RESEARCH OF LSTM MODEL FOR VEHICLE CONTROL SYSTEM OF AUTOMATED DRIVING SYSTEMS (ADS)

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Paper Number 23-0108

ABSTRACT

Research Question/Objective: This study aims to construct a long short-term memory (LSTM) model of the vehicle control system for automated driving systems (ADSs) that does not cause annoyance or distrust. Furthermore, this study investigates the effect of LSTM hyperparameters on model accuracy. A survey showed that certain drivers did not use levels 1 and 2 of the ADS function because they were annoyed with the driving behavior of the ADS-controlled vehicle. Although the driving behavior of the ADS-controlled vehicle causes distrust in passengers, it cannot effectively enable safe driving. This study focuses on a novel vehicle control method that reduces annoyance and distrust in passengers and contributes to the safe operation of ADSs. These control methods involve the application of a long short-term memory (LSTM) model that learns long-term time-series data. This system enables the construction of ADS control algorithms from LSTM models based on personalized driver operations during ordinary driving.

Methods and Data Sources: LSTM models were constructed for highway driving in the following three driving scenarios. Scenario-1: following a preceding vehicle, Scenario-2: passing a preceding vehicle at low speed with lane change, Scenario-3: a sudden lane change by a vehicle in the passing lane in front of the vehicle. The effect of LSTM hyperparameters on the accuracy of the LSTM model was investigated for each driving scene. The data of these models were sourced from an experiment using a driving simulator conducted to determine driver behavior.

Results: The results verified the accuracy of the model that simulated the driving operation of the driver. The model accuracy was improved by setting LSTM hyperparameters. In Scenario-1, the number of units, learning rate, and the number of epochs affected the coefficient of determination. The coefficient of determination tends to be particularly high for a large number of units. In Scenario-2, unlike Scenario-1, a large number of units was not required to obtain a high coefficient of determination. The coefficient of determination did not change with the epoch. In Scenario-3, similar to Scenario-1, the number of units, learning rate, and epoch affected the coefficient of determination, whereas the coefficient of determination decreased at epochs above 800.

Discussion and Limitations: In each scenario, the hyperparameters affecting the accuracy were different. A limitation of this study is that it focuses on the driver model. The LSTM model applying ADS was evaluated.

Conclusions: For the ADS control algorithm (SAE Levels 3, 4, and 5), we constructed LSTM models that reflect the characteristics of personalized drivers. The results showed that the LSTM hyperparameters affecting the

coefficient of determination tended to differ among different scenarios. In the future, evaluation of the effectiveness of the LSTM model when applied to ADS is necessary. Novel control systems for ADS with LSTM models contribute to the development of ADS system design.

INTRODUCTION

In recent years, vehicles that use automated driving systems (ADSs) and other automated driving technologies have become increasingly popular. According to a survey of the global market for ADSs, the number of vehicles equipped with advanced driver assistance systems (ADAS)/ADS is expected to reach 79,153,000 units by 2030 [1]. Although ADS contributes to reducing a driver's driving burden by replacing the driver and improving safety, there are potential problems that need to be solved in the future. According to a survey of driver feelings regarding ADAS functions widely used currently, more than 54% of those who own ADAS-equipped vehicles believe that ADAS functions conversely increase the possibility of accidents, and 70% of drivers have turned off ADAS functions [2]. The cause is attributed to the low personal adaptability of the system to each driver that significantly affects the function unacceptability [3][4]. This distrust of the ADAS can also be applied to ADS. For example, when following a preceding vehicle, the driver may be annoyed by the system's frequent acceleration and deceleration despite a sufficient distance, or the driver may distrust the system when the system does not make such a decision even though the preceding vehicle may be traveling at a low speed, and the driver intends to overtake it. To solve these problems, considering personal adaptability in automatic driving control systems is necessary [5][6]. The purpose of this study is to develop a long short-term memory (LSTM) model of the vehicle control system for ADS that does not cause annoyance or distrust and to investigate the effect of LSTM hyperparameters on model accuracy. Therefore, we propose an algorithm for a new personalized vehicle control system that contributes to safe driving for ADS, and we use a driver model based on LSTM to construct this system. Two methods are available for constructing driver models. The first method constructs driver models corresponding to various driving scenarios by modeling the driver's driving behaviors, such as cognition, decision-making, and operation. The second method involves constructing and integrating driver operation models that fit each driving scenario. The second method integrates several driver operation models that are constructed for each driving scenario. Driving scenarios include free driving, following, lane change, and merging. Operational models are easier to construct than cognitive and assessment models, and numerous previous studies have been conducted [7][8][9]. In addition, by limiting the target driving scenario, the driver's cognitive information can be identified. In this study, driver models were constructed using the latter method. In this study, several personalized driver models were developed to demonstrate their feasibility of constructing personalized models. The driving scenarios targeted in this study include car-following, overtaking, and cut-in behaviors. In modeling each scenario, the effect of the LSTM hyperparameters on accuracy was investigated.

METHODOLOGY

Driving Experiment Using a Driving Simulator

Driving experiments were conducted using a driving simulator (DS) to obtain data regarding a driver's ordinary driving behavior. The experiment was conducted using a DS, as shown in Figure 1. A six-axis sway device equipped with electric actuators was used to simulate the sensation of driving a DS. The six-axis sway device can simulate the pitch motion caused by the driver's gas pedal and brake operations and the roll motion caused by the steering operation. The upper part of the six-axis sway device includes a turntable that can rotate ±180° and simulate yaw motion. The screen is cylindrical with a radius of 2.5 m, and six projectors are used to simulate the traffic scene in all directions. The experiment was conducted on five male participants in their 20s (average age: 21 years). The experimental conditions include three driving scenarios: car-following, overtaking, and cut-in. The participants were informed to drive under each condition as they typically do, to obtain their driving characteristics. All these scenarios were simulated in an environment similar to a standard Japanese highway. This study was approved by the Ethics Committee of the Shibaura Institute of Technology.

Figure 1. Driving Simulator.

<u>Car-following Scenario</u>

An overview of the car-following scenario is shown in Figure 2. In Figure 2, the red, blue, and black vehicles represent the ego, preceding, and other vehicles, respectively. Participants boarded and drove the ego vehicle; the preceding vehicle traveled in front of the ego vehicle. The ego vehicle travelled at 100 km/h and followed the last car in a line of cars traveling at 40–60 km/h caused by a traffic accident until the congestion was cleared. Each scenario spanned approximately 2 min and 30 s. The drivers were asked to drive in the scenario 10 times to obtain the training data. During the experiment, we obtained the ego vehicle's velocity, acceleration, velocity relative to the preceding vehicle, and the headway distance from the preceding vehicle. Driving behaviors of the sequence of drivers from the beginning to the end of the journey were modeled.

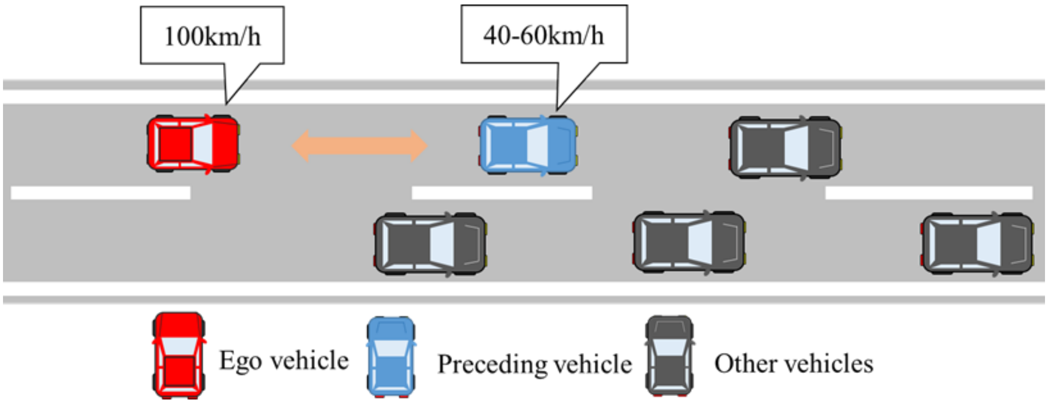


Figure 2. Overview of the car-following scenario.

Overtaking Scenario

An overview of the overtaking scenario is shown in Figure 3. In Figure 3, the red, blue, and green vehicles represent the ego, the preceding vehicle in the travel lane, and the preceding vehicle in the overtaking lane, respectively. The participants boarded and drove the ego vehicle, and the preceding vehicle was placed in front of the ego vehicle. The green vehicle in Figure 3 travels in the passing lane at a speed of 100 km/h. The ego vehicle traveled at 100 km/h, approached the preceding vehicle traveling at approximately 80 km/h, and decelerated eventually. The driver subsequently changed lanes to the overtaking lane, passed the vehicle, and changed lanes back to the original lane, while focusing on the vehicle in the overtaking lane. Each scenario spanned approximately 1 min and 10 s. The driver was asked to drive the scenario 10 times to obtain training data. In the experiment, we obtained the ego vehicle's steering angle, acceleration, relative velocity, and headway distance relative to the preceding vehicle and the relative velocity and distance relative to the vehicle in the overtaking lane. The model targeted the period spanning from the time the driver turned on the blinker and performed the overtaking maneuver until he returned to his original lane.

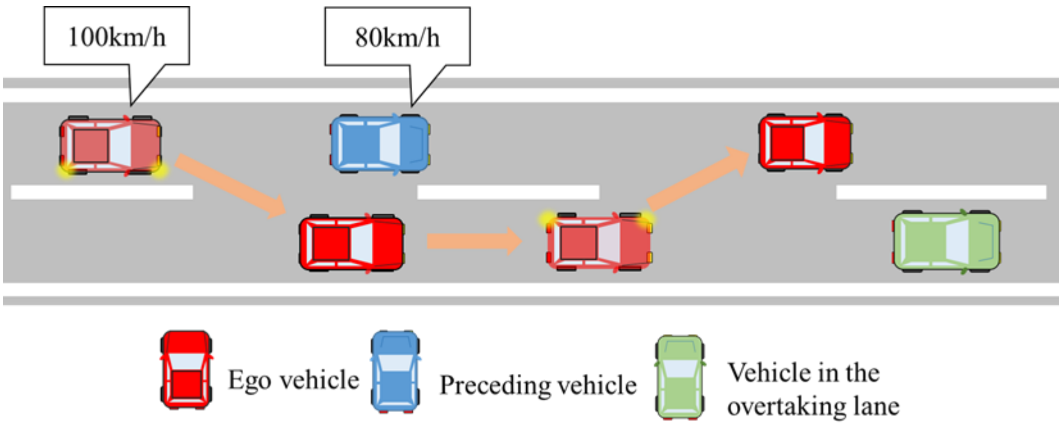


Figure 3. Overview of the overtaking scenario.

Cut-in Scenario

An overview of the cut-in scenario is shown in Figure 4. In Figure 4, the red, blue, and black vehicles represent the ego, cut-in, and other vehicles, respectively. In this scenario, when the ego vehicle was traveling at 70–80 km/h, a cut-in vehicle passed it at 100 km/h from the passing lane on the right side and cut in front of it. The distance between the ego vehicle and the preceding vehicle in the travel lane at the time of the cut-ins was set at intervals of 1 m from 7 m to 13 m. The driver was asked to run the scenario 10 times to obtain the training data. During the experiment, the driver acquired the ego vehicle's velocity, acceleration, relative velocity, and headway distance relative to the cut-in vehicle. The model targeted 5 s after the cut-in vehicle cut in.

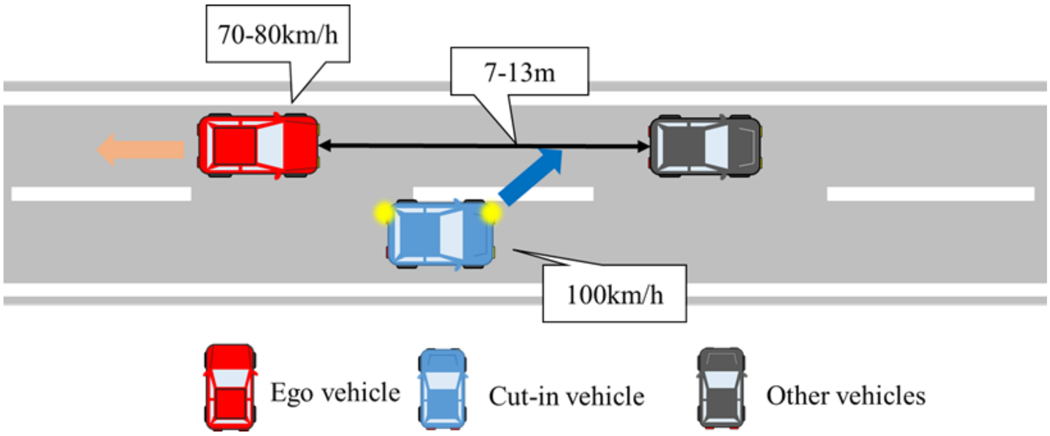


Figure 4. Overview of the cut-in scenario.

Novel Personalized Vehicle Control System

The proposed LSTM-based ADS control algorithm is illustrated in Figure 5. The data source stores information such as the relative position and relative velocity of the vehicle with respect to the road user (vehicles, pedestrians, bicycles, etc.) and the shape of the road on which the vehicle travels in the experiment. The data source can utilize a connected vehicle system, the V2X (Vehicle-to-Everything) system [10], in which information can be mutually obtained through communication between the vehicle, road user, and infrastructure. The lower layer of the data source is a scenario classification model that classifies driving scenarios. Based on the information obtained from the data source, the system classifies driving scenarios corresponding to the current vehicle environment and applies a driver model that is appropriate for that scenario. By personalizing the scenario classification model, it is possible to adapt it to each driver (for example, whether and when to change lanes). After classification, the driver model was provided with the necessary input data. As mentioned previously, these driver models were constructed for each driving scenario. In this study, driver models were constructed for car-following, overtaking, and cut-in scenarios, as an example. A personalized driver model is a position- or acceleration-based model that considers the driving characteristics of each driver. Because the personalized driver model outputs the vehicle position and acceleration/deceleration, it cannot control the vehicle directly. The control mechanism (controller) calculates the acceleration stroke, brake stroke, and steering amount based on the predicted data (acceleration/deceleration and position) output by the driver model and controls the vehicle. The calculated operation amounts are applied to the vehicle model to obtain the necessary information for the next control step that is subsequently fed back into the data source. Consequently, performing personalized ADS control corresponding to various time-varying driving scenarios is feasible. Based on the premise of this vehicle control system, we discuss the construction of a personalized driver model using LSTM.

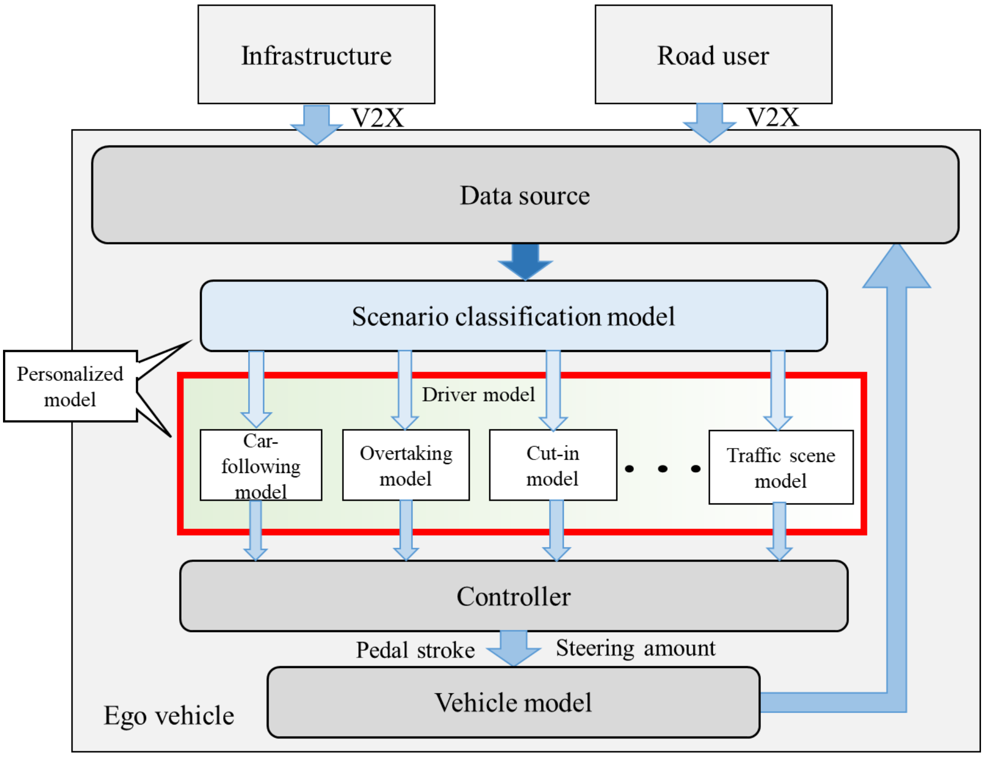


Figure 5. Proposed ADS control algorithm.

Method of Constructing Personalized Driver Model

We constructed personalized driver models using LSTM. Figure 6 shows the construction flow of the personalized driver model. LSTM is a type of recurrent neural network that exhibits a superior processing capability for time-series data. Figure 7 shows the personalized driver models constructed in this study. The inputs for the car-following and cut-in models include the velocity of the ego vehicle, relative velocity, and headway distance to the preceding or cut-in vehicle. The inputs for the overtaking model include the steering angle of the ego vehicle, relative velocity, and headway distance to the preceding vehicle in the travel lane, and the relative velocity and headway distance to the vehicle in the overtaking lane. The output of the car-following and cut-in models is longitudinal acceleration. However, the outputs of the overtaking model were longitudinal and lateral accelerations considering the driving maneuvers. In the LSTM, the number of hidden units, initial learning rate, and number of epochs were set as parameters for training. Table 1 shows the parameter setting. The numbers of hidden units were 25, 50, 100, 150, and 200. The initial learning rates were 0.001, 0.005, 0.01, 0.015, and 0.02. The number of epochs was 400, 600, 800, 1000, 1200, and 1400. In other words, LSTM was trained 150 times for each scenario and for all the participants. To ensure reasonable impact of the parameters on model accuracy, we fixed the initial values that were randomly output. The learning rate was set to decay by 0.999 per epoch. Data obtained from the driving experiments using a driving simulator were divided into 80% training data and 20% test data to construct the model. To confirm the feasibility of the model, a highly accurate driver model was constructed based on 150 training sets, and acceleration simulations were conducted.

Table 1. LSTM learning parameters

Parameters	Value
Hidden units	25, 50, 100, 150, 200
Initial learning rate	0.001, 0.005, 0.01, 0.015, 0.02
Epochs	400, 600, 800, 1000, 1200, 1400

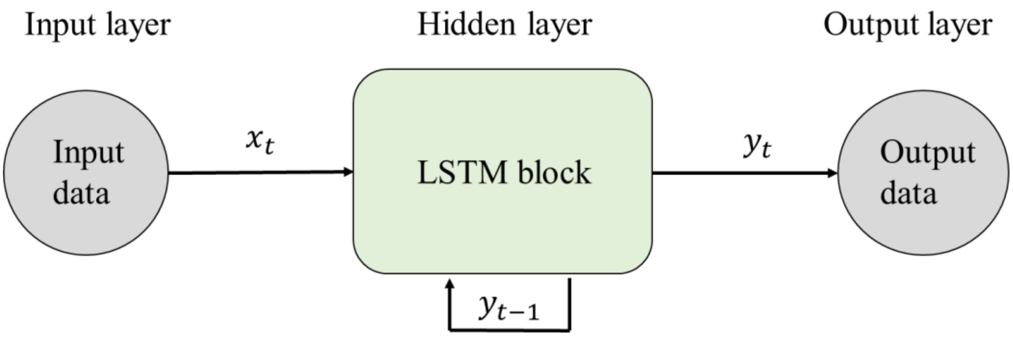


Figure 6. Personalized driver model construction flow.

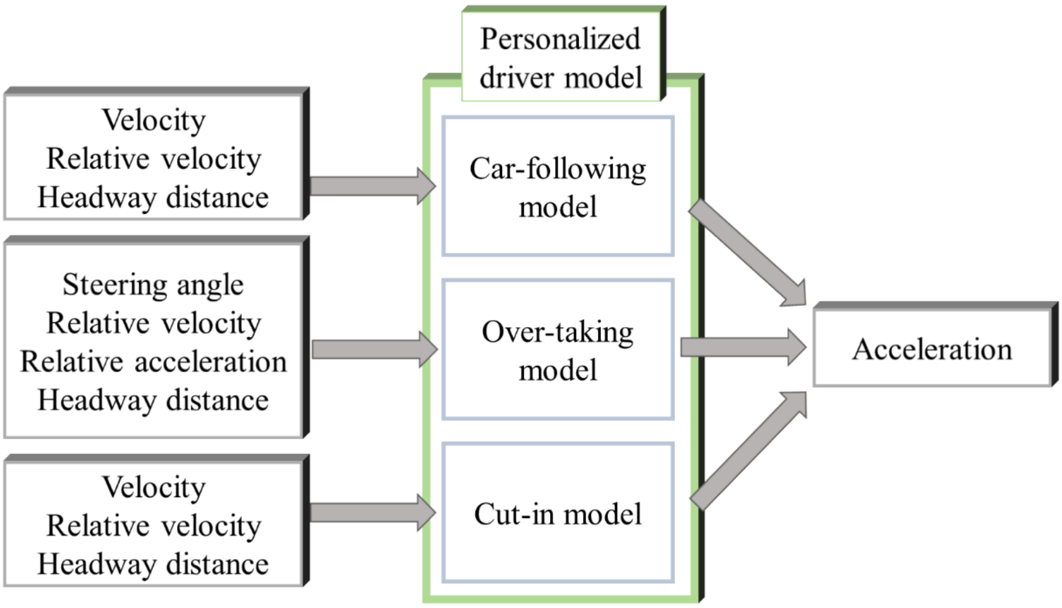


Figure 7. Personalized driver mode .

Analysis Method

To investigate the impact of LSTM hyperparameters on modeling accuracy, LSTM trained 150 scenarios and calculated the coefficient of determination from the test results. The formula for calculating the coefficient of determination is given by Equation (1). The closer the coefficient of determination is to 1, the better the model fits the test data and the higher the model accuracy.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - y_i')^2}{\sum_{i=1}^{n}(y_i - y_i'')^2} \qquad \text{Equation (1)}$$

(y_i: measured acceleration; y_i': predicted acceleration; y_i'': average value of the measured acceleration)

Acceleration simulations were conducted using highly accurate driver models that were constructed based on a study using the above coefficients of determination. Simulation results were evaluated using the root mean squared error (RMSE). The formula for calculating the RMSE is shown in Equation (2). The smaller the RMSE, the smaller the error, and the higher the prediction accuracy.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - y_i')^2} \qquad \text{Equation (2)}$$

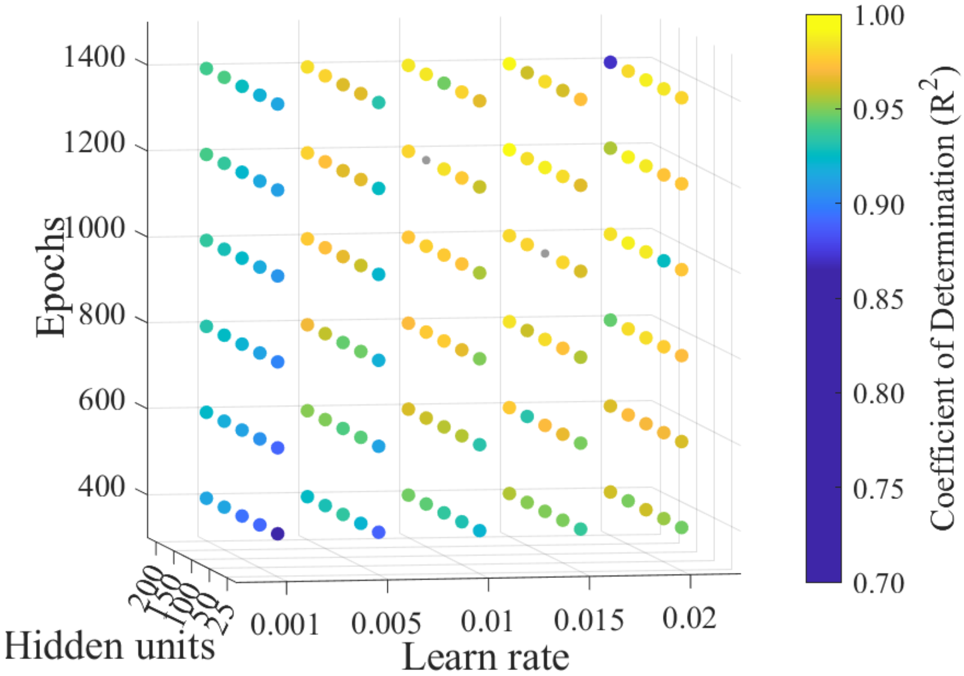
(y_i: measured acceleration; y_i': predicted acceleration)

RESULT

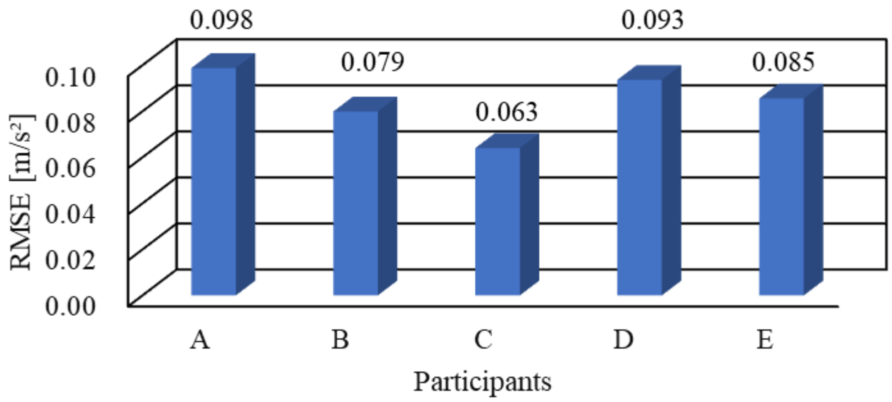
The results of the coefficients of determination for the driver model constructed with 150 hyperparameters for each scenario are described below.

Car-following Model

Figure 8 (a) shows a three-dimensional plot of the relationship between the average coefficient of determination and the hyperparameters for all participants in the car-following model. The color of the plotted points changes with the value of the coefficient of determination, with a yellow scheme for points closer to 1 and a blue scheme for points further away from 1. The larger the number of units, learning rate, and epoch, the larger the coefficient of determination and the more accurate the model. In particular, the coefficient of determination tended to be higher when the number of units was larger. However, when the number of learning epochs was high for a large number of units, as in the case of 200 units, 1400 epochs, and a learning rate of 0.02, the expressiveness of the model became exceedingly high, resulting in overlearning. Figure 8 (b) shows the model with the highest accuracy (lowest RMSE) from 150 training results for each participant in the experiment. The acceleration simulation results showed low errors with RMSE values of less than 0.1 [m/s^2], and the car-following behavior could be modeled with high accuracy.



(a) Average coefficient of determination for all participants in the car-following model.



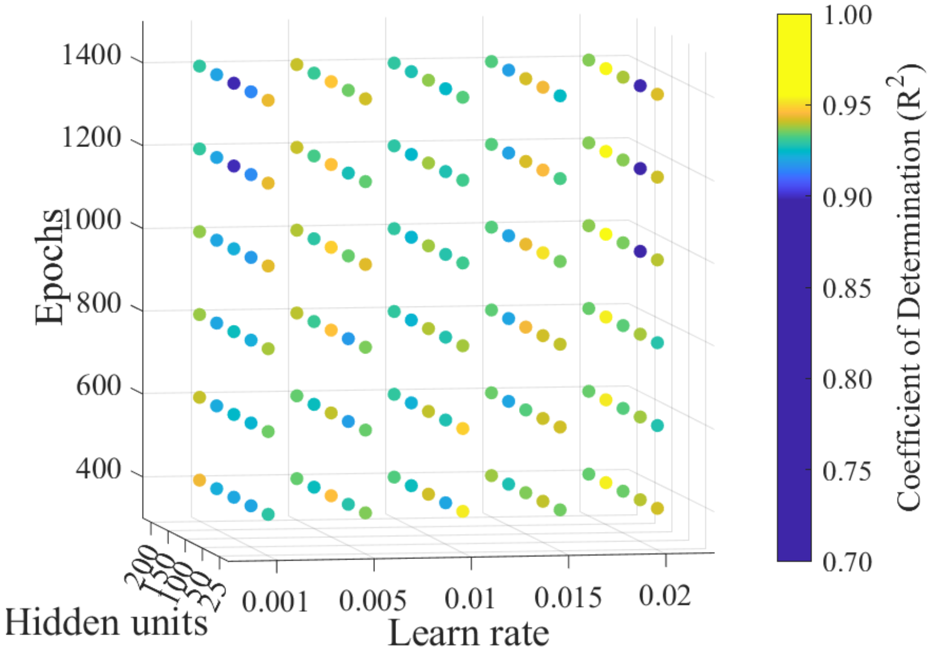
(b) RMSE values with the highest accuracy of acceleration simulation for each participant.

Figure 8. Car-following model construction results.

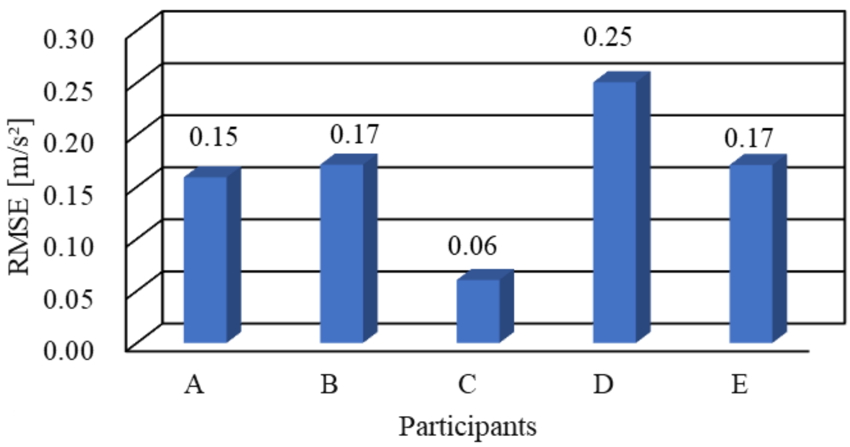
Overtaking Model

Figure 9 (a) and 10 (a) show three-dimensional plots of the relationship between the average coefficient of determination and the hyperparameters for all participants in the longitudinal and lateral directions of the overtaking model, respectively. As shown in Figure 9 (a), in the longitudinal direction, the coefficient of determination changed significantly with changes in the number of units and learning rate; nonetheless, no specific trend was observed. However, the coefficient of determination did not change significantly with the number of epochs. In particular, a high coefficient of determination independent of epoch was obtained when the number of units was 150 and the learning rate was 0.02. As shown in Figure 10 (a), in the lateral direction, as in the longitudinal direction, the coefficient of determination was unaffected by changes in the number of epochs. Figure

9 (b) and 10 (b) show the model with the highest accuracy (lowest RMSE) among the results simulated from 150 learning results. In both the longitudinal and lateral directions, Participant C exhibited a smaller RMSE for the simulation results, whereas Participant D exhibited a larger RMSE for the simulation results.

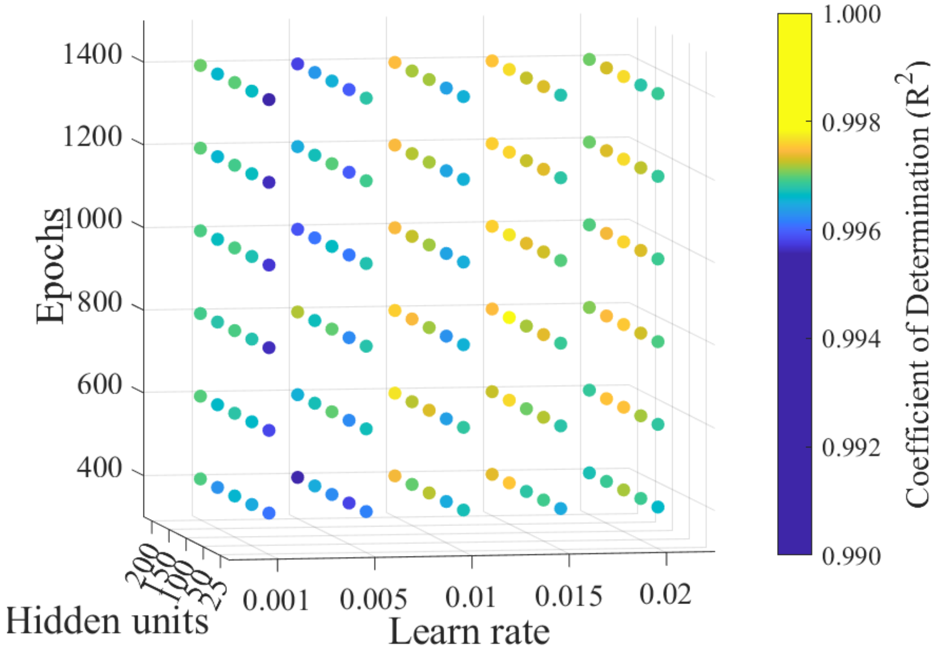


(a) Average coefficient of determination for all participants in the overtaking model.

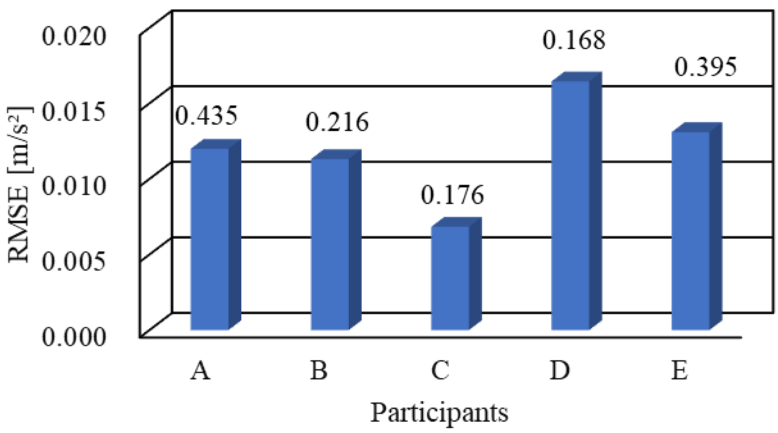


(b) RMSE per experiment participant.

Figure 9. RMSE values with the highest accuracy of acceleration simulation for each participant.



(a) Average coefficient of determination for all participants in the overtaking model (lateral).

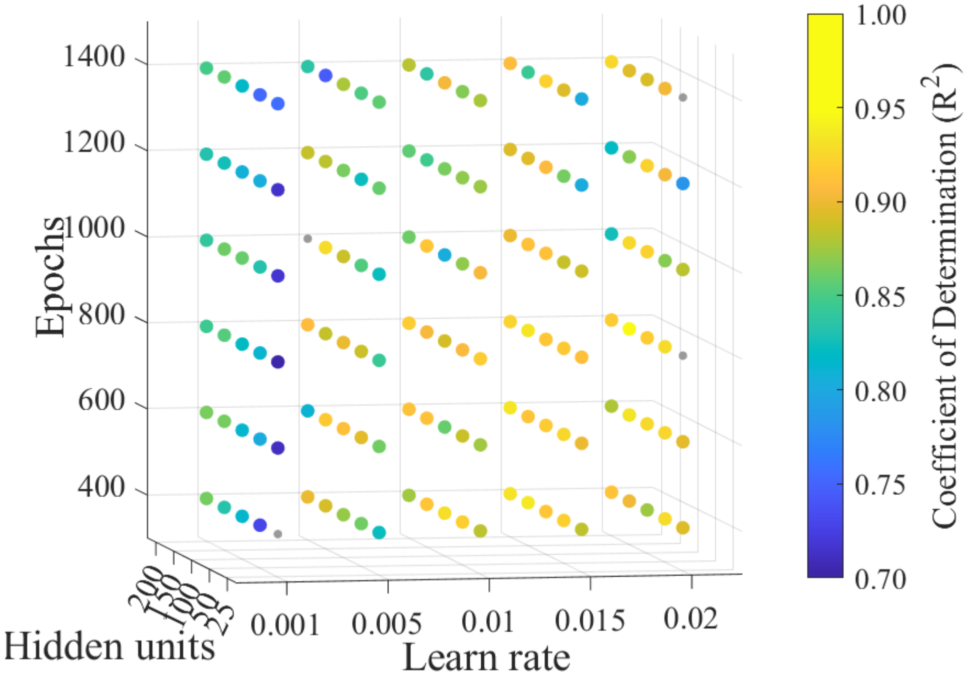


(b) RMSE values with the highest accuracy of acceleration simulation for each participant.

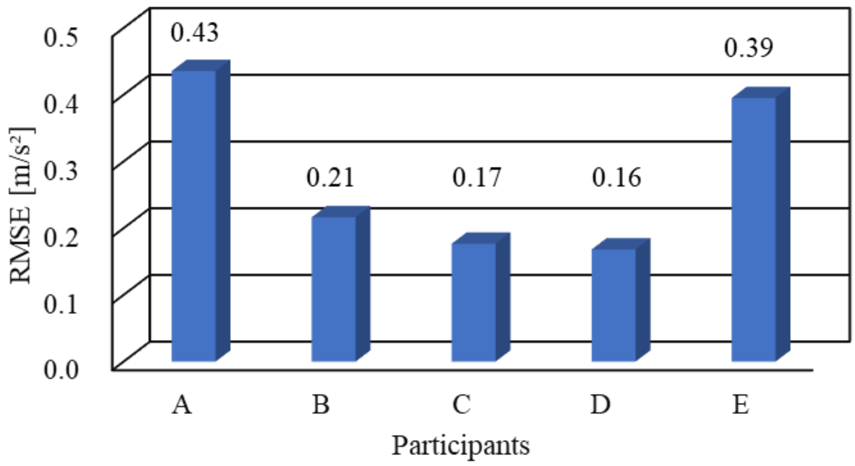
Figure 10. Results of constructing an overtaking model (lateral).

Cut-in Model

Figure 11 (a) shows a three-dimensional plot of the relationship between the average coefficient of determination and the hyperparameters for all participants in the cut-in model. The coefficient of determination tended to increase with the number of units, learning rate, and epoch. In particular, stable, high coefficients of determination were obtained for epochs below 800. Figure 11(b) shows the model with the highest accuracy (lowest RMSE) from 150 training results for each participant. As per the acceleration simulation results, participants B, C, and D were characterized by small RMSEs of 0.21, 0.17, and 0.16 [m/s²], respectively, while participants A and E were characterized by large error RMSEs of 0.43 and 0.39 [m/s²].



(a) Average coefficient of determination for all participants in the cut-in model.



(b) RMSE per experiment participant.

Figure 11. RMSE values with the highest accuracy of acceleration simulation for each participant.

DISCUSSION AND LIMITATION

The hyperparameters affecting the coefficients of determination tended to differ among the 150 modeled scenarios in this study. Below, we discuss the LSTM hyperparameters that affect the coefficient of determination for each model and the RMSE for each participant in the experiment.

Car-following Model

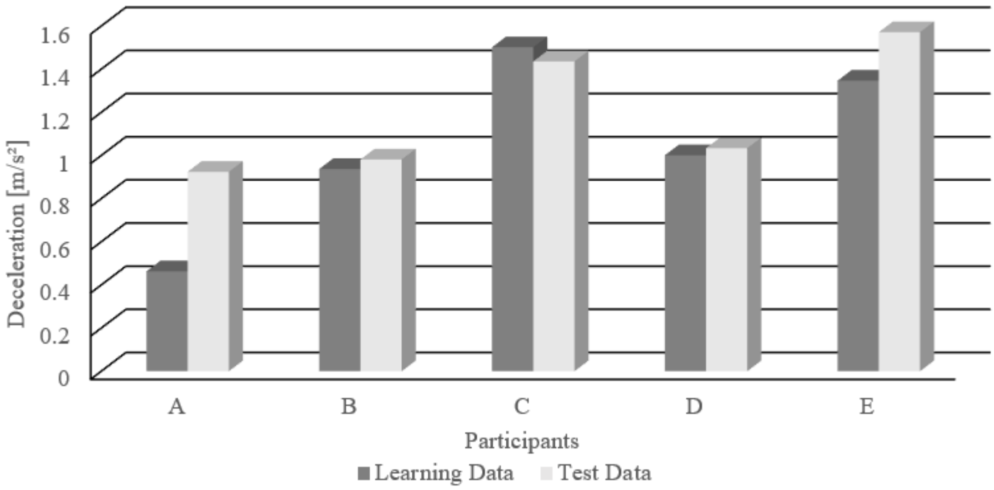
For the car-following model, the number of units, learning rate, and epoch affected the coefficient of determination. The car-following scenario in this experiment features a more complex acceleration/deceleration behavior and various patterns than the overtaking and cut-in scenarios, and a large number of units are required to represent the driver's driving characteristics. The RMSE values were less than 0.1 [m/s²] for all participants in the experiment, indicating that the experiment adequately reproduced the driving behavior of individual drivers.

Overtaking Model

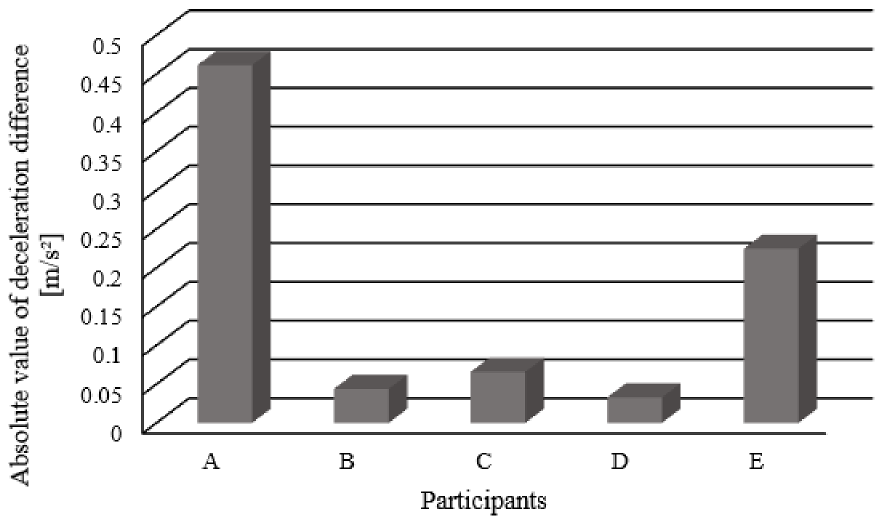
In the longitudinal direction, the overtaking model afforded high coefficients of determination, independent of the number of epochs in the case of 150 units and a learning rate of 0.02. In the lateral direction, high coefficients of determination were obtained independent of the number of epochs in the case of 100 or more units and a learning rate of 0.01 or more. The coefficient of determination does not change with the number of epochs. In machine learning, the accuracy of the model increases as the training progresses; however, after a certain level of training, the accuracy of the model decreases owing to over-training. As shown in Figure 11 (a), in one case, the accuracy of the cut-in model decreased at epochs above 800, owing to overlearning. As shown in Figures 9 (a) and 10 (a), the coefficient of determination did not change with the epoch, suggesting that the parameter set for the number of learning epochs was insufficient for identifying the trend. The acceleration simulation results for each participant in the experiment showed that participant D exhibited a slightly larger RMSE than the other participants that may be attributed to the fact that Participant D performed the overtaking maneuver at a different time from the other participants in the driving simulator experiment. The other participants in the experiment started to change lanes after the vehicle in the overtaking lane passed their vehicle, whereas participant D changed lanes before the vehicle in the overtaking lane passed his/her vehicle. In this study, the intention to begin lane change was not considered, and only the overtaking maneuver was targeted; therefore, the input data were not optimized. In the future, the scenario classification model shown in Figure 5 can be used to personalize lane-change decisions, and the accuracy is expected to be improved by examining the optimal driver model input.

Cut-in Model

In the cut-in model, the number of units, learning rate, and epoch affected the coefficient of determination; however, unlike the car-following model, the coefficient of determination decreased when the epoch was exceedingly large. A decrease in the coefficient of determination was observed for epochs greater than 800. This may be because the driver's driving behavior in the cut-in scenario requires only braking in this study, and thus a highly accurate model could have been constructed even at low epochs. The results of the acceleration simulations for each experimental participant showed that participants B, C, and D were characterized by smaller RMSEs, while participants A and E were characterized by larger RMSEs. A feature of data-driven models is that their prediction accuracy depends on the training and test data. The reason for the large RMSE for participants A and E in the experiment may be that they did not have sufficient training data. Figure 12 (a) shows the average acceleration of the training and test data for each participant during the experiment. Figure 12(b) shows the difference between the average accelerations of the training and test data for each participant during the experiment. The difference in average acceleration between the training data and test data was large for participants A and E, indicating that the training data used in this study were not sufficient to cover the acceleration range of the test data.



(a) Average acceleration of training and test data for each participant.



(b) Difference between the training and test data.

Figure 12. Comparison of training and test data for each participant.

A limitation of this study is that it focuses on the driver model, as shown in Figure 5. We constructed a driver model for following, overtaking, and cut-in. Nonetheless, there are other scenarios that need to be validated as well; examples include merging and driving on curved roads. In addition, in the future, we intend to evaluate the effectiveness of the constructed LSTM driver model when applied to the proposed ADS control algorithm.

CONCLUSIONS

For automated driving technologies such as advanced driver assistance systems (ADAS) and automated driving systems (ADS) to be accepted by drivers, the elimination of annoyance and distrust is important. Therefore, this study proposes an algorithm for a novel personalized vehicle control system for ADS. The proposed system includes a personalized driver model constructed using LSTM. A driver model is constructed for each driving scene. In this study, a driver model was constructed for car-following, overtaking, and cut-in behaviors, and the effect of LSTM hyperparameters on the model accuracy was investigated. The results are as follows.

1. For the car-following model, the number of units, learning rate, and epoch affected the coefficient of determination. The coefficient of determination tends to be particularly high for a large number of units.
2. Unlike the CF model, the overtaking model does not require a large number of units for realization of a high coefficient of determination. The coefficient of determination did not change with the epoch.
3. The cut-in model, similar to the car-following model, showed that the number of units, learning rate, and epoch affected the coefficient of determination; however, the coefficient of determination decreased at epochs above 800.

Acceleration simulations were performed using the most accurate 150 models constructed. Highly accurate simulation results were obtained by optimizing the input and training data acquisition methods and the LSTM hyperparameters. Future evaluation of the effectiveness of the driver model when applied to the ADS is necessary. We expect that the new control system for ADS using the LSTM model proposed in this study will contribute to the development of an ADS system design.

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