Prediction of Head Injury Severity for Pedestrians in Car-Pedestrian Accidents using Deep Learning Methodology

Shouhei Kunitomi, Atsuhiro Konosu

I. INTRODUCTION

Since 2008, the number of pedestrian serious-to-fatal injuries has remained around 10,000 per year in Japan [1], and head injuries account for more than 30% of those [2]. Advanced Automatic Collision Notification (AACN) is a system that aims to reduce the number of serious-to-fatal injuries. AACN predicts the occupant injury severity in car-to-car accidents using data obtained by an event data recorder (EDR), and then reports the severity to an emergency call centre, which can then determine the appropriate medical institution for the injured person. However, little research has been conducted into the ability of the AACN to predict pedestrian injury severity [3,4]. In addition, there is no study using pedestrian collision image data obtained from dash cam to predict severity. If the image data are utilised, it is expected that the accuracy of pedestrian injury severity prediction will be improved. Recently, image recognition technology has been dramatically improved through deep learning methods [5]. These methods make it possible to learn the features of the image efficiently and to carry out classification by computer without human assistance. In this study, we aimed to establish a prediction method of head severity of a pedestrian through use of pedestrian collision images and deep learning methods.

II. METHODS

An overview of the prediction method of head severity of pedestrian using pedestrian collision images and deep learning methods is presented in Fig. 1. In this study, as an initial trial, we utilised car-to-pedestrian collision CAE data. First, we developed a car-to-pedestrian collision model, then conducted CAE analysis. Secondly, pedestrian collision images and Head Injury Criterion (HIC) values obtained from the pedestrian model were collected as image data set for deep learning. Thirdly, deep learning was conducted based on the data set to identify the correlation between the collision image and the HIC value. Finally, HIC prediction (classification into three categories: under 650, 650–1,000 and over 1,000 [6,7]) was performed using a pedestrian collision image for validation (not the same collision image as for learning).

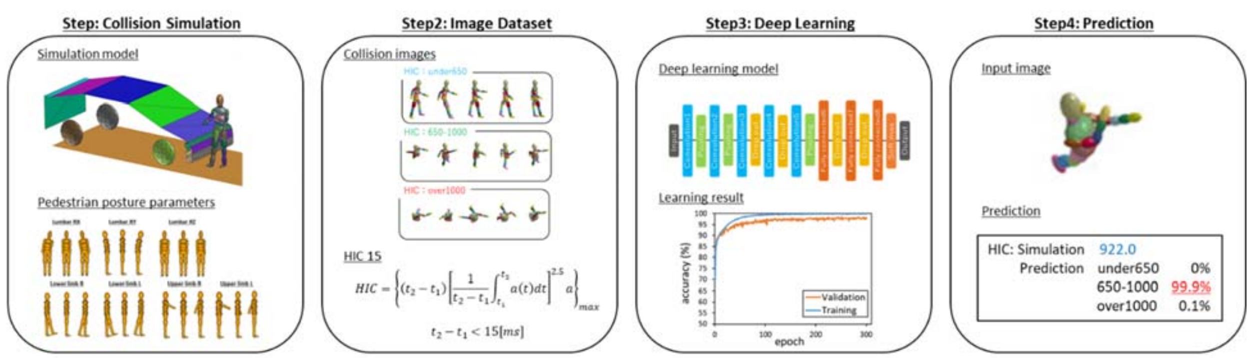

Fig. 1. Overview of the prediction method.

Step 1: Collision Simulation

In this study, car-to-pedestrian collision simulation was conducted using MADYMO 50th percentile pedestrian model and a compact car model [8]. The HIC adopted was HIC15, which is stricter than HIC36 and correlated with skull fracture [9]. Impact velocity parameter set six velocities (10–60 km/h 10 km/h interval), based on the impact velocity distribution associated with pedestrian impacts [2]. Initial pedestrian posture is defined by combining the seven pedestrian model joints with three angle settings and reconstructing the pedestrian pre-crash reactions [10,11] . Therefore, the total number of simulations is 13,033 models.

S. Kunitomi (e-mail: skunitomi@jari.or.jp; tel: +81 29 856 0885) and A. Konosu are Research Engineers at the Japan Automobile Research Institute (JARI) in Tsukuba, Japan.

Step 2: Image Data set

The image data set for deep learning was created from pedestrian model images and HIC15 values of collision simulation. These are pedestrian collision images viewed from the vehicle and resized to 128 × 128 pixels × 3 channels, and those images were divided into three HIC categories: under 650, 650–1,000 and over 1,000. In addition, we prepared those image data sets every 10 ms, from 40 ms to 130 ms after collision, and a total of 10 data sets were created for each collision elapsed time (40–130 ms 10 ms interval).

Steps 3 & 4: Deep Learning & Prediction

Deep learning was performed using Alexnet model [12] and Chainer [13] for all image datasets. After deep learning, we predicted HIC from the collision image using the set of collision images for validation, then evaluated the prediction accuracy of each data set.

III. INITIAL FINDINGS

Figure 2 shows the influence of the collision elapsed time on the prediction accuracy. The prediction accuracy sharply increased from 50 ms to 60 ms and reached a maximum of 90.4% at 90 ms. This result shows that the collision elapsed time has a great influence on prediction accuracy, and the 90 ms data set shows the highest accuracy in this case.

Figure 3 shows the influence of the collision elapsed time on the pedestrian behaviour. As the collision elapsed time is longer, the difference of the behaviour at each velocity becomes larger, so that it is easy to judge the velocity and HIC [14]. Therefore, we estimated that features of images that deep learning can recognize appear in the datasets after 60 ms and accuracy improve. In other words, our data suggested that the difference of the pedestrian behaviour is a key factor in recognising and classifying the injury severity of pedestrian by deep learning.

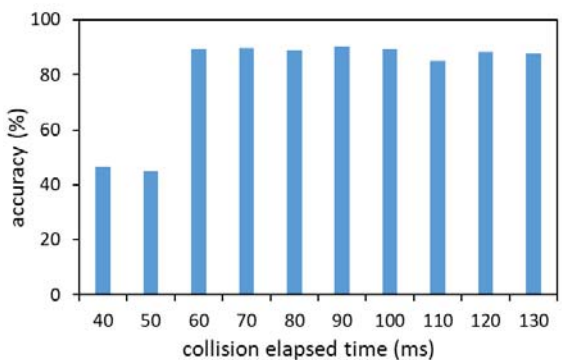

Fig. 2. Influence of the collision elapsed time on the prediction accuracy.

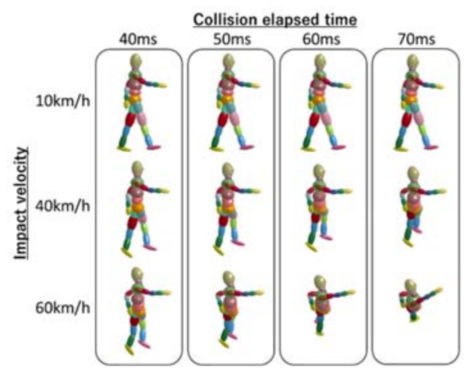

Fig. 3. Influence of the collision elapsed time on the pedestrian behaviour.

IV. DISCUSSION

This study demonstrated the effectiveness of predicting pedestrian head severity in car-to-pedestrian accidents using deep learning methods and CAE image data. In addition, it confirmed that collision elapsed time has a great influence on HIC prediction accuracy.

However, its effectiveness to predict the pedestrian severity in real-world accidents is unclear. It may be difficult to clearly record pedestrian kinematics by dash cam only, plus the learning results using CAE need to have their applicability to the real-world confirmed.

Therefore, in order to predict pedestrian severity in the real-world, it is necessary to train the deep learning model using more realistic image data sets and human FE models that take into account age, sex, vehicle shape and collision conditions, and then apply this technique to real-world pedestrian collision image data.

V. REFERENCES

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