Proceedings of 8th Transport Research Arena TRA 2020, April 27-30, 2020, Helsinki, Finland

Modeling driver behavior in interactions with other road users

Prateek Thalya^{a,b,*}, Jordanka Kovaceva^a, Alessia Knauss^b, Nils Lubbe^c, Marco Dozza^a

^a *Mechanics and Maritime Sciences, Chalmers University of Technology, Sweden,*

^b *Veoneer Research, Veoneer Sweden AB, Vårgårda, Sweden,*

^c *Autoliv Research, Vårgårda, Sweden*

Abstract

Driver models help improve and evaluate systems for road crash mitigation and avoidance. As systems develop and address increasingly complex scenarios. Driver models also need to be developed to be able to account for the interactions among these road users. Even as we improve driver modeling with control-theory models and actual data-driven implementations, existing driver models fail to sufficiently take interaction among road users into consideration. This paper addresses this insufficiency by proposing a new operational framework to computationally model interactions among road users. For this purpose, we introduce a definition for interaction among road users. The modeling framework is demonstrated by a specific driving scenario: the overtaking of a cyclist when an oncoming vehicle may be present. In this scenario, modeling driver interaction using Unified modeling language within our framework can lead to improved crash mitigation and avoidance through tailored system activation of automated emergency braking.

Keywords: Driver modeling; road-user interaction; advanced driver-assistance systems; autonomous emergency braking; overtaking

* Corresponding author. Tel: +46733614396;

Email address: prateek.thalya@veoneer.com

Nomenclature

ADAS	Advanced Driver Assistance Systems
AEB	Autonomous Emergency Braking
UML	Unified Modeling Language

1. Introduction

Advanced Driver Assistance Systems (ADAS) aim to increase safety and comfort by supporting the driver in both critical and non-critical situations. For example, Autonomous Emergency Braking (AEB) prevent or mitigate collisions by braking the car automatically when drivers do not initiate braking and a crash is imminent. In a complex traffic situation, deterministic prediction approaches for ADAS assume full knowledge of the states and intentions of the other road users. These approaches often ignore interaction between road users. Interactions can lead to driver expectations of future maneuvers not being matched by current ADAS, and in turn to a driver subjective hazard perception not reflected by the ADAS threat assessment (Kaß, Schmidt, & Kunde, 2018). Drivers will regard system actuations as nuisance and source of irritation if the systems and their own view of the situation do not match (Ljung Aust & Dombrovski, 2013).

The knowledge about driver behavior is crucial for mitigating or avoiding crashes and evaluating new ADAS. The behavior (current and expected) of road users plays an important role in assessing the criticality of a situation (e.g., the probabilities of a rear-end collision). Interactions have been described in both cognitive e.g., (Gibson J & Crooks E, 1938) and analytical e.g., (Markkula, Boer, Romano, & Merat, 2018) driver models.

Interactions have not yet been explicitly modeled or included in current ADAS, and the integration of interactions in driver models is still in its infancy; especially between cyclists and passenger cars. The potential safety improvement of a development in this area is huge, due to an increasing number of cyclists on the road. Currently, cyclist fatalities in collisions with motorized vehicles make up for 7.8% of all fatalities in the EU (European Road Safety Observatory, 2017) and 3% of all fatalities in the world (WHO, 2018).

The overtaking of a cyclist by a motorized vehicle (hereafter referred to simply as “overtaking”) is a complex driving task. Misjudging the oncoming vehicle’s speed and distance can reduce both longitudinal and lateral safety margins (Vassilis, Dimitris, Evangelia, & Nicolas, 2015), possibly resulting in a crash (Clarke, Ward, & Jones, 1999). Overtaking has been previously studied (Bianchi Piccinini, Moretto, Zhou, & Itoh, 2018; Dozza, Schindler, Bianchi-Piccinini, & Karlsson, 2016; Kovaceva, Nero, Bärgerman, & Dozza, 2018). During overtaking, the interaction between the driver and the cyclist has been highlighted as relevant by Dozza et al. (2016).

This paper proposes a new operational framework for computationally modeling interactions among road users. We introduce a definition for interaction among road users derived from existing literature and use this definition within the modeling framework. Interaction modeling is operationalized with Unified Modeling Language (UML) diagrams. The modeling framework is exemplified by one specific driving scenario: overtaking. For this scenario, we also discuss how modeling the driver’s interaction with the cyclist and the oncoming vehicle can improve AEB system activation.

2. Background

2.1. Interaction in driver modeling

Current literature takes interactions into consideration in *qualitative* driver models. Qualitative driver models are models which use qualitative quantities such as risk or task (e.g. Zero risk theory by Nääätänen and Summala (1974; 1996, 2007)). Within the hierarchical model of driving tasks proposed by Michon, interaction may be observed at all levels, i.e. strategic, tactical, and operational levels (Michon, 1985). Interaction at the operational level may include honking, waving, flickering head lights, etc. Interaction at the tactical level may include checking for oncoming vehicles in preparation to an overtaking maneuver, while examples of interaction at the strategic level may include choosing a route based on the expected congestion.

Quantitative driver models, reviewed in (Macadam, 2003; McRuer, 1980; Nash, Cole, & Bigler, 2016) are computational process models which generally do not incorporate the limitations of human sensory physiology, attention, memory or internal models (Toledo, 2007; van Winsum, 1999). Quantitative models are rather associated with critical situations (e.g., crashes) instead of general traffic scenarios (Elvik, 2014). Interaction within human behavior is defined by Dennett (1987) as a goal-oriented activity, who claims that drivers adapt to the other road users' (vehicles, pedestrians or cyclists) intentional stance and assign intentions and goals to them, essentially predicting their behavior. Furthermore, according to Bjørnskau (2017), road-user interactions evolve over time. The author developed a model based on game theory, describing how cyclists and cars interact when approaching a crossing: the driver observed the cyclist's behavior and tried to predict what they would have done. The cyclists had the opportunity to signal their intentions, thus enjoying the first-mover advantage.

According to Rasanen & Summala (2000), interactions between road users in a traffic environment are largely based on expectations, experience, and predefined routine actions. Silvano, Koutsopoulos, & Ma (2016) describe interactions at an unsignalized intersection between car drivers and cyclists based on expectations. In a complex traffic situation, road users might communicate non-verbally to show their intentions and ensure a smooth interaction (Kitazaki & Myhre, 2012; Schramm, Rakotonirainy, & Haworth, 2008).

A driver model may be used to represent drivers' understanding of the surroundings. A way to extend a driver model could be using the concept of a hierarchical generative model which calculates a prediction of the driver's action based on sensory input (Clark, 2006). This concept has been demonstrated in the predictive-process framework, in which drivers actively try to minimize the sensory-prediction error by updating their perceptions or by performing an action. The framework says that driver expectations are shaped gradually as their internal generative model is tuned to statistical regularities of the environment (Engström et al., 2018). In the predictive process context, interaction is implicit because it continuously shapes any road-user generative model.

when describing driver models using hierarchical models such as (Engström et al., 2018; Michon, 1985), interaction has been defined as the interplay between different layers of the model; it could be a top-down or bottom-up process. In these interactions and predictions, expectancy plays a key role, in line with Rasanen & Summala (2000) who say interaction is an expectancy, experience and predefined actions. Even though expectancy plays a key role in interaction, reason for interaction can be related to work of Dennett (1987), who defines interaction as a goal-oriented action. The goal of interaction can also be linked to concepts from qualitative driver models, such as 'field of safe travel' (Gibson J & Crooks E, 1938); zero-risk theory models, where driver action is related to maintaining safety margins (Näätänen & Summala, 1974; Summala, 1996, 2007); and comfort-zone models (Ljung Aust & Engström, 2011; Summala, 2007).

Based on our understanding of different models in the literature and how interaction has been implicitly defined in these models, the definition that we propose should consider perception, planning, and action, tied to a goal which can be related to safety (reduction of risk), comfort (comfort-zone boundaries), and communicating intent (intentional stance). The aim is to operationalize the definition of interaction, so perception, planning, and action can be linked to different phases of ADAS intervention, situation assessment, threat assessment, decision making, and actuation. Thus, interactions are given a systems perspective.

3. Interaction modeling framework

We propose a definition for interaction between road users to guide the future development of quantitative driver models.

3.1. Interaction definition

We propose the following definition of interaction: *"In traffic, interaction among road users is a cyclic process (including perception, planning, and action) that occurs when two or more road users share the infrastructure. Interaction is based on predictions and expectations and its main goal is to keep road users safe and comfortable while satisfying their need for mobility. Interaction may also serve to communicate one's intentions and to probe the intentions of others."*

3.2. Interaction framework

We propose a four-step process to operationalize our definition of interaction within existing driver modeling approaches. Based on our proposed definition of interaction, we break each interaction down into perception, planning, and actions performed in a traffic scenario. We describe these steps and link them to existing literature on driver behavior (including qualitative, and quantitative modeling). Furthermore, we take a step in the direction of system implementation by suggesting how to use Object Management Group (OMG) standard – UML, version 2.5.1 (Object Management Group (OMG), 2017) in the different steps of this framework.

The selection of the traffic scenario to which the driver modeling should be applied is not part of the framework but is a precondition. The selected scenario could address normal driving and a safety-critical situation. This selection is typically carried out based on a safety analysis using different types of data, such as naturalistic data or national crash data (STRADA or NHTSA). There are existing frameworks for selecting target scenarios (e.g., Dobberstein et al., 2017; Engström & Wege, 2016; Page et al., 2015; Sander, 2018).

Step 1: Actors

The main goal of this step is to define the actors involved in the selected scenario and their states. Because our framework guides the development of quantitative driver models to support ADAS, the main actor is always the driver in the ego vehicle. The goals of the driver in the scenario are defined in terms of mobility. Other actors are identified by exploring all potential interactions, in terms of sharing the infrastructure and influencing each other's fields of safe travel. The states of the actors are then defined by breaking down the maneuvers that ego-vehicle drivers may perform to reach their mobility needs while keeping safe and comfortable (main goals).

To help identify and visualize the actors and their states, UML- use case diagrams are used (Object Management Group (OMG), 2017, sec. UseCases). Use case diagrams serve as a first step before the development of interaction models. In the selected traffic scenario, the ego vehicle is considered the primary actor initiating the sequence of actions. All other vehicles are considered secondary actors who react to the actions of the ego vehicle. The use case diagram is aligned with the description of driver behavior in the driver modeling literature.

State machine diagrams (Object Management Group (OMG), 2017, sec. StateMachines) are then used to highlight the transition of road users from one state to another. The transition is demonstrated by specifying the sequence of events that the actors go through. In our framework, the state machine diagram is used to understand different states of the ego vehicle and the factors that trigger its state changes. These states and triggers may help creating requirements for driver models by highlighting the different components to model (typically variables defining the states and their transitions).

Step 2: Models

The main goal of this step is to select a suitable existing driver model from the literature for each of the actors and for the driver in the ego vehicle specifically. The choice of the models depends on which states and transitions we want to model. This process builds on the existing knowledge about driver modeling and extends it with interactions, avoiding the need to develop a completely new model. Different models may be suitable for different scenarios. For instance, longitudinal control models (Lappi & Mole, 2018; Lee, 1976) would be particularly suitable for a rear-end situation and lateral control models (Salvucci & Gray, 2004) for negotiating a curve.

Step 3: Interactions

In this step, we determine how the presence of all actors identified in Step 1 may influence the perception, planning, and action of the driver in the ego vehicle. In other words, the aim of this step is to identify the potential interactions between the actors in the traffic scenario. The interaction is identified based on our definition, in which actors in the scenario perform actions to stay within their comfort zone or within a certain safety margin—or communicate to understand other road users' intentions. Thus, interactions can be used to give context to driver actions in the selected driver model. Identified interactions can be related to different driver models, such as a predictive-process model (Engström et al., 2018) in which the driver tries to minimize the prediction error

To help identify and visualize interactions between road users, we use UML sequence diagrams (Object Management Group (OMG), 2017, sec. Sequence Diagrams). These diagrams are usually used in software engineering to define the interaction between actors in a sequential order. These diagrams can be useful for demonstrating the chronology of actors' interactions. Each road user in a sequence diagram is an actor represented

by an object on a timeline, where time increases as the line extends downwards. The timeline does not represent a literal measurement of time. The interactions of different actors are mapped sequentially. Activation boxes are drawn to show when the actors are actively interacting.

Step 4: Including interaction in driver models

The challenge of this step is to determine how the interactions identified in Step 3 serves as inputs for the model selected in Step 2 so that the actions predicted by our models depend on the presence and actions of other road users. This step is highly dependent on the specific scenario (Step 1) and the model selected (Step 2) and may not have a simple solution (depending on the models selected). In fact, without further development, the models from Step 2 may not allow for interaction to be considered. In this case, this step will identify the limitation of the model and highlight the potential role of interaction in the specific scenario. Nevertheless, in the example below, we show that accumulation models (Markkula et al., 2018) are already able to integrate some of the interaction features that Step 3 may highlight.

4. Application of framework: overtaking a cyclist

During the overtaking, the presence of an oncoming vehicle influences which overtaking maneuver (flying or accelerative) an ego vehicle performs, depending on arrival time of the oncoming vehicle (Bianchi Piccinini et al., 2018; Dozza et al., 2016; Kovaceva et al., 2018). The decision to overtake the cyclist is made in the approaching phase (Figure 1). The different phases of overtaking are mapped based on the field of safe travel and comfort zone boundaries. Different boundaries are quantified through the lateral distance between the ego vehicle and the cyclist in both flying and accelerative maneuvers, these boundaries also consider the distance to the oncoming vehicle (Dozza et al., 2016).

Figure 1. Phases of an overtaking maneuver as defined in Dozza et al. (2016)

Step 1: Actors

In the overtaking scenario, the ego vehicle initiates the overtaking maneuver. Both the cyclist and the oncoming vehicle represent secondary actors responding to the actions taken by the ego vehicle and, in turn, influencing subsequent decisions made by the ego vehicle. Figure 3 shows the use case diagram for overtaking.

The use cases were defined to reflect the existing driver modeling approaches, which divide the behavior of the driver into perception, planning, and action. First, the driver perceives the traffic scenario by understanding the position and speed of the cyclist and oncoming vehicle (if present). The driver then decides to overtake the cyclist (planning) and performs a suitable overtaking maneuver (action). These three instances in the use case identify the tasks required to accomplish the final goal of overtaking. All actors influence all phases of the overtaking (with the exception that, for accelerative maneuvers, i.e. when the overtaking occurs after the oncoming vehicle has passed, the oncoming vehicle directly influences only the approaching phase).

The state machine diagram for the ego vehicle is aligned with the phases of an overtaking scenario as defined in the literature (Dozza et al., 2016), as detailed in Figure 4. The state machine diagram depicts the entire overtaking scenario, including the initial and final states of the ego vehicle along with the events that trigger the state changes. Note that there might be more states for the ego vehicle than those shown in Figure 4 (such as the ego vehicle steering into the other lane to pass the cyclist—or passing the cyclist without crossing over to the other lane, due to a large lateral distance between the cyclist and the ego vehicle). Even though interactions between the ego

Figure 3. Use case diagram for overtaking

Figure 4. State machine diagram for overtaking

vehicle and other road users are implicitly mentioned in both the use case diagrams and state diagrams, the different interactions have not been identified yet (they are included in Step 3).

Step 2: Models

The ego vehicle is modeled using existing modeling approaches. The selection of the driver models is based on compatibility of interactions into the existing driver model. We chose the accumulation model by Markkula et al. (2018) for modeling the ego vehicle. Both cyclist and oncoming vehicle are modeled kinematically. Accumulation model was selected for ego vehicle as potential interaction identified could be used to operationalize safety metrics such as time gap to ego vehicle or lateral overlap to the cyclist that could be used to model the driver during overtaking.

The accumulation model by Markkula et al. (2018) represents driver control as a series of intermittent, open-loop control adjustments. The timing of new adjustments is determined by accumulating evidence, which can be both excitatory and inhibitory inputs. Based on these adjustments, the driver makes a prediction of how accumulated

evidence will affect future sensory inputs and plans the action. Potential interactions identified in Step 3 are separated into excitatory and inhibitory evidence in Step 4.

Step 3: Interactions

The potential interactions between the ego vehicle, the cyclist, and the oncoming vehicle are identified using a sequence diagram (depicted in Figure 5). The sequence diagram (read from left to right and top to bottom) shows the passing of time. The interactions between the actors are indicated using solid or dashed lines and according to our definition capture different aspect of interaction (supporting perception, planning, and action but also including communication of intent). Interactions between the ego vehicle and 1) the cyclist and 2) the oncoming vehicle are separated using alternative loops. Figure 5 shows how the interactions relate to the driver's decision to overtake the cyclist or to delay the overtaking. Once the decision to overtake is made, the overtaking is performed according to the states highlighted in the state machine diagram (Figure 4).

Figure 5. Sequence diagram for overtaking scenario

Step 4: Including interaction in driver model

The interactions identified for the ego vehicle, the cyclist, and the oncoming vehicles are categorized into excitatory (in dash dot line and in green) and inhibitory inputs (in dotted line and in red), as shown in Figure 5. This division is particularly useful because in step 2 we decided to use an accumulation model. Interactions are tied to the ego vehicle's actions to overtake the cyclist or delay the overtaking. Some interactions which are not categorized as excitatory or inhibitory inputs are marked as neutral. For the ego vehicle, the cyclist's moving to give way and an indication by the oncoming vehicle to the ego vehicle to overtake by slowing down can be categorized as excitatory evidence. If the cyclist does not move when the ego vehicle approaches, the presence of

an oncoming vehicle with a short time gap can be considered inhibitory evidence, since the overtaking by the ego vehicle will be inhibited (delayed or executed with less lateral clearance to the cyclist). Excitatory and inhibitory inputs should be calibrated so that our model can predict their interplay (e.g. the relative weight of a cyclist increasing overlap as an oncoming vehicle accelerates). This can be accomplished by tuning the models with experimental data that includes these inputs and their influence on the ego-vehicle driver behavior in this specific scenario. It is worth noticing that the two main interaction (with the cyclist in terms of lateral displacement and with the oncoming traffic in terms of enhanced time to collision), may be directly measured with in-vehicle sensing.

Summarizing, in our example we 1) identified three actors, 2) selected an accumulation model for the ego vehicle and simple kinematic models for the cyclist and the oncoming vehicle, 3) identified lateral displacement of the cyclist and distance to the ego vehicle as important interactions, and 4) included these interactions as inhibitory or excitatory branches in a model predicting whether the ego vehicle would overtake or not.

5. Discussion

5.1. Importance of interaction modeling in driver models

Driver modeling is an important part of traffic safety research and promises to improve active safety (Brännström, Coelingh, & Sjöberg, 2010; Ljung Aust & Engström, 2011). These models often include assumptions regarding drivers' decision making or driver's expected behavior. Several previous frameworks for driver modeling exist, but interactions have often been overlooked—or the frameworks failed to implement the interactions between road users in driver models. Communication of intent and response to the environment—two actions that affect road-user kinematics—have not been differentiated.

Interaction, which includes perception, planning, and action as key components, plays an important role in determining the criticality of driving situations. In most driver modeling approaches, other road users are treated as stimuli or factors. In these approaches drivers typically act as satisfiers rather than optimizers. In the proposed framework, other road users are treated as independent actors whose communication and actions can influence the driver's behavior. Thus, other road users' behavior is seen more as an “optimizer” to stay safe and comfortable. This is in line with game theory approaches, where commonly observed road user's behavior is modeled as games and road users make decisions that can potentially affect the outcome of the scenario. These approaches are suitable for modeling the interaction between road users (Bjørnskau, 2017; Elvik, 2014).

The steps proposed in this framework rely on the alignment of UML diagrams with driver modeling approaches. Steps 2 and 3 are crucial in identifying the potential interactions between road users. Data from field tests, driving simulator experiments, and naturalistic data can be used to verify the extent to which the potential interactions in Figure 5 are plausible in different cultural settings and contexts. Sequence diagrams are used to identify these interactions; as with any other method, they have limitations. They do not explicitly show the relationships between actors, so it becomes difficult to develop and map all possible interactions for complex traffic scenarios involving multiple road users.

As with all driving scenarios, drivers' actions in the overtaking example are tightly linked to how drivers perceive the environment. The driver's communication of intent to overtake the cyclist and the cyclist's yielding can be linked to being safe. Similarly, the communication of intent by both the ego vehicle (turn indicator) and the oncoming vehicle (slowing down) results in safe overtaking. Thus, interaction is based on assessment and communication of intent between road users and plays an important role in determining the driver's behavior and maintaining safety.

5.2. Implications for AEB development

Threat assessment of AEB predicts future trajectories based on past and current states and driver actions. Actuators are typically triggered if a threat threshold is met, either because time to collision becomes too low or collision avoidance by steering or braking within comfort limits is becoming impossible (Brännström et al., 2010; Brännström, Coelingh, & Sjöberg, 2014; Kaempchen, Schiele, & Dietmayer, 2009). AEBs are highly effective at mitigating intersection crashes (Sander, 2017) and rear-end crashes (Cicchino, 2017; Fildes et al., 2015). AEBs

have also been shown to reduce cyclist fatalities (Rosén, 2013). The effectiveness of AEB is dependent on intervention thresholds; for cyclist AEB, they can be based on driver comfort limits (Duan et al., 2017). Using the interaction framework proposed, we can identify interactions that might take place between the ego vehicle driver, the cyclist, and the oncoming vehicle. Actions such as an increase in engine noise, turning on the turn indicator, or moving to the other lane by ego vehicle or oncoming vehicle slowing down to let overtaking occur, these indicate to the systems what the driver in the ego vehicle intends to do. Corresponding interactions can be bundled together to enrich driver models, implanted directly in the situation assessment or threat assessment, so that active safety interventions may be more effective and still highly acceptable.

6. Conclusion

We proposed a new definition for interactions among road users (including communication and probing of intent of other road users) based on our literature review of interaction modeling. Furthermore, we depicted how this definition may be operationalized within a four-step process supported by UML modelling. We demonstrated the usability of the framework with an example of drivers' longitudinal interactions with cyclists during overtaking. Modelling interactions explicitly and considering them like driver modelling in ADAS development (e.g., AEB) as indications to the system on what the driver intends to do could improve the effectiveness and usability of these systems. In fact, interventions from these systems will become more intuitive to the driver. Our future work will investigate the potential of implementing this framework for improving ADAS, such as AEB, and evaluate its effectiveness for different scenarios and road users.

Acknowledgements

The authors would like to thank Jonas Bärgman, Alexander Rasch, and Tobias Aderum for discussion on interaction definition. We would also like to thank Kristina Mayberry for language revisions. The work was partly carried out at SAFER, the Vehicle and Traffic Safety Centre, at Chalmers, Sweden. We thank Vinnova, the Swedish innovation Agency, the Swedish Transport Administration and the Swedish vehicle industry for funding parts of this work through the strategic vehicle research and innovation (FFI) program for the project 2017-05522 Modelling Interaction between Cyclists and Automobiles (MICA).

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