Crash Pulse Prediction for Scenario-based Vehicle Crash FE-Simulations

Julian Hay, Jörg Fehr, Lars Schories

I. INTRODUCTION

Driven by Advanced Driver Assistance Systems (ADAS) and Automated Driving (AD) technologies, scenario-based testing will be implemented in the future design of integrated safety systems. The development and performance assessment of holistic vehicle safety systems will require scenario-based simulation methods that combine the pre- and in-crash phases [1]. While Finite Element (FE) simulations provide highly accurate results, computational costs increase dramatically and become infeasible when a large number of scenarios are included in the assessment. Thus, surrogate models are needed that allow a fast approximation of relevant simulation results and enable cost- and time-efficient safety performance evaluations. The first step of this study on a safety performance simulation framework is the development of a surrogate model for vehicle crash simulations and the approximation of the resulting crash pulse for the driver [2].

II. METHODS

For an initial proof of concept, a training dataset is generated by performing vehicle crash simulations in LS Dyna with the open-source NHTSA Honda Accord model, which was validated on standard crash tests [3]. As shown in Fig. 1, the crash scenario is defined by three parameters: the initial velocity v (km/h) of both target and bullet vehicle; the collision angle α (degree); and the vehicle offset d (m) between the ego and bullet vehicle.

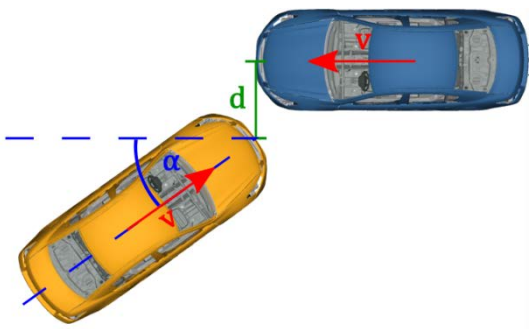

Fig. 1. Definition of the crash scenario by the initial velocity, the collision angle and the vehicle offset.

TABLE I
SCENARIO PARAMETERS

Parameter	Units	Range
angle	Deg	-30–30
offset	m	-0.96–0.96
initial velocity	km/h	12–56

The dataset consists of 100 simulations, which were sampled using a Latin Hypercube [4]. Since state-of-the-art occupant restraint systems are validated in a specific area of effect, the scenario parameters are limited to the range in Table I. Due to the limited amount of training data, a Gaussian Process Regression (GPR) model was chosen for the prediction of the crash pulse. The GPR model is trained on 80% of the randomly shuffled dataset; the remaining samples are used for the validation of the model. Validation criteria include the mean absolute error (MAE) and the occupant load criterion (OLC) [5].

Gaussian Process Regression (GPR)

The GPR model is implemented in python. The hyperparameters of the kernel, also referred to as covariance function, are optimised by minimising the marginal likelihood, as described in [6], and the kernel with minimal prediction error is selected for further studies. The GPR model with a radial basis function (RBF) kernel is trained on the dataset, with the crash scenario parameters as input and the crash pulse vector as output. In comparison to other machine learning algorithms, one advantage of GPRs is that in addition to the prediction, they also provide the variance, which can be used for an adaptive sampling strategy to improve the prediction accuracy [7].

J. Hay (e-mail: julian.hay@zf.com; tel: +49 7541 77969379) is a Doctoral student at the Institute of Engineering and Computational Mechanics and at ZF Friedrichshafen, J. Fehr is a Professor at the University of Stuttgart and L. Schories is researcher at ZF Friedrichshafen.

III. INITIAL FINDINGS

The prediction made by the GPR model generally agrees well with the test data (see Fig. 2). However, the simulation data show more significant oscillations than the predictions, which results in a large MAE of 14.15 (±5.6). Since oscillations in a higher frequency domain do not affect the occupant's kinematics, these deviations can be neglected, and thus other error measures are needed. The OLC, on the other hand, which describes an idealised occupant forward displacement, considers only the velocity of the vehicle, such that oscillations in the acceleration have minor impact. Hence, the mean OLC error of 0.07 (±1.12) is much smaller in comparison to the MAE. For the majority of the test set the velocity error is very small, however, outliers with larger errors exist, caused by predictions on the edges of the parameter space (see Fig. 3).

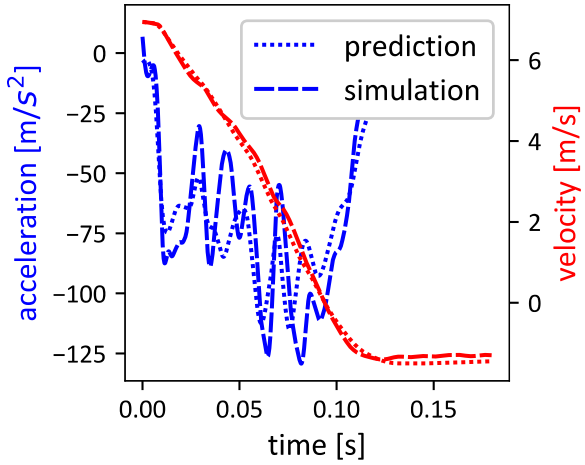

Fig. 2. Prediction, its integral and simulated signals for v = 25 km/h, α = -16.6 deg, d = -0.163 m.

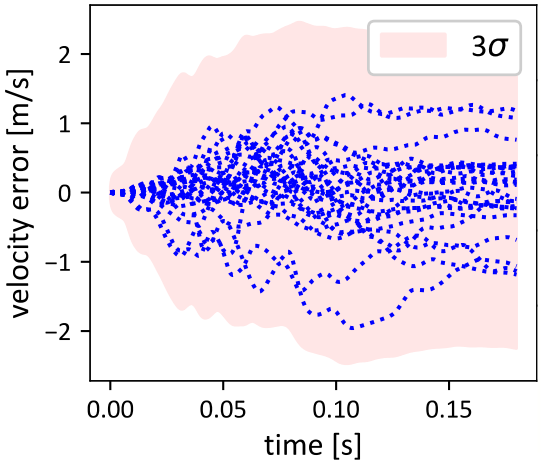

Fig. 3. Velocity error of the entire test set and standard deviation of the error.

The huge benefit of such a data-driven surrogate model lies particularly in the fast computation of the simulation results, taking only 0.19 ±0.008 s on an Intel i7-8550H 2.6GHz processor in comparison to the full FE simulation, which takes approximately 20 hours on a high-performance cluster with 20 cores.

IV. DISCUSSION

The GPR model proved a real-time capability to predict the crash pulse in longitudinal, lateral and rotational directions for frontal vehicle collisions with high accuracy. However, due to the computational cost of the FE simulations, which are needed to generate the dataset, the validation set is still of a small size and therefore the model couldn't be fully validated in the entire parameter space. Especially at the edges of the sample space, additional training data could improve the prediction accuracy. In addition, the predictions are still limited to one vehicle type without any variation of mass, e.g. the number of passengers or the weight of the luggage. Furthermore, structural differences in other vehicles must be considered as well. The OLC was originally developed for full frontal collisions and the application to collisions with larger angles and offsets must first be proven. Preliminary results of a study on occupant safety simulations show a correlation between the OLC and the injury criteria for large angles, but further investigations are necessary. In future work: (i) the training set will be extended to increase the validation set; (ii) other open source NHTSA vehicle models will be included; and (iii) the scenario parameter space will be extended. The crash pulse predicted by the GPR model will then be applied to occupant safety system simulations to create a training dataset for a subsequent surrogate model and to predict the injury severity based on the crash scenario and restraint system parameters.

V. REFERENCES

[1] Kramer, F., *Springer*, 2013.
[2] Huang, M., *CRC Press*, 2002.
[3] Singh, H., *et.al*, *NHTSA DOT HS 812 237*, 2016.
[4] Siebertz, K., *Springer*, 2017.
[5] Park, C. K., Kan, C. D., ESV, 2015.
[6] Rasmussen, C. E., Williams, C. K. I., *MIT Press*, 2006.
[7] Chen, Y., Peng, C., *Meas Sci Technol*, 2017.