A Training Framework for Occupant Injury Prediction Algorithms to Enhance the Monotonicity between Impact Velocity and Injury Severity

Jiajie Shen, Qingfan Wang, Qing Zhou, Bingbing Nie

I. INTRODUCTION

With the development of intelligent vehicles, researchers are managing to mitigate potential occupant injuries prior to a crash, even if the crash is inevitable due to limited time to react [1]. Accurate and robust occupant injury prediction becomes paramount in guiding vehicles to make optimal safety decisions when confronting inevitable obstacles. Existing data-driven injury prediction algorithms emphasise enhancing the prediction accuracy [2-3]. When putting them into application, predicted results showed that in some scenarios, where only the impact velocity varies, the predicted occupant injury risks paradoxically decrease as the impact velocity increases, probably due to unevenly distributed data, overfitted models and some unknown prediction errors (illustrated by the red curve in Fig. 1). This could prompt vehicles to make incorrect acceleration decisions towards the obstacle ahead, thereby increasing the risk of casualties, which is unacceptable in practical application. To address this, this study proposed a training framework for occupant injury prediction algorithms by developing a customised loss function to enhance the monotonicity between impact velocity and predicted injury severity, eventually achieving robust injury prediction.

II. METHODS

Following previous research [4], we utilised a lightweight multilayer perceptron (MLP)-based network to predict occupant injury severity, represented by the Head Injury Criterion (HIC), from the initial collision condition information. To train this data-driven model, the Mean Square Error (MSE) between the target HIC (HIC_{target}) and predicted HIC (HIC_{pred}) is applied to calculate the training loss. A 5,000-case numerical crash dataset was generated through integrated simulations combining Visual Crash Studio and MADYMO [5].

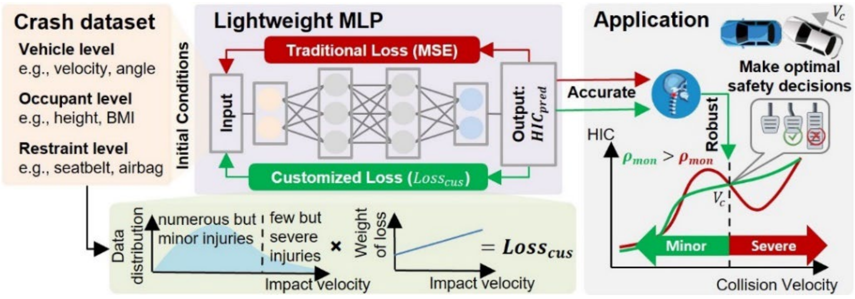

Fig. 1. The Framework to Enhance the Monotonicity between Impact Velocity and Injury Severity.

Customised Loss Function

Our analysis revealed that the non-monotonic issue of injury prediction mainly manifests itself in collision conditions with high impact velocity and severe injuries, which are rare cases in the training dataset. Therefore, inspired by the focal loss [6], a technique designed to address data imbalance by focusing more on hard, misclassified samples, we modified the traditional MSE function for injury prediction by introducing a weight parameter that can be adjusted adaptively based on the impact velocity v_{imp}, which can be represented as:

$$Loss_{cus} = \left(1 + \frac{v_{imp}}{v_{max}} \cdot w\right) \cdot MSE\left(HIC_{target}, HIC_{pred}\right) \tag{1}$$

where v_{max} denotes the maximum impact velocity in the dataset, w is a weight parameter optimised by prediction performance, and MSE (·,·) denotes the mean square error.

Metrics for monotonicity

Theoretically, occupant injury severity in a given collision condition should increase with impact velocity if other

B. Nie (e-mail: nbb@tsinghua.edu.cn; tel: +86-10-6278-8689) is an Associate Professor, J. Shen and Q. Wang are PhD students and Q. Zhou is a Professor, all in the School of Vehicle and Mobility at Tsinghua University and State Key Laboratory of Intelligent Green Vehicle and Mobility, China.

parameters remain unchanged. To quantitatively assess the monotonicity between the two factors, we defined a metric ρ_{mon} based on Spearman's rank correlation coefficient, developed as:

$$\rho_{mon} = 1 - \frac{6\sum_{i=1}^{n}(L_{HIC} - L_{vel})^2}{n(n^2 - 1)} \tag{2}$$

where L_{vel} and L_{HIC} denote the rankings of current impact velocity and injury severity, respectively, after sorting, and n is the total number of data samples in the current collision condition.

III. INITIAL FINDINGS

To prove the effectiveness of the proposed method, we compared the prediction performance of two injury prediction algorithms trained with the traditional MSE loss function (baseline) and the customised loss function (our model), respectively, shown in Table I. Accuracy denotes the prediction accuracy of head AIS, while Root Mean Square Error (RMSE) represents the prediction errors of HIC. The results highlighted that our model's monotonicity improved from 0.955 to 0.993, with accuracy increasing from 56% to 57.5%. To conduct a more thorough analysis of monotonicity, we generated 300 sets of collision scenarios. For each set, the impact velocity of different scenarios is evenly sampled from 25 km/h to 65 km/h, while other collision information remains unchanged. From Table II, we observed an obvious decrease in the number of scenarios with $\rho_{mon} < 0.9$ from 31 to 7, indicating the improvement of velocity-related monotonicity. Four prediction cases were randomly selected to visualise the prediction results (Fig. 2). It is clear that the predicted injury severity of our model (green lines) increases with the impact velocity more monotonically and steadily when compared with the baseline (red lines).

TABLE I
PERFORMANCE OF THE BASELINE AND OUR MODEL

	Accuracy	RMSE	ρ_{mon}
Baseline	56%	264.3	0.955±0.019
Our Model	57.5%	271.1	0.993±0.002

TABLE II
MONOTONICITY IN THE 300 SETS OF SCENARIOS

ρ_{mon}	0~0.6	0.6~0.8	0.8~0.9	0.9~1.0
Baseline	17	9	5	269
Our Model	1	3	3	293

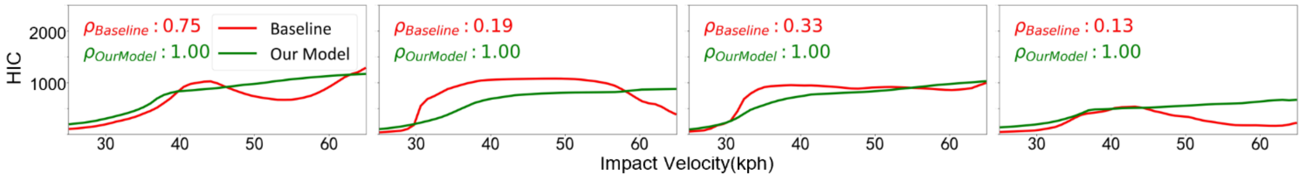

Fig. 2. Visualisation Prediction Results of the Four Selected Sets of Collision Scenarios.

IV. DISCUSSION

When applying injury prediction algorithms to guide intelligent vehicles under safety-critical scenarios, algorithm robustness (i.e. monotonicity between impact velocity and predicted injury severity) is as crucial as prediction accuracy. By developing a customised loss function, we incorporated the physical relationship between impact velocity and occupant injuries into the training process of injury prediction algorithms, ensuring that the prediction results align with theoretical understandings. Specifically, the proposed training framework significantly enhanced the monotonicity while maintaining accuracy. Moreover, the optimisable weight parameter within the loss function can also reduce the injury prediction algorithms' reliance on the quality of training data, lowering the cost of manual data cleaning. To sum up, the proposed method is expected to enhance the robustness of existing injury prediction and to expedite their practical application, eventually contributing to better occupant protection. However, this study focuses on the impact-velocity-related monotonicity. Our future work will consider other initial crash parameters to make occupant injury prediction more robust.

V. ACKNOWLEDGEMENTS

This study is supported by the National Natural Science Foundation of China (52131201, 52072216).

VI. REFERENCES

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