Validation of Predicted Head Contact Location of Vehicle-to-Pedestrian Based on Deep Neural Network Using Field Data

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I. INTRODUCTION

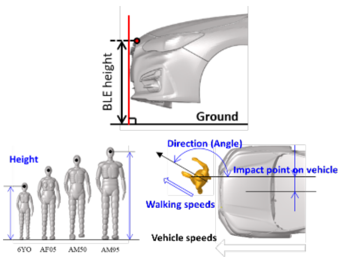
As a percentage of traffic fatalities in the U.S. pedestrians have increased to 17% [1] over the past decade, with 6,205 fatalities in 2019. We aim to achieve Zero Fatal Traffic Accidents in 2030 [2] and have been investigating effective safety features not only for vehicle-to-vehicle crashes but also for vehicle-to-pedestrian crashes, which are on the rise in the U.S. It is well known that the fatality rate of head injuries in pedestrian crashes is high, and various safety features have been implemented to mitigate head injuries [3]. In order to estimate the effectiveness of pedestrian airbag protection [4], which is one of our proposed safety features, it is important to be able to predict where the head strikes the vehicle and at what speed. One study [5] applied a surrogate model derived from the Deep Neural Network (DNN) [6] based on CAE analysis (MADYMO) to predict the location of head contact on the vehicle. Accuracy of the prediction was verified using Vulnerable Road User Injury Prevention Alliance (VIPA) [7] data from the state of Michigan in the U.S., and the effect of each parameter used in the prediction model was discussed.

II. METHODS

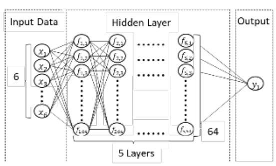
Figure 1 shows the flow of the validation process between a surrogate model and the crash data. Based on crash simulations (5,760 cases) involving pedestrians (6YO, AF05, AM50, AM95) and vehicles (four vehicle types: Car, SUV), the surrogate model was constructed to predict the head contact location using DNN. Parameters used for the vehicle were _impact speed_ and _bonnet leading edge (BLE) height_, while the parameters used for the pedestrian were _head centre of gravity (CG) height_, _impact point on vehicle_, _walking speeds_ and _directions_. DNN was designed as shown in Fig. 1(b). 80% of 5,760 cases were randomly selected and used as training data and the remaining 20% as validation data.

The following section describes the process of extracting each parameter defined in the surrogate model from the crash data. Vehicle-to-pedestrian collision speeds ranged from 30 kph to 60 kph, and 33 cases were selected in which the vehicle collided with a pedestrian while moving straight ahead, with head contact marks on the vehicle. *BLE height* was defined as the height from the ground to the front-edge of the hood, and the head-CG height was replaced by the *pedestrian's height*. Pedestrian's *walking speeds* and *directions* were taken from the VIPA database, and the initial *point of impact* between the vehicle and pedestrian was determined from the position of contact with lower limbs or pelvis. These were used as input parameters for the surrogate model to verify the accuracy of the head contact location. In addition, the effect of each parameter applied in the surrogate model was also investigated.

	Predictors	Levels
	Impact speeds	3
	BLE height	4
	Height	4
	Impact point on vehicle	5
	Walking speeds	3
	Directions	8
Total		5760

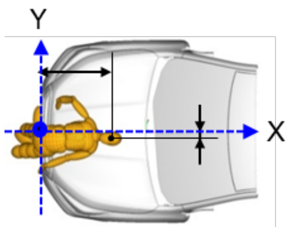


(a) Parameters defined in the surrogate model.



Input Data: 6 nodes
Hidden Layer: 64x5

(b) Deep Neural Network.



(c) Comparison of the head contact location with the surrogate model and the VIPA.

Fig. 1. Flow of prediction and validation of head contact location.

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III. INITIAL FINDINGS

Relationship between the measured and predicted values for the head contact location were shown in Figs 2 and 3, with the dotted line representing the boundary for error rate of ±20%. The surrogate model was an accurate reflection of the crash data, with correlation coefficients of 0.716(X-coordinate) and 0.930(Y-coordinate), respectively, and Y-coordinate had a higher correlation than X. For X-coordinate, the prediction tends to be higher because the head-CG height was substituted for the *pedestrian's height* as an input parameter. In particular, the error tended to be larger in cases where the pedestrian collided with the corner of the frontal vehicle (near headlights), suggesting that the difference in the vehicle front-end shape affected the correlation. On the other hand, Y-coordinate correlated well with the measured values. Red dots in Figs 2 and 3 show 6YO child case, where both X- and Y-coordinates were predicted to be higher than the measured values. Results of the relationship between measured and predicted values (correlation coefficients) under conditions excluding each parameter related to pedestrians are shown in Table I. It can be seen that the pedestrian's *height* had an influence on X-coordinate, while the *impact point on vehicle* had a greater influence on Y-coordinate. Both parameters were essential for predicting head contact location. For *walking direction*, due to the effect of suppressing an overfitting of the prediction model, X-coordinate had slightly improved, but Y-coordinate had worsened. *Walking speeds* had an effect on X-coordinate.

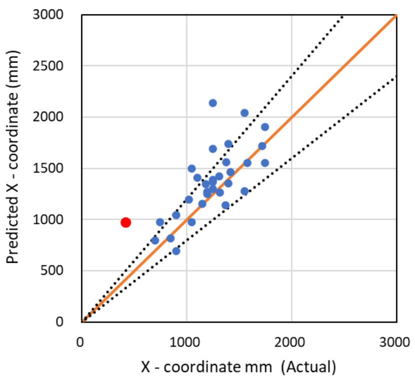

Fig. 2. Correlation of head contact location (X-coordinate).

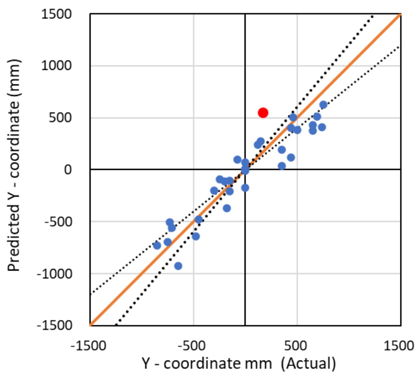

Fig. 3. Correlation of head contact location (Y-coordinate).

TABLE I
CORRELATION COEFFICIENTS WHEN EACH PARAMETER WAS EXCLUDED

Parameters	X	Y
All parameters	0.716	0.930
w/o Pedestrian direction	0.727	0.816↓
w/o Pedestrian speeds	0.645↓	0.896
w/o Pedestrian height	0.123↓	0.925
w/o Impact point of vehicle	0.632	-0.217↓

IV. DISCUSSION

Prediction of head contact location using pedestrian crash data showed good results for both X- and Y-coordinates, demonstrating the effectiveness of the surrogate model based on DNN. The main reason for the lower accuracy of the predicted values compared to the measured values in X-coordinate compared to Y-coordinate could be the vehicle front-end shapes. While the crash data have a variety of vehicle front-end shapes, the surrogate model applied vehicle models from the same manufacturer and the other related parameters, such as bumper lead/hood angle, were trained under constant conditions. Monfort [8] suggested that differences in the shape of the vehicle's front-end affect the pedestrian's kinematics, and that it is important to consider not only the *BLE height* but also the geometry of front-end to improve the accuracy of X-coordinates. The same reason could be considered for the case of the 6YO child shown in Figs 2 and 3, but the factors contributing to error in Y-coordinate are currently under investigation.

The effect of each parameter defined in the surrogate model on the head contact location was examined, and it was found that *height* and *impact point of vehicle* were essential parameters. The advantage of using field data (VIPA) is that it allows for comparative verification between measured and predicted values, which can increase the robustness of the prediction model. A surrogate model using DNNs can be applied to various applications, and we would like to contribute to the development of safer vehicles by expanding the scope of application to pedestrian behaviour evaluation that takes into account posture and body shape of pedestrians.

V. REFERENCES

[1] NHTSA: Pedestrian Safety Action Plan, 2020.

[2] SUBARU website: 2024.

[3] Zhang, G., *et al.*, AAAM Conference, 2008.

[4] Hashimoto, Y., *et al.*, JSAE Proceeding, 2017.

[5] Todokoro, R., FOCUS, 2023.

[6] Igari, W., *et al.*, *Deep Learning*, 2021.

[7] Wang, S., *et al.*, IRCOBI, 2019.

[8] Monfort, S., *et al.*, IIHS, 2023.