



HAL
open science

Uncertainty-aware RSS

Francesco Carella, Oleg Oleinichenko, Philipp Schleiss

► **To cite this version:**

Francesco Carella, Oleg Oleinichenko, Philipp Schleiss. Uncertainty-aware RSS. SAFECOMP 2023, Position Paper, Sep 2023, Toulouse, France. 10.48550/arXiv.1708.06374 . hal-04191516

HAL Id: hal-04191516

<https://hal.science/hal-04191516v1>

Submitted on 30 Aug 2023

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

Uncertainty-aware RSS

Francesco Carella, Oleg Oleinichenko, Philipp Schleiss

Fraunhofer IKS

name.surname@iks.fraunhofer.de

Abstract—In this preliminary work, the authors present a potential solution on the issue of real time parameter estimation within a safety critical application. When computing the frontal safety distance, each vehicles type requires, in principle, a different safety distances depending on its capability to brake at a greater or lower rate. In order to account for different braking capabilities, an object detection and recognition algorithm must be employed, and thus, some classification uncertainty is introduced in the system. We propose to employ such a solution, in order to maximise the utility of the system by accounting for different vehicle types, while considering the uncertainty, in order to preserve safety.

Index Terms—real-time parameter estimation, safety critical application, safety distances

I. INTRODUCTION

Today’s standard practice of offline safety assurance is not sufficient for the technical systems of the future, such as autonomous vehicles. Shifting parts of the assurance task to run-time is likely to become a necessity, with systems and their operating environments becoming increasingly complex. Especially the issue of not being able to accurately predict the situations that the system will encounter makes complete offline assurance an unattainable task. Residual risk caused by unforeseen dangerous scenarios necessitates built-in reactivity, such as a safe fallback operation mode. Once these triggering conditions become known, an offline reaction is also required to fix the discovered functional insufficiency of the system. Dynamic Risk Management (DRM) is an approach for leveraging run-time information to optimize utility while maintaining safety. Particularly, when accounting for the Responsibility-Sensitive Safety (RSS) safe distance which currently rely on static parametrization. Hence, we propose to consider dynamic adaptation of the parameters of RSS to the other road agents. As such, we would improve utility while keeping safety in the system. In the following sections, we motivate why these methods are necessary and describe our proposed solution approaches for DRM.

II. DYNAMIC RISK MANAGEMENT

DRM involves the continuous evaluation of risks and the subsequent response to them. This approach is particularly valuable in the realm of safety-critical software as it allows for adaptability in addressing changing environments and circumstances. As emphasized in [7], without the implementation of

This work was funded by the Bavarian Ministry for Economic Affairs, Regional Development and Energy as part of a project to support the thematic development of the Institute for Cognitive System

DRM, it would be necessary to constantly assume the worst-case scenario. However, adopting a perpetual worst-case scenario mindset significantly hampers performance. Moreover, in situations involving machine learning algorithms or other opaque algorithms, an excessively cautious approach to safety often results in the abandonment of utilizing such technologies altogether. While DRM encompasses various domains like cybersecurity [2] and process engineering [8], this discussion will primarily focus on the automotive field.

Autonomous Systems face challenges when operating within complex and unpredictable scenarios, which makes it difficult to anticipate the conditions they will encounter. In this context, Trapp et al. emphasize the significance of dynamically assessing risk [7] and propose an initial framework, with a specific focus on the automotive field.

III. SCENARIO

Any functionality that employs real-time data could benefit from some form of DRM, however, for this work, we focus on RSS. As part of traditional RSS model, Shwartz et al. [5] propose a formula, denoted in equation 1 to calculate the minimum safety distance. The formula takes into account worst-case scenarios where the ego vehicle accelerates with a maximum acceleration value of $a_{max,accel}$ during its response time ρ while the leading vehicle brakes with a maximum deceleration of $a_{max,brake}$. After the response time, the ego vehicle then brakes with a minimum deceleration value of $a_{min,brake}$ while the leading vehicle continues with arbitrary acceleration. When the initial distance d is greater than or equal to d_{min} as determined by Equation 1, it ensures that there will be no rear-end collision with the leading vehicle.

$$d_{min} = \left[v_r \rho + \frac{1}{2} a_{max,accel} \rho^2 + \frac{(v_r + \rho a_{max,accel})^2}{2a_{min,brake}} - \frac{v_f^2}{2a_{max,brake}} \right]_+ \quad (1)$$

To calculate the current d_{min} the ego vehicle requires real-time knowledge of all parameter values. If the driving environment is unknown, all parameters must be statically set to their worst-case values during the design phase. However, this approach would result in overly cautious driving since the worst-case parameters for the Operational Design Domain (ODD) would limit the system’s functionality in all driving environments. To achieve acceptable utility, the system must

TABLE I
MAXIMUM BRAKING CAPABILITY BY CLASS OF VEHICLE. SOURCES:
[4][1][9]

Class	$a_{max,brake}$ (m/s ²)
automobile	6.9
truck	5.2
motorcycle	5.9

be capable of dynamically determining parameter values at runtime. This necessitates the use of technologies that monitor the current driving scenario, which are integral components of the perception system.

This work focuses on the parameters and inputs of Equation 1 that pertain to the other vehicle, namely $a_{max,brake}$ and v_f . Obtaining these values for the ego vehicle is more challenging compared to the parameters related to its own capabilities, such as ρ , v_r , $a_{max,accel}$ and $a_{min,brake}$. Additionally, in order to keep a safe distance, d is necessary to ensure that the ego vehicle maintains the calculated minimum safe distance plus a given margin. However, this and other parameters and related uncertainties fall outside the scope of this work.

For the maximum braking capability, $a_{max,brake}$ of the leading vehicle, it is assumed that there is a direct correspondence between the object class and the braking capability (as shown in Table I). The perception module employs deep neural networks for object classification, allowing for uncertainty estimation. Deep ensembles [3], a network architecture that supports uncertainty estimation, can provide uncertainty values for each class. The output of such a neural network trained with "n" classes is a distribution $\mathcal{P} = \{p_i \in [0, 1]\}_{i=1}^n$ with $\sum_{p_i \in \mathcal{P}} = 1$ where each p_i represents the likelihood of the object belonging to class i .

To estimate the system's uncertainty in the maximal acceleration parameter, the Jensen-Shannon uncertainty measure [6] is utilized, which is based on the Jensen-Shannon divergence shown in Equation 2. This divergence measure quantifies the similarity between two probability distributions, that is in this case the difference between a delta distribution (Dirac distribution) and the classification distribution. Essentially, the measure indicates that a discrete distribution has maximum uncertainty when it is uniformly distributed (i.e., $p_i = \frac{1}{n}$ for all $i \in \{1, \dots, n\}$), and minimum uncertainty when there is only one $p_i = 1$ (i.e., it is a Dirac distribution). Therefore, the closer the distribution obtained from the object recognition neural network is to a uniform distribution, the greater the uncertainty regarding the maximum acceleration of the leading vehicle should be assumed. Conversely, if the distribution is closer to a Dirac distribution, less uncertainty can be assumed. With this method we aim to calculate uncertainty, and thus account for it in the computation of the safety distance, by means of an additional margin term to be added that is a function of the uncertainty.

$$U_{JS}(\mathcal{P}) = \log \left(\frac{4n^2}{(n+1)} \right)$$

$$1 + n - \sum_{i=1}^n p_i \log(p_i) + \frac{2}{n} \sum_{i=1}^n \frac{np_i + 1}{2} \log \left(\frac{np_i + 1}{2} \right), (2)$$

IV. CONCLUSION AND FUTURE WORK

This work presents a potential approach for incorporating dynamic safety distance estimation with DNN-based uncertainty quantification. The original RSS formula consists of static parameters that can be transformed into dynamic variables using machine learning techniques. However, introducing machine learning brings a level of uncertainty into the equation. To address this, providing an estimation of the associated uncertainty allows for leveraging the outcomes of the machine learning component, thereby enhancing utility without compromising safety.

Future research aims to implement this approach and compare the performance of the standard RSS approach with an uncertainty-aware RSS approach. By conducting such a comparison, the potential benefits and trade-offs between the two approaches can be evaluated. Aspects of particular interest will be whether or not the safety of the system is maintained and the utility of the system sees a relevant improvement.

REFERENCES

- [1] UK Department for Transport. *The Highway Code*. Rule 126. 2015.
- [2] Gustavo Gonzalez-Granadillo et al. "Dynamic risk management response system to handle cyber threats". In: *Future Generation Computer Systems* 83 (2018), pp. 535–552.
- [3] Balaji Lakshminarayanan, Alexander Pritzel, and Charles Blundell. "Simple and scalable predictive uncertainty estimation using deep ensembles". In: *Advances in neural information processing systems* 30 (2017).
- [4] NA Rose. *Braking capabilities of motorcyclists—a literature review*. 2017.
- [5] Shai Shalev-Shwartz, Shaked Shammah, and Amnon Shashua. *On a Formal Model of Safe and Scalable Self-driving Cars*. 2018. DOI: 10.48550/arXiv.1708.06374. arXiv: 1708.06374 [cs, stat].
- [6] Gautam Sharma and Sk Sazim. "A geometric way to find the measures of uncertainty from statistical divergences for discrete and finite probability distributions". In: *arXiv preprint arXiv:2106.14874* (2021).
- [7] Mario Trapp, Daniel Schneider, and Gereon Weiss. "Towards safety-awareness and dynamic safety management". In: *2018 14th European Dependable Computing Conference (EDCC)*. IEEE. 2018, pp. 107–111.
- [8] Valeria Villa et al. "Towards dynamic risk analysis: A review of the risk assessment approach and its limitations in the chemical process industry". In: *Safety science* 89 (2016), pp. 77–93.
- [9] State of Virginia. *46.2-880. Tables of speed and stopping distances*.