibly small compared to the rotation of the front wheel. The front wheel sensor would probably deliver a smooth speed signal, of which the first derivate could deliver a signal facilitating triggers on acceleration and the second derivate would deliver the opportunity to analyse jerk.

In this respect, the assumption that an incident button, rider interviews or other "less naturalistic" methods would deliver better results, has an alternative hypothesis, i.e. speed signals captured by wheel speed sensor. This could deliver signals, which facilitate triggering of safety-critical events. However, wheel speed of the front wheel could not deliver information on any other movement of the whole vehicle than longitudinal speed and would hardly be useful in triggering falls.

A signal from the real wheel is more problematic. It is influenced by driving forces, nearly all motorcycles are rear-wheel driven. During harsh braking, a rear wheel can lift and would not deliver any useful signal in the very moment of danger.

If there were a considerable number of safety-critical events found, this would have been limited to the circumstances at the UDRIVE operation site, including riders, infrastructure and vehicles:

- Mainly urban traffic
- scooter-type motorcycles with low engine power

- no passenger on the bike
- the road infrastructure in and around one Spanish municipality

An important issue refers to what was already mentioned in the introduction to the chapter on powered two-wheelers. The "riding world" has two parts, which hardly overlap (Winkelbauer, 2012). In countries like Austria or Germany, riding a motorcycle is predominantly a leisure time activity. On the other hand, Greek, Italian and Spanish riders, in general terms, have better weather, good enough for riding the whole year and good enough for considering a powered two-wheeler a true replacement for a car in terms of daily commuting. There used to be a sharp line between these two modes of mobility, which got more permeable recently. Leisure riders purchase scooters in addition to their large and powerful travelling motorcycles, which are less convenient for urban commuting. Scooters are extending their range increasingly towards the typical "motorcycle routes" - with new models of increasing engine performance. However, in traditional terms, the Piaggio Liberty Delivery is a low-power scooter, easy to handle, a vehicle which is predominantly designed and used for daily urban commuting. UDRIVE data from powered two-wheelers, hence, is not expected to include high-speed rides on highways or ambitious rides on winding, mountainous rural roads. Urban commuting is associated with many, but low severity crashes, while fatal crashes are mainly found on exactly those roads, where nobody would ever go with a Piaggio Liberty 125cc scooter. Nota bene, both urban commuting and the number of scooters registered are tremendously increasing in large parts of Europe, most likely as an answer to increasingly congested urban roads. That means that the data collected in UDRIVE are most relevant considering what currently happens on the roads and what will happen in the near future, but the relevance of these powered-two-wheeler-related findings to leisure riding is rather limited.

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10 Everyday riding behaviour in common urban traffic scenarios

10.1 Introduction

Motorcycles are popular in Spain: in 2009 there were approximately 58 motorcycles per 1.000 inhabitants, a number only exceeded by Italy and Greece (DaCoTa, 2012). In Barcelona particularly, the number of motorcycles has grown over 10 years to represent one in four vehicles in 2016 (Marquet & Miralles-Guasch, 2016). While motorcycle riding is a compact, agile and fuel efficient way of travel (Stedmon et al., 2009), the European Transport Safety Council has estimated that proportionally motorcycles are the vehicles most frequently involved in road accidents (Hakamies-Blomqvist, 2003), and motorcycle riders are thought to be responsible in 26% of these accidents (Assing, 2002). A possible explanation for the increased risk of motorcycle crashes is that a motorcycle is a balance vehicle, which makes riding it more complex (Kooijman & Schwab, 2011).

Several solutions to improve motorcycle safety have been researched. These solutions include advanced training on hazard perception and vehicle handling (Boele, Craen, & Erens, 2013), solutions that improve the conspicuity of motorcyclists (Gershon, Ben-Asher, & Shinar, 2012; Gershon & Shinar, 2013), and the integration of intelligent warning systems in motorcycles (Martinez, Toh, Cano, Calafate, & Manzoni, 2010). While the advanced rider training had the effect that hazard perception of trained motorcyclists was improved up to 1,5 years after the training (Boele & de Craen, 2014), the effect of increased conspicuity disappeared after only a short time (Gershon & Shinar, 2013). Integration of intelligent warning systems on motorcycles may be the best solution to improve motorcycle safety, but this solution has its own complications. Adapting such systems from cars to motorcycles is difficult (Bayly, Regan, & Hosking, 2006; Huth, Biral, Martín, & Lot, 2012), because such the system must accept different circumstances as ‘normal’ for a motorcycle, such as a smaller angle in a bend and different G-forces during acceleration and braking. These differences may be further exeggerated by the fact that a) motorcycles offer far greater accelerative power than cars, and b) riders may differ in the degree to which they make use of such power.

This brings us to the root of the problem: we do not know exactly which speeds, forces and angles are ‘normal’ in everyday motorcycle riding, and how this varies across riders. Naturalistic riding data may increase our understanding of such behaviour. However, previous naturalistic riding studies were either targeted at (near-) accidents (Williams et al., 2015), which are by definition not ‘normal’, or at assessing novice rider behaviour during riding lessons (Aupetit et al., 2013).

The objective of the present study is to describe how riding speed varies across riders in common urban traffic scenarios, using UDRIVE naturalistic riding data. We have chosen to focus on intersections, because this is where one can expect large changes in speed and acceleration, especially if a full stop is involved. Furthermore, intersections are continuously encountered in urban environments. Four scenarios have been covered: free flow followed by a left turn or by a right turn, and a full stop followed by a left turn or a right turn. This study has been performed with the PTW data as available by March 2017.

10.2 Method

10.2.1 Rider demographics

The sample consisted of 32 Spanish motorscooter riders. There were 23 males and 9 females, with ages ranging between 24 and 46 years (*M* = 37.4, *SD* = 5.9).

10.2.2 Manoeuvre identification

Map matched GPS signals have been used to identify events corresponding with four common urban intersection scenarios: 1) left turn manoeuvres under free flow, 2) right turn manoeuvres under free, 3) left turn manoeuvres following a full stop, and 4) right turn manoeuvres following a full stop.

Left and right turn manoeuvres were identified based on kinematics and locality, using a procedure similar to Chapters 3 and 5. First, a sequence of data points was tagged as candidate manoeuvre when the derivative of map heading (i.e., yaw rate) exceeded 5 deg/sec for right turns (7 deg/sec for left turns), and when this sequence covered a total map heading change between 50 and 160 degrees (see the graph next to 'Kinematic data' in Figure 10.1).

Before drawing a distance window around the candidate manoeuvre, a distinction was made between the free flow and full stop scenarios. Speed data were evaluated in the 50m preceding the onset of the candidate manoeuvre. If the speed did not drop below 1 km/h, the candidate manoeuvre was tagged as free flow, and a distance window was drawn from 50m before the manoeuvre onset to 50m after the manoeuvre offset. In case the speed did drop below 1 km/h, the candidate was tagged as including a full stop, and the start of the distance window was established at 50m prior to the last timestamp below 1 km/h.

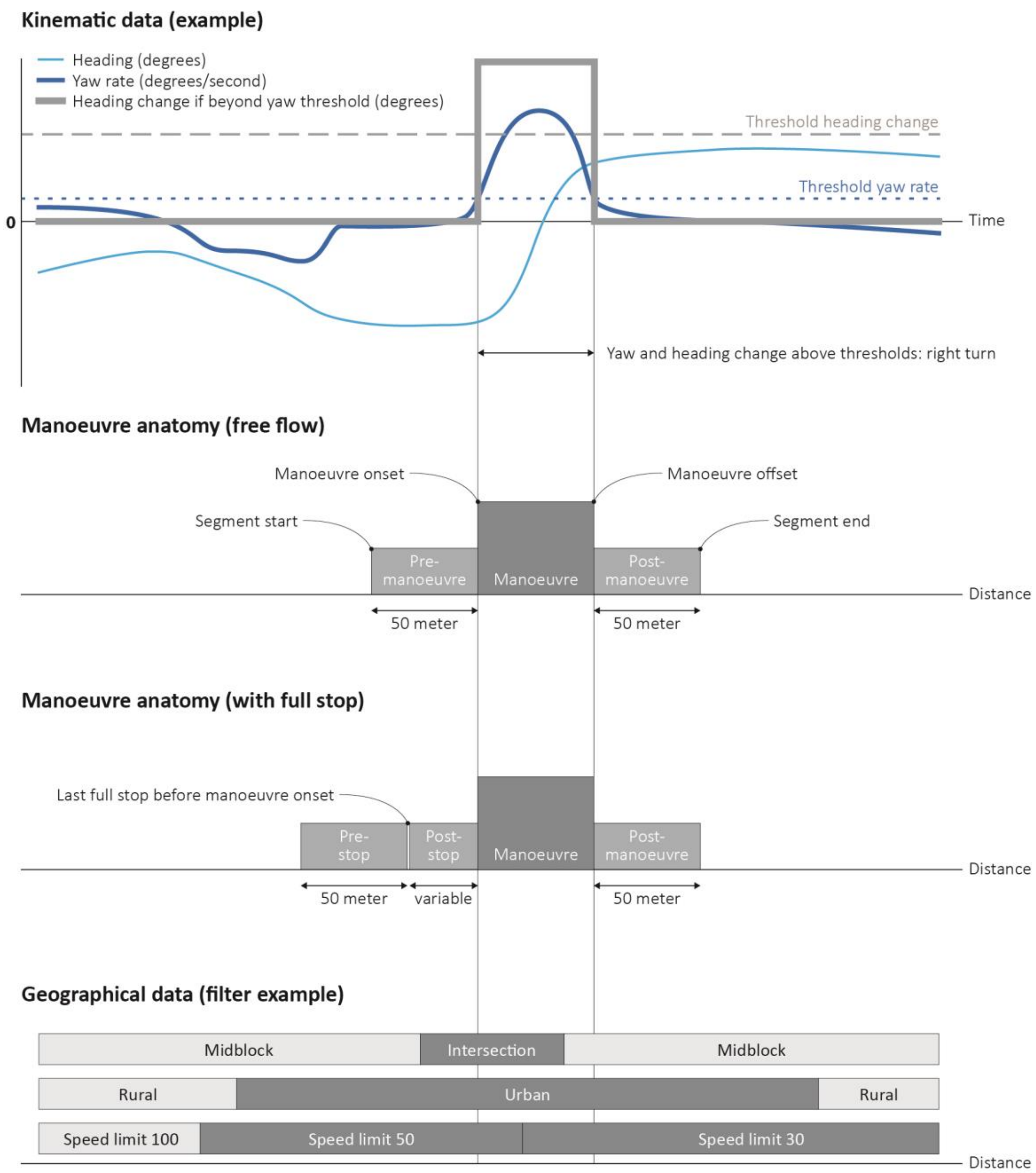

Figure 10.1: Extraction and filtering of manoeuvres based on kinematic data of the PTW and geographical data.

Candidate manoeuvres were only considered for subsequent analysis if there was an overlap with an intersection, and no overlap with a roundabout. Furthermore, it was required that the location type in their distance window was exclusively urban (i.e., not rural), and the speed limit in the distance window was not allowed above 50km/h. Contrary to the analysis of Chapters 3 and 5, the present study includes all manoeuvres of interest, even if they are part of the same trip. Finally, for each scenario, riders with less then 10 manoeuvres were excluded from further analysis.

10.2.3 Data analysis

Speed data were pre-processed with Matlab version R2015b to obtain the following measures on speed (see Figure 10.1 for more details): onset speed, offset speed, average speed during the manoeuvre, maximum and minimum speed during the manoeuvre. Acceleration has been calculated as the difference in speed in two adjacent speed samples. Given that the GPS speed signal was sample at the frequency of 1Hz, the acceleration signal was thus calculated in bins of 1 second. The measures acceleration onset and acceleration offset correspond with the first and the last second of the manoeuvre, respectively. Furthermore, the acceleration profile in each manoeuvre was split into positive acceleration and negative acceleration (i.e., deceleration). The final measures on acceleration concerned the average and maximum positive acceleration, as well as the average and maximum deceleration. A Univariate General Linear Model (SPSS version 24) was performed to examine the influence of scenario and rider on speed and acceleration measures. A bonferroni correction was applied to post-hoc pair-wise comparisons on scenario.

10.3 Results

After data reduction, 32 riders were found with a minimum of 10 manoeuvres in at least one of the four scenarios. In total, these riders yielded 7350 manoeuvres, see Table 10.1. We first examine the kinematics of manoeuvres across scenarios, followed by an examination of manoeuvres across riders. Finally, the kinematics of coming to, and accelering from a full stop are explored.

Table 10.1: Distribution of riders and manoeuvres across intersection scenarios.

Scenario	Riders	Duration (sec)		Minimum # manoeuvres	Maximum # manoeuvres	Total # manoeuvres
		M	*SD*			
1: Free flow, left turn	32	5.73	.44	10	676	2773
2: Free flow, right turn	30	6.59	.61	10	801	3117
3: Full stop, left turn	16	5.95	.61	11	256	879
4: Full stop, right turn	16	6.48	.99	10	179	581

NOTE: The riders in scenarios 2-4 are a subset of scenario 1. Scenarios 3 and 4 have an overlap of 13 riders. *M* = mean duration (first calculated per rider, then across riders), *SD* = standard deviation of mean duration.

10.3.1 Speed and acceleration across scenarios

Figure 10.2 displays speed over time of manoeuvres by four invididual riders, distributed across the scenarios, and aligned at the manoeuvre onset. Due to space restrictions it is not possible to show such graphs for each rider. These riders have been chosen as examples, because they appear to represent observations found across the riders.

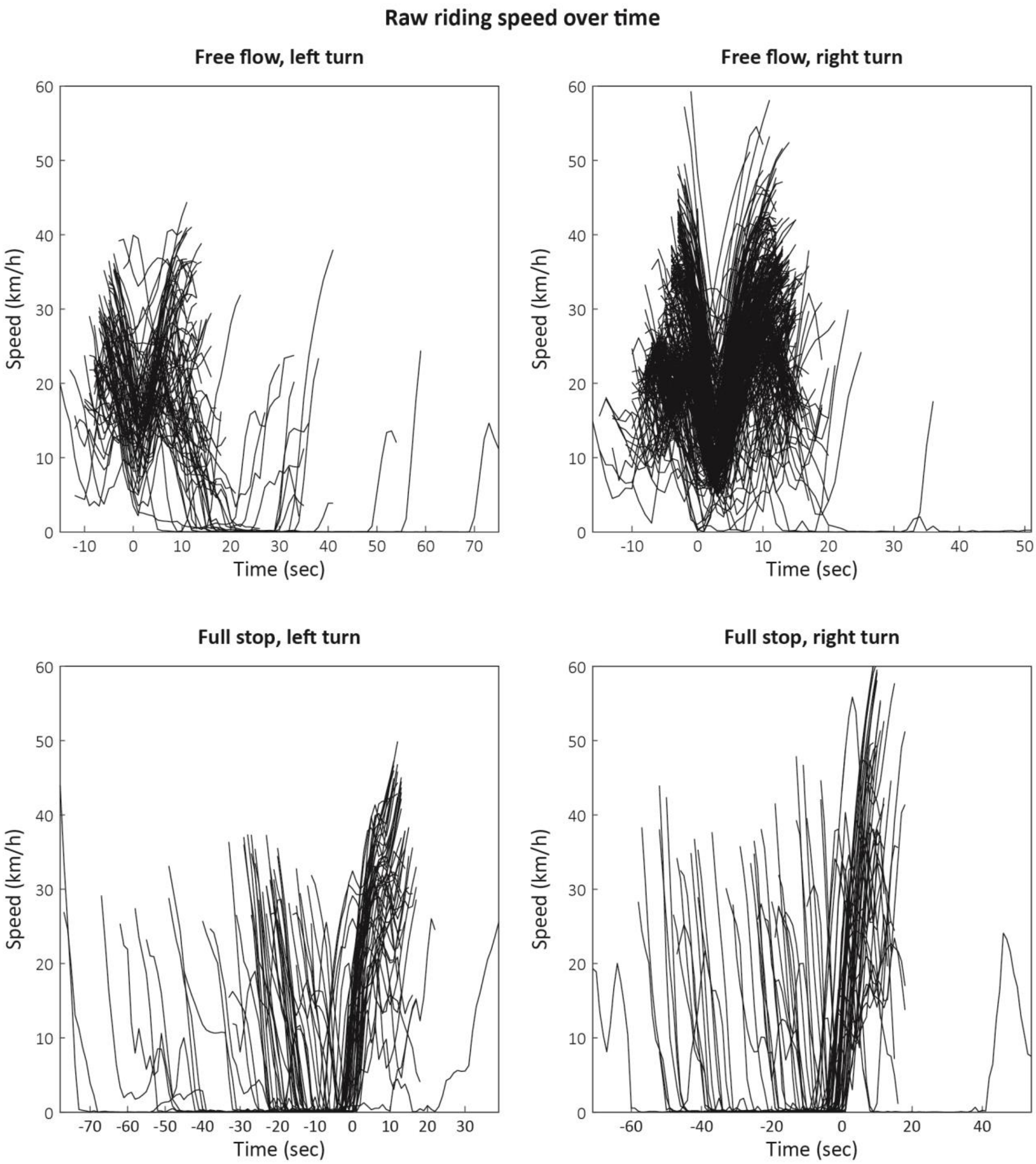

Figure 10.2: Examples of riding speed over time at intersection scenario 'free flow, left turn' (top left), 'free flow, right turn' (top right), 'full stop, left turn' (bottom left), and 'full stop, right turn' (bottom right). NOTE: t0 corresponds with the manoeuvre onset. Each panel corresponds with a unique rider.

One observation is the 'V' shape that emerges around the manoeuvre onset in the free flow scenarios (see top panels Figure 10.2). The centre of the shape occurs at approximatly 1-2 seconds after the manoeuvre onset (i.e., t=0sec), which suggests that riders were typically still breaking when they entered a manoeuvre in free flow. Another observation is that many manoeuvres are followed by a full stop (i.e., a long period with a speed below 1 km/h). An analysis of the map matched GPS signals has revealed that the median distance between two adjacent intersections was 46 meter. Given that the post-manoeuvre data were collected until 50 meter after the manoeuvre offset, it is likely that subsequent full stops corresponded with riders waiting at a next intersection.

Tables 10.2 and 10.3 show the average speed and acceleration as function of the intersection scenario. Given that for some riders more manoeuvres were collected than for other riders, the averages were corrected such that each rider had an equal share. The results of the univariate tests yielded significant main effects on scenario and rider, as well as significant interaction effects between scenario and rider, on all measures (see Tables 10.4 and 10.5). Note that not each manoeuvre featured deceleration (this was especially the case in the full stop scenarios), and in some manoeuvres the acceleration could not be computed on each timestamp due to missing speed data (which is mainly an issue for the onset and offset calculations). Consequently, the degrees of freedom in the univariate tests are not equal on each measure.

Post-hoc tests serve to interpret the significant main effects of scenario on the speed and acceleration measures, see Table 10.6. For example, riding speed at the manoeuvre onset was significantly higher in the free flow scenarios than in the full stop scenarios. Furthermore, in free flow the riding speed at the manoeuvre onset was significantly higher at right turns than at left turns. When leaving the manoeuvre, the offset speed was found to be significantly higher in the free flow right turn scenario, whereas similar riding speeds were found in the other scenarios. When these riding speeds were met, the momentary acceleration was also similar across the scenarios, with the only exception that the acceleration in the free flow right turn scenario was significantly higher than in the free flow left turn scenario. Finally, the manoeuvre direction did not have an effect on any measure in the full stop scenarios.

Table 10.2: Riding speed in km/h during manoeuvres across intersection scenarios.

Scenario	Riders	Onset		Offset		Average		Minimum		Maximum	
		M	*SE*	*M*	*SE*	*M*	*SE*	*M*	*SE*	*M*	*SE*
Free flow, left turn	32	22.86	.38	24.70	.37	21.73	.31	16.75	.33	28.08	.34
Free flow, right turn	30	26.40	.34	28.08	.33	24.09	.28	18.90	.30	31.14	.30
Full stop, left turn	16	12.21	.53	25.36	.50	18.65	.43	10.91	.46	26.58	.46
Full stop, right turn	16	13.33	.59	25.22	.57	18.99	.48	11.16	.52	26.98	.52

NOTE: *M* = mean speed across manoeuvres, corrected for riders, *SE* = standard error of mean speed.

Table 10.3: Riding deceleration and acceleration in m/s^2 during manoeuvres across intersection scenarios.

Scenario	Riders	Onset		Offset		Average acc.		Average dec.		Maximum acc.		Maximum dec.	
		M	*SE*	*M*	*SE*	*M*	*SE*	*M*	*SE*	*M*	*SE*	*M*	*SE*
Free flow, left turn	32	-.60	.041	.48	.030	.72	.016	-.70	.022	1.05	.024	-1.03	.032
Free flow, right turn	30	-.81	.036	.64	.027	.75	.014	-.76	.020	1.08	.021	-1.14	.028
Full stop, left turn	16	.60	.057	.61	.041	.87	.022	-.40	.039	1.43	.031	-.56	.056
Full stop, right turn	16	.57	.063	.58	.047	.88	.024	-.49	.040	1.40	.035	-.70	.056

NOTE: Acc = Acceleration (positive), Dec = deceleration (negative), *M* = mean acceleration across manoeuvres, corrected for riders, *SE* = standard error of mean acceleration.

Table 10.4: Results of Univariate model on riding speed.

Factor		Onset		Offset		Average		Minimum		Maximum	
	df	*F*	*p*	*F*	*p*	*F*	*p*	*F*	*p*	*F*	*p*
Scenario	3,7256	294.72	< .001	24.16	< .001	75.64	< .001	124.44	< .001	52.32	< .001
Rider	31,7256	13.93	< .001	15.45	< .001	18.72	< .001	10.29	< .001	25.68	< .001
Scenario * Rider	59,7256	4.90	< .001	3.93	< .001	4.51	< .001	4.11	< .001	4.03	< .001

Table 10.5: Results of Univariate model on acceleration.

Factor	Onset		Offset *		Average acc.		Average dec.		Max. acc.		Max. dec.	
	F	*p*	*F*	*p*	*F*	*p*	*F*	*p*	*F*	*p*	*F*	*p*
Scenario	253.08	< .001	4.44	< .001	9.49	< .001	44.21	< .001	39.79	< .001	57.86	< .001
Rider	3.53	< .001	6.67	< .001	19.58	< .001	12.78	< .001	17.61	< .001	12.66	< .001
Scenario * Rider	4.59	< .001	2.74	< .001	2.00	< .001	2.74	< .001	2.35	< .001	2.97	< .001

NOTE: Numerator df for scenario: 3, rider: 31, scenario*rider: 59. Denominator df for onset: 6276, offset: 7256, Average acc.: 6841, Average dec.: 6034, Maximum acc.: 6841, Maximum dec.: 6034.

Table 10.6: Results of post-hoc pairwise comparisons across scenarios.

Measure		Free flow left turn			Free flow right turn		Full stop left turn
		FR	**SL**	**SR**	**SL**	**SR**	**Full stop right turn**
Speed							
	Onset	X	X	X	X	X	
	Offset	X			X	X	
	Average	X	X	X	X	X	
	Minimum	X	X	X	X	X	
	Maximum	X			X	X	
Acceleration							
	Onset	X	X	X	X	X	
	Offset	X					
	Positive average		X	X	X	X	
	Negative average		X	X	X	X	
	Positive maximum		X	X	X	X	
	Negative maximum	X	X	X	X	X	

NOTE: 'X' marks significant effect of post-hoc comparison. FR = free flow right turn, SL = full stop left turn, SR = full stop right turn.

10.3.2 Manoeuvre kinematics per rider

As mentioned in the previous section, the results of the univariate model also yielded a significant main effect of rider on each measure. Thus, at least one rider shows different speed and acceleration behaviour than the average of all riders. Furthermore, a significant interaction effect between scenario and rider

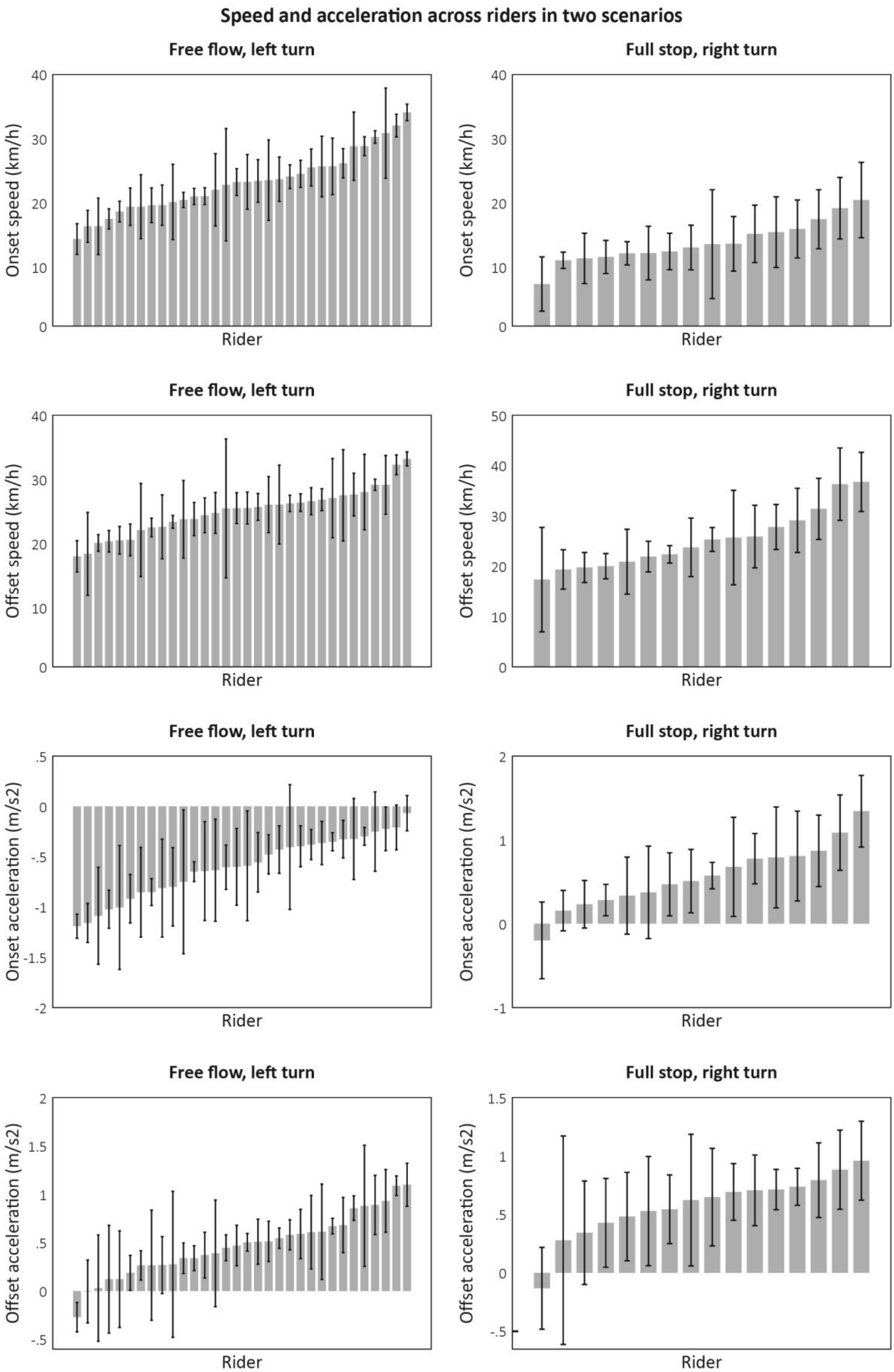

Figure 10.3: Distribution of speed and acceleration onset and offset in two scenarios as function of rider. NOTE: Riders have been ordered according to the value of speed or acceleration in the corresponding panel. Errors bars: 95% CI.

indicates that the way in which at least one rider differs in his/her speed and acceleration behaviour depends on the scenario at hand. To explore these differences, Figure 10.3 shows a subset of the measures for two scenarios as function of rider. These panels are intended as an example of the 44 of panels (i.e., 11 measures x 4 scenarios) that could have been created. Figure 10.3 clearly shows that in free flow some riders typically entered a manoeuvre at a higher speed and chose to break harder than other riders. Following a full stop, some riders tend to accelerate faster than other riders, resulting in higher riding speeds throughout the manoeuvre (i.e., higher speeds at the onset and the offset). Looking at the confidence intervals of each bar, Figure 10.3 also shows that some riders are relatively consistent in their speed and acceleration choice, whereas others show a large variation.

10.3.3 Kinematics around full stop

The bottom panels in Figure 10.2 suggest that the slope with which riders come to a full stop (i.e., deceleration) is similar across manoeuvres within a rider. Likewise, there appears to be consistency in the slope of acceleration directly following a full stop. To examine the degree of consistency within and across riders, we first removed the data in each manoeuvre between the first moment of coming to a full stop, and the last moment that the full stop occurred before initiating the manoeuvre. Figure 10.4 shows the results of this procedure for four riders, with a time window of +/- five seconds surrounding the last moment that the full stop occurred (i.e., aligned at t=0sec). The riders in the top panels of Figure 10.4 correspond with the riders in the bottom panels of Figure 10.2.

Figure 10.4 shows 'V' shapes akin to what was observed at the free flow scenarios in Figure 10.2, albeit at a lower riding speed. Cleary, not every full stop was preceeded by a similar riding speed and deceleration, neither was every full stop followed by similar acceleration. Momentary traffic situations and local infrastructure may account for such differences. Furthermore, the bottom right panel in Figure 10.4 shows that, for that particular rider, many full stops were preceeded by riding speeds below 5 km/h. This may be an indication for filtering behaviour (i.e., slowly moving between cars to the front of a queue), which has not been observed with all riders.

The mean riding speed and acceleration have been calculated for each rider to facilitate a comparison across riders, see Figure 10.5. The grey lines depict the mean speed and acceleration of individual riders, whereas black lines correspond with speed and acceleration averaged over all riders. The panels in Figure 10.5 suggest that riders do not only differ in speed choice and acceleration during manoeuvres at intersections, but also at the full stops preceeding those manoeuvres. Furthermore, deceleration in the five seconds prior to a full stop appears to be at a constant value for the majority of riders.

In the first second following the full stop, the variation in acceleration across riders appears relatively small compared to the other time bins (but note that within a rider there may still be large variation, see Figure 10.4). Overall, acceleration increases to approximately 1.5 m/s^2 in the first two seconds following a full stop, and then decreases to .5 m/s^2 in the remaining three seconds. The median time between the last full stop and the manoeuvre onset was 4.00 seconds at left turns (M = 4.63, SD = 4.07) and also 4.00 seconds right turns (M = 5.09, SD = 4.40). These statistics suggest that riders started to reduce the magnitude of acceleration before entering a manoeuvre. Furthermore, riders are likely still accelerating during the first part of the manoeuvre (i.e., approximately half of the manoeuvres according to the median, and likely also after 5 sec in Figure 10.5).

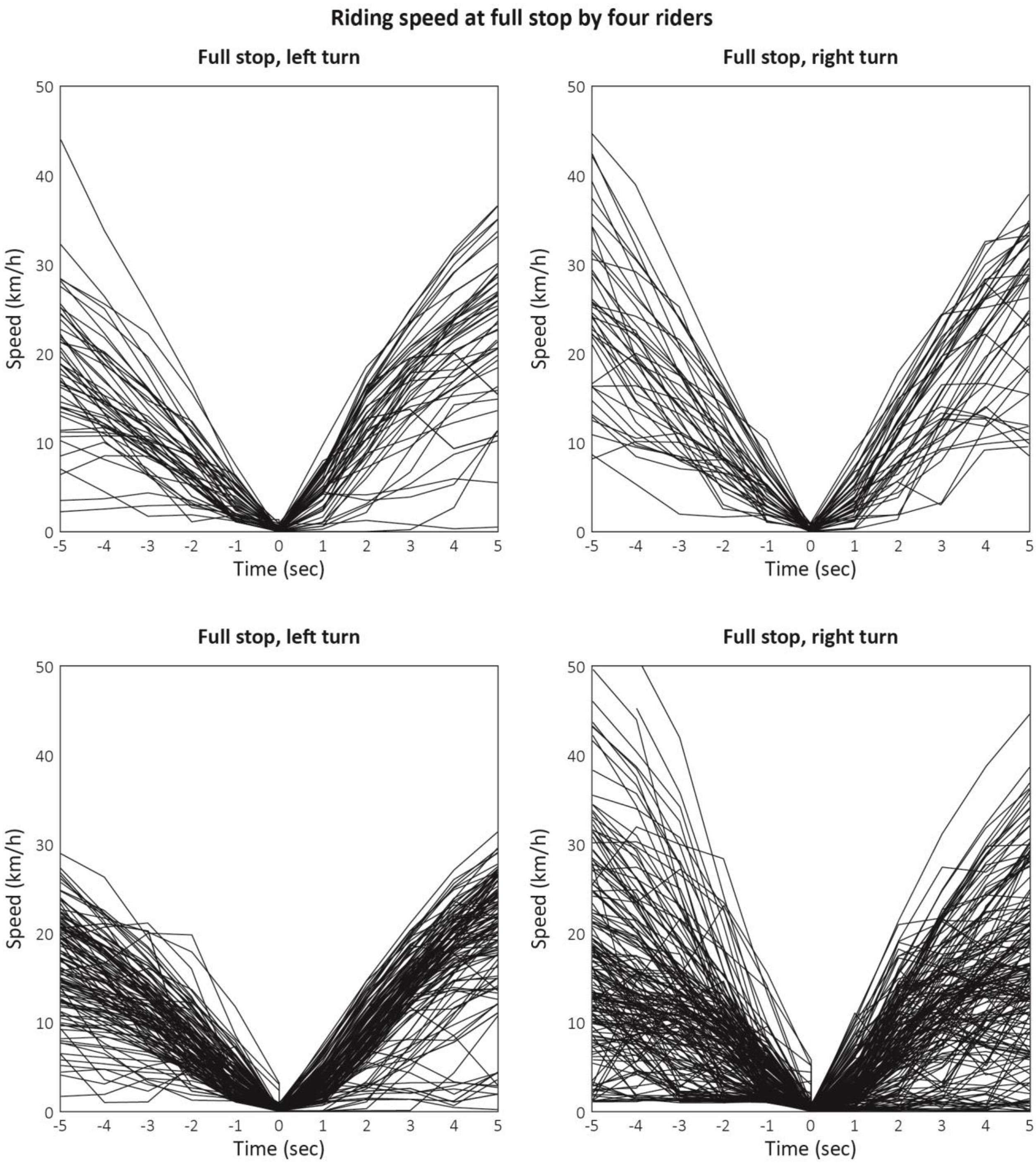

Figure 10.4: Speed data by four riders with a full followed by a left turn (left panels), or a right turn (right panels).
NOTE: t=0sec corresponds with the last moment at which the full stop occurred. Speed data below 1 km/h has been removed.

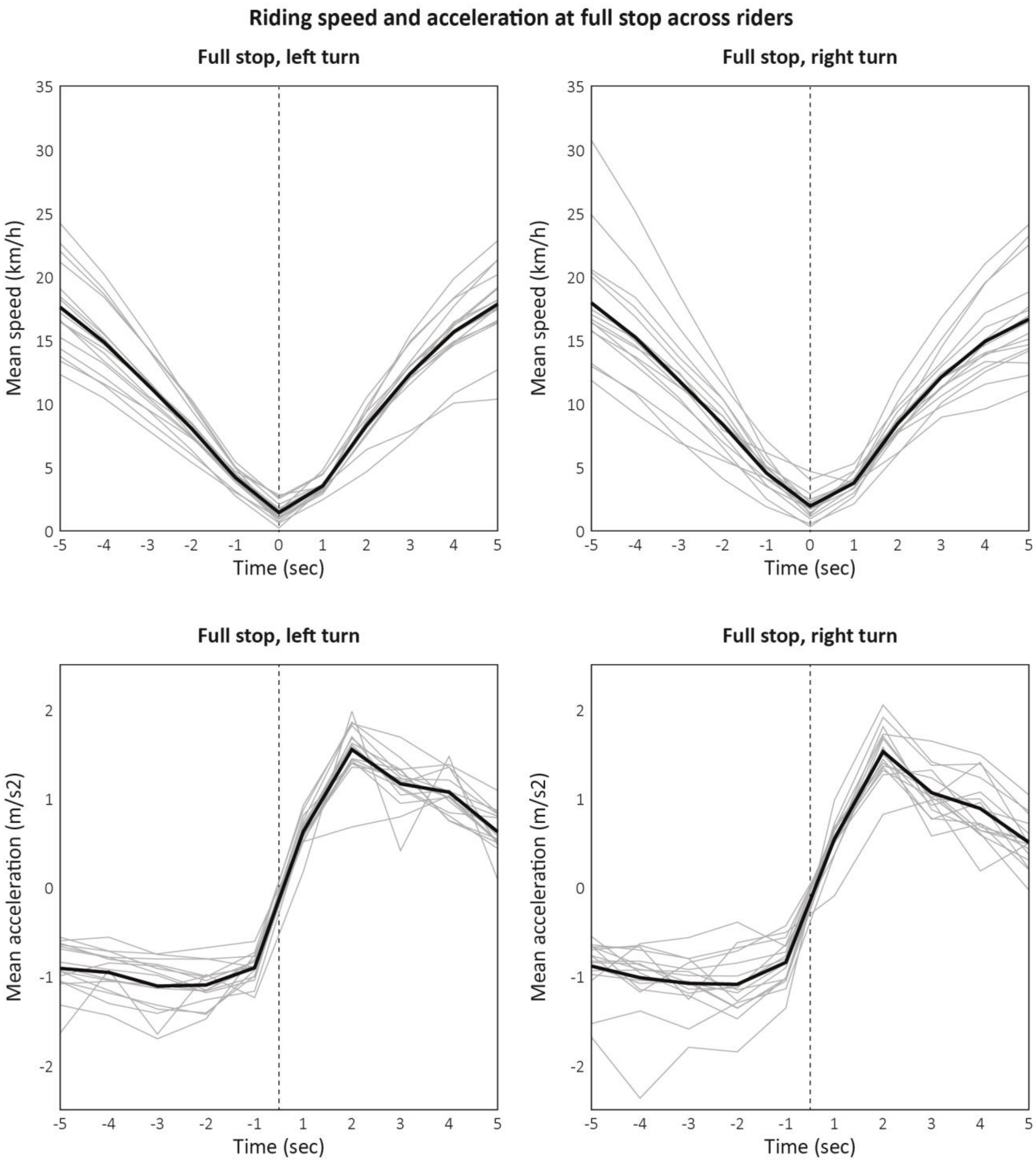

Figure 10.5: Speed and acceleration as function of time in full stop scenarios preceding left turns (left panels) and right turns (right panels). NOTE: t=0sec corresponds with the last moment at which the full stop occurred. Speed below 1 km/h has been removed. Timestamps at acceleration corresponds with bins of 1 second relative to t=0sec. Grey lines: average speed/acceleration of individual riders. Black lines: average speed/acceleration across riders.

10.4 Discussion

There are two main findings in this study on speed choice and acceleration in everyday riding; one related to differences across the intersections scenarios, and one related to differences across riders.

First, we have found significant differences between the scenarios in speed choice and acceleration during manoeuvres. Pair-wise comparisons showed that most scenarios were significantly different from each other on all measures, these being speed at the manoeuvre onset, speed at the manoeuvre offset, average speed, maximum speed, minimum speed, acceleration at the manoeuvre onset, average positive and negative acceleration, and maximum positive and negative acceleration.

Two observations are note-worthy. The measure acceleration at the manoeuvre offset yielded a significant effect when comparing the scenario ‘Free flow, left turn’ with ‘Free flow, right turn’, but not in any of the other five pair-wise comparisons. Thus, it appears there is some consistency in the level of acceleration reached by the end of a manoeuvre. The other observation is that no significant effects have been found in comparing the scenarios ‘Full stop, left turn’ and ‘Full stop, right turn’. In terms of onset speed, this is not surprising (i.e., both scenarios include a full stop). However, in theory the larger radius of a left turn allows for a higher riding speed, yet no significant effect has been found on offset speed. The absence of such an effect may be explained by situational factors. For example, riders may have needed to negotiate priority with other traffic (note: this is less of an issue at right turns).

The second main finding concerns a comparison between riders. Across riders we have found significant differences in speed choice and acceleration during manoeuvres, as well as in the time window surrounding full stops prior to the manoeuvres. Furthermore, riders appear to use a constant deceleration in the five seconds preceeding a full stop, but the magnitude of this deceleration varies across riders. These findings suggest that riders have different preferences (i.e., riding styles) regarding speed choice and acceleration.

If such preferences indeed exist, they may inform the development of intelligent warning systems on what is ‘normal’ and ‘abnormal’ riding behaviour. Furthermore, the existence of preferences warrants further research on whether groups of riders share similar preferences. This could be done with a bottom-up, or data-driven, approach (e.g., cluster analysis), or through a top-down approach (e.g., with behavioural questionnaires).

There are some caveats, however, with regard to the existence of preferences. Within riders, a large variation in speed choice and acceleration has been found across the corresponding manoeuvres. The larger such variation, the smaller the certainty with which one can speak of a preference. Therefore, a better understanding of the variation across manoeuvres is needed. For example, GPS locations could be used to identify unique intersections, and the degree with which riders take the same route. This knowledge would help in compensating for the influence of infrastructural factors on speed choice and acceleration. Furthermore, an examination of video data may help in understanding the influence of momentary traffic (e.g., presence of lead vehicles, restricted flow).

We view the present study as a first step to understanding everyday riding behaviour using naturalistic riding data. For future studies, we recommend to also investigate g-forces and roll angle. Furthermore, in the present study all riders used a 125CC motorscooter, which is not representative for all powered two-wheelers. On average, riders showed a similar level of acceleration in the first second following a full stop. Possibly, riders could and have applied full throttle, given the limited power of 125CC motorscooters. With larger motorcycles, it is unsafe to apply full throttle when departing from a full stop. A larger variation in acceleration could thus be expected, which provides another opportunity to examine individual preferences in speed choice and acceleration. A new naturalistic riding study with larger motorcycles is therefore warranted. Finally, the present study focuses exclusively on Spanish PTW riders. Given that infrastructural designs and their prevalence (e.g., see cyclist facilities in Chapter 3) vary across countries, the generalizability of the present study is limited. Therefore, future studies on naturalistic riding should also involve riders in other countries.

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11 Time headway between cars and powered two-wheelers

11.1 Introduction

Initially, the idea for this research question was based on professional experience of the researchers involved in this part of the UDRIVE project. Austrian accident statistics (own analysis based on police recorded data) show that rear-end collisions make up about 10% of motorcycle crashes. However, in about 65% of the cases, the police considered the car driver being at fault for the crash. In terms on rear-endings, jurisdiction – with very few exceptions – considers the driver of the rear vehicle to be at fault for a crash. A too small headway is the most plausible cause for rear-end-collisions. A related cause, lack of attention, and in particular distraction, is subject to other analysis in UDRIVE. This research focuses on time headway, which is compared between cars, trucks and powered two-wheelers.

11.1.1 Acceptable Values of Time Headway

As a reference for the results in this study, legal provisions and recommendations were used. A driver caught by police keeping time headway of less than 0.2 s will be dispensed from road traffic for at least six months. A time headway between 0.2 to 0.4 seconds leads to monetary penalty and a penalty point in the Austrian penalty point system. With two points within one year, an offender has to attend a specific driver improvement course. With three points, the driving licence will be dispensed for three months.

The Austrian courts normally accept one second delay for reaction in criminal cases (frequently called “reaction time”, but in legal terms, it is the delay of a driver’s reaction to the appearance of a circumstance, which requires action),, in civil cases the accepted delay may be shorter (0.8 s). If particularly high attention is required (e.g. driving in front of schools) the accepted duration may also be shortened. The generally accepted recommendation of all road-safety related organisations in Austria is 1 s below 50 km/h, 2 s from 50 to 100 km/h and 3 to 4 seconds at higher speeds.

11.1.2 Research Questions and Hypotheses

UDRIVE’s Research Question 4.8 reads:

Do car drivers keep PTW riders at a different distance (in TTC) than other motorized traffic on straight road sections, and does rider conspicuity play a role in this difference?

According to the explanation in the introduction of this chapter, the researchers argue that drivers follow powered two-wheelers closer than they follow other vehicles. In case this appears to be true, it will be investigated whether this could be caused by the visual appearance of the powered two-wheeler rider and the vehicles, e.g. in terms of colour, brightness, probably lights or other optical properties.

11.2 Method

11.2.1 Sensor Data

This analysis is based on UDRIVE car data. It is particularly facilitated by Mobileye data on up to four other objects (pedestrian, bicycle, bike, car, truck).

Apart from that, we have used some basic information from GPS data, in particular map-matched speed and local speed limit.

11.2.2 Triggers

Mobileye provides data for up to four obstacles. However, the obstacles do not have a fixed identity. In other words, a PTW may be first captured as obstacle number two, if one other obstacle was captured before. If this first obstacle drops out, the PTW immediately changes to be obstacle one. That makes it difficult to follow different obstacles.

We first created a new variable, which includes that:

- There is at least one “bike” present, or car or truck respectively.
- The analysis should focus on almost-free-flow situations; in other words, avoid long episodes of PTW, car or truck moving in front of a car in congestion at very low speed. Hence, we triggered speeds of at least 30 km/h and at least 50% of the local speed limit.
- The analysis should focus on vehicles in the same lane. Hence, we triggered vehicles moving at a maximum of 3.5 m left or right of the subject vehicle. This value was tested and validated by video observation. The difficulty of the task was not to capture lead vehicles in another lane but to capture vehicles in the same lane in curves.
- An additional trigger was implemented in order to avoid capturing vehicles crossing the path of the subject vehicle.
- Another intention was to capture a “steady-state” of the subject vehicle behind another one, i.e. episodes with a continuous scenario. Hence, analysis was limited to episodes, which lasted for at least ten seconds.
- The selected episodes should not include overtaking manoeuvres (with the subject vehicle being the overtaken part), i.e. the “lead” vehicle appears from right or left behind the subject vehicles – depending on UK or other operation site – and leaves the scene at continuously higher speed than the subject vehicle. In other words, this analysis should not include situations, where another vehicle just passes by the subject vehicles. Video observation showed that such episodes could be successfully excluded by use of variable “x_value_rel”, a variable delivered by Mobileye describing the longitudinal distance to another road user. All episodes, where the average of this parameter on relative speed was more than 1, were excluded.

11.2.3 Total Sample

The queries for this analysis were executed on March, 21st. The extent of data at this date is displayed in Table 11.1. This table as well as Figure 11.1 and Figure 11.2 show that the operation sites in France and United Kingdom have provided most of the data for this analysis. Records (one record is one line of data, of which 30 are stored per second) with operation site unknown were excluded from the analysis.

Table 11.1: Records by Operation Site as of 21.03.2017 (Date of analysis)

Country	Records	Drivers	Duration [h]	Travel Distance [km]	Average Speed [km/h]	Days with trips
DE	4.841	14	1.106	35.410	32	415
FR	23.227	43	5.874	260.911	44	474
NL	3.490	15	921	53.302	58	304
PL	3.914	18	914	27.572	30	346
UK	23.274	50	5.373	231.093	43	494
unknown	2.446	12	737	36.029	49	226
Total	61.192	152	14.925	644.317		

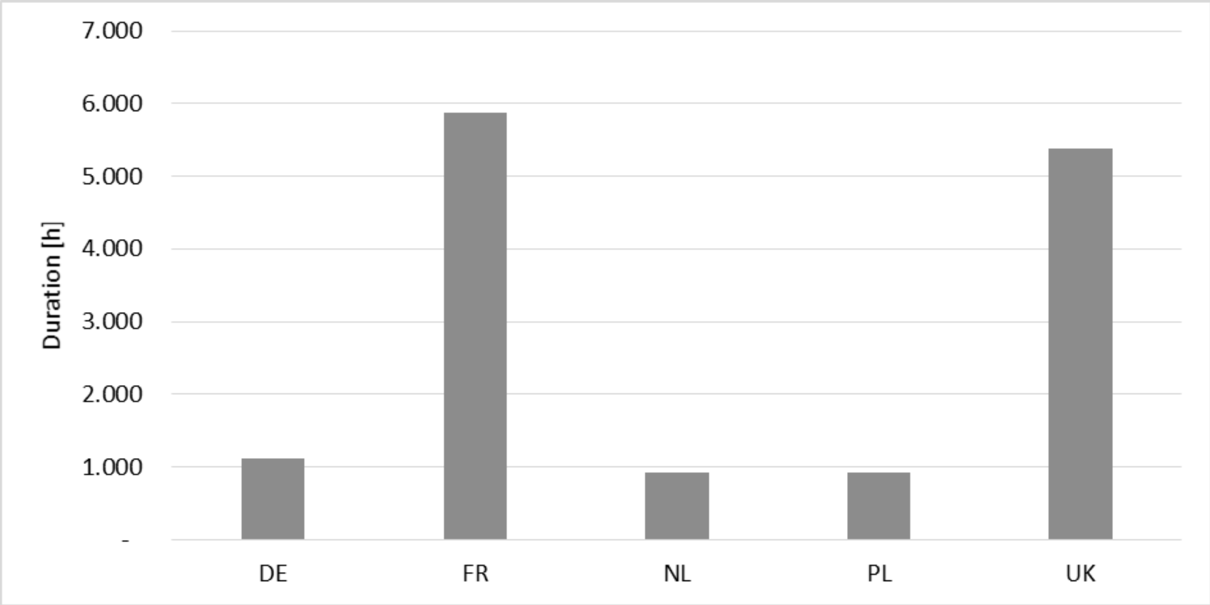

Figure 11.1: Duration of all recorded trips [h] by Operation Site as of 21.03.2017 (Date of analysis)

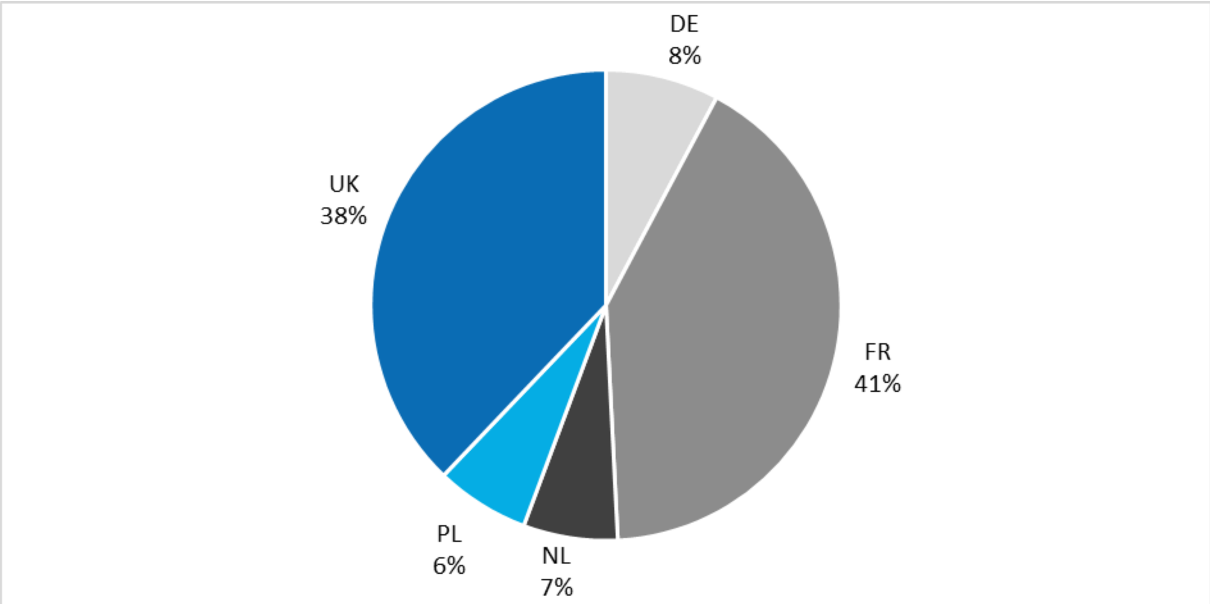

Figure 11.2: Proportion of duration of all recorded trips [h] by Operation Site as of 21.03.2017 (Date of analysis)

The total number of records, which were in the database for analysis, is listed in Table 11.2. Interactions with bikes (i.e. records where at least one of the obstacles is a motorcycle) are rather rare compared to the other vehicle categories, but about 370,000 records are still more than enough.

Table 11.2: Proportion of interaction by vehicle type

	Data items	Proportion (%)
total N	537,490,379	100.00%
Car interaction with:		
bike	369,235	0.07%
car	106,869,877	19.88%
truck	6,116,808	1.14%

11.2.4 Reduced sample

It was necessary to reduce the amount of data, since the analysis using MySQL queries on the UDRIVE remote environment time-outed after 5 minutes. The following restrictions were implemented:

- Distance [s] < 3 s. It was found that higher distances may easily lead to detection of vehicles in other lanes in slight curves. In addition, such high distances are actually out of scope of the analysis, since low distances are considered dangerous and the exclusion of higher distances for all vehicle categories would not disturb comparison.
- Speed was categorised: 5 km/h categories, e.g. “55 km/h” includes 55,00 – 59,99 km/h
- Distance of a car to a bike in front (car to bike following situations): all data
- Car to car following situations: every 5th record (Record ID ending with 1 or 6), every 30th data item
- Car to truck following situations: every 10th data item

Statistical tests on differences in means were not applied, because the huge amount of data with several 100.000 per group would always result in significant differences.

The analysis data set was not organised in interactions (e.g. minimum of distance during interaction with a specific vehicle). Of course it would have been useful to analyse a complete episode of interaction from the other vehicle appearing in front of the subject vehicle until the same vehicle leaving the scene (e.g. changing to another lane, turning into another road od just fading on the horizon pod behind a corner). However, this turned out complicated or even impossible, because interactions are frequently interrupted. Hence, it was decided to do the analysis based on records.

Table 11.3: Analysis data set: data items per country and vehicle type

Records (N) by country	Car to bike	Car to car	Car - truck
DE	23,714	24,357	26,702
NL	57,448	38,333	43,910
FR	122,963	233,206	200,705
PL	21,654	38,075	34,513
UK	123,586	237,217	189,781
Total	349,365	571,188	495,611

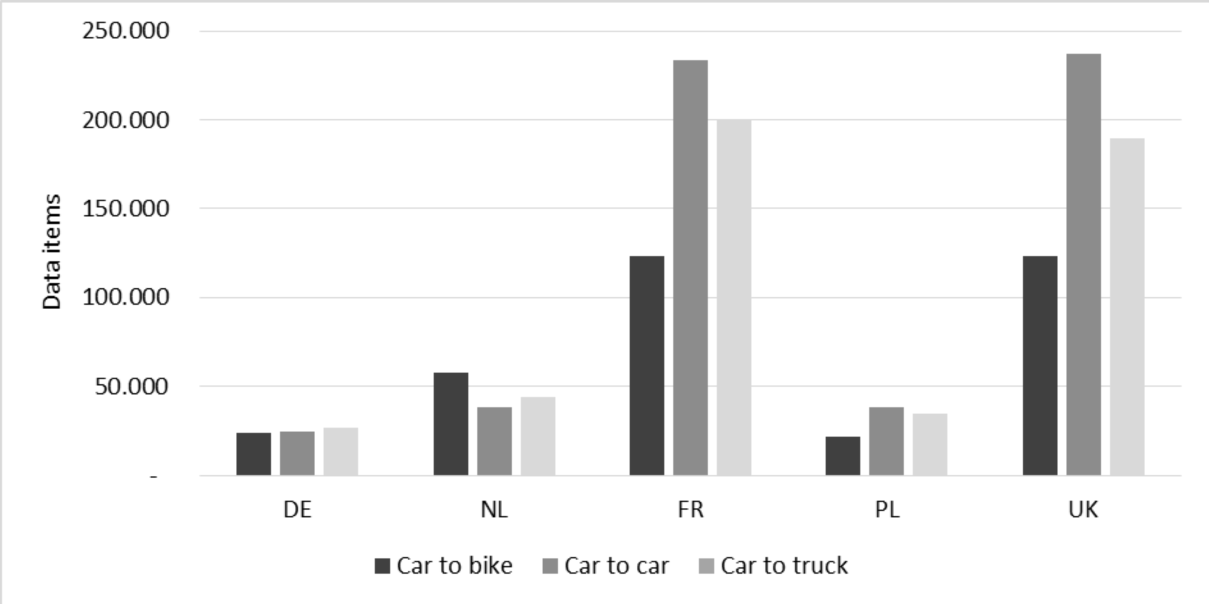

Figure 11.3: Analysis data set: data items per country and vehicle type

11.2.5 Comparison to Data from Site-Based Observation

KFV runs continuous data collection about some basic parameters of road traffic for more than three decades. These data serve as a basis for longitudinal comparison in the sense of safety performance indicators. Among many other parameters, KFV measures driving speed and time headway (for the technical method of data collection, please see below), which provides an opportunity to compare it to the same parameters measured within UDRIVE. Such a comparison may also be considered a kind of cross validation of the two databases.

Nota bene, this data collection was not done as part of UDRIVE, but is was done at the same time and accidently by the same team, which considered comparison to be a promising source if information for both sides, UDRIVE and the Austrian data collection.

KFV collects parameters like driving speed, seat belt and child restraint use rates, red light running and helmet use rates. The methodology of this data acquisition was only slightly changed for a long time, but two years ago, three important changes were implemented:

- All paper/pencil acquisition was replaced by data collection via tablet computer. We now use “SODA” software to program questionnaires; the data entered by the data collectors are directly sent to a central database via the internet and immediately available for analysis.
- Speed data acquisition was changed from a manual method using radar guns to an automatic system. The new sensors will be described later in this chapter.
- The time and money saved by the previous two changes were used to significantly diversify the data acquisition, e.g. to curve trajectories and use of personal protective equipment by powered two-wheeler riders, starting and stopping behaviour at intersections; and particularly to increase the amount of speed data records by a factor of about 100.

Figure 11.4: Sierzega SR4 Side Radar device

The Sierzega SR4 Side Radar Device (Figure 11.4) provides five pieces of information: Speed, direction, length of a vehicle, distance to previous vehicle and a time stamp of each record. Using length of vehicle, we determine the type of vehicle, which after a lot of calibrating works at satisfactory accuracy.

KFV has six of these side radar devices, and remounts them all once a week. Besides individual driving data they acquire metadata like exact location, local speed limits for all categories of vehicles, category of road, width of all lanes, etc. During 2015 and 2016, 1.6 million motorcycles, 16.5 million cars and 0.9 million trucks were recorded.

11.3 Results

11.3.1 Mode of Distance by Speed Category

At low speeds (up to 60 km/h), there is almost no difference in time headway between car to car following situations and car to PTW following situations. However, car-drivers kept less distance behind trucks. Frequencies of values from 0.3 to 0.9 s are almost equal for all three vehicle categories, but values from 1.0 to 1.5 s are more frequent for subject vehicles behind trucks (Figure 11.5). Remind that 0.3 s - if recognised by Austrian police in Austria – have led to acquisition of a penalty point.

This means that in the most relevant range of time-headway up to 1 s at this range of speed (up to 60 km/h), there is no relevant difference between the three vehicle categories.

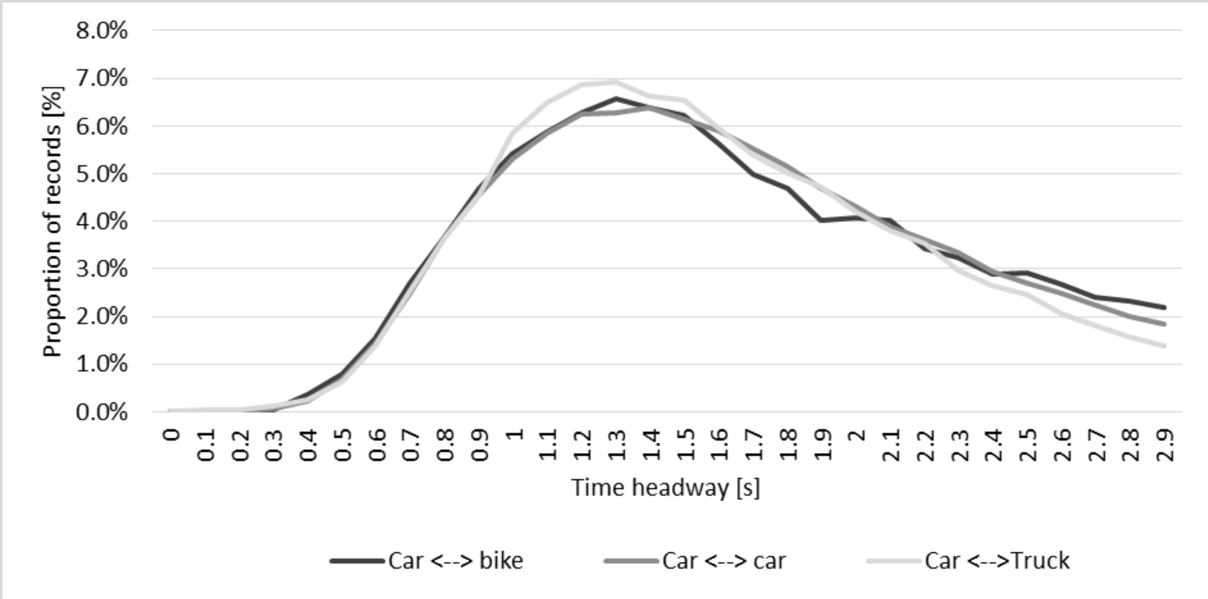

Figure 11.5: Distribution of time headway [s], driving speed < 60 km/h

At higher speed, distributions of time headway show a slightly different picture. Up to 0.8 s the three following-categories of following situations show similar values, but the frequency of 0.9 to 1.2 seconds is remarkably lower for cars behind motorcycles (at this speed, there should not be any mopeds recorded). The frequency distribution of time headway of cars behind motorcycles at speeds between 60 and 85 km/h shows two peaks. There's no evident explanation for this result. One could argue that this is caused by a small share of car drivers, that ignores the existence of the powered two-wheeler and is geared to the next vehicle in front of the rider. However, there is 0.6 s between the two peaks, which would mean that the powered two-wheelers in this case keep an average distance of only 0.6 s behind their lead vehicles. These findings seem not to support this hypothesis; therefore, another (unknown) issue might have had an influence on choice of time headway.

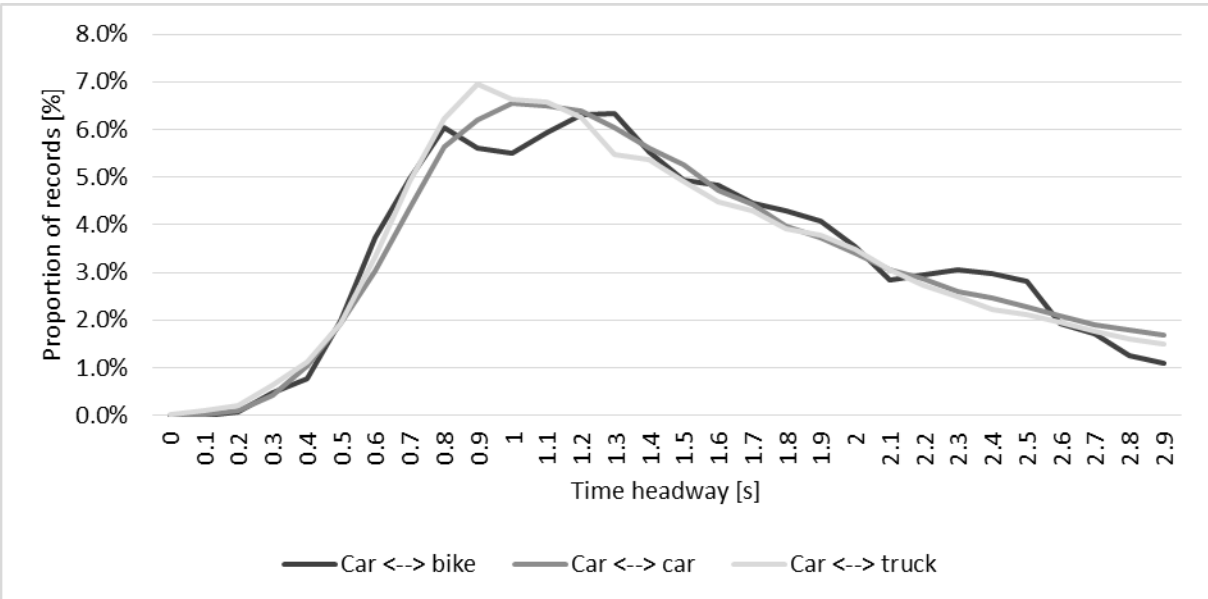

Figure 11.6: Distribution of time headway [s], driving speed 60-85 km/h

The distribution of time headway at speeds of 85 km/h and above (Figure 11.7) is possibly biased by methodology and sensors. We argue that powered two-wheelers are hardly detected by Mobileye from further away. More precisely, the data suggest that there are hardly any riders detected at time headway of 2.2 s or more. The analysts argued that this is not because there are no riders there. More likely, it may be a question of technical feasibility and video resolution of the Mobileye camera that riders are not detected at higher distances. It has to be noted that this does not disparage the quality of Mobileye with respect to its purpose, since the main purpose of the Mobileye does not require detection of powered-two-wheelers at this distance.

Trucks and cars are detected by Mobileye at higher distances than powered two-wheelers. There is a big difference between cars and trucks, which is logical considering the size of the different vehicle categories. In any case, the different curves found for cars and trucks (Figure 11.7) are caused by many more observations at higher distances for these two categories of vehicles. It appears that the most frequent value is about one second for all three ranges of speed and all three categories of vehicles. That leads to the conclusion that car drivers in general do not keep enough distance (time headway) at higher speed. Drivers do not sufficiently adopt their safety distance – measured as time gap - to the speed they are driving.

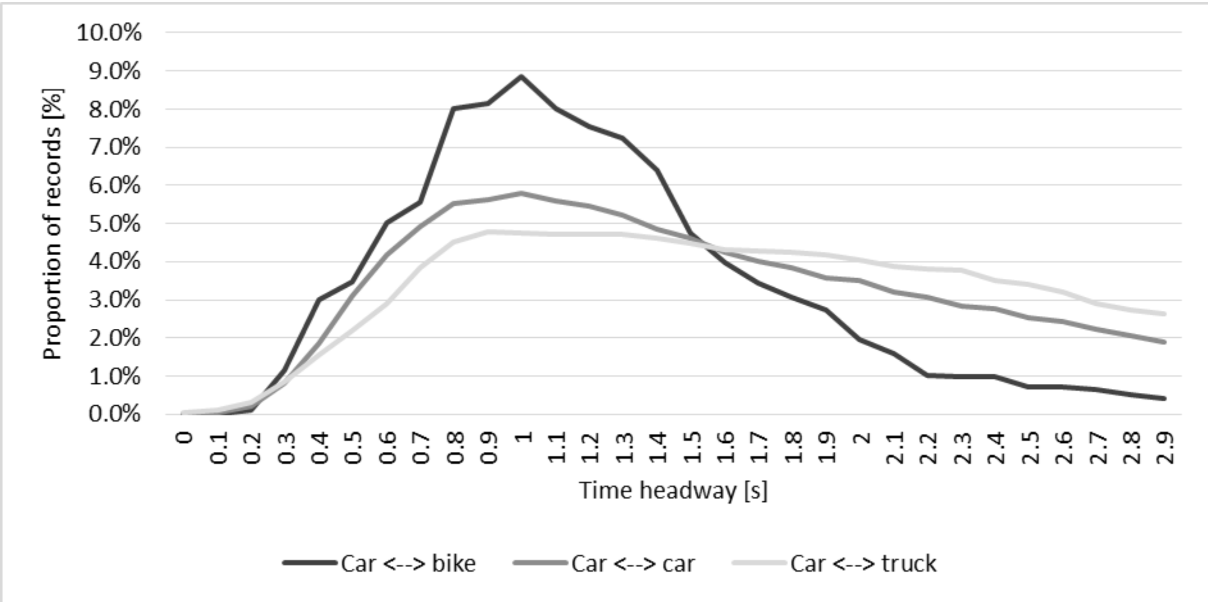

Figure 11.7: Distribution of time headway [s], driven speed > 85 km/h

11.3.2 Average Values of Time Headway by Speed

Figure 11.8 displays the proportion of records by speed category. It appears that the curves for cars and powered two-wheelers look similar, but differ in total numbers. The curve for trucks, however, looks very different. According to European law, heavy goods vehicles (i.e. goods vehicles with a gross design weight of more than 3.5 tons) have to be equipped with a speed limiter, which prevents them from driving faster than 90 km/h. There are some records with a measured speed higher than 90 km/h, which may most likely be caused by either fraud with heavy goods vehicles or the false detection of light goods vehicles as trucks by Mobileye.

As displayed in Figure 11.8, there were relatively few records of trucks at low speeds. The distribution suggests that there are much more heavy goods vehicles moving at higher speeds. It may be concluded that this is related to the roads they are moving on. Heavy goods vehicles, in particular the very big ones, are not frequent in dense urban traffic. They are vehicles for trunk roads and highways, where speeds are higher.

Another explanation could be that Mobileye more likely detects trucks at higher distances than it detects cars or powered two-wheelers, as already found a plausible explanation for other particularities above.

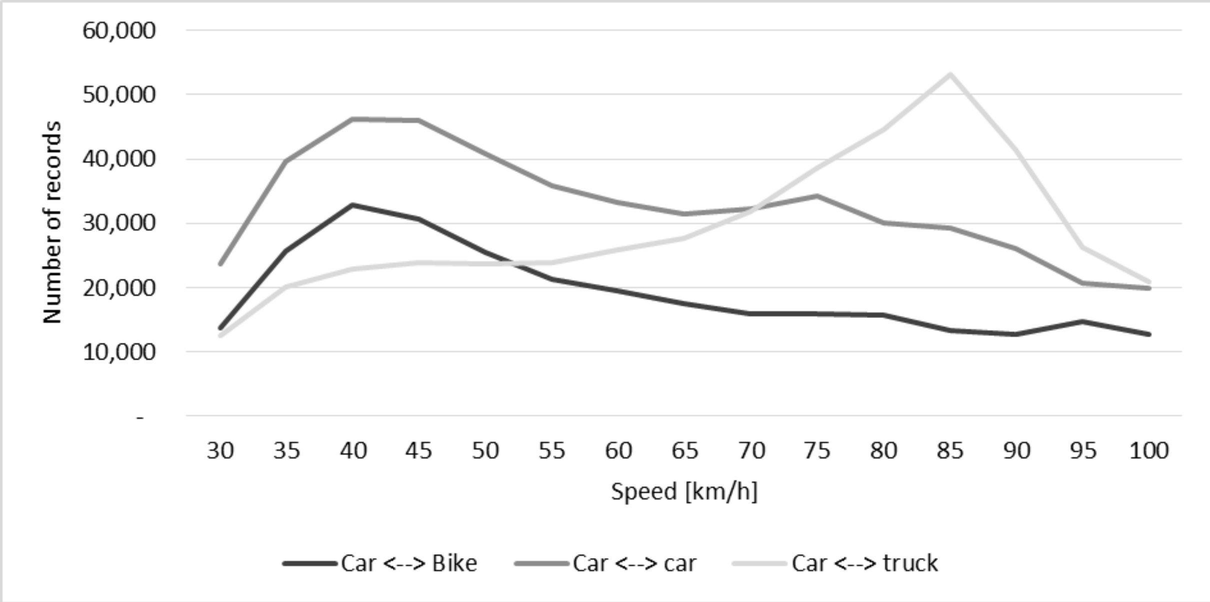

Figure 11.8: Number of records (N) by speed and vehicle type

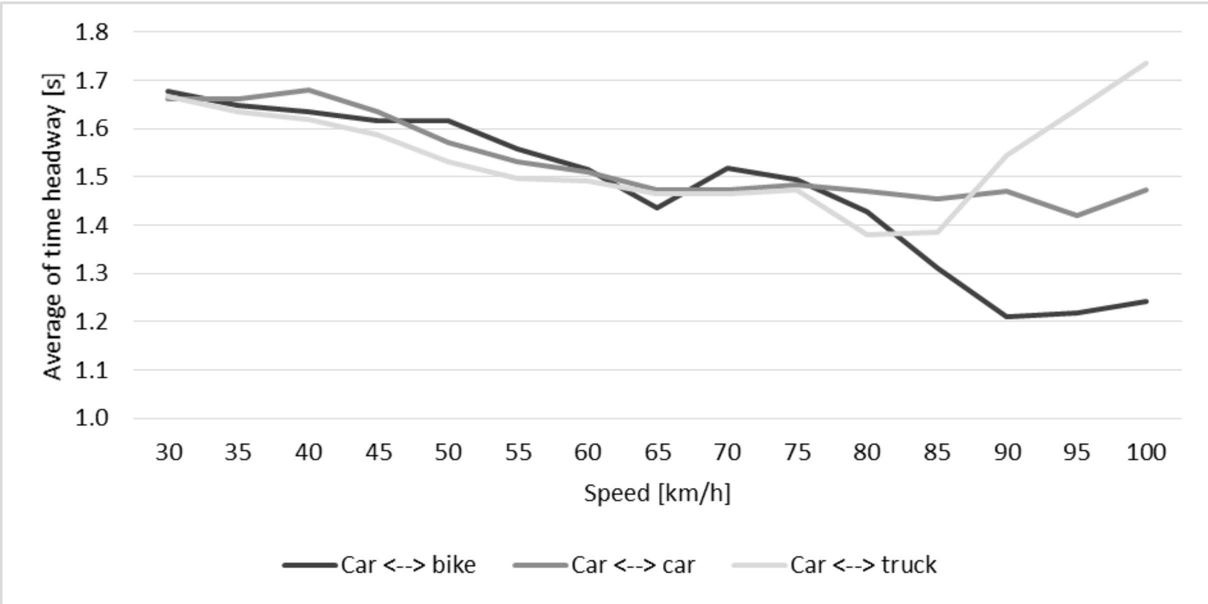

Figure 11.9: Average of distance [s] by speed and vehicle type

From the preventive point of view, the information in Figure 11.9 and Figure 11.10 could be considered alarming. Instead of keeping higher distances at higher speeds, the drivers do exactly the opposite. Although the length of a safety gap measured in time (time headway) automatically increases with higher speed (e.g. 1 second of time headway means a distance of about 14 meters at 50 km/h and about 28 m at 100 km/h, given vehicles move at the same speed), there should also be longer time gaps at higher speeds. This is necessary due to an increase of the difference in stopping distance among different vehicles of different brake performance, and a larger impact of reaction delay. In other words: If a vehicle with poor deceleration capabilities (e.g. a car with brakes in poor condition, a motorcycle rider with poor skills or a fully loaded truck) travels, at same speed, behind another vehicle with better deceleration properties and has to perform an emergency braking manoeuvre, the impact speed increases with the initial driving speed of the two vehicles. Hence, the general rule recommends to keep more time headway at higher speed.

As the results show, the opposite is the case. At least up to a speed of 90 km/h, drivers keep less time headway at higher speeds. There is no relevant difference with respect to what kind of vehicle is ahead. The analysis indicates dangerous behaviour by drivers, but is does not indicate particular dangerous behaviour against powered two-wheelers.

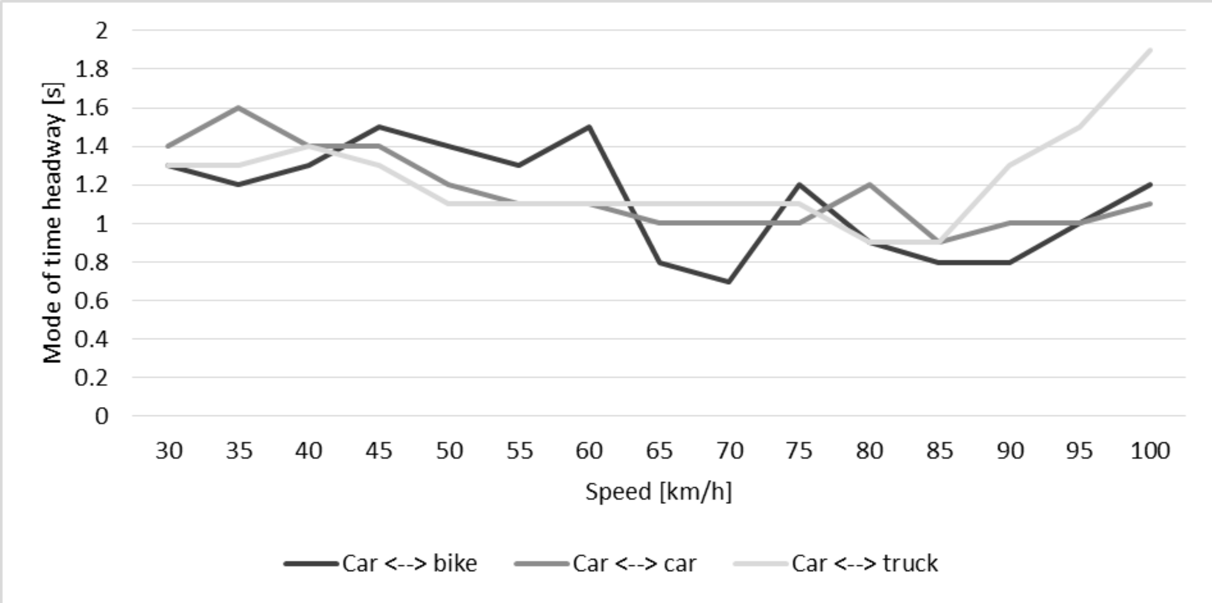

Figure 11.10: Mode of distance [s] by speed and vehicle type

11.3.3 Comparison to KFV's Data from Site-Based Observation

A speed limit of 50 km/h, with respect to speeds actually measured, is well comparable with speeds up to 60 km/h as displayed for UDRIVE data. Practically, the threshold of 60 km/h in UDRIVE data analysis was chosen because it would be most comparable to common speed behaviour where speed limits in Austria are set to 50 km/h.

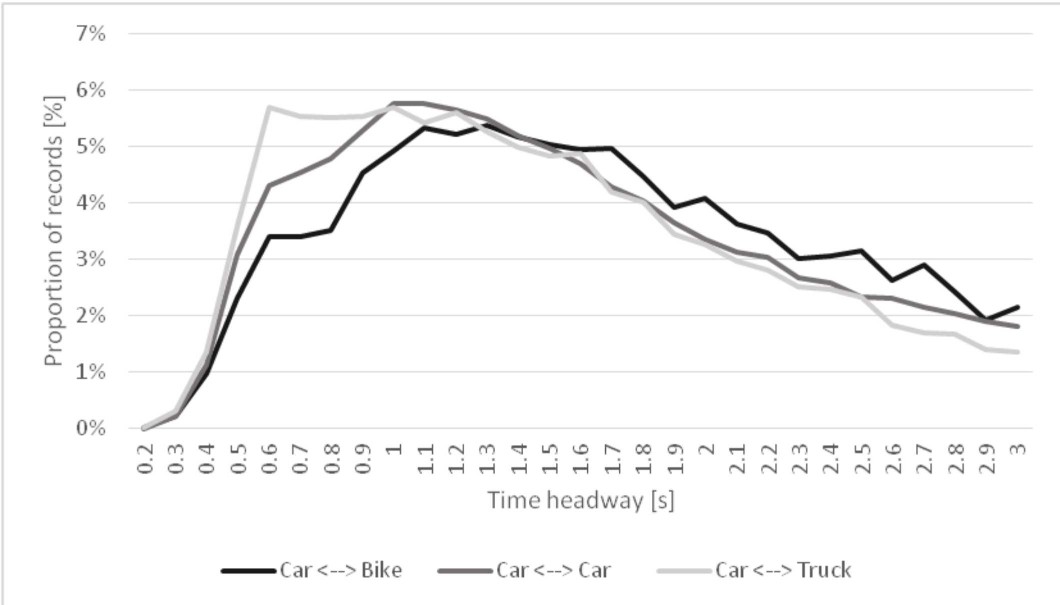

Figure 11.11: Time headway from side radar at 50 km/h speed limit by vehicle category

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The distribution of distance behind passenger cars (Figure 11.11) at a speed limit of 50 km/h looks quite similar to UDRIVE data; however, the mode differs. In UDRIVE data, the mode[4] of time headway (1.3 s) is remarkably higher than for the Austrian data (0.9 s). For distance behind powered two-wheelers, the curves for UDRIVE data and Austrian data are almost congruent, which means that in the Austrian data, there is a significant difference between cars and powered two-wheelers. The explanation for this difference most likely will be caused by methodology.

Mobileye's capability is limited to about 2 to 3 seconds, an exact value is not known. The side radar devices limit their detection of time gaps to 23 seconds. The same principle is valid for the difference between cars and trucks. For Mobileye, it is easier to detect a larger and closer object than a smaller object at a longer distance. On the other hand, the distances that are relevant for warning a driver are well covered by Mobileye.

Side radar devices were never mounted along highways. UDRIVE data, though, include driving on highways. This is important, since time headway and speed are typically higher on highways. This difference in methodology may be relevant for differences in results.

The hypotheses of a systematic difference between the site-based data and UDRIVE data is supported by the results for a speed limit of 100 km/h (Figure 11.12) and their difference to the site based data at 50 km/h speed limit. The differences between powered two-wheelers, cars and trucks found at 50 km/h are all bigger at 100 km/h.

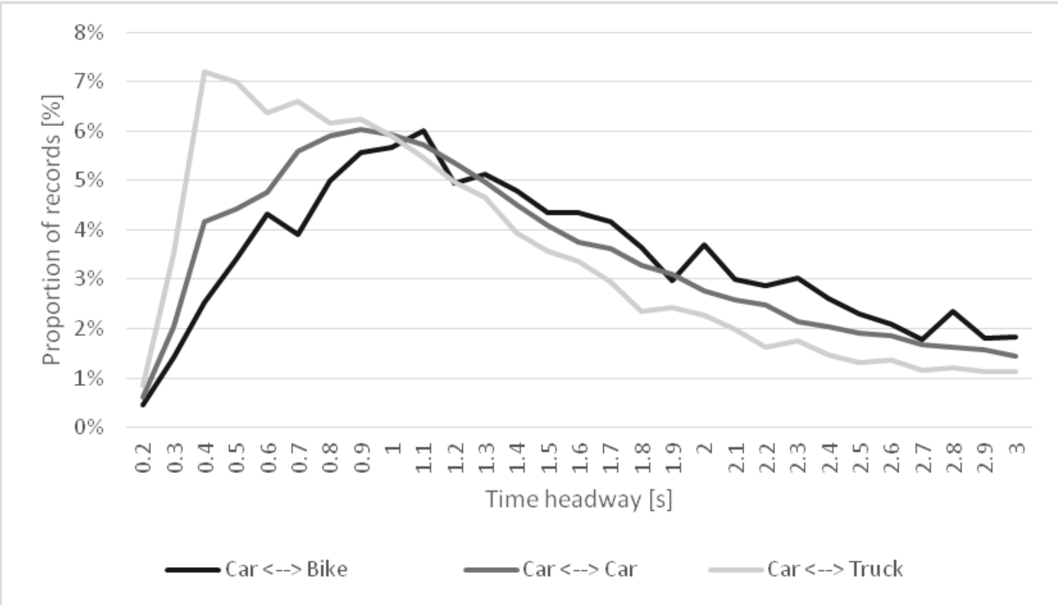

Figure 11.12: Time headway from side radar at 100 km/h speed limit by vehicle category from site-based data

Comparison of average values for distance by speed category also shows similarities between UDRIVE and site-based data. In particular, the curve for time headway behind cars is almost congruent in UDRIVE data and site-based data (Figure 11.13). Time headway behind trucks remarkably differs. According to site-based data, car drivers in Austria follow trucks closer than drivers in countries with UDRIVE car operation sites. However, the difference is not more than 0.15 s, which is about 10% of the total values. Time headway behind powered two-wheelers is even slightly higher in the Austrian site-based data over the whole range of

[4] Value of the 50th percentile

UDRIVE European Naturalistic Driving Study speeds, but the difference is less than one tenth of a second for all categories of speed. Nevertheless, the two methods of measuring time headway deliver similar results. There are some differences, but wherever differences appear, reasonable explanations can be found. It may be concluded that this comparison supports the assumptions that Mobileye delivers accurate and useful data for research on relative positions of different kinds of vehicles.

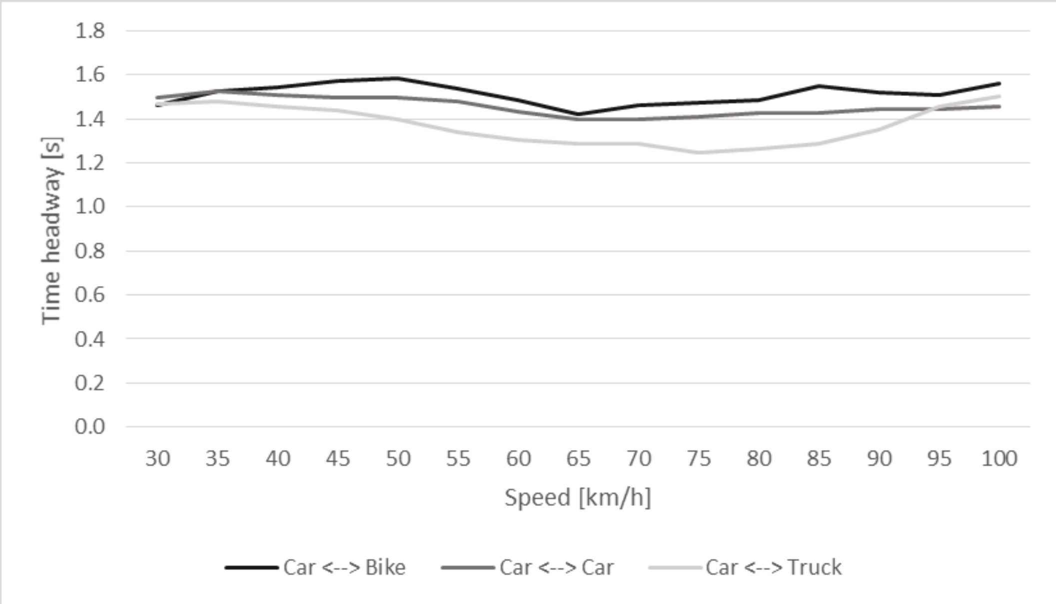

Figure 11.13: Time headway from side radar by speed and vehicle category

11.3.4 Time Headway by Vehicle Category, Speed and Country

Before focussing on time headway itself, it is necessary to look at comparability of data between the five countries with car operation sites. The number of records collected by category of speed may be considered a reflection of mobility of the UDRIVE subject vehicles in the various countries. As already shown above, driving speed is an important moderating variable for time headway. Hence, similar distributions of driving speeds in the five countries would be advantageous for a good comparison of time headway. Figure 11.14, Figure 11.15 and Figure 11.16 show these distributions for powered two-wheelers, cars and trucks.

In general, the graphs for all countries look quite similar. There are two exceptions to this: Data from the Netherlands are a general exception as the UDRIVE subject cars seem to have moved predominantly at speeds above 85 km/h, since most of the records for all three categories of vehicles were collected within this range of speed. The other exception appears with the Polish subject vehicles. Their distribution of records is similar to the other countries for cars and powered two-wheelers, but it is not for trucks. This may indicate that

- Trucks in Poland move less frequently at speeds above 70 km/h than trucks in other countries
- subject vehicles in Poland moved less frequently behind trucks at speeds above 70 km/h than subject vehicles in other countries
- There was no road within the operation area of the Polish subject vehicles, where cars would typically move behind truck at this range of speed. Most likely, the Polish cars did not use highways as frequent as subjects from other countries did, from whichever reason.

The data extracted from the database for this task did not give evidence whether one of these three of other circumstances caused this difference to the data in the other UDRIVE countries.

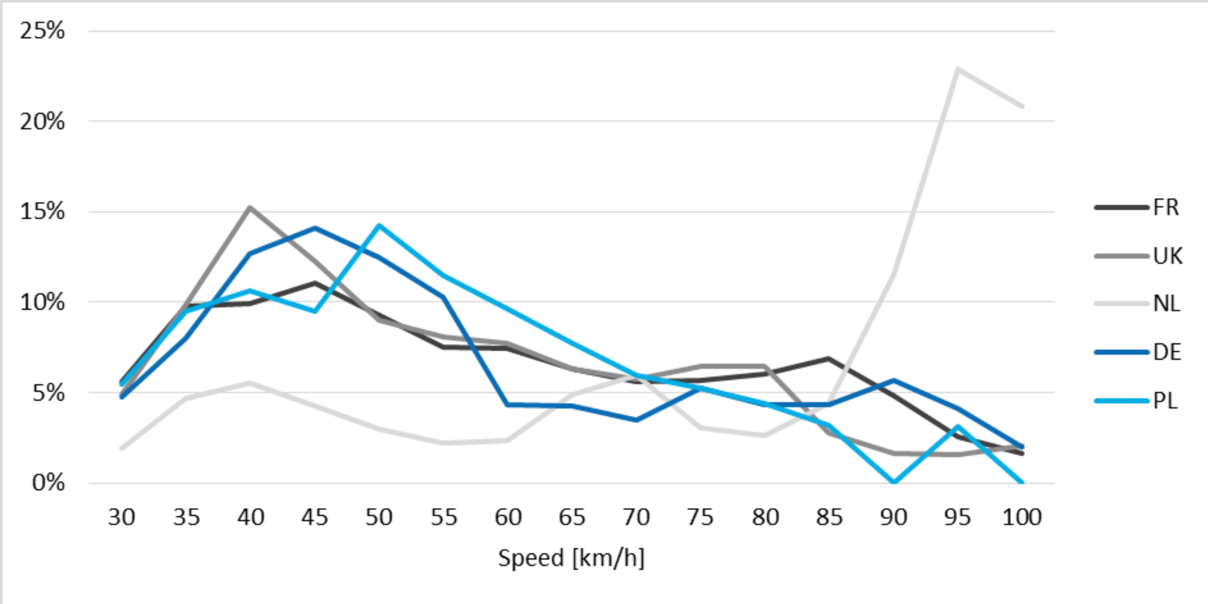

Figure 11.14: Distribution of records, cars following bikes, per country and speed from UDRIVE data

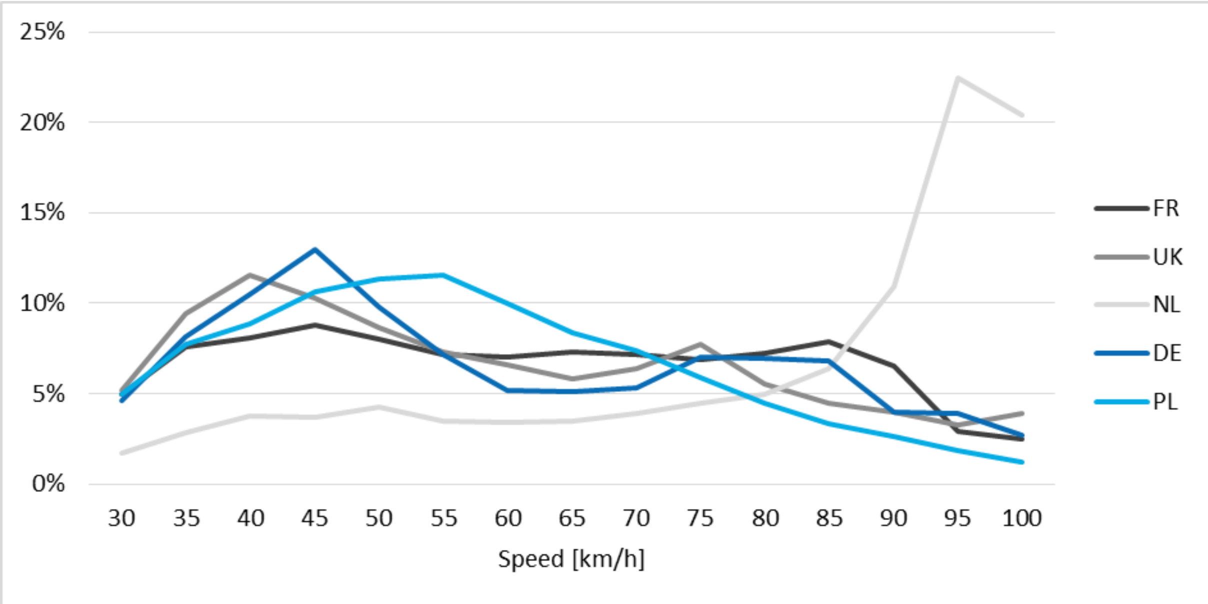

Figure 11.15: Distribution of records, cars following other cars, per country and speed from UDRIVE data

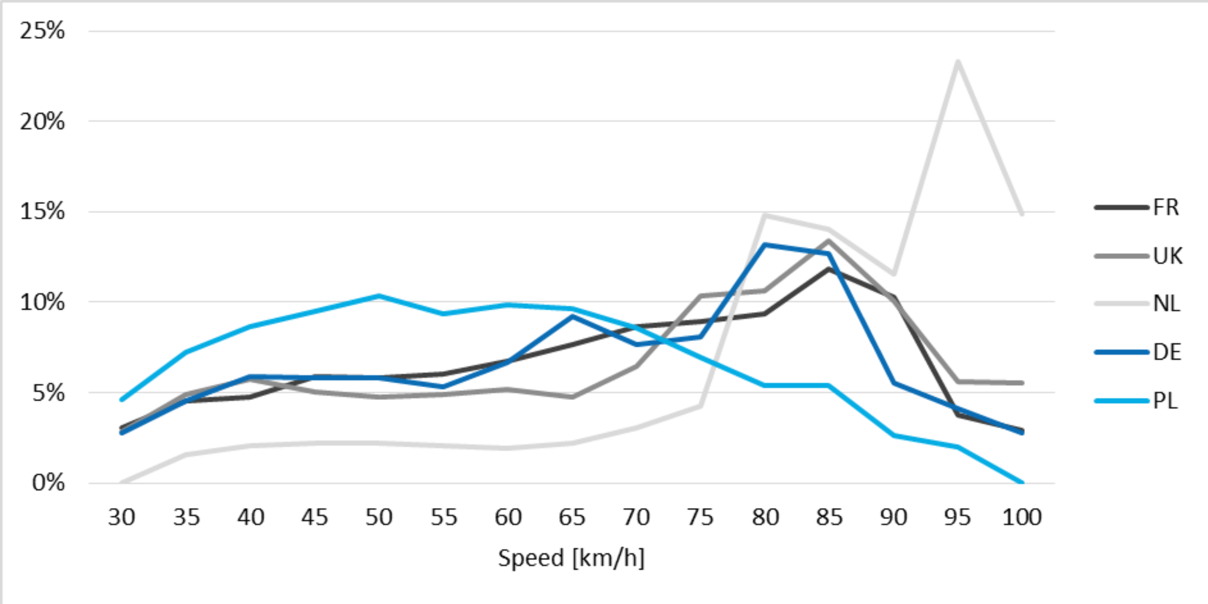

Figure 11.16: Distribution of records, cars following trucks, per country and speed from UDRIVE data

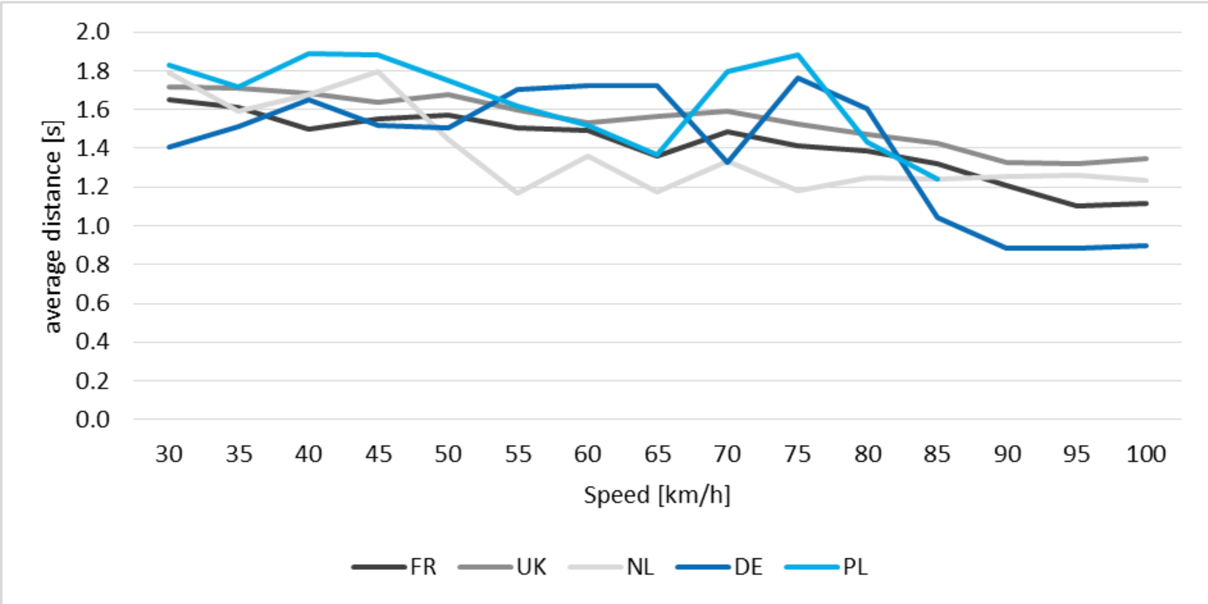

Figure 11.17: Average time headway [s] cars following bikes, by country and speed from UDRIVE data

Figure 11.17 showing the distances of subject cars behind powered two-wheelers clearly indicates that there are fewer records for powered two-wheelers than for other categories of vehicles. The curves in Figure 11.18 and Figure 11.19 are much smoother. Although the values lie within a range of about 0.4 s, there is no indication to conclude on drivers in one country following powered two-wheelers closer than in other countries. If we neglect the drivers from the Netherlands due to reasons indicated above. The data displayed in Figure 11.18 suggest that French drivers follow other cars about 0.2 seconds closer than drivers in the other countries do. As for trucks, the behaviour of the German drivers slightly differs from the drivers in all other countries: At medium speed, they keep a distance of about 0.2 s longer.

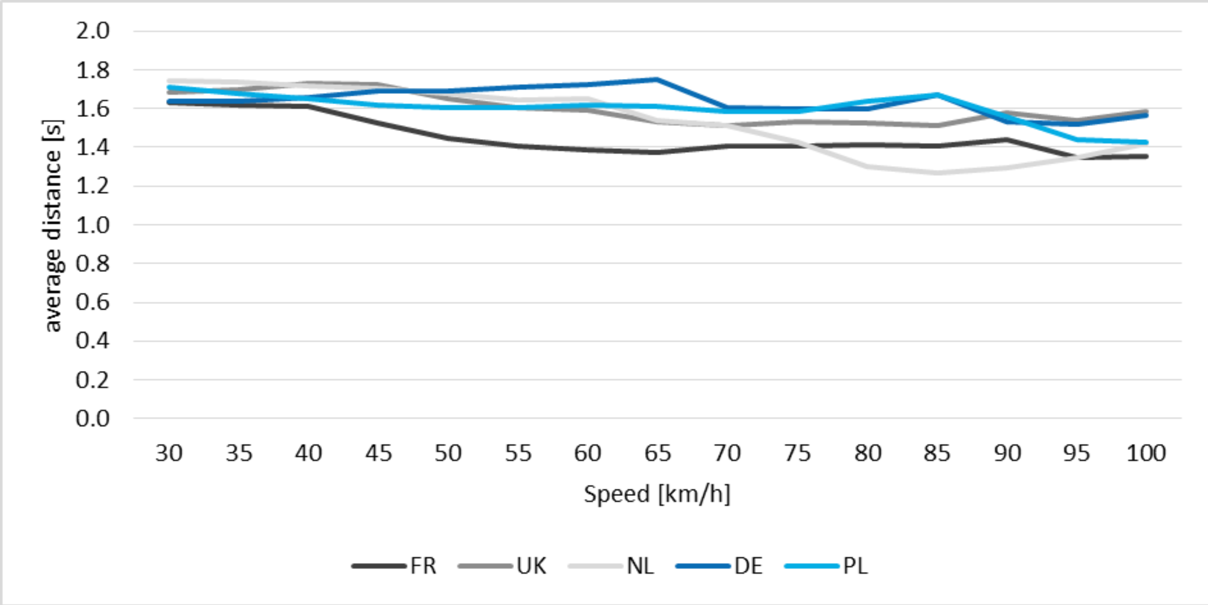

Figure 11.18: Average distance [s], cars following other cars, by country and speed from UDRIVE data

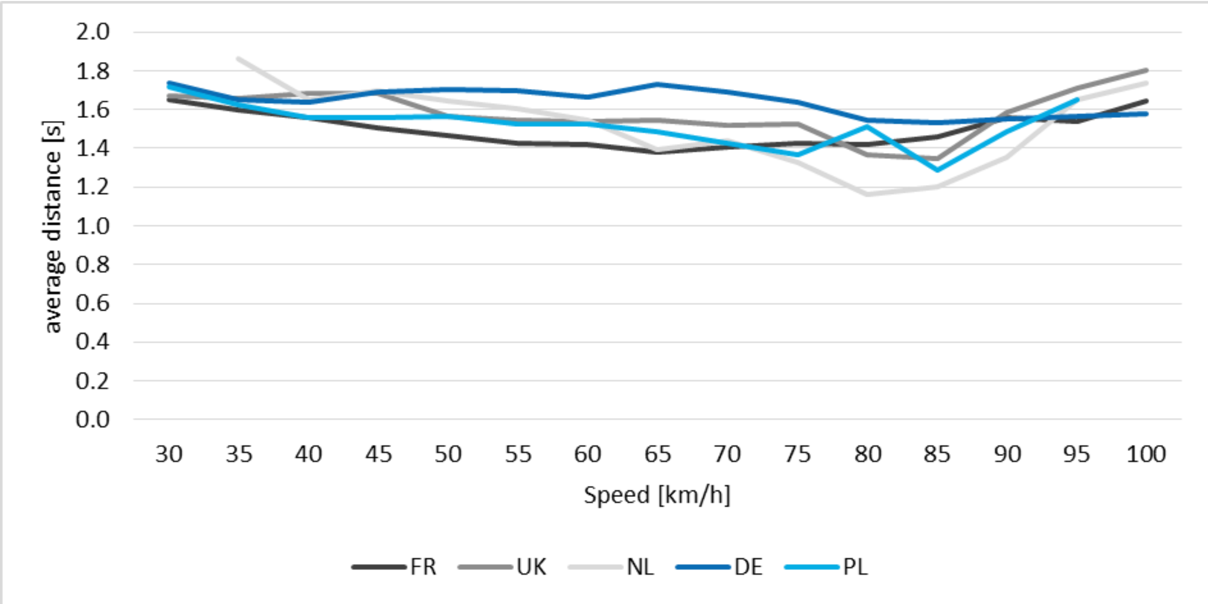

Figure 11.19: Average distance [s], trucks following cars, by country and speed from UDRIVE data

11.4 Discussion

11.4.1 Analysis of Time Headway

All the results show that the relatively low number of records of cars behind powered two-wheelers cause less smooth curves than for other vehicle categories, i.e. a low number of data caused a high variance. Nevertheless, the data seem more than good enough to provide a clear picture. The distribution of frequencies of different values for time headway found by Mobileye for three different categories of road users (powered two-wheelers, cars, truck) are very similar. There are minor exceptions to this general conclusion: At low speed, UDRIVE subjects followed trucks slightly closer than they followed powered two-wheelers and cars. At medium speed (60 to 85 km/h), values of 0.8 to 1.5 s are less frequent for powered two-wheelers, which means that UDRIVErs kept a longer distance behind powered two-wheelers.

Although it should be the other way round from preventive safety point of view, UDRIVErs in general kept less time headway at higher speeds than at lower speeds.

The comparison of UDRIVErs in different countries, showed only minor differences. Polish drivers had remarkably less records of driving behind trucks at typical highway speeds. German UDRIVErs kept more distance behind trucks at medium speed and French UDRIVErs seemed to follow other cars closer than the drivers from the other countries. For powered two-wheelers, all values for all UDRIVE countries at all speeds were within a range of 0.4 s, but there is no indication for differences between the countries.

If the numbers of records for time headway are controlled for their origin (i.e., counts of the respective country are weighted by the number of vehicles within the respective country), there is hardly any observed differences in time headway between following situations with cars, trucks and PTWs, as shown by Figure 11.20.

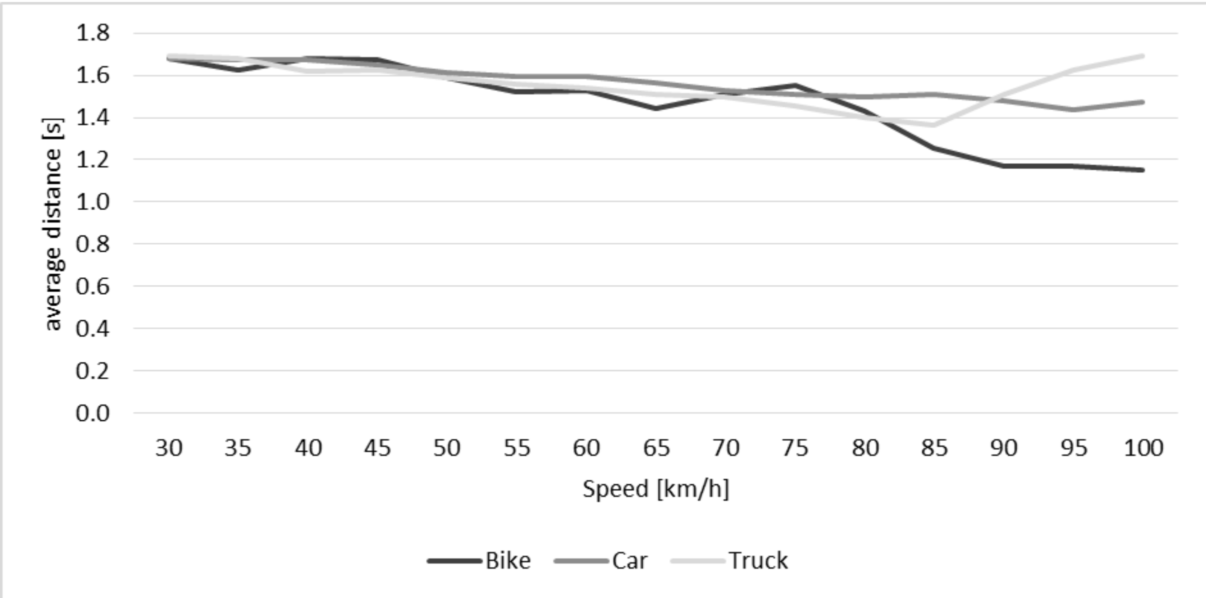

Figure 11.20: Average distance [s] per speed and vehicle type, all countries equally weighted

11.4.2 Comparison of Site-based and Mobile Naturalistic Data

Comparison of UDRIVE data to data acquired by site-based observation shows some differences. UDRIVE data would suggest that car drivers keep less distance behind trucks and the longest distances behind powered two-wheelers. However, it seems that the methodology has a significant impact to these differences: On the one hand, the capability of Mobileye is limited; it is not (and does not have to be with respect to its purpose) a long-distance sensor, while the site-based radar sensors record values of time headway up to 23 seconds. This difference could actually be overcome by limiting both data sets to the same maximum for time headway. However, there is another difference, which cannot easily be overcome: None of the side-radar devices was ever installed along a highway. It will be a task to carry out more analysis on these data after the end of UDRIVE and follow up on these two differences. Although it may not be of high importance for this task within UDRIVE, which focusses on powered two-wheelers; however, it was found that the distribution of time headway of cars behind other cars is very similar for the two methodologies.

11.4.3 Concerning Research Question and Hypothesis

The hypothesis of car drivers keeping less time headway behind powered two-wheelers being the reason for rear-end collisions has to be rejected according to the results of this research.

The hypothesis of little time headway being responsible for rear-end collisions of powered two-wheelers cannot be rejected by this research. The required or useful time headway behind a powered two-wheeler is not necessarily equal to the safety-gap required for cars behind other cars or trucks. On the contrary, the smaller silhouette of a powered two-wheeler which reduces the change of the size of its projection on the iris. Hence, it might be that driving behind a powered two-wheeler requires more time headway than driving behind a passenger car or a truck.

Dependencies on issues of conspicuity could not be answered by the data available. With a reasonable number of safety-critical events, it would have been possible to analyse whether conspicuity of the bike and its rider has an impact on timely recognition of a sudden decrease of the distance. However, this would preferably be subject to a controlled experiment in a laboratory.

11.4.4 Generalizability of Results; Limitations

There are some limitations within the setup of UDRIVE. There are about 120 car drivers at six different operation sites in six European countries, most of them within urban areas. Further, there are only small subject cars by one make only and a small number of models in the UDRIVE fleet. This limits the validity of the results twofold: On the one hand, the sample consists of subjects typically purchasing vehicles of this type; and second, the analysis does not consider vehicle-related parameters, such as the driver perspective (the panorama is different in a family van, in a sports utility vehicle as well as in a small sports car). The impression of driving speed might also be different in a high-power sports car or in a luxury limousine (e.g. with respect to internal noise).

There is some evidence that car drivers, who also ride motorcycles, have less accidents with powered two-wheelers (several sources cited in de Craen, 2011). If that is applied to the results of the UDRIVE analysis, drivers should – on their own – conclude that more time headway is required behind powered two-wheelers; and consequently adopt their behaviour according to such a believe. That is possible, but UDRIVE data on drivers do not include relevant information on the subjects to facilitate such an analysis.

11.4.5 Statistical Limitations

Analysis on statistical power is difficult or even impossible for the kind of data that were used for this analysis. In terms of the site-based data, there are 18 million records. Any, even the smallest difference would appear to be statistically significant. In terms of UDRIVE data, there is no sample to test. Actually the sample is a full record of the population, in other words, we have included any record in the UDRIVE, where the selected triggers applied. There is no selected sample, which to a certain likeability would reflect the actual status of the full population. Since there is no information on neither systematic nor random differences between the UDRIVEers and their vehicles and the rest of the driver population in the world (or at least the UDRIVE operation sites), significance tests, if they can be applied at all, are of limited value.

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12 Conclusions and discussion

12.1 Conclusions

12.1.1 Aim and background

Within UDRIVE there has been a specific focus on pedestrians, cyclists and powered two wheelers (PTW). These groups of road users are particularly vulnerable in traffic because they lack the protective shell that helps preventing serious injury once involved in a collision. In addition, these transport modes have several features that make them more prone to getting involved in a crash, e.g. related to reduced conspicuity and for the two-wheelers the difficulty to remain in balance, either or not in combination with high speeds. This type of factors make that pedestrians, cyclists and PTWs have a high risk of getting fatally or seriously injured in traffic.

Within UDRIVE, a large amount of 'naturalistic' data was collected to get more in-depth insight in the interactions of these groups with passenger cars and trucks. The aim was to identify and understand the everyday behavioural patterns in these interactions as well as the circumstances of conflicts or safety critical events in these interactions. The current Deliverable reported on the analyses and results of a number of specific interaction types.

12.1.2 Method

Data were collected by a naturalistic driving approach. In a naturalistic driving study data are collected by equipping people's own vehicle with various sensors and cameras and unobtrusively registering characteristics of the vehicle, the driver/rider and the environment over longer periods of time and during normal, everyday trips. The analysis of the interactions of car and truck drivers with pedestrians and cyclists was based on data collected from the participating cars and trucks. The analysis of the safety critical events and interactions of PTWs was also based on data from equipped, naturalistic riding PTWs. Data were collected between October 2015 and May 2017.

12.1.3 Features and size of sample

Starting point for the analyses of the pedestrian and cyclist interactions was the UDRIVE database with data from 186 car drivers in Great Britain, France, Germany, Poland, and the Netherlands, and from 48 truck drivers based in the Netherlands. By April 2017, the database consisted of a total of 42724 hours of car data, and 41397 hours of truck data. The results related to PTWs stem from 47 motorscooter (125CC) riders in Spain, resulting in a database 859 hours of PTW data. (Note that these numbers may be slightly different from other UDRIVE deliverables as the dataset was still growing at the time of writing the deliverables.) Depending on the exact research question, the analyses were conducted on a part of the database that fulfilled the selection criteria, e.g. right turning manoeuvres, straight sections, urban areas, et cetera. The next three sections briefly summarize the main findings with respect to pedestrians, cyclists and PTWs as based on the UDRIVE database analyses. For more background information and overviews of findings in previous, mainly non-naturalistic studies, we refer to the main text.

12.1.4 Main results and conclusions for cyclists

The analyses of the cyclist data looked at interactions between cyclists and both passenger cars and trucks.

Safety critical events in interaction

First, we investigated which behavioural and situational factors contributed to the occurrence of what was called safety critical events (SCEs) in these interactions, i.e. to real or near-crashes. A near-crash was defined as a situation which was not planned and required an immediate, urgent evasive manoeuvre by at least one of the conflict partners to avoid a crash. The analysis was based on just over 13,200 hours of car data from 125 drivers collected in Germany, Great Britain, France, Poland, and the Netherlands, and on around 6,000 hours of truck data from 41 drivers collected in the Netherlands.

The analysis of the car/truck-cyclist interactions revealed very few SCEs. Overall 11 SCEs were identified: three in interactions with a car, and eight in interaction with a truck. All were near crashes; no actual crashes have been found in the database. All SCEs took place on urban roads with a speed limit of 50 km/h or less. An explanation could be that there are less encounters between cyclists and motorised vehicles on higher speed roads. Given the small number of SCEs only a qualitative analysis was conducted. That indicated that the identified SCEs were caused by a combination of features of the infrastructure (a curve or a too narrow road), features of the manoeuvre (often overtaking), the presence of other traffic, and an error or unexpected behaviour of the cyclist (slowing down). Drivers didn't seem to make any judgment or performance errors in the observed SCEs. None of the drivers were involved in a secondary task or exceeded the speed limit when they started their evasive manoeuvre and nearly all drivers avoided a collision by further decreasing their speed.

Interactions at intersections and roundabouts

We then zoomed in on a specific type of interaction between vehicle drivers and cyclists, notably interactions on intersections and roundabouts. A first analysis looked at the looking behaviour of car drivers who turned right (left in the UK) passing the path of a (potential) cyclist who wants to go straight through the intersection. This is the typical scenario of a blind-spot crash. The final dataset consisted of 961 intersection manoeuvres by 69 drivers from France, the Netherlands, Poland, and United Kingdom. Furthermore, there were 826 roundabout manoeuvres by 46 drivers from France, the Netherlands, and United Kingdom. Approximately half of the data stem from the United Kingdom, due to it being available early in the project. The results show that on average car drivers actively check the blind spot, i.e. by looking over their shoulder, in around 8% of the cases at intersections and around 4.5% of the cases at roundabouts. Car drivers mostly (between 65 and 95% of the cases) looked in the direction of the road into which they intended to turn, followed by the directions 'elsewhere' and 'sidewalk'. Checking the 'blind spot' was done least often. There was a large difference between the investigated countries. On average, at intersections, Dutch car drivers checked their blind spot 6 times more often than drivers in the other three countries (in 27% of the cases), and at roundabouts they did so 21 times more often (in 19% of the cases). The most logical explanation for this difference is that in the Netherlands the prevalence of cyclists is higher.

A second analysis of the interactions at intersections and roundabouts focused on the looking behaviour of truck drivers. For this analysis the final dataset consisted of 159 right turn manoeuvres by 10 truck drivers and 209 roundabout manoeuvres by largely the same 10 truck drivers. All of the drivers were Dutch, driving in the Netherlands. On average, truck drivers were observed to check the blind spot in 19% of the cases at intersections and in 27% of the cases at roundabouts. Compared to Dutch car drivers, these Dutch truck drivers checked their blind spot somewhat less often at intersections, and somewhat more often at roundabouts. It should be noted, however, that some of the trucks may have had in-vehicle camera information about the situation in the blind spot, and hence could not be 'seen' to look by observing their head or eye movements.

Overtaking manoeuvres

Finally, we had a look at car-cyclist interactions during overtaking manoeuvres. A total of 147 overtaking manoeuvres were analysed. These were manoeuvres by 41 car drivers from France, Germany, Poland and United Kingdom, and concerned rural roads only. It was found that on average overtaking manoeuvres took 9.3s (± 3.5s) and the car speed during overtaking was 61km/h (± 15km/h).

A distinction was made between 'flying' overtaking and 'accelerating' overtaking. It is called a flying overtaking manoeuvre when the speed of the overtaking vehicle speed remains more or less constant before and during the overtaking. It is called an accelerating overtaking manoeuvre when the overtaking vehicle first stays behind the cyclist and then starts overtaking by increasing its speed. Around 70% of the overtaking manoeuvres was found to be 'flying', apart from Poland, where around 50% of the overtaking manoeuvres was 'flying'.

The main variable of interest in this analysis was the lateral distance between the car and the bicycle, during the actual overtaking manoeuvre. On average the lateral distance was 1.65m (± 0.64m). This is close to the lateral distance of 1.5m that most European countries require by law for overtaking. There were several factors, however, that affected the actual lateral distance. Lateral distances were larger when the speed of the car was higher, when the speed of the cyclist was higher, and when the overtaking vehicle was following another vehicle. Lateral distances were found to be smaller when the cyclist was positioned further away from the edge of the road (towards the centre of the road), when (in case of a flying overtaking manoeuvre) the car driver was a woman, and (in case of accelerative overtaking manoeuvres) when there was an oncoming vehicles.

12.1.5 Main results and conclusions for pedestrians

For detecting interactions between cars and pedestrians, the cars were equipped with a Mobileye system. This system provides continuous measures of the distance of the car to 'objects' around the car, including pedestrians, calculating, for example, the expected time-to-collision. A detailed analysis of the car-pedestrians interactions was based on car data from Great Britain and France. It could be concluded that the real dangerous interactions (real or expected conflicts) were associated with higher car speeds than less dangerous interactions, and required more severe braking. Just over 400 conflicts were identified, that could be clustered into four subgroups linked to the car's speed profile.

5. Conflicts that involved the highest speed group mainly concerned a situation in which the pedestrian (still) was on the pavement.
6. Conflicts that involved a group of car drivers that had just increased their speed before the conflict occurred; again generally a conflict conflicts in which with a pedestrian was who (still) was on the pavement.
7. Conflicts in which the high speed drivers probably had noticed the potential conflict well in advance, and had reduced speed to avoid a collision.
8. Conflicts in which the car driver had not reduced speed until very late, seemingly because he had not at all noticed the pedestrian. This group of potential conflicts contained the highest percentage of real conflicts (SCEs).

As indicated, the current study used the Mobileye system as a means to identify interactions with pedestrians. Originally, however, this system is meant to be an in-vehicle system that warns drivers when they approach a pedestrian. Based on the UDRIVE data it was investigated whether this system, if used as a warning device, would indeed be able to provide the correct and relevant information to the driver. It was concluded that in some cases an early alert as provided by Mobileye may be potentially beneficial for preventing a conflict to turn into a real collision. Analysis of the videos showed that the large majority of (expected) conflicts as identified by the system were indeed (potential) conflicts. Hence, the system is good and relevant for detecting potential conflicts with pedestrians. In around three quarters of these situations, the driver him/herself had spotted the pedestrian in time. In the still substantial share of remaining situations, a warning system could have been of help. A warning system can be expected less useful in conditions with relativly many pedestrians. In those cases car drivers appeared to be already more alert to pedestrians' presence and potential conflicts.

12.1.6 Main results and conclusions for PTWs

Where information about pedestrians and cyclists was inferred from the data collected by the instrumented cars and trucks, the information about the powered two-wheelers (PTWs) also comes from instrumenting the PTWs themselves, i.e. from Naturalistic Riding. The work on PTWs looked at the possibilities and challenges of identifying conflicts or safety critical events. Furthermore, it looked at characteristics of everyday riding with a special focus on speed choice and acceleration at urban intersections, and on the distance (time headway) between cars and PTWs on straight road sections.

The identification of safety critical events

Obviously, PTWs have their own very specific dynamics, posing specific requirements to the data collection equipment and to the interpretation of the collected data. Some of the previous attempts with Naturalistic Riding showed that one of the challenges is the identification of safety critical events (SCEs). In our study SCEs were identified by looking at a set of kinematics-related variables (including longitudinal acceleration, lateral acceleration, vertical acceleration, rotation speed) and identifying the extremes or outliers: the high-g events. For these events, the video material was studied to assess if there had actually been an SCE and in case it had, to identify the circumstances related to rider, other traffic and infrastructure.

Analyses were based on 497 hours of data (equalling 13.654 kilometres driven) from 39 riders in Spain. A total of almost 1,300 potentially relevant events were identified based on the motion-related variables. Because only around 70% of the video registrations were usable, around 500 events could be checked based on video registration. The vast majority of the identified events appeared to be related to a non-safety relevant manoeuvre, such as a speed bump, a tight curve, starting from or braking to a stand-still, entering or leaving a parking lot, etc. In other words there were a large amount of 'false alarms'. Only two safety relevant events were identified based on these high-g events. One was based on an extreme longitudinal acceleration (harsh braking) in a one directional dual lane situation where the view off a pedestrian who started to cross at a zebra crossing was blocked by vehicles in the other lane. The other was based on extreme lateral acceleration (swerving) due to a passenger car entering from a side road into the path of the motor rider. Obviously, based on this approach it is unknown how many SCEs were missed. Situations in which it is the other road user who takes evasive actions rather than the motor rider who might not even have perceived the potential hazard, will never be identified based on g-forces from the motor cycle.

Characteristics of everyday riding behaviour

This analysis focused on speed choice and acceleration by PTW riders in four common urban intersection scenarios: free flow followed by a right turn, free flow followed by a left turn, full stop followed by a left turn, and full stop followed by a right turn. The analysis was based on 7350 manoeuvres by 32 riders, where each rider featured at least 10 manoeuvres in at least one of the above scenarios.

There are two main findings in this study. First, significant differences have been found between the scenarios. Pair-wise comparisons showed that most scenarios were significantly different from each other on all measures, these being speed at the manoeuvre onset, speed at the manoeuvre offset, average speed, maximum speed, minimum speed, acceleration at the manoeuvre onset, average positive and negative acceleration, and maximum positive and negative acceleration.

The second main finding concerns a comparison between riders. Across riders significant differences have been found in speed choice and acceleration during manoeuvres, as well as in the time window surrounding full stops prior to the manoeuvres. Furthermore, riders appear to use a constant deceleration in the five seconds preceeding a full stop, but the magnitude of this deceleration varies across riders. These findings suggest that riders have different preferences (i.e., riding styles) regarding speed choice and acceleration.

If such preferences indeed exist, they may inform the development of intelligent warning systems on what is 'normal' and 'abnormal' riding behaviour. Furthermore, the existence of preferences warrants further research on whether groups of riders share similar preferences. This could be done with a bottom-up, or data-driven, approach (e.g., cluster analysis), or through a top-down approach (e.g., with behavioural questionnaires).

Time headway between cars and PTWs

This analysis focused on the time headway, i.e. the following distance expressed in seconds, on straight sections of roads between cars and PTWs in comparison to the time headway between two cars and between cars and trucks. For this analysis the starting point was the car. Data came from 140 car drivers from France, Germany, Netherlands, Poland and the United Kingdom who together had driven almost 650,000 km and waswhich were searched to identify relevant interactions. Final analyses included over one hundred million situations where the car was behind another car, over 6 million situations where the car was behind a truck and almost 370,000 situations where the car was behind a PTW. Different road types with different speed profiles were included in the analysis.

Overall, the time headways for following another car, a truck or a PTW were very similar. At lower driving speeds (< 50km/h) the average time headways were around 1.7s, at medium speeds (60 - 80km/h) the average time headways varied somewhat between 1.4 and 1.6s. At speed over 80km/h the time headway in car-car situations remained around 1.4s, but the time headway in car-truck situations tended to increase again to around 1.7s. Whereas the general picture showed very similar time headways for the different vehicle combinations there are two exceptions worth mentioning: cars followed trucks slightly closer than they followed other cars and PTWs, and at medium speed cars followed PTWs at a slightly longer distance than cars or trucks. There were hardly any differences between the five countries in the choice of time headway. We just saw that the German car drivers seemed to keep somewhat more distance behind trucks at medium speed, and the French car drivers seemed to keep somewhat less distance to other cars. Distances to PTWs were very comparable between countries.

All together the data did not show that car drivers tend to follow PTWs closer than cars or trucks. There was even an indication that car drivers followed at some larger distance.

12.2 Discussion and recommendations

12.2.1 Naturalistic Driving as a research method

Overall it can be concluded that Naturalistic Driving (ND) is a very interesting method to collect in-depth and valid insights in road user behaviour, also the behaviour of pedestrians, cyclists and motor riders. Other than for example in cross-sectional or experimental studies, ND offers the opportunity to study the ‘natural’ behaviour of road users in a variety of circumstances during a longer period of time. As such it gives a much better insight in what road users normally do and don’t.

A general disadvantage of ND studies is that it is a rather time consuming and consequently expensive research method, both related to the data collection equipment and to the data analysis phase which requires huge efforts for data annotation and data reduction. As a consequence, the number of subjects is generally fairly limited. This was also the case for UDRIVE. Whereas the many driving hours and driving kilometres resulted in huge amounts of data, relatively few drivers/riders were involved. Therefore, it is difficult to generalize the findings in the sample to the complete population of road users and road traffic situations. For further discussion of the features of the UDRIVE database we refer to deliverable D41.1: ‘The UDRIVE dataset and key analysis results’.

There are several developments that can be expected to reduce the workload of ND research substantially. First, in some cases, a less elaborate data acquisition system, e.g. a “DAS-light” (see deliverable D52.1: ‘The feasibility of using ND studies incorporating simple DAS as a tool for performance monitoring’) would reduce the resources needed for expensive equipment, integration and storage. Obviously, the usefulness of future NDs depends on the exact research questions and the related data requirements. Furthermore, techniques for automatic data identification, annotation and data reduction (e.g., machine learning algorithms) are developing rapidly and can also be expected to reduce required manpower in (the near) future.

Despite some disadvantages, ND research has, however, proven to be very useful for getting information about the characteristics of day-to-day road behaviour and the way interactions take place, as well as the progression of conflicts and their circumstances. This was already known from previous ND studies that focused on motorised vehicles (e.g. Dingus et al., 2016), but has now been found to be also true for the area of pedestrians and (powered) two-wheelers.

12.2.2 Naturalistic Driving for generating hypotheses

ND data, even if not representative due to limited sample sizes, are a good basis for generating knowledge for developing concrete hypotheses that can then be tested in more experimental conditions. Just as an example, the current ND data showed that in some instances the distance between a car and a bicycle during overtaking is very small. The data also showed that this depended on several factors related to the road lay-out and the behaviour of the driver or the cyclist. Several of these factors, however, are known to be interdependent, e.g. road width, car speed, cyclist's position on the road. A subsequent well demarcated (quasi) experimental design could shed light on these supposed interdependencies and disentangle their relative influence.

The interaction between (partly) automated cars and pedestrians and (motorised) two-wheelers is a promising future area for using an ND approach. It would be an important basis for generating testable research hypotheses, in particular because this type of car is as yet not very common in everyday traffic. Consequently, traditional roadside observations are not very effective and would produce insufficient relevant information. In addition, current knowledge about the challenges and potential problems in these type of interactions in as yet insufficient to formulate scientifically-based hypotheses. Providing a sample of partly automated cars with ND equipment can be expected to be a useful way of identifying relevant aspects for further targeted research.

12.2.3 Further exploiting the UDRIVE database

It must be noted that the analyses reported in the current Deliverable are just the tip of the ice berg. The UDRIVE database is very rich and many more questions can be studied based on the currently available data. In addition, some of the analyses reported here would benefit from additional analyses. An example is the finding concerning the blind spot checks of car and truck drivers in turning manoeuvres. The data indicated that relatively few car and truck drivers actively checked the blind spot for cyclists when making a right (left in the UK) turn at an intersection or roundabout. It would be useful to explore whether specific road or traffic conditions can be identified that affect the visual search strategies of drivers or to see whether there is a relationship with particular driver characteristics (e.g. age, gender, driving experience).

Just as another example, the data on the car-pedestrian interactions indicated that there were less conflicts in situations with many pedestrians. This finding supports what is known as the safety-in-numbers effect (Elvik & Bjørnskau, 2017). It would be interesting to explore further in what way drivers behave differently in the presence of many rather than few pedestrians. The finding that Dutch drivers more often checked the blind spot for the presence of cyclists could also be related to the safety-in-numbers effect, since the Netherlands is a typical cycling country. It would be interesting to see if this effect only applies in the actual presence of cyclists or that it can also be based on just the likelihood of encountering a cyclist and the expectations of the drivers. The current ND database provides the possibility for such an additional analysis.

Finally, subsequent analyses of the UDRIVE data would allow for further identification of safety critical events and their circumstances. Unfortunately, for the current analyses only limited effort was available for identifying (potential) safety relevant events in pedestrian/cyclist-vehicle interactions and for PTWs. These efforts produced a fairly limited number of safety critical events for cyclists and powered two-wheelers. The actual number of (potential) conflicts in pedestrian-vehicle interactions was larger, due to other, less strict criteria. For subsequent analyses, it is advisable to elaborate and redefine the methods for defining and identifying safety relevant events. This appeared to be a special challenge for the group of PTWs. Using triggers based on severe g-forces produced large amounts of false alarms which is probably related to the characteristics of the vehicle, but to some extent maybe also to the characteristics of its users. More in general, it should be noted that this kind of 'automatic' identification of safety relevant events based on triggers produced by the instrumented vehicle will logically lead to misses of relevant events that were not at all noticed by the driver/rider but that were 'solved' by an evasive response of the conflicting partner, e.g. a crossing pedestrian stepping backwards or a cyclist steering away into pavement to avoid an approaching car.

12.2.4 Towards (more) naturalistic riding, cycling and walking?

In case of pedestrians and cyclists the current study had to rely on data gathered by the naturalistically instrumented cars and trucks and potential conflicts occurring in day-time. As a result, it is only possible to study their behaviour in these interactions. Even though many of the fatal pedestrian and cyclist crashes do indeed occur in collisions with vehicles, Dutch data show that a large share of the serious injury cyclist crashes occur as a result of a collision or fall without the (direct) involvement of a motorised vehicles (Weijermars et al., 2016). The circumstances of this type of crashes remain invisible when just looking at vehicle-cyclist interactions. Though far less documented, a similar reasoning could apply to pedestrians. Instrumenting cyclists and pedestrians and registering their everyday trips, i.e. naturalistic cycling and naturalistic walking, would provide more insight in their traffic participating and the problems they encounter from their own perspective. In addition, it would allow for the identification of safety relevant events in interaction with motorised traffic where the driver did not or hardly react, and which, consequently, would otherwise remain undetected (see also previous section). There have already been several initiatives for naturalistic cycling in Europe (e.g. Dozza & Werneke, 2014; Schleinitz et al., 2017), and it would be great if efforts across Europe could be aligned and feed into a joint database. Naturalistic walking, requiring the unobtrusive collection of data through instrumenting pedestrians, might be more difficult to realise, but it could be worthwhile to consider the options of a naturalistic-light-version. Finally, the Naturalistic Riding studies so far (e.g. Wear et al., 2011; Pommer et al., 2014), as well as the current study in the UDRIVE framework, showed that reliable and robust data collection is not at all obvious for this type of vehicle. However, the current study can form a useful base for further development of the naturalistic riding methodology and equipment.

In sum, UDRIVE has defined in more detail the behaviour of car drivers, truck drivers and PTW riders in interaction with vulnerable road users. These interactions have been studied at varying levels of criticality, ranging from Safety Critical Events and blind spot checks to overtaking manoeuvres and everyday riding. The findings have given rise to recommendations on vehicle safety, for awareness campaigns and training, and on the design of road infrastructure (for more details, see deliverable D51.1: 'Recommendations for safety and sustainability measures'). It is our hope that the recommendations, once implemented, will improve the safety of vulnerable road users, and in this way contribute to the EU target (European Commission, 2010) of halving the number of road deaths by 2020.

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List of abbreviations

Abbreviation	Meaning	Comments
ADAS	Advanced Driver Assistance Systems	
AEB	Automatic Emergency Braking	
AWS	Advance Warning System	
DZ	Danger Zone	Relates to ME warning
FCW	Forward Collision Warning	
FOV	Field Of View	
IR	Infra Red	
LB	Location Based	Relates to control
PCW	Pedestrian Collision Warning	Relates to ME warning
PSM	Propensity Score Matching	
PTW	Power Two Wheeeler	
SCE	Safety Critical Event	Concerns crashes and near-crashes
TTC	Time To Contact/ Time To Collision	
VRU	Vulnerable Road Users	Relates to pedestrians, cyclists and PTWs
km/h	Kilometres per hour	
m	Meters	
abs	absolute	
acc	Acceleration	
gyro	Motion measured by gyroscopic sensor(s)	
ABS	Anti-lock braking system	
DE	Germany	
FR	France	
NL	The Netherlands	
PL	Poland	
UK	United Kingdom	

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Appendix A Annotation safety critical events with vulnerable road users

In Appendix A an overview is shown of the variables used for the annotation of safety critical events involving cyclists and safety critical events involving pedestrians. The variables that are similar to the variables in the general UDRIVE codebook are named and those that are added or changed are fully explained. Descriptions of all variables can be read in the UDRIVE codebook, see deliverable D41.1 'UDRIVE synthesis of results'.

A.1 Safety critical events involving cyclists

An overview is given of the variables used for the annotation SCE's involving cyclists. The chapter and paragraph is stated wherein the variable can be found in the original codebook. The variables that were used to describe safety critical events are shown in table A.1. The adjusted variables are described in paragraph A.1.1.

Table A.1 An overview of used variables and the chapter and paragraph wherein the variable can found in the UDRIVE codebook

VRU-Related variables	**Chapter 1.9**
- VRU type	Par. 1.9.1
- VRU age	Par. 1.9.2
- VRU gender	Par. 1.9.3
- VRU secondary task	Par. 1.9.4
- VRU impairment	Par. 1.9.5
Environment and infrastructure variables	**Chapter 1.4**
- Weather	Par. 1.4.1 (adjusted)
- Light condition	Par. 1.4.2
- Locality	Par. 1.4.4
- Road type (design based)	Par 1.4.5
- Intersection type (only for intersections)	Par 1.4.8
- Intersection priority situation (only for intersections)	Par 1.4.9
- VRU facilities	Par. 1.4.10
VRU conflict interaction	**Chapter 1.5**
- Conflict Outcome	Par. 1.5.3
- Crash not with SV	Par. 1.5.7
- Begin time SCE	
- Number of interactions	Par. 1.5.1
- Interaction class	Par. 1.5.2
- Interaction type	Par. 1.5.5
- Interaction partner type	Par. 1.5.6
- Conflict severity	Par. 1.5.4
- Visual obstructions	Par. 1.5.8
- Precipitating event	Par. 1.5.9
- Precipitating event start	Par. 1.5.10
- Surprise reaction	Par.1.5.11
- Evasive manoeuvre	Par. 1.5.13
- Evasive manoeuvre time	Par. 1.5.14
Driver state/distraction	Chapter 1.7
- Driver drowsiness	Par. 1.7.6
- Driver impairment	Par. 1.7.7
- Secondary task	Par. 1.7.1 (Adjusted)
Additional information	**Chapter 1.10**
- Narrative	1.10.1

A.1.1 Adjusted variables

- Begin time SCE
    - Description: The point in time where the SV and cyclist are closest together. If there are multiple SCE's with cyclists, take the first one and write it down in comments.
- Weather
    - Description: Weather type in the segment.
    - Categories:
        - 1: Good sight
        - 2: Bad sight (For example because of heavy rain, dark, fog, snow)
        - 3: Unsure
- Secondary task
  Description: Driver was involved in a secondary task before the SCE. If there are multiple secondary tasks present, select the task with the most modalities involved.
    - Categories:
        - 1: Visual
        - 2: Auditory
        - 3: Manual
        - 4: Visual and Auditory (e.g., looking at conversation partner)
        - 5: Visual and Manual (e.g., texting)
        - 6: Auditory and Manual (e.g., calling)
        - 7: Visual and Auditory and Manual
        - 8: Unknown

A.2 Safety critical events involving pedestrians

Central Annotation categories for PCWs

- **Record.Name/ Driver.ID/ Operation.Site/ Start.Time/ End.Time**
- **Annotator ID**
- **Video.Face/ Video.Hands/ Video.RoadAhead/ Video.Left/ Video.Right** - Good/ Bad/ Unknown
- **Segment.Valid** – Existing interaction of a vehicle with VRU, while the vehicle is moving forward and the VRU is seen in a close distance - Yes/ No/ Unknown
- **VRU.NR.Relevant** - How many VRUs related to the PCW are present - 1/2/3/Many/ Unknown
- **VRU.Type1-4** - Pedestrian/ Cyclist/ PTW/ Group pedestrians/ Group cyclists/ Group PTW/ Mix / Two-wheeler unknown/ Unknown
- **VRU.Age1-4** - Child (or group)/ Teenager (or group)/ Adult (or group)/ Elderly (or group)/ Mix/ Unknown
- **VRU.Gender1-4** - Female/ Male/ Mixed group/ Unknown
- **VRU.ST1-4** - No secondary tasks/ Manual interaction/ Calling/ Talking/ Listening/ Smoking/ Other/ Unknown
- **VRU.Impairment1-4** - Obviously impaired/ No obvious impairment/ Unknown
- **Weather.VRUped** - No Adverse Conditions/ Wind Gusts/ Fog/ Mist, Light Rain/ Raining/ Snowing/ Sleeting/ Rain and Fog/ Snow, Sleet and Fog/ Other/ Unknown
- **LightConditionsVRUped** - Dawn/ Daylight/ Dusk/ Darkness, lighted/ Darkness, not lighted/ Unknown
- **RoadType.VRUped** - Dual Carriageway Multiple lanes/ Single Carriageway / Wide Lane Road/ Single Track Road/ Parking lot, ramp/ Entrance, exit ramp/ Driveway, alley/ Gravel road/ Intersection/ Other/ Unknown
- **Locality.VRUped** - Open country/ Open Residential/ Moderate Residential/ Business, industrial/ School, church, playground/ Urban, Interstate, bypass, divided highway, controlled access/ Bypass, divided highway, access not controlled/ Other/ Unknown

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- **VRUfacilities.VRUped** - No VRU facilities/ Zebra crossing/ Pavement / Bicycle lane/ Bicycle track/ Bicycle street/ Expanded Bicycle Stacking Lane/ Unknown
- **IntersectionType.VRUped** - Not an intersection/ X Intersection/ T Intersection/ Y Intersection/ Roundabout/ 5 or more legs/ Merging lane/ Passing by merging lane/ Exit or turning lane/ Complex intersection
- **Conf.Int.Class1-4** – Classical/ Run-Off-Road / Proximity / Non-Conflict/ Unknown
- **Conf.Int.Outcome1-4** – Crash/ Near-Crash/ Crash-Relevant/ Non-Participant Conflict/ Not applicable/ Unknown
- **Conf.Int.Severity1-4** – Most Severe/ Moderate / Minor / NA/ Unknown
- **Conf.Int.Type1-4** – Rear-end, striking/ Rear-end, struck / Road departure / Sideswipe, same direction/ Opposite direction/ Straight crossing path/ Turn across path/ Turn into path/ Backing, fixed object/ Backing into traffic/ Other/ Unknown
- **Conf.Int.Partner1-4** – Vehicle/ VRU/ Animal/ Other/ Unknown
- **Conf.Int.PartnerCrash1-4** –
- **VisualObstruction1-4** - No obstruction/ Rain, snow, fog, smoke, sand, dust/ Reflected glare/ Sunlight/ Headlights/ Curve or hill/ Building, billboard, or other roadway infrastructure design features/ Trees, crops, vegetation/Vehicle/ Splash or spray of passing vehicle/ Vehicle system or features/ Other obstruction/ Vision obscured - no details/ Unknown whether vision was obstructed.
- **Precipitating.Event -** SV Loss of control/ Subject vehicle action/ Other vehicle action / Pedestrian related actions/ Animal related actions/ Object related
- **Precipitating.Event.Time**
- **SCE -** existence of a conflict (classical conflict according to the code book is present) and/or of an evasive maneuver - Yes/ No/ Unknown
- **Surprise.React –** Yes/ No/ Unknown
- **Surprise.React.Time**
- **Evasive.Man –** No driver present/ No reaction/ Braked /Released brakes/ Steered/ Braked and steered/ Accelerated/ Accelerated and steered / Other actions/ Unknown if action was attempted/ NA
- **Evasive.Man.Time**
- **Drowsy.Driver -** Alert/ Possibly drowsy/ Clearly drowsy/ Unknown
- **Impaired.Driver -** Obviously impaired/ No obvious impairment/ Unknown
- **Hand.on.Wheel –** None/ Both hands/ One hand/ Unknown
- **SecondaryTask.Driver1-4 -** None/ Cell phone1/ Electronic device/ Food and drink/ Smoking/ Personal grooming/ Reading and writing/ Controls/ Interaction - object/ Interaction - passenger/ External/ Other/ Unknown
- **Eyes.on.Road** – Yes/ No/ Unknown
- **VRU.Early.Spotted** – Is the VRU present during the PCW event was spotted for some time before the event or he suddenly appeared. Yes/ No/ Unknown
- **Narrative**

Appendix B Annotation right turn manoeuvres

In Appendix B an overview is given of the variables used for the annotation of right turn manoeuvres. The variables that are the same as the variables in the general UDRIVE codebook are named and those that are added or changed are fully explained. Descriptions of all variables can be read in the UDRIVE codebook, see deliverable D41.1 'UDRIVE synthesis of results'.

The variables that were used to for the annotation of right turn manoeuvre are shown in Table B.1. The added and adjusted variables are described in paragraph B.1.1.

Table B.1 An overview of used variables and the chapter and paragraph wherein the variable can found in the UDRIVE codebook

Round 1 | Identifying valid segments	
- Manoeuvre direction	
- Manoeuvre location	
- Manoeuvre timing	
- Manoeuvre speed	
- Video quality (face, cabin, front, blind spot)	Par. 1.3.3 (adjusted)
Round 2 | General attributes	**Chapter 1.4**
- Weather	Par. 1.4.1 (adjusted)
- Intersection type	Par. 1.4.8 (adjusted)
- Intersection Primary/ Secondary Road	Par. 1.6.5
- Priority regulation	Par. 1.4.9
- Facilities for pedestrians	Par. 1.4.10 (adjusted)
- Facilities for cyclists	Par. 1.4.10 (adjusted)
Round 2 | Pre manoeuvre	
- Manoeuvre start	
- Traffic density	Par. 1.4.12 (adjusted)
- VRU early presence	
- VRU presence own direction	
- VRU presence opposite direction	
- VRU presence front left to right	
- VRU presence front right to left	
- Secondary task pre manoeuvre	Par. 1.7.1 (adjusted)
- Visual obstruction obstacles	Par. 1.5.8 (adjusted)
Round 2 | During manoeuvre	
- Manoeuvre end	
- Secondary task during manoeuvre	Par. 1.7.1 (adjusted)
- Manoeuvre enter encroachment zone	
- Manoeuvre leave encroachment zone	
- Gaze	Par. 1.7.4 (adjusted)

B.1.1 Adjusted and added variables

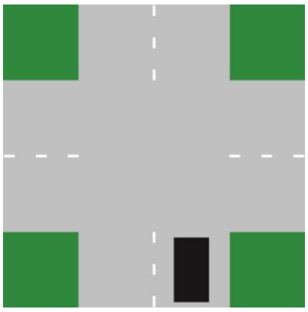
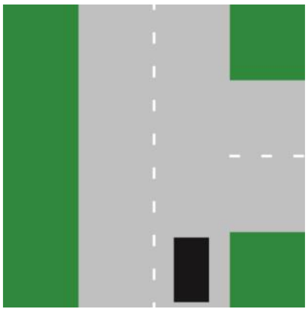
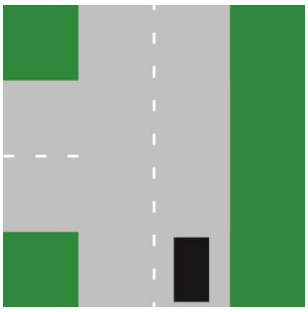
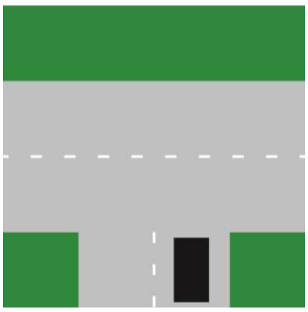
Round 1 – Identifying valid segments

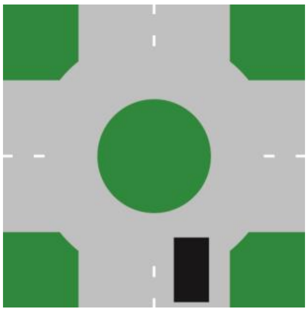
- Valid Manoeuvre Direction
  - Description: Select whether the direction of the manoeuvre is correct. For non-UK countries the manoeuvre is turning right, in the UK the manoeuvre should be left.
  - Categories:
    - 1: Correct
    - 2: False
    - 3: Unsure
    - 4: No manoeuvre in segment
- Valid Manoeuvre Location
  - Description: Select the location of the manoeuvre
  - Categories:
    - 1: Intersection
    - 2: Roundabout
    - 3: Other
    - 4: No manoeuvre in segment
- Valid Manoeuvre Timing
  - Description: Do the videos correspond with the selected segment and speed? Is there a delay in timing?
  - Categories:
    - 1: Match
    - 2: Delay
    - 3: No manoeuvre in segment
- Valid Manoeuvre Speed
  - Description: Is the shown speed data plausible?
  - Categories:
    - 1: Speed data plausible
    - 2: Speed data NOT plausible
    - 3: Unsure
- Video Quality DriverFace
  - Description: Is the driver's face visible?
  - Categories:
    - 1: Full
    - 2: Partial
    - 3: Not visible
    - 4: Upside down – Full
    - 5: Upside down – Partial
    - 6: Upside down – Not visible
    - 7: No video
- Video Quality Cabin; Video Quality FrontLeft; Video Quality FrontMiddle; Video Quality FrontRight; Video Quality BlindSpotLeft; Video Quality BlindSpotRight
  - Description: Quality of the camera view
  - Categories:
    - 1: Good
    - 2: Bad
    - 3: Upside down
    - 4: No video
    - 5: Unsure

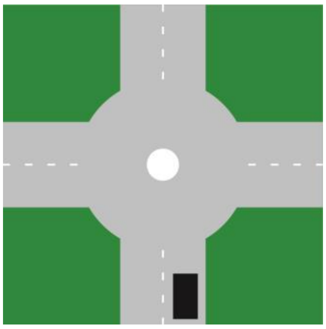
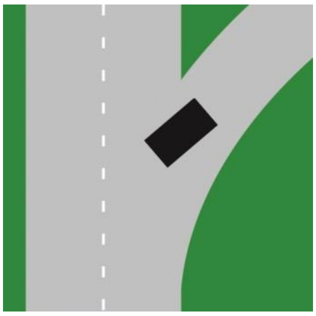
Round 2 – General attributes

- Weather
  - Description: weather type in the segment.
  - Categories:
    - 1: Good sight
    - 2: Bad sight (For example because of heavy rain, dark, fog, snow)
    - 3: Unsure

- Intersection Type
  - Description: type of intersection at which the manoeuvre takes place
  - Categories:

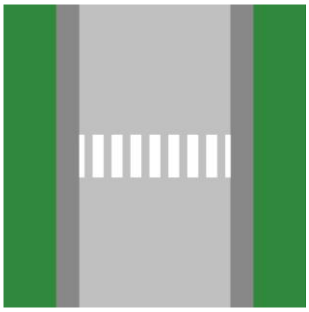
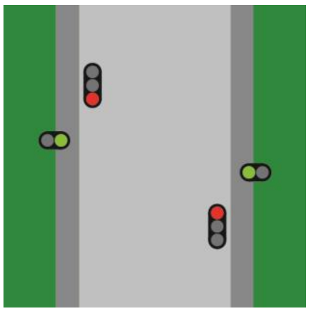
	Category	Definition	Example and Hints
1	X Intersection	A 4-road X intersection	
2	T Intersection (right)	A 3-leg T intersection with a by-road on the right side	
3	T Intersection (left)	A 3-leg T intersection with a by-road on the left side	
4	T Intersection (by-road)	A 3-leg T intersection, approached from the by-road.	

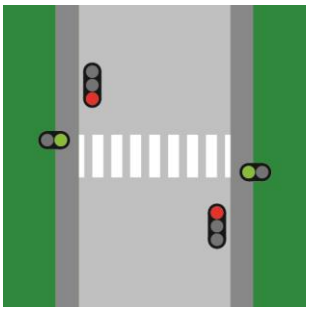
5	Y Intersection	A 3-leg Y intersection.	
6	5 or more legs	An intersection with 5 or more road leg.	
7	Roundabout: single lane	A roundabout.	
8	Roundabout: Multiple lanes	A roundabout with multiple lanes	
9	Roundabout: Turbo	A roundabout requiring drivers to choose their direction before entering.	

10	Roundabout: Mini / dot	A mini / dot roundabout	
11	Merging lane	Merging onto a main road.	
12	Passing by merging lane	Passing by a road that merges onto the main road.	
13	Exit lane: entering	Taking an exit lane. Note that this may involve crossing a bicycle lane.	
14	Exit lane: passing by	Passing by an exit lane.	
15	Other	This is an intersection not covered by any of the above. Use rarely.	

16	Unknown	The intersection type cannot be derived from the video data.	

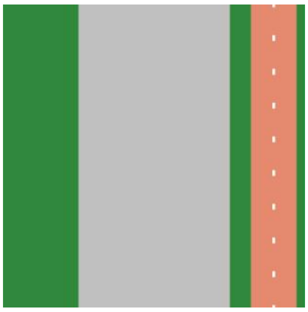
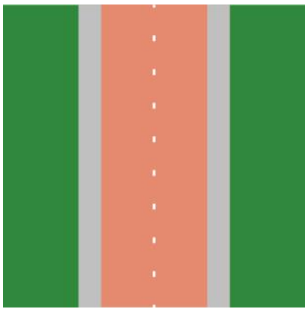
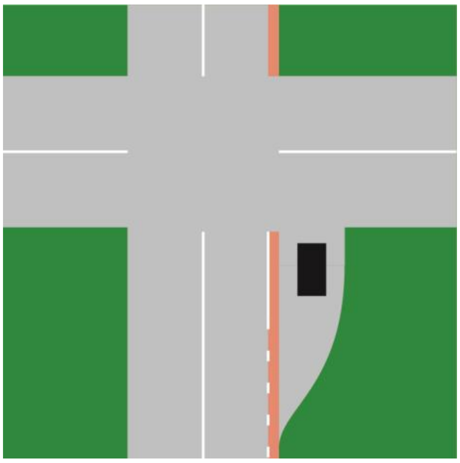
- VRU Facilities Pedestrians
    - Description: pedestrian facilities. Zebra and lights concern the intersection leg to which the manoeuvre is being made. Pavement concerns presence on the right side in general.
    - Note: if additional markers for pedestrians are present (e.g., ‘wegbelijning’, ‘kanalisatiestrepen’ (Dutch)), add ‘ped_marker’ in ATT_Comments.
    - Categories:

	Category	**Definition**	**Example and Hints**
1	No pedestrian facilities	There is none of the traffic controls below applicable to the intersection or mid-block.	
2	Pavement	Pavements are present.	
3	Pavement & Zebra crossing	A zebra crossing is present.	
4	Pavement and Crossing pedestrian lights	A crossing with pedestrian lights is present.	

5	Pavement Zebra crossing pedestrian lights	A zebra crossing with pedestrian lights is present	
6	Unknown	Unable to determine the presence or absence of VRU facilities.	

- VRU Facilities Cyclists
  - Description: cyclist facilities in the direction of the subject vehicle (i.e., direction prior to the onset of the manoeuvre), on the right side (UK: left side) of the subject vehicle. Only facilities for crossing the intersection straight. ('voorzieningen voor doorgaande stroom')
  - Note: if additional markers for cyclists are present (e.g., 'wegbelijning', 'kanalisatiestrepen' (Dutch)), add 'cyc_marker' in ATT_Comments.
  - Categories:

	Category	**Definition**	**Example and Hints**
1	No cyclist facilities	There is none of the traffic controls below applicable to the intersection or mid-block.	
2	Adjacent cycle lane, broken line	An adjacent bicycle lane is present on the right sides. The bicycle lane is marked with a broken line.	
3	Adjacent cycle lane, solid line	An adjacent bicycle lane is present on the right side. The bicycle lane is marked with a solid line.	

4	Separated cycle track, one-way	Separated one-way bicycle track is present.	
5	Separate cycle track, two-way	Separated two-way bicycle track.	
7	Bicycle street	A road section intended for bicycles, with motorized vehicles as guest users.	
8	Left hand cycle lane in own direction (UK right)	An intersection where cyclists go straight while the driver goes right (non-UK) and which has a cycle lane in the middle of the road.	
9	Other	An intersection that does not fit the described categories	
10	Unknown	Unable to determine the presence or absence of VRU facilities.	

Round 2 – Pre manoeuvre

Annotations before the start of the manoeuvre.

- Manoeuvre Start
  - Description: determine where the manoeuvre starts, which is at the start where the driver starts to turn the wheel. Time stamp where the manoeuvre starts. That is, the timestamp when the direction of the subject vehicle no longer matches the direction of the initial road. This may be earlier than the 'bump' in, e.g., RightTurnDetected.
  - Type: Time attribute annotation
- Traffic Density
  - Description: traffic flow in own lane prior to the manoeuvre (i.e., focus on lead vehicle).
  - Note: restricted flow: speed is or has to be adapted to traffic ahead.
  - Note: waiting: some time prior to manoeuvre is spent waiting, for example, for a traffic light, or before entering a roundabout.
  - Categories:
    - 1: Free flow
    - 2: Restricted flow
    - 3: Waiting then free flow
    - 4: Waiting then restricted flow
    - 5: Unsure
- VRU Early Present
  - Description: VRU visible in video in first 3 seconds of the time window (starting from the blue line), regardless of position (i.e., also counting left side (UK: right side)).
  - Categories:
    - 1: Early VRU present on LEFT side
    - 2: Early VRU present on RIGHT side
    - 3: Early VRU present on BOTH sides
    - 4: No early VRU present
    - 5: Unsure
- VRU Presence Own_Direction
  - Description: VRU moving or intending to move in the SAME direction as the subject vehicle prior to manoeuvre, at the right side of the subject vehicle (UK: left side).
  - Note: multiple pedestrians counts as option 2: Pedestrian. Five pedestrians and one cyclist counts as option 5: Pedestrian & Cyclist. Scootmobiles and skateboarders are counted as pedestrians.
  - Categories:
    - 1: No VRU present
    - 2: Pedestrian
    - 3: Cyclist
    - 4: Powered Two-Wheeler
    - 5: Pedestrian & Cyclist
    - 6: Pedestrian & PTW
    - 7: Cyclist & PTW
    - 8: Pedestrian & Cyclist & PTW
    - 9: Unsure
- VRU Presence Opposite Direction
  - Description: VRU moving or intending to move in the OPPOSITE or conflicting direction as the subject vehicle prior to manoeuvre, at the **right side** of the subject vehicle (UK: left side). For example a VRU coming towards you or crossing your path.

  - Note: multiple pedestrians counts as option 2: Pedestrian. Five pedestrians and one cyclist counts as option 5: Pedestrian & Cyclist. Scootmobiles and skateboarders are counted as pedestrians.
  - Categories:
    - 1: No VRU present
    - 2: Pedestrian
    - 3: Cyclist
    - 4: Powered Two-Wheeler
    - 5: Pedestrian & Cyclist
    - 6: Pedestrian & PTW
    - 7: Cyclist & PTW
    - 8: Pedestrian & Cyclist & PTW
    - 9: Unsure
- VRU Presence Front Left to Right
  - Description: VRU moving or intending to move from left to right in front of the subject vehicle, prior to the manoeuvre.
  - Note: multiple pedestrians counts as option 2: Pedestrian. Five pedestrians and one cyclist counts as option 5: Pedestrian & Cyclist. Scootmobiles and skateboarders are counted as pedestrians.
  - Categories:
    - 1: No VRU present
    - 2: Pedestrian
    - 3: Cyclist
    - 4: Powered Two-Wheeler
    - 5: Pedestrian & Cyclist
    - 6: Pedestrian & PTW
    - 7: Cyclist & PTW
    - 8: Pedestrian & Cyclist & PTW
    - 9: Unsure
- VRU Presence Front Right to Left
  - Description: VRU moving or intending to move from right to left in front of the subject vehicle, prior to the manoeuvre.
  - Note: multiple pedestrians counts as option 2: Pedestrian. Five pedestrians and one cyclist counts as option 5: Pedestrian & Cyclist. Scootmobiles and skateboarders are counted as pedestrians.
  - Categories:
    - 1: No VRU present
    - 2: Pedestrian
    - 3: Cyclist
    - 4: Powered Two-Wheeler
    - 5: Pedestrian & Cyclist
    - 6: Pedestrian & PTW
    - 7: Cyclist & PTW
    - 8: Pedestrian & Cyclist & PTW
    - 9: Unsure
- Secondary Task Pre Manoeuvre
  - Description: driver was involved in a secondary task in the time window PRIOR to the start of the maneuver. If there are multiple secondary tasks present, select the task with the most modalities involved.
  - Categories:
    - 1: Visual

        - 2: Auditory
        - 3: Manual
        - 4: Visual and Auditory (e.g., looking at conversation partner)
        - 5: Visual and Manual (e.g., texting)
        - 6: Auditory and Manual (e.g., calling)
        - 7: Visual and Auditory and Manual
        - 8: Unknown
- Visual Obstruction Obstacles
    - Description: any obstacle-related visual obstruction that hinders the driver in identifying whether a VRU was present on the right side of the vehicle, prior to the manoeuvre. In case of multiple simultaneous obstacles, choose the obstacle with the largest impact on the visibility of VRUs. Note: ONLY consider obstacles large enough to cover the view of a cyclist. For example, a narrow tree trunk does not count as an obstacle.
    - Timeseries annotation
        - Always start with 'start of the manoeuvre' (cue: steering wheel movement), and then work from the beginning of the complete segement.
    - Categories:

	Category	**Definition**	**Example and Hints**
1	No obstruction	No visual obstructions for the subject vehicle driver were obvious.	
2	Start of the manoeuvre		
3	Curve or hill	The presence of a curve or hill in the field of view decreased visibility.	
4	Building, billboard, or other roadway infrastructure design features	The presence of a man-made structure in the field of view decreased visibility.	Includes sign, embankment, building.
5	Trees, crops, vegetation	The presence of trees, crops, or vegetation in the field of view decreased visibility.	
6	Moving vehicle (with or without load)	The presence of a vehicle in motion on the trafficway (with or without a load) in the field of view decreased visibility.	
7	Stopped/Parked vehicle	The presence of a stopped/parked vehicle in the field of view decreased visibility.	
8	Obstruction interior to vehicle	An interior feature (other than head restraints) of the subject vehicle decreased visibility.	Includes interior mirrors, objects hanging from rear view mirror, objects piled on the rear or passenger seat blocking windows.
9	Other obstruction	A known visual obstruction not listed in previous categories decreased	Can be external or internal to the vehicle (e.g., driver drinking from

		visibility.	a water bottle that obscures the vision).
10	Unknown whether vision was obstructed	Cannot determine whether any Visual Obstructions are present due to limitations in video views, lighting, visual obstructions, or limited perspective.	Ex. Part of the video is missing or there is insufficient information in the video to make a determination.

Round 2 - During maneuver

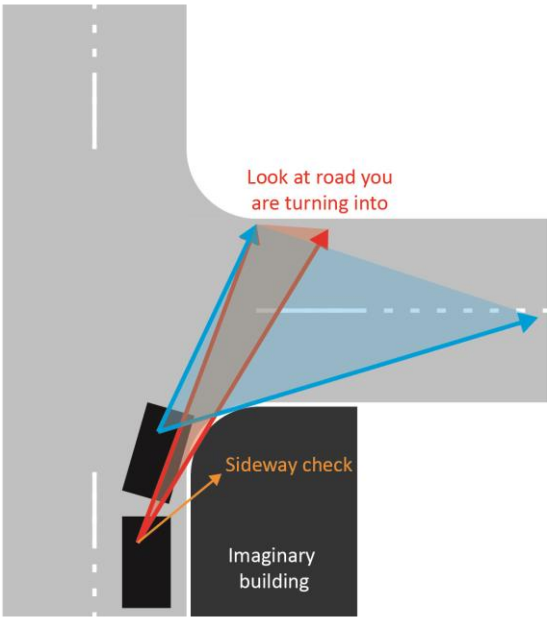
Annotations during the maneuver.

- Manoeuvre End
  - Description: time stamp where the manoeuvre ends. That is, when the direction of the subject vehicle corresponds with the direction of the new road. This may be later than the 'bump' in, e.g., RightTurnDetected.
  - Type: Time attribute annotation
- Secondary Task During Manoeuvre
  - Description: driver was involved in a secondary task DURING the maneuver (i.e., between maneuver start and maneuver end). If there are multiple secondary tasks present, select the task with the most modalities involved.
  - Categories:
    - 1: No secundary tasks
    - 2: Visual
    - 3: Auditory
    - 4: Manual
    - 5: Visual and Auditory (e.g., looking at conversation partner)
    - 6: Visual and Manual (e.g., texting)
    - 7: Auditory and Manual (e.g., calling)
    - 8: Visual and Auditory and Manual
    - 9: Unknown
- Manoeuvre Enter Encroachment Zone
  - Description: time stamp where the front of the car enters the encroachment zone (i.e., the zone where, had both the vehicle and the bike occupied the same space, they would overlap).
  - Type: Time attribute annotation

- Manoeuvre Leave Encroachment Zone
  - Description: time stamp where the car leaves the encroachment zone (i.e., the zone where, had both the vehicle and the bike occupied the same space, they would overlap).
  - Note: As there is not back view, it is not possible to see the length of the car. Therefore, enter the time where you think the car driver him/herself leaves the encroachment zone (i.e., the part of the car behind the driver is not taken into account).
  - Time attribute annotation

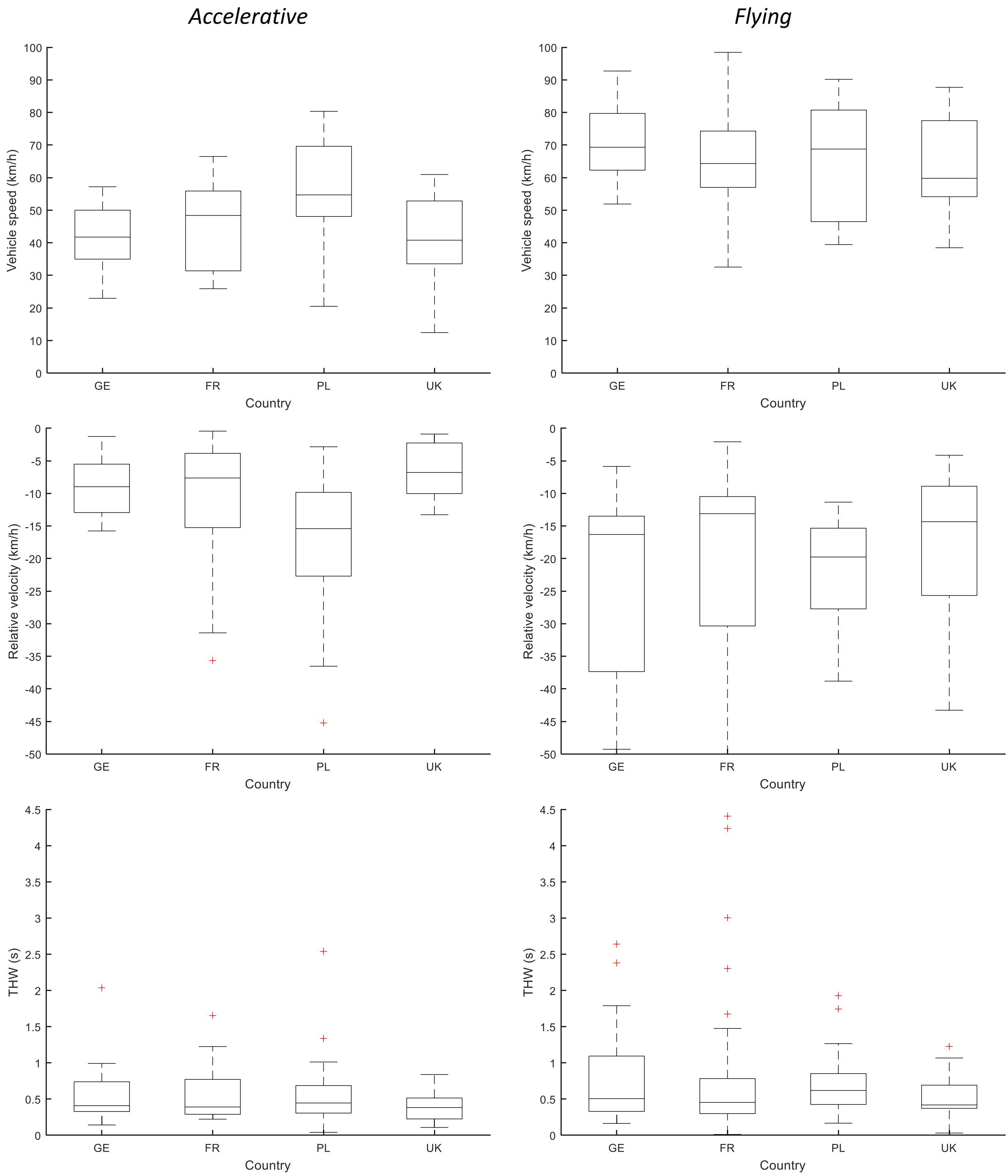
- Gaze
    - Description: from start of time window until the driver has finished the manoeuvre.
    - Focus primarily on the head, but preferable also involve eyes.
    - Type: TimeSeries annotation
    - Categories:

	Category	Definition
1	Blind spot check to near side: VRU present	Driver checks his/her blind spot when making a right turn on an urban intersection (UK: left turn) and there is a VRU present. For trucks: looking somewhat down into the right outside mirror.
2	Blind spot check to near side: No VRU present	Driver checks his/her blind spot when making a right turn on an urban intersection (UK: left turn) and there is a VRU present. For trucks: looking somewhat down into the right outside mirror.
3	Sideway check to near side: VRU present	Looking sideways, but not looking over the right shoulder or for trucks in the somewhat down into the right outside mirror.
4	Sideway check to near side: VRU not present	Looking sideways, but not looking over the right shoulder or for trucks in the somewhat down into the right outside mirror.
5	Looking towards road driver is turning into	Not looking sideways or checking the right shoulder
6	Looking Elsewhere	
7	Unsure	
8	Impossible to determine	



Appendix C Cyclist overtaking manoeuvres across countries

The appendix relates to section 6: 'Cyclist overtaking manoeuvres by car drivers'. The vehicle speed, relative velocity, THW, TTC, distance between lane edge and VRU and lane width, with respect to country in the two phases for the accelerating and the flying manoeuvres, are shown in Figure C.1 and Figure C.2.



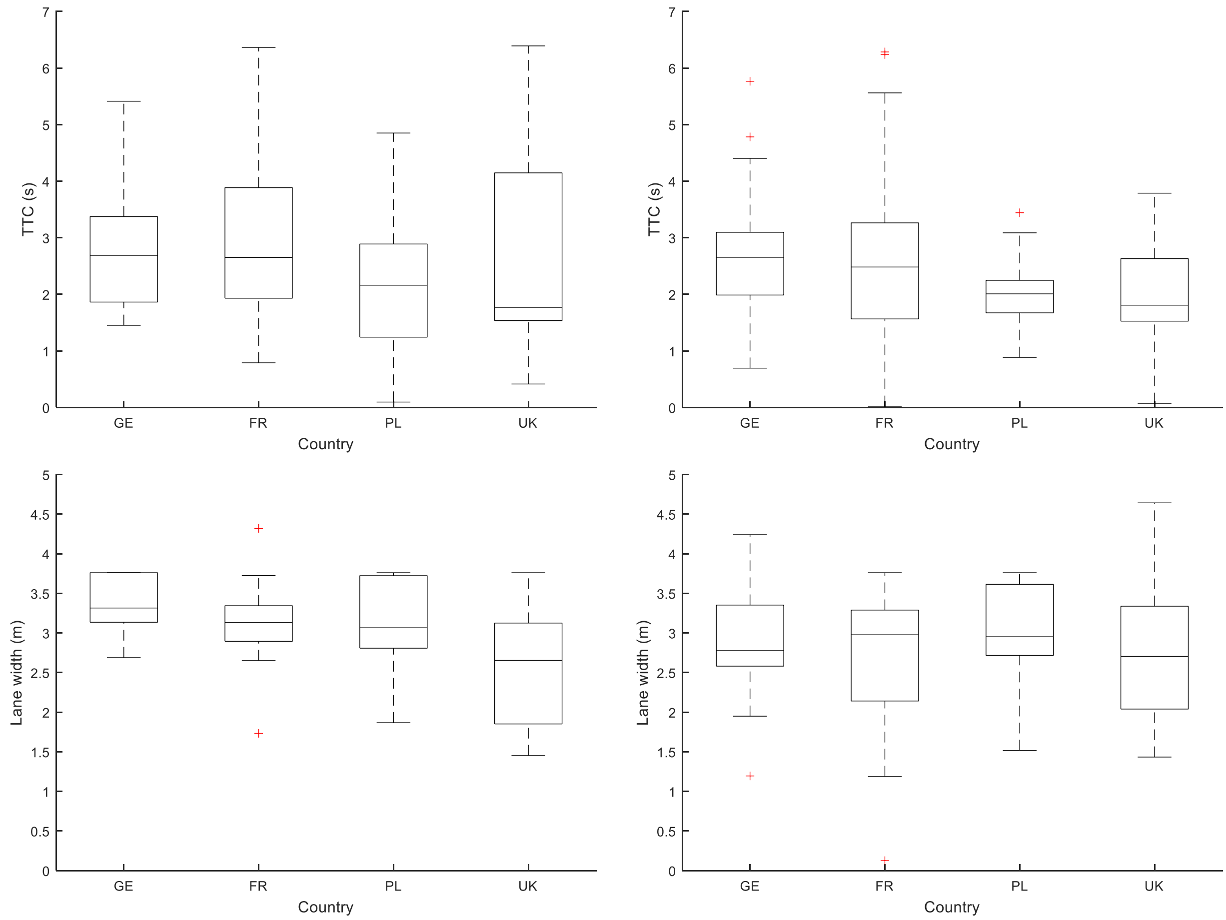
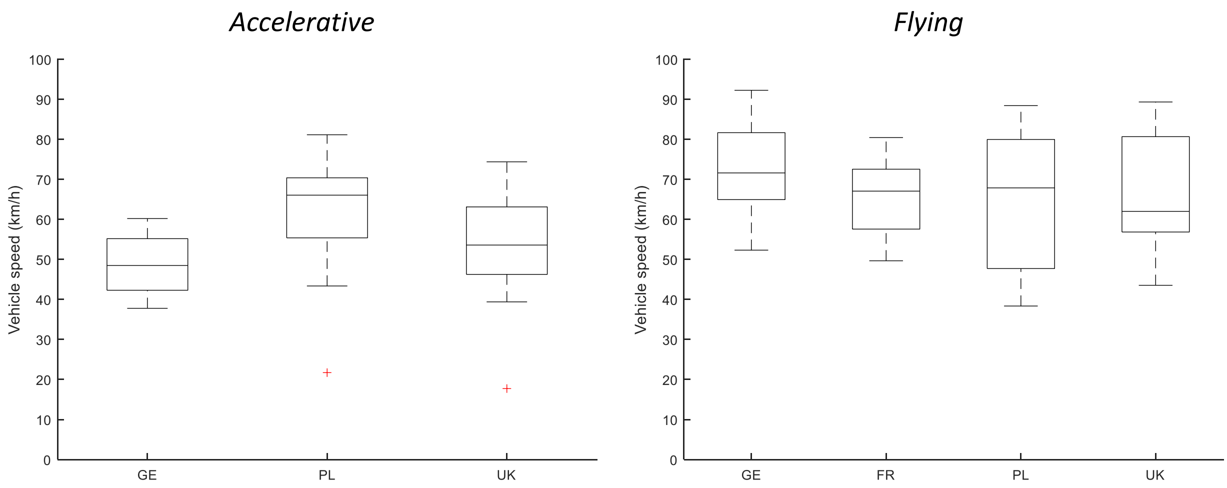


Figure C.1: Vehicle speed, relative velocity, THW, TTC, and lane width, with respect to country at start of the overtaking for the accelerating and the flying manoeuvres.



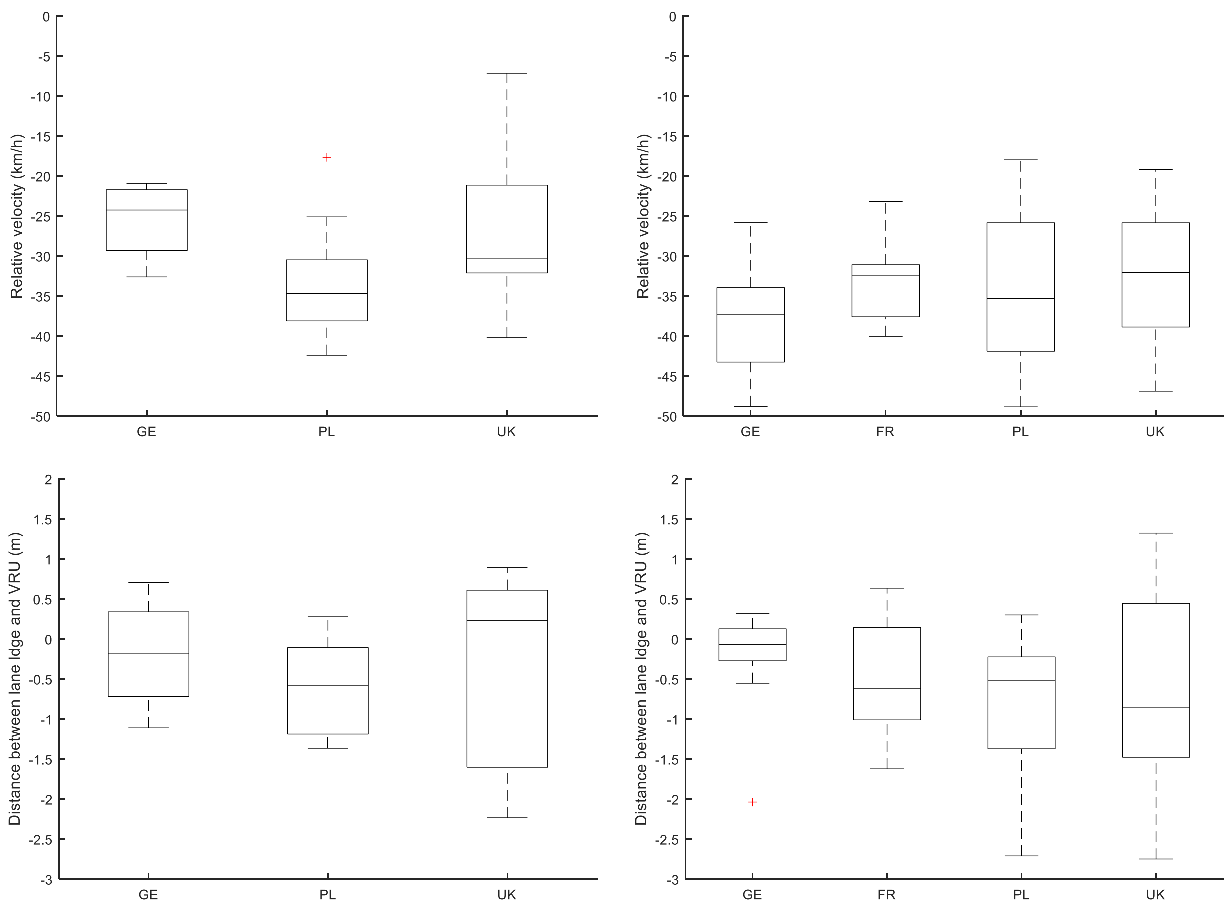


Figure C.2 Vehicle speed, relative velocity, and distance between lane edge and VRU, with respect to country at passing phase for the accelerating and the flying manoeuvres.

Appendix D Review report template; checklist for reviewers

D.1 Overall judgement: readibility, structure and format

		Yes	No	N/A
	Does the deliverable reflect the content described in the Description of Work?			
Comments				
	Is the deliverable sufficiently understandable: did you fully understand it (even if slightly off topic for you)?			
Comments				
	Does the deliverable include learning from mistakes/challenges encountered and does it stimulate to further research?			
Comments				
	Is the document template applied properly?			
Comments				
	Is the structure of the deliverable easy to follow? Do you suggest any changes to the structure to make the deliverable more accessible?			
Comments				
	Is the English in the deliverable good? Is it clear and accessible?			
Comments				
	Are the figures and tables understandable and refered to in the text?			
Comments				

D.2 Scientific judgement

		Yes	No	N/A
	Is the issue which is being researched clearly and simply stated?			
Comments				
	Are the objectives as described in the deliverable in line with the Description of Work (description of the Task)?			
Comments				
	Is the quality of the study design sufficient, are the methods/procedures as well as their actual application appropriate/correct?			
Comments				
	Do the results match the objectives as described in the Description of Work?			
Comments				
	How are the findings and results of the work described in the deliverable? Does the conclusion chapter reflect all described main important issues in the report and are the conclusion well based? Are the conclusions clearly stated? Are the conclusions relevant and applicable?			
Comments				
	Does the report include the relevant and necessary references? If relevant, is the			

	necessary wider view on the field of work properly given?			
Comments				
	Other comments			