CEPSTRAL ANALYSIS OF DRIVING BEHAVIORAL SIGNALS FOR DRIVER IDENTIFICATION

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ABSTRACT

Spectral analysis is applied to such driving behavioral signals as gas and brake pedal operation signals for extracting drivers' characteristics while accelerating or decelerating. Cepstral features of each driver obtained through spectral analysis of driving signals are modeled with a Gaussian mixture model (GMM). A GMM driver model based on cepstral features is evaluated in driver identification experiments using driving signals collected in a driving simulator and in a real vehicle on a city road. Experimental results show that the driver model based on cepstral features achieves a driver identification rate of 89.6 % for driving simulator and 76.8 % for real vehicle, resulting in 61 % and 55 % error reduction, respectively, over a conventional driver model that uses raw driving signals without spectral analysis.

1. INTRODUCTION

The numbers of driver's license holders and car owners are increasing every year, and the car has obviously become indispensable to our daily life. To improve safety and road traffic efficiency, intelligent transportation system (ITS) technologies including car navigation systems, electronic toll collection (ETC) systems, adaptive cruise control (ACC), and lane-keeping assist systems (LKAS) have been developed over the last several years. ACC and LKAS assist drivers by automatically controlling vehicles using observable driving signals of vehicle status or position, e.g., velocity, following distance, and relative lane position. Other research addressing driving signals includes driving behavior modeling that predicts the future status of a vehicle [1] [2], drowsy or drunk driving detection with eye-monitoring [3] [4], and the cognitive modeling of drivers [5]. Driving behaviors are different among drivers, and as such, modeling of drivers' characteristics in driving behaviors has also been investigated for intelligent assistance for each driver [6] [7]. In [6] and [7], drivers were modeled using Gaussian mixture models (GMMs) [8] that characterized the distributions of gas and brake pedal pressure, velocity, and following distance.

In this research, we focused on drivers' characteristics in driving behavior of gas and brake pedal operation, with drivers' characteristics extracted through spectral (cepstral) analysis of the pedal operation signals. We applied spectral analysis to the gas and brake pedal signals to obtain cepstral coefficients, which are the most widely used spectral features for speech recognition. From a theoretical point of view, a cepstrum is defined as the inverse Fourier transform of the log power spectrum of the signal, which allows us to smooth the structure of the spectrum by keeping only the first several lower-order cepstral coefficients and setting the remaining coefficients to zero. Cepstral coefficients are therefore convenient for representing the spectral envelope.

Assuming that drivers' characteristics in driving behaviors while accelerating or decelerating could be represented by spectral envelope of pedal operation signals, we modeled the characteristics of each driver with a GMM using the lower-order cepstral coefficients. GMM driver models based on cepstral features were evaluated in the identification of 276 drivers and compared to conventional GMM driver models that used raw driving signals without any applied spectral analysis techniques.

2. DRIVING BEHAVIORAL SIGNALS

2.1. Driving Signals

Observable driving signals can be categorized into three groups:

i) Driving behavioral signals
(e.g., gas pedal pressure, brake pedal pressure, and steering angle)
ii) Vehicle status signals
(e.g., velocity, acceleration, and engine speed)
iii) Vehicle position signals
(e.g., following distance, relative lane position, and yaw angle).

Among these signals, we focused here on the driving behavioral signals, especially on the drivers' characteristics with respect to gas and brake pedal pressures.

2.2. Data Collection

A driving simulator was used for data collection, which simulated a two-lane expressway and displayed the view from a driver's seat in a monitor. Each driver was instructed to follow the lead vehicle displayed in the monitor without passing it. The moving pattern of the lead vehicle was collected on a relatively congested expressway in Japan. Twelve experimental participants with driver's licenses drove in the simulator 20 minutes each. Identical moving patterns of the lead vehicle were used for all drivers. Driving behavioral signals of velocity, headway distance, and gas and brake pedal positions were collected and sampled at 100 Hz.

Driving behavioral signals were also collected using a data collection vehicle (TOYOTA REGIUS), which has been specially designed for data collection in the Center for Integrated Acoustic Information Research (CIAIR) project. Detailed information on this corpus can be found in [9]. Each driver drove the car on a city road, and five-channel driving signals as well as 16-channel speech signals, three-channel video signals, and GPS were recorded. The driving signals included force on gas and brake pedals, engine speed, car velocity, and steering angle. These signals were originally sampled at 1 kHz and down-sampled at 100 Hz in experiments.

Figure 1 shows examples of driving behavioral signals collected in the vehicle. The top, center and bottom figures corre-

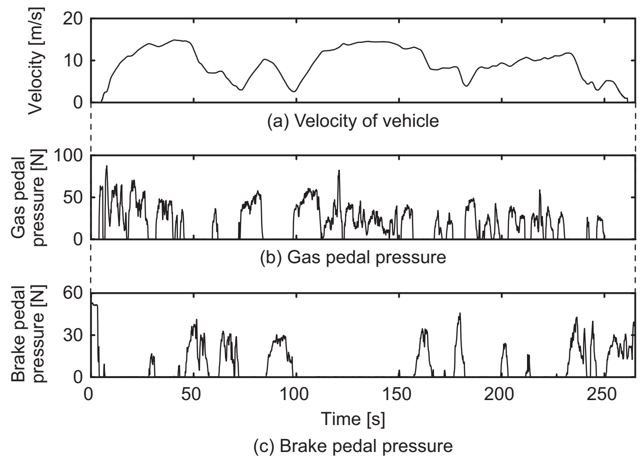

Figure 1: Examples of driving behavioral signals. (Top: velocity; Center: gas pedal signal; Bottom: brake pedal signal)

spond to velocity, force on gas pedal, and force on brake pedal, respectively.

3. DRIVER MODELING

3.1. Spectral Analysis of Pedal Signals

Examples of gas pedal operation signals for two drivers are shown in Fig. 2 (top) and their corresponding spectra are shown in Fig. 2 (bottom). Each figure shows three examples of 0.32-second long gas pedal signals. Driver A in Fig. 2 (left) tends to increase the pressure on the gas pedal gradually, whereas driver B in Fig. 2 (bottom) accelerates in two stages. After the initial acceleration, driver B momentarily reduces the pressure on the gas pedal, and then resumes acceleration.

We can see that the spectra shown in the bottom figures are similar in the same driver but different between the two drivers. Assuming that the spectral envelope can capture the differences between the characteristics of among different drivers, we focused on the differences in spectral envelopes represented by cepstral coefficients (cepstrum). Cepstrum is the most widely used spectral feature for speech and speaker recognition [10].

3.2. GMM Driver Modeling and Identification

A Gaussian mixture model (GMM) [8] was used to represent the distributions of feature vectors of cepstral coefficients of each driver. The GMM parameters were estimated using the expectation maximization (EM) algorithm. The GMM driver models were evaluated in driver identification experiments, in which the unknown driver was identified as driver $\hat{k}$ who gave the maximum weighted GMM log likelihood over gas pedal and brake pedals:

$$\begin{aligned}\hat{k} = \arg\max_{k} \{ & \gamma \log P(\boldsymbol{G} \mid \lambda_{G,k}) \\ & +(1-\gamma)\log P(\boldsymbol{B} \mid \lambda_{B,k})\}, \quad 0 \le \gamma \le 1, \end{aligned} \qquad (1)$$

where $\boldsymbol{G}$ and $\boldsymbol{B}$ are the cepstral sequences of gas and brake pedals, and $\lambda_{G,k}$ and $\lambda_{B,k}$ are the k-th driver models of gas and brake pedals, respectively; γ is the linear combination weight for the likelihood of gas pedal signals.

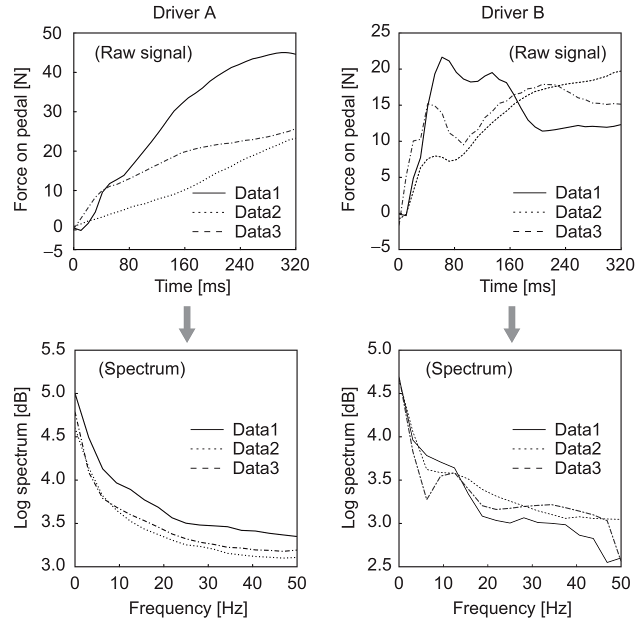

Figure 2: Gas pedal signals (top) and their spectra (bottom). (Left: driver A ; Right: driver B)

4. DRIVER IDENTIFICATION EXPERIMENT

4.1. Experimental Conditions

Driving data of twelve drivers for the driving simulator and driving data of 276 drivers for the real car were used for experiments, excluding the data gathered while not moving. The driving signals of the three minutes were used for training, and another three minutes for testing. We modeled the distribution of cepstral coefficients and their dynamic features (Δ coefficients) using GMMs with 8, 16 or 32 Gaussians and diagonal covariance matrices.

As in the case of speech recognition, we also use the dynamic features of the driving behavioral signals defined as linear regression coefficients:

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

where $x(t)$ is the raw signal at time t, and K is the half window size for calculating the Δ coefficients. We selected $2K = 800$ ms as the best window size from preliminary experiments. Frame length, frame shift, and the range of cepstral coefficients were also determined in the preliminary experiments. We also compared the driver models based on cepstral features to the conventional driver models based on the raw driving signals.

Examples of distributions of raw gas pedal signals are shown in Fig. 3 and distributions of the 0-th cepstral coefficient are given in Fig. 4. Significant differences in distributions among drivers can be observed in both figures.

4.2. Preliminary Experiment using Driving Simulator Data

We carried out a preliminary driver identification experiment using driving signals collected on a driving simulator. Figure 5 shows the results for conventional driver models using raw driving signals modeled with 8, 16, and 32-component GMMs [6]. In the figure, velocity, following distance, and gas pedal position are denoted as V, F, and G, and their dynamics as ΔV,

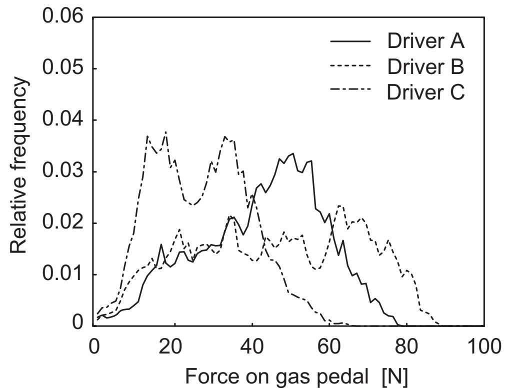

Figure 3: Distribution of raw signal.

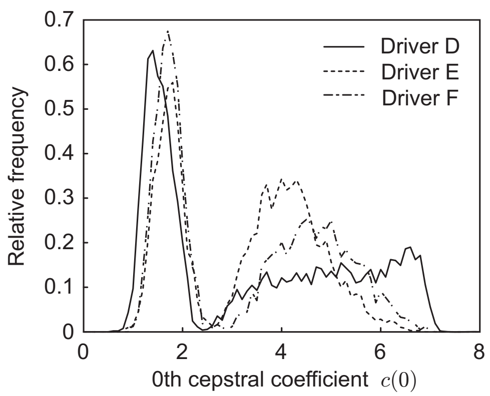

Figure 4: Distribution of 0th cepstral coefficient.

ΔF, and ΔG, respectively. Brake pedal signals were not used in experiment of driving simulator because drivers less frequently press the brake pedal when driving on an expressway. Gas pedal signals with their dynamics outperformed the combination of velocity and following distance including their dynamics. The best performance of a 72.9% identification rate was obtained when using all three signals and their dynamics.

Figure 6 shows the results for the proposed driver model using cepstral coefficients obtained through cepstral analysis of gas pedal signals. Sequence of cepstral coefficients were obtained with 1.28 second frame length and 0.1 second frame shift. In the figure, "$c(0)-c(m)$" represents $m+1$ cepstral coefficients including from the 0-th to the m-th cepstral coefficients. Cepstral features achieved much better performance than conventional features, and an identification rate of 89.6% was obtained GMM, which corresponds to 61% error reduction over the conventional feature.

4.3. Experimental Results for Real Car Data

Figures 7 and 8 show identification results for the gas and brake pedal signals collected in the real car when using raw signals and cepstral coefficients (cepstrum), respectively. The leftmost results correspond to the identification rates when using only the brake pedal signals, and rightmost results were obtained with gas pedal signals alone. We can see that the gas pedal signals gave better performance than brake pedal signals. This is because drivers hit the gas pedal more frequently than the brake pedal as shown in Fig. 1.

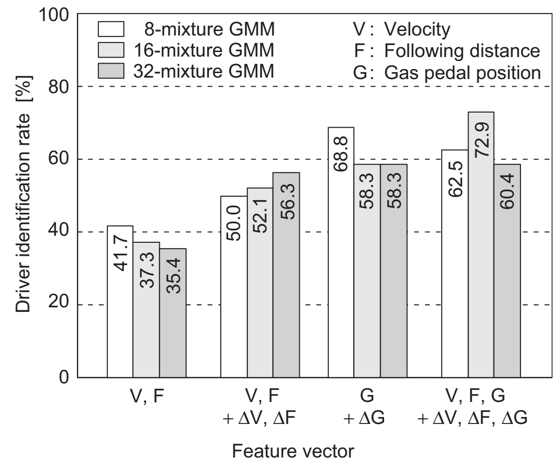

Figure 5: Driver identification rate for conventional GMM driver models using raw driving signals (driving simulator).

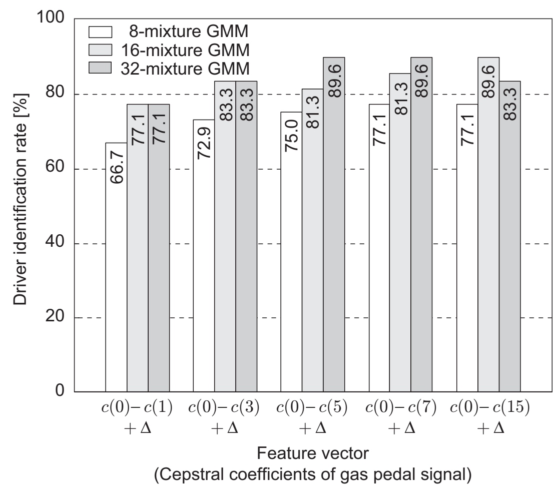

Figure 6: Driver identification rate for proposed GMM driver models using cepstral features (driving simulator).

The results for 16-component GMM in Figs. 7 and 8 are summarized in Fig. 9. The identification performance was rather low when using the raw driving signals: the best identification rate for raw signals was 47.5% with $\gamma = 0.80$. By applying cepstral analysis, however, the identification rate increased to 76.8% with $\gamma = 0.76$. We can thus conclude that cepstral features could capture the individualities in driving behavior better than raw driving signals, and could achieve better performance in driver identification.

4.4. Experiment for Different Test Lengths

We investigated the identification performance for different test lengths. Figure 10 shows identification rates when changing the the test data length as 1, 1.5, and 3 minutes. Although the identification rate for cepstral features deteriorated to 59.5% with the one-minute test data, it still performed better than the identification rate of raw signals with the three-minute test data.

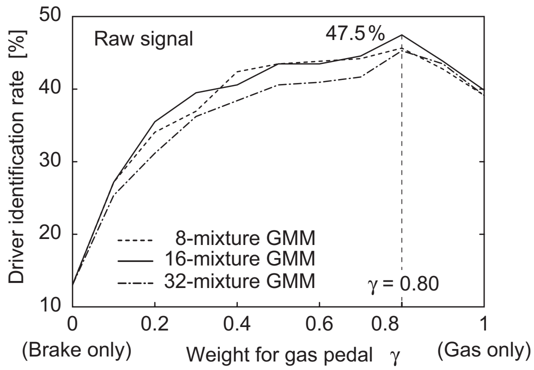

Figure 7: Results for combination of gas and brake pedals (raw signals).

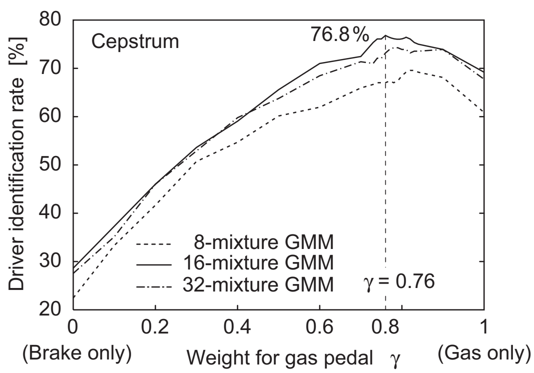

Figure 8: Results for combination of gas and brake pedals (cepstrum).

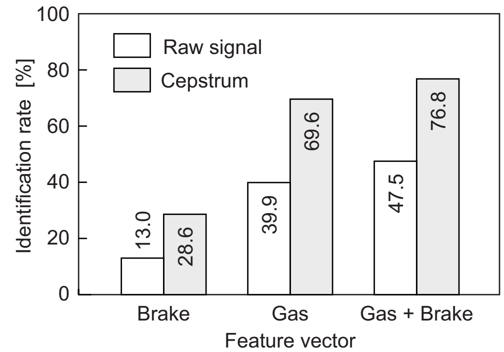

Figure 9: Comparison of the identification rate between the conventional model and the proposed model

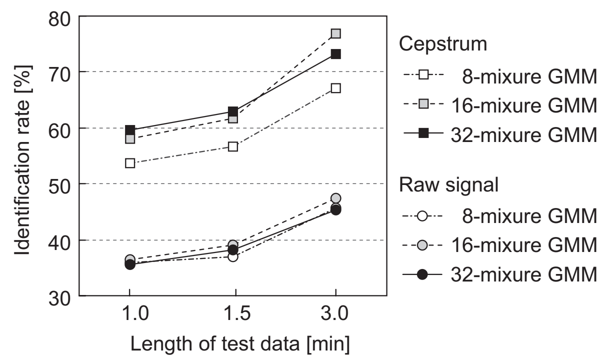

Figure 10: Results for the test length.

5. CONCLUSION

In this paper, we investigated the modeling of individuality's in driving behavioral signals. We modeled the distribution of cepstral coefficients of gas and brake pedal operation signals using the property that the spectral envelopes are similar in the same driver and the different among different drivers. Driver models were evaluated in driver identification experiments, and by using cepstral features we achieved an identification rate of 89.6 % for driving simulator and 76.8 % for real vehicle, resulting in 61 % and 55 % error reduction, respectively, over a conventional driver model based on raw pedal operation signals.

The selective use of driving signals while accelerating or decelerating and the modeling of characteristics in longer-term driving signals (e.g., more than a 2-second frame length) must be addressed in future work. Other driver modeling techniques apart from GMM, such as hidden Markov models, can be employed for more efficient modeling of the time series of feature vectors. We also plan to extend driver modeling to driver-type modeling to intelligently assist individual driver by clustering the drivers into certain groups (e.g., impatient, aggressive, alert, $\cdots$).

6. REFERENCES

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