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PAPER

Driver Identification Using Driving Behavior Signals

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SUMMARY In this paper, we propose a driver identification method that is based on the driving behavior signals that are observed while the driver is following another vehicle. Driving behavior signals, such as the use of the accelerator pedal, brake pedal, vehicle velocity, and distance from the vehicle in front, were measured using a driving simulator. We compared the identification rate obtained using different identification models. As a result, we found the Gaussian Mixture Model to be superior to the Helly model and the optimal velocity model. Also, the driver's operation signals were found to be better than road environment signals and car behavior signals for the Gaussian Mixture Model. The identification rate for thirty driver using actual vehicle driving in a city area was 73%.

key words: driving behavior, signal processing, pattern recognition, biometrics

1. Introduction

With increased emphasis being placed on the practicality and safety of vehicles, the recognition of drivers and their driving behaviors has become much more important. The ability to recognize a driver and his/her driving behavior could form the basis of many applications, such as driver authentication for security purposes, the ability to detect the driver becoming drowsy, and the customization of vehicle's functions to suit that driver's personal preferences. A key technology is "human behavior signal processing", which involves the processing and recognition of human behavior signals such as the operation of the accelerator pedal. In this paper, we present a driver identification method that is based on such behavior signals.

"Driving behavior" is a cyclic process, as described below (Fig. 1).

1. The driver recognizes the road environment, consisting of, for example, the road layout and the distance from the vehicle in front.
2. The driver determines the action that he or she should take, such as, accelerating, braking, and/or steering.

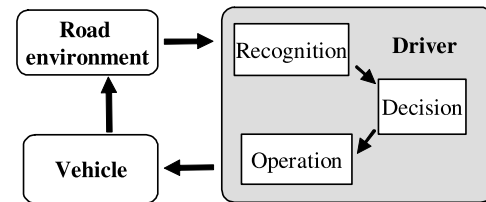


Fig. 1 Basic dynamics of driving behavior, vehicle status, and road environment.

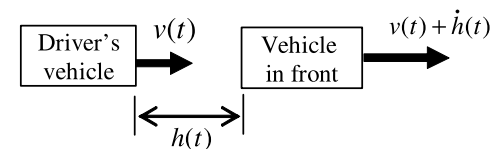


Fig. 2 Car following.

3. The driver operates the accelerator pedal, brake pedal, and/or steering wheel.
4. The vehicle status (ex. velocity, yaw rate) changes according to the driver's operation.
5. The road environment (ex. distance from the vehicle in front) changes according to the vehicle status.

The most elementary and familiar driving behavior is "car following", which involves maintaining a constant distance from the vehicle in front and adjusting the relative velocity accordingly (Fig. 2).

In this figure, $v(t)$ is the velocity of the driver's vehicle, and $h(t)$ is the distance from the vehicle in front. The velocity of the vehicle in front is $v(t) + \dot{h}(t)$. $\dot{h}(t)$ is the temporal differential of $h(t)$.

In this research, we aimed to identify a driver by using the driving behavior signals that are observed while the driver is performing the "car following" task.

2. Driving Simulator

We used a driving simulator to collect the driving behavior signals. The driving simulator acquires signals corresponding to the operation of the accelerator pedal, brake pedal, and steering wheel, calculates the corresponding vehicle behavior, and then displays a representation of the road environment on an LCD monitor (Fig. 3). The road is a two-lane highway with a layout typical of an actual Japanese highway. The vehicle in front acts as if it were negotiating mild

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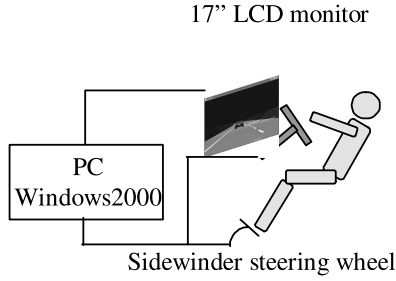


Fig. 3 Driving simulator.

traffic congestion.

3. Model Comparison

We compared two different strategies for driver identification based on driving behavior signals. In the first approach, a physical driving model was used for characterizing the driving in a parametric manner, i.e. the parameters of the dynamic system characterize the driver. For the physical model of car following, we use the Helly model [4] and the optimal velocity model [5], since these two models are frequently used in a wide range of applications [2], [3].

In contrast, in the second method, the characteristics of the driver is represented by the distributions of the signals based on Gaussian Mixture Model (GMM). In the GMM approach, by estimating the joint distributions of the signals and its time derivatives, we can model both static and dynamic properties of the signals implicitly.

3.1 Parametric Approach: Helly Model

3.1.1 Model

The most familiar model for car following is the “stimulus-response model” [1]–[3]. A difference in the velocity of the vehicle in front, as well as a change in the distance from that vehicle, act as stimuli to the driver, who responds by either accelerating or decelerating.

$$\dot{v}(t + T) = C_1 \dot{h}(t) + C_2 \{h(t) - D\} \quad (1)$$

C_1 , C_2 is the response sensitivity to the stimulus, D is the optimum distance from the vehicle in front, and T is the response delay. These values may be the constants or the functions of other variables. While many models have been proposed to represent C_1 , C_2 , D , T , we chose to use the Helly model.

$$\dot{v}(t + T) = \beta_1 \dot{h}(t) + \beta_2 h(t) + \beta_3 v(t) + \beta_4 \quad (2)$$

$T, \beta_1, \beta_2, \beta_3, \beta_4$ are constant parameters. As this is a linear model, the parameter estimation is stable and the physical meanings of these parameters can be interpreted easily.

Table 1 Experiment conditions for model comparison.

Test subjects	Eight males, all in their twenties, all holding driver's licenses
Task	Three minutes of car following
Sessions	Four attempts at each of two different road layouts (total of eight sessions for each subject)
Measured signals	Velocity of driver's vehicle, velocity of vehicle in front, distance from vehicle in front

3.1.2 Identification Method and Results

We performed the experiment described in Table 1.

For the T parameter, we used a value of 500 ms, which we derived from other simple stimulus-response experiments.

The identification process was as follows.

1. Parameter vector $x = (\beta_1, \beta_2, \beta_3, \beta_4)'$ was calculated for the data obtained from each session, using the least-square-error method.
2. For each driver c , the data obtained from the eight sessions was divided into six blocks of learning data and two blocks of estimation data.
3. For each driver c , the average parameter vector μ_c and the covariance matrix Σ_c were calculated using the parameter vectors x of the six blocks of learning data.
4. For each block of estimation data, we calculated the Mahalanobis distance D_c between the estimation data and the average for each driver. The estimation data was identified as that for the driver having the smallest Mahalanobis distance.

$$D_c = (x - \mu_c)' \Sigma_c^{-1} (x - \mu_c) \quad (3)$$

A cross-validation test with the above process gave an identification rate of 43.8%.

3.2 Parametric Approach: Optimal Velocity Model

3.2.1 Model

Another model that can be applied to the car following task is the “optimal velocity model”. This model assumes that a driver has his/her own optimal velocity for a given distance from the vehicle in front, and accelerates/decelerates according to the difference between the current velocity and the optimal velocity.

$$\dot{v}(t + T) = \alpha \{V_{\text{opt}}(h(t)) - v(t)\} \quad (4)$$

$$V_{\text{opt}}(h) = V_{\text{max}} [1 - \exp\{-a(h - h_0)\}] \quad (5)$$

$V_{\text{opt}}(h)$ is the optimal velocity function, α is the sensitivity parameter, V_{max} is the maximum velocity, and a, h_0 is the parameter that represents the driver's optimal velocity property.

3.2.2 Identification Method and Results

For the parameter T, V_{max} , we used 500 ms and 32 m/s which we derived from another simple experiment.

The identification method is same as that described in Sect. 3.1. The parameter for identification is a, h_0, α .

The identification rate was found to be 54.7% with a cross-validation test.

3.3 GMM Approach

3.3.1 Model

The Gaussian Mixture Model (GMM) is well known and used in many applications [6]. GMM is a statistical model that is a linear combination of Gaussian basis functions. The output probability of a GMM λ to the observation vector \mathbf{o} is as follows:

$$b(\mathbf{o} | \lambda) = \sum_{m=1}^M \omega_m \mathcal{N}_m(\mathbf{o}) \quad (6)$$

$$\lambda = \{\omega_m, \mu_m, \Sigma_m | m = 1, 2, \dots, M\} \quad (7)$$

where \mathbf{o} is an observation vector, λ is a Gaussian mixture model, $b()$ is an output probability, M is the number of mixture functions, μ_m is the centroid vector of the m th mixture function, and Σ_m is the covariance matrix of the m th mixture function.

ω_m is the mixture weight for the m th mixture function and satisfies the following equation:

$$\sum_{m=1}^M \omega_m = 1 \quad (8)$$

$\mathcal{N}_m(\mathbf{o})$ is the m th mixture function and is defined by the equation below:

$$\mathcal{N}_m(\mathbf{o}) = \frac{1}{\sqrt{(2\pi)^D |\Sigma_m|}} \cdot \exp \left\{ -\frac{1}{2} (\mathbf{o} - \mu_m)' \Sigma_m^{-1} (\mathbf{o} - \mu_m) \right\} \quad (9)$$

where Σ_m, Σ_m^{-1} is the covariance matrix and the inverse of the covariance matrix, and $(\mathbf{o} - \mu_m)'$ is the transpose of $(\mathbf{o} - \mu_m)$. In this work, we use a diagonal matrix for Σ_m .

The likelihood of the model λ to the observation vector $\mathbf{O} = (o_1, o_2, \dots)$ is defined by the next equation:

$$P(\mathbf{O} | \lambda) = \prod_{t=1}^T b(o_t) = \prod_{t=1}^T \sum_{m=1}^M \omega_m \mathcal{N}_m(o_t) \quad (10)$$

3.3.2 Identification Method

The experimental data was the same as that described in Sect. 3.1. The identification process was as follows:

1. For each driver c , the eight items of session data were divided into six blocks of learning data and two blocks of estimation data.
2. For each driver c , we estimated the Gaussian mixture model λ_c . The mixture weight ω_m , centroid vector μ_m , and covariance matrix Σ_m are calculated using feature vectors \mathbf{o} of six blocks of learning data with the EM algorithm. The elements of the feature vector were some of $v, \Delta v, h, \Delta h$, where Δx represents the temporal change in value x and is calculated using the following equation:

$$\Delta x(t) = \frac{\sum_{k=-K}^K k x(t+k)}{\sum_{k=-K}^K k^2} \quad (11)$$

where $x(t)$ is the original feature, K is the time window duration (in this work, $2K = 600$ ms). The mixture number is any of 2, 4, 8, or 16.

3. For each block of estimation data, we calculated the likelihood $P(\mathbf{O} | \lambda_c)$ for each driver c . The estimation data is identified for the driver for whom the likelihood is the greatest.

A cross-validation test was done using the above process.

3.3.3 Results

The identification results are shown in Fig. 4. V is the velocity, H is the distance from the vehicle in front, and Δ represents the temporal change. Modeling the dynamics of the

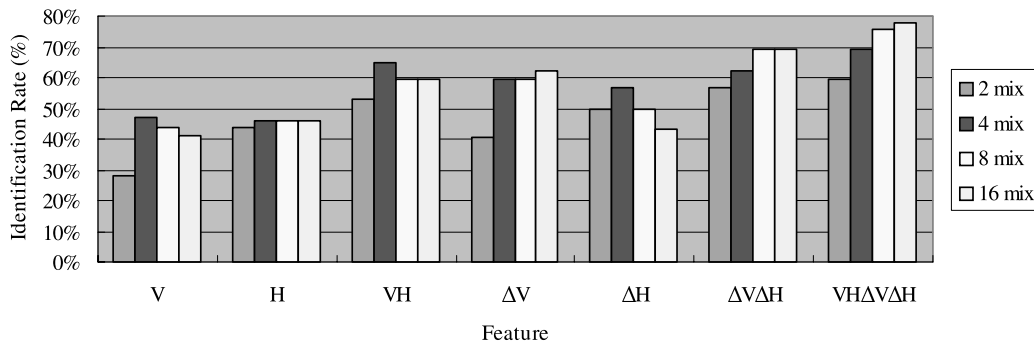


Fig. 4 Driver identification rate of GMM for driving signals (V : car velocity, H : headway distance, ΔV : temporal change of V , ΔH : temporal change of H).

driving signals is also important in the GMM approach [7]. The best identification rate was 78%, which was obtained using V , ΔV , H , ΔH .

The Helly model described in Sect. 3.1 uses the variable v , \dot{v} , h , \dot{h} and the identification rate was 43.8%. The identification rate of GMM using a similar feature V , ΔV , H , ΔH was 78%. The optimal velocity model described in Sect. 3.2 uses the variable v , \dot{v} , h and the identification rate is 54.7%. The identification rate of GMM using less feature V , H is 69%. In each case, the GMM model was found to be better than the parametric physical model. This result suggests that:

- GMM can be used to represent the underlying dynamics between features with the joint distribution function.
- GMM can represent the non-linearity and the stochastic aspects with a probabilistic distribution function.

4. Feature Comparison for GMM

In the previous section, we showed that the GMM model exhibits good identification performances. In this section, then, we compare the features of GMM.

To check the properties of the features, we performed another experiment (Table 2). The identification method was the same as that described in Sect. 3.3.

4.1 Single Feature

The identification results are shown in Figs. 5 and 6. V is

Table 2 Experiment conditions for feature comparison.

Test subjects	Twelve males, all in their twenties, all holding driver's licenses
Task	Three minutes of car following
Sessions	Four attempts at each of two different road layouts (total of eight sessions for each subject)
Measured signals	Driver's vehicle velocity V , distance from the vehicle in front H , accelerator pedal angle A , brake pedal angle B

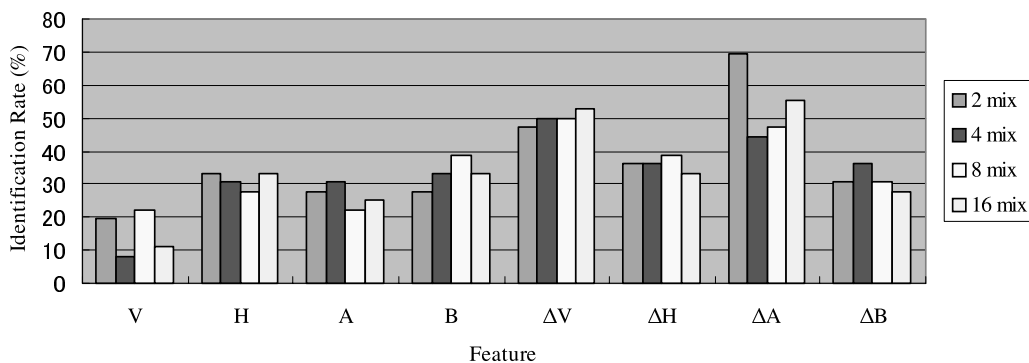


Fig. 5 Driver identification rate of GMM for driving signals (A : accelerator pedal angle, B : brake pedal angle, ΔA : temporal change of A , ΔB : temporal change of B).

the driver's vehicle velocity, H is the distance from the vehicle in front, A is the accelerator pedal angle, B is the brake pedal angle, and Δ represents the temporal change. The result shows that the accelerator pedal behavior signal offers the best means of identification. This suggests the reason as follows:

- As the accelerator pedal is operated directly by the driver, it is best at preserving the personal property information.
- The accelerator pedal is operated more frequently than the brake pedal.
- As the vehicle velocity and the distance from the vehicle in front are both results of the convolution of the driver's operation, the physical properties of the vehicle, and the properties of the vehicle in front (Fig. 7), the personal property information can be unclear.

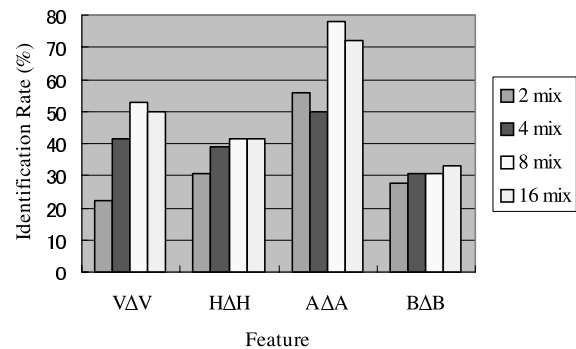


Fig. 6 Driver identification rate of GMM for combination of various driving signals.

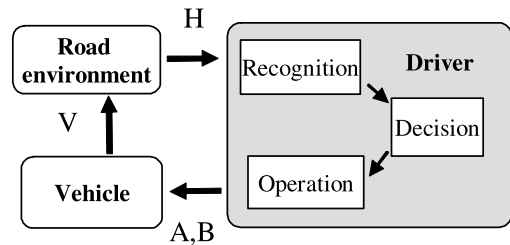


Fig. 7 Basic dynamics and feature variables.

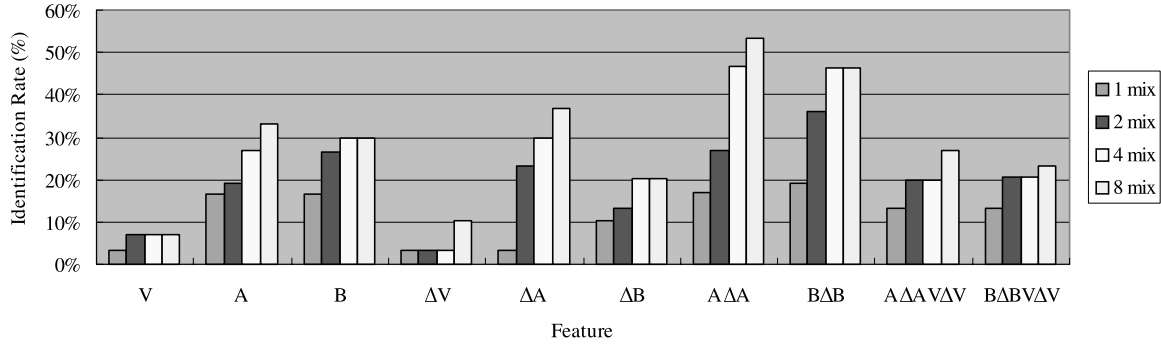


Fig. 9 Driver identification rate of GMM for driving signals of actual vehicle.

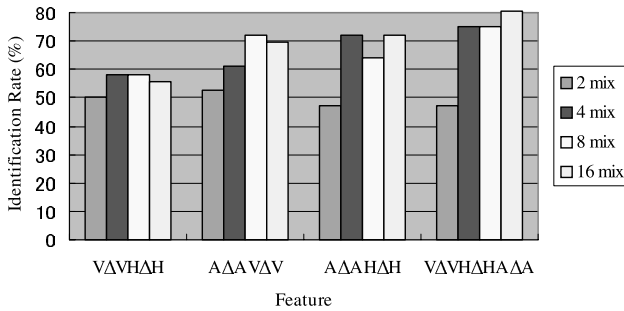


Fig. 8 Driver identification rate for multiple features driving simulator.

Table 3 Experiment conditions for actual vehicle.

Test subjects	Thirty persons, all holding driver's license
Task	Driving in a city area
Session	One attempt (same route for each subject)
Measured signals	Driver's vehicle velocity V , force on accelerator pedal A , force on brake pedal B

4.2 Multiple Features

Figure 8 shows the results for multiple features. This result shows that the feature of the accelerator pedal and the distance from the vehicle in front offer the best combination. This is reasonable, because that these features provide the input and the output for the driver (Fig. 7).

5. Experiments Using Actual Vehicle

5.1 Experiment

As part of an ongoing study of the collection and analysis of multi-layered in-car spoken dialog corpus [9], [10], 800 drivers have driven a specially equipped vehicle in a city area between 1999 and 2001. We used the driving behavior data for thirty drivers in the corpus (Table 3).

5.2 Identification Method

The identification method was the same as that described in Sect. 3.3. The average length of the driving data for each

driver was around 20 minutes. We used the first half 10 minutes for training and the remaining 10 minutes for testing.

5.3 Results

Figure 9 shows the identification rates using single feature and multiple features. A , B , V and Δ indicate the force on the accelerator pedal, the force on the brake pedal, the vehicle speed, and the dynamics respectively.

$A\Delta A$ gives the highest performance. This is similar to the result using the driving simulator because the highest performance feature without H (distance from the vehicle in front) in Figs. 5, 6 and 8 is $A\Delta A$.

To improve the identification rate, we combined the features of the accelerator pedal and brake pedal. As drivers cannot press both pedals simultaneously, the joint distribution of the force on the accelerator pedal and that on the brake pedal have no effect. We used the sum of the log-likelihood of the force on the accelerator pedal and brake pedal. Figure 10 shows the result. The highest identification rate of 73% was obtained using $A\Delta A + B\Delta B$.

6. Conclusion and Future Work

We have proposed a driver identification method based on the driving behavior signals that are observed while car following. The driving behavior signals of the accelerator pedal, brake pedal, vehicle velocity, and distance from the vehicle in front were measured using a driving simulator. We compared the identification rate using different identification models and different features. We obtained three results.

- The Gaussian Mixture Model is better than the Helly model and the optimal velocity model for driver identification.
- A driver's operation signals are better than the road environment signals and vehicle behavior signals for driver identification using GMM.
- The identification rates were 81% for twelve drivers using a driving simulator and 73% for thirty drivers using an actual vehicle.

The physical model and statistical model are not competitive models. As the next step of this research, we aim

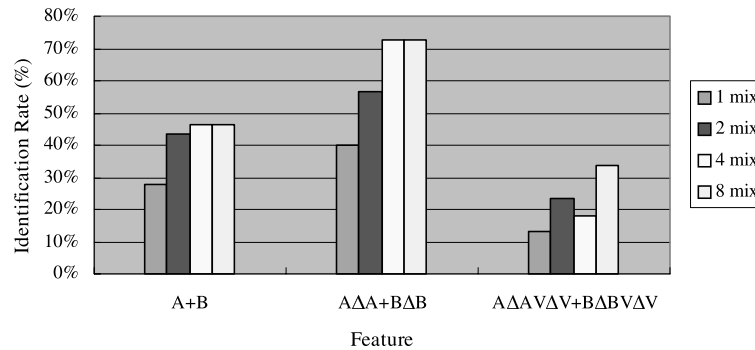


Fig. 10 Driver identification rate for multiple likelihoods of actual vehicle.

to analyze the underlying properties of the behavior signals, merge these two models, and develop a more precise identification method.

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