Analysis of Driving Skills based on Deep Learning using Stacked Autoencoders

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***Abstract*—Due to the advancement of automobile technology and increasing consumers demands, it is expected that automatic driving vehicles and manual driving vehicles will coexist in future automobile society. There are a number of people who are interested in driving and, they may think that the automatic driving vehicles are unnecessary. However, if the vehicle is operated manually, there is a possibility for driving skills of a driver to fluctuate due to drowsiness and fatigue and that may lead to accidents. In such a situation, it is important for vehicle to monitor the driver's driving conditions and provide with a driving support system or automatic driving options. In this research, we propose a method to classify driving skills of an individual driver with high precision based on deep learning (stacked autoencoders). In the experiments, driver's driving skills were classified by combining sensor signals of curve driving data acquired from a driving simulator. As a result, a maximum driving skill recognition rate of 98.1% was achieved. In addition, the recognition rate was improved compared to the previous researches.**

***Keywords*— Neural network; Deep learning; Stacked autoencoderes; Driving behavior; Driving skill**

I. INTRODUCTION

Automobile technology continues to evolve. Some examples are Toyota Motor Corporation's Automated Highway Driving Assist (AHDA) [1], Nissan Motor Corporation's ProPILOT [2], and Honda Motor Corporation's Honda Automated Network Assistant (HANA) [3]. The realization of fully automatic driving vehicles will be near at hand. Results of a survey of the willingness of American consumers to buy automated driving vehicles in 2014 is shown in Fig. 1[4]. The graph on the left side of Fig. 1 shows the response to the question "How much would you like to purchase a partial automatic driving vehicle, assuming that you are going to purchase a car within the next 5 years?". 55% of respondents replied that they want to purchase a partially automatic driving vehicle. The graph on the right side of Fig. 1 depicts the answer to the question "How much would you like to purchase a fully automatic driving vehicle, assuming that you are going to purchase a car within the next 10 years?". 44% of respondents replied that they would like to purchase fully automatic driving vehicles. From these results, it is shown that about half of the people are affirmative in buying automatic driving vehicles.

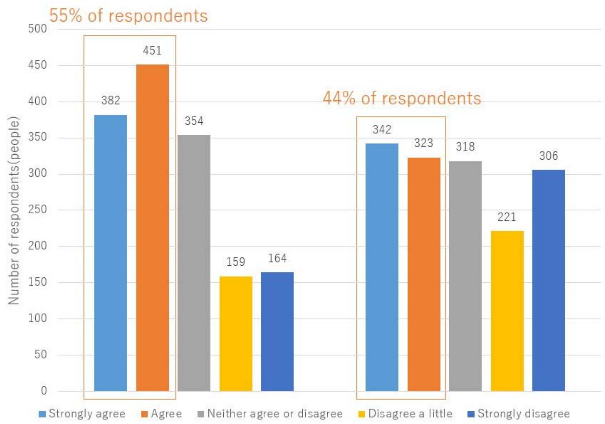

Fig. 1 American consumers' willingness to buy automated driving vehicles (Left: Answer to the question "How much would you like to purchase a partial automatic driving vehicle by assuming to purchase a car within the next 5 years?" Right: Answering the question "How much would you like to purchase a fully automatic driving vehicles by assuming to buy a car within the next 10 years?")

While automatic driving vehicles are becoming popular, manual driving vehicles will coexist with them in the future. Therefore, it is an important task for the automobile society to use the driving support systems according to the situation and driving skills of the driver. To accomplish that, it is necessary to analyze driving skills of an individual driver.

In this research, the driving data analysis method we use differs from the previous research. We use the stacked autoencoders of the deep learning method for classifying the driving skills of individual drivers. The deep learning is a machine learning method using a multilayered neural network. It is possible to let the neural network to automatically extract the features from the data, and it can handle a large amount of data. In the most of previous research, researchers themselves define suitable features to classify driving skills. In this research, we take advantage of automatic feature extraction using stacked autoencoders. Our aim is to propose a method for classifying driving skills of individual drivers with higher precision by using stacked autenoders of deep learning.

II. METHOD

We combine the sensor signals of the driver operation and vehicle behavior data acquired from a driving simulator and classify the driving skills of the driver using stacked autoencoders.

A. Driving simulator

Curve running driving data were acquired by a driving simulator (Fig. 2). These data were recorded at the Institute of Industrial Science, the University of Tokyo [5].

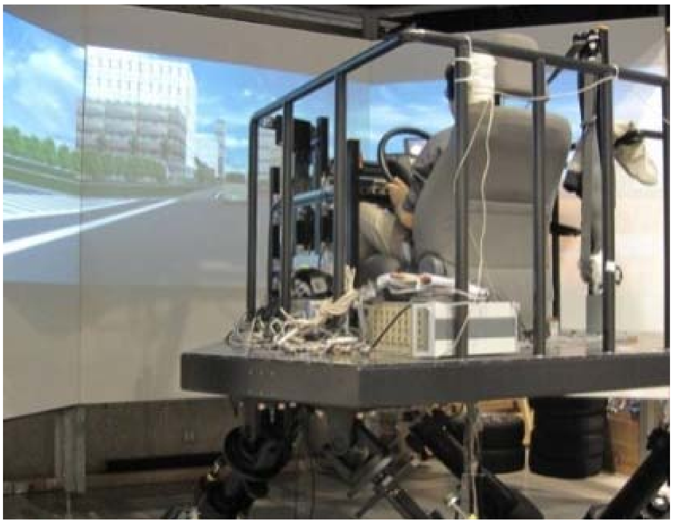

Fig. 2 Driving simulator (Source: [5])

The data acquired by the driving simulator that were used in this research consists of eight kinds of data regarding the operation and behavior of the vehicle. The collected data include speed, steering angle, accelerator pedal control, brake pedal control, longitudinal acceleration, lateral acceleration, yaw rate and lateral displacement. These are time series data. As shown in the left part of Fig. 3, the driving course consisted of six curves (radius = 50, 100, or 200 m; intersection angles = 45°or 90°).

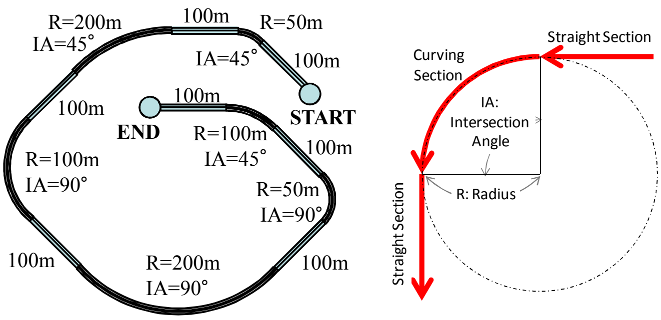

Fig. 3 Driving course (Source: [5])

A traffic sign indicating the speed limit of 60 km/h as shown in Fig. 4 was set 50 m before the curve and the drivers were instructed to keep the curve approaching speed and always run in the left lane and not cross the yellow line. In the driving simulator, 16 drivers aged between 20 and 40 participated, and each driver ran up to 12 runs in an urban scene with 2 practice runs. There are various ways for defining driving skills. We can define faster or eco driving, etc., as high-skilled driving. In this research, we defined smooth driving as high-skilled driving. Based on expert judgment in the field of driving skills, the driving skills of the drivers who participated in the experiment were evaluated in two levels: high skill or low skill. As a result, 5 drivers were evaluated as high-skilled drivers, and the remaining 11 drivers were evaluated as low-skilled drivers [6].

Fig. 4 Experimental scenario (Source: [5])

B. Data conversion

The data that are acquired by the driving simulator are time series data. As each traveling data cannot be compared simply, they are converted into distance series data at fixed distance intervals. This makes it possible to compare different runs of the drivers at the same distance point on the curve [6]. Fig. 5 shows an example before and after this conversion.

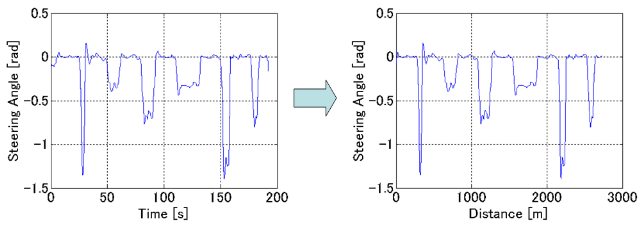

Fig. 5 Conversion of time series data into distance series data (Source: [6])

In this research, Curve of radius (R) = 50 m and interior angle (IA) = 90 ° is chosen for the data analysis here, as driving of sharp curves require high driving skills.

C. Combination of sensor signals

Eight sensor signals that are converted into distance series data. We investigated which combination of sensor signals can obtain classification results of highed precision by stacked autoencoders. When choosing sensor signals, we focused on the driver's direct operation, the behavior of the vehicle, and ease of data acquisition, etc., and created six combinations (Table 1). Also, as the units of "steering angle" and "speed" of the sensor signals are different, the data for learning and test are standardized using the Z score method.

Table 1 Combination of sensor signals

	Combination					
Sensor signals	***A***	***B***	***C***	***D***	***E***	***F***
Speed	○	○		○	○	○
Steering angle	○	○	○		○	○
Accelerator pedal control	○	○	○			
Brake pedal control	○	○	○			
Longitudinal acceleration	○			○		○
Lateral acceleration	○			○		○
Yaw rate	○					○
Lateral displacement	○					

D. Construction of stacked autoencoder

The stacked autoencoders used in this research has three internal layers, and the output layer uses the softmax function (Fig. 6). The number of dimensions of the input layer is 929 × the number of sensor signals. As the number of units in the internal layer change, the output result of the stacked autoencoders change, therefore the number of units in each internal layer is varied based on the results of preliminary experiments, the first layer (L1) is varied between 100 to 150, the second layer (L2): 50 to 90, and the third layer (L3): 10 to 40. The experiment was carried out by varying the number of units of each layer (L1 to L3) by 10 for finding the best combination.

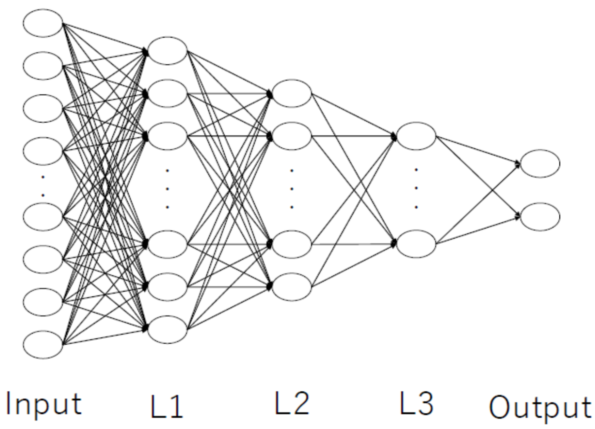

Fig. 6 Construction of stacked autoencoders

The stacked autoencoders are used as the most basic prior learning of the deep neural networks [7]. The reason for the selection of soft max function in the output layer is to perform class classification.

As the learning algorithm, we used the back propagation method. The back propagation method is one of the learning methods used in feed forward neural networks. When training examples of input and output data vector pairs are given, it is a method of adjusting the weights of each network connection for predicting outputs for unknown inputs. The purpose is to reduce the squared error between the output value calculated by the network and the target output value. For that the amount of weight update is determined by using the gradient decent method [8]. As a feature of the back propagation method, the connection structure of the network used for output calculation is utilized in learning. It is possible to propagate the error information from the output side to the input side and use only the information existing on both sides of a connection to determine the amount of update of the connection weights. Therefore, the learning process becomes simpler.

E. Classification of driving skills

In order to classify whether it is a high skilled driver or a low skilled driver, we performed a 5-fold cross validation for all 16 drivers × 10 runs using stacked autoencoders.

Driving skill classification accuracy is defined as follows:

$$Accuracy = \frac{N_{HH} + N_{LL}}{N} \tag{1}$$

Here, the following are used:

N_{HH}: Number of correctly classified high-skilled driving runs.

N_{LL}: Number of correctly classified low-skilled driving runs.

N: Total number of runs.

III. Results

We used Matlab 2016a and it's Neural Network Toolbox for implementation of artificial neural network in this experiments.

When all 8 sensor signals were selected, the recognition rate recorded the highest value of 98.1%. All combinations recorded recognition rate of more than 90% (Fig. 7). Table 2 shows the number of units in the Internal layer that recorded the maximum recognition rate in each combination. Table 3 displays result comparison with previous research. All the researches were done using a driving simulator. Tang used wavelet transforms (WTs), applying this to the steering angle and using a neural network and support vector machine (SVM) for learning [9]. Zhang et al. have applied discrete Fourier transform (DFT) to the steering angle and used a neural network, SVM, and decision trees for learning [10]. Chandrasiri et al. have experimented with a combination of multiple features that cover both lateral and longitudinal controls and used principal component analysis (PCA) and SVM and k-nearest neighbor (k-NN) for learning [6]. The accuracy was improved compared to these previous researches.

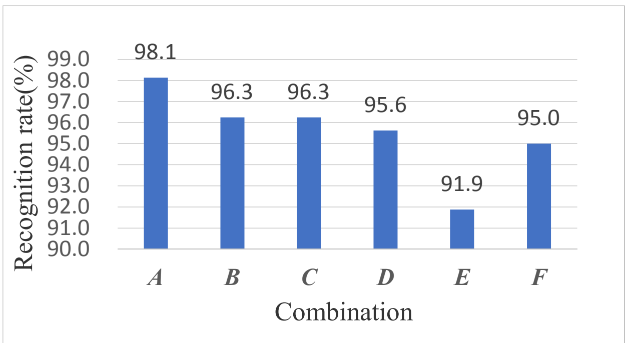

Fig. 7 The maximum recognition rate of each sensor signal combination

Table 2 Number of units in each internal layer that recorded the maximum recognition rate

	Combination					
Internal layer	***A***	***B***	***C***	***D***	***E***	***F***
L1	120	100	130	110	110	110
L2	70	70	80	70	80	70
L3	10	20	10	10	20	10

Table 3 Result comparison with previous research

Research	**Target driving Scene**	**Data**	**Method**	**Classification accuracy(%)[a.]**
This research	Curving section	16 drivers, Total of 160 runs for a sharp curve	Stacked autoencoders	98
Chandrasiri et al. [6]	Curving section	16 drivers, Total of 160 runs for each curve	PCA + SVM	96
			PCA + k-NN	88
	Curving section with segmentation	16 drivers, Total of 160 runs for each segment	PCA + SVM	89
			PCA + k-NN	82
Tang [9]	Double lane change	12 drivers, Total of 403 runs	WT + FFNN[b.]	85
			WT + RBFN[c.]	90
			WT + SVM	91
Zhang et al. [10]	Double lane change	12 drivers, Total of 551 runs	DFT + FFNN	88
			DFT + Decision tree	87
	Lane change on the curve	12 drivers, Total of 514 runs	DFT + SVM	88

[a.] The classification accuracy is shown based on the best case in the original paper
[b.] FFNN feed forward neural network, [c.] RBFN radial basis function networks

IV. DISCUSSION

From the experimental results, it is considered that the recognition rate varies depending on the combination of sensor signals. In this experiment, we focused on the behavior of the driver and the vehicle, the direct operation by the driver, the speed of the vehicle and the ease of obtaining data when combining sensor signals. Among the six combinations, when all eight sensor signals were selected (combination A), the highest recognition rate of 98.1% was recorded. From this results, we can say that it is possible to classify driving skills with high accuracy by considering combinations of multiple sensor signals using stacked autoencoders.

In the stacked autoencoders, the recognition rate changes as the number of internal layers and the number of units change. It may be possible to improve the maximum recognition rate by increasing the number of internal layers and number of units in each internal layer over a wider range.

V. CONCLUSIONS AND FUTURE WORK

We were able to classify the driving data of high skilled and low skilled drivers with high accuracy using stacked autoencoders. In the experiments, driver's driving skills were classified by combining sensor signals of curve driving data acquired from a driving simulator. As a result, a maximum driving skill recognition rate of 98.1% was achieved. In this research, a sharp curve with a radius (R) of 50 m and an intersection angle (IA) of 90 ° was used in the analysis. However, it is necessary to verify whether a high recognition rate can be recorded at other curves. Also, we used stacked autoencoders in this research, however there are other deep learning method such as convolution neural networks. It is necessary to try whether these methods can obtain high recognition rate in our future research.

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