A drift-diffusion model to explain vehicle deceleration detection of vulnerable road users

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Abstract

The development of automated vehicles is accompanied by the question of how this technology will interact with vulnerable road users (VRUs; e.g. pedestrians, cyclists). Especially in shared spaces, implicit communication signals, such as vehicle deceleration, proved to be crucial. However, previous studies on the parameterization of vehicle deceleration indicated that human detection of vehicle deceleration may depend on various situational and individual factors. This research has two aims: (1) We want to investigate how the detection and perceptual decision-making on vehicle deceleration can be formally described using a computational model. For this, we discuss the applicability of a drift-diffusion model (DDM). (2) Further, we will follow up on previous research regarding the influence of different situational and individual factors on the detection performance and examine how these factors could be related to the DDM parameters. With this research, we would like to contribute to a better understanding and a consistent, formal description of different factors influencing the detection of vehicle deceleration. This could be associated with improved interaction between automated vehicles and VRUs.

Keywords: Automated vehicles; Vulnerable road users; Implicit communication; Deceleration detection; Drift-Diffusion Model

Introduction

The development of automated vehicles is accompanied by challenging issues in the field of human factors (Kyriakidis et al., 2019). One of these issues concerns the communication between automated vehicles (AVs) and vulnerable road users (VRUs, e.g. pedestrians, cyclists; Rasouli et al., 2017). There is a lot of research effort to design an adequate implicit (e.g., vehicle speed adaption) and explicit (e.g., light signals) communication (Markkula et al., 2020). Due to findings which show that the majority of communication in road traffic is realized in an implicit way, especially in the low-speed area (e.g. parking spaces), we take a closer look on this communication approach (Lee et al., 2021).

Deceleration maneuvers are a common implicit communication signal, for example, to indicate the intention of car drivers to give priority to a VRU. However, the implementation in automated vehicles seems to be non-trivial. On the one hand, the deceleration rate must be strong enough to be perceived by VRUs (Markkula et al., 2018). On the other hand, it should not be too strong to avoid a discomfort for vehicle passengers or a congestion of the road (Markkula et al., 2018).

In this paper, we aim to further investigate the pedestrians detection of vehicle deceleration. First, we summarize empirical results on factors influencing the detection performance of vehicle deceleration. Then, we describe the drift-diffusion model and its previous applications in the transportation context. Next, we present assumptions on how determinants of detection performance may be related to the DDM parameters. Finally, we show preliminary results from an analysis of empirical data.

Background

Factors influencing the detection performance of vehicle deceleration

Ackermann et al. (2019) investigated the relationship of different variables with the detection performance of a vehicle deceleration. In video studies, participants saw the approaching vehicle from the perspective of a pedestrian at the curb. The independent variables included the deceleration rate, vehicle size, different daylight conditions, initial vehicle speed and the onset of the deceleration (early or late onset). The reaction time between the start of the deceleration and the response of the participants was measured as dependent variable.

The results showed no significant effect of daylight conditions on reaction times, in contrast to another study regarding gap acceptance (Beggiato et al., 2017). For the low speed conditions (i.e. 20 km/h), the authors found significant effects for deceleration rate and onset of deceleration. For higher deceleration rate and later onset, participants showed faster reaction times. In addition, the authors found a significant interaction between these main factors. In particular, the onset of deceleration influenced the detection of the lowest deceleration rate. For the lower and faster speed conditions, the authors found a significant effect of vehicle speed and deceleration rate, as well as a significant interaction of both factors. This means that the higher the vehicle speed and the lower the deceleration rate, the higher the reaction time. However, it was found that there were a high number of missing reaction times (i.e. deceleration was not detected) for conditions with higher speed (40 km/h), low deceleration rate and later onset of deceleration. The influence of vehicle size remained ambiguous. At early onset of deceleration, participants tended to react faster for vehicles with medium size. At late onset of deceleration, participants tended to respond more faster for vehicles with large size. However, the results also varied depending on the deceleration rate.

In their discussion, the authors assume several ways the different variables could influence the detection of vehicle deceleration. They consider the changes in the retinal image size of the approaching, decelerating vehicle as a bottom-up process of information processing. Furthermore, top-down processes such as expectations are discussed.

This view is, among others, consistent with research on collision perception, which also assumes that different sources of information are used for these perceptual decisions (DeLucia, 2015). A possible further influencing factor could be varying risk behaviour under different conditions (e.g. different vehicle sizes). Finally, it might be useful to look at the whole process in which a pedestrian observes a vehicle and not just the time from the onset of deceleration.

Drift-diffusion models in transportation and traffic research

An established model for perceptual decision-making in signal detection tasks or two-alternative forced-choice tasks is represented by the drift-diffusion model (DDM; Ratcliff & McKoon, 2008). The most famous of the evidence accumulation models decomposes behavioral data (i.e., response times and response accuracies) into the underlying cognitive processes and their characteristics. The DDM assumes that humans accumulate (noisy) evidence (information) in the direction of one of two boundaries. This process can be described with a few parameters: The most relevant parameters for our research are drift rate (v), bound height (a), starting point (z) and non-decision time (NDT). The drift rate describes the rate of evidence accumulation which is influenced by the quality of evidence. Thus, the drift rate is associated with the stimulus difficulty. The lower the quality, the lower the drift rate and the higher the difficulty. Evidence is accumulated until it reaches the upper or lower bound representing the two choice alternatives (criteria). The bound height influences the required amount of evidence which is necessary for a decision. A larger bound height is associated with more response caution and more accuracy in decision-making. The starting point defines the position where the accumulation starts. This point can be influenced by expectations or prior knowledge. In this case, the accumulation starts closer to one of the two boundaries. The non-decision time summarizes the duration for all non-decisional components of response time (i.e. all components except of evidence accumulation), such as stimulus encoding or motor execution (Ratcliff & McKoon, 2008).

While the DDM became increasingly established in the cognitive psychology and cognitive neurosciences (Ratcliff et al., 2016), it was initially unclear to what extent the model could be transferred to the transportation and traffic domain. However, recent studies provide very encouraging indications that the model is also suitable in this context and thus can make valuable contributions to the further development of automated driving. For example, the willingness of pedestrians to cross the road (Giles et al., 2019; Markkula et al., 2018; Tian et al., 2020), car driver reactions to a braking lead vehicle (Engstrom et al., 2017; Xue et al., 2018) or the decision-making of car drivers during unprotected left turns (Zgonnikov et al., 2020) have been successfully modeled so far using the drift-diffusion model.

However, there are also some open questions. Among others, there is limited knowledge about the influence of various situational and individual variables on the DDM parameters in the context of traffic and transportation.

Present work

It seems obvious that the DDM is applicable to the scenario described in Ackermann et al. (2019). A pedestrian at the curb has to make the perceptual decision on a signal detection task, i.e. whether an approaching vehicle is decelerating or not. Furthermore, the DDM seems to be particularly well suitable for our use case because it takes into account both bottom-up (e.g., visual information) and top-down processes (e.g., expectations, cautiousness) of information processing. Therefore, we would like to follow up on this research and investigate how the detection of a vehicle deceleration can be described using a DDM. In particular, we aim investigate the influence of different variables investigated in Ackermann et al. (2019) on the DDM parameters. As a result, we would like to contribute to a better understanding of the cognitive processes involved in the detection of a vehicle deceleration.

Drift-diffusion model for the detection of a vehicle deceleration

In this section, we will discuss our assumptions on the relationship between the variables investigated in Ackermann et al. (2019) and the DDM parameters. We take a closer look on four main parameters of the DDM: Drift rate, bound height, starting point and non-decision time.

Drift rate The drift rate describes the rate of evidence accumulation and is influenced by the quality of evidence (Ratcliff & McKoon, 2008).

We assume that the drift rate results from the pedestrians' speed (change) perception of the vehicle. However, it is questionable which visual information are used. Current research suggests that different cues like looming or distance/duration cues can be used for this task (Lee et al., 2020). In previous research (e.g. Xue et al., 2018), the use of looming proved to be successful. Therefore, we focus on this visual information.

Looming refers to the change rate of the retinal image size and visual angle related to an object (Lee, 1976). The retinal image and the visual angle becomes larger as a vehicle approaches. The faster the vehicle approaches, the greater the looming. The looming becomes smaller while decelerating. So far, the general looming theory (Lee, 1976) was defined only for frontally approaching objects with constant speed and a small visual angle. Therefore, it is questionable to what extent the looming can be applied to our use case. In an important article by Tian et al. (2020), the looming theory was adapted to the perspective of a pedestrian in a crossing scenario. This shows that looming is a time dependent function depending on speed, distance between vehicle and pedestrian, vehicle size and the pedestrian's distance from the lane. A deceleration would influence the looming via a change in speed.

In addition, we assume that lightness influences the perception of the vehicle. With better daylight, a better vision is possible and a vehicle can be observed more easily. Therefore, we assume that the daylight conditions influence the drift rate with lower drift rates for dusk or in the evening.

Bound height The bound height describes the amount of evidence which is necessary for a decision. This parameter is influenced by the response caution (Ratcliff & McKoon, 2008).

We assume that the bound height is related to the vehicle size. Here, we consider the findings that pedestrians tend to accept a larger gap for larger vehicles (Yannis, Papadimitriou, & Theofilatos, 2013). We assume that pedestrians may be more cautious in decision-making when facing with a larger vehicle which can be associated with a larger bound height.

The same is assumed for daylight conditions. We assume that pedestrians might behave more cautiously in poor light conditions, which could be associated with a larger bound height.

In addition, gender and age might be related to the bound height. Findings indicated that women behave more cautiously and less risky in road traffic than men (Yannis, Papadimitriou, & Theofilatos, 2013). Further, studies indicated that older people are in general more conservative in signal detection tasks than younger people (Ratcliff et al., 2001). Therefore, we assume a larger bound height among women and older people.

Starting point The starting point describes a bias in the evidence accumulation toward one of the two boundaries, for example, due to expectations or prior knowledge (Ratcliff & McKoon, 2008).

We assume that pedestrians tend to not expect a deceleration for faster vehicles. Thus, the starting point would be closer to the corresponding boundary. It is possible that the opposite effect occurs for slower vehicles, i.e. that pedestrians expect a deceleration.

Non-decision time The non-decision time summarizes the duration of nondecisional components of the response time, such as time for stimulus encoding and motor execution pressing a response button (Ratcliff & McKoon, 2008).

Previous studies showed longer non-decision times for older participants (Ratcliff et al., 2001). Consequently, we hypothesize that non-decision time is related to the age of participants.

Preliminary results

To begin examining our assumptions for the first variables, we conducted an online study using jsPsych (de Leeuw, 2015) following the experiments by Ackermann et al. (2019). $N = 62$ participants ($n = 19$ male, $n = 43$ female) saw videos of approaching vehicles. The initial speed (20 and 40 km/h) and deceleration rate (no deceleration; slight deceleration, i.e. -1.5 m/s²; strong deceleration, i.e. -3.5 m/s²) were varied as independent variables. Participants were instructed to press a button when they decided whether the vehicle decelerated or not. If there was a deceleration, it started immediately after the video's onset. Reaction times and responses were recorded.

Figure 1 and 2 show the mean reaction times and the response accuracy depending on the deceleration rate and the initial vehicle speed.

This shows that the reaction times were always higher for vehicles with higher than for lower initial speed. Furthermore, there are differences in the response accuracy. While the detection of no deceleration was more accurate for vehicles with higher speed, the accuracy for slight and strong decelerations was higher for vehicles with lower speed. The poor detection performance of slight deceleration of vehicles with higher speed confirms the findings of Ackermann et al. (2019)

We conducted a preliminary parameter estimation for a drift-diffusion model using PyDDM (Shinn et al., 2020). Table 1 shows the results for the drift rate (depending on time and deceleration rate), the bound height (depending on gender and age), the non-decision time (depending on age) and the starting points for vehicles with lower and higher speed. To investigate age effects, we divided the participants into two age groups. Participants with an age under 30 years were classified to “young participants”. Participants with an age of 30 years and older were classified to "middle-aged participants". This classification was chosen in order to investigate two groups of approximately equal size.

The results show that the drift rate varied with deceleration rate. Here, the values for the slight deceleration were lowest for vehicles with lower as well as higher speed.

The bound height varied slightly depending on gender and age. However, no consistent pattern can be observed. For vehicles with lower speed, the bound height for men were slightly higher than those for women. The opposite direction was observed for vehicles with higher speed. Similarly, the results for the age groups were contrary. Younger participants showed a lower bound height for vehicles with lower speed and a higher bound height for vehicles with higher speed compared to middle-aged participants. Furthermore, it can be seen that the bound height is generally higher for vehicles with higher speed.

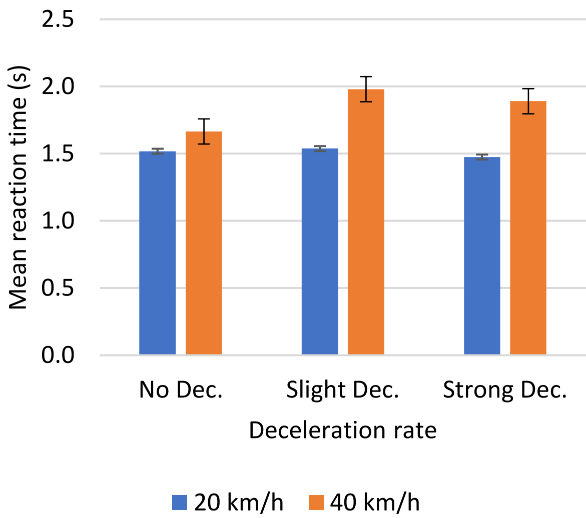

Figure 1: Mean reaction times depending on deceleration rate and initial speed.

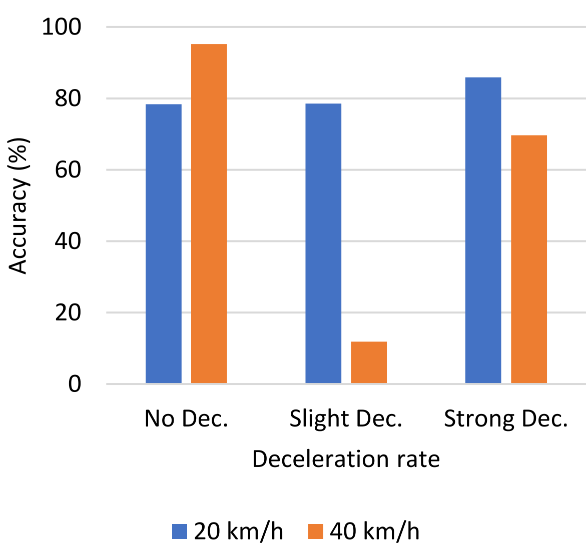

Figure 2: Response accuracy depending on deceleration rate and initial speed.

Furthermore, younger participants showed a lower non-decision time for both vehicles with lower and higher speed compared to middle-aged participants.

Finally, a slightly negative value for the starting point for vehicles with higher speed can be observed.

Table 1: Results from the parameter estimation for a drift-diffusion model.

		Vehicle speed	
		20 km/h	40 km/h
Drift rate	No Dec.	2.303	3.310
	Slight Dec.	1.708	-1.433
	Strong Dec.	2.775	1.804
Bound height	Male	1.999	2.029
	Female	1.898	2.101
	Young participants	1.855	2.389
	Middle-aged participants	1.917	2.227
NDT	Young participants	0.575	0.611
	Middle-aged participants	0.616	0.711
Starting point		0.026	-0.100

Discussion and further work

In this paper, we presented a model for the detection of a vehicle deceleration from the perspective of pedestrians. For this purpose, we used a drift-diffusion model. Previous research showed that several variables can affect the detection performance of a vehicle deceleration. We proposed assumptions on how these variables might be related to the DDM parameters with the aim to formally describe and better understand this cognitive process. Further, we presented a study to examine first variables and their relation with the DDM parameters. The results revealed a strong relation between the deceleration rate and the drift rate and thus the process of decision-making. No and strong decelerations were related to higher drift rates, while slight decelerations were related to lower drift rates. This shows that the deceleration rate represents an important variable regarding the quality of evidence.

Gender and age only slightly affected the bound height and non-decision time. However, it can be emphasized that the bound height were slightly larger for vehicles with higher speed compared to vehicles with lower speed. Here, participants were more cautious in their decision-making.

Finally, a negative value for the starting point for vehicles with higher speed indicates a slight bias, i.e. participants rather expected no deceleration in this speed condition. For vehicles with lower speed, there was no bias observable.

This study, with preliminary estimation of DDM parameters for different conditions represents a first step. In further studies, it seems important to confirm the results within standardized laboratory settings and to investigate further influencing factors on the DDM parameters. These include, among others, the effect of vehicle size, different daylight conditions and the onset of deceleration on the drift rate and the bound height.

Furthermore, it is necessary to investigate the importance of individual characteristics (gender, age) in the decision making process in more detail using a more balanced sample and a broader range of participants' age.

In addition, a validity study is crucial to check the fit between the model and empirically observed reaction times and response accuracies.

The results extend our understanding of VRUs' perception of vehicle deceleration and, in particular, the effects of bottom-up (evidence) as well as top-down processes (e.g., expectation, cautiousness) in information processing due to various situational (e.g., time of day) and individual (e.g., age) variables. This has several advantages: First, vehicle deceleration can be designed more context-sensitive, which could lead to higher acceptance and user-friendliness both for VRUs and vehicle passengers. Second, a more detailed understanding of human perception and decision-making can be used to derive implications on how to use the communication signals appropriately, for example, through a specific enhancement of implicit communication signals by explicit signals (i.e., external HMI) in case of a low drift rate (Markkula et al., 2018). And third, the findings can be used to improve the feasibility of driving simulations. Currently, developers are focusing on a highly realistic physics for vehicle simulations. Another important focus could be a more realistic behavior of virtual VRUs by modeling their perceptions (Markkula et al., 2018). This would allow a more precise investigation of interactions between (human) drivers and VRUs.

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