

MODELING OF INDIVIDUALITIES IN DRIVING THROUGH SPECTRAL ANALYSIS OF BEHAVIORAL SIGNALS

Koji Ozawa[†], Toshihiro Wakita^{†,‡}, Chiyo Miyajima[†], Katsunobu Itou[†] and Kazuya Takeda[†]

[†] Graduate School of Information Science, Nagoya University,
[‡] Toyota Central R&D Labs.,
k-ozawa@sp.m.is.nagoya-u.ac.jp, wakita@mosk.tytlabs.co.jp,
{miyajima, takeda, itou}@is.nagoya-u.ac.jp

ABSTRACT

Driving behavior modeling using such driving signals as velocity, following distance, and gas or brake pedal operations, has been investigated for accident prevention and vehicle design. Driving behaviors are different among drivers, and research on driver modeling has also been carried out from different points of view in cognitive and engineering approaches. In this paper, driver's characteristics in driving behaviors are modeled with a Gaussian mixture model (GMM) using "cepstral features" obtained through spectral analysis of gas pedal operation signals. The GMM driver model based on cepstral features is evaluated in driver identification experiments and compared with a conventional GMM driver model that uses raw driving signals without spectral analysis. Experimental results show that the proposed driver model achieves an 89.6% driver identification rate, resulting in 61% error reduction over the conventional driver model.

1. INTRODUCTION

With increasing emphasis on safety and driving comfort, advanced driver assistance systems including adaptive cruise control (ACC) and lane-keeping assist systems (LKAS) have been developed over the last several years. These systems 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]. Modeling of drivers' individualities in driving behavioral signals has also been investigated in [6] and [7] in which each driver was modeled using an optimal velocity model [8] [9] represented by a function of the relationship between velocity and following distance or using a Gaussian mixture model (GMM) [10] that characterized the distribution of gas and brake pedal pressure, velocity, and following distance.

In this paper, drivers' characteristics were extracted through spectral analysis of driving behavioral signals. We applied spectral analysis to gas pedal signals to obtain "cepstrum" (cepstral coefficients), which is the most widely used spectral feature for speech recognition [11]. From a theoretical point of view, 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 low-order cepstral coefficients and setting the remaining coefficients to zero. Cepstral

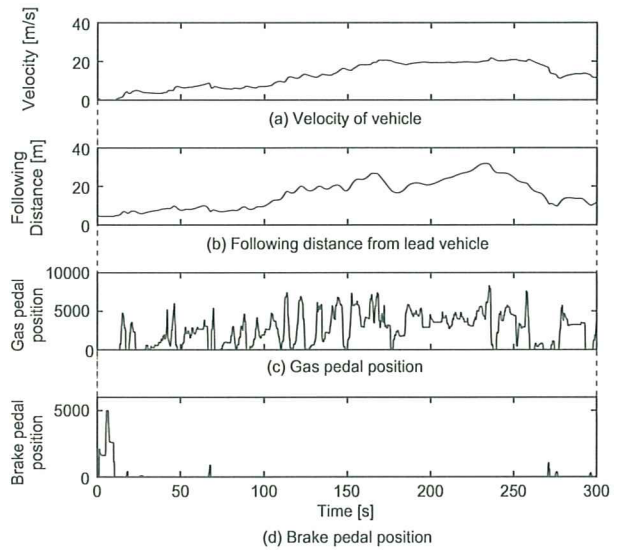


Fig. 1. Examples of driving behavioral signals.

coefficients are therefore convenient to represent the spectral envelope. In this work, assuming that drivers' characteristics in driving behaviors while accelerating or decelerating could be represented by spectral envelope of gas pedal signals, each driver was modeled with a GMM using the lower-order cepstral coefficients. The GMM driver model based on cepstral features was evaluated in driver identification experiments and compared to a conventional GMM driver model that uses raw driving signals without applying any spectral analysis techniques.

2. COLLECTION OF DRIVING BEHAVIORAL SIGNALS

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. Experimental participants included eleven males and one female from 21 to 31 years old with driver's licenses. They drove in the simulator four times for five minutes each. Identical moving patterns of the lead vehicle were used for all drivers. Driving behavioral signals of velocity, headway distance, and gas

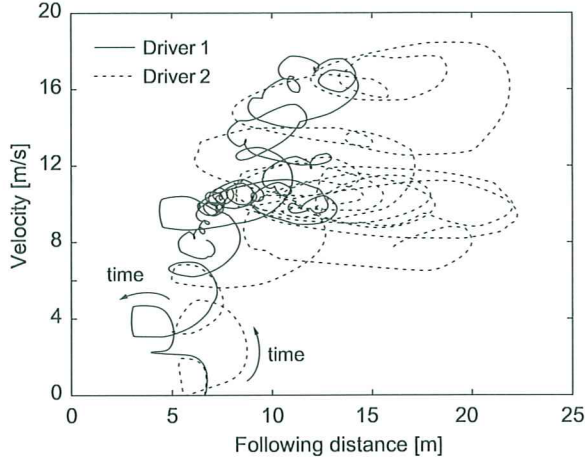


Fig. 2. Relationship between velocity and following distance for two different drivers.

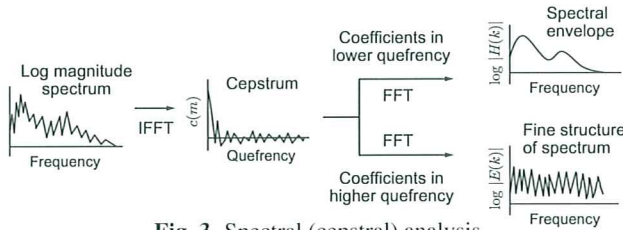


Fig. 3. Spectral (cepstral) analysis.

and brake pedal positions were collected and sampled at 100 Hz. Pedal positions were digitized to 0–10,000 levels so that 10,000 corresponded to full throttle or completely braked positions.

Examples of the collected driving signals are shown in Fig. 1. Drivers maintain a longer distance behind the lead vehicle as velocity increases and less frequently press the brake pedal when driving on an expressway.

3. DRIVER MODELING USING DRIVING BEHAVIORAL SIGNALS

3.1. Driver Modeling Using Raw Driving Signals

Igarashi et al. [6] proposed statistical driver modeling based on a Gaussian mixture model (GMM) [10] using the distribution of such driving behavioral signals as gas or brake pedal pressures and vehicle velocity. They showed that a combination of pedal pressures and their dynamic features gave the best driver identification performance. Dynamic features are defined as the linear regression coefficients of raw signal $x(n)$, calculated in the range of window size $2K$:

$$\Delta x(n) = \frac{\sum_{k=-K}^K kx(n+k)}{\sum_{k=-K}^K k^2}. \quad (1)$$

Wakita et al. [7] modeled each driver using an optimal velocity model, which was originally used for traffic flow modeling [8] [9], to represent the relationship between velocity and following distance from the lead vehicle. Each driver was modeled with a monotonically increasing nonlinear function that approximates the trajectory of the relationship between velocity and following distance

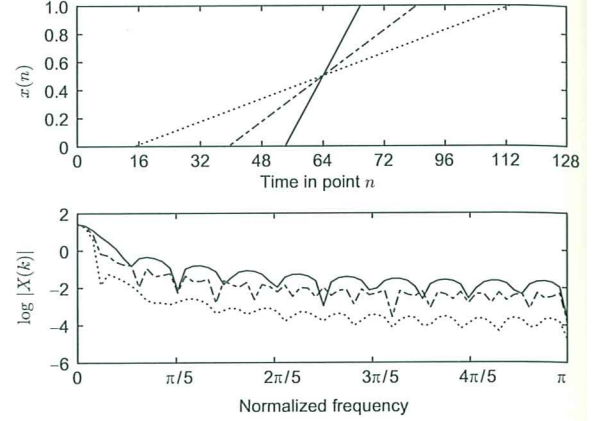


Fig. 4. Spectra of three kinds of signals approximating pedal operation.

tance. Examples of such trajectories are shown in Fig. 2. The trajectories are assumed to represent the following distance with which drivers feel comfortable. We can see that driver 1 is more aware of the velocity of the lead vehicle and adjusts velocity more frequently in accordance with the following distance. On the other hand, driver 2 tends to maintain a constant velocity up to a certain following distance. By comparing the optimal velocity model with GMM, they found that the GMM driver modeling gave a better performance.

3.2. Driver Modeling Using Cepstral Features

In this work, drivers' features are extracted through the spectral analysis of gas pedal signals by using a spectral feature called "cepstrum," which is defined as the inverse Fourier transform of the short-term log power spectrum. Cepstral coefficients are obtained by the following equation:

$$c(m) = \frac{1}{N} \sum_{k=0}^{N-1} \log |X(k)| e^{2\pi k m j / N}, \quad (2)$$

$$m = 0, 1, \dots, N-1,$$

where $X(k)$ denotes N -point discrete Fourier transform of the windowed signal $x(n)$. As shown in Fig. 3, cepstral analysis allows us to obtain a spectral envelope by keeping only the first several cepstral coefficients in the lower "quefrency" range and setting the remaining coefficients to zero, while on the other hand, a fine structure of the spectrum is obtained by keeping the cepstral coefficients in the higher quefrency range and setting the lower quefrency coefficients to zero. Cepstrum is the most widely used spectral feature for speech recognition [11].

Figure 4 shows the log power spectra of 0-1 step-like signals with three different slopes approximating fast, normal, and slow pedal strokes. We can see significant differences between the overall structures of the spectra, which motivated the use of cepstral coefficients in the lower quefrency range for driver modeling to characterize short-term pedal signals. Figure 5, which compares the spectrograms of 150 second gas pedal signals obtained from three drivers, shows the differences between the spectra of the actual pedal signals.

Speech modeling assumes that vocal cord excitation (vibration), represented by the fine structure of the spectrum, is filtered

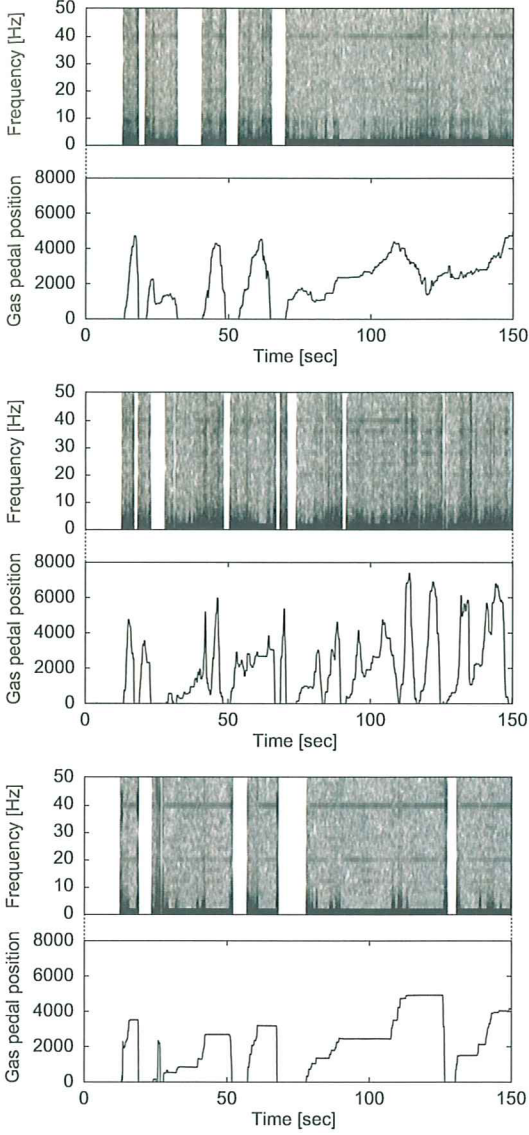


Fig. 5. Three different ways of hitting gas pedals and their respective spectrogram.

with the vocal tract represented by the spectral envelope. As shown in Fig. 6, in driver modeling, we assume that a command signal for hitting a pedal $e(n)$ is filtered with driver model $H(e^{j\omega})$ represented as the spectral envelope, and the output of the system is observed as pedal signal $x(n)$, e.g., in the case of gas pedal operation, a command signal is generated when a driver decides to hit the gas pedal, and $H(e^{j\omega})$ represents the process of acceleration. This can be described in frequency domain as follows:

$$X(e^{j\omega}) = E(e^{j\omega})H(e^{j\omega}), \quad (3)$$

$$\log |X(e^{j\omega})| = \log |E(e^{j\omega})| + \log |H(e^{j\omega})|, \quad (4)$$

where $X(e^{j\omega})$ and $E(e^{j\omega})$ are the Fourier transforms of $x(n)$ and $e(n)$, respectively. We focus on drivers' individualities represented as frequency response $H(e^{j\omega})$.

4. GAUSSIAN MIXTURE MODEL (GMM)

A Gaussian mixture model (GMM) was used for modeling driver's characteristics in driving behavioral signals. A GMM is a well-known statistical model widely used in pattern recognition including speech and speaker recognition [10]. It is defined as a mixture of multivariate Gaussians, and the probability of D -dimensional observation vector \mathbf{o} for GMM λ is obtained as follows:

$$b(\mathbf{o} | \lambda) = \sum_{i=1}^M w_i \mathcal{N}_i(\mathbf{o}), \quad (5)$$

where M is the number of Gaussians of the GMM and $\mathcal{N}_i(\mathbf{o})$ is the D -variate Gaussian distribution of the i -th component defined with mean vector $\boldsymbol{\mu}_i$ and covariance matrix $\boldsymbol{\Sigma}_i$:

$$\mathcal{N}_i(\mathbf{o}) = \frac{1}{\sqrt{(2\pi)^D |\boldsymbol{\Sigma}_i|}} \exp \left\{ -\frac{1}{2} (\mathbf{o} - \boldsymbol{\mu}_i)' \boldsymbol{\Sigma}_i^{-1} (\mathbf{o} - \boldsymbol{\mu}_i) \right\}, \quad (6)$$

where $(\cdot)'$ and $(\cdot)^{-1}$ denote transpose and inverse matrices, respectively. w_i is a mixture weight for the i -th component and satisfies

$$\sum_{i=1}^M w_i = 1. \quad (7)$$

Each driver k was modeled with GMM λ_k , and an unknown driver was identified as driver \hat{k} that gave the maximum value of the log likelihood for observation sequence $\mathbf{O} = (\mathbf{o}_1, \mathbf{o}_2, \dots, \mathbf{o}_T)$:

$$\hat{k} = \arg \max_k \sum_{t=1}^T \log b(\mathbf{o}_t | \lambda_k). \quad (8)$$

5. EXPERIMENTS

5.1. Experimental Conditions

Drivers' characteristics were modeled using cepstral coefficients and their dynamics obtained from Eq. (1) with regression window size $2K = 0.8$ sec. To obtain a sequence of cepstra from a gas pedal signal, 1.28 second frame length and 0.1 second frame shift were chosen for spectral analysis in preliminary experiments. To compare the driver model based on cepstral features to the conventional driver model, drivers were also modeled using the raw driving signals of vehicle velocity, gas pedal position, and their dynamics obtained with the same regression window size. The distributions of driver features were modeled using GMMs with 8, 16, or 32 Gaussians and diagonal covariance matrices based on the expectation maximization (EM) algorithm.

Twelve drivers drove four times for five minutes each. A four-fold cross-validation approach was used for evaluation. Three of

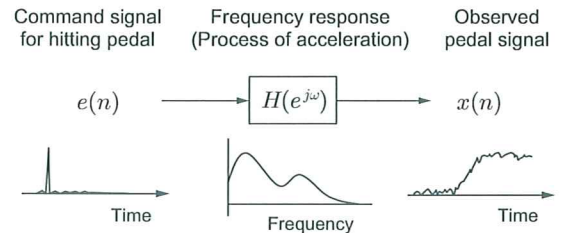


Fig. 6. General modeling of driving signals.

the four driving data were used for GMM training, and the excluded data was used as a test. An average driver identification rate was obtained from the four cross-validation tests.

5.2. Experimental Results

Driver identification experiments were conducted according to the decision rule in Eq. (8). Figure 7 shows the results for the conventional driver model using raw driving signals. In the figure, velocity, following distance, and gas pedal position are denoted as V, F, and G, and their dynamics as ΔV , ΔF , and ΔG , respectively. 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 8 shows the results for the proposed driver model using cepstral coefficients obtained through spectral analysis. In the figure, " $c(0)-c(m)$ " represents $m + 1$ cepstral coefficients in the lower quefrequency range 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. From the experimental results, we confirmed that cepstral features representing the spectral envelope can capture drivers' characteristics more efficiently than raw driving signals.

6. CONCLUSION AND FUTURE WORK

In this paper, we investigated the modeling of individualities in driving behavior. Gas pedal signals were modeled with cepstral features obtained through spectral analysis, and the distributions of cepstral coefficients were modeled with GMMs. Driver models were evaluated in driver identification experiments, and cepstral features achieved an identification rate of 89.6%, which corresponds to 61% error reduction over the conventional feature.

We are conducting further experiments using the driving signals of 300 drivers collected in an actual vehicle on actual roads. The selective use of driving signals while accelerating or slowing down and the modeling of characteristics in longer-term driving signals must be addressed in future work.

7. REFERENCES

- [1] A. Pentland and A. Liu, "Modeling and prediction of human behavior," *Neural Computation*, vol. 11, pp. 229–242, 1999.
- [2] N. Oliver and A.P. Pentland, "Driver behavior recognition and prediction in a SmartCar," *Proc. SPIE Aerosense 2000, Enhanced and Synthetic Vision*, Apr. 2000.
- [3] R. Grace, V.E. Byrne, D.M. Bierman, J. Legrand, D. Gri-court, B.K. Davis, J.J. Staszewski, and B. Carnahan, "A drowsy driver detection system for heavy vehicles," *Proc. 17th Digital Avionics Systems Conference*, vol. 2, pp. I36/1–I36/8, Oct. 1998.
- [4] P. Smith, M. Shah, and N. da V. Lobo, "Monitoring head/eye motion for driver alertness with one camera," *Proc. ICPR 2000*, vol. 4, pp. 636–642, Sept. 2000.
- [5] D.D. Salvucci, E.P. Boer, and A. Liu, "Toward an integrated model of driver behavior in a cognitive architecture," *Transportation Research Record*, 2001.

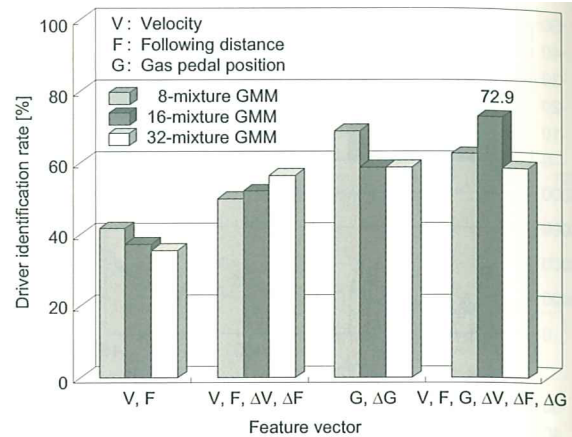


Fig. 7. Driver identification performance for conventional GMM driver models using raw driving signals.

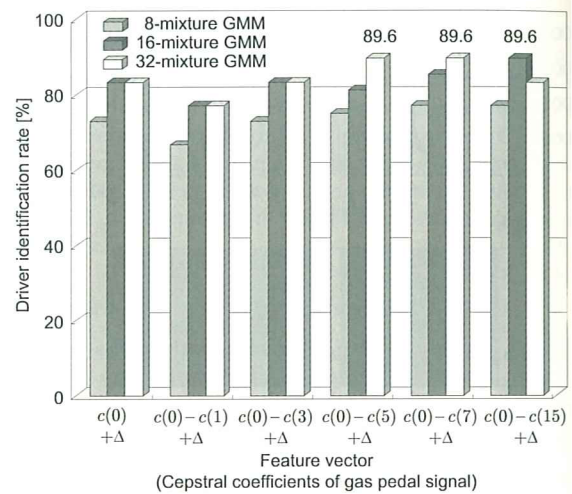


Fig. 8. Driver identification performance for proposed GMM driver models using cepstral features.

- [6] K. Igarashi, C. Miyajima, K. Itou, K. Takeda, and F. Itakura, "Biometric identification using driving behavioral signals," *Proc. ICME 2004, TP1-2*, Jun. 2004.
- [7] T. Wakita, K. Ozawa, C. Miyajima, and K. Takeda, "Parametric Versus Non-Parametric Models of Driving Behavior Signals for Driver Identification," *Proc. AVBPA 2005*, July 2005, (to appear).
- [8] M. Brackstone and M. McDonald, "Car-following: a historical review," *Transformation Research, Part F*, vol. 2, no. 4, pp. 181–196, Dec. 1999.
- [9] M. Bando, K. Hasebe, A. Nakayama, A. Shibata, and Y. Sugiyama, "Dynamical model of traffic congestion and numerical simulation," *Physical Review, E*, vol. 51, no. 2, pp. 1035–1042, Feb. 1995.
- [10] D.A. Reynolds and R.C. Rose, "Robust text-independent speaker identification using Gaussian mixture speaker models," *IEEE Trans. Speech and Audio Processing*, vol. 3, no. 1, pp. 72–83, Jan. 1995.
- [11] L. Rabiner and B. Juang, "Fundamentals of Speech Recognition," Prentice Hall, Apr. 1993.