A Generation Model of Vehicle Crash Pulse for Injury Severity Prediction Based on a Typical Sedan

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I. INTRODUCTION

Injury Severity Prediction (ISP) is an increasingly important topic in improved vehicle safety for mitigating crash severity and improving rescue efficiency in Motor Vehicle Crashes (MVCs) [1-2]. Deep Learning (DL) methods have captured researchers' attention for their surpassing performance in dealing with non-linear system prediction. The occupant response is a highly non-linear process involving dynamic large deformation and failure, which can be influenced by the crash pulse, restraint system configuration, and occupant physical conditions during vehicle impact [3]. Bance et al. (2019) proved that the occupant injury responses could be accurately predicted given the complete crash pulse and restraint system configurations based on a large-scale mathematical database [4-5] (Fig. 1). Nevertheless, how to obtain the crash pulse is an unsolved problem. Considering the real-time requirements of ISP, delta-*v* has been widely used as the key feature of the crash pulse in existing safety predictions [6] (Fig. 1). However, delta-*v* cannot reflect the crash process on the temporal scale, which largely limited the prediction accuracy on occupant injury. A few mechanism studies have focused on extracting more suitable ISP metrics based on the crash pulse shape. For example, Ydenius et al. (2002) suggested that peak acceleration or mean acceleration from crash pulse yields better ISP accuracy than delta-v [7]. Yet, the application of DL on ISP metric extraction is rare due to the lack of a large-scale reconstruction method of biofidelic crash pulses. In this study, we propose an effective Crash Pulse Prediction (CPP) model to predict the crash pulse given the vehicle characteristics using a simulation dataset. To prove the model's effectiveness, three different input groups were used for training, i.e., initial conditions (i.e., impact velocity, impact angle, overlap ratio, and friction coefficient), Event Data Recorder (EDR) data, and the combination of the above two. The prediction performance of the models trained with the three different inputs was assessed and compared via ISO-rating (i.e., ISO/TS 18571) on the simulation dataset. The best model of the three was further tested in real tests.

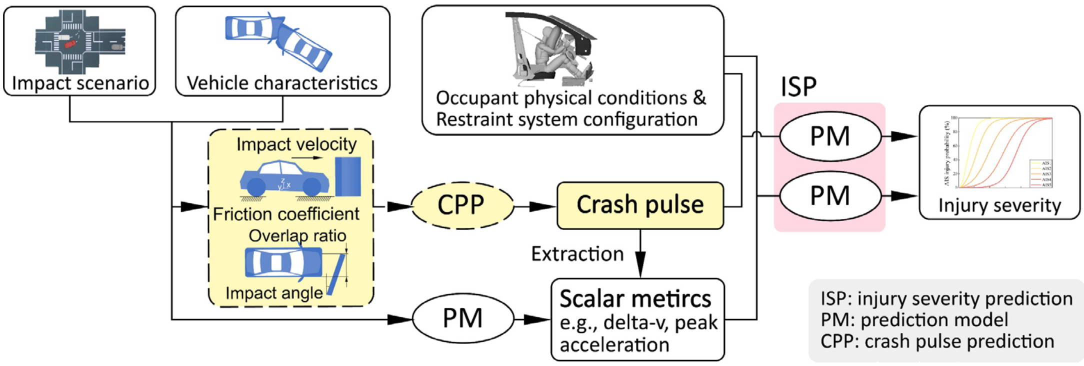

Fig. 1. The data flow of ISP. PM represents existing prediction models, and the yellow color indicates the work in this study.

II. METHODS

A large-scale crash pulse dataset was generated first. Then, the structure of the CCP model was designed and empirically optimized. Finally, the model was trained under three kinds of input groups, and the feature importance ranking was probed.

Simulation dataset.

We utilized a highly computational-efficient numerical tool (i.e., Visual Crash Studio, VCS) to generate the large-scale dataset of vehicle crash pulses for training the CPP model. In the dataset, we kept the vehicle characteristics invariant so that the crash pulse was dominated by initial impact conditions. A representative sedan model (i.e., TOYOTA Camry) was built up and impacted with a rigid wall at different initial conditions. The sedan model was calibrated with a 56 km/h NCAP frontal impact test (No. 6953) performed by NHTSA and validated with the simulation results of the Camry FE model of [8] under four different scenarios. Only the deceleration in the longitudinal axis was considered.

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Impact velocity (in the range of 25-65 km/h), impact angle (in the range of -30-30°), overlap ratio (discrete variable of ±25, ±75, ±50, and 100%), and friction coefficient (in the range of 0.2-0.8) were chosen as initial conditions to formulate a 5000-case simulation matrix. The initial conditions were independent with each other and randomly selected within the corresponding real statistics range to realize realistic results and exclude data imbalance problems [9]. It took less than 60 s to simulate a 200-ms impact process (Intel i7-9700K 3.60GHz processor). The crash pulse (i.e., x-axis linear deceleration) was recorded at the B-pillar.

EDR, as a widespread device on modern vehicles, records the impact velocity at 10-ms intervals [10]. The recorded velocity is too sparse to retrieve accurate pulse information (e.g., peak values) with traditional numerical derivation. How much information it can provide for CPP is intriguing. Therefore, the synthetic EDR data (12 sequential data points cover 120-ms impact process) were generated from the simulated crash pulses, and further applied to CPP.

Model design.

The CPP model is shown in Fig. 2. The initial conditions have four independent features (i.e., 4 data points), and the synthetic EDR data have 12 data points. Both had far fewer data points than the crash pulses (i.e., 150 data points). Therefore, the Temporal Augmentative Network (TAN) units were stacked to increase the data points. The Constant Convolution Network (CCN) units were used after TAN to improve the prediction accuracy without changing the number of data points [11].

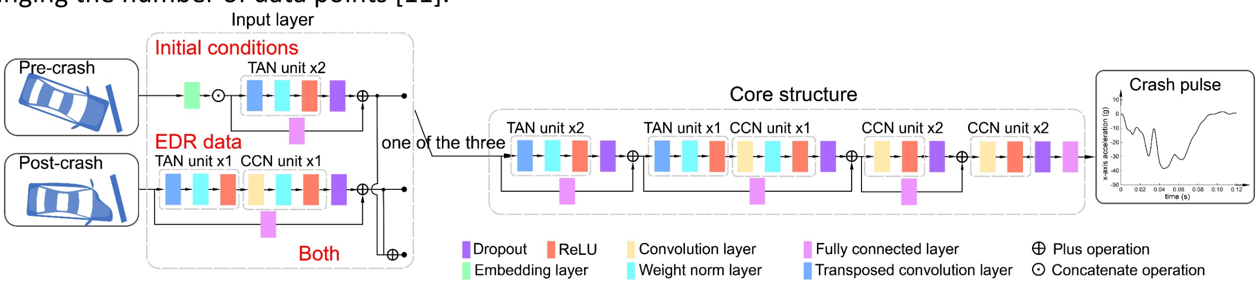


Fig. 2. The structure and the data flow of the CPP model. 'xN' means the units in the dotted frame were repeated N times in sequence.

Model inputs.

To prove the model's effectiveness and seek the best inputs for ISP, three input groups were adopted. The first group was the 4 independent features of the initial conditions. They were embedded respectively, then concatenated in the length dimension as input. Further, different combinations of initial conditions were used to re-train the CPP model to figure out which initial condition has more information (i.e., feature importance ranking). The second group was the synthetic EDR data. It was input into the model directly thanks to the sequential characteristic. The third group is the combination of the initial conditions and the EDR data to expect a better prediction result by including more information. The initial conditions and the EDR data were added together after the processing of the input layer.

Model training.

The essence of the training process is to minimize the difference between the predicted result and the target result. The cross-entropy loss was preferred as the loss function because it outperformed the mean square error loss in this application.

We preprocessed the target crash pulse to provide a systematic reference for the CPP model (Fig. 3). The free motion, which refers to the non-collision distance because of the impact angle and the overlap ratio alteration, was truncated at the critical instant when the impact occurs [12]. The following 120-ms was preserved, and zero paddings at the right end for which length is less than 120-ms. Then the pulse was compressed to 150 data points and normalized. The compressed curves and original data have a mean R^2 of 0.9998, which means almost no information loss. The predicted pulse accepted an extra moving average to improve the performance, and the window size is a hyperparameter.

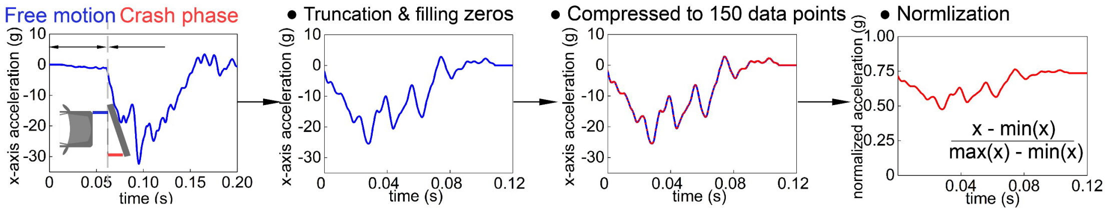


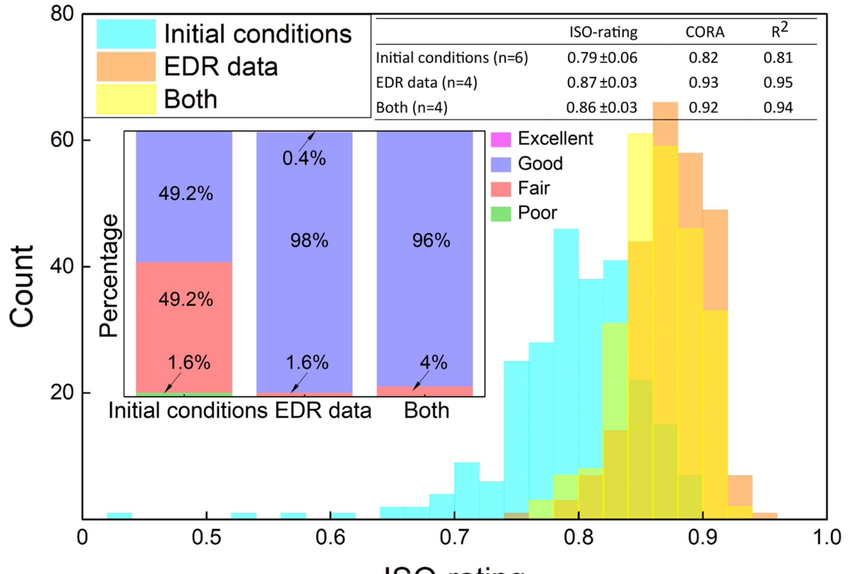
Fig. 3. Preprocessing pipeline of the crash pulses.

Performance evaluation.

ISO-rating was adopted to assess the prediction ability of the models quantitively. Because all the crash pulse was preprocessed to have the same starting point, the predicted pulse should not have lag with the target pulse. Hence, we only calculated the phase score of ISO-rating but did not eliminate the "phase lag". CORA and R^2 were provided as references. All three metrics are between 0-1, and the higher, the better. To sufficiently train the model and reduce the calculation burden of ISO-rating, training and validation subsets were split by a 95% to 5% ratio.

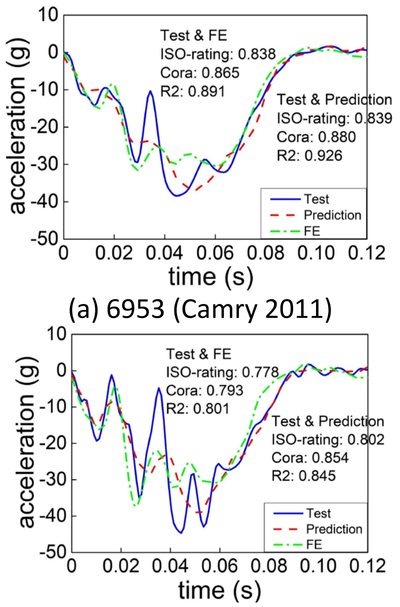
III. INITIAL FINDINGS

The ISO-rating distributions and the grade portions on the validation set are compared (Fig. 4). ISO-ratings are categorized into four grades (i.e., poor, fair, good, and excellent) by the boundary of 0.58, 0.8, and 0.94. When using EDR data as input, the model yielded the best average ISO-rating of 0.88 and an R^2 value of 0.95.



*The value in the parentheses is the best window size

Fig. 4. The ISO-rating distributions and the grades portion.



(a) 6953 (Camry 2011)

(b) 7520 (Camry 2012)

Fig. 5. Testing with impact tests.

For a more intuitive perception of the model prediction performance, we compared the prediction ability of the optimal CPP model (i.e., only using EDR data as input) with that of the FE model (Fig. 5). Two NHTSA 56 km/h standard tests (i.e., No. 6953 and No. 7520) were selected as instances. The input EDR data for the CPP prediction was computed from the measured accelerations. While the FE model was the same as the validation one, and the simulation curve underwent different filter parameters to maximize the ISO-rating score. The similarity of the test curve with the FE simulation curve and the model prediction curve were calculated, respectively. The current CPP model purely trained with the simulation dataset exhibited better performance than FE simulation.

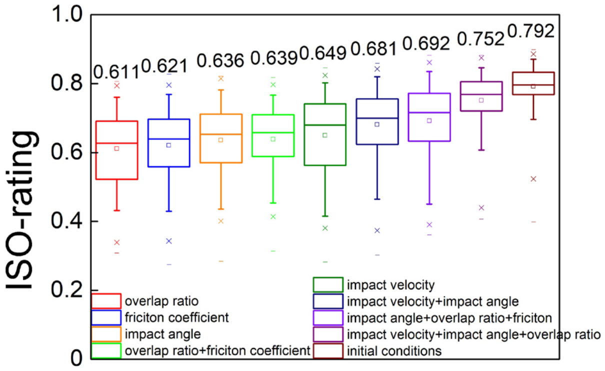


Fig. 6. Feature importance ranking of initial conditions.

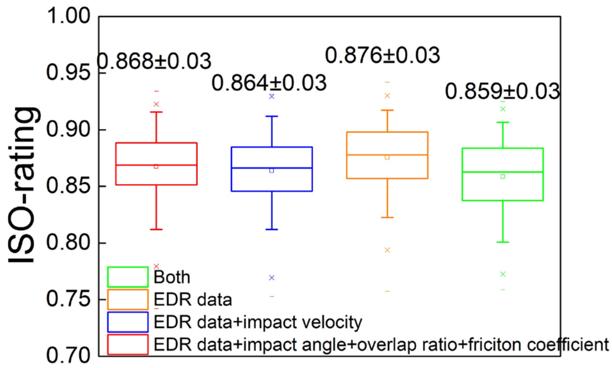


Fig. 7. Feature importance ranking of "both".

The prediction results of the CPP model with different combinations of initial conditions as input are displayed in Fig. 6. The order of feature importance from high to low is impact velocity, impact angle, friction coefficient, and overlap ratio.

IV. DISCUSSION

We proposed a CPP model to fill the gap in crash pulse prediction to perform ISP. The results from three different input groups demonstrated the feasibility and efficacy of the model. The CPP model with only EDR data as input has the best performance; the model only using initial conditions delivered the lowest average ISO-rating of about 0.8, but the performance is still acceptable from an engineering point of view (Fig. 4). EDR data, compared to initial conditions, are more informative, and therefore improved the performance. However, simultaneously feeding initial conditions and EDR data into the model, which was supposed to bring more information in, deteriorated the overall performance. To figure out this issue, we re-trained and evaluated the models with a combination of EDR data and different initial conditions, respectively (Fig. 7). It turned out that the coexistence of impact velocity and EDR data exhibited the worst performance. It might be attributed to the data conflict brought by collinearity between impact velocity and the first point of the EDR data, as the first point in EDR is essentially the impact velocity as well. DL models can automatically do feature engineering, but they cannot eliminate redundant information, and therefore the collinearity might puzzle the models [13]. This applies to the other initial conditions as well. In practice, EDR data are directly measured by sensors and are supposed to be more reliable, while the initial conditions are usually estimated from evidence after impact. Therefore, we recommend using only EDR data when making crash pulse prediction.

In the rank of feature importance among the initial conditions, it is counter-intuitive that the friction coefficient turned out to be more important than the overlap ratio. We speculate that this may be due to the data types of the two variables. The overlap ratio was treated as discrete with only seven prescribed levels, and the friction coefficient was randomly sampled in a continuous range. Weights corresponding to the friction coefficient were easier to train as for the continuous data type, and the trained model was more sensitive to the input. Thus, when there are both continuous and discrete variables in a dataset, it is advisable to combine prediction with mechanism research to correctly understand the importance of features.

The simulation dataset with simplified impact scenarios limits the authenticity of the data and further limits the application of the CPP model in real accidents. However, the CPP model only trained by the simulation dataset has a better result than the FE simulation on two standard crash tests, which means the model learned part of the crash mechanism rather than memorizing the data. Therefore, we think the CPP model and the simulation dataset are acceptable for practical applications in ISP. When there are more measured real accident data in the future, it is feasible to adjust the parameters or structure of the model by transfer learning method to improve the performance of the model in dealing with real accidents. What's more, if we have a reconstructed biofidelic crash pulse dataset by the prediction method, it is possible to find a more suitable scalar metric for faster ISP by the interpretability of the DL models [14].

Several limitations must be noted. First, the baseline model of the simulation was slightly adjusted after 200 cases at the beginning to eliminate calculation errors under extreme conditions (e.g., small overlap ratio with big impact velocity). This adjustment leads to performance compromises of the simulation data. Second, the performance of DL model was controlled by the loss value and the ISO-rating, both of which pay more attention to the overall prediction performance. Thus, although the ISO-rating of the CPP model is higher than FE simulation, the prediction curve missed the high-frequency content, which is more important for occupant ISP. To provide better prediction for high-frequency content, more reasonable indices or network structures is necessary. Third, some simplifications were used in the process of dataset generation, which limited the application of the dataset.

In further dataset enlargement, the overlap ratio should be randomly sampled within a realistic continuous range, and more factors (e.g., side-impact, vehicle types.) need to be considered.

V. ACKNOWLEDGEMENTS

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VI. REFERENCES

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