Biometric Identification Using Driving Behavioral Signals

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Abstract

In this paper, we investigate the uniqueness of driver behavior in vehicles and the possibility to use it for personal identification with the objectives to achieve safer driving, to assist the driver in case of emergencies, and to be a part of multi-mode biometric signature for driver identification. We use Gaussian Mixture Models (GMM) for modeling the individualities of the accelerator and brake pedal pressures, and focus on not only the static features, but also the dynamics of the pedal pressures. Experimental results show that the dynamic features significantly improve the performance of driver identification.

1. Introduction

Automated biometric identification is a multidisciplinary scientific field to determine the identity of individuals from a set of features based on who they are, what do they possess and how they behave. A number of biometrics have been evaluated in trust building for numerous civic and business transactions, and in forensic authentication applications [1]–[6]. These include the identification of individuals from their physical features such as fingerprints, hand geometry, face, retina, and iris. The second class is classified as behavioral signatures, which include voice, style of hand-writing, key-stroke dynamics, motion video, and lip-reading. DNA characteristics and dental records have also been used in personal identification mostly for forensic applications. Finally, personal identification by digital signatures based on Public Key Infrastructure (PKI), passwords and smart-cards fall into the class of what we possess. Since the last two groups do not involve signal processing and they have not been generally studied in the domain of signal processing. Traditionally, features used in identification have been extracted from answers to only one of the three questions above.

Depending on the application, the performance in terms of accuracy and robustness can vary from excellent to unacceptable. In particular, the environment, where the systems are deployed has been the major deciding factor between success and failure. For instance, systems which give excellent results in a controlled testing environment have yielded almost all the time unacceptably poor performance in real-life situations. These include cockpits, crowded rooms, shopping centers and moving vehicles. Many practical and even costly signal enhancement procedures have been reported to improve the performance without much success, which in turn, has significantly effected the penetration of biometrics into the realm of e-transactions, i.e., e-business, m-commerce (business in mobile environment) and p-commerce (secure transaction over phone.)

In this paper, we focus on behavioral signals obtained from the driving characteristics of individuals, namely, the distributions of force readings from the accelerator and brake pedals, while driving. We would like to address the issue of using these behav-

Table 1: Specification of Recorded Data

Speech	16kHz, 16bit, 16ch
Video	MPEG-1, 29.97fps, 3ch
Control signals	Force on accelerator pedal Force on brake pedal Steering wheel angle Engine RPM Vehicle speed (16bit sampled at 1.0 kHz)
Location	Differential GPS (each 1sec)

ioral signals in the frameworks of a driver identification for safer driving, for intelligent assistance in case of emergencies, and robust communications.

2. In-car data collection

As part of an on-going study on collection and analysis of multi-layered in-car spoken dialog corpus, 800 drivers have driven a specially equipped vehicle in a city area between 1999 and 2001. Specification of the recorded data is listed in Table 1, which consists of dialog speech, video, force on accelerator pedal and break pedal, vehicle speed in km/h, engine speed in rmp and steering angle. In addition, the location of the vehicle has been recorded every second by a differential GPS devices mounted in the vehicle. Detailed information on this corpus study can be found in [9] and [10]. In this work, we utilize only force on accelerator pedal and break pedal. These signals were were sampled at 1.0 kHz. Figure 1 shows an example of driving behavioral signals. From the top, force on accelerator pedal, force on brake pedal and vehicle speed are plotted.

3. Distribution of force on pedal

Figure 2 shows the distributions of force on accelerator and brake pedal among drivers. Relative frequency as a function of force in kilogram-force per centimeter square (kgf) is plotted. It is worth noting that 1.0 kgf is equal to 9.8 Newtons. As can be seen, it is not difficult to observe noticeable differences between drivers. For instance, the relative frequencies of force on accelerator pedal is concentrated around 4.0 kgf for driver 1, whereas that of driver 4 is concentrated under 2.0 kgf. We show differences in the way drivers apply force on accelerator and break pedals used in identification.

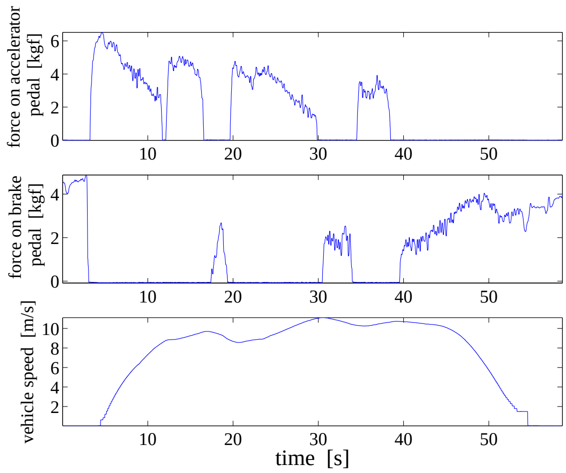

Figure 1: Plots of force on accelerator pedal, force on break pedal and the vehicle speed as a function of time.

4. Dynamics of the driving signals

In speech recognition, it has been reported that dynamic features can improve the performance [11]. So, we focus on the dynamics of driving signals. Dynamics refer to the rate of change of the signals. Figure 3 shows the dynamics of force on accelerator pedal, force on brake pedal, and vehicle speed (acceleration signal).

5. Experiments

5.1. Experimental conditions

We used Gaussian Mixture Models (GMM) for modeling driving behavior for each driver. We employed 30 drivers. The average length of the driving data was around 20 minutes. We used the first half 10 minutes for training and the remaining 10 minutes for testing. Driving data includes force on accelerator pedal, force on brake pedal, vehicle speed, dynamics of force on accelerator pedal, dynamics of force on brake pedal and acceleration signal. We did not use the joint distribution of force on accelerator pedal and force on brake pedal because drivers

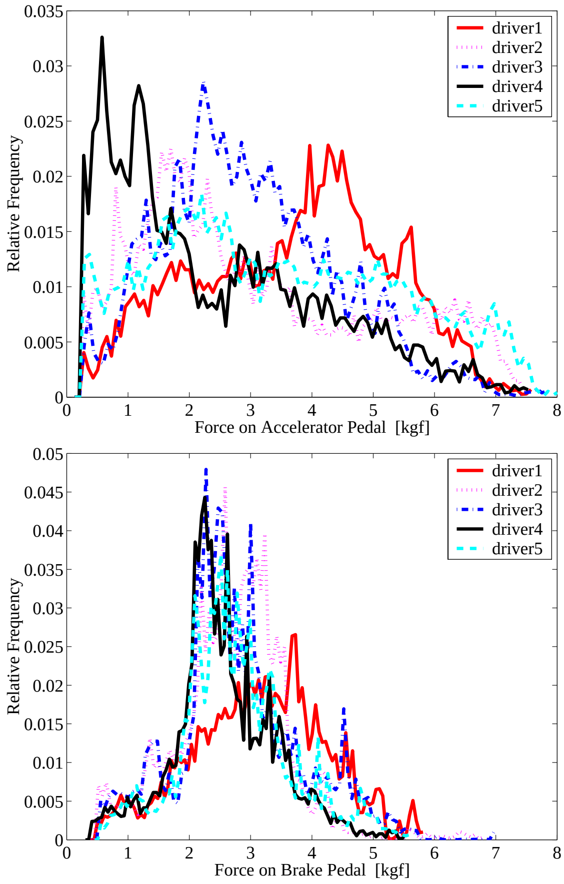

Figure 2: Distributions of force on accelerator pedal (top) and break pedal (bottom).

cannot press both of them simultaneously. We also investigated how the performance would change for the number of mixtures 1, 2, 4, 8. The behavioral signals were digitized at a sampling rate of 1.0 kHz in the data collection phase, and we down-sampled the driving signals to 100 Hz in our experiments.

5.2. Experimental results

Identification was performed according to the following equation.

$$\arg\max_{k} p(\mathbf{X}|\lambda_k) \tag{1}$$

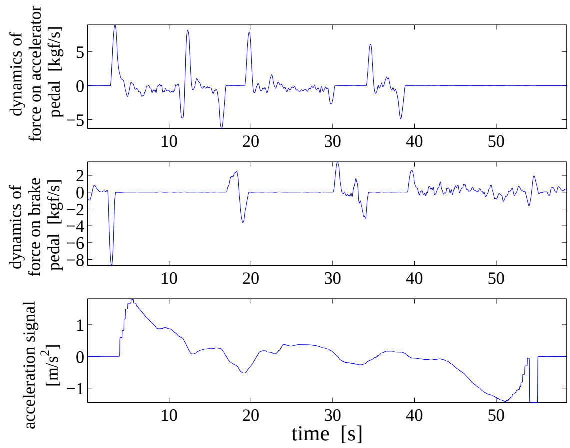

Figure 3: The dynamics of force on accelerator pedal, force on break pedal and the vehicle speed as a function of time.

$\mathbf{X}$: A sequence of feature vectors
λ_k : GMM of driver ID k
k : Driver ID $1, 2, \ldots, 30$

Figures 4 and 5 show the rate of identification using force on accelerator and brake, respectively. A, B, V and Δ mean force on accelerator pedal, force on brake pedal, vehicle speed, and dynamics respectively. As can be seen, AΔA in Fig. 4, and BΔB in Fig. 5 give the highest performance, respectively. This means the dynamics can improve the performance of driver identification. Vehicle speed cannot improve the accuracy of identification. Figure 6 shows the results of the identification using the sum of the log-likelihood of force on accelerator pedal and brake pedal. As shown in the figure, using both static and dynamic information of force on accelerator and brake pedals, the highest identification rate of 73% was obtained.

6. Conclusion

In this study, we have explored the possibility of driver identification from two measured quantities, the pressures applied to accelerator and break pedals. There are significant differences among drivers in the way they apply pressure to accelerator and break pedals from the perspective of histograms. We have attempted to model the driver behavior using GMMs.

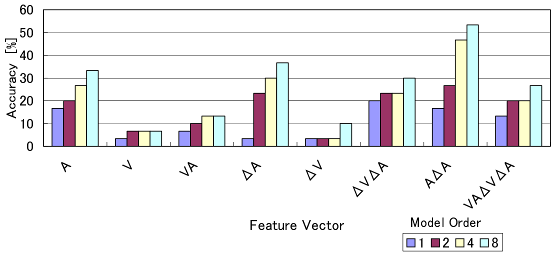

Figure 4: Identification rate using force on accelerator pedal.

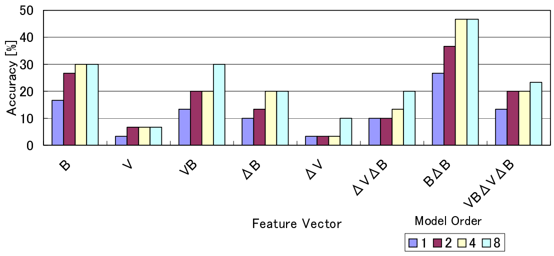

Figure 5: Identification rate using force on brake pedal.

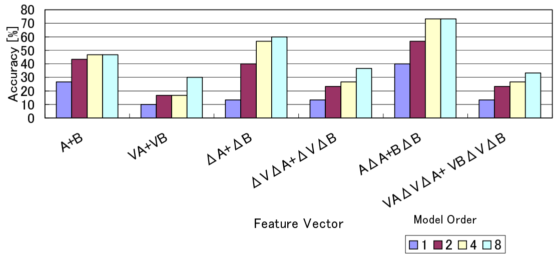

Figure 6: Identification rate using both force on accelerator and force on brake pedal.

Pedal pressure dynamics have improved the driver identification performance. This means that there is individuality in pedal pressure dynamics, as well as in static information.

7. References

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