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Modeling Driver Operation Behavior by Linear Prediction Analysis and Auto Associative Neural Network

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***Abstract*—This paper presents a new method for modeling driver operation behavior. The proposed method is based on using the predictor coefficients as feature vectors extracted from driving operation signal by linear prediction analysis (LPA). The distribution of the feature vectors is captured by employing auto associative neural networks (AANN) model. The performance of the model was evaluated through driver identification process and the results obtained demonstrate that the model can grasp the individual characteristics of the driver.**

***Index Terms*—driver model, linear prediction analysis, auto associative neural network, driver identification**

I. Introduction

Traffic accident is a serious problem causing not only high number of death but also impact to economic losses [1]. It is reported that in 2002 roughly 1.2 million people died as a results of traffic accident. In addition, more than 20 million people around the world are estimated to be injured or disabled each year. In economic perspectives, the costs of road accident have been estimated at US$518 billion in 2004 and increasing every year. Analysis studies on causal factors of road traffic accidents concluded that human error is the major factor contributes to the accidents, while environmental and vehicular contribute to the second and third factors of the accidents, respectively [2,3,4]. Human error here means that the behavior of the driver has deviated from the expected standard of performance prior to the accident. Thus, understanding human driving behavior is a key recipe to find better solution to eliminate or at least decrease the problem.

A problem of fundamental interest is characterizing such driving behavior in term of driver models. There are two major reasons why we are interested in developing driver model. First of all, the model usually work well in practice, and enable us to realize important practical systems such as prediction systems, recognition systems, identification systems, etc., in a very efficient manner. Secondly, driver model can provide the basis for a theoretical description of human behavior in particular driving situation which can be used to analyses in order to understand the driver characteristic and performance that cause the accident. Numerous of research works to understanding and modeling human driver have been conducted for the past five decades [5,6]. Most of the previous research uses vehicle status signal and environment information in their modeling [7,8,9]. However, for the purpose of analyzing driver behavior, it is appropriate to use in-vehicle signal (i.e. speed, gas, brake and steering operation signal) in the modeling because these signal contain more information about the driver [10]. Moreover, collecting outside signals such as range and relative speed are sensitive to environmental condition as well as relatively at higher cost.

Traditionally, Gaussian mixture model (GMM) is used to represent the complex plane characterizing the distribution of the features. Although, the GMM appears to be sufficient to describe the feature vectors, the model have some drawbacks which are the shape of the components of the distribution is assumed to be Gaussian and the number of mixtures should be fixed in advance. In order to overcome these drawbacks, we proposed a new method for modeling driver operation behavior using linear prediction analysis (LPA) and auto associative neural network (AANN) as alternative to GMM. The method involved with features extraction from driver operation signal by calculating coefficients of linear predictive model. These feature vectors are then discriminated through an auto associative neural network. Eventually, the model performance was evaluated by driver identification process where feature vectors from the same and different driver are used and proved the effectiveness of our approach. Furthermore, we shows that the model can be used for driver behavior classification.

II. Review of LPA and AANN

A. Linear Prediction Analysis (LPA)

Data reduction is a crucial step in any analysis and modeling process. In general, original data contains irrelevant information that will cost for high use of memory and affect the model

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performances. Therefore, it is important to extract relevant features that can best describe the data. In this study, linear prediction analysis (LPA) [11,12] was used to obtain features vector from output signal, where the value of the output signal at time n is predicted based on linear combination of its past values and present and past inputs as described in (1).

$$\hat{g}(n) = \sum_{k=1}^{p} a_k g(n-k), \qquad 1 \leq k \leq p \tag{1}$$

Where $\hat{s}(n)$ is the predicted output at time n, a_k, 1¡k¡p, b_l, 1¡l¡q, are the predictor coefficients and the parameter of the system. The mean square of the prediction error E over N data point is defined as in (2).

$$E = \sum_{n=0}^{N} e^2(n) = \sum_{n=0}^{N} [g(n) - \hat{g}(n)]^2 \tag{2}$$

The square error, E is minimized by setting:

$$\frac{\delta E}{\delta a_i} = 0, \qquad 1 \leq i \leq p \tag{3}$$

The system parameters are estimated in a least-squares sense, through clustering-based technique [13]. More in detail, this technique composed of six steps: build small local data sets (LDs) from the original data; identify a parameter vector based on each LD; partition the parameter vectors in s clusters; classify the original data; estimate the s sub models; and estimate the model partition. The identified parameters are used as feature vector of driver operation signal.

B. Auto Associative Neural Network (AANN)

AANN is a feed forward neural network consists of an input layer, a number of hidden layers and an output layer connected in the manner of classic back propagation network. The aim of this network is to perform an identity mapping of the input space. Thus, the target used to train the network is the input vectors themselves, which means the input and output layers have same number of units [14]. Theoretically, three hidden layers are sufficient for the AANN. The first and third hidden layer is known as mapping and demapping layer, respectively. The second hidden layer is called as bottleneck layer. An example of AANN architecture with five layers is shown in figure 1. The bottleneck layer plays an important role in the functionality of the AANN. Its dimension required to be smallest in the network in order to prevent the network from performing one-to-one mapping during the training process, which would insignificantly satisfy the objective function. The training process computes network weights so that residual between the reconstruction of the value at the output layer and the input vectors are smallest, in a least-squares sense.

III. Experimental Setup and Method of Data Collection

The experiment was conducted using the Mitsubishi Precision Co. Inc., DS6000 driving simulator as shows in figure 2. The aim of this experiment is to collect ordinary driving signal of the test drivers. Eleven drivers (males and females) performed driving task up to thirteen times in predetermined computer simulated driving course. The driving course was designed to imitate real environment in town and residential areas with includes various situation such as intersection, single lane, double lane, traffic light, turn left and turn right. Figure 3 shows the outline of driving course used in this study.

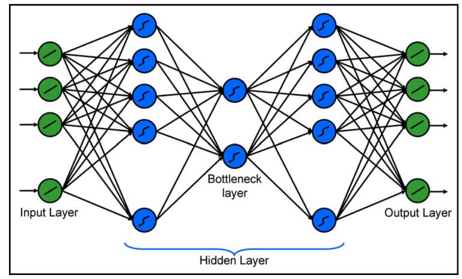


Fig. 1. The proposed structure of AANN model

Fig. 2. Mitsubishi Precision Co. Inc., DS6000 driving simulator

The method of data collection is shown in figure 4. Two types of driving course (A and B) are used with same outline but different in traffic volume. In addition, three driving condition that are normal driving, time constrain and free style was applied to each driver in the experiments. The type of courses and conditions are given in Table I. During the experiment, driver behavior data (gas and brake pedal levels and steering angles) and vehicle status data (speed, acceleration and positions) were measured and recorded by a computer at 100ms time interval. In this paper, only pedal, speed and acceleration signal are used in the analysis. Figure 5 shows example of gas pedal operation signal from two different drivers.

IV. A proposed method for modeling driver operation behavior

The suggested method for modeling driver operation behavior can be summarize into three steps: (1) features extraction from training and testing data, (2) construct AANN model for each driver and (3) testing the model using sets of feature from

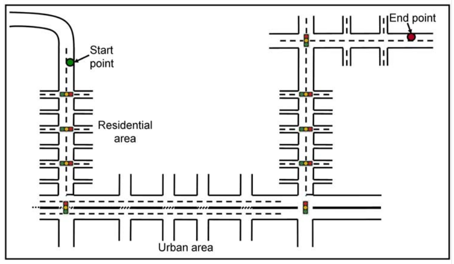


Fig. 3. Outline of driving course

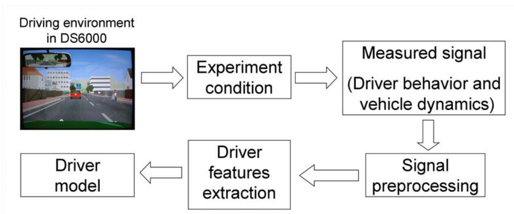
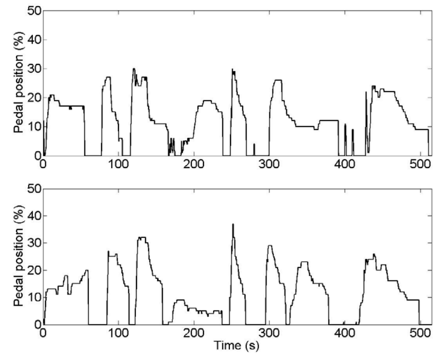
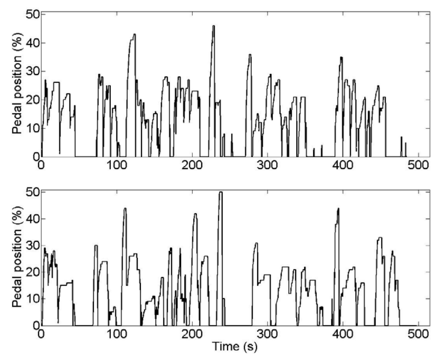


Fig. 4. Method of data collection



(a) Driver A



(b) Driver B

Fig. 5. Example of gas pedal operation signal from two different drivers

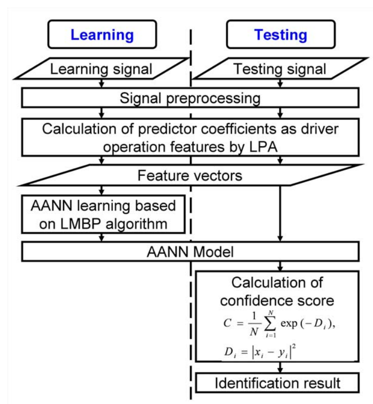


Fig. 6. flowchart of method for modeling driver operation behavior

the same and different driver. The flowchart of the process is shown in figure 6.

AANN is a feed-forward network with the desired output being same as input vector and hence the input and output layers have the same number of units. This architecture allows the network to learn and capture associative properties of features vectors. Five-layer AANN model as shown in figure 1 was used in this study with first and fifth layer are input and output layer, respectively. The second and fourth layers have double number of neurons than input layer whereas the center layer has two neurons. flow chart

The Levenberg-Marquardt (LM) algorithm [15] has been used for training function because this algorithm is widely used for optimization and it outperforms simple gradient descent and other conjugate gradient methods in a wide variety of problems. In this study, the aim of the Levenberg-Marquardt algorithm is to compute the weight vector w such that $E(w)$ is minimum.

TABLE I
TYPES OF COURSE AND CONDITION USING THIS EXPERIMENT

Experiment Number	Course	Condition
1-3	A	Normal driving
4	C (special environment)	(No data recorded)
5-8	A	Normal driving
9	C (special environment)	(No data recorded)
10	B	Normal driving
11	A	Time constrain
12	B	Time constrain
13	A	Free driving

$$E(w) = \sum_{l=1}^{k} e_l^2(w) \tag{4}$$

where $e_l(w) = (x_l - y_l)$ and x_i is the desired value of output neuron i, y_i is the actual output of that neuron. Using the Levenberg-Marquardt algorithm, a new weight vector $w_k + 1$ can be obtained from the previous weight vector w_k as follows:

$$w(k+1) = w_k + \delta w_k \tag{5a}$$

TABLE II
SUMMARY OF DRIVER MODEL PERFORMANCE

Driver	Positive Test Data (P)	Negative Test Data (N)	Accuracy (%)
	True Positive (TP)	True Negative(TN) (TN)	$\frac{TP+TN}{P+N}$
A	5/6	97/126	77.27
B	5/6	107/126	84.85
C	6/6	106/126	84.85
D	3/4	92/128	71.97
E	5/6	106/128	82.84
F	6/6	114/126	90.91
G	5/6	105/128	82.09
H	5/6	113/128	88.06
I	4/6	105/128	81.34
J	4/6	92/128	71.64
K	5/6	106/128	82.84
Average Identification Rate			81.70

where

$$\delta w_k = \frac{-(J_k^T f(w_k))}{(J_k^T J_k + \lambda I)} \tag{5b}$$

In (5b), J_k is the Jacobian of f evaluated at w_k, λ is the Marquardt parameter, I is the identity matrix [16]. The Levenberg-Marquardt algorithm was summarized as follows:

(i) Calculate $E(w_k)$,
(ii) Begin with a small value of λ e.g. λ= 0.01,
(iii) Solve (5b) for δw_k and compute $E(w_k + \delta w_k)$,
(iv) If $E(w_k + \delta w_k) <$ target error, stop the training process,
(v) If $E(w_k + \delta w_k) \geq E(w_k)$, increase λ by a factor of 10 and repeat step (iii),
(vi) If $E(w_k + \delta w_k) < E(w_k)$, decrease λ by a factor of 10, update $w_k : w_k \leftarrow w_k + \delta w_k$ and repeat step (iii).

V. EXPERIMENTAL RESULT AND DISCUSSIONS

Driving data from eleven drivers with six experiments of each driver have been used for feature extraction and modeling. For each experiment, two sets of predictor coefficients are calculated. Half of these sets were used for training, while the other half was used for testing. The model of each driver will captures the distribution of the features for that driver, which is expected to be unique and gives high confidence score for same driver. The confidence score of the model for all test feature vectors was calculated as in (7):

$$C = \frac{1}{N}\sum_{i=1}^{N} e^{-D_i}, \qquad D_i = [x_i - y_i] \tag{6}$$

Where x_i is the input vectors, y_i is model output and N is number of features vector.

Performance of the model was evaluated through driver identification process. Identification rate is calculated based on confidence score of the model for each positive test data (same driver) and negative test data (different driver). Table II shows the summary of driver's model performance.

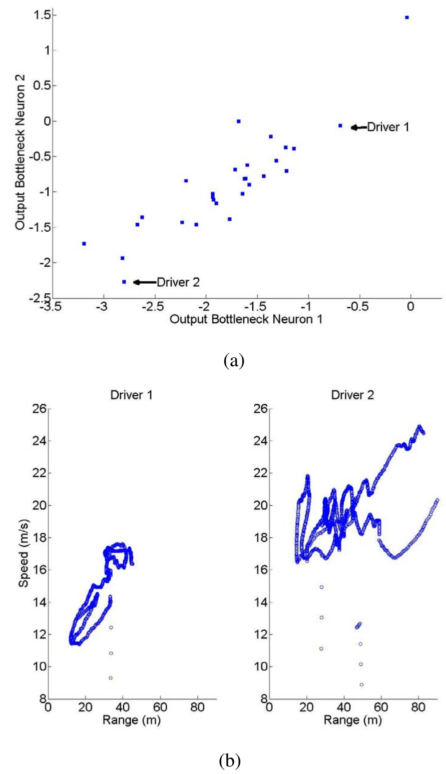


Fig. 7. (a) Output of bottleneck layer and (b) observation of two driving behavior

VI. DIAGNOSIS OF DRIVER BEHAVIOR BY AANN MODEL

The bottleneck layer of AANN provide an important information of the driver operation behavior. In order to the network to accurately reproduced the network input at the output layer, the information in the input must be preserved at the bottleneck layer. Therefore, this layer contains principal characteristic of the feature vectors. Figure 7 show the output of bottleneck layer for several driver and the observation of two driving behavior. As can be seen from the figure, the value of the bottleneck layer can be used to demonstrate different style of driving operation behavior. For example, driver 1 is more sensitive to the range and velocity of the lead vehicle compare to driver 2.

VII. CONCLUSIONS AND FUTURE WORK

LPA provides a good approximation of driver operation signal and reduce a number of raw data into a number of features vector. AANN can capture and learn well the distribution of features vector of the driver. This is proved by having high confidence score for data from same driver and low confidence score for different drivers. The average performance of driver model using the proposed method is 81.70%. Moreover, the output of the bottleneck layer shows an important information of the driver operation behavior. Nevertheless, the model performance still can be improved through coefficients selection and optimizing network structure, which will be explored in future.

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