

Effect of Input Data on Model Accuracy for LSTM Driver Models in Car-Following Situation

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KEY WORDS: Human engineering, Driver model, Driving Simulator, LSTM[C2]

In traffic scenes, car following is a frequently experienced driving scenario. In car following scenario, there are large changes in vehicle speed, and the occurrence of traffic jams and accidents can increase the stress on the driver. Driving characteristics of human drivers need to be considered when developing automated driving systems. This study constructed the personalized driver models in car following situation using Long Short-Term Memory (LSTM) to represent human driving control. Although LSTM is widely used to model car following behavior, there is not a lot of researches in the paper that examines the input data, which greatly affects model accuracy. The purpose of this study is to investigate the effect of input information on model accuracy by constructing LSTM driver models for each individual using 10 input data sets. The 10 input data sets consist of own vehicle velocity (V), relative velocity (ΔV), distance between vehicles (ΔX), logarithm of distance between vehicles ($\log \Delta X$), THW (Time Head Way), and TTC (Time To Collision).

The experiment was conducted using a driving simulator to obtain driving data from five participants (average age: 22 years, male). The scenario used in the experiment was a simulated traffic jam on a straight road on the two-lane highway. We used LSTM for modeling. LSTM model is one of the RNN, and is particularly good at time series processing and long-term memory. We trained with the previously studied LSTM parameter set. Tables 1 and 2 show the parameters used for training. The output was set to the acceleration.

The results of accuracy for all experiment participants are shown in Figure 1. The activation function was set to the Relu function, the optimizer to Adam, and the learning rate decay to 0.999 per epoch. The accuracy of the regression model of acceleration created in this experiment was evaluated using the coefficient of determination (R^2). Figure 1 shows the model accuracy results for the five participants. The numbers in Figure 1 indicating the patterns in the input data show the numbers of the patterns shown in Table 1.

Figure 1 shows that Patterns 1 through 6 result in high model accuracy for all participants' models, and Table 1 shows that Patterns 1 through 6 are cases of using the velocity as input data. Velocity was found to be the most influential feature in modeling of the car following behavior.

Driving characteristics of drivers can be classified by THW. Participants A and B are aggressive drivers and experimental participants C, D, and E are safety drivers. The low model accuracy of participants A and B in Patterns 7 through 10 suggests that aggressive drivers have lower feature values obtained from relative velocity and distance than safety drivers in modeling following behavior.

In this study, we constructed LSTM driver models for each individual using a 10 pattern input data set in a traffic scene for car following, and investigated the effect of input information on model accuracy. The results showed that the the velocity of own vehicle is a parameter that contributes to the improvement of model accuracy for modeling the car following behavior. It was found that the input information that affects model accuracy differs depending on the driving characteristics of the driver. It is necessary to select the input data in consideration of driving characteristics of drivers in order to construct personalized driver models with high accuracy.

Table 1 Input Variables

Pattern	Input Variables		
1	V	ΔV	ΔX
2	V	ΔV	$\log \Delta X$
3	V	ΔV	THW
4	V	ΔV	TTC
5	V	ΔX	THW
6	V	ΔX	TTC
7	ΔV	ΔX	THW
8	ΔV	ΔX	TTC
9	ΔX	$\log \Delta X$	THW
10	ΔX	$\log \Delta X$	TTC

Table 2 Hyper Parameter Settings

Parameters	Setting
Units	50, 100, 150, 200, 250
Initial learning rate	0.001, 0.005, 0.01, 0.015, 0.02
Epochs	400, 600, 800, 1000, 1200

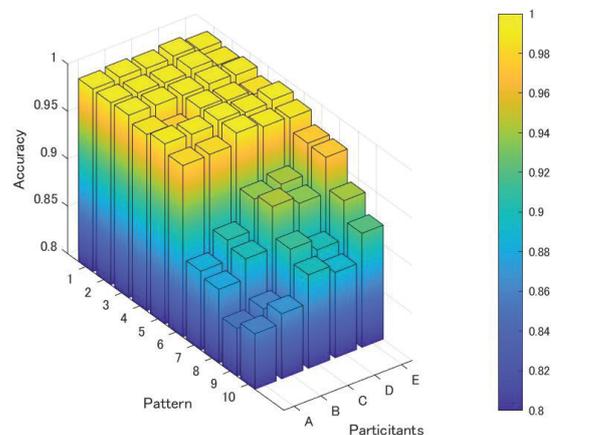


Fig. 1 Maximum Accuracy for Each Participant