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Quantitative analysis of rear-end crash causation mechanisms based on naturalistic crash data

Master's thesis in Biomedical Engineering

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Abstract

Until recently, little has been known about what exactly happens in the seconds leading up to a car crash. Due to the emergence of naturalistic driving data, e.g. video data of the forward roadway and of the driver combined with various sensor readings from real traffic incidents, it is now possible to research underlying crash causation mechanisms with much greater detail. An analysis of a 100 different rear-end events, 70 crashes and 30 near-crashes, was performed with the aim of replicating the findings of the SHRP2 naturalistic driving study performed by SAFER. The findings were in correspondence with those of the SHRP2 study; that rear-end crashes usually occur due to a combination of glance duration and change rate of the situation kinematics, and that a short glance usually requires a rapid change in the situation kinematics while a longer glance could cause a crash even if the kinematic situation changes relatively slowly. The key mechanism behind crashes was found to be the timing of the last glance off the road relative to the change in urgency, represented optically by looming cues, during the glance. Brake lights were frequently ignored and the act of missing the brake light onset (BLO) in itself was not found to be a key mechanism in causing crashes and near-crashes. Drivers that ended up in a crash were twice as likely to have looked away from the road after having seen the last BLO as those who ended up in a near-crash.

Key words: Driver distraction, Off-path glances, Crash analysis, Brake lights, Adapted time headway, Missed looming, Inopportune glances, Perfect mismatch

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Hrafnhildur Hekla Eiríksdóttir,
Reykjavík, Iceland, 1/3/16

Contents

Abbreviations

AOI	Area of interest
EOP	Eyes-off-path
InvTau	Inverse Tau
LG	Last glance
NDS	Naturalistic driving study
NHTSA	National Highway Traffic Safety Administration
OBSM	On board safety monitoring
POV	Principle other vehicle
SV	Subject vehicle
TTC	Time-to-collision
WHO	World Health Organization

1 Introduction

About 1.25 million people lose their lives in traffic accidents each year and additionally up to 50 million people suffer injuries. Traffic accidents are currently ranked number nine of the leading causes of fatalities in the world and are the leading cause amongst young people in the age of 15-29 years (WHO, 2015). Understanding the detailed mechanisms underlying crash causation is of fundamental importance for crash prevention. In traditional crash data, such as police reports and in-depth/on-site investigations, relatively little information is available from the seconds preceding the crash. The information is typically about the severity of the crash in terms of injuries and deaths, and environmental circumstances, such as road condition, weather and time of crash. Usually little information can be found about pre-crash factors that lead to the crash. Driver inattention has often been mentioned as the dominant factor behind traffic accidents. It has however been difficult to gain an understanding on how exactly inattention contributes to accidents.

In 2009 distracted driving was considered a contributing factor in 20% of injury crashes, and 16% in the fatal ones in the United States (NHTSA, 2010). These figures do however have very big uncertainties since it can be problematic for police officers to point out at the site of the accident when inattention was a contributing factor to the crash and when it wasn't (Engström, 2011). Most crash data collections are gathered by observation and self-report methods that are usually obtained in a retrospective investigation after the crash has occurred. The data often comes from police reports or in-depth investigations that are done on-site of the accidents. Information is gathered from those involved in the crash and other witnesses so their remembrance of the scenario is very important. There are however known factors that limit how accurate the recollection of events is, and chances are that a person's memory is influenced and modified after the crash occurs (Loftus, 1979). Many basic motor and perception processes also become automated very quickly when people learn how to drive, drivers are therefore unaware of performing those processes, or they simply do not tell the truth about what happened.

Nowadays however, thanks to the availability of naturalistic crash data the situation has changed. Significant public funding has been assigned to performing naturalistic driving studies (NDS) in order to get a better understanding on what causes accidents. This has mainly been done in the US but there are also some initial studies being conducted in Europe and Japan. Detailed crash data, offered by NDS, has not been available to analysts in this quantity up until recently and such data has great promises to increase the understanding of driver behavior. (Dozza et al., 2012)

Naturalistic driving studies, such as the 100-car study (Dingus et al., 2006), the first extensive NDS, have confirmed the role of inattention in crashes further. In fact in the 100-car study driver inattention was found to be contributing to the crash risk in 78 % of the crashes, 93% of rear-end crashes and 65% of the near-crashes (Dingus et al., 2006).

In NDS vehicles are equipped with video cameras and sensors and data is collected unobtrusively in real traffic. The data can be collected continuously, like in the 100-car study, or it can be collected only during specific safety critical events, for example crashes and near-crashes, where a certain event triggers the data sampling. The sensors offer a large number of time-history measurements, such as speed and acceleration, and the video cameras record both the driver's behaviour as well as the traffic environment. This builds up to a detailed information base about the driver, vehicle and environmental factors in real traffic (Klauer et al., 2011). NDS data that is collected continuously usually contains a large amount of information about normal driving situations, a decent amount of near-crashes and a small amount of crashes. Crashes are rare events so it takes time to gather up enough records of a specific crash type in order to be able to analyse it. In contrast, NDS that are event-triggered do not have information about driving exposure but are a cost-efficient way to gather crash data and study contributing factors leading to a crash or a near-crash.

Since crash video data can be very sensitive and not intended to be distributed freely, gathering data for research purposes has been somewhat limited. There are certain privacy legislations that must be obeyed when handling this kind of NDS data. In Sweden, for example, an employer is not allowed to record his employees while driving with an in-vehicle camera without them giving their consent first. The camera might also catch number plates or pedestrians and other commuters that have not given any consent for the data being used. However, new sources of naturalistic data is arising where the researchers get the video annotated but are not able to access the videos themselves. This is the case with the LYTX data that was made available for SAFER, the vehicle and traffic safety center at Chalmers University. The events are therefore completely anonymous and untraceable.

Volvo and Chalmers initiated collaboration with the US-based company LYTX (http://www.lytx.com), formerly known as DriveCam, which offers a video-based service for coaching drivers towards safer driving behaviour and more efficient way of driving. The service is mainly aimed at commercial vehicle fleets, such as bus fleets and logistic companies. The service uses an on-board safety monitoring (OBSM) devices, currently installed in about 200.000 vehicles, to record safety-critical events based on kinematic triggers (such as an impact, hard braking or other evasive maneuvers). This data is then used as the basis for a behaviour-based safety management program. As part of this service, a large number of crashes are regularly captured on video. One such dataset was used for the ANNEXT project.

A set of 193 rear-end and intersection crashes and near-crashes with trucks, buses and passenger cars was made available for analysis at SAFER as part of the ANNEXT project. Based on this data, Engström et al. (2013) investigated the contributing role of driver inattention in crashes compared to other contributing factors. Furthermore the roles of different forms of inattention were examined, especially driver distraction involving the diversion of gaze from the forward roadway, versus distraction that is purely cognitive. The main findings were that the role of driver inattention as a crash-contributing factor varies significantly with which types of crashes are being considered. For rear-end crashes it was especially driver distraction requiring the driver to look away from the forward roadway that was the leading crash-contributing factor (Engström et al., 2013). This supported what had been found in previous findings from NDS, namely that visual diversion from the forward roadway is the key mechanism by which inattention leads to rear-end crashes (Klauer et al., 2006; Olson et al., 2009; Victor et al., 2015).

Rear-end crashes constituted for approximately 33% of all police reported crashes in the US in 2010 and 2011 according to data collected by the General Estimate System (GES) (Kusano and Gabler 2013). One third of all reported crashes is a considerable part of the whole and therefore really important to dive deeper into what factors are causing those particular accidents in order to being able to prevent them. In order to gain an understanding on how looking away from the forward road really contributes to rear-end crashes, a team at SAFER conducted an analysis of rear-end crashes and near-crashes from the SHRP2 driving study, the largest NDS that has been carried out (Victor et al., 2015). In the study, data was collected continuously from over 3000 passenger vehicles in the US over a period of three years. The main aim of the study was to address the role of driver performance and behaviour in relation to traffic safety and understand how the driver interacts and adapts to the vehicle, as well as the traffic environment. The data that was collected consisted of the speed of the vehicle, acceleration, braking, lane position, vehicle control when it was available, forward radar and video with a view of the forward and rearward roadway as well as the face and hands of the driver. The data collected contained about 50 million vehicle miles and more than 1 million hours of video.

The SHRP2 analysis included a detailed analysis of the timing of off-road glances relative to the kinematics of the crash scenario. The key finding was that rear-end crashes typically occur due to a specific combination of glance duration and the rate at which the situation kinematics changes (as determined by the deceleration rate of the lead vehicle, the initial speed, time headway etc.). More specifically, the data revealed how a short glance typically requires a rapidly changing situation to produce a crash while a longer glance may lead to crash even if the situation changes relatively slowly.

The main objective of this Master's thesis was to replicate the rear-end crash mechanism analysis conducted on SHRP2 data on the ANNEXT data mentioned above to see if the findings would further support the role of driver inattention in rear-end crashes. In the present analysis the data, obtained from the ANNEXT dataset, included 100 rear-end events, thereof 70 crashes and 30 near-crashes. A specific objective of the thesis was to implement the data processing algorithm so it would be possible to perform the same analysis on the ANNEXT dataset as was done on the SHRP2. That included data manipulation relevant to adapting the filtering, smoothing, interpolating and extrapolating necessary to be able to perform similar analysis on lower sample rate data set. One objective was to look into how the timing of off path glances relates to crash risk by analyzing the timing relation between the driver’s visual behavior and the changes in situation kinematics. The main goal was thus to understand better what characterizes safe glances by analyzing how the timing relation distinguished crashes from near-crashes. Furthermore the aim was to analyze the relation between the duration of the last glance and the changes in visual cues, mainly focusing on brake light onsets and visual looming.

2 Empirical and theoretical background

2.1 Inattention and crash risk

As mentioned previously, driver inattention contributes very often to the causes of traffic accidents. New sources of inattention are emerging and driving habits are rapidly changing with new technology. In order to estimate how big part inattention plays in road-safety and compare study results a common taxonomy for concepts regarding driver inattention was needed. A work group on Driver Distraction and Human Machine Interaction was formed by the initiative of the US-EU Bilateral ITS TF (United States and European Union Bilateral Intelligent Transportation Systems Technical Task Force) to define a theoretical framework and taxonomy of driver inattention (Engström et al., 2013). The group divided inattention broadly into two categories; (1) insufficient attention, relating to the activation of attention and (2) misdirected attention that refers to the selective aspect of attention. Insufficient attention was then sub-divided to sleep-related impairment and insufficient attentional effort, which refers to the driver failing to allocate enough resources to activity that is critical to safe driving to match the needed attention for the specific task. A sub-category of misdirected attention is driver distraction where the driver allocates resources to a non-safety critical activity and not enough resources are allocated to activities crucial for safe driving.

One advantage of data from NDS is the possibility to calculate the associated risk of distraction from various activities and secondary tasks. Additionally to the SHRP2 analysis mentioned above, three naturalistic driving studies that have been made with special focus on driver inattention should be mentioned here. The US 100-car study (Dingus et al., 2006 and Klauer et al., 2006) was one of the first major NDS. CVO (Olson et al., 2009) was aimed especially at driver distraction in commercial vehicle operation and finally in 2010 Hickman et al. analysed commercial vehicle data from LYTX (then known as DriveCam) that included a large amount of safety critical events. See Table 1.

Table 1: Number of safety critical events in the four NDS analysis mentioned in the text that focused especially on driver's inattention.

Study	Crashes	Near-crashes
100-car study (Dingus et al., 2006; Klauer et al., 2006)	69	761
CVO (Olson et al., 2009)	21	197
DriveCam (Hickman et al., 2010)	2421	24239
SHRP2 (Victor et al., 2015)	46	211

In all studies listed in the table above the odds ratios for various secondary tasks was calculated. Odds ratios are used to estimate the relative risk of a certain event happening by means of secondary task distraction. The equation is as following:

$$OR = \frac{Odds(Safety{-}critical\ event)}{Odds(Comparison\ event)} \qquad (1)$$

The higher the odds ratio is for a secondary task, the stronger the association of that task with crash or a near-crash risk. (Victor et al., 2015) Also, if the ratio is significantly lower than 1.0 it implies a considerably lower relative risk of being involved in a safety-critical event. Some of the odds ratios calculated in the studies can be seen in Table 2.

Table 2: Odds ratio for different secondary task activities found in the four studies. The numbers in bold indicate ratios that differ significantly from one and show either an increased or decreased relative risk. This table is based on a table from Engström (2011) and used here with his permission.

Activity	100-car study (Klauer et al., 2006)	CVO (Olson et al., 2009)	DriveCam (Hickman et al., 2010)	SHRP2 (Victor et al., 2015)
Looking at external object	**3.7**			**2.1**
Reading	**3.38**	**3.97**		0.6
Applying makeup	**3.13**			0.6
Dial cell phone	**2.79**	**5.93**	**3.5**	**2.7**
Talking/listening to a hand-held phone	1.29	1.04	0.9	**0.1**
Talking/listening to a hand-free phone		**0.44**	**0.65**	
Text messaging on a cell phone		**23.2**	**163.6**	**5.6**
Interact with/look at a dispatching device		**9.93**		**1.6**
Write on pad/note-book		**8.98**		
Use calculator		**8.21**		
Talk or listen to citizens band radio		**0.55**		

It should be noted that in both the 100-car study and the SHRP2 study only crashes and near-crashes were considered when the ORs was calculated while Olson et al. (2009) and Hickman et al. (2010) also considered other types of safety critical events in their OR calculations.

As can be seen in Table 2 the types of secondary tasks that were analyzed vary between the studies. The 100-car and SHRP2 studies included merely private cars while the other two involved commercial vehicle drivers and therefore the nature of the secondary tasks differs. The ever-changing technology also offers new types of distraction every year and can explain to some extent how the secondary tasks vary from study to study. The resulting ORs are however

generally consistent between studies and suggest that secondary tasks that require the driver to take his eyes of the road are considerably riskier than others. In the commercial vehicle studies, the secondary task that showed the most extreme OR in both of them was text messaging on a cell phone. The same was the case for the SHRP2 analysis. However, text messaging was not possible in the US at the time of the 100-car study and was therefore not included in that study. Olson et al. (2009) looked into this mechanism further, and their analysis revealed that the relative risk linked with a secondary task was strongly correlated to the degree of which the task required the driver to take his eyes of the road. Secondary tasks that had the highest OR were also associated with the largest proportion of eyes of the forward road. (Engström, 2011)
Tasks that were purely cognitive and did not require any visual efforts, such as having a conversation on a mobile phone, did not increase the risk in any of the studies. In both Hickman's and Olson's commercial studies the risk of being involved in a safety-critical event was found to be significantly reduced when engaging in a hand-free phone conversation. The strongest protective effect was however noticed in the SHRP2 analysis (Victor et al., 2015), which only included rear-end events, where talking/listening on cell phone was found to decrease the risk significantly compared to not engaging in a phone conversation, with an OR value of 0.1 representing an estimated ten-fold decrease in risk when compared to a baseline event. Olson et al. also found the usage of a CB radio to have the same effect.

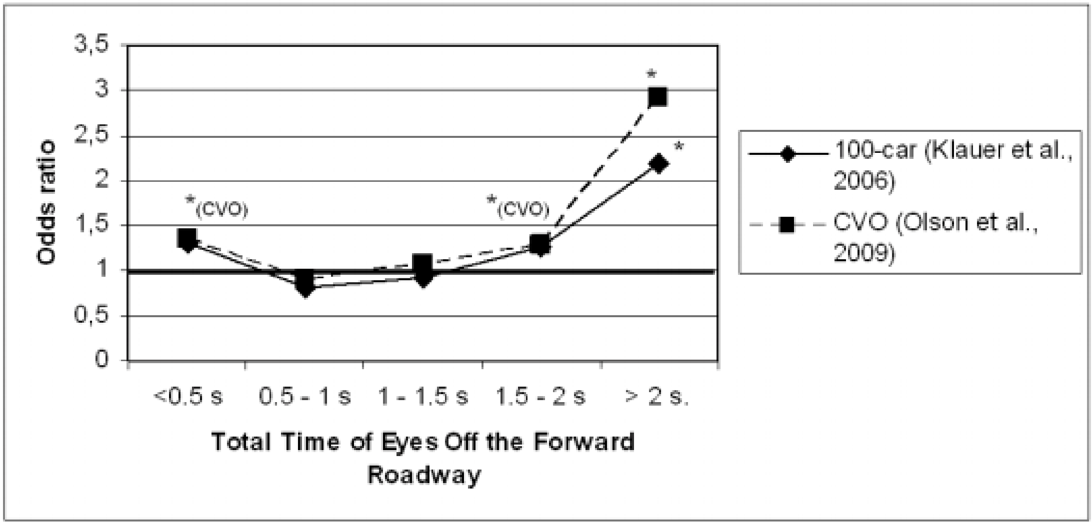

Figure 1: Odds ratios as a function of the duration of eyes off path. Asterisks indicate odds ratios that differ significantly from one. The graph is from Engström's Ph.D thesis (2011), based on data from the studies of Olson et al. 2009, and Klauer et al. 2006 and reprinted here with his permission.

Klauer et al. (2006) and Olson et al., (2009) also estimated the odds ratios of getting into a safety critical event or a crash or a near-crash as a function of the duration of eyes off path for the period of 5 seconds prior to and 1 second after the start of the critical event. The results, as can be seen in Figure 1, are very consistent between studies and indicate that the main increase in risk is when the total eyes off path time exceeds 2 seconds.

It is clear from existing studies that performing visually demanding tasks while driving increases risk. However, this does not say anything about the mechanisms behind this effect.

2.2 Off road glances as crash-contributing factor

In the ANNEXT project 70 rear-end LYTX crashes were analysed based on a new methodology for assigning and combining crash-contributing factors (Engström et al., 2013a). In this study, the contributing role of driver inattention in crashes compared to other contributing factors was analysed, as well as how the factors contributed and to what extent. Unlike risk analysis like those mentioned in the previous chapter, this analysis was built on an expert judgement of what factors actually had a contributing role to the crash, the mere existence (prevalence) of a factor was not sufficient for it being considered as a crash contributing factor.

Furthermore the roles of different forms of inattention were of interest, especially driver distraction involving the diversion of gaze from the forward roadway, versus distraction that is purely cognitive.

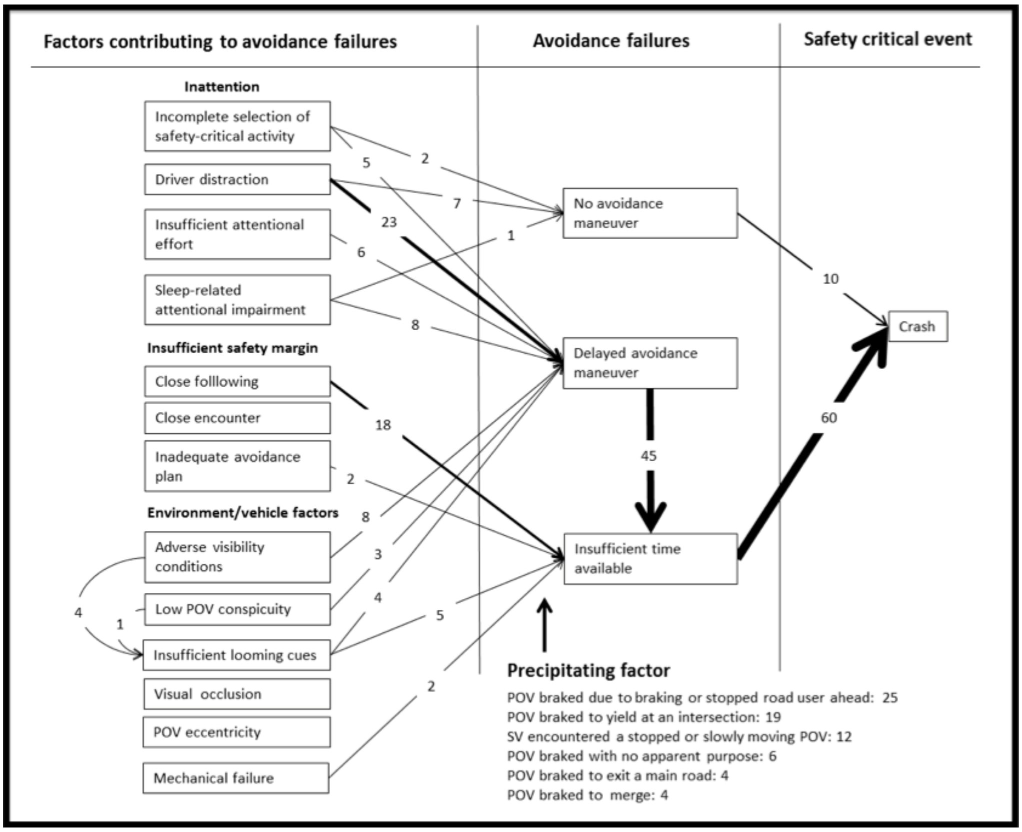

Figure 2: Contributing and precipitating factors in the 70 rear-end crashes from ANNEXT. The chart was published in an analysis by Engström et al. (2013a) and is reprinted here with permission.

Figure 2 shows the distribution of crash-contributing factors for the rear-end crashes, where it can be seen that in 52 of the 70 rear-end crashes at least one form of drivers inattention contributed to the crash. For rear-end crashes it was especially drivers distraction requiring the driver to look away from the forward roadway that was the leading crash-contributing factor. (Engström et al., 2013a) The underlying mechanism was found to be the delay of the drivers avoidance maneuver due to the co-occurrence of the drivers' diversion of gaze from the road and the initiation of the lead vehicle braking, hereafter referred to as POV (principle other vehicle). The second main contributing factor was close following, contributing to 18 of 70 crashes, where the majority involved a heavy vehicle that was following the POV to close given its limited brake capacity. Visual occlusion and insufficient selection of safety margins were however found to be the main crash-contributing inattention factors in the intersection crashes. Furthermore, cell phone conversations and other cognitively distracting activities that do not demand a look away from the road, were not found to contribute often to neither rear-end nor intersection crashes (Engström et al., 2013a). The results of this qualitative analysis supports previous findings from naturalistic driving studies, suggesting that visual diversion from the forward roadway is the key mechanism by which inattention leads to rear-end crashes (Dingus et al., 2006).

To better understand these mechanisms, a closer look is needed on drivers' visual behaviour and what critical information drivers are actually missing during a glance away from the road and under what circumstances it leads to a crash.

2.3 Visual time sharing

Driving is an ever-changing task, which relies heavily on a steady stream of visual information (Sivak, 1998). Drivers get detailed information using the foveal vision, in the direction of gaze, while the peripheral vision senses motion but cannot be used to extract precise information. In order to get a comprehensive overview of the road situation the drivers therefore use visual time sharing and constantly shift their gaze to different areas of the traffic environment (Tivesten, 2014). Although a driver constantly needs new information he can get by with surprisingly sparse periodic samples of the roadway. Between these periodic samples the driver becomes increasingly uncertain about the state of the vehicle relative to the road. When the uncertainty exceeds a certain threshold the driver needs to refresh his visual state (Senders et al., 1967).

Wierwille (1993a, 1993b) quantified this uncertainty threshold and concluded that drivers feel comfortable taking glances off the road for up to one second but try to avoid exceeding 1,5 seconds. When drivers need to perform a visually demanding secondary task, which takes longer than 1,5 seconds to perform, they therefore tend to shift their attention periodically between the forward view and the secondary task until they have completed the task (Wierwille, 1993b).

Several other models have been proposed to describe normal driving behaviour. The comfort zone model describes a certain safety margin that controls the driver's behaviour and the drivers strive to maintain a state where they feel comfortable. When pushed towards a shorter safety margin, e.g. because of time constraint, the drivers experience discomfort. They then tend to compensate for the discomfort by e.g. putting extra effort into attention and vigilance or adjusting the task, e.g. slowing down. (Summala, 2007) In a car-following situation, drivers usually do not look away from the road unless the range rate between them and the lead vehicle is effectively zero. (Tijerina et al., 2004) They do not, in general, appear to take range or time headway into account to any substantial degree.

2.4 What visual stimuli trigger avoidance reactions in a car following situation?

As mentioned above the drivers do not to take their eyes of the road unless the relative velocity of their vehicle and the lead vehicle is close to zero. The visual cues that are considered relevant for longitudinal vehicle control have been classified as contextual, augmenting or primary cues. (Tijerina et al., 2004) Traffic queues building up ahead, red lights at the next intersection or upcoming curves are all examples of contextual cues. Augmenting cues refer to synthetic alerts such as brake lights of the lead vehicle or in-vehicle collision warnings. Brake lights are activated before the range between two cars in a car following situation gets smaller and they are therefore generally the first signal that alerts the driver that there is a possible risk of a rear-end collision. The onset of brake lights is however common in a non-threatening situation, e.g. when the driver of the lead vehicle is only tapping the brakes lightly. The brake light onset does therefore not necessarily imply that he is breaking with a force. Crash records have shown that although being available, brake light onsets may not be effective for triggering avoidance reactions (Tijerina et al., 2004, Markkula, 2015). Similarly have in-vehicle collision warnings been found to re-orient the gaze to the road without having a direct effect on the avoidance reaction of the drivers (J.D. Lee et al., (2002), Engström, Ljung Aust and Viström (2010)).

Finally there are primary cues, such as changes in optical kinematics, which in several studies have found to be the main factor initiating avoidance manoeuvres in rear-end safety critical events (Engström et al., 2013a). The term optic flow was introduced by Gibson in the 1940s to describe the optical stimulus presented to animals when they are moving. His followers have then further demonstrated the role of optic flow in perceiving movement. When a driver approaches a leading vehicle that is slowing down or stopping, the impending vehicle will expand on the retina with an optical angle θ, at an optical expansion rate $\dot{\theta}$, commonly referred to as visual looming. The ability of detecting looming has been located in specialized neural circuits in animal brains which are used e.g for collision-avoidance (Fotowat et al., 2011, Sun et al., 1998). Looming is directly linked to changes in the kinematics and does therefore, unlike the previously mentioned visual cues (e.g., brake lights), represent the urgency of the situation. According to Lee (1976) the decision to initiate braking is determined by estimating an optically specified time-to-collision (TTC), often referred to with tau (τ). The parameter tau is specified for small angles and defined as:

$$\mathrm{TTC} \approx \tau = \frac{\theta}{\dot{\theta}} \tag{2}$$

Where θ is the optical angle of the impending object and $\dot{\theta}$ is its time derivative. Drivers initiate braking manoeuvre however only when a certain threshold of tau is obtained regardless of their speed. (Lee. D, 1976)

The inverse of tau was used as the key measurement of looming in the SHRP2 analysis (Victor et al., 2015). Since tau decreases from infinity when approaching the POV, the inverse tau, which increases from zero was chosen as a more convenient variable. Inverse tau can be directly translated into the relative rate of change of the POVs' optical expansion on the retina. For example, if the POV grows on the retina by a third in 1 second, then $1/\mathrm{TTC} \sim 1/3$, implying that the collision is 3 seconds away under all circumstances, no matter the vehicle's approaching speed or distance (Markkula, 2015).

2.5 Glance timing vs. situation kinematics; SAFER SHRP2 analysis

Does the occasion of an unexpected event occurring at the same time as eyes off path play a fundamental role in rear-end crash causation? Drivers have certain expectation about how the traffic situation will evolve which they base on their current understanding of the environment and their experience. An unforeseen event violates driver expectations and if it occurs during an off path glance, it might result in a crash.

One of the objectives of the SHRP2 analysis performed by SAFER (Victor et al., 2015) was to observe how common the "inopportune glance due to expectation violation" mechanism was in the data set. The kinematic situation was therefore analysed at the start and end of the last glance (LG) before a crash or near-crash. T-tests were performed on each of the kinematic variables (e.g. relative velocity, time headway and inverse Tau) to evaluate if there was a statistically significant difference between crashes, near-crashes and matched baseline events.

The mean values for relative velocity at the start of LG proved to be similar for crashes and near-crashes but significantly lower compared to the matched baseline events. Negative values represent that the SV was closing in on the POV. In all event types the majority of cases had a relative velocity close to zero at the start of the LG, as was expected in line with Tijerina et al. (2004). When measured at LG end, the difference between relative velocity values for crashes and near-crashes was not statistically significant and it was therefore concluded that changes in relative velocity during LG does not have an impact on whether or not the event develops into a crash or not.

The distribution of time headway at the start of the LG was similar for all event types, but at the end of LG the time headway had reduced significantly for crashes and near-crashes, with the reduction being a significantly larger for the crashes. The time headway at the start of LG was also analysed with regards to the duration of the glance. There were some indication of drivers adopting longer time headway for the longer glance duration (>2 s) but in general it seemed like the time headway was not taken into account when the drivers decided on how long they should look away from the road. Crashes with time headway larger than 2 seconds at the start of LG were very rare, and only occurred when the glances were extremely long (>4 s).

For the majority of the events in the data set, the inverse tau (invTau) was close to zero at the start of the LG, indicating a normal non-critical car following situation. There was no significant difference between the invTau value at LG start for crashes and near-crashes. There was however a significant difference between the matched baseline and the crashes/near-crashes combined, which indicated that some crashes or near-crashes involved drivers look away despite already being closing in on the lead vehicle. At the end of LG the invTau had notably changed in both crashes and near-crashes, representing that the situation had turned critical over the glance period. Crashes could be distinguished from near-crashes by a larger invTau value and shorter time headway at the end of LG, indicating a higher criticality.

Another objective of the analysis in Victor et al. (2015) was to understand better how brake light onsets affected the drivers' behaviour. The co-occurrence of brake light onsets and off-path glances in the dataset was investigated and turned out to be the case in 23% of the crashes, 34% of the near-crashes and 31% of the matched baselines. That indicates that whether the driver misses the brake light onset or not does not play a significant role for whether the event develops into a crash or a near crash. What was even more interesting was that drivers took their eyes off the road, despite having seen the brake light onset (assuming that weather conditions were good and the brake lights salient enough to be noticed), in almost half of the crashes and 30% of near-crashes and matched baselines. From that it can be concluded that the brake lights are often ignored.

The relative contribution of LG duration and invTau change rate to crash and near-crash causation was also analysed. The invTau change rate was calculated with the robustfit function in Matlab that gave a linear slope that fitted the invTau data over the last glance period. It was concluded that the change rate of invTau during LG was able to distinguish many of the crashes from near-crashes (Figure 3). The events that are located above the hypothetical boundary for safe glances, see Figure 3, occur due to a "perfect mismatch" mechanism in line with the general mismatch model of driver inattention (Engström et al., 2013b). The "perfect mismatch" mechanism strongly violates the driver's expectations and is explained as a "perfect mismatch" between the visual attention to the road and the kinematic change of the surrounding traffic. The longer the glance duration, the more likely it is that the kinematics will change so that a "perfect mismatch" occurs. Since long glances occur less often than short glances, many crashes result from a combination of high change rate and shorter glances. An important finding of that analysis was thus that glances do not have to be long to produce a crash.

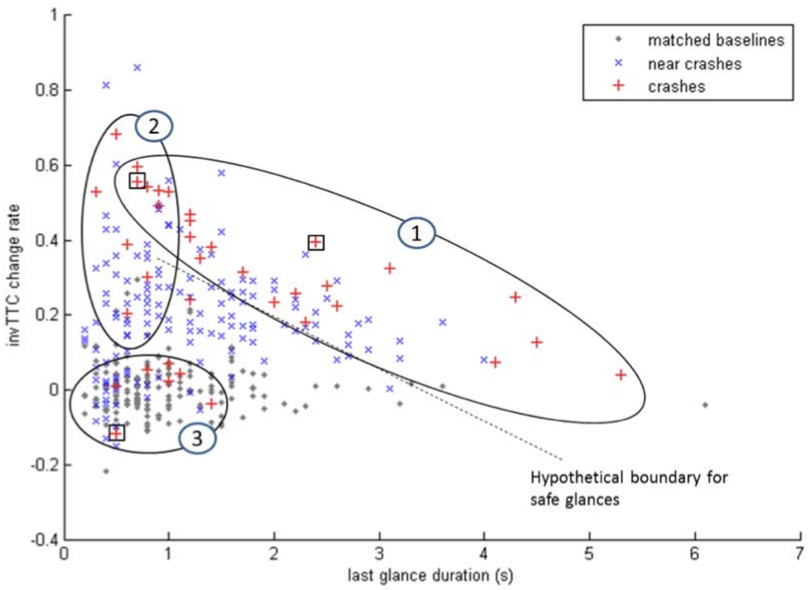

Figure 3: SHRP2 analysis (Victor et al., 2015) on the interaction on invTau change rate and LG duration. The figure is reprinted here with permission.

In the SHRP2 analysis, the crashes in Figure 3 were divided into three main categories. Majority of the crashes (60%) were grouped in Category 1, as inopportune glance, where the drivers looked away from the road in a non-critical situation (invTau close to zero). Those crashes occur largely due to the "perfect mismatch" mechanism mentioned above. In Category 2, the drivers looked away in an already kinematically critical situation, which was suggested to be mainly due to reduced visibility. In Category 3, the drivers looked back on the road before the situation got critical and in those few cases the short time headway between the vehicles appeared to be the main crash causation.

2.6 Research questions

2.6.1 General objectives

As reviewed above, previous research has shown that off-road glances, especially those longer than 2 seconds are strongly related to crash risk, especially in rear-end crashes. The goal of this analysis was to understand further how off-path glances lead to rear-end crashes. To this end, the timing relations between off-road glances, kinematics and visual cues were analyzed and compared between crashes and near-crashes. As mentioned before, the main objective of the present analysis was to replicate the rear-end crash analysis conducted on the SHRP2 data on a different naturalistic dataset, the ANNEXT data.

The ANNEXT dataset differs in some ways from the SHRP2 data:

- It contains rear-end crashes and near-crashes but no matched baselines.
- Different vehicle types, with passenger cars only being about 1/3 and the rest trucks and buses.
- It has more crashes that are also more severe.
- The sampling frequency is lower, 4 Hz in the ANNEXT compared to 10Hz in SHRP2.
- The data collection is event triggered as compared to SHRP2 where the data collection is continuous. That results in fewer possible interval samples of recorded data both before and after the crashes.

2.6.2 Specific research questions

The following specific research questions were addressed in this thesis:

1. What is the prevalence of off-path-glances in crashes and near-crashes?
    a. What is the proportion of crashes and near-crashes where the driver looked away just prior to the crash (also split between cars, trucks and buses)
2. How is the duration of the last glance (LG) before the crash/near-crash distributed? Is there a difference between crashes and near-crashes?
3. What does the situation look like at the start of the last glance and does it differ between crashes and near-crashes?
    a. Has the brake light onset (BLO) of the POV already illuminated while the driver still looked forward?
    b. What safety margin (time headway) does the driver adopt before looking away? Is it related to the duration of the subsequent glance?
    c. Is the distance to the POV constant when the driver looks away (a steady-state situation, as would be predicted by Tijerina et al. (2004)) or do drivers often look away when the POV is closing in? (i.e., relative velocity different from zero)
    What is the urgency of the situation when the driver looks away, as optically represented by invTau (looming)?

4. What does the situation look like when the driver looks back the last time, and does it differ between crashes and near-crashes?
    a. Has the POV brake light onset (BLO) illuminated while the driver looked away?
    b. How much has the kinematics (THW and relative velocity) changed?
    c. How much has the urgency of the situation (invTau) changed?

3 Method

3.1 Data

In this project a total of 100 rear-end events from the ANNEXT project were analysed. The data set used consisted of the 70 rear-end crashes that have previously been partly analysed by Engström et al., (2013a) and additional 30 rear-end near-crashes that have not been analysed before.

3.1.1 The ANNEXT data set

The data from the 70 rear-end crashes were sampled between the 4th of October 2011 and the 1st of March 2012. The near-crash events were sampled over a shorter period of time, from the 24th of January until the 29th of February 2012. Most of the 100 rear-end events occurred in the US, or 53 of the crashes and 24 of the near-crashes, and the remaining 17 crashes and 6 near-crashes occurred in Africa (South Africa, Nigeria, Zambia and Zimbabwe). 92 of the subject vehicle (SV) drivers were male and the crashes occurred at various times of the day, with most crashes happening between 6 and 8 AM.

The SV was a truck in 28 crashes (40%) of all crashes, a passenger car in 26 crashes (37%) and a bus in the remaining 16 crashes (23%). The near-crash events were then selected to match the distribution of SV types from the crash event set, with the SV being a truck in 11 cases (36,5%), a bus in 8 cases (27%) and a passenger car in the remaining 11 cases (36,5%).

Table 3: Distribution of SV vehicle types in the dataset

SV Type	Truck	Bus	Passenger car	Total
Crashes	28 (40%)	16 (23%)	26 (37%)	70
Near-crashes	11 (36,5%)	8 (27%)	11 (36,5)	30

The following criteria were used for selecting the events for the ANNEXT dataset: heavy vehicles were prioritized, the driver should be an adult and he should not be wearing sunglasses, the speed of the SV should be higher than 15 km/h at the initiation of the evasive manoeuvre (or at the crash point when no evasive manoeuvre was present) and the POV should remain in the same lane from the beginning of the event until the evasive manoeuvre or the crash point.

The OBSM device used by LYTX consists of an event-triggered video, with a forward scene view as well as a view of the driver/cabin, and a data-recording unit that measures lateral and longitudinal acceleration, vehicle ground speed based on GPS data and global position (GPS based). The video data is collected at

4 Hz, the acceleration at approximately 8 Hz and the GPS sample rate is close to 1 Hz. The video cameras record 8 seconds prior to the kinematic trigger point and 4 seconds after. Data collection is triggered when the SV faces an impact or if there is a hard braking or other kind of evasive maneuvers.

3.1.2 Initial data reduction

The actual video data was not made available for analysis and therefore the parameters of interest for this analysis had to be extracted in another way. The data was reduced based on a reduction scheme that was used in the 100-car ND study (Dingus et al., 2006), but adapted for current purposes. A trained analyst at LYTX performed the reduction of the videos manually. For each event a variety of general information (e.g. the type of SV and POV, the weather conditions and the SV driver gender) was coded. Furthermore, time series data for the driver visual behavior, onset of POV brake lights and the POV optical size in the video image were gathered, frame-by-frame. The visual behavior of the SV driver was coded according to the area of interest to which the driver directed his gaze, for example towards the mirrors, the windows, the instrument cluster etc. If the transition of the gaze was captured, that frame was assigned to the following glance. Eyes closure or coverage was also coded.

The optical size of the POV in the video was used to derive parameters such as the range, optical angle, optical expansion rate, and tau based on camera calibration. The width of the lead-vehicle was measured between the outer edges of the two rear-lights as seen from the forward video and manually annotated for each video frame. The LYTX annotator used the same screen when measuring the POV width in all events. The annotations were done for each video frame and therefore had the frequency of 4 Hz. In order to align the GPS data gathered at 1 Hz with the other data gathered from the video at 4 Hz, the GPS data was upsampled to 4 Hz with a linear interpolation.

The real vehicle width was estimated based on the car model or by selecting a standard width for that vehicle type, see Table 4.

3.2 Crash scenario reconstruction

The range to a lead vehicle, the optical angle, optical expansion rate and tau of the vehicle as seen by the SV driver were estimated using methods developed by Bärgman et al. (2013). These methods use manual annotation of video together with established image-rectification and transformation algorithms to estimate useful kinematics and optical parameters from videos. The following subsections describe how the measured width is filtered and how it is possible to retrieve the useful optical parameters from the measured POV width on a screen, the screen resolution and information about the camera optics. Additionally it is described how estimation of the estimated real width of the POV can be used to obtain the kinematic parameters.

3.2.1 Filtering the POV measured width and reducing noise

The initially measured width of the lead vehicle was filtered in order to minimize the effect of noise, image compression artifacts etc. The width was used in order to reconstruct the visual angle from the video and since the measurements were done manually the accuracy depends a lot on how precise the annotator was when measuring the outer edges of the POV since the tool used for the width annotation was a regular ruler. Limited screen resolution and noise lowered the accuracy of the measurements. All optical variables that were calculated based on the visual angle were affected by this noise. It was especially problematic when measuring the POV at a long distance, where the uncertainty was large compared to the pixel size, and for those variables that involve time-derivatives (theta-dot and invTau). The filter that was applied to the raw manually measured width data in order to reduce the noise-effect was the square-kernel smoothing filter with amplitude-adapted width. The kernel averages across a dynamic number of POV width measurements (frames), which number in this case was $N = (W_0/W)^2$ with $W_0 = 60$ mm, and W the measured width in millimeters at each frame. The maximum kernel size was limited to 2 in order to react to rapid changes in the observed pixel width and instead the filter is added 3 times. The same smoothing filter was used in the SHRP2 analysis (Victor et al., 2015) with some modifications to reduce edge artifacts. In the modified version the edge value was kept constant between filter passes instead of letting the filter clip the edge value and thereby loose information. This was crucial in the slower sampled ANNEXT data while not as important in SHRP2.

3.2.2 POV edges out of frame

One problem with the vehicle width annotation is that the POV edges, at close distances, sometimes appeared outside the video frame. In order to address this problem, these occasions had previously been annotated based on video observation at Lytx. This annotation represented the time stamp in each event time series where the POV edges first went out of frame. This annotation was used to define up to what time point the data was reliable. In a few cases, where the POV edges went out of frame before the end of the LG was reached, the data was extrapolated. The last second of reliable data, or 4 data points, were used as a base for a 2nd degree polynomial fit.

3.2.3 Camera rectification

To compensate for optical distortion in the image, the pixel coordinates of the width on the right and left side of the lead vehicle were adjusted as if the vehicle was in the center of the screen. In order to do this a linear model, which parameters were extracted from the Camera Calibration Toolbox for Matlab (Bougeuet, 2010), was used, see equation 1.

$$S_{rect} = \left(0.37 + 1.0127 \cdot S_{dist} \cdot \frac{W_S}{W_{NS}} - 0.000203 \cdot \left(S_{dist} \cdot \frac{W_S}{W_{NS}}\right)^2 + 0.00000151 \cdot \left(S_{dist} \cdot \frac{W_S}{W_{NS}}\right)^3\right) \cdot \frac{W_{NS}}{W_S} \quad (2)$$

Where the filtered size of POV vector, S_{dist}, comes from the square-kernel filter and W_S / W_{NS} is used as a screen scaling, so the equation fits for other sizes of screens. The W_S stands for the width of screen used in the method development, W_S = 449 mm, and the W_{NS} for the new screen width, which in this case was W_{NS} = 330 mm. The result is a vector, S_{rect}, which contains the rectified size of POV in millimeters. This model is specially intended for rectifying measurements from the DriveCam Event Recorder video (Bärgman et al., 2013).

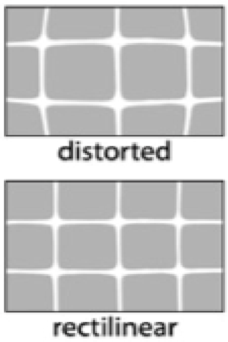

Figure 4: A schematic of how an image can be rectified by using camera calibration techniques

3.2.4 Optical parameters

The optical parameters were calculated by using knowledge about the focal length of the camera. No knowledge of the POVs real width is required to get the visual angle and, hence, no small angle approximations are needed in the calculation of the optical variables.

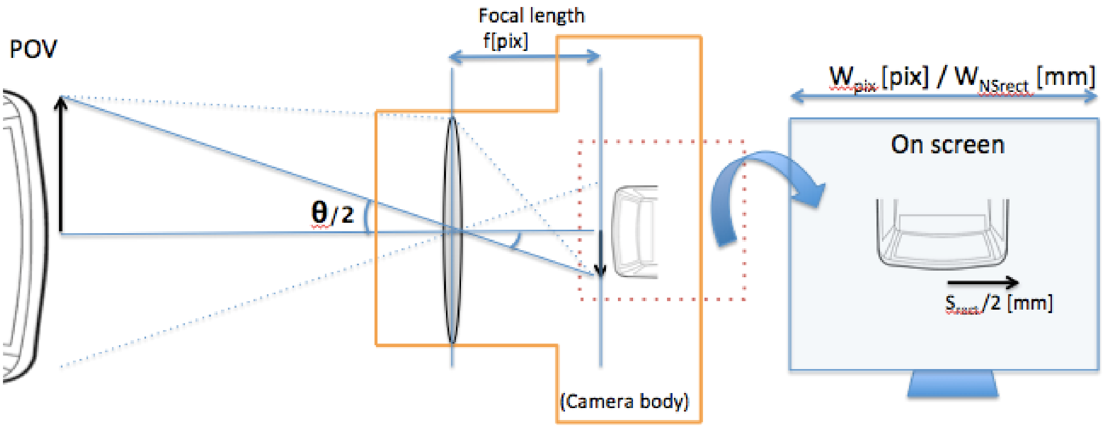

Figure 5: A schematic showing how the visual angle, θ, is obtained. The black arrows represent the POVs real width, the width captured by the camera and the width as measured on the screen.

Theta (θ) is the visual angle of the rear end of the POV as seen from the camera. By looking at Figure 5 it can be seen that the angle θ/2 is given by the focal length and half of the width of the POV as measured on the screen. Since the focal length of the Lytx camera was given in pixels (f_{pix} = 545,9 pixels), and the POV width measured in mm, the focal length is converted to millimeters by using the pixel width of the screen. W_{NSrect} is the rectified maximum screen width (obtained from equation 1 by having $S_{dist} = W_{NS} = 330$ mm), W_{pix} is the width of the video in pixels (here W_{pix} = 655 pixels) and f_{pix} is the focal length in pixels .

Theta was calculated according to equation 2 where S_{rect} is, as before, the rectified POV width on the screen in mm.

$$\theta = 2 \cdot arctan\left(\frac{\left(\frac{S_{rect}}{2}\right)}{\frac{f \cdot W_{NSrect}}{W_{pix}}}\right) \qquad (2)$$

Before deriving other optical parameters needed for this analysis from the theta a 3- point floating average filter was applied to the theta calculation.

Theta dot ($\dot{\boldsymbol{\theta}}$), the optical expansion rate of the POV is obtained by taking the time derivative of θ. This is done with a 3 point floating linear regression. Special care must be taken at the ends of the time series to minimize bias. Points outside the edges of the data are therefore first extrapolated and then the linear regression filter is applied.

Tau ($\boldsymbol{\tau}$), equals the ratio of θ to $\dot{\theta}$, and **InvTau ($\boldsymbol{\tau^{-1}}$)** is the inverse of Tau, or 1/ Tau.

3.2.5 Kinematics / Derived parameters

By assuming the real width of the POV the kinematic parameters can be obtained. The assumed widths for the three vehicle types are given in Table 4.

Table 4: The estimated width of the lead vehicle. Used to calculate the range from POV pixel width.

Vehicle type	Estimated width (m)
Lighter passenger cars	1.6
SUV (Sport utility vehicle)	1.75
Heavier vehicles (e.g. buses, trucks, ..)	2.5

The range between the vehicles could be calculated with the second least square linear regression model given in equation 3 where S_{rect} comes from equation 1 and S_t is the width of the reference vehicle (1.56 m) that was used to produce the model. The actual width of the lead vehicle in the image, S_{NCReal}, is estimated based on the type of vehicle, see Table 4.

$$R_{real} = -0.278 + \frac{559.27}{S_{rect}} \cdot \frac{S_t}{S_{NCreal}} \qquad (3)$$

The range was then filtered with a 3-point floating average filter.

The range rate was then obtained with the same method used for theta-dot calculations, namely taking a time derivative of the range using a 3-point floating linear regression with data points outside the edges first being extrapolated to minimize the bias at the ends when the regression is used

The Time Headway (THW) between the SV and the POV was calculated as the ratio of the range over the SV speed.

The SV speed / relative velocity consists of the merged velocity from the GPS and the velocity obtained from integrating the accelerometer signal. The velocity from the GPS was used until the start of the evasive maneuver and then the acceleration based velocity after that. If there was no evasive maneuver, the GPS signal was used until 1 second before the trigger. Before adding the acceleration-based velocity, the values were offset according to the difference between them and the GPS. This was done to smooth the curve.

3.3 Analysis Methodology

In this section key terms used in this analysis are defined and explained. These terms describe where the driver is directing his gaze. The event data was furthermore aligned to mutual reference points, which was the contact point for crashes and the point of minimum tau for near-crashes. Only data that was logged prior to the reference point was of interest in this analysis, in most cases that included about 8 seconds of data.

3.3.1 Aligning data

For time-series analysis, the events were aligned according to a reference point that was specified for each event type. The crash events were aligned so that the collision point as determined from the video annotator was set to as the reference point. The near-crash events were aligned according to the optically defined inverse time-to-collision (invTau) so that the maximum invTau point was specified as the reference point and set to 0s.

3.3.2 Key concepts

3.3.2.1 Eyes On Path and Eyes Off Path

The driver's visual behavior was categorized based on the ANNEXT coding scheme mentioned earlier. Each time frame of the videos was assigned an area of interest (AOI) towards which gaze was directed. In this analysis the variable Eyes-On-Path was defined as all instances where the driver directed his gaze out of the straight forward windshield. This definition could include glances that are directed to vehicles in the adjacent lanes or other external distraction in front of the car. It could exclude instances where the vehicle is turning and the driver's gaze, although directed to the path, is not straight through the forward windshield. Eyes Off Path does then represent all other instances, including eyes closure or obstructed vision of the driver due to eyes being covered by e.g. hand as well as all glances away from the forward path.

3.3.2.2 Last Glance

Last glance (LG) was defined as the last glance off the forward roadway to take place prior to the reference point, which was set as the contact point for the crashes and the maximum value off the inverse tau for the near-crashes. However, if the driver showed an evasive manoeuvre reflex (braking or steering) prior to the onset of a last glance, then that glance was discarded and the previous glance, if existing, noted as the last one. The start of the last glance was annotated when the driver took his eyes of the road and the end was when the eyes were back on the road. This was not completely in line with SHRP2 where the off-path glance ended when the driver took his eyes off the AOI, before the gaze was back on the forward roadway. In cases where the eyes were closed or covered it was not considered as a glance away from the road.

4 Results

4.1 Prevalence of off path glances

In the ANNEXT dataset, some events did not contain any off-path glances before the reference point. Overall, there were 22 such crashes (6 passenger cars, 6 buses and 10 trucks) and 9 near-crashes (5 passenger cars, 2 buses and 2 trucks)

There were additionally 4 crashes and 2 near-crashes that were missing in the glance onset. These events were excluded when the change in situation kinematics relative to glance duration was analyzed. Table 5 shows the prevalence of off path glances and summarizes the number of excluded events due to missing or incomplete glances.

Table 5: Prevalence of off path glances in the dataset

Event type	Original number of events	Cases excluded due to lack of off-path glances	Additional missing LG start	Additional missing LG ends	Remaining LG starts	Remaining LG ends
Crashes	70	22	4	0	44	48
Near-crashes	30	9	2	0	19	21

An off-path glance was prevalent in total of 69 % of the crash events (48/70=0.69), of which 42% were passenger cars, 21% buses and 37% trucks. The prevalence of off-path glances was similar for near-crashes with 70% of them containing at least one (21/30 = 0.7). The distribution of vehicle types was the following: 28.5% passenger cars, 28.5 % buses and 43 % trucks.

Prevalence of eyes closure and coverage

In 8 of the 22 crash events (11% of the total crash events) that were excluded due to lack of off path glances, drivers closed their eyes or they were covered. These were drivers of 3 passenger cars and 5 trucks. Eyes closure was prevalent in 2 of the 9 excluded near-crash events (7% of the total near-crashes), one of them was a passenger car and one truck.

To conclude, the majority of crashes and near-crashes involved off-path glances or eyes closure/coverage, but the specific action of looking away could not distinguish between crashes and near crashes.

4.2 Distribution of the last glance

In this analysis, the difference in the duration of the last glance for crashes and near-crashes was mainly in the tail, where long glances (exceeding 2 seconds) were slightly more prevalent in crashes (see Figure 6. This difference is however minor and not statistically significant. This result is fairly consistent with the SHRP2 analysis although the glances in general are slightly longer for the ANNEXT dataset. The mean duration of LG for crashes and near-crashes in the present dataset was 1.84 and 1.51 respectively compared to 1.52 and 1.20 for SHRP2. A part of the explanation could be that due to lower sampling rate in this analysis, the glance durations might be annotated as slightly longer than they would be with higher sampling rate.

For shorter glances, glance duration does not distinguish between crashes and near-crashes. Are these glances causally unrelated to the crash? Or is the key issue what happened while looking away? This is further addressed in the result sections below.

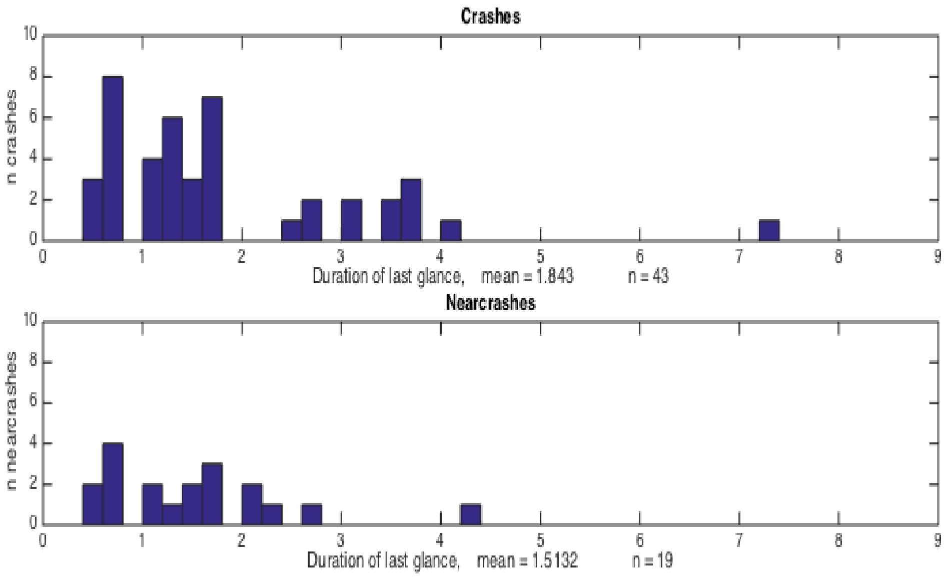

Figure 6: Duration of last glances in crash and near-crash events

4.3 Timing of glances relative to brake light onsets

In this analysis all events that had at least one brake light onset prior to the reference point were included. The dataset then contained 55 crashes and 25 near-crashes, see Table 6. It should be noted that 10 of the excluded crashes and 2 of the excluded near-crashes had a brake light onset prior to the recorded 12-second timeframe. Thus, for these events, the light was on for the whole event but there was no BLO recorded.

The co-occurrences of any brake light onset and eyes off path were investigated in the remaining events and found to occur in 25% of the crashes and 24% of the near-crashes. The co-occurrences of the last brake light onsets and eyes off path were almost the same as for any brake light onset (Table 6). However, drivers ending up in a crash were about twice as likely to look away from the road after having seen the last brake light onset.

Table 6: Off path glances relative to brake light onsets, where EOP = Eyes-off-path , BLO = Brake light onset

Event type	Total number of valid events	N events with brake light onset	N events with BLO where any BLO occured during EOP (%of N BLO)	N events with BLO where the last BLO occured during EOP (% of N BLO)	N events with BLO where the driver looked away after having seen the last BLO (%of N BLO)
Crashes	70	55 (79%)	14(25%)	14 (25%)	8 (15%)
Near-crashes	30	25 (83%)	6 (24%)	5 (20%)	2(8%)

According to these results, the share of drivers missing the BLO was about the same whether the event ended up in a crash or not. The drivers saw the last brake light onset in the majority of crashes and near-crashes, but still ended up in a safety critical situation. This indicates that the brake lights are often ignored and that missing the BLO in itself is not a key mechanism distinguishing crashes from near-crashes. Drivers that ended up in a crash were twice as likely to have looked away from the road after having seen the last BLO as those who ended up in a near-crash. The same relation between crashes and near crashes was found in SHRP2 (Victor et al., 2015). However, compared to SHRP2, there were relatively fewer drivers in this dataset that looked away after having seen the BLO. That is somewhat difficult to explain.

4.4 Timing of the last glance relative to situation kinematics

So far the results have indicated that the prevalence of an off-path glance, the LG duration or missing a BLO does not play a fundamental role in distinguishing rear-end crashes from near-crashes. It may be that the situation kinematics at the end of a LG is more critical in crashes than in near-crashes. To investigate this hypothesis, t-tests were used to test for statistically significant differences at the start and end of a last glance for different kinematic variables and between the event types. Two-sample t-tests were used to compare on one-hand crashes vs. near-crashes at LG start and on the other at LG end. Paired sample t-tests were then used to look at the situation at LG start vs LG end for crashes and near-crashes. The significance level in all tests was $\alpha = 0.05$.

Events where the invTau < 0.2 s^{-1} at the end of the last glance are referred to as eyes-on-threat events in accordance to what was done in the SHRP2 analysis

(Victor et al. 2015). When invTau > 0.2 s^{-1} at the end of the last glance that event is referred to as eyes-off-threat event.

4.4.1 Time head way

The distribution of initial time headway at the start and end of a last glance is shown in Figure 7. The mean time headway is slightly more than 2 seconds when the driver looks away, with no significant difference being between crashes and near-crashes, 2.62 and 2.54 seconds respectively. This is in line with SHRP2 and Tijerina et al. (2004) and indicates that the situation at the start of a glance typically represents a normal following situation. These mean values are considerably higher compared to the initial time headways recorded at the start of glances in SHRP2 analysis, which on average were closer to 1.5 seconds. That difference is not easily explainable. Since different vehicle types are being used in the two studies one assumption could be that drivers of heavier vehicles adapt longer time headway due to a longer stopping distance. Figure 8 does however not show any apparent difference between the adapted headway of light and heavy vehicles.

At the end of the last glance the time headway has become significantly reduced for both crashes and near-crashes ($t_{43} = 6.34, \mathrm{p} \ll 0.001$ and $t_{19} = 2.65, \mathrm{p} = 0.016$), the left tail is however, slightly more pronounced for crashes.

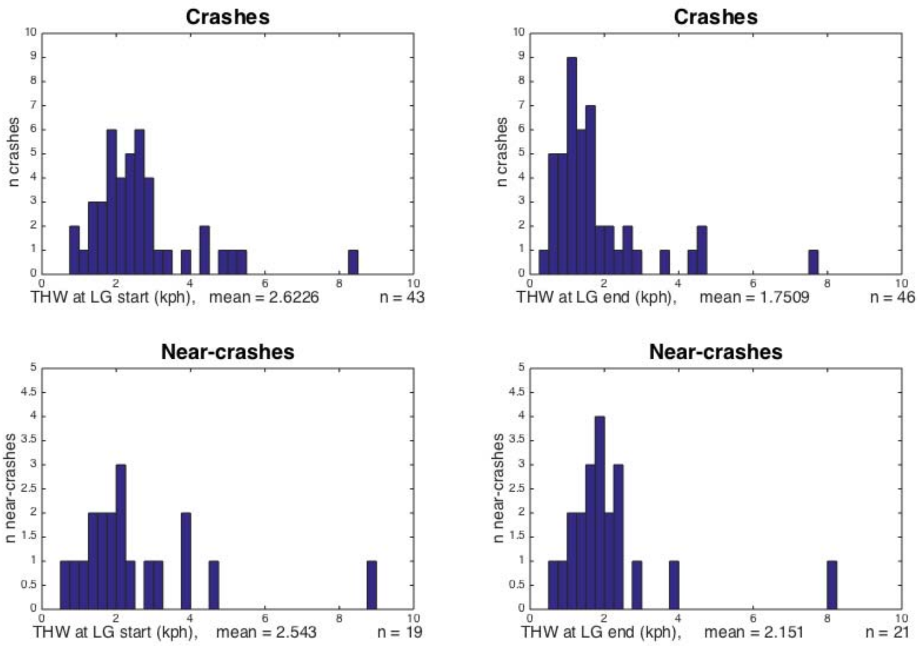

Figure 7: THW at start and end of LG

Figure 8 shows the time headway at the start of the last glance versus the duration of the glance. Most events occur at a short THW with relatively short glances. There is some weak indication that the drivers allow longer glances at longer time headways. A linear regression gave a correlation of $R^2 = 0.1721$, after the two extremely long THW cases had been excluded.

All in all, at the start of LG the time headway alone could not predict whether or not the event would evolve into a crash or a near-crash ($t_{62} = -0.1868$, $p = 0.8525$). At the end of a last glance the time headway had on average reduced more for crashes than near-crashes and short headways were more common for crashes. The difference was however not significant ($t_{67} = 1.07$, $p = 0.2897$).

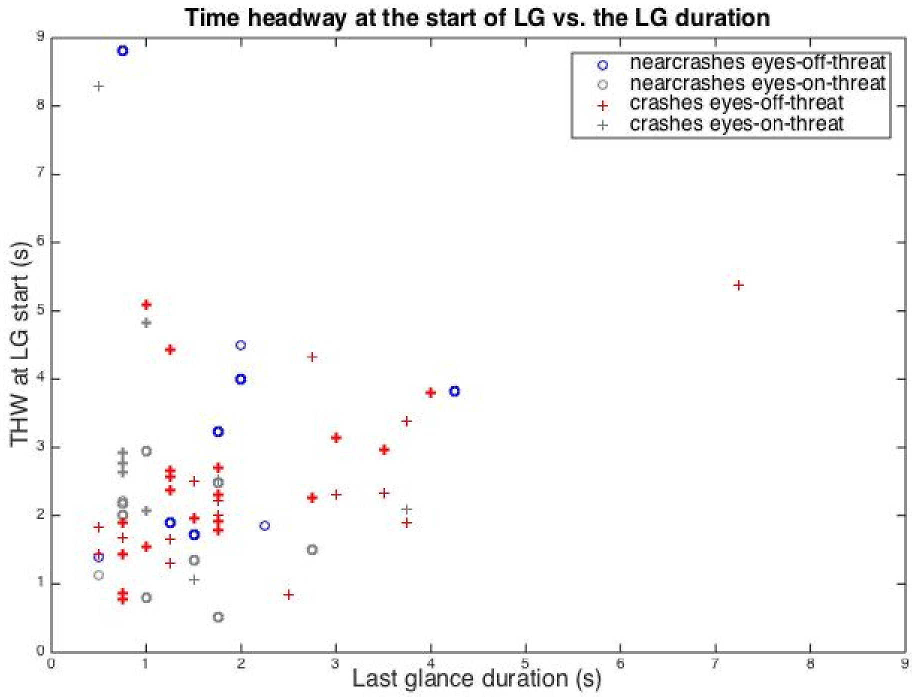

Figure 8: Time headway at the start of the LG vs. the duration of the LG. Heavier vehicles (trucks, buses) are represented with bolder markers.

4.4.2 Relative velocity

In Figure 9 the relative speed is plotted at the start and end of the last glance. For the majority of the events, in both crashes and near-crashes, the drivers looked away when the relative velocity was small, indicating a normal following situation and thus supporting the findings of Tijerina et al. (2004). The negative tails at the start of LG indicate that a significant proportion of drivers did look away when the POV was closing at a relatively high speed. As can be seen in Figure 10 this was mainly the case when the time headway was large and the drivers did therefore perhaps not perceive a great urgency.

Looking back at Figure 9 a difference can be seen between crashes and near-crashes in how the relative velocity has changed during the last glance. The change over the LG duration is statistically significant for the crashes ($t_{43} = 4.5113$, $p \ll 0.001$), indicating that the amount of closing that is missed while looking away from the forward road place a role in why some events evolve into a crash and others not. The change over LG duration for near-crashes is not statistically significant (t_{19} = 1.238, p = 0.2315) and the difference between near-crashes vs. crashes at LG start (t_{62} = 0.9958 , p = 0.3233) and at LG end (t_{67} = 1.888, p = 0.0634) is neither.

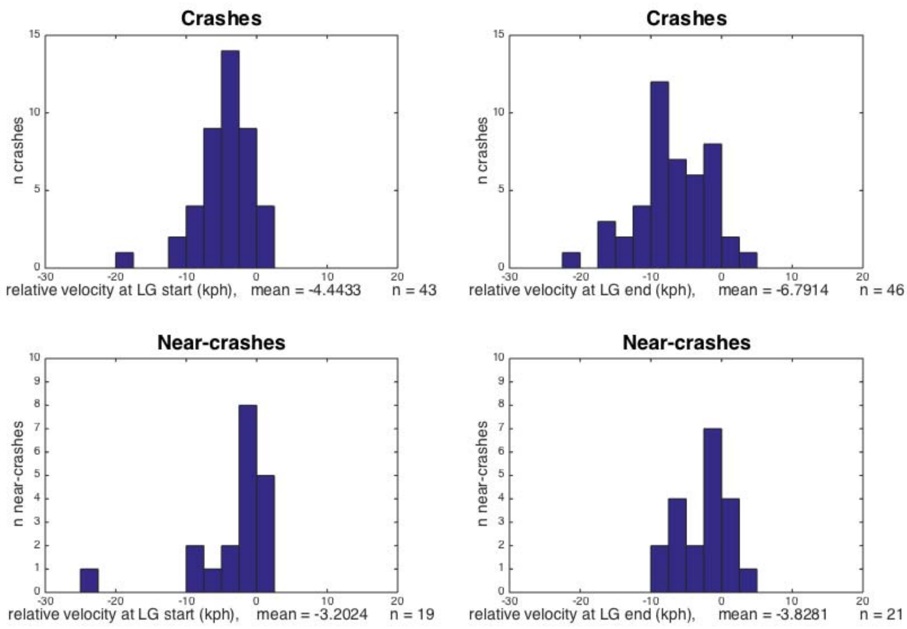

Figure 9: Relative velocity at the start and end of the LG.

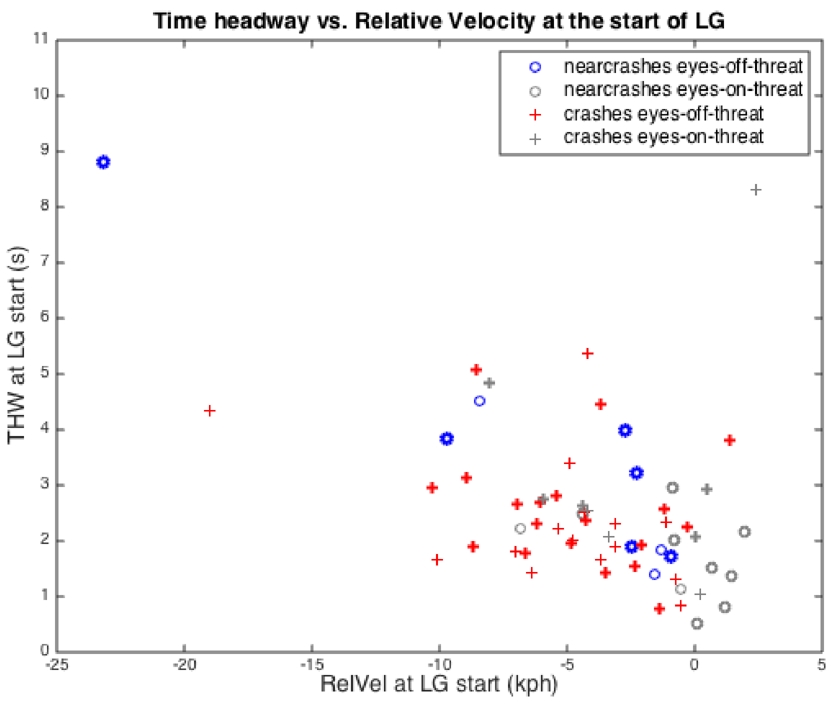

Figure 10: The relative velocity vs. the THW at start of LG. Heavier vehicles (trucks, buses) are represented with bolder markers.

4.4.3 Inverse Tau

The distribution of inverse tau at the start and end of an LG can be seen in Figure 11. The invTau is approximately the inverse time-to-collision, and as such representing of the urgency of the situation. Since it is optically specified in terms of relative rate of the angle subtended by the POV, or looming, it would be expected to also represent the degree of the urgency perceived by the driver. In support of Tijerina et al. (2004), the majority of the drivers looked away when the invTau was close to zero or when the situation was still non-critical, and there was no statistically significant difference at LG start between crashes and near-crashes.

However, in some cases, more frequently in crashes, the driver looked away despite rather high values of invTau. It may be hypothesized that the main mechanism for this was erroneous expectancy; the drivers expected the situation to develop differently than it did due to missed contextual cues. Moreover, in few cases the visibility was not ideal, heavy rain or glare from the sun impaired looming detection.

The invTau changed significantly during the last glance, both for crash and near-crash events ($t_{43} = -6.23, \mathrm{p} \ll 0.001$ for crashes and t_{19} = -3.17 , p<0.01 for near-crashes). At the start of LG the difference between near-crashes and crashes was already statistically significant (t_{62} = -2.543, p = 0.0136) and the change at the end of LG also differed substantially between crashes and near-crashes ($t_{67} = -3.3450, \mathrm{p} = 0.0014$). That suggests that the missed urgency information (amount of looming) during the LG is a key factor in developing crashes.

At the end of LG the prevalence of eyes-on-threat events (invTau < 0.2 s^{-1} at LG end) was 26% for crashes (12/46 = 0.26) and 57%(12/21=0.57) for the near-crashes, further supporting that conclusion that the change in urgency (or missed looming) during the last glance is also a key factor in crash causation.

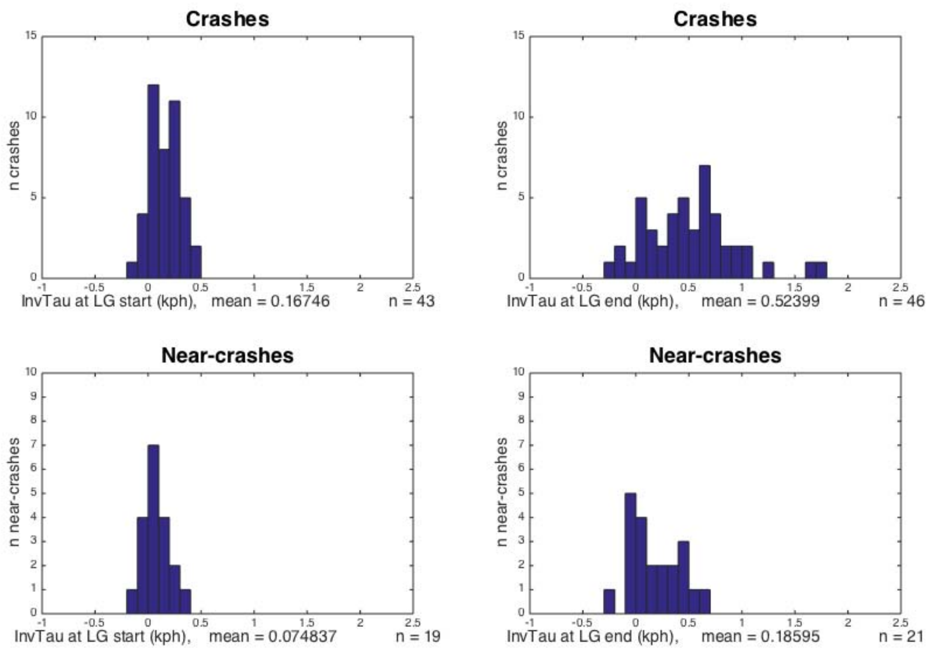

Figure 11: Inverse tau at the start and end of LG.

The amount of missed looming depends partly on the glance duration, but also on the kinematics of the situation. For example, the looming will grow faster at shorter initial headways and for higher closure rates. To investigate the relation between these factors, the invTau difference was plotted against LG duration (see Figure 12).

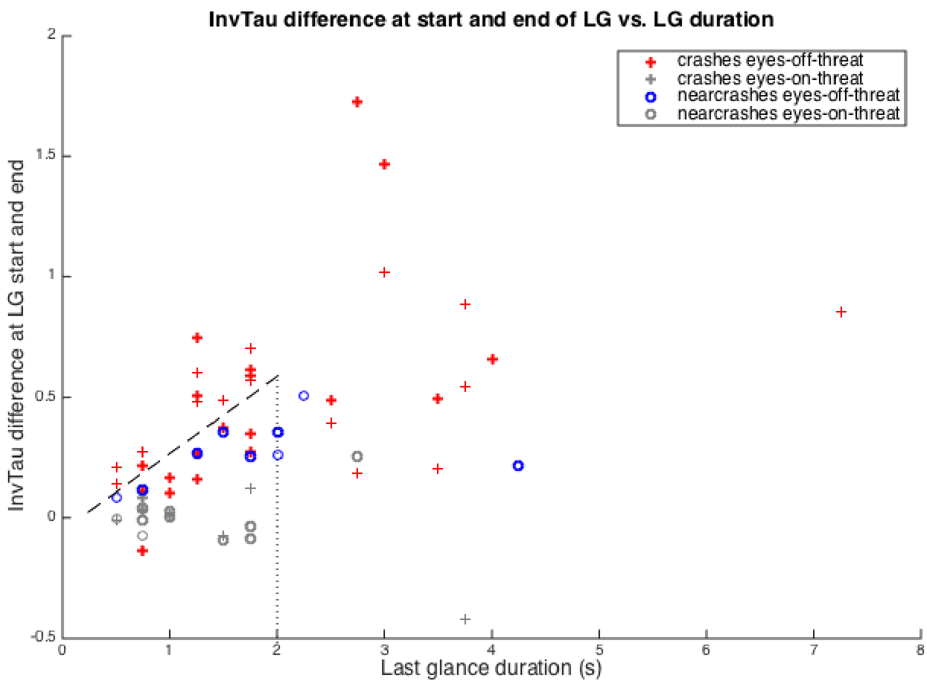

Figure 12: The change of inverse tau over the LG period vs. the duration of the glance. Heavier vehicles (trucks, buses) are represented with bolder markers. The dotted and dashed lines enclose an area for “safe glances”, more about that in the text.

The plot seen in Figure 12 indicates that both factors play a role. Most eyes-on-threat events, shown in gray in the figure, have a missed invTau value clustered around zero regardless of the LG duration, as would be expected. The vertical dotted line divides the glances in shorter and longer glances (above/below 2 seconds). There are not many near-crashes with LG longer than 2 seconds but there is a considerable amount of crashes with LG longer than 2 seconds. For longer glances, crashes may occur for a wide range of missed invTau values (depending on at what point during the glance the lead vehicle brakes), with the requirement that the situation must be sufficiently urgent when looking back to become a crash. For shorter glances, the missed invTau for both near-crashes and crashes increases approximately linearly with LG duration. However, the urgency (invTau) needs to change more rapidly to produce a crash. The dashed line represents a hypothetical threshold that decently separates crashes from near-crashes. When put together, the lines in Figure 12 enclose an area of what could be seen as relatively “safe glances”. Thus, for a subset of the events, the outcome seems almost solely determined by the combination of glance duration and change rate.

The invTau change rate was then plotted against LG duration in order to replicate the SHRP2 analysis. In SHRP2 the cornerstone of the findings was the invTau change rate mechanism (Figure 13).

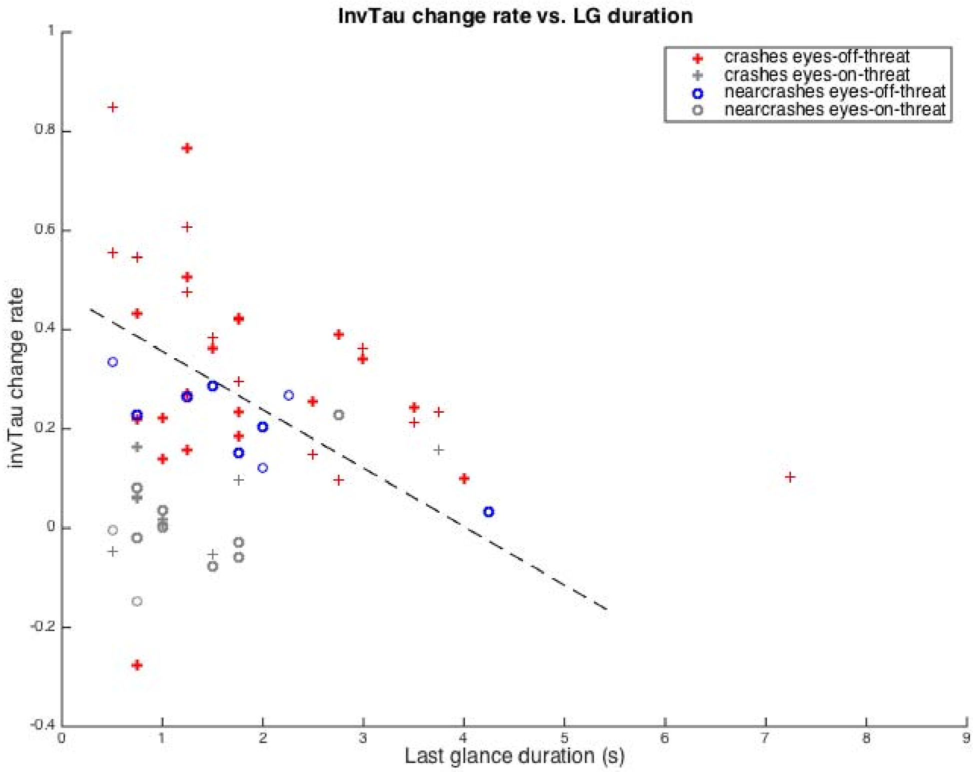

Figure 13: Inverse tau change rate during a last glance. Heavier vehicles (trucks, buses) are represented with bolder markers. The dashed line represents hypothetical boundaries for “safe glances”.

The change rate of the inverse tau during the last glance was computed as the slope of a linear function fitted to the invTau data during the last glance. This was done by using a Matlab function called robustfit. In events where the last glance was short and there were not enough values to use the *robustfit*, the data was fitted with a multiple linear regression function from Matlab called *regress*.

The property of the robustfit function is to give the mean slope over the selected data segment of interest, in this case the last glance. The change rate is thus very dependent on the length of the last glance and usually the longer the glance, the lower the change rate.

Figure 13 replicates the findings in SHRP2 (Figure 3), indicating that a large portion of the crashes occur due to a “perfect mismatch” between the timing of the last glance and the change in urgency of the situation. For short glances, the urgency (invTau) needs to change fast during the LG in order to produce a crash.

These relatively short glances clearly play a causal role in the development of the crashes, or at least in the outcome impact. However, like in SHRP2, there are also some crashes intermingled with the near-crashes. These may involve other factors like skidding, adverse visibility etc. that increases the stopping distance, or slows down the reaction, which then makes an event that would normally have resulted in a near-crash develop into a crash.

Although both the invTau change rate plot (Figure 13) and the invTau difference plot (Figure 12) manage to distinguish crashes from near-crashes fairly well the invTau change rate and the LG duration are very dependent variables and thus the change rate may perhaps not be the best indicator of urgency. As can be seen in Figure 14, the invTau change rate flattens drastically with longer glance duration. By comparing two variables this dependent a linear behavior is automatically created, like the one seen in Figure 13. Longer glances have an intrinsically lower, more flattened out, change rate.

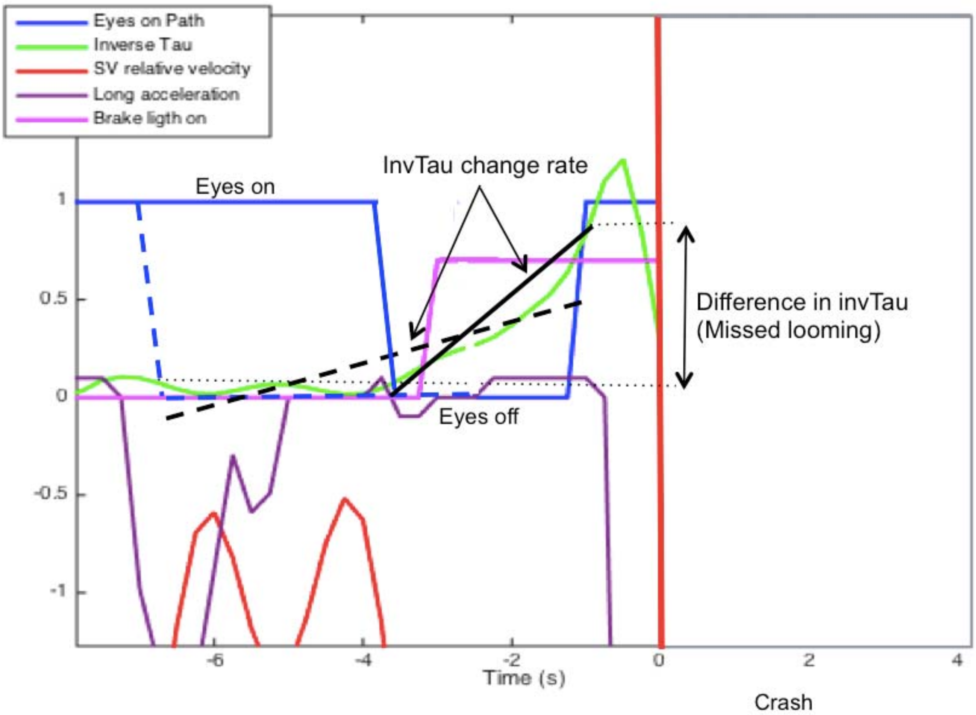

Figure 14: A diagram explaining the fundamental difference between invTau change rate and the difference in invTau (missed looming) during a last glance. The dashed lines show a hypothetical event where the glance duration is much longer and how that affects the invTau change rate.

Figure 14 also shows that the difference of invTau at the start and end of LG, or missed looming, appears to be a much more independent variable. For different LG durations the missed amount of looming is still the same. It could therefore be stated that less bias is introduced by plotting the missed looming against the LG duration (Figure 12) and that missed looming might be a better indicator of the change of urgency during a glance than the invTau change rate.

5 Conclusions

In the previous chapter the results of the present analysis were displayed and compared with what was found in the SHRP2 analysis (Victor et al., 2015). When all is taken together it can be concluded that the findings are very consistent with what was found in the SHRP2 analysis. Namely that the combination of glance duration and the change in urgency, represented optically by looming cues during the glance, is a key crash causation mechanism. These findings add great support to the design of active safety systems and other driving support countermeasures that protect the driver during a critical situation. If there is a sudden change in the situation kinematics during a glance off the forward road the active safety systems could initiate braking to create more time headway as well as alert the driver about the oncoming threat.

The main difference found between those two datasets was that the drivers in the present analysis adopted significantly larger safety margin than drivers in SHRP2. One of the mechanisms found in SHRP2 was that the onset of brake lights was generally ignored as a possible crash indicator with drivers looking away from the road after having seen the brake light onset in 50% of the crashes. This mechanism did however only occur in 15% of the crashes in the present analysis. It is therefore difficult to draw any safe conclusions about how the brake light onset affects drivers in crash avoidance behaviour.

The research questions asked in section 2.6.2 are answered here below:

1. *What is the prevalence of off-path-glances in crashes and near-crashes?*

This refers to the proportion of crashes and near-crashes where the driver looked away within the time window (also split between cars, trucks and buses). The prevalence of off-path glances did not differ between crashes and near-crashes and was in both cases around 70%. However, the proportion of eyes-off-threat glances was higher for crashes, indicating that the timing of the glance in the time window played a crucial role for event outcome.

2. *How is the duration of the last glance distributed? Is there a difference between crashes and near-crashes?*

The main difference is in the tail – several crashes involve very long glances that do not occur for near-crashes. SHRP2 included baselines and also found that crashes and near-crashes mainly differ from baselines in the tail (separate glance distributions for crashes and near crashes were not plotted in Victor el at. (2015). This indicates that, for shorter glances, glance duration alone cannot explain crash outcome.

3. *What does the situation look like at the start of the last glance and does it differ between crashes and near-crashes?*

a. *Has the brake light onset of the POV already illuminated while the driver still looked forward?*

In this study, looking away after having seen the BLO was quite rare for both crashes and near-crashes. This was in strong contrast to SHRP2, where this happened in 50% of crashes. That could perhaps be explained somewhat by shorter time recorded prior to the crash, were in many of the cases, the BLO had already happened and was perhaps seen by the driver. In this analysis those cases were not considered because of lack of data.

b. *What safety margin (time headway) does the driver adopt have when looking away? Is it related to the duration of the subsequent glance?*

The THW at LG start was on average 2,5 seconds, which is about 1 second larger than in SHRP2. One explanation could be that the drivers in the current dataset were professional drivers while the drivers in SHRP2 were not. No significant difference in adapted time headway between crashes and near-crashes indicates that time headway did not determine the outcome. A safety margin of 2,5 seconds is considered relatively large, so in the present crashes (where drivers looked away at least once), headway does not seem strongly involved in crash genesis.

c. *Is the distance to the POV constant when the driver looks away (a steady-state situation, as would be predicted by Tijerina et al. (2004)) or do drivers look away when the POV is closing?*

Most drivers looked away in a steady state situation (as indicated by both relative velocity and invTau), thus supporting Tijerina's et al. (2004) hypothesis that drivers looked away in a situation they perceived as non-critical and the POV braked shortly thereafter. However, some drivers did look away during closing, even at relatively high urgency (invTau). This was somewhat more common in crashes (however, not in SHRP2). Several mechanisms may lead to this (expectations, adverse visibility, short look back before LG), but this was not further analysed here.

4. *What does the situation look like when the driver looks back the last time, and does it differ between crashes and near-crashes?*
   a. *Has the POV brake light onset illuminated while the driver looked away?*

This only occurred in 25% of the crash cases and 24% of the near-crash cases. That indicates that whether the BLO is seen or not may not be critical for the outcome.

b. *How much has the situation changed when looking back?*

Both THW, relative velocity and invTau changed significantly, indicating that POV braking after looking away is a key mechanism in producing crashes and near-crashes. InvTau, representing urgency, led to the clearest difference between crashes and near-crashes. This indicates that the timing of the last

glance relative to the change in urgency, represented optically by looming cues, during the glance is a key mechanism behind crashes.
This was confirmed by analysis of the relation between the invTau difference (missed looming) and LG duration. Further, plotting the invTau change rate against LG duration yields a relatively strong separation between crashes and near-crashes. This indicates that crashes are sometimes produced also by short glances given that the urgency changes quickly enough during the glance. However, the strong prevalence of short glances that do not lead to crashes generally means that the relative crash/near-crash risk associated with short glances alone is not significant. On the other hand, the present analysis indicates that some of these short glances are indeed involved in crashes, and if they could be selectively mitigated, rear-end crash rate would be expected to go down.

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