A Statistics and Reaction Time based Framework for Impact Prediction of Automated Vehicles on Road Safety of Vulnerable Road Users

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Abstract

We present an easy to implement method to estimate safety impacts of the introduction of automated vehicles (AVs) on crashes between cars and vulnerable road users (VRUs). Our approach is based on utilizing the power model of the relation between driven speeds and injury crashes, as well as a formula tying reaction times and deceleration capacity to braking distances. Braking distances are used to transform improvements in reaction time into an equivalent speed and quantitative impacts are then derived from the power model. Additionally, the share of injury crash causes assumed to be eliminated by AVs is removed from injury crash estimates. This results in a dose-response curve of the impact of market penetration of AVs on VRU injury crashes. This approach to safety impact estimation can serve to augment simulation results, such as would be produced by microsimulation software like AIMSUN, by the safety impacts on VRUs.

Keywords: Automated Vehicles; Accident Statistics; Power Model; Vulnerable Road Users; Reaction Times; Dose-Response Curve

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1. Introduction

We combine well known models of safety impacts of driven speeds (see [1],[2]) to gauge the impacts of introducing automated vehicles (AVs) on vulnerable road users (VRUs). We utilize data on accident causes and the at-fault share of VRUs (see [3-8]) to predict that share of VRU injury crashes that should be eliminated, under the assumption of safe AV operation (see [9-11]). For this work, vehicles are assumed to be at SAE level 5 (see [12]).
This work thus augments microsimulation efforts on estimating AV impacts, by providing VRU related impacts based on the model assumptions made on AVs. The described method was derived within the project LEVITATE ("Societal Level Impacts of Connected and Automated Vehicles", see [13]) for this very purpose.
Considerable work on microsimulation-based safety impacts of AV market penetration exists in the literature [14-22]), yet interactions between VRUs and AVs are not typically included in these approaches quantitatively.
We derive a consistent estimate of AV-VRU interaction safety, by finding the types of present day accidents that would be assumed to no longer occur given a model of AV capabilities. Assuming a proportional reduction of number of crashes as AVs are introduced, we are then faced with accidents remaining i.e. those that AV systems are unlikely to prevent. At a minimum this includes those accidents in which VRUs were assumed to be primarily "at-fault", according to official reports. We provide an estimation of further reduction in even those accidents, based on the reaction times and braking capabilities of AVs, which are assumed to be better-than-human at the time of broad introduction of AVs on our roads. Translating reaction time and better braking capabilities into a speed equivalent (i.e. a vehicle braking faster and decelerating more strongly can brake at least as good as a human driving at a lower speed), we employ the power model (see [1],[2]) of the effects of driven speed changes on injury crash numbers, to estimate how accident numbers would be reduced further. Basing estimates on reaction times and deceleration is convenient, since microsimulation models, using surrogate safety measures like conflicts (see [22-26]), are likely to make an assumption on these quantities already and thus these quantities are likely to be available for use in the approach presented here as well.
The outcome of this approach is a dose-response curve for impact of AV market penetration on VRU injury crash numbers.

2. Methodology and Results

Firstly, we utilize available accident data and form an assumption on what the share of "AV-avoidable" accidents is, under a given AV model (See also [27], for similar considerations). We then assume a proportional reduction of the number of accidents given the market penetration of AVs. This concerns, in particular, accident causes like distraction, intoxication, fatigue or ignoring traffic rules, which AVs' driving systems and policies would avoid.
Secondly, it is assumed that accidents in which VRUs were assumed primarily at fault will not be prevented fully by AVs. Yet, given assumptions on the braking capabilities (reaction time and deceleration) of AVs, it is possible to argue for further reductions in injury crashes.
Following up on the second assumption, we outline how improvements in reaction time and braking capabilities should lead to a reduction in injury crashes: Below in Equation (1) we show how the braking distance d (in meters) is derived from the vehicle speed v (meters per second), the reaction time in seconds RT and the (maximum) deceleration a. The distance driven until a reaction can be initiated is assumed to be $(v * RT)$ and the following deceleration stretch is $(v^2/(2 * a))$:

$$d = v * RT + v^2/(2 * a) \qquad (1)$$

If we now have reaction time parameters for an assumed human RT_{Human}, as well as for an AV RT_{AV} and the same holds for deceleration capacity for humans a_{Human} and AVs a_{AV} respectively , then Equation (1) can be used to calculate a speed equivalency between both vehicles, if they were to have the same braking distance. Equation (2) expresses this idea i.e. $v_{equivalent}$ is the speed a human would have to drive to brake as capably as an AV driving at speed $v_{physical}$:

$$v_{physical} * RT_{AV} + v_{physical}{}^2/(2 * a_{AV}) = v_{equivalent} * RT_{Human} + v_{equivalent}{}^2/(2 * a_{Human}) \qquad (2)$$

Having derived $v_{equivalent}$, the "power model" (see [1],[2]) of injury crash numbers offers a means to estimate expected reductions in crash numbers, compared to human drivers, despite **both** humans and AVs driving at $v_{physical}$.The power model for 2 speeds v_{old} and v_{new} is shown in Equation (3):

$$N_{new} = N_{old} * (v_{new}/v_{old})^{model\_exponent} \quad (3)$$

The element N_{new} stands for the (expected) number of injury crashes at speed v_{new}. It is derived from N_{old}, which is the expected number of crashes found at speed v_{old}. The $model\_exponent$ determines the shape of the resulting relation and depends on several properties (urban, rural, crash severity, road user types). See [1] and [2] for details. Given a known share of f percent of not-fully-AV-mitigated injury crashes (for instance if VRUs were assumed primarily at fault) then, if vehicles on the road are driving at speed $v_{physical}$ and AVs are capable of braking as well as a human driving at speed $v_{equivalent}$, an estimate of VRU-injury crash numbers based on the market penetration of AVs can be derived. Using a $model\_exponent$ of 2 in Equation (3) (suggested in [2] for general injury crashes), results in the estimate in Equation (4):

$$\pi_{new} = \frac{1-f}{100}\pi_{Human} + \frac{f}{100} * (\pi_{Human} + \pi_{AV} * (\frac{v_{equivalent}}{v_{physical}})^2) \quad (4)$$

Here π_{new} is the share (as a fraction of 1) of accidents remaining following a hypothetical AV market penetration of π_{AV} (as a fraction of 1). Similarly, π_{Human} stands for the share (as a fraction of 1) of human vehicles in traffic. By design we have Equation (5):

$$\pi_{Human} + \pi_{AV} = 1 \quad (5)$$

Using any starting value of injury crashes $N_{initial}$, then the estimate N_{est} of the number of injury crashes given a market penetration of AVs can be calculated as in Equation (6):

$$N_{est} = \pi_{new} * N_{initial} \quad (6)$$

This approach was used in the project LEVITATE, in combination with 2 models of automated vehicles, defined for microsimulations in the AIMSUN microsimulation software. 1st generation AVs were assumed to have a reaction time of 1 seconds and a deceleration capability of 7 m/s^2. 2nd generation AVs were assumed to have a reaction time of 0.5 seconds and a deceleration capability of 9 m/s^2. Human drivers were assumed to have a reaction time of 1.5 seconds and a deceleration capability of 5 m/s^2.
Additionally, following a study of [3-8], as well as Austrian injury crash data, the irreducible share of car-VRU accidents (VRU at fault) in an urban setting was set at 30% (i.e. $f = 30$ in Equation (4)).
We show a comparative curve for the introduction of the 2 types of AVs in Figure 1.

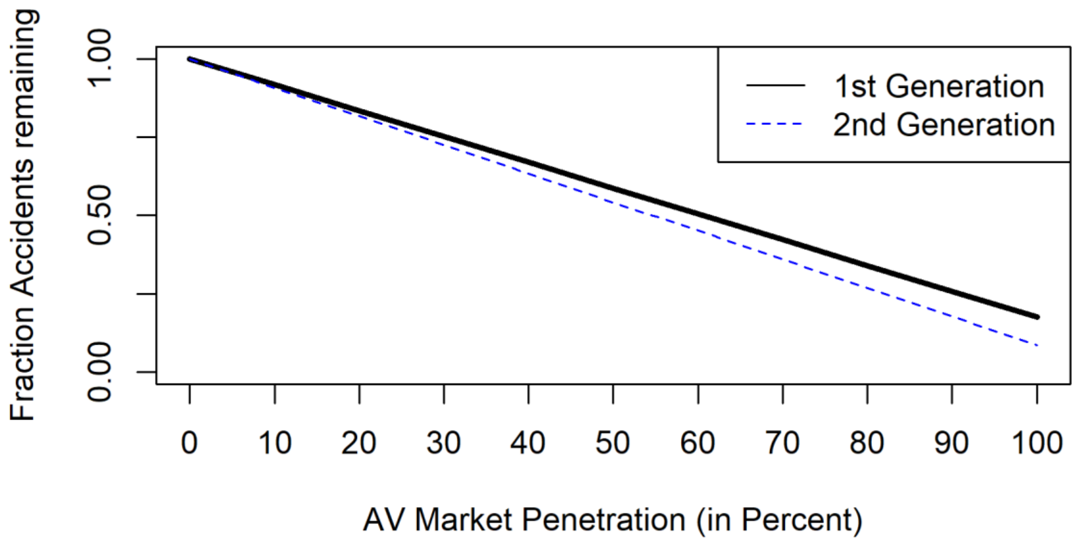

Figure 1: Development of π_{new} against the market penetration of 2 types of AVs: 1st generation (black solid line) and 2nd generation (blue dotted line).

3. Summary and Discussion

We combined considerations on accident cause statistics, driven speeds, reaction times and the power model of accident numbers to derive an estimate of VRU safety impacts as a function of AV market penetration. We achieved this by determining the types of accidents preventable by AV systems and their share of all accidents, as well as by deriving a relationship between reaction times, braking distances and the power model of accident numbers (as a function of driven speed, see [1] and [2]). The approach was designed to provide a means to enrich microsimulation estimates of AV market penetration safety impacts in a fast and consistent (with the model assumptions made for microsimulation) way.

The results were framed as a proportional reduction in injury crashes, which could be applied to different measures, such as crashes per vehicle kilometers driven or absolute numbers of crashes in a city or traffic volume. The presented method can be adapted to several needs, for instance having separate estimates for separate VRU types or having multiple types of AVs or including limitations of AV operability (day times, weather) into the estimates. In the latter situation, the share of non-AV-mitigable accidents/crashes might be increased accordingly for instance.

Limitations include the uncertainty of accident cause attribution (needed to quantify the preventable share of accidents) and the non-included added risks specific to automated driving (system failures, cyberattacks), which are highly system specific and thus hard to provide general estimates on, unless very detailed models of the employed systems are provided.

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