Accident Analysis and Prevention 156 (2021) 106149

Contents lists available at ScienceDirect

Accident Analysis and Prevention

journal homepage: www.elsevier.com/locate/aap

A data-driven, kinematic feature-based, near real-time algorithm for injury severity prediction of vehicle occupants

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ARTICLE INFO

Keywords:
Motor vehicle crashes
Occupant protection
Injury risk
Prediction models
Machine-learning algorithms

ABSTRACT

Accurate real-time prediction of occupant injury severity in unavoidable collision scenarios is a prerequisite for enhancing road traffic safety with the development of highly automated vehicles. Specifically, a safety prediction model provides a decision reference for the trajectory planning system in the pre-crash phase and the adaptive restraint system in the in-crash phase. The main goal of the current study is to construct a data-driven, vehicle kinematic feature-based model to realize accurate and near real-time prediction of in-vehicle occupant injury severity. A large-scale numerical database was established focusing on occupant kinetics. A first-step deep-learning model was established to predict occupant kinetics and injury severity using a convolutional neural network (CNN). To reduce the computational time for real-time application, the second step was to extract simplified kinematic features from vehicle crash pulses via a feature extraction method, which was inspired by a visualization approach applied to the CNN-based model. The features were incorporated with a low-complexity machine-learning algorithm and achieved satisfactory accuracy (85.4 % on the numerical database, 78.7 % on a 192-case real-world dataset) and decreased computational time (1.2 ± 0.4 ms) on the prediction tasks. This study demonstrated the feasibility of using data-driven and feature-based approaches to achieve accurate injury risk estimation prior to collision. The proposed model is expected to provide a decision reference for integrated safety systems in the next generation of automated vehicles.

1. Introduction

Road traffic accidents resulted in more than 12.5 million fatalities worldwide from 2006 to 2016 (World Health Organization, 2018). The recent development of highly automated vehicles (HAVs) is expected to improve traffic safety by avoiding some collisions in dangerous conditions and reducing injury severity in unavoidable collisions (Audenhove et al., 2018). In near-crash scenarios, the occupant injury severity prediction algorithm is critical for enhancing the protection of occupants in motor vehicle crashes (MVCs) (Bance and Nie, 2019; Kidando et al., 2020; Pipkorn et al., 2020). The predicted occupant injury risk guides the trajectory planning system to select the optimal emergency trajectory and/or the adaptive restraint system for instant adjustments to minimize injury severity.

Elements of real-world vehicular traffic systems, such as driving conditions and human factors, lead to a complicated, high-dimensional, nonlinear dynamical system. Inaccuracy and uncertainty of the predicted results scale with the number of factors influencing the vehicle–occupant dynamical system, which causes the main difficulty in injury severity prediction. A number of approaches have been developed for predicting occupant injury severity and investigating the effects of multiple influencing factors, as summarized in Table 1. Three major methodological approaches include statistical regression, machine-learning, and deep-learning methods. Aimed at improving trauma triage, URGENCY (Malliaris et al., 1997), OnStar (Bahouth et al., 2012), and OTDA (Stitzel et al., 2016) are three classic regression-based algorithms that use event data recorder (EDR) information to predict the post-crash occupant injury severity. With the rapid progress in data-driven methods, machine-learning algorithms have become another popular tool in predicting vehicle dynamics, crash rates, and injury risks (Zeng and Huang, 2014; Müller et al., 2016). There are a host of studies that evaluated the performance of different machine-learning algorithms (e.g., K-nearest-neighbors, decision trees, support vector machines, and random forests) in injury severity prediction, and the best-performance method varies depending on the database (Delen et al., 2017; Wang and Kim, 2019; Mansoor et al., 2020; Al-Moqri et al., 2020). Besides classic machine-learning algorithms, some researchers attempted to establish hybrid or two-layer stacking models that were composed of more than one machine-learning algorithms for the further

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https://doi.org/10.1016/j.aap.2021.106149
Received 7 January 2021; Received in revised form 14 March 2021; Accepted 15 April 2021
Available online 29 April 2021
0001-4575/

Nomenclature

AIS	abbreviated injury scale
AUC	area under the curve
CNN	convolutional neural network
DT	decision tree
EDR	event data recorder
EES	equivalent energy speed
FE	finite element
HAV	highly automated vehicle
HIC	head injury criterion
KNN	K-nearest-neighbors
LPM	lumped parameter model
LR	logistic regression
MACC	multiply-accumulate operation
MB	multi-body
MVC	motor vehicle crash
RMSE	root mean squared error
RNN	recurrent neural network
SVM	support vector machines
TCN	temporal convolutional network

improvement of prediction performance (Chen et al., 2016; Tang et al., 2019; Siamidoudaran and İşçioğlu, 2019; Mansoor et al., 2020). For mining intrinsic interactions between samples and variables of collision scenarios, deep-learning algorithms with a higher computational complexity have recently been integrated into occupant injury prediction and obtained better prediction performance (Sameen and Pradhan, 2017; Song et al., 2018; Zheng et al., 2019; Assi, 2020b). Alkheder et al. (2017) applied an artificial neural network to predict injury severity in traffic accidents with 48 different attributes as independent variables, and obtained a significantly higher accuracy than logistic regression (74.6 % vs. 59.5 %). A sequence-to-sequence deep-learning algorithm achieved a prediction accuracy of 88.5 % for the whole-body injury metric by predicting occupant kinetic response sequences during collision from pre-crash information, such as vehicle crash pulses (i.e., time histories of vehicle acceleration during collision) (Bance and Nie, 2019).

Although there are numerous approaches on occupant injury severity prediction, three-fold limitations remain. First, the majority of previous research focused on dichotomy or ternary classifications of injury severity. More severity levels will provide more exact prediction results for HAVs. Second, the generalization performance of some existing algorithms is questionable. Most existing algorithms were evaluated solely on the training and test datasets, which were divided from the same collision database. Yet, their prediction performance on other collision databases (i.e., the generalization ability) was not evaluated. Last, how to balance the prediction accuracy and computational efficiency remains an intractable problem. Since most existing

Table 1
Summary on methods and performance of the recent studies on injury prediction*.

	De Oña et al., 2011	Lubbe and Kiuchi, 2015	Chen et al., 2015	Stitzel et al., 2016	Chen et al., 2016	Delen et al., 2017	Alkheder et al., 2017	Sameen et al., 2017
Category	ML	SR	ML	SR	ML	ML	DL	DL
Algorithm type	BN	LR	Logit + BN	LR	DTBN	SVM	RNN	RNN
Severity levels	Ternary	Dichotomy	Ternary	Dichotomy	Ternary	Dichotomy	4	Ternary
Crash mode	All	All	Rear-end	Frontal	Rear-end	All	All	All
Accuracy	59 %	74.3 %	65.8 %	52.3 %	62.7 %	90.4 %	74.6 %	73.76 %
Recall	–	0.897	–	0.941	–	0.886	0.401	–
Precision	–	0.077	0.640	0.081	0.614	0.910	–	–
AUC	0.62	0.908	0.658	–	0.627	0.928	0.752	–

	Sameen and Pradhan, 2017	He et al., 2018	Song et al., 2018	Siamidoudaran and İşçioğlu, 2019	Lamba et al., 2019	Tang et al., 2019	Wang and Kim, 2019	Zheng et al., 2019
Category	DL	ML	DL	ML	ML	ML	ML	DL
Algorithm type	RNN	SDSE	Inception v3	MLP + SVM	SVM	RF + AdaBoost + GBDT	RF	CNN
Severity levels	Ternary	5	Dichotomy	4	Dichotomy	5	Ternary	Ternary
Crash mode	All	All	All	All	All	All	All	All
Accuracy	71.77 %	81.0 %	86.48 %	90.6 %	96.6 %	57.7 %	66.2 %	–
Recall	–	0.677	0.868	0.622	0.966	0.20	0.66	0.387
Precision	–	0.208	–	0.554	0.967	–	0.79	0.401
AUC	–	–	–	–	–	–	–	–

	Fiorentini and Losa, 2020	Mansoor et al., 2020	Al-Moqri et al., 2020	Assi, 2020a	Assi, 2020b	Rezapour et al., 2020	Rezapour and Ksaibati, 2020
Category	SR	ML	ML	DL	DL	DL	DL
Algorithm type	RUMC + LR	KNN + DT + AdaBoost + SVM + ANN	RF	ANN	ANN	RNN	LSTM
Severity levels	Dichotomy	Dichotomy	Ternary	Dichotomy	Dichotomy	Dichotomy	Dichotomy
Crash mode	All	All	All	All	All	All	All
Accuracy	62.5 %	76.7 %	94.8 %	82.73 %	95 %	70.78 %	70.00 %
Recall	0.525	0.767	0.948	0.840	0.940	0.651	0.681
Precision	0.195	0. 766	0.949	0.795	0.950	0.668	0.695
AUC	–	–	–	–	–	0.74	–

[*] SR = Statistical Regression method, ML = Machine Learning method, DL = Deep Learning method, BN = Bayesian Network, LR = logistic Regression, DTBN = Decision Table and Naïve Bayes, SVM = Support Vector Machines, RNN = Recurrent Neural Network, SDSE = Supervised Data Synthesizing and Evolving, MLP = Multilayer Perceptron, RF = Random Forests, AdaBoost = Adaptive Boosting, GBDT = Gradient Boosting Decision Tree, CNN = Convolutional Neural Network, RUMC = Random Under-sampling the Majority Class, KNN = K-Nearest-Neighbors, DT = Decision Tree, ANN = Artificial Neural Network, LSTM = Long Short-Term Memory.

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algorithms estimated occupant injury severity at the post-crash stage and had sufficient computational time, the computational efficiency has been ignored, especially for the high-complexity deep-learning methods. Although the high complexity contributes to the strong capability of processing complicated data, the resultant heavy computational burden severely restricts application in the pre-crash stage, considering limited onboard computing resources and the incredibly short time before the collision.

To mine intrinsic interactions among high-dimensional inputs, deep-learning algorithms usually require deeper network layers, which is the leading cause of high complexity. Hence, using an appropriate feature extraction method to extract the simplified but critical features from the initial inputs is a promising means to improve efficiency. Due to the high nonlinearity of the vehicle collision process and injury biomechanics, there are technical difficulties in manually simplifying the initial inputs without sacrificing useful information. With the recent development of studies on neural-network interpretability, the model visualization method is an emerging technology to analyze how deep-learning methods process information (Yosinski et al., 2015; Qin et al., 2018) and has the potential to be a powerful tool for the design of a feature extraction method. Using the simplified but critical features, a low-complexity prediction algorithm is expected to obtain a satisfying accuracy comparable to that of deep-learning methods.

The objective of this study is to construct a statistical model to accurately predict occupant injury severity in vehicle collisions in near real time. Occupant injury was assessed by exploring all available vehicle-, restraint-, and occupant-specific information from a large-scale numerical database. The problem was decomposed into two phases: (1) predicting occupant injury severity with deep-learning algorithms to achieve high accuracy on a seven-category classification task; (2) extracting simplified kinematic features via model visualization and using these features to construct a prediction model with lower computational complexity to achieve accurate prediction in near real time. The application scope and generalization ability of the developed model were validated in a real-world collision dataset.

2. Methods

The technical framework of this study is depicted in Fig. 1. A large-scale numerical database of frontal MVCs was established with a focus on the kinetic response of in-vehicle occupants. We used the database to train a deep-learning model with a convolutional neural network (CNN) capable of predicting the time histories of occupant kinetic responses. The kinetics were translated into injury severity levels based on the injury risk criteria. The two-layer pooling was used to extract the simplified but critical kinematic features (1×3 vector) of the collision process from the initial inputs (i.e., vehicle crash pulses, 1×120 vector) based on a visualization approach. With the simplified kinematic features, occupant gender, and restraint configuration as inputs, the occupant injury severity prediction model was finalized by using a

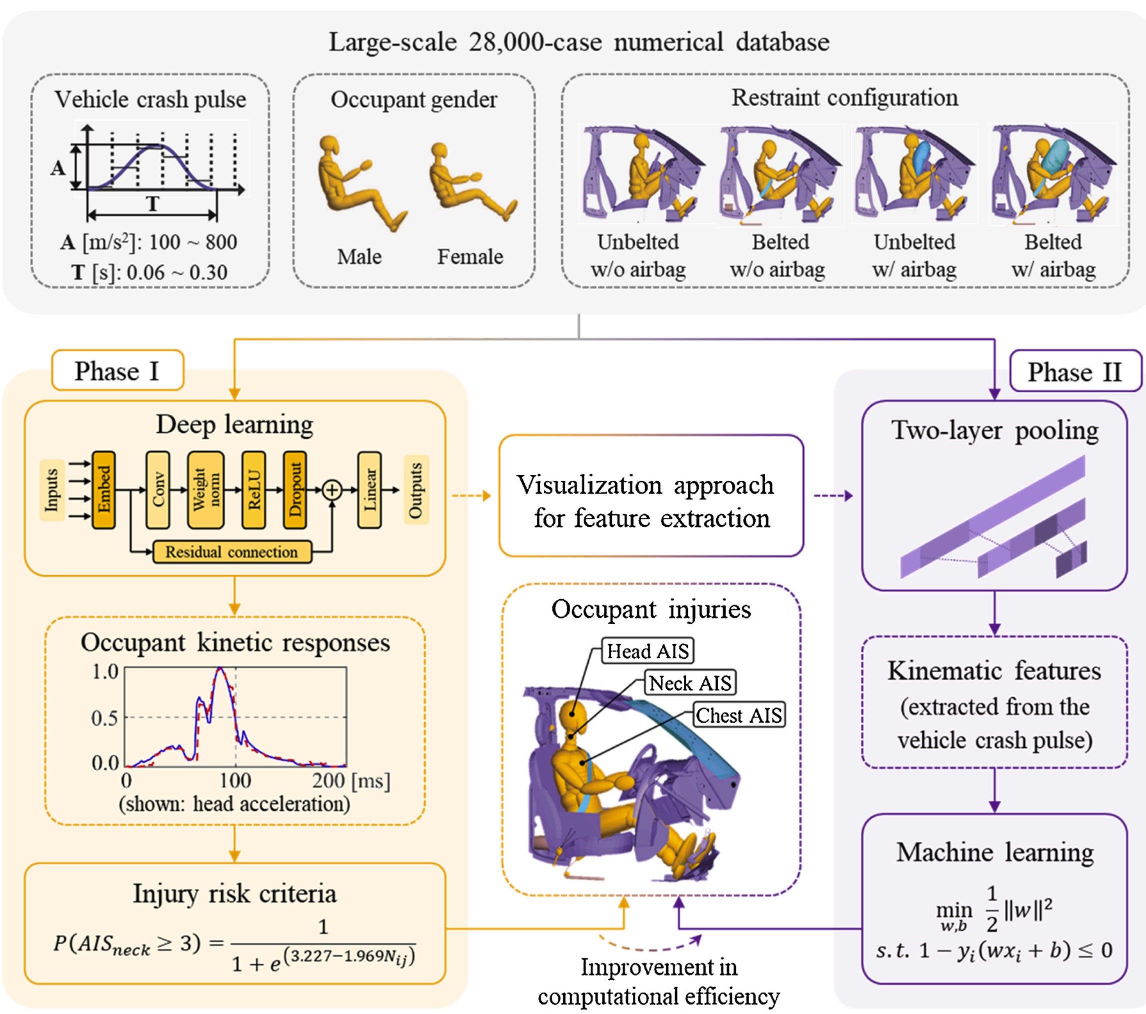

Fig. 1. Technical framework of near real-time occupant injury prediction: Phase I: deep-learning prediction; Phase II: machine-learning prediction with feature extraction. The solid lines with arrows represent the data flow among the different components. The solid boxes and dashed boxes represent the data processing modules and the (processed or to be processed) information, respectively.

selected machine-learning algorithm with lower computational complexity to improve computational efficiency and achieve near real-time prediction performance.

2.1. Database of occupant kinetics and injury responses in frontal vehicle crashes

The efficiency of the occupant injury prediction algorithm depends largely on the quality of the database, which is used for training and validation. Models at different biofidelity levels provide a computationally efficient approach to characterize the occupant kinematics and basic vehicle structural response, permitting mechanism analysis of complex events considering possible influencing factors (Crandall et al., 2011). With the decreasing computational complexity, finite element (FE), multi-body (MB), and lumped parameter model (LPM) are three of the most widely used numerical solvers for MVCs and occupant injury simulation. We generated a large-scale numerical training database to develop a credible prediction model by combining existing FE, MB, and LPM solvers.

2.1.1. Numerical database for training and test

For training of the occupant injury prediction model with deep-learning algorithms, we used a previously constructed 28,000-case numerical database representative of frontal MVCs (Bance et al., 2020). The database covers occupant kinetics and injury responses with variations in vehicle crash pulse, occupant gender, and restraint configuration. Vehicle crash pulses with delta-v ranging from 40 km/h to 60 km/h with an interval of 10 km/h, and impact angles ranging from -20° to 10° with an interval of 10° were obtained from FE simulations. The curves were further fitted to the haversine functions by calibrating the magnitude and duration (Eq. 1).

$$a_{veh}(t) = A_{amp} sin^2\left(\pi \frac{t}{\theta_{dur}}\right) \quad (1)$$

where $a_{veh}(t)$ is the vehicle crash pulse; A_{amp} and θ_{dur} are the magnitude and duration of the vehicle crash pulse, respectively; t is the time sample point, satisfying $0 \le t \le \theta_{dur}$.

The vehicle delta-v and impact angle were mapped to the magnitude and duration of the vehicle crash pulse in haversine form for near real-time prediction. The resultant occupant kinetics were obtained by hybrid FE-MB simulations and were used to calibrate the parameters of an LPM. The LPM was used to generate the database covering different vehicle crash pulses (haversine functions with magnitude ranging from 10 g to 80 g with an interval of 0.5 g, duration ranging from 60 ms to 300 ms with an interval of 10 ms), restraint use (belted w/o airbag, unbelted w/o airbag, belted w/ airbag, and unbelted w/ airbag), and occupant gender (male and female). All parameters were uniformly distributed in the design space. The output occupant kinetic responses included time histories of head acceleration, chest displacement, neck force, and neck moment, and were used to calculate injury severity measured by the abbreviated injury scale (AIS) (Fig. 2) (see details in Appendix A and Appendix B). The numerical database consists of 28,000 cases of frontal MVCs, and we randomly selected 80 % for training dataset and 20 % for testing dataset.

2.1.2. Validation dataset screened from real-world collisions

We constructed a small-sized dataset of real-world MVCs to further validate the developed injury prediction model's performance by screening vehicle crash cases from the National Automotive Sampling System/Crashworthiness Data System (NASS/CDS) (Radja, 2016). NASS/CDS was established by the National Highway Traffic Safety Administration (NHTSA) at 24 locations throughout the United States. It can provide detailed records of MVCs, including crash-level variables (e.g., crash location, time, and road condition), vehicle-level variables (e.g., vehicle type, restraint use), and occupant-level variables (e.g., occupant physical characteristics and injuries). Importantly, the most distinct advantage of NASS/CDS is that it provides body-region-specific occupant injury severity coded as AIS scale, which is an indispensable variable of our body-region-specific injury prediction. We firstly screened the frontal vehicle-to-vehicle MVCs considering the collision condition (i.e., delta-v ranging from 35 km/h to 65 km/h, impact angles ranging from -20° to 10° for frontal collisions, and no rollovers) and data integrity (i.e., the completeness of necessary elements, including occupant gender, use of seatbelts and airbags, and body-region-specific AIS), and formed a 754-case data pool. We then excluded crash cases with multiple impacts or with vehicle body types differing from the sedan model used in the numerical database, such as pickup, utility, and van. Finally, the validation dataset contained 192 frontal collision cases with occupant injury AIS levels for the head, neck, and chest ranging from 0 to 6. The vehicle crash pulse for each case in the real-world dataset was regenerated from the recorded delta-v and impact angle in the haversine function form (Eq. 1) using the same mapping relation used in the process of building the numerical database. Both the numerical training database and the real-world validation dataset are available on public platforms (https://github.com/wangqf1997/Vehicle-Crash-Database).

2.2. Prediction of occupant kinetic responses

2.2.1. Construction of deep-learning models

To achieve high prediction accuracy, the prediction model for occupant injury severity was established based on a comparison of two main categories of deep-learning algorithms. Both algorithms have been widely used in big data analysis and sequence generation tasks, i.e., recurrent neural networks (RNNs) (Goodfellow et al., 2016) and convolutional neural networks (CNNs) (Gehring et al., 2017) (Fig. 3). Both deep-learning models were implemented and validated in Python v3.7.0 (Python Software Foundation, United States) and Pytorch v1.3.1 (Facebook AI Research, United States) with an Intel Core i5−6300HQ 2.30 GHz processor.

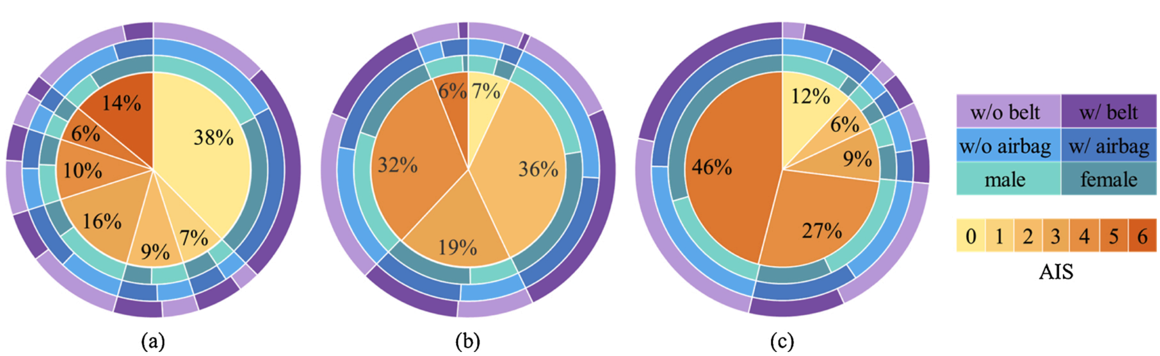

Fig. 2. Ratios of cases with different AIS levels in the numerical database, and distributions of occupant gender, airbag usage, and belt usage in cases with the same AIS level: (a) head; (b) neck; (c) chest.

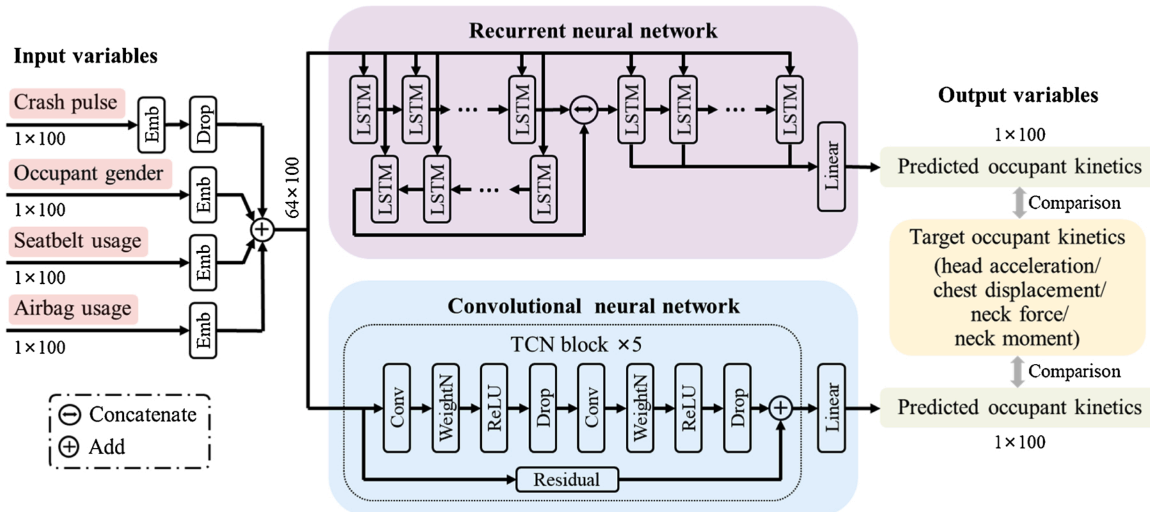

Fig. 3. Optimized architectures of RNN and CNN (Emb: embedding layer; Drop: dropout layer; Conv: convolution layer; WeightN: weight normalization; Residual: residual connection).

The prediction models used the vehicle crash pulse, occupant gender, and usage of seatbelts and airbags as inputs and predicted the occupant kinetic responses, which were translated into AIS levels as injury metrics on human body regions. The prediction of occupant kinetic responses from vehicle crash pulses is a typical sequence modeling task defined as follows: Given an input sequence $(x_0, \cdots, x_t)$, predict the corresponding outputs $(y_0, \cdots, y_t)$ at each time t. We used a classic encoder–decoder architecture with long short-term memory (LSTM) units in the RNN-based model (Eq. 2). By comparison, we found that bi-directionality effectively improved prediction performance (Cho et al., 2014). The processed inputs were fed to the encoder and decoder without a teaching mechanism. For the CNN-based model, a special architecture with causal convolution and dilated convolution, a temporal convolutional network (TCN), was used to guarantee that the networks looked into the past for a comprehensive prediction (Eq. 3) (Bai et al., 2018). Five TCN blocks were used, and each TCN block contained two dilated causal convolution layers with the same dilation factor d, which increased exponentially with the depth of the network (i.e., $d = 2^i$ at level i of the TCN block). A weight normalization layer was added after each convolution to improve the training efficiency. A rectified linear unit (ReLU) activation function was used.

$$\begin{aligned} & c_t^{(1)},\ h_t^{(1)} = f^{(1)}\left(c_{t-1}^{(1)},\ h_{t-1}^{(1)}, x_t\right),\ \forall t \in [1, T_{in}] \\ & c_t^{(2)},\ h_t^{(2)} = f^{(2)}\left(c_{t+1}^{(2)},\ h_{t+1}^{(2)}, x_t\right),\ \forall t \in [1, T_{in}] \\ & \qquad c_0 = c_{T_{in}}^{(1)} \oplus c_1^{(2)},\ h_0 = h_{T_{in}}^{(1)} \oplus h_1^{(2)} \\ & c_t, h_t, o_t = g(c_{t-1}, h_{t-1}, x_t),\ \forall t \in [1, T_{out}] \end{aligned} \tag{2}$$

where x_t, o_t represent the input and output; $c_t^{(1)}$, $c_t^{(2)}$, c_t denote the forward, backward, and concatenated cell states; $h_t^{(1)}$, $h_t^{(2)}$, h_t denote the forward, backward, and concatenated hidden states; $f^{(1)}(\cdot), f^{(2)}(\cdot)$ are the forward and backward LSTM units in encoder; $g(\cdot)$ is the LSTM unit in decoder; T_{in}, T_{out} represent the length of input sequence and output sequence; $\oplus$ denotes the concatenation operation.

$$\begin{aligned} h^1 &= x_{1:T_{in}} + f^1(x_{1:T_{in}}), \\ h^l &= h^{l-1} + f^l\left(h^{l-1}\right),\ \forall l \in [2, L-1] \\ o_{1:T_{out}} &= h^{L-1} + f^L\left(h^{L-1}\right), \end{aligned} \tag{3}$$

where $x_{1:T_{in}}$, $o_{1:T_{out}}$ represent the input sequence $x_0, \cdots, x_{T_{in}}$ and output sequence $o_0, \cdots, o_{T_{out}}$, respectively; h^l is the hidden state of the convolution at level l; $f^l(\cdot)$ represents the dilated causal convolution; L is the total number of convolution layers.

All input variables were embedded in lookup tables and transmitted to the hidden layers in a high-dimensional form. The outputs of the two models were discretized and normalized into integers 0–999. Thus, the cross-entropy loss between the predicted and target kinetics could serve as the loss function. We used adaptive moment estimation (ADAM) as an optimizer for model training, and implemented learning rate attenuation in the training process to obtain better performance. Different measures were used to prevent over-fitting, including L2 regularization in the cost function, dropout in the input and intermediate layers, and early stopping when testing loss increased in five consecutive epochs. Grid-search approaches were used to tune the hyper-parameters of the two models (Table 2).

2.2.2. *Performance of the deep-learning models*

The prediction models were trained separately for each body region (head, neck, and chest). The CNN-based model demonstrated better overall performance in the prediction tasks for head, neck, and chest injuries in terms of accuracy (86.1 %, 95.6 %, and 90.2 %, respectively) and computational time (69 ms for all injuries). The prediction performance for the head is presented in this section as an example (details on other body regions can be found in Appendix C).

Most normalized, predicted kinetics for the head (acceleration curves) from both deep-learning models agreed with the ground truths (Fig. 4a and b). Some disparities were observed, especially at the peak of the curves in the RNN-based model (Fig. 4c and d) due to the recurrent network structure; RNN often neglected short duration peaks to

Table 2
Hyper-parameters of RNN-based and CNN-based prediction models.

	RNN-based model		CNN-based model	
Hyper-parameters	Search space	Optimal	Search space	Optimal
Batch size	32, 64, 128	64	32, 64, 128	64
Embedding size	32, 64, 128	64	32, 64, 128	64
Hidden size	64, 128	64	64, 128	128
Embedding dropout rate	5 %, 10 %, 15 %	5 %	5 %, 10 %, 15 %	5 %
Hidden dropout rate	5 %, 10 %, 15 %	5 %	5 %, 10 %, 15 %	5 %
Learning rate	0.001, 0.01, 0.03, 0.1	0.01	0.001, 0.01, 0.03, 0.1	0.03
Epoch number	5, 10, 20, 30	20	10, 100, 300	300
RNN layer size	1, 2	1	–	–
TCN block layers	–	–	4, 5, 6	5
Kernel size	–	–	3, 5	3

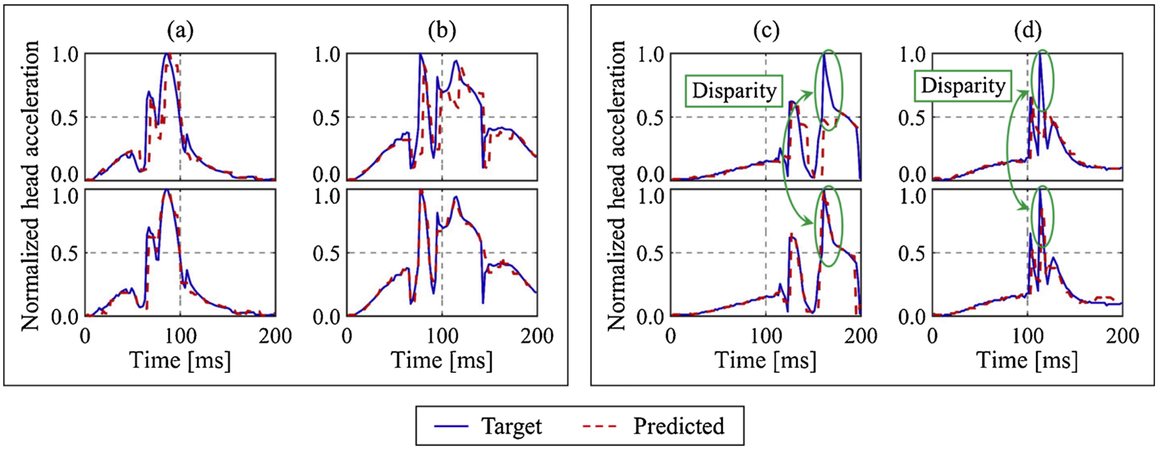

Fig. 4. Randomly selected examples of normalized head acceleration prediction of two deep-learning models in the test database. The predicted results of the RNN-based model and the CNN-based model are shown in the first and second row, respectively.

maintain temporal continuity. R^2, as a statistical measure of the fitting degree between the prediction sequences and target sequences, was used to quantify the model's ability to predict occupant kinetic responses (Fig. 5). The CNN-based model exhibited a higher R^2 than RNN for head acceleration (0.76 vs. 0.61) (Fig. 5a), and a much lower root mean squared error (RMSE) for the head injury criterion (HIC) (117.0 vs. 274.3) (Fig. 5b). Consequently, the accuracy of head AIS level predicted by the CNN-based model was also higher than that of the RNN (86.1 % vs. 75.2 %). When the sequences are long, RNN always suffers from long-term dependencies with a limited memory capacity (Hochreiter et al., 2001), reducing prediction accuracy. In contrast, the CNN processes information in parallel, without the limitation of memory capacity. In terms of efficiency, the CNN-based model achieved a shorter computational time (69 ms vs. 108 ms) benefitted from parallel computation, although its parameter size and multiply-accumulate operations (MACCs) were both larger (Table 3).

Table 3
Computational complexity of the two deep-learning models.

Model	Parameter size	MACCs	Computational time [ms]
RNN	**0.48M**	**33M**	108 (± 36.6)
CNN	0.58M	106M	**69 (± 12.4)**

2.3. Kinematic feature-based prediction of occupant injury severity

We selected the CNN-based model because of the high accuracy of the occupant kinetics prediction. However, the high computational complexity associated with its strong nonlinear processing capability restricts the real-time prediction performance in onboard decision-making systems. Critical kinematic features that reflect the kinematic essence of the vehicle collision process are needed to increase the computational efficiency of the prediction model. Thus, we used a visualization method, an emerging technology to enhance the interpretability of CNN, to analyze how the proposed high-precision CNN model processed information step by step. Based on the understanding of the CNN's internal mechanism, a mathematical calculation (i.e., two-layer pooling) was used to approximate the high-complexity CNN model and extract simplified kinematic features from the initial inputs. Finally, a machine-learning algorithm with lower computational complexity was adopted to directly predict occupant injury severity using the extracted kinematic features and other available inputs (occupant gender and restraint use).

2.3.1. Two-layer pooling for feature extraction from vehicle crash pulses

We analyzed the internal mechanism of the CNN-based model on vehicle crash pulses using the convolution kernel visualization method to guide the design of the feature extraction algorithm. The convolution

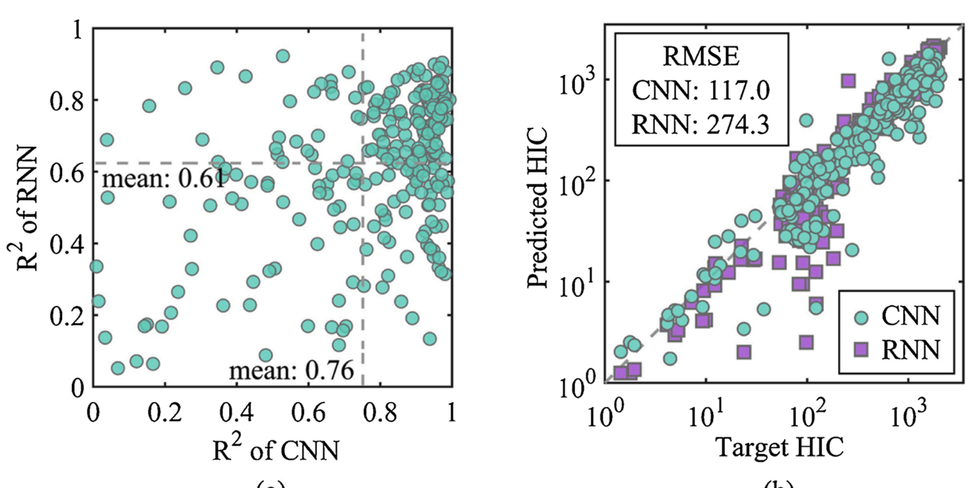

Fig. 5. Comparison of prediction performance of the two deep-learning models (shown: 300 samples randomly chosen from the test database): (a) R-squared (R^2) of head acceleration sequences predicted by RNN and CNN; (b) distribution of the predicted HIC and target HIC.

kernel visualization method obtains input values that maximize the activation of a specific convolution kernel (Yosinski et al., 2015) (Eq. 4). Based on gradient ascent, the kernel visualization was realized in four steps (Qin et al., 2018): (1) initialize the input with random values $x = x_{ini}$; (2) use backpropagation to compute the gradients $\frac{\partial a_{i,j}}{\partial x}$; (3) update the input x under the guidance of the gradient $x = x + \eta \frac{\partial a_{i,j}}{\partial x}$; (4) obtain the final input x^* when the optimization process converges.

$$x^* = \underset{x}{\mathrm{argmax}}\, a_{i,j}(x\theta) \tag{4}$$

where x denotes the input; x^* is the specific input that maximizes the activation; $a_{i,j}$ is the activation of the convolution at layer level i and channel j; θ denotes the network parameters.

To maximize the activation of a specific convolution kernel, the required values of the input fluctuated significantly with a high frequency and formed periodic waves (Fig. 6). The spectral analysis showed that the input curves for all channels had the same frequency band; the number of crests or troughs was the same for all input curves. The smoothing effect in the operation process of the convolution layers was identified by preserving only low-frequency components in the outputs. To reduce the computational burden, the complex convolution can be replaced with a simple structure that achieves a similar smoothing effect. We used pooling layers, a low-complexity mathematical calculation, for dimension reduction of the vehicle crash pulse. The pooling layers effectively smooth the high-dimensional inputs with appropriate parameters that primarily refer to the kernel size and stride. In this study, the number of pooling layers was set to two. Two-layer pooling is a heuristic method to extract kinematic features (1 × 3 vector) from the vehicle crash pulse (1 × 120 vector). The parameters of the two-layer pooling were tuned based on grid-search approaches to obtain the best prediction performance (Table 4).

2.3.2. Machine-learning algorithms for prediction of occupant injury severity

The kinematic features extracted by the two-layer pooling, occupant gender, and restraint configuration were input into machine-learning algorithms to directly predict occupant AIS levels. Four widely used machine-learning algorithms were investigated and compared, including decision tree (DT), logistic regression (LR), K-nearest-neighbors (KNN), and support vector machines (SVM). The prediction model was finalized with the model that returned the best performance on the numerical test database, and was tested extensively on the real-world dataset. Besides, sensitivity analysis was conducted to empirically discover the relationships between the input and output variables (see details in Appendix D). This section presents a brief introduction to the four algorithms.

(1) The decision tree is a classic non-parametric tool for classification tasks with a flowchart-like structure. Two classic categories, C4.5 and CART (Quinlan, 2014; Breiman et al., 1984), were evaluated based on the information entropy and Gini index, respectively. The maximum tree depth was set to 20 to avoid overfitting and reduce the computational burden. To obtain balanced prediction performance, we set a corresponding weight for each class, which was inversely proportional to the sample numbers. The same weight was also used in the other three algorithms.

(2) Logistic regression is the most commonly used classifier in the field of occupant injury severity estimation (Malliaris et al., 1997; Bahouth et al., 2012; Stitzel et al., 2016). Its transparent structure provides predictions with good statistical significance. We used ordinal logistic regression for injury severity (AIS 0–6), and chose the Newton method as the optimization algorithm.

(3) The K-nearest-neighbors algorithm classifies a given sample based on the distances between its neighbors as an unsupervised algorithm. There are different ways to calculate the distances, determining the category of KNN, such as linear, quadratic, and cubic KNN. In this study, five neighbors were used to classify a sample.

(4) The support vector machine is a widely used supervised learning model that relies on support vectors to define the hyperplane. Using different kernel methods, such as polynomial, Gaussian, and sigmoid kernel methods, SVM can be used in different nonlinear classification tasks. For Gaussian SVM, the regularization parameter C and kernel coefficient *gamma* were set to 10,000 and 30, respectively.

Table 4
Hyper-parameters of two-layer pooling.

Hyper-parameters		Search space	Optimal
First layer	Mode	Average/Maximum	Maximum
	Kernel size	2/4/5/6/12	12
	Stride	2/3/5/12	12
Second layer	Mode	Average/Maximum	Average
	Kernel size	2/4/5/6/12	4
	Stride	2/3/5/12	3

3. Results

3.1. Occupant injury severity prediction performance

The performance of the LR, KNN, DT, and SVM machine-learning models were evaluated on the numerical test database. The SVM with Gaussian kernels significantly outperformed the others, with an accuracy of 85.4 % and an AUC of 0.964 (Table 5). The computational time was relatively long (1.2 ms), reflecting the high computational complexity and guarantees the ability of mining the potential information behind the data samples. Inappropriate nonlinear kernels, such as polynomial and sigmoid kernels, were unable to improve the SVM performance. The next best model type was CART, with slightly better accuracy than quadratic KNN (81.0 % vs. 78.4 %). The computational time for KNN was significantly longer (2.5 ms), as it is representative of "lazy learning"; it only stores samples in the training period, increasing the computational burden in the application period. LR, as a conventional statistical approach, produced the lowest accuracy (57.4 %), mainly because its linear structure could not handle the high uncertainty and

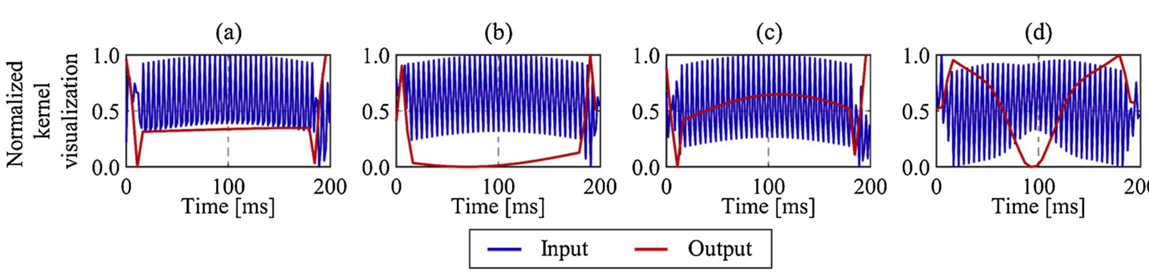

Fig. 6. Visualization of the convolution kernel: examples of the input and output of convolution channels under maximum activation of specific kernels: (a) 1 st channel; (b) 2nd channel; (c) 3rd channel; (d) 4th channel.

Table 5
Comparison of head AIS prediction performance of four machine-learning models. The best candidate model for each indicator is marked in bold.

Machine-learning algorithms	Type	Accuracy	Precision	Recall	F-score	AUC	Computational time [ms]
Logistic regression (LR)	–	57.4 %	0.437	0.573	0.482	0.867	**0.31 (± 0.46)**
K-nearest-neighbors (KNN)	Linear	78.1 %	0.771	0.780	0.774	0.949	2.3 (± 1.5)
	Quadratic	78.4 %	0.778	0.784	0.780	0.946	2.5 (± 0.6)
	Cubic	75.5 %	0.746	0.755	0.746	0.947	4.8 (± 1.8)
Decision tree (DT)	C4.5	80.6 %	0.805	0.806	0.806	0.889	0.36 (± 0.48)
	CART	81.0 %	0.809	0.810	0.810	0.889	0.35 (± 0.48)
Support vector machines (SVM)	Linear	59.9 %	0.533	0.598	0.537	0.856	0.83 (± 0.47)
	Polynomial	63.1 %	0.594	0.631	0.590	0.878	0.89 (± 0.44)
	Gaussian	**85.4 %**	**0.853**	**0.854**	**0.853**	**0.964**	1.2 (± 0.4)
	Sigmoid	62.5 %	0.589	0.626	0.585	0.872	1.1 (± 0.4)

nonlinearity of traffic events. Similar results were obtained for the prediction of neck and chest injuries (see Appendix C for details). The SVM-based prediction model was chosen for the final occupant injury severity prediction model based on its high prediction accuracy and acceptable computational time.

Based on the kinematic features extracted from the two pooling layers, the SVM-based model obtained a prediction accuracy similar to that of the CNN-based model without kinematic features (85.4 % vs. 86.1 %). A detailed comparison is presented in Fig. 7. More important, the SVM-based model reduced the computational time by 98.3 % (1.2 ms vs. 69 ms) and significantly improved the computational efficiency, demonstrating the effectiveness of the extracted key features in the representation of vehicle kinematics in a low-dimensional form.

3.2. Extended validation in real-world collision dataset

The performance of the SVM-based prediction model was further evaluated using a 192-case real-world collision dataset. Considering the heterogeneity between the numerical database and the real-world dataset, we retrained the prediction model and adopted five-fold cross-validation to assess it comprehensively. The prediction accuracy, precision, recall, and AUC were 78.7 %, 0.636, 0.787, and 0.698, respectively.

4. Discussion

Advanced safety systems for highly autonomous driving are expected to enhance traffic safety, with reduced fatalities and injuries. Considering the highly uncertain, multidimensional, nonlinear, and time-varying traffic characteristics, unavoidable collision scenarios will still exist far into the future (Bonnefon et al., 2016). We proposed a model to provide near real-time prediction of occupant injury severity in collision scenarios to provide reference for pre-crash and in-crash safety configurations toward minimal injury. Compared with other existing prediction models, the proposed model has advantages in prediction accuracy and computational efficiency to guarantee its reliability and near real-time performance.

4.1. Performance of the occupant injury severity prediction models

Compared with some recent injury prediction models in Table 1, the present SVM-based model obtained a satisfactory prediction performance (accuracy: 78.7 %, precision: 0.636, recall: 0.787, AUC: 0.698) on a more detailed prediction task (i.e., seven injury severity levels). For the independent variables, the existing models make use of only the scalar information, including occupant characteristics, restraint configuration, vehicle parameters, and road conditions. In contrast, with two-layer pooling, the present model also uses the sequence information (vehicle collision pulses) in addition to scalars. The sequence

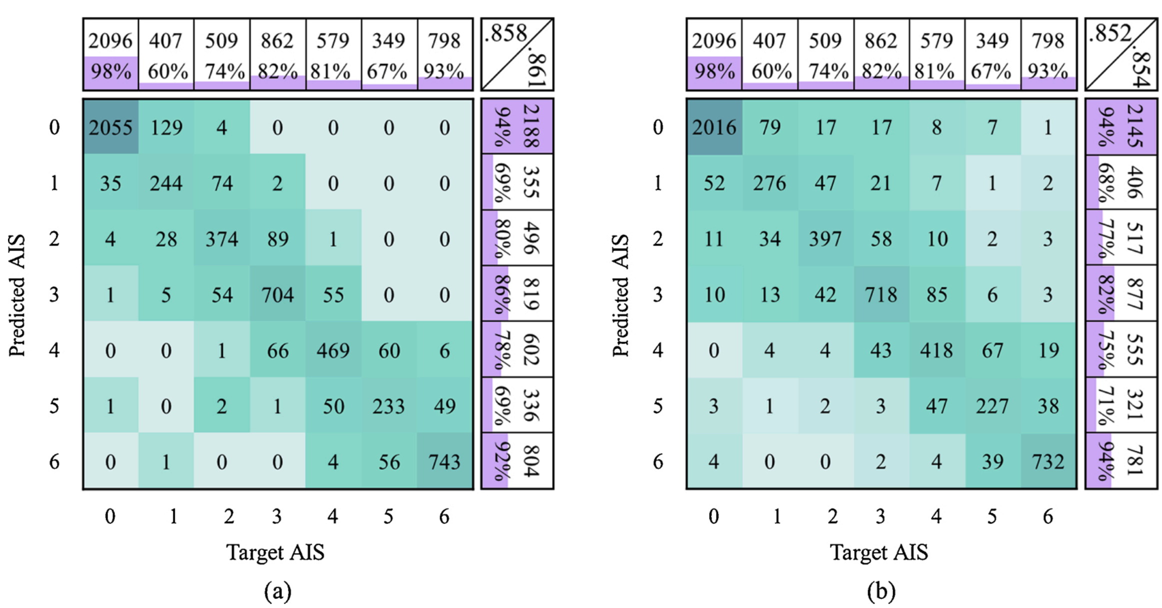

Fig. 7. Confusion matrices of head injury severity prediction: (a) CNN-based model; (b) SVM-based model. The rightmost column displays the number and accuracy for each predicted AIS class and the top row displays the number and accuracy for each true class, reflecting the precision and recall rate, respectively. The top right cell displays the overall weighted precision and recall rate.

information carries more information than the scalar information, providing the prediction model better insight into a collision. For the dependent variables, most existing models predict the overall occupant injury severity with two or three levels from mild to severe; the present model was developed for head injury with seven levels, and can provide a more exact injury severity estimate. Although more injury severity levels increase the difficulty of the prediction task, the present model can be used to differentiate emergency decisions producing similar occupant injury severity, and suggest the safest one. Consequently, more injury severity levels are a significant guarantee of its practical application.

4.2. Kinematic features in the occupant injury severity prediction

Though the deep-learning model achieves a high prediction accuracy, the resultant long computational time severely restricts its application in actual near-crash scenarios. To overcome this issue, based on a comprehensive visualization analysis of the proposed CNN-based model, two-layer pooling was used to extract kinematic features from vehicle crash pulses and effectively capture the kinematic essence of the vehicle collision process.

Existing metrics for crash severity have been mostly limited to the available information at the vehicle level, such as delta-v and equivalent energy speed (EES). Such metrics were manually designed to measure the absorbed energy or damage severity of the collision (Tsoi and Gabler, 2015), but do not reflect the dynamic responses passed to the occupant. Thus, they are not the most suitable for injury prediction. In contrast, the kinematic features identified in this study aim to indicate the injury severity during collision at the occupant level. Owing to the high nonlinearity and uncertainty of the multi-dimensional interactions between the vehicle interior and the occupant, the extraction of features at the occupant level is more difficult than obtaining the existing vehicle-level metrics. Thus, we used visualization analysis to heuristically extract the kinematic features instead of using traditional manually defined extraction. The extracted kinematic features serve as direct inputs to the prediction models, replacing the high-dimensional vehicle crash pulses, resulting in a simpler model structure and higher computational efficiency without reducing accuracy.

In the numerical crash database, we approximated the vehicle crash pulses in haversine form with two variables (magnitude and duration) (Eq. 1). In essence, the extracted kinematic features from pooling layers return a linear combination of the pulse magnitude and duration, which are significantly associated with crash severity. Demonstrating straightforward feature extraction, the developed SVM machine-learning prediction model achieved accurate prediction in near real time. The validation results in the real-world dataset prove its generalization ability, demonstrating the potential of kinematic features in the occupant injury prediction task. When a larger-scale, more systematic collision database is available in subsequent studies, retraining a simple CNN can be another practical means of obtaining the most appropriate kinematic features.

4.3. Performance in the real-world dataset

The performance of the present prediction model was further tested and evaluated on a real-world dataset. Considering the heterogeneity between the numerical database in model training and the real-world dataset in model validation, the present SVM-based prediction model did not perform as well in the real-world dataset with an approximately 10 % decrease in accuracy, but still demonstrated good generalization ability, with a 78.7 % prediction accuracy. The prediction capability of the present model can be preliminarily transferred to real-world applications.

Several factors influencing the prediction accuracy shall be discussed. The far more diverse factors in the real-world dataset partially restrict the prediction performance trained from a numerical database. For example, the vehicle mass, stiffness, occupant age, and physical status were not considered in the establishment of the numerical database, leading to the heterogeneity between the established numerical database and the real-world dataset. When evaluating the proposed models in the real-world dataset, we used the FE vehicle collision simulation results to translate collision delta-v and impact angle into haversine vehicle crash pulses because the dataset lacks real-world vehicle crash pulses extracted from EDR. The absence of specific vehicle information during the translation may have a negative influence on the accuracy.

4.4. Limitations and future application in the automotive trajectory planning system

There are several limitations to this study. First, considering the inherent simplifications of the LPM used in generating the large-scale numerical database, more biofidelic computation models (e.g., human body models) are needed for a more refined database for model training. The approximation error of the parametrization of vehicle crash pulses can also reduce the fidelity of the numerical database. Second, the database used in this study only provides the occupant head, neck, and chest injury severity, which should be further extended to other body regions for a more comprehensive injury estimation. The proposed injury severity prediction algorithm considers a limited impact angle (-20° to 10° for frontal collisions); consequently, it can only provide an occupant injury estimation in the ego vehicle. In the future, the considered collision scenarios should be extended to provide a complete risk estimate for all parties involved in the collision. Other factors are also recommended for integration into the database for better performance, including vehicle parameters, occupant age, stature, and posture.

For optimal occupant protection, the proposed SVM-based model can be applied to the automated vehicle trajectory planning system to provide occupant injury severity estimation in near real time. Considering safety and reliability, the widespread implementation of trajectory planning systems requires comprehensive validation under a wide range of traffic scenarios, including both avoidable and unavoidable collisions. When confronted with the latter, an emergency decision of trajectory selection must be made. The proposed SVM-based model makes use of pre-crash information to comprehensively predict occupant injury severity at the body region level. Such information provides reference to guide the trajectory planning system to select an optimal trajectory, or to guide the adaptive restraint system into a tailored configuration anticipated to minimize occupant injury severity.

5. Conclusions

This study proposed a data-driven and kinematic feature-based framework aimed at real-time injury severity prediction in near-crash traffic scenarios. The framework consists of two phases: (1) constructing a CNN-based prediction model to achieve high accuracy on a seven-category classification task, and (2) extracting kinematic features via model visualization applied to CNN and using them to construct an SVM-based prediction model to achieve near real-time prediction without reducing accuracy. The developed model was validated in two databases with occupant head injury severity prediction task, obtaining accuracy of 85.4 % over a 5600-case numerical database, and accuracy of 78.7 % over a 192-case real-world dataset, with a computational time of 1.2 ± 0.4 ms. The results suggest that extracted kinematic features at the vehicle level can improve computational efficiency on risk estimation at the occupant level. This study demonstrated a data-driven approach in injury risk estimation for on-vehicle safety systems, and the feasibility of using the visualization method in feature extraction. The proposed model, which is capable of near real-time safety prediction with available vehicle–occupant information, provides a decision reference for the integrated safety system covering the pre-crash and in-crash phases, enhancing protection performance for the next generation of safer vehicles.

Author statement

All authors have read and approved the final document.

Authorship contributions

Qingfan Wang: Conceptualization, Methodology, Software, Writing - Original Draft, Writing - Reviewing and Editing.

Shun Gan: Methodology, Software, Writing - Reviewing and Editing.

Wentao Chen: Methodology, Data curation, Writing - Reviewing and Editing.

Quan Li: Validation, Investigation.

Bingbing Nie: Conceptualization, Writing - Reviewing and Editing, Supervision, Project administration, Funding acquisition.

Declaration of Competing Interest

The authors declare no conflict of interest.

Acknowledgments

This study is supported by the National Natural Science Foundation of China (52072216, 51705276), Young Elite Scientist Sponsorship Program by CAST (2018QNRC001), and Tsinghua-Toyota Joint Research Fund.

Appendix

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.aap.2021.106149.

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