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Drivers' response to attentional demand in automated driving

ALBERTO MORANDO

Division of Vehicle Safety
Department of Mechanics and Maritime Sciences

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Division of Vehicle Safety
Department of Mechanics and Maritime Sciences
Chalmers University of Technology
SE-412 96 Göteborg, Sweden
Telephone: +46 (0)31-772 1000

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Abstract

Vehicle automation can make driving safer; it can compensate for human impairments that are recognized as the leading cause of crashes. Vehicle automation has become a central topic in transportation and human factors research. This thesis addresses some unresolved challenges on how to guide attention for safe use of automation and on how to improve the design of automation to account for humans' abilities and limitations. Specifically, this thesis investigated how driver attention changed with automation and the driving situation. The objective was to inform the design of vehicle systems and develop design knowledge to support safe driving. A novelty of this thesis was in the use of real-world driving data and Bayesian methods (improved statistical modeling techniques). The analysis of driver behavior was based on data collected in naturalistic driving studies (to study the effect of assistive automation) and in a simulator experiment (to study the effect of unsupervised automation). Driver behavior was examined with measures of visual and motor response, together with contextual information, on the driving situation. The results show that assistive automation affected driver attention in real-world driving. In general, drivers devoted less attention at the forward path with automation than without. However, driver attention was sensitive to the presence of other traffic and changes in illumination—variations in the surrounding environment that increased the uncertainty of the driving situation—and it was elicited by visual, audio, and vestibular-kinesthetic-somatosensory information (perceptual cues) that alerted to an impending conflict. Driver response to a critical situation with unsupervised automation had a reflexive component (glance on-path, hands on wheel, and feet on pedals) and a planned component (decision and execution of evasive maneuver). Warnings primarily alerted attention rather than triggering an intervention. Expectation, which changed over time depending on experience, affected driver response substantially. This thesis found that the safety implications of diverting attention away from the driving situation need to be interpreted in relation to the characteristics and criticality of the driving situation (driving context) and need to consider the reduction of risk exposure due to automation (e.g., headway maintenance and collision warnings). Drivers were, for example, successful at changing their behavior in the presence of other vehicles and in different light conditions independently of automation. If drivers are not attentive at critical points, warnings are effective

for triggering a quick shift of attention to the driving task in preparation to an evasive action. The results improved on those of earlier studies by providing a comprehensive assessment of driver attentional response in routine driving and critical situations. The results can support evidence-based recommendations (inattention guidelines) and be used as a reference for driver modeling and vehicle systems development.

Keywords. Attention, visual behavior, response process, vehicle automation, naturalistic data, driving simulator data, human factors.

Popular abstract

Automated vehicles promise to make driving safer and more comfortable. They can compensate for human limitations that may cause crashes. Automated vehicles can also reduce a driver's effort of keeping the vehicle in the lane and at safe distance from other vehicles. Today's vehicles have assistive automation systems that use automation to keep a vehicle within the lane and from driving too close to the vehicle in front. These systems, however, do not work at all times, and require constant supervision by the driver. An important question is then whether assistive automation may give drivers the false impression that their attention to the road is no longer important. In fact, if automation fails when the driver is not attentive, a crash may happen. The aim of our research was to make automated vehicles safer. We did so by studying the theory of attention, which explains how humans perceive and interact with the environment, and by measuring how drivers behave in automated vehicles. We found that drivers looked less to the road ahead when the vehicle had assistive automation compared to when the vehicle was manually driven. This result seems to suggest that automation may compromise safety. However, drivers were successful at changing their behavior according to the context (e.g., presence of other vehicles, and light conditions) independently of automation. Our findings indicate that today's automated systems may not reduce drivers' ability to react to hazards on the road. We described our findings with mathematical models that will help future automated vehicles to be safer. The novelty of our research is in the use of real-world driving data and new methods for data analysis.

Better at x than anyone who is better at y
Better at y than anyone who is better at x

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I dedicate my work to my family and to Emma. Thank you for your love.

Appended papers

Paper I: Tivesten, E., **Morando, A.**, & Victor, T. (2015). *The timecourse of driver visual attention in naturalistic driving with adaptive cruise control and forward collision warning.* Paper presented at the Driver Distraction and Inattention conference, Sydney, New South Wales.

Paper II: **Morando, A.**, Victor, T., & Dozza, M. (2016). *Drivers anticipate lead-vehicle conflicts during automated longitudinal control: Sensory cues capture driver attention and promote appropriate and timely responses.* Accident Analysis & Prevention, 97, 206-219. doi: 10.1016/j.aap.2016.08.025.

Paper III: **Morando, A.**, Victor, T., & Dozza, M. (2018). *A reference model for driver attention in automation: Glance behavior changes during lateral and longitudinal assistance.* IEEE Transactions on Intelligent Transportation Systems. doi: 10.1109/TITS.2018.2870909.

Paper IV: **Morando, A.**, Victor, T., & Dozza, M. (2019). *A Bayesian reference model for visual time-sharing behavior in manual and automated naturalistic driving.* IEEE Transactions on Intelligent Transportation Systems. doi: 10.1109/TITS.2019.2900436.

Paper V: **Morando, A.**, Victor, T., Bengler, K., & Dozza, M. (2019). *Users' response to critical situations in automated driving: Rear-ends, sideswipes, and false warnings.* Submitted. doi: 10.13140/RG.2.2.18560.89603/1.

Contents

1. Introduction

Vehicle automation is advancing rapidly. Assistive automation is already available in the market as a combination of adaptive cruise control (ACC) and lane centering system (SAE, 2018). Unsupervised automation, which may revolutionize driving, is being tested on public roads (California Department of Motor Vehicles, 2018).

In addition to reducing driving demand and increase comfort, automation has enormous potential to enhance safety. Automation can compensate for drivers' errors (e.g., due to inattention), which have been identified as the main reason for crashes (Singh, 2015). Ironically, automation could as well compromise safety because of unintended behavioral effects (Bainbridge, 1983; Merat et al., 2018; Seppelt and Victor, 2016; Victor et al., 2018). Vehicles equipped with assistive automation require constant supervision (SAE, 2018): if the system reaches its operational limits, or fail because of sensors' malfunction, the driver needs to intervene quickly—with or without notification. Unfortunately, a large body of research questioned drivers' ability to resume control if needed (de Winter, Happee, Martens, and Stanton, 2014; Merat et al., 2018). One reason is the poor monitoring skills, which may further degrade as automation evolves and failures becomes rarer (out-of-the-loop concept; J. D. Lee, Wickens, Liu, and Boyle, 2017; Merat et al., 2018). In fact, if automation handles most of the driving situations smoothly, drivers may believe that automation can handle any situations (Victor et al., 2018).

Along with increasing interest in advancing vehicle automation, there has been an increasing interest in capturing what are the repercussions on driver behavior (J. D. Lee, 2008). The effect of vehicle automation has become a major—and controversial—topic of research. If the interference of automation on human performance cannot be solved, it must be balanced on whether automation has a positive net-benefit compared to manual control (Seppelt and Victor, 2016; Victor et al., 2018).

Research on automation has been mostly experimental (e.g., simulator studies), because data on real-world driving were scarce. Driving simulators facilitate the evaluation of emerging technology at the cost of low ecological validity, but the decisive test of any technology is the real-word application. Thus, further

research on the real-world effect of automation was needed. Part of the novelty of this thesis comes from the unique opportunity to use real-world driving data collected as part of two naturalistic studies, which include manual and assistive automation driving: EuroFOT (Kessler et al., 2012) and EyesOnRoad (Karlsson et al., 2016).

Earlier analyses on EuroFOT stated again the controversial effect of automation on safety. It was found that ACC (sustained assistance of the longitudinal vehicle control) reduced the exposure to critical situations by maintaining a safe headway to the traffic ahead, but, in routine driving, drivers tended to monitor the driving situation less compared to manual driving (Malta et al., 2012). The effect of ACC can give insights on how automation, albeit with limited functionality, influences driver behavior. Unfortunately, real-world data collected with vehicles equipped with more sophisticated automation are yet to be available, but on-road naturalistic studies are planned or ongoing (Fridman et al., 2018).

As the performance of automation depends on the interaction between the human and the system (J. D. Lee et al., 2017), several human factors challenges arise: What are the effects of automation on driver's attention to the driving task? What are the safety implications of those changes? Are drivers prompt to respond to critical situations? How can attention be elicited in situations that require an intervention by the driver? This thesis will address these questions by looking directly at the human. The overall objective is to inform the design of vehicle systems that accounts for human perceptual and cognitive abilities to promote safe driving.

For example, with assistive automation, the human is responsible, at any time, for safe operation of the vehicle (SAE, 2018). Therefore, humans need to monitor the driving situation (i.e., the surrounding environment and the system) to recognize hazards and react upon them. As humans are notoriously poor at sustained monitoring tasks (Merat et al., 2018), there may be a need for in-vehicle systems to assess whether the monitoring task is appropriate for the context at hand, otherwise alerts could be triggered to inform drivers of their deteriorated performance. Despite an increase interest on the subject, and few limited solutions available in the market, the development of real-time systems to evaluate monitoring behavior remains a complex challenge. In fact, monitoring (and its quantification and assessment) has shown to be an elusive concept (Merat et al., 2018). However, a key to understand monitoring may be the concept of attention. Attention is closely related to monitoring task, being a perceptual and cognitive mechanism that guides actions to interact with the surrounding environment. Attention will be the core concept of this

thesis and it will guide the interpretation of the findings from the empirical research.

There is a large and growing body of literature on attention, in driving and other contexts. The purpose of the forthcoming chapter 3 is to summarize the topic, based on research on cognitive psychology and neuroscience, and to apply this knowledge to study driving behavior. Section 3.1 introduces the concept of attention, which is essential to perceive, comprehend, and interact with the environment. Section 3.1 emphasizes that attention is not a passive information processing mechanism: people are actively engaged in the perception-action cycle, which is driven by bottom-up stimuli and top-down goals. Moreover, section 3.1 highlights the primary role of visual perception for interacting with the environment and it indicates that visual behavior is a strong indicator for what people attend to. Section 3.2 narrows the scope of what was described in section 3.1 to driving, an activity that heavily relies on vision. Section 3.2 introduces why visual behavior is crucial for driving and it emphasizes that driving safely requires appropriate allocation of attention. Section 3.3 explains that the appropriate allocation of attention depends on the driving context. Bottom-up stimuli and top-down goals interplay in detecting relevant changes in the driving context and interact with it. Section 3.3 defines driving context as the interaction between components in the driver-vehicle-environment system. Section 3.4 applies the concepts presented in section 3.3 to the car-following scenario, one of the most common driving situation. This example reveals the complex dependencies in the driver-vehicle-environment system and confirms the competition between bottom-up stimuli and top-down goals to maintain a safe headway to the vehicle in front. The car-following scenario also illustrates how automation can affect driver behavior (and its interpretation) compared to manual driving.

2. Objectives

This PhD project was devoted to promoting a safe interaction between the driver and the automated vehicle. The general objectives of this project were a) to advance the understanding of driver's behavior and performance in the context of vehicle automation and b) to inform the design of vehicle systems that support appropriate driver behavior, by acknowledging perceptual and cognitive abilities.

The main research questions addressed in this thesis were:

1. *What are the effects of automation on drivers' attention to the driving task?*
2. *What are the safety implications of those changes?*
3. *Are drivers prompt to respond to critical situations?*
4. *How can attention be elicited in situations that require an intervention by the driver?*

3. Background

3.1. Visual attention

Attention is the mechanism to select and prioritize aspects important for carrying out an activity, among a range of information in the environment coming from sensory inputs (Carrasco, 2011; Desimone and Duncan, 1995; Findlay and Gilchrist, 2003; E. E. Smith and Kosslyn, 2014a).

Vision dominates our experience. It has a crucial role for planning and executing a variety of daily tasks, for example driving (Goodale, 2011; Land, 2006, 2009). Vision enables us to perceive the environment and guide motor actions to interact with it (Carrasco, 2011; Goodale, 2011; Land, 2006, 2009; E. E. Smith and Kosslyn, 2014b, 2014c).

Visual attention is the process of allocating visual system's resources (the eye and the cortex) to a location informative for interacting with the environment (Carrasco, 2011; Corbetta and Shulman, 2002; Goodale, 2011). Visual attention can be allocated by moving the eyes to an area of interest (overt attention), or by attending to an area in the visual periphery without moving the eyes (covert attention; Carrasco, 2011; Corbetta and Shulman, 2002). Overt and covert attention are integral part of the visual attention process. The covert attention allows for monitoring the visual field, and it usually precedes the shift of overt attention towards a new location of interest (Carrasco, 2011; Corbetta and Shulman, 2002; Goodale, 2011; Land, 2006, 2009; Nobre, Gitelman, Dias, and Mesulam, 2000). The resolution of the visual field, in fact, is not uniform. Because of the anatomy of the retina, only the central part of the visual field (fovea) is capable of high resolution (Carrasco, 2011; Land, 2006; E. E. Smith and Kosslyn, 2014a, 2014c). The fovea is a small area of the retina where there is a concentration of the cone cells; the visual resolution rapidly decreases with eccentricity from the fovea toward the periphery, where the rod cells are more numerous (Carrasco, 2011; Land, 2006; E. E. Smith and Kosslyn, 2014c). Some information can be extracted only with the peripheral vision (e.g., color, luminance, movement), but it is necessary to move the eyes to shift the foveal vision and enhance the perception on a precise spot (Land, 2006, 2009). Thus, eye movements are a strong indicator of where the

visual attention allocated (Carrasco, 2011; Corbetta et al., 1998; Corbetta and Shulman, 2002).

The movement of the eyes is a combination of saccades, fixations, and smooth pursuit movements (Kowler, 2011; Land, 2006). Saccades are quick ballistic movements to move the eyes to a new location. Fixations are periods between saccades in which the eyes are held stationary to enable perception. Smooth pursuit movements allow to track moving targets. Eye movements and visual behavior can be described by several metrics at different levels of details (Duchowski, 2017b; Victor, Engström, and Harbluk, 2008). Because we are usually interested on where attention is devoted with respect to an area larger than the foveal region, and because of limitations in eye-tracking technology, visual behavior is described in this thesis at the level of glance—a construct that embeds fixational, saccadic, and smooth pursuit movements (see also section 4.3).

Visual attention is a combination of bottom-up and top-down processes (Carrasco, 2011; Corbetta and Shulman, 2002; Desimone and Duncan, 1995; E. E. Smith and Kosslyn, 2014a, 2014c). Bottom-up processes are involuntary and driven by sensory inputs. For example, they allow for detecting basic features of the visual scene (e.g., color, edges). Top-down processes, instead, are voluntary and driven by task goals. They allow for seeking, extracting, and interpreting relevant information for the current activity (Corbetta and Shulman, 2002; Desimone and Duncan, 1995; Land, 2006, 2009; E. E. Smith and Kosslyn, 2014c). Context, prior knowledge, and (spatial and temporal) expectation guide top-down processes. They facilitate the attentional process by making it more efficient and accurate to the current situation (Corbetta and Shulman, 2002; Desimone and Duncan, 1995; Land, 2006, 2009; E. E. Smith and Kosslyn, 2014c). Bottom-up and top-down processes continuously interact and compete. For example, a salient visual stimulus in the periphery may elicit a bottom-up process and interrupt an on-going top-down process, causing an automatic shift of attention from the current focus towards the stimuli. It is hypothesized that such salient stimuli, which can quickly capture attention, may be associated with behavioral urgency (Corbetta and Shulman, 2002; Desimone and Duncan, 1995; Franconeri and Simons, 2003; Lin, Franconeri, and Enns, 2008). For example, given visual stimuli of the same magnitude, looming objects indicate an impending collision and would trigger a reflexive response, whereas receding objects should not elicit the same response, being neither potentially urgent nor threatening.

The perception of the external world is enhanced by integrating stimuli from different sensory modalities. Visual stimuli are not the only external stimuli

that can prompt reflexive orienting of attention (Spence and Santangelo, 2009). Other examples include abrupt, unexpected onset of auditory and tactile stimuli, which have implications for the design of warning strategies in applied settings (Spence and Santangelo, 2009). In general, redundant multisensory warnings are more effective than unimodal signals (J. D. Lee, McGehee, Brown, and Marshall, 2006; Spence and Santangelo, 2009), because such cues can provide information about events occurring far outside the field of view. Other types of attention orienting stimuli are related to the perception of self-motion (i.e., the result of vestibular, proprioceptive, and kinesthetic information). Such cues, for example, can originate from an externally-induced deceleration of a vehicle (J. D. Lee, McGehee, Brown, and Nakamoto, 2007; SAE, 2018). Unfortunately, a systematic understanding of how vestibular cues contributes to capture attention is still lacking, as they are little researched in the cognitive neuroscience and experimental psychology literature.

3.2. Visual attention in driving

Driving is an example of visually-guided action that requires efficient visual attention allocation to safely operate the vehicle (Land, 2006; Shinar, 2017b): scan the environment to detect obstacles and events (vision for perception) and support the longitudinal and lateral control of the vehicle based on this information (vision for action).

Drivers, in general, direct their visual attention at the forward roadway, because that is the most relevant location for safe driving (P. Green, 2015; Shinar, 2017b; Victor et al., 2015; Victor, Harbluk, and Engström, 2005). Because of the limited field of view in the eyes, however, driving entails short glances directed away from the forward roadway to attend to other sources of information—to be aware of the surroundings of the vehicle, look at road signs, and check the instrument cluster (P. Green, 2015; Shinar, 2017b). In general, drivers spend about 15% of their time looking away from the forward path in routine driving (Victor et al., 2005). These off-path glances are part of scanning activities that are driven by expectation and becomes more efficient with experience (top-down process; Engström, Victor, and Markkula, 2013; P. Green, 2015; Shinar, 2017b). Such scanning activities are related to the driving task; they serve a significant role in perceiving the driving environment and maintaining safety. Some aspects of driving rely on covert attention. Peripheral view alone has been shown to be sufficient to maintain the lane position of the vehicle (Summala, Nieminen, and Punto, 1996). Moreover, unexpected visual stimuli in the peripheral view—a

pedestrian suddenly stepping on the road, or a flashy light—can trigger bottom-up processes and capture the driver's attention (Engström et al., 2013; Shinar, 2017b).

Visual scanning activities require efficient and timely attention allocation—looking at the right place at the right time—otherwise the driver may fail to notice objects and events, and to successfully respond to hazards (Hancock, Mouloua, and Senders, 2008). Hazards are objects, conditions, or situations that tend to produce an accident if not handled correctly (Dewar and Olson, 2015). The *"mismatch between the current allocation of resources and that demanded by activities critical for safe driving"* is defined as inattention in driving (Engström et al., 2013, p. 34). When attention is misdirected towards an activity not required for safe driving (i.e., secondary to the driving task), it is usually referred as to distraction (J. D. Lee, Young, and Regan, 2008). The visual behavior of an inattentive driver is often characterized by a switch of visual attention back and forth between the forward path and another location (visual time-sharing; Victor et al., 2009; Wierwille, 1993).

Improper allocation of visual attention—because of inattention and distraction—is a longstanding issue in traffic safety. Visual inattention and distraction have been identified as the most common crash contributing factor by large scale naturalistic studies (Dingus et al., 2006; Klauer, Dingus, Neale, Sudweeks, and Ramsey, 2006; Victor et al., 2015) and in-depth crash investigations (Singh, 2015). There is a strong relationship between visual behavior and crash risk. Long off-path glances, and the consequent deficit of attention allocation on path (Seppelt et al., 2017), have been a main concern, as it is also evident in recently released guidelines for reducing the attention demand of in-vehicle interfaces (NHTSA, 2013). However, as argued by Victor et al. (2015), even short lapses of attention from the forward path can lead to crashes—timing and driving context matter more than glance duration per se. For example, during visual time-sharing, frequent and inappropriate off-path glances increase the uncertainty of the driver situation (Horrey and Wickens, 2007; Klauer et al., 2006; Liang, Lee, and Horrey, 2014; Senders, Kristofferson, Levison, Dietrich, and Ward, 1967; Victor et al., 2015), and short on-path glances may not be long enough to make up for the information decay or to uptake enough information to predict a critical situation (Senders et al., 1967; Seppelt et al., 2017).

There is an increased desire to counteract inattention and its consequences. This is reflected by the demand of new advanced driver assistance systems (ADASs) to reduce the exposure to critical situations and prevent accident to happen. By providing information, warning, and interventions, ADASs

compensate and countermeasure drivers' attentional limits (J. D. Lee, 2008). Unfortunately, ADASs that monitor the attentiveness of the driver (in a direct fashion rather than from indirect measures of vehicle control; J. D. Lee et al., 2013; Young, Regan, and Lee, 2008) are still in their infancy (J. D. Lee et al., 2013), with few solutions already available in the market (Kelly, 2017). The main challenge is the identification of relevant, robust, and unobtrusive measure of inattention.

There are, in fact, many causes for inattention, both internal and external the vehicle (Engström et al., 2013). For example, the 100-car study has identified about 60 categories of causes for inattention—mainly related to secondary tasks being performed (Klauer et al., 2006). This method of analysis has limitations: because it requires video annotations (often done manually) it is time consuming, it has issue related to validity and reliability of the coded variables, and it cannot be done in real-time. Additionally, this approach does not take into account that even if the demand of the task is low, if this task is done frequently or for an extended time, the increase in crash risk may be comparable to that of a more demanding task performed less often (NHTSA, 2013).

Despite uncertainty still exists about the relationship between visual behavior and inattention (e.g., it is unclear if unsafe behavior is dependent of glance characteristics and independent of task type; Victor et al., 2015) and technical solutions are still immature (J. D. Lee et al., 2013), the approach based on the quantification of visual behavior is promising. First, because of the scientific evidence that vision plays a crucial role in regulating attention and guide motor actions. Second, because eye-tracking systems installed in the vehicle enable real-time and unobtrusive data collection.

3.3. Visual attention and driving task demand

The level of attention one should devote to driving depends on the task demand. Task demand can be understood as the amount of resources (e.g., visual, motor, and cognitive) required to perform an activity (Engström et al., 2013).

Safe driving requires an attentional state that keeps matching that which is required by the driving task (Engström et al., 2013). As the driving task can be understood in terms of its component—the driver, the vehicle driven, and the driving environment form a joint system (DVE system; Coughlin, Reimer, and Mehler, 2011; Engström and Aust, 2011)—to study visual behavior and attention in driving, a broader situated approach should be taken. The

components of the DVE system influence and interact with each other. Each component can be represented as a set of features with different temporal dimensions. Some features may vary slowly during a trip, whereas others may change rapidly. In general, the driving task demand evolves gradually, but sometimes changes occur abruptly. The traffic environment can become highly complex, and critical situation may appear unexpectedly, which is why it is crucial to continuously detect, identify, and assess the many dynamics and changing elements on road (Wickens and Horrey, 2008).

3.3.1. Driver features

Driving is, to large extent, a self-paced task (Summala, 2007). It means that the drivers themselves, being the operators of the vehicle, can actively control the evolution of the task demand and adapt to it (Engström and Aust, 2011). For example, they can choose a different road, reduce the speed, or increase the headway to the surrounding traffic to compensate for an increased demand in case of complex and less predictable scenarios. Summala (2007) proposed that, in general, drivers aim to keep themselves inside their subjective comfort zone, whose boundary is primarily determined by safety margins to obstacles in the environment. Thus, routine, non-critical driving may be understood as acting to maintain a comfortable level of task demand throughout the drive (adaptive behavior; Engström and Aust, 2011; Summala, 2007).

The comfort zone's boundary, however, may be stretched by extra motives if the driver could gain a benefit that justifies the cost of getting closer to the discomfort zone—and in turn increases the amount of demanded attentional resources (Summala, 2007). For example, drivers may adopt shorter headway when in a hurry, but doing so they are more vulnerable to crash. Hence, to prevent a collision, they deploy an increase attentional effort to compensate to intentionally reduced safety margins (Engström et al., 2013) and be able to timely respond to sudden changes of other road users' behavior.

To avoid a critical situation and reduce the feeling of discomfort, drivers adopt safety margins to obstacle on the road. Safety margin can be defined as the spatial and temporal distance between the boundary of the comfort zone and safety zone (Engström and Aust, 2011). The safety zone represents the set of parameters in the DVE system in which a collision can still be avoided (Engström and Aust, 2011).

The safety zone is (to large extent) objective (Engström and Aust, 2011): it depends on the properties of the vehicle (e.g., brake capacity), the environment

(e.g., surface condition), and the drivers themselves (e.g., their reaction time). The safety margins, however, are subjective, and they may be inadequate for the current driving context if there is a mismatch with the allocated attentional resources. Even short off-road glances can be dangerous if the safety margin adopted is not sufficient to cope with sudden changes in the traffic environment (proactive barrier; Engström et al., 2013).

The drivers' abilities to preserve the comfort zone depends substantially on expectancy (Engström and Aust, 2011). Expectancy is the proactive, top-down allocation of attentional resources based on the prediction on how the current driving situation will evolve, from previous experience and other contextual information (Engström et al., 2017; Engström et al., 2013; Senders et al., 1967; Victor et al., 2008). For example, if the need for a response is expected to disappear, drivers may delay their action. Conversely, if a need for a response is anticipated, drivers may act proactively (Summala, 2000). Expectation can be failed: many accidents happen because of a mismatch of expectations (Engström et al., 2013; Victor et al., 2018).

3.3.2. Vehicle features

The properties of the vehicle influence the attention required for the driving task too. For example, Senders et al. (1967) showed an increase of attentional demand (and an increase of discomfort) at higher speed, and when the handling of the vehicle is poor, making lane keeping more difficult.

Recently, there has been an increasing interest in how ADASs, and higher forms of automation, may influence the attentional demand of driving. For example, electronic stability control (ESC) and anti-lock braking system (ABS) were shown to help drivers adapting properly to changes of the DVE system and reduce control loss (Markkula, 2015); a reduced attentional effort to the vehicle control task would be expected. However, such systems have also shown to cause unintended effects (negative behavioral adaptation; OECD, 1990; Rudin-Brown, 2010): studies have shown a reduction of safety margins (increase of speed and shorter following headway) when using ABS and ESC, claiming detrimental effects on safety (Rudin-Brown, 2010). Behavioral adaptation can be understood as the tendency to maintain a chosen, subjective level of task difficulty (task difficulty homeostasis; Fuller, 1984; Rudin-Brown, 2010). As new automated features are introduced, unintended behavioral effects may become more accentuated (e.g., Jamson, Merat, Carsten, and Lai, 2013; see also section 3.4).

3.3.3. Environment features

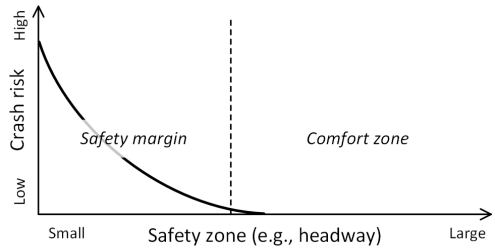

Figure 3.1.: Visualization of safety zone, comfort zone, and safety margin applied to the car-following scenario. Headway is an example of feature of the driver-vehicle-environment (DVE) system relevant in car-following driving situations.

The features related to the driving environment that affect driving demand can be related to the infrastructure (e.g., road type, road geometry), traffic (e.g., traffic flow, and behavior of other road users), and other variables such as illumination and weather. For example, on-road studies showed an increase of attention devoted to the forward road on curvy roads (Olson, Battle, and Aoki, 1989; Senders et al., 1967; Tivesten and Dozza, 2014), on trafficked roads (Jamson et al., 2013; Senders et al., 1967; Tivesten and Dozza, 2014), in car-following (Olson et al., 1989; Tivesten and Dozza, 2014) especially when approaching the lead vehicle (Tijerina, Barickman, and Mazzae, 2004), and in night driving (Olson et al., 1989). As introduced in the previous paragraph, these environmental features in turn influence the safety zone (e.g., the road grip affects the braking capabilities of the vehicle), and the driver's perception capabilities (e.g., ability to see in low light conditions), and driver's expectancy (e.g., in busy traffic the driver needs to predict how the road users will behave). Some of the features of the DVE system can be directly measured from signals in controller area network (CAN) bus (e.g., illumination and presence of other vehicles). Others driving demand variables can be inferred by the pedal and steering activities (Harry, Matthew, and Gerald, 2008).

3.4. An example: Visual attention in car-following

3.4.1. Car following in manual driving

Car following is one of the most common driving situations, and rear-end collisions are the most frequently occurring (and studied) type of accident.

Rear-end crashes accounts for approximately 27% of all light-vehicle crashes (Najm and Smith, 2007).

Safely following a lead vehicle requires continuous adjustment of kinematic parameters to maintain the safety margin to the lead vehicle, which in turns reduces the crash risk and the feeling of discomfort (Figure 1). Drivers do these adjustments based on the estimation of the time and space distance to the lead vehicle, while taking into account the current state of other components of the DVE system (e.g., drivers need to evaluate the characteristics of driving environment and of the vehicle, because the stopping distance depends on the brake capacity and the road grip). Furthermore, drivers need to estimate their performance, for example their response time to an event on the road. These adjustments can be proactive, when based on the expected evolution of the DVE system (e.g., the lead vehicle will not suddenly brake), or reactive, when the response is to a change of the DVE system (Engström and Aust, 2011; Engström et al., 2013).

The most common metric to measure the safety margin to a lead vehicle is time to collision (TTC). TTC is the ratio of the distance between the vehicles and their relative speed, and it expresses how long it will take to a collision if no action is taken. (According to this definition, if the cars are traveling at the same speed, TTC tends to infinite; if the lead vehicle is faster than the following one, TTC is undefined.) In order to estimate TTC, drivers may predominantly use visual cues, such as looming—the optical expansion of the lead vehicle at the eyes of the driver (Hoffmann, 1968; Hoffmann and Mortimer, 1994; D. N. Lee, 1976; Mortimer, 1990). This theory is corroborated by previous research that shows drivers change their visual scanning pattern in the presence of lead vehicle, which becomes the focus of attention (P. Green, 2015; Tijerina et al., 2004; Tivesten and Dozza, 2014). Drivers may rely on the visual angle subtended by the lead vehicle (θ), its rate of change ($\dot{\theta}$), or the combination thereof (τ) to estimate the headway (Hoffmann, 1968; Hoffmann and Mortimer, 1994; Lamble, Laakso, and Summala, 1999; D. N. Lee, 1976; Mortimer, 1990; Summala, Lamble, and Laakso, 1998). Appendix A provides further details on how to compute these looming quantities. The perception threshold of looming (e.g., θ, $\dot{\theta}$, or τ) increases with retinal eccentricity, hence the further away the glances are from the forward path, the longer the time will be before the driver may realize that a collision is impending (Lamble et al., 1999; Summala et al., 1998.

There is a range of other contextual cues that may support the driver to control the distance to a lead car. For example, another visual cue is the brake light onset, which signals that the lead vehicle started braking. However, brake light

onset alone may not be the cue that elicit a brake reaction, since it does not consistently signal a critical situation (Markkula, Engström, Lodin, Bärgman, and Victor, 2016; Victor et al., 2015).

3.4.2. Car following in automated driving

ACC is an assistive system that automates the longitudinal control and allows following a lead vehicle by maintaining the headway according to chosen settings. ACC uses a combination of sensors (e.g., a front facing radar and a camera) to detect the vehicle in front. ACC is intended as a comfort system—to release the driver from some of the control task in normal driving situations—especially on highways. ACC has shown to reduce the exposure to critical situations due to an increase of safety margins with respect to manual driving (Jamson et al., 2013; Malta et al., 2012).

ACC's braking capacity is limited to a level sufficient for normal car-following situations, not extreme braking (the braking authority varies among implementation, but it is usually about 0.3 g as suggested in the standards ISO 15622:2010 and ISO 22179:2009). When the braking capacity is exceeded, for example because of a highly decelerating lead vehicle, a frontal collision warning (FCW) is issued. The FCW is usually a visual and auditory warning that is designed to capture driver's visual attention to the forward road and prompt an evasive maneuver to an impending collision. The FCW exploits bottom-up processes to capture drivers' attention via salient stimuli (see also section 3.1 and 3.3). ACC requires drivers' constant supervision and readiness to regain control when necessary—without solely relying on the warning (SAE, 2018). In fact, drivers should be receptive to silent failures, for example, due to sensor limitations (SAE, 2018; Strand, Nilsson, Karlsson, and Nilsson, 2014).

The driving task demand is reduced when driving with ACC, because some control tasks are allocated to the vehicle automated system (i.e., accelerating and braking to maintain a safe headway to the vehicle in front). As a consequence, the use of ACC in routine driving has been shown to generally decrease the attention allocated for monitoring the road, which is considered potentially unsafe (Jamson et al., 2013; Malta et al., 2012; Rudin-Brown, 2010; Rudin-Brown and Parker, 2004). There has been a growing concern, mostly from experimental studies, that drivers would not respond appropriately in critical situations (de Winter et al., 2014), but it was not clear what would be the effects in real-world driving. Further research on the real-world effects of automation was needed.

4. Methods

4.1. Overview of the research approach

The research in this thesis was quantitative; it was based on data collected from two naturalistic driving studies and from a driving simulator experiment. The analysis of driver behavior was based on psycho-physical data (visual and motor activities), which were obtained with manual video reduction or with an eye-tracker system. Statistical description of the data was used extensively. Table 4.1 gives an overview of the research approach used in this thesis. The forthcoming sections describe the research approach in detail.

The naturalistic driving data used for this thesis were collected in earlier projects, in which ethical requirements were fulfilled by consulting with the national ethical board in Sweden. The driving simulator study was conducted in agreement with national regulations and local guidelines in Germany. All participants in the experiment provided written consent prior to participation, which informed them about the study (including how data was stored and treated) granted their right to interrupt the study at any time without having to provide any explanation. For all data, procedures to warrant data privacy and protection were applied, for instance data analysis was performed in dedicated rooms (either at SAFER, the Vehicle and Traffic Safety Center at Chalmers, or at Volvo Cars) with secured and limited access to password-protected data

Table 4.1.: Overview of the research approach.

Paper	**Data collection**	**Psychophysical data**	**Statistics**
I	Naturalistic	Visual (Video reduction)	Frequentist
II	Naturalistic	Visual (Video reduction)	Frequentist
III	Naturalistic	Visual (Eye-tracker)	Frequentist
IV	Naturalistic	Visual (Eye-tracker)	Bayesian
V	Simulator	Visual, motor (Video reduction)	Bayesian

4.2. Data collection: Naturalistic and driving simulator data

Investigating and understanding driver behavior is challenging because of the interplay between the human and the driving context (section 3.3), and because there is not a single method that alone can capture the nuances of how people drive (Bärgman, 2016; Shinar, 2017a). The empirical research included in this thesis leveraged on two data sources: data collected with naturalistic driving studies (Paper I–IV) and with a driving simulator experiment (Paper V). Naturalistic driving studies and simulator experiments differ on many levels (Shinar, 2017a; Young et al., 2008). Because they have their own merits, the choice of the better test venue depends on the research questions and on practical constraints (e.g., cost and time). However, because drivers normally adapt their driving strategy to the driving situation at hand, differences between test venues may largely impact results (Engström and Aust, 2011). In general, these data collection methods are complementary, and they can yield a better understanding of driver behavior if considered together (Bärgman, 2016; Shinar, 2017a).

Much of the human factors research on automation has been carried out with simulator studies. The are many reasons that justify this approach. First, and foremost, the high experimental control over participants and driving context. High experimental control eases the manipulation of one (or more) independent variables to test the effect on one (or more) dependent variables. Moreover, it is possible to control for contextual effects and for the intrinsic variability due to individual differences (Kantowitz, Roediger, and Elmes, 2009; Shinar, 2017a). Second, driving simulators are a relatively economical tool—depending on their sophistication—to collect data in a short time (Shinar, 2017a). Finally, because driving is simulated, it is a safe environment in which participants can try innovative technologies and get exposed to critical situations without harm (Shinar, 2017a; Young et al., 2008). This latter reason was the main motivation to use a driving simulator to collect systematic data on the response process to different critical situations in highly automated driving (Paper V).

The major drawback of driving simulator studies is that it is questioned how well driver behavior in the simulator translates to real-world driving. Even high-fidelity simulators have issues associated with the ecological validity of driver behavior under artificial driving conditions (Young et al., 2008). Thus, further research on the real-world effect of automation to enhance our understanding of driver behavior during automated driving. Most of the research included in

this thesis (Paper I–IV) is based on data collected from two naturalistic studies, EuroFOT (Kessler et al., 2012) and EyesOnRoad (Karlsson et al., 2016). These studies are unique, as that they could give novel insights on how drivers used and interacted with assistive automated technology in condition representative of actual driving.

Naturalistic driving studies are, usually, strictly observational. When a system is being tested, these studies are known as field operational tests (FOTs; Bärgman, 2016; Barnard et al., 2017). The main, distinctive property of naturalistic studies is that they allow to investigate driver behavior with the highest ecological validity. Data are, in fact, collected unobtrusively from instrumented vehicles on everyday driving in real traffic—a procedure that requires considerable investment in terms of money and time as the testing period varies between few month to few years (Bärgman, 2016; Barnard et al., 2017; Shinar, 2017a). The main disadvantage of naturalistic driving studies is the low experimental control over participants and driving context (Bärgman, 2016; Shinar, 2017a). To ameliorate the low experimental control, careful inclusion criteria need to be set to extract relevant portion of data for fulfill the objective of the research. However, it remains difficult to isolate—and impossible to repeat—the circumstances of, for example, rare hazardous event.

Depending on the inclusion criteria, naturalistic data can be more or less extensive, sparse, and unbalanced. Moreover, naturalistic data are often corrupted by sensors noise and malfunctions. These properties make data analysis arduous. Thus, new methods for data analysis and statistical modelling were needed, as it is discussed in the forthcoming sections.

4.3. Psycho-physical data: Visual and motor behavior

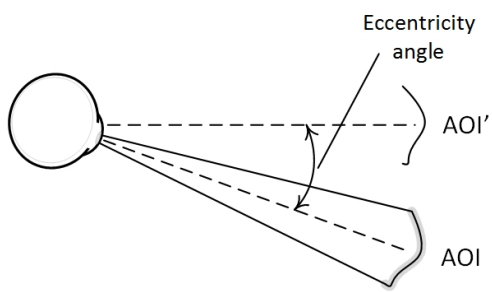

Figure 4.1.: Eccentricity between the area of interest (AOI) the eyes are directed to (i.e., glance location) and a reference AOI (AOI').

Driving is a visually-guided task that is largely regulated by visual attention mechanisms (vision for perception and action; chapter 3). The scientific evidence suggests that visual behavior is a strong indicator of where attention is allocated, which is why visual behavior is central to this thesis (chapter 3).

The most common technique to measure eye movements is the use of eye-tracking systems based on pupil detection and corneal reflection, as they offer a good trade-off between data quality and invasiveness (Duchowski, 2017a). This type of eye-tracker comes in two variants: head-mounted and remote. Head-mounted eye-trackers are more invasive than remote eye-trackers, and, in theory, yield higher data quality. In practice, however, major data quality issues have hindered the use of any eye-trackers in traffic safety research—even in well-constrained laboratory settings (e.g., eye-glasses are often one of the reasons for data losses). Naturalistic settings are even more challenging because of changes in illumination, vehicle vibrations, and the inability to re-calibrate the eye-tracker if the tracking quality deteriorates. (The cost of installing a high-quality eye-tracker in each vehicle would also be prohibitive.)

Because of questionable data quality, it is common to analyze visual behavior based on frame-by-frame manual reduction from video recordings of the driver's face—especially in naturalistic settings (Klauer et al., 2006; Victor et al., 2015). The same approach was used for Paper I, II, and V. Manual video reduction is a tedious and intensive task, but it is necessary. Based on first-hand experience, each frame of video requires on average 5 s. This means that 1 min of video recorded at 10 Hz (600 frames in total) would require about 50 min. As a consequence, it can be performed on small fraction of the recorded data, and, of course, not in real-time.

Manual video reduction is routinely done in terms of glances, which combine fixations, saccades, and smooth pursuits (Chapter 3.1). A glance is defined as the transition of the eyes to an area of interest followed by one or more contiguous fixations within that area, until the eyes move to another area of interest (standard ISO 15007-1). While the level of detail is relatively limited, it is sufficient, as we are usually interested on where the attention is devoted with respect to an area of interest larger than the foveal region (e.g., if the driver is looking on path or at the center stack). Several glance-based metrics can be derived, but there is no general agreement on the features that best describe attention or deficit thereof (J. D. Lee et al., 2013). For example, basic metrics of visual behavior include the glance location and eccentricity (and the duration and frequency of those glances; see also methods in Paper I–V). Glance location is the area of interest the eyes are directed to. Glance eccentricity is

defined as the radial angle between the current location of the glance and a reference direction (Fig. 4.1). (Further information on key terms, parameters, and measurement of visual behavior in the context of road vehicles can be found in the standard ISO 15007.)

Recent advances in machine vision algorithms now enable automatic measurement of glance behavior in real-world driving with simpler setups (Fridman, Langhans, Lee, and Reimer, 2016; Hansen and Ji, 2010). The dataset EyesOnRoad (Karlsson et al., 2016) used in Paper III–IV is an example of this. A large dataset of naturalistic glance data was a prerequisite for Paper III–IV in order to develop a novel reference model of visual behavior. Basing a reference model of visual behavior on data from simulator studies would have been unsuitable due to validity issues (see previous section 4.2). The system used to collect the data in the EyesOnRoad project automatically classified glances as being either on- or off-path. Binary classification of glances as on- and off-path is common (Klauer et al., 2006; Victor et al., 2015). This classification is motivated by the fact that drivers tend to look at the forward path about 85% of the time, and that off-path glances are a sensitive indicator of increase of crash-risk (Klauer et al., 2006; Liang, Lee, and Yekhshatyan, 2012; Victor et al., 2015). However, there are certain drawbacks associated with this coarse glance classification, as off-path glances towards, for example, the mirrors have different safety implications compared to glances towards a secondary, distracting task. Similarly, as discussed in chapter 3, glances at low eccentricity may still allow to detect threats on the road.

Successful driving performance depends on seeing and detecting events on the road, but also on acting upon them (chapter 3). While Paper I–IV were mainly based on visual behavior, the objective of Paper V was to obtain further in-depth information on the complete response process in critical situations (visual behavior, motor readiness, and intervention). Different authors have measured the response process in a variety of ways. Traditionally, the response process in manual driving has been assessed by measuring brake reaction time (M. Green, 2000). Brake and steer reaction time remain the most common measure in the recent literature on vehicle automation (McDonald et al., 2019). The benefit of these measures is that they are easy to collect from the CAN bus (or other sensors on the pedals and steering wheel), both in naturalistic and simulated driving. However, the disadvantage is that these measures do not capture the motor readiness stage (i.e., preparation to act on the pedal or on the steering wheel). If the motor readiness stage is discounted, the results may lead to misinterpretation on driver behavior in automated driving. For example, as discussed in sections 3.3–3.4 (and partly in Paper II), an increase in brake/steer reaction time during automation may be the consequence of drivers waiting,

until the last second, to intervene—they expected the system to resolve the issue or because the need for intervention may disappear.

Paper V relied, as in the case of visual behavior, on manual annotation of hands and feet movement. Participants, in fact, may hover their feet on the pedals, or their hands on the steering wheel, without touching the controls. There are some solutions to track hands and foot motion based on computer vision. Unfortunately, they are still in their development stage (Ohn-Bar and Trivedi, 2016; Tran, Doshi, and Trivedi, 2012); automatic video annotation is promising for reducing the burden of manual video reduction and for enabling real-time assessment of drivers' response process.

4.4. Statistical framework: From frequentist to Bayesian statistics

Data collection is followed by data analysis, to answer research questions and generalize the results to a broader population of interest. Traditionally, human factors researchers have relied on classical (frequentist) statistical techniques to describe the data and perform inference, for example, by using confidence intervals (CIs) and p-values (Wagenmakers, 2007; Wagenmakers et al., 2018). CIs provide information on the sampling error of the parameter of interest (Morey, Hoekstra, Rouder, Lee, and Wagenmakers, 2016). The CI is the interval that is likely to cover, with a set long-run probability (usually 95%), the constant, unknown value of the parameter of the population from which the data sample was drawn (Morey et al., 2016). The p-value is the usual criterion for null-hypothesis significant testing. The null-hypothesis significant testing sets out the inference problem based on a test statistics (e.g., the t-test) and two alternate hypotheses: a null hypothesis (i.e., the manipulation of the independent variable has no effect on the dependent variable) is tested against an alternate hypothesis (i.e., the manipulation yields a difference in the quantity of interest). The p-value is used as a measure of the strength of the evidence against the null hypothesis. If the p-value is smaller than an arbitrary threshold (usually 5%), the difference measured by the test statistics from the experimental manipulation is deemed significant, and the null-hypothesis is rejected. Confidence intervals and p-values are used for substantiating research findings, but they are often misinterpreted (Wagenmakers et al., 2018). Moreover, a statistical significance difference may be practically insignificant (Ellis, 2016). The general shortcomings with the practice of the frequentist statistics is topic of debate and they are beyond the scope of this thesis (for a

discussion see Kruschke and Liddell, 2017a; Morey et al., 2016; Wagenmakers, 2007; Wagenmakers et al., 2018).

In the beginning, the research included in this thesis used frequentist methods, because they are standard in the field (Paper I–III). However, by the end of the PhD, it was clear that these methods were inadequate for the objective of this PhD work (Paper IV–V). In fact, frequentist methods have two main, practical limitations. First, null-hypothesis significant testing yields a dichotomous answer (e.g., presence or absence of an effect due to automation on driver behavior), whereas the research aimed at estimating the magnitude of the effect (e.g., how much does automation affect driver behavior). Second, confidence intervals do not carry any distributional information (e.g., the 95% CI of the estimated mean is not the interval in which the true parameter lies with 95% probability).

Paper IV–V adopted the Bayesian framework because it offered attractive alternatives to classical frequentist statistics (Kruschke and Liddell, 2017a; Wagenmakers, 2007; Wagenmakers et al., 2018). Regarding the limitations mentioned before, Bayesian methods focus on the estimation of the magnitude of the effects, not on the dichotomous rejection of a null hypothesis. Moreover, the quantification of the uncertainty of the estimation can be interpreted—intuitively—in terms of probability (e.g., the 95% credible interval of the estimated mean is the interval in which the true parameter lies with 95% probability). Another pragmatic advantage is that Bayesian methods accommodate any data distributions (i.e., is not limited to normal distributions as many frequentist tests are), apply to any parameterized model of data, and ease the construction of complex hierarchical models that incorporate nuisance in the parameters due to individual differences (Kruschke and Liddell, 2017a; Kruschke and Vanpaemel, 2015). Thanks to the Bayesian approach we were able to capture the characteristics of driver behavior in greater detail than before. Moreover, the results enable accurate and robust models for computer simulations.

Bayesian methods are gaining traction in many fields; Paper IV–V were one of the few examples in traffic safety research and in the human factors field in general. With the Bayesian framework it was possible to encode domain knowledge, understand the data generation process, make predictions, and update beliefs based on new evidence—all by preserving uncertainty in the measurement and estimation (Kruschke and Liddell, 2017a). Because Bayesian methods are computational demanding, their application was limited. Recent advances in computation, algorithms, and probabilistic programming libraries now make Bayesian data analysis possible for a wide range of problems

(Bürkner, 2016; Carpenter et al., 2017; Salvatier, Wiecki, and Fonnesbeck, 2016).

5. Results

This thesis work resulted in five scientific papers: one conference paper (Paper I) and four journal papers. Three of the journal papers (Paper II, III, and IV) have already been published in some of the leading international scientific journals for traffic safety research. The papers are summarized in the next sections. Table 5.1 indicates how the papers contributed to answering the research questions of this thesis.

Table 5.1.: Overview of the research questions addressed by the appended papers.

Research question	**Paper**
What are the effects of automation on drivers' attention to the driving task?	I–V
What are the safety implications of those changes?	I–V
Are drivers prompt to respond to critical situations?	I, II, V
How can attention be elicited in situations that require an intervention by the driver?	I, II, V

Paper I. The timecourse of driver visual attention in naturalistic driving with adaptive cruise control and forward collision warning

Full citation: Tivesten, E., **Morando, A.**, & Victor, T. (2015). *The timecourse of driver visual attention in naturalistic driving with adaptive cruise control and forward collision warning.* Paper presented at the Driver Distraction and Inattention conference, Sydney, New South Wales.

Introduction ACC automates the longitudinal control of the vehicle. It is a comfort system that have been shown to have a positive effect on safety-related measures—despite a general decrease of attention devoted to monitor the road ahead. Safety concerns have been raised (e.g., lack of supervisory control by the driver and the inability to cope with critical situations).

Objective The objective of this paper was to investigate driver's visual behavior in critical situations (those exceeding the braking ACC's braking authority) and understand if drivers were prompt to respond to impending conflicts.

Method The naturalistic dataset EuroFOT was used. Visual behavior was manually annotated based on videos of the driver's face. Signals recorded from the controller area network (CAN) bus were used for events selection. Critical events were defined as hard deceleration by the ACC or the FCW onset. Glance location-based metrics were used.

Results Drivers were already looking on path at the onset of the critical situation—they anticipated the lead-vehicle conflict. Instead, in non-critical situations they were more willing to take their eyes off-path when using ACC than in manual driving.

Discussion The safety consequences of visual behavior needs to be assessed according to the real-time evolution of the driving context. In routine driving, there was a reduction of attention to the forward path with automation compared to manual driving—a symptom of reduction of task demand. However, drivers reoriented their visual attention to the forward path and anticipated an impending lead vehicle conflict before the situation became critical. The reason for this behavior was not identified yet; we speculated that sensory stimuli from the driving environment may have captured drivers' attention.

Paper II. Drivers anticipate lead-vehicle conflicts during automated longitudinal control: Sensory cues capture driver attention and promote appropriate and timely responses

Full citation: **Morando, A.**, Victor, T., & Dozza, M. (2016). *Drivers anticipate lead-vehicle conflicts during automated longitudinal control: Sensory cues capture driver attention and promote appropriate and timely responses.* Accident Analysis & Prevention, 97, 206-219. doi: 10.1016/j.aap.2016.08.025.

Introduction This paper extends the results from Paper I by focusing on the threat-anticipation mechanism.

Objective The objective of this paper was to identify the mechanism that captured drivers' attention to the forward path before the lead-vehicle conflict. The main hypothesis was that sensory cues from the driving scenario were indicative of an impending conflict.

Method The analysis used the naturalistic driving database EuroFOT. Analysis of visual behavior was done in the context of critical lead-vehicle scenarios when driving with ACC. Critical situations were identified as the FCW onset. Eye movements were manually annotated from videos of the driver's face. The main glance metric used thorough the paper were glance location and glance eccentricity from the forward path. The time course of visual attention was related to vehicle data (e.g., speed, acceleration, and radar information.

Results Visual and deceleration cues were relevant for capturing driver attention to the forward path in anticipation of the threat. The FCW was an effective attention-orienting mechanism when no threat anticipation was present (i.e., false warnings).

Discussion The results provide new insights on drivers' response to conflicts when longitudinal control is automated, proving that contextual sensory cues are important for alerting drivers of an impending critical situation, allowing for a prompt reaction. Moreover, off-path glances were shown to have different safety implications than off-threat glances. Therefore, we concluded that visual behavior is to be interpreted in the context of critical events.

Paper III. A reference model for driver attention in automation: Glance behavior changes during lateral and longitudinal assistance.

Full citation: **Morando, A.**, Victor, T., & Dozza, M. (2018). *A reference model for driver attention in automation: Glance behavior changes during lateral and longitudinal assistance.* IEEE Transactions on Intelligent Transportation Systems. doi: 10.1109/TITS.2018.2870909.

Introduction Drivers adapt their visual behavior to the driving context. However, information on the effect of different driving context is little, scattered across studies, or limited to manual driving.

Objective The objective of this paper was to parametrize drivers' on- and off-path glance behavior in routine driving and quantify the effect of a) the use of low-automation, b) the presence of other traffic, and c) illumination.

Methods The analysis used the naturalistic driving database EyesOnRoad. The data included eye-tracking information classified as on- and off-path glances. Visual behavior was examined with respect to a range of glance-based metrics, including glance distribution fitting.

Results A reference model for on- and off-path glance behavior in routine driving was developed. There was a reduction of attention to the forward path when a) using automation compared to manual driving, b) in open-road driving compared to car-following, and c) in daylight compared to night driving. Other results include a novel post-processing technique to enhance the quality of eye-tracking data collected in real-world environment.

Discussion Drivers' visual response is coupled to features of the driving situation. The analysis of the on-path glances (often discounted) suggests that they may be more sensitive to the driving context than the off-path glances. The reference model (a set of metrics and target values) that was developed in this study can improve simulations for driving safety assessment and the design of inattention countermeasures.

Paper IV. A Bayesian reference model for visual time-sharing behavior in manual and automated naturalistic driving

Full citation: **Morando, A.**, Victor, T., & Dozza, M. (2019). *A Bayesian reference model for visual time-sharing behavior in manual and automated naturalistic driving.* IEEE Transactions on Intelligent Transportation Systems. doi: 10.1109/TITS.2019.2900436.

Introduction Visual time-sharing (VTS) behavior characterizes an inattentive driver. A comprehensive assessment of VTS behavior in real-world driving (with and without automation) is currently lacking.

Objective This objective of this paper was to model drivers' on- and off-path glance behavior during visual time-sharing and quantify the effect of automation on this model.

Methods The analysis used a subset of naturalistic driving database EyesOnRoad from Paper III but limited to open road driving in daylight. VTS sequences were extracted with a rule-based algorithm. Visual behavior was examined with respect to a range of glance-based metrics, including glance distribution fitting. Bayesian generalized linear mixed models (GLMMs) were applied.

Results The effect of automation on VTS behavior was minimal across all glance metrics under analysis. The percentage of time glances fell on-path was the only metrics that was considerably lower during VTS compared to all routine driving (but it did not differentiate between manual and automated driving).

Discussion The findings from the new Bayesian analysis proposed in this paper enable the quantification of the difference in VTS behavior in greater detail than the classical (frequentist) method. Bayesian methods have practical advantages, for example they yield results that are interpretable in terms of probabilities and that are robust to unbalanced dataset. The reference model (a set of metrics and target values) that was developed in this study can improve simulations for driving safety assessment and the design of inattention countermeasures (including guidelines).

Paper V. Users' response process to critical situations in automated driving: Rear-ends, sideswipes, and false warnings

Full citation: **Morando, A.**, Victor, T., Bengler, K., & Dozza, M. (2019). *Users' response to critical situations in automated driving: Rear-ends, sideswipes, and false warnings.* Submitted. doi: 10.13140/RG.2.2.18560.89603/1.

Introduction The understanding on how users resume control of a highly automated vehicle in critical situations is crucial for safety. However, a systematic analysis of the users' response process is currently lacking.

Objective The objective of this paper was to provide a comprehensive account of user's visual-motor response process to critical situations (front and lateral vehicle conflicts). The study also investigated the effect of false warnings and expectation.

Methods A simulator study (high fidelity, fixed-based, 45 participants) was designed. Participants performed a visual-manual distracting task. The response chain was broken down in its visual, motor, and intervention component. The carryover effect, typical of within-subjects design, was modeled with Bayesian GLMMs.

Results The collision warning was effective at capturing users' visual attention and prompt the resumption of control. The time for reorienting the glance to the away from the secondary task and motor readiness was similar across trials and participants, whereas glance location, the time and choice of evasive maneuver was influenced by the driving situation at hand and by carryover effect from previous exposures.

Discussion The study provides new insights to direct the research into drivers' response process to critical situations in automated driving. We concluded that, to understand users' response process, it is essential to consider the visual, manual, and intervention components of the response chain. Collision warnings are primarily attention alerting, rather than directly associated with a brake or steer reaction. Moreover, the carryover effect should not be discounted in the analysis of data from simulator experiments.

6. Discussion

The real-world safety impact of vehicle automation is a controversial topic in the human factors' community. For example, assistive automation such as ACC (SAE, 2018) has shown positive effects in reducing the exposure to critical situations in real-world driving by maintaining safety margins (Malta et al., 2012). However, ACC has also shown to decrease drivers' attention to the forward road compared to manual driving, especially from experimental studies (Carsten, Lai, Barnard, Jamson, and Merat, 2012; de Winter et al., 2014; Malta et al., 2012). This is potentially unsafe, as drivers may not be able to cope with critical situations, those beyond system's capabilities (Merat et al., 2018; Nilsson, Strand, Falcone, and Vinter, 2013; Rudin-Brown and Parker, 2004; SAE, 2018).

Paper I confirmed, in routine real-world driving, a lower attention level to the forward path with ACC than without. The use of ACC might have reduced the driving task demand, which in turn affected visual attention allocation at an aggregate level (section 3.3 and 3.4). However, by looking at the time course of visual attention in critical situations (at aggregate level), Paper I unveiled an anticipatory mechanism: drivers anticipated an impending lead-vehicle conflict by increasing the visual attention to the forward road before the situation became critical. This was evidence that allocation of attention away from the road is a function of the current driving situation demand (Ranney, 1994; Summala, 2007), as introduced in section 3.3 and 3.4. A situated approach is then essential for understanding driver visual behavior: context and timing matter. This paper also concluded that drivers may have reacted to perceptual cues from the surrounding environment signaling a threat before a warning may be triggered; these cures may not be available in a simulated environment (Engström and Aust, 2011). The reason for this anticipatory response was, however, not clearly identified in Paper I.

Paper II set out to understand what cues may have alerted the drivers of an impending conflict in Paper I. Based on a similar dataset used in Paper I (critical events were selected anytime a FCW was issued while the ACC was active in real-world driving), Paper II provided a comprehensive account for how driver responded to critical situations. The paper suggested that a combination of

sensory cues may have captured drivers' attention in anticipation to lead-vehicle conflicts: looming, brake light onset, and deceleration cues. Section 3.2 and 3.3 highlighted that visual information is the dominant in driving. However, visual detection performance generally deteriorates towards the retinal periphery, therefore the further the driver diverts the eyes away from the forward path the worse the ability to detect threats and objects on the road (Victor et al., 2008). Paper II added that vestibular-kinaesthetic-somatosensory cues, originating from ACC-induced deceleration, may have played a role in capturing drivers' attention because of an arising headway conflict. Deceleration cues are often discounted in simulator studies, but they were acknowledged as beneficial in several studies (Fancher et al., 1998; J. D. Lee et al., 2007; J. D. Lee et al., 2006). Once attention was shifted to the forward roadway, drivers might have relied on visual stimuli (looming and brake light onset) to perceive and assess the imminent threat. These findings help to resolve the controversy of improved performance in safety despite a decrease in attention to the road during routine driving when using ACC (Malta et al., 2012). Moreover, the findings have implications for testing and developing automated systems: simulator experiments and real-world applications may exploit deceleration cues from brake actuation as a cue to look ahead because of an evolving headway conflict. If drivers are not receptive to such stimuli, and they do not anticipate the impeding threat, warnings are effective to capture attention quickly (J. D. Lee et al., 2006), even if drivers' attention is further away from the forward path (as shown from the analysis of a collection of false-positive warnings).

Paper I and Paper II relied on the manual annotation of glances from video recordings of the driver's face. This method is time consuming and hinders real-time applications (see section 4.3). Real-time inattention countermeasures could enhance driving safety by providing feedback to the driver (alerts or other forms of intervention, e.g., brake pulses to reorient driver's attention back to the driving task) and by adapting vehicle functionalities to compensate for the deteriorated performance. Despite the potential, few limited solutions are available in the market (Kelly, 2017). The development of real-time systems to evaluate human behavior is a complex challenge, further worsened by technological limitations (J. D. Lee et al., 2013). Yet, real-time systems based on eye-tracking remain promising, especially because data can be collected unobtrusively. This is because eye-movements are a strong indicator of attention (Chapter 3), and also because of recent advances in technology and machine vision algorithms that enable robust and extensive measurement of glance behavior in real-world driving (Fridman, Lee, Reimer, and Victor, 2015; Hansen and Ji, 2010). The design of these assistive systems would benefit from a reference model (a set of metrics and target values) to compare and thereby detect abnormal visual

behavior; such model was lacking. Current measures of inattention are limited because they rely on fixed thresholds (e.g., off-road glances longer than 2 s in single or aggregated form; Horrey and Wickens, 2007; Klauer et al., 2006; Liang et al., 2014).

Paper III presented the analysis of naturalistic data collected with vehicles equipped with a prototype eye-tracker that proved to be suited for real-world applications. The paper proposed a comprehensive data analysis procedure that captured important features of glance behavior in real-world driving, with and without automation. Importantly, the study provided a reference model of routine driving, which was lacking in the literature. Part of the contributions of this paper were methodological: a) a filtering routine to account for physiological constraints, b) a weighting procedure to address unbalanced data, and c) a method to describe glance data. The latter, in particular, attempted to improve how glance data are summarized in the literature—usually by the mean. The mean does not accurately describe skewed and noisy distributions (Rousselet, Pernet, and Wilcox, 2017). In the paper, glance analysis used quantiles, which are better choice for describing the tendency of the data (Rousselet et al., 2017), and distribution fitting, which summarizes the distribution with a minimum set of parameters. The model and its metrics described how visual response was tightly coupled to the interplay between features of the driving context (i.e., use of automation, presence of lead vehicle, changes in illumination), which corroborates the information presented in section 3.3. Moreover, the paper included the analysis of on-path glances that are critical to uptake information on the driving situation, but few studies have investigated them (Seppelt et al., 2017). The results from Paper III (in particular the fitted distributions) can be used to simulate glance time-series for computer simulations (e.g., counter-factual simulation for safety benefit analysis; Bärgman, Lisovskaja, Victor, Flannagan, and Dozza, 2015) and to inform the design of inattention countermeasures based on visual behavior (J. D. Lee et al., 2013).

Paper III provided a reference model for routine driving (with and without assistive automation). However, there are instances in which drivers are particularly vulnerable to an increase crash risk as they visual time-share (VTS) between the forward path and another location for extended time (Victor et al., 2008; Wierwille, 1993). This behavior was not captured by the model in Paper III.

Paper IV added to the results in Paper III by focusing on the visual time-sharing (VTS) behavior. The main objective was similar: to develop a novel reference model of VTS for targeted interventions against drivers' inattention.

Another objective was to introduce Bayesian statistical modeling techniques, which are still underused in the human factors' community. Bayesian methods are attractive (Kruschke, 2013; Kruschke and Liddell, 2017a, 2017b; Kruschke and Vanpaemel, 2015). For example, a) the results are interpretable in terms of probabilities, b) they accommodate sparse, unbalanced, and non-normal data, c) they focus on the estimation of the magnitude of the effect (and its uncertainty) rather than on the significance of the hypothesis testing, and d) they yield the estimation of the parameters of distribution of the data (see section 4.4). Thanks to the Bayesian approach, the analysis in Paper IV provided a detailed and comprehensive account of the effect of automation on a range of VTS metrics, which was lacking in the published research. There was a minimal change in VTS behavior between manual and automated driving, but the proportion of glances towards the forward path was found to be a sensitive metrics to discriminate VTS sequences among all routine driving. As the model in Paper III, this model can be used a) in counter-factual simulations (Bärgman et al., 2015), b) in the design of real-time inattention countermeasures (J. D. Lee et al., 2013), and c) in the development of inattention guidelines (NHTSA, 2013).

Recent development of unsupervised automated driving has led to a proliferation of studies to understand how drivers may resume control in critical situations. In fact, drivers are allowed—by design—to forgo the control of the vehicle and the monitoring of the surrounding environment, but they are expected to intervene promptly to any situation beyond the vehicle's operational design (SAE, 2018). Thus, unsupervised automated driving may require different strategies to elicit driver's attention than assistive automation (Merat et al., 2018), but it is unclear how this transition of control should be planned and executed. As real-world driving data on unsupervised automated driving are scarce, most research is still conducted with driving simulators. However, different authors have studied drivers' response process in a variety a way; the results are scattered across studies (McDonald et al., 2019).

Paper V proposed a procedure, based on Bayesian methods, for analyzing the outcome of a driving simulator experiment in a comprehensive way. This procedure enabled examination of the drivers' response chain in greater detail than previously done. Additionally, it addressed some common limitations in the literature on the topic (e.g., how to deal with the carryover effect typical of within-subjects designs) that may hinder the understanding of driver behavior if not properly handled (Aust, Engström, and Viström, 2013; Kantowitz et al., 2009). The response chain to a collision warning was broken down in its visual, motor, and intervention components. Typically, research has focused on one of the components or only on measures of reaction time (McDonald et al.,

2019). The results indicated that the choice and timing of the intervention (e.g., braking) depended on the critical situation at hand, while the visual and motor components (glance on road, hands on wheel, feet on pedals) were mostly a reflexive reaction to the warning. These results suggest that collision warnings are attention orienting mechanism rather than maneuver initiator. Furthermore, the carryover effect from earlier exposure to critical situations affected the response substantially (e.g., a threat on the side of the vehicle primed the drivers to look at the side, rather than at the forward path, in the next event), as shown in earlier studies on manual driving (Aust et al., 2013; M. Green, 2000). Paper V was one of the few studies which modeled explicitly the effect of repeated exposure, showing that the full sequence of exposures guides driver's action, not only the single previous one. Critical situations included rear-end crashes (one of the most studied; Gold, Naujoks, Radlmayr, Bellem, and Jarosch, 2017), but also sideswipes and false warnings which have not been investigated before. Sideswipes gave insights on how drivers responded to critical scenarios of greater surprise, requiring greater glance eccentricity to be noticed than rear-ends. False warnings gave insights on if and how drivers responded to imperfect warnings. The results revealed that most participants (70%) performed an evasive maneuver in response to a false warning. The safety consequences of this behavior require further investigation, however, as inappropriate responses may undermine the operation of automation and compromise safety (J. D. Lee et al., 2006).

Limitations The generalizability of the findings from this thesis is subject to certain limitations that derive from the methodology followed for data collection, data analysis, and statistical modeling. In general, the same considerations presented in Chapter 4 apply. There are other sources of uncertainty. First, it is unknown the extent to which the findings from Paper I–IV can be extrapolated to different social norms and cultural values (Sagberg, Selpi, Bianchi Piccinini, and Engström, 2015); the participants in the naturalistic studies EuroFOT and EyeOnRoad were recruited from Volvo Car personnel, who drove a company car in the Göteborg area (the second-largest city in Sweden). Similar issues surround the results from the simulator study in Paper V, as the participants were mostly students at the Technical University of Munich (Germany). Second, Paper I, II, and V relied on manual video reduction, which was performed only by the author of the thesis; the intra- and inter-rater reliability was not established. Third, the eye-tracker used for Paper III–IV did not provide information about the off-path areas of interest nor the glance eccentricity; some off-path glances (e.g., towards the mirror) may be critical for safety and the ability to detect threats on the road degrade with increasing visual eccentricity.

Future research Further research, which considers the limitations mentioned, is recommended. First, future studies may examine more closely, and under tighter experimental control, the effectiveness of sensory cues to communicate system limits though actuation found in Paper I–II. Second, future studies may quantify how the results (e.g., the reference models in Paper III–IV) can be tuned according to a broader range of driving situations. Third, future studies may improve the reliability of glance-based methods for studying inattention by leveraging on eye-trackers that measure glance location and eccentricity. Fourth, future studies may apply more sophisticated probabilistic modeling technique (e.g., hidden Markov models), which incorporate visual-motor response and features from the driving context, to model driver's response process. Finally, a natural progression of this work is to extend it to future analyses of real-world driving data with more sophisticated automation, both in routine driving and in critical situations.

7. Conclusions

By using naturalistic driving data with high ecological validity, proposing novel and robust processing for behavioral data, and introducing Bayesian statistics in traffic safety research, this thesis made major contributions to the current literature on the human factors in automated driving. Specifically, this thesis advanced our knowledge for answering four topical research questions.

1. *What are the effects of automation on drivers' attention to the driving task?*

   This work showed that, in routine real-world driving, drivers allocated less attention to the driving situation with automation than without (Paper I–IV). However, drivers' attention was sensitive to other changes in the driving context and the interplay thereof (e.g., the presence of a lead-vehicle and darkness). We quantified these effects in a novel reference model that was lacking in the literature (Paper III). Moreover, the Bayesian data analysis that we introduced allowed to model—in greater details than previously done—the characteristics of visual behavior during visual time-sharing (Paper IV).

2. *What are the safety implications of those changes?*

   This thesis found that the implications of diverting attention away from the driving situation needs to be interpreted in the specific context (e.g., the characteristics and criticality of the driving situation; Paper I–III) rather than at a general level as done in previous research. Although attention was reduced at an aggregate level, drivers were attentive at critical points, for example to upcoming lead-vehicle conflicts (Paper I–II); this indicates that drivers can proactively increase their attention to promptly respond in case of sudden changes in the traffic environments. Moreover, the reduction of risk exposure due to automation needs to be acknowledged (Paper I–III); the safety implications of eyes off-path are different than when the eyes are off-threat if automation maintains a safe headway to other traffic.

3. *Are drivers prompt to respond to critical situations?*

We demonstrated that driver attention is not a static mechanism, but it adapts and responds specifically to the evolution of the real-world driving situations and with experience (Paper I–III). While drivers may anticipate critical situations, warnings are an effective strategy for triggering a quick shift of attention to the driving task in preparation to an evasive action (Paper II and V). This thesis also provided novel in-depth information on the complete response process in critical situations under unsupervised automated driving (using advanced Bayesian methods; Paper V).

4. *How can attention be elicited in situations that require an intervention by the driver?*

   Our studies unveiled that attention can be elicited by sensory cues from the driving situation (e.g., visual, vestibular-kinesthetic-somatosensory) that signaled an impending conflict (Paper I–II). Traditional warnings (e.g., audio) were found to be primarily attention alerting, rather than directly associated with a brake or steer intervention as previous research has implied (Paper II and V).

The outcome of this PhD work has a number of other implications for assessment and testing of vehicle systems (ADASs and automation). First, the findings are valuable for the development of computational driver models to be used in computer simulations for driving safety assessment, for example counterfactual analysis for evaluating the safety benefit of ADASs (Bärgman et al., 2015). Second, the findings can support the design of real-time inattention countermeasures, for example attention reminder systems based on eye-tracking (J. D. Lee et al., 2013), or attention-sensitive ADASs (Victor et al., 2008). Third, the findings can inform the rule-making process, for example inattention guidelines (NHTSA, 2013).

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A. Mathematical derivation of looming quantities

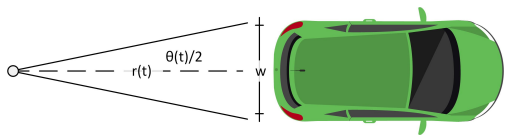

Figure A.1.: Schematic for the mathematical derivation of the measures of looming in car-following situation.

Measures of looming can be computed from trigonometry. Based on Fig. A.1, the range $r(t)$ to the lead vehicle, in meters, is given by

$$r(t) = \frac{\frac{w}{2}}{\tan\left(\theta(t)/2\right)} \tag{A.1}$$

where θ is the angle (in rad) of the lead vehicle at the eyes of the driver, and w is the width of the lead vehicle (in meters). From (A.1), we get

$$\theta(t) = 2 \cdot \tan^{-1}\left(\frac{w}{2\,r\,(t)}\right) \tag{A.2}$$

The time derivative of (A.2) yields

$$\dot{\theta} = 2 \cdot \frac{d}{dt}\left[\tan^{-1}\left(\frac{w}{2\,r\,(t)}\right)\right] \tag{A.3}$$

By applying the chain rule on (A.3), we get

$$\dot{\theta} = 2 \cdot \left[\frac{d}{du}\tan^{-1}(u) \cdot \frac{du}{dt}\right] \tag{A.4}$$

where

$$\frac{d}{du}\tan^{-1}(u) = \frac{1}{1+u^2}$$
$$u = \frac{w}{2\,r\,(t)} \tag{A.5}$$

By substituting (A.5) into (A.4), we obtain

$$\dot{\theta} = 2 \cdot \left[\frac{1}{1+\frac{w^2}{4\,r(t)^2}} \cdot \left(-\frac{w}{2} \cdot\ r(t)^{-2} \cdot \dot{r} \right) \right] \tag{A.6}$$

By simplifying (A.6), we get the final expression for $\dot{\theta}$

$$\begin{aligned} \dot{\theta} &= 2 \cdot \left[\frac{1}{1+\frac{w^2}{4\,r(t)^2}} \cdot \left(-\frac{w}{2} \cdot \frac{1}{r(t)^2} \cdot \dot{r} \right) \right] \\ &= -2 \cdot \left[\frac{4\ r(t)^2}{4\,r(t)^2 + w^2} \cdot \frac{w}{2} \cdot \frac{\dot{r}}{r(t)^2} \right] \\ &= -\frac{4\ w\dot{r}}{4\ r^2 + w^2} \end{aligned} \tag{A.7}$$

The rate of dilation of the image of the lead vehicle on the retina (in s), τ, is computed as the ratio of θ and $\dot{\theta}$ (D. N. Lee, 1976).

It turns out that τ is the optical approximation of TTC (D. N. Lee, 1976). In fact, the time derivative of (A.1) yields the range rate $\dot{r}$

$$\dot{r} = \frac{w}{2} \cdot \frac{1}{\cos^2\left(\theta/2\right)} \cdot \frac{\dot{\theta}}{2} \tag{A.8}$$

Given that

$$TTC = \frac{r(t)}{\dot{r}} \tag{A.9}$$

if we substitute (A.1) and (A.8) in (A.9), we obtain

$$
\begin{aligned}
TTC &= \frac{\frac{w}{2} \cdot \tan\left(\theta/2\right)}{\frac{w}{2} \cdot \frac{1}{\cos^2(\theta/2)} \cdot \frac{\dot{\theta}}{2}} \\
&= \frac{\sin\left(\theta/2\right)}{\cos\left(\theta/2\right)} \cdot \cos^2\left(\theta/2\right) \cdot \frac{2}{\dot{\theta}} \\
&= \frac{2}{\dot{\theta}} \cdot \sin\left(\theta/2\right) \cdot \cos\left(\theta/2\right)
\end{aligned} \tag{A.10}
$$

The equation (A.10) can be simplified using the trigonometric identity

$$
\sin\left(a\right) \cdot \cos\left(b\right) = \frac{1}{2} \cdot \left[\sin\left(a+b\right) + \sin\left(a-b\right)\right] \tag{A.11}
$$

The equation (A.10) can then be written as

$$
TTC = \frac{2}{\dot{\theta}} \cdot \frac{1}{2} \cdot \sin\left(\theta\right) = \frac{\sin\left(\theta\right)}{\dot{\theta}} \tag{A.12}
$$

which shows that TTC is optically specified, and that TTC is equal, save the small angle approximation, to the quantity τ (as defined in D. N. Lee, 1976)

$$
TTC = \frac{\sin\left(\theta\right)}{\dot{\theta}} \approx \frac{\theta}{\dot{\theta}} = \tau \tag{A.13}
$$