A Quantitative Method to Determine What Collisions Are Reasonably Foreseeable and Preventable

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Abstract

The development of Automated Driving System (ADS) has made significant progress in the last years. To enable the deployment of Automated Vehicles (AVs) equipped with such ADSs, regulations concerning the approval of these systems need to be established. In 2020, the World Forum for Harmonization of Vehicle Regulations has submitted a proposal for a new United Nations regulation concerning the approval of an Automated Lane Keeping System (ALKS). An important aspect of this proposal is that "the activated system shall not cause any collisions that are reasonably foreseeable and preventable." The phrasing of "reasonably foreseeable and preventable" might be subjected to different interpretations and, therefore, this might result in disagreements among AV developers and the authorities that are requested to approve AVs.

The objective of this paper is to propose a method for quantifying what is "reasonably foreseeable and preventable". The proposed method considers the Operational Design Domain (ODD) of the system and can be applied to any ODD. Having a quantitative method for determining what is reasonably foreseeable and preventable provides developers, authorities, and the users of ADSs a clear understanding of the residual risks to be expected when deploying these systems in real traffic.

Using our proposed method, we can determine what collisions are reasonably foreseeable and preventable. This will help in setting clear requirements regarding the safety of ADSs and can lead to stronger justification for design decisions and test coverage for developing ADSs.

Keywords: Safety; Automated Driving System; Automated Vehicle; Automated Lane Keeping System; Reasonably foreseeable; Preventable

Extended summary

1. Introduction

It is generally expected that Automated Driving Systems (ADSs) will make traffic safer by eliminating human errors, enable more comfortable rides, and reduce traffic congestion [1]. Lower levels of automation systems, such as adaptive cruise control [2] and lane keeping assist systems [3], are already widely deployed in modern cars and trucks. Since the development of ADSs has made significant progress, it is expected that ADSs addressing higher levels of automation and covering the full dynamic driving task, i.e., SAE level 3 or higher [4], are soon to be introduced on public roads [5–7].
New regulations concerning the approval of higher levels of automation are needed. Therefore, the World Forum for Harmonization of Vehicle Regulations has submitted a proposal for a new United Nations regulation concerning the approval of an ADS, with the title "proposal for a new UN Regulation on uniform provisions concerning the approval of vehicles with regards to automated lane keeping system" [9]. Regarding the system safety and fail-safe response, the following requirement is mentioned [9, Chapter 5]: "The activated system shall not cause any collisions that are reasonably foreseeable and preventable." This requirement leaves room for different interpretations, because the terms "reasonably foreseeable" and "preventable" have not been quantified. The different interpretations might result in disagreements among ADS developers and the authorities that are requested to approve an ADS.
We assume that "reasonably foreseeable" refers to the scenarios that are potentially leading to a collision. If a scenario is reasonably foreseeable, it is expected from the developers to consider this scenario during the design process and, therefore, ensure that the ADS safely handles such a scenario so that no collision occurs in this scenario. The proposed standard does not further specify the meaning of "reasonably foreseeable". Hence, this work addresses the following research question:

Research question 1. *How to determine what are reasonably foreseeable scenarios?*

The other term in the aforementioned requirement of the proposed standard [9] that leaves room for different interpretations is "preventable". To make this more measurable, this paper also proposes a method to answer the following question:

Research question 2. *How to determine to which extent a collision given a scenario is preventable?*

This extended summary is organized as follows. Section 2 describes on a high level the two methods to answer Research questions 1 and 2. To illustrate the proposed methods and as a proof of concept, the results of a case study are presented in Section 3. After a short discussion in Section 4, this extended summary is concluded in Section 5.

2. Methodology

In the following subsection, we propose a method for answering Research question 1. Next, Section 2.2 presents a method for answering Research question 2.

2.1. Determining what reasonably foreseeable means

To answer Research question 1, a method consisting of three steps is proposed:

1. Identify the scenarios that are part of the so-called Operational Design Domain (ODD) of the ADS. Here, the ODD refers to the operating conditions under which a given ADS is specifically designed to function [4].
2. Determine the exposure of these scenarios, i.e., the expected number of occurrences per hour of driving.
3. Determine the probability of encountering scenarios within a specified parameter range.

An ADS is designed to operate within its ODD, which is defined by the ADS developer and typically consists of a geofence and some known operational conditions. Once deployed, the ADS needs to deal with many scenarios and the ODD in which the ADS is operating determines the variety of these scenarios. To determine the reasonably foreseeable scenarios, the ODD needs to be known.
Considering the wide variety of scenarios, we propose to distinguish between quantitative scenarios and qualitative scenarios, where scenario categories refer to the latter. It is assumed that all possible scenarios within a given ODD

can be categorized into one or more scenario categories. For example, a *scenario category* could refer to all cut-in *scenarios* in the ODD of the ADS. This assumption does not limit the applicability of the methodology proposed in this work, though it might require many scenario categories to describe all these scenarios. See [15] for more examples of scenario categories.

We propose to determine the exposure of a scenario category based on data. Assuming that the data are collected with the same conditions as specified by the ODD of the ADS, the data provides an objective way to estimate the exposure. The probability can be estimated by counting the number of occurrences of the scenarios that belong to the scenario category. A method to find the scenarios belonging to the scenario category is explained in [16].

We use the extracted scenarios from the data set to extract the parameter values that describe these scenarios. For each extracted scenario, a vector of parameter values is obtained. To determine the parameter range of the foreseeable scenarios, a probability density function (pdf) of the parameters is estimated. The pdf is estimated using Kernel Density Estimation (KDE) because this does not require any assumptions regarding the shape of the pdf. Based on the earlier calculated exposure of scenarios belonging to the specified scenario category and the pdf, a lower bound and an upper bound of the parameter values can be estimated, such that the probability of encountering a scenario with its parameter values outside the parameter range within one hour of driving is smaller than a predetermined threshold.

2.2. Determining what preventable means

To answer Research question 2, a skilled and attentive human driver is considered as a benchmark for an ADS. Therefore, we estimate the probability that a skilled and attentive human driver is able to prevent collisions. We employ two stages of Monte Carlo simulations to estimate this probability; first crude Monte Carlo simulations and then Monte Carlo simulations using importance sampling.

With the crude Monte Carlo simulations, simulations are conducted of scenarios, where the scenario parameters are drawn from the pdf that has been used to calculated the parameter range of the foreseeable scenarios. In general, it can be expected that the probability of a collision is small. As a result, none or few of the scenario simulations may end with a collision and the relative uncertainty will be high. With importance sampling, the scenario parameters are sampled from a different distribution — the so-called importance density — such that the simulation runs focus more on scenarios in which the probability of collision is high. This will lead to a lower relative uncertainty of the estimated probability of collision.

3. Analysis and Results

To illustrate the proposed method for determining in a quantitative manner what are reasonably foreseeable scenarios and preventable collisions, the method is applied in a case study. In this case study, the Intelligent Driver Model plus (IDM+) [26], including a non-zero reaction time and a non-infinite braking capacity, is used to describe the driver behavior. This case study considers 3 scenario categories named “leading vehicle decelerating (LVD)”, “cut-in”, and “approaching slower vehicle (ASV)”. Details regarding the used data set are mentioned in [29].

Based on the analysis, it has been estimated that with 99 % probability in a one-hour drive, one will not encounter an LVD scenario with a leading vehicle initially driving more than $50.0\,\mathrm{m/s}$, or reducing more than $35.0\,\mathrm{m/s}$, or decelerating with more than $5.47\,\mathrm{m/s^2}$. Similarly, it has been estimated that the probability of encountering a cut-in scenario closer than 0.81 m in one hour of driving is less the 1 %. The probability of approaching a standstill vehicle with $38.6\,\mathrm{m/s}$ or more in a one-hour drive is also less than 1 %.

Based on Monte Carlo simulations with importance sampling, the estimated probability of a collision in an LVD scenario is $2.43 \cdot 10^{-4}$ with an estimated standard deviation of $4.11 \cdot 10^{-5}$. Similarly, the estimated probabilities of a collision in cut-in and ASV scenarios are $3.19 \cdot 10^{-3}$ and $4.77 \cdot 10^{-8}$, respectively.

4. Discussion

This extended summary summarized a method to determine which scenarios are reasonably foreseeable and to which extent collisions are preventable. More details regarding the proposed method and the case study will be published in a forthcoming publication. The results of applying the proposed method can be used as a benchmark for the approval of ADSs, such as specific designs of an Automated Lane Keeping System (ALKS). In this section, we discuss some limitations of the presented research that are to be addressed in future research.

The proposed method relies on data. It is, therefore, important that the data are adequate. This means that the data need to match the ODD of the ADS. The estimated exposure of the scenarios and the estimated parameter pdfs might not be accurate for the specified ODD in case the data have been recorded under different circumstances. As a result, the estimated parameter range of the reasonably foreseeable scenarios and the extent to which collisions

are preventable might not be accurate enough. The adequacy of the data also concerns the amount of data. It is important that we have enough data to accurately determine the pdf of the scenario parameters. To determine whether enough data have been collected to estimate the pdf accurately, the metric proposed in [31] can be used.
An important parameter for determining the parameter range of the reasonably foreseeable parameters is the threshold. This threshold is the probability of encountering a scenario outside the parameter range in one hour of driving. For the sake of illustration, in the case study, we have used a threshold of 1 %. This means that, on average, one scenario in 100 hours of driving is found with its parameters not within the found parameter range. When deploying an ADS on a large scale, however, a much lower value of this threshold might be better. This automatically results in a larger parameter range of the reasonably foreseeable scenarios. The reason that the presented case study has used 1 % is that 63 hours of data has been used. Smaller values of ε_F require more data to accurately determine the parameter range of the reasonably foreseeable scenarios.
The estimated probability that collisions are preventable by a skilled and attentive human driver strongly depends on the chosen human driver model. As a proof of concept, the case study has used a simple well-known driver behavior model with few adaptations. On the one hand, using a simple model contributes to the explainability of the results, ensures short simulation run times, and facilitates the reproducibility of the case study. On the other hand, the fidelity of the simulation results may be compromised by the simplicity of the simulations. When using the proposed method to assess the risk of deploying an ADS in the real world, evidence is needed to justify the fidelity of the simulation results. More research is needed to actually verify the fidelity of the simulation results.

5. Conclusions

The proposal for a new United Nations regulation concerning the approval of an Automated Driving System (ADS) has been an important milestone toward the deployment of highly-automated vehicles. This proposal has stated that "the activated system shall not cause any collisions that are reasonably foreseeable and preventable." In this extended summary, we have summarized a novel method to provide more clarity on the meaning of "reasonably foreseeable and preventable". More specifically, the proposed method provides a data-driven approach to determine the scenarios that are "reasonably foreseeable" and, therefore, are to be considered during the development of an ADS. Furthermore, the proposed method includes an approach to determine to which extent a skilled and attentive human driver is able to avoid collisions, i.e., to quantify whether or not in potentially challenging scenarios, a collision is "reasonably preventable". The result can be used as a benchmark for an ADS.
Future work involves applying the proposed method with more data, thereby providing more accurate results. Additionally, it would be of interest to investigate appropriate values for the threshold that is used to determine the set of reasonably foreseeable scenarios. Other future work involves investigating whether the chosen human driver model is appropriate and, if needed, improving the human driver models to better mimic the behavior of a skilled and attentive human driver.

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