A Study of Driver State Classification Using In-vehicle Sensors by Neural Networks

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ABSTRACT

A driver support system for a safeguard against human errors, which cause traffic accidents, has created considerable interests in recent years. Identification of driver states is needed for a suitable driver support system. In this paper, we have proposed the method of classifying driver states using in-vehicle sensors, for a stable measurement with the non-extra workload, by feed-forward neural networks. To investigate the realizability of the method, the data sampling experiment was carried out in the simple circumstance. The data on each driver state are obtained by ordering a driver to drive under some condition. The simple data analysis is carried out by plotting the time series, and we can see the time series of left/right gravity is the most characteristic indicator on the simple left curved course. As a simulation result, it is confirmed that the simple neural network classification system was created by the data screening method using the shape of the neural network's learning curve.

Keywords: Advanced Safety Vehicle, Active Safety, Driver Support System, Driver State, Neural Network

1. INTRODUCTION

A driver support system for a safeguard against human errors, which cause traffic accidents, has created considerable interests in recent years [1-8]. Motor-vehicle traffic accident is considered as one of the biggest problems in Japan, and it is said that most traffic accidents are caused by human errors. Therefore, it is important for a driver's advanced safety to avoid human errors by supporting him or her.

For a suitable driver support system, identification of driver state (e.g. usual, tired, rough, drowsy, etc.) is needed. Because, an unusual driver state often causes driver's cognitive error, judgment error, or operation error [1], and the suitable way of supporting driver depends on the driver state.

Broadly speaking, there are two ways of identifying driver states: one is physiological, where an electrocardiogram or a frequency of a blink is used [4, 5]; and the other is physical, where in-vehicle sensors are used [6-8]. The use of most physiological ways enforces the extra workload on drivers, or makes a stable measurement difficult. Realization of practical driver support system, the extra workload on drivers should be as minimized as possible.

In this paper, we propose the method of classifying driver states using in-vehicle sensors by artificial neural networks [9-13], and investigate the realizability of the method. For a stable measurement with the non-extra workload, the time series of speed, accelerator stroke, brake stroke, steering angle, left/right gravity, etc. acquired by in-vehicle sensors are used. On the other hand, multi-layered neural networks are used as the adaptive nonlinear pattern classification system.

In section 2, we state the concept of the proposed method of driver state classification. In section 3, we present the data sampling experiment that was carried out on the simple left curved course. After that, a simple data analysis is carried out by plotting the acquired data. In section 4, we present driver states classifying experiment by neural networks, and the data screening method using the shape of the neural network's learning curve is proposed. In section 5, we conclude the paper.

2. METHOD

We adopt the strategy of classifying driver states in three phases: driver identification, circumstance identification, and driver state classification (Fig. 1). A driver state can have a dependence on a driver and a circumstance. Therefore, under the divide-and-conquer strategy, first of all, a driver is identified, secondary, a circumstance is identified and, thirdly, a driver' state is classified using time series by in-vehicle sensors.

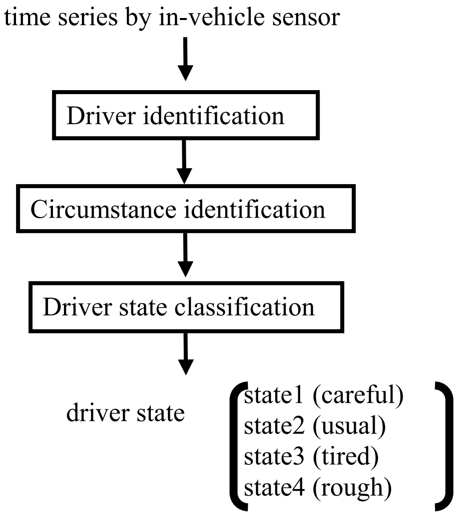


Fig. 1 Strategy of Driver State Classification

Driver states are classified by multi-layered feed-forward neural networks using the time series. We adopt the error back-propagation method [9-13] for learning given by

$$\Delta W_{ij}(t) = -\eta \delta_j O_i + \alpha \Delta W_{ij}(t-1) + \beta \Delta W_{ij}(t-2),$$

where $Wij(t)$ is weight from unit i to j, $\Delta Wij(t)$ is the change of weight $Wij(t)$, t is the sample, δ is the generalized error, O is the output value, η is the positive learning coefficient, α is the proportional coefficient of inertia term, β is the proportional coefficient of oscillation term.

In this paper, we consider a driver and a circumstance to be identified in advance for conciseness. They could be identified by using an identification number, or the global positioning system, etc.

3. DATA SAMPLING EXPERIMENT

The time series by in-vehicle sensors are collected by a driving experiment in a simple circumstance. The data on each driver state are obtained by ordering a driver to drive under some condition. As an experimental result, it was found that the time series of left/right gravity was the most characteristic indicator by plotting the time series.

3.1. Data Sampling Method

The time series by in-vehicle sensors are collected by a driving experiment in a simple circumstance. The experiments are carried out for four beginner drivers, within three years of experience as a driver, as we think beginner drivers tends to show distinctive time series.

The driving course is curved left simply (Fig. 2), no other cars on the course, for simplicity. For each run, it spends about 1 minute to drive a car on the complete course. The in-vehicle sensors can collect the time series of left/right gravity, speed of car, accelerator stroke, brake stroke, steering angle, etc.

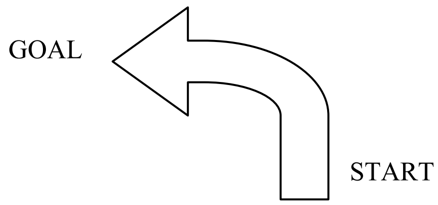


Fig. 2 The Simple Left Curved Driving Course

The data on each driver state are obtained by ordering a driver to drive under some condition (Table 1). For each driver, two trials are carried out basically in different days; for each trial, four driver states experiments, careful, usual, rough, and tired in order, are carried out for about one hour.

Table 1 The Method to Get the Data on Each Driver State

careful	Ordering a driver to drive like taking a driver license examination
usual	Ordering a driver to drive as usual; and measuring the driving time
rough	Ordering a driver to drive faster than the time measured in the usual case
tired	Ordering a driver to drive as usual after above experiments

3.2. Data Analysis by Plotting Time Series

As an experimental result, it was found that the time series of left/right gravity was the most characteristic indicator by plotting the time series (Fig. 3).

Fig. 3 shows that the time series vary greatly, which means that it is difficult to clasify them into four classes by simple statistic, e.g. mean value, even though we could classify them manually into four classes roughly each driver.

In detail observation, we can see that some of the shapes of the different driver states time series are very similar. In addition, it was confirmed that the shape of left/right gravity time series was different among drivers. It was also confirmed that the shape is a little bit different between trials even the same driver.

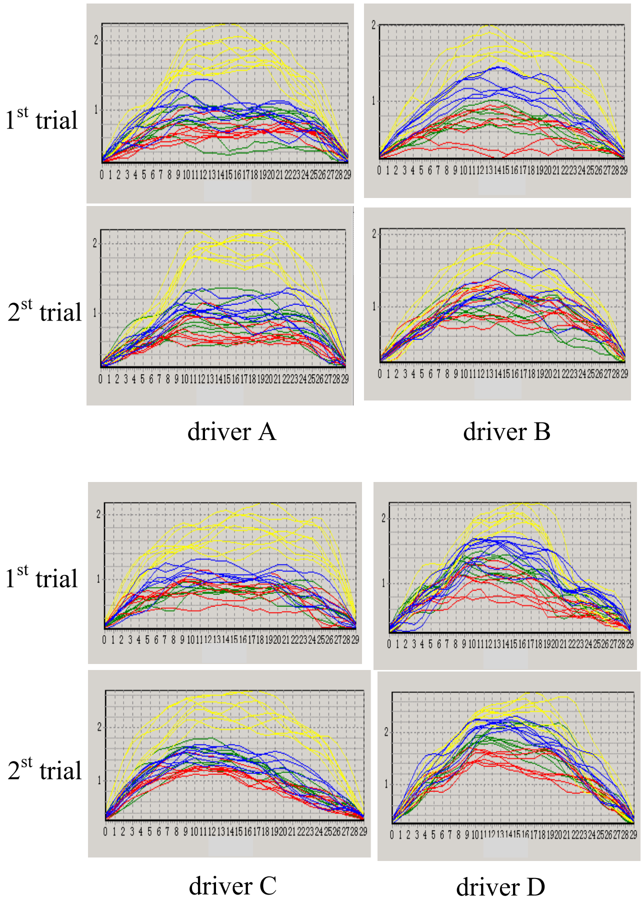


Fig. 3 Time Series of Left/Right Gravity
(time vs. gravity; normalized)
red lines: careful; green lines: usual; blue lines: tired;
yellow lines: rough

4. DRIVER STATES CLASSIFYING EXPERIMENT BY NEURAL NETWORKS

In this chapter, we try to classify driver states by three-layered feed-forward neural networks [9-13] using the left/right gravity time series at the left curve. At first, we make the classifier corresponding to a single trial, secondary, corresponding to a single driver. As a result, it was confirmed that the simple classification system was created using the time series data by the data screening method using the shape of the neural network's learning curve.

4.1. Classifying Method by Neural Networks

We try to classify driver states by three-layered feed-forward neural networks using the left/right gravity time series, which is confirmed to be the most characteristic indicator, at the left curve. We input the date consisting of 30 samples, moving average of the time series. The hidden unit number is 30, and the output unit number is 4, which corresponds to classification patterns, careful, usual, tired, and rough. The range of the left curve course is defined as the range while the amplitude of left/right gravity is larger than a constant value.

At first, we make the classifier corresponding to a single trial, secondary, corresponding to a single driver. From the shape of the left/right gravity time series, the difficulty of converging in learning process is predictable, because some of the shapes of the different driver states time series are very similar, and the shape is a little bit different between trials each driver (Fig. 3).

Therefore, the data screening method using the shape of the neural network's learning curve is proposed. When the learning does not converge or it is difficult to converge, the boundary hyper-plane can be too complex or similar data can exist in different classes, i.e., abnormal data can exist in the learning data.

In this experiment, we not only try to classify driver states by feed-forward neural networks using the left/right gravity time series, but also study whether the data screening method using the shape of its learning curve works correctly.

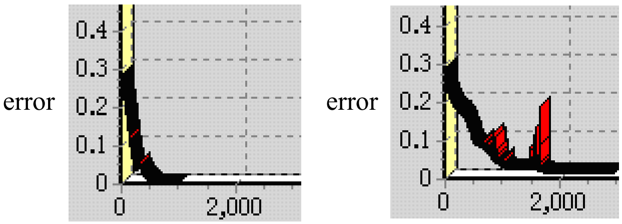
At last, we apply the time series of both of accelerator stroke, brake stroke, and steering angle, where each consists of 30 moving average samples, instead of left/right gravity for comparison.

4.2. Simulation Results

At first, we tried to make the classifier corresponding to a single trial by using all of the data for training. Withdrawing the abnormal data, which were determined by the shape of the learning curve (Fig. 4), enabled the learning to converge. By the screening method, about 5% of all the data is cosidered as the abnormal data. In addition, it was confirmed that the shape of the abnormal data is similar to that of another driver state's data by plotting the data.

Secondary, we evaluated another trial of same driver using the learned neural network. As a result, the correct classification ratio was about 50%, for the difference of time series between trials each driver (shown in Fig. 2), and the small data sets for learnig.

Thirdly, we tried to make the classifier corresponding to a single driver by using all of the data for training. Withdrawing the abnormal data, which were also determined by the shape of the learning curve, enabled the learning to converge, where about 10% of all the data is considered as the abnormal data.



iteration

(a) easy to converge

iteration

(b) difficult to converge

Fig. 4 Shapes of the Neural Networks' Learning Curve (lerning iteration vs. error)

Hence, it was confirmed that the simple classification system was created using the time series data by the data screening method using the shape of the neural network's learning curve for any driver.

At last, we tried to make the classifier corresponding to a single trial by using all of the time series of both of accelerator stroke, brake stroke, and steering angle instead of left/right gravity for learning. As a result, almost all of the learning converged without withdrawing the abnormal data. It is thought that the results are caused by huge dimension of input space respect to the amount of learning data and almost all of the shapes of the time series being different.

5. CONCLUTIONS AND FUTURE WORKS

In this paper, we have proposed the method of classifying driver states using in-vehicle sensors by neural networks. To investigate the realizability of the method, the data sampling experiment was carried out in the simple circumstance. As a simulation result, it is confirmed that the simple neural network classification system was created by the data screening method using the shape of the neural network's learning curve.

Future works are as follows, 1) investigating whether the classifier can absorb the difference among trials, and 2) studying that the experimental data on each driver state are obtained correctly.

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