DRIVER RECOGNITION SYSTEM USING FNN AND STATISTICAL METHODS

Abdul Wahab and Tan Chin Keong
School of Computer Engineering, Nanyang Techonological University
Nanyang Avenue, Singapore 639798. email: asabdul@ntu.edu.sg
Hüseyin Abut
ECE Department, San Diego State University
San Diego, CA 92182, email: abut@akhisar.sdsu.edu
and
Kazuya Takeda
School of Information Science, Nagoya University, Japan

ABSTRACT

Advancements in biometrics-based authentication have led to its increasing prominence and are being incorporated into everyday tasks. Existing vehicle security systems rely only on alarms or smart card as forms of protection. A biometric driver recognition system utilizing driving behaviors can be incorporated into existing vehicle security system to form a multimodal identification system and offer a higher degree of multi-level protection. The system can be subsequently integrated into intelligent vehicle systems where it can be used for detection of any abnormal driver behavior for purpose of achieving safer driving. In this paper we present features extracted using Gaussian Mixture Models (GMM) from accelerator and brake pedal pressure signals which are used as inputs to a driver identification/verification system. The Evolving Fuzzy Neural Network (EFuNN) was used to demonstrate the validity of the proposed system. Results obtained from the experiments are compared to that of the statistical method and shows potential of the recognition system to be used for real-time application. A high identification rate and low verification error rate were obtained using the GMM-based features indicating considerable difference in the way different drivers apply pressure to the pedals.

1. Introduction

Biometric Identification is a broad category of technologies that performs automatic recognition of an individual based on the individual's physiological or behavioral characteristics. Physiological characteristic is a relatively stable physical feature such as fingerprint, iris, facial features or hand geometry [1-4] while behavioral characteristic is influenced by the individual's personality such as voiceprint, hand-written signature or keystroke dynamics [1,2,3]. The first class of biometrics, in particular fingerprint, has been widely evaluated in banking transactions as well as in forensic authentication applications for many years. The second class of biometrics is gaining prominence in recent years with speaker recognition garnering the most attention [4].

Currently, vehicle security relies mainly on alarm or smart cards. A biometrics system can be incorporated into existing vehicle security systems to form a multimodal identification system. In a recent research conducted, driving characteristics such as the amount of pressure a driver applies on the accelerator pedal and brake pedal have been utilized in personal identification [5]. The encouraging experimental results indicate that there is uniqueness in driving behavior among individuals. The utilization of driving behavioral signals can serve as a good alternative or incorporated into existing vehicle security systems and offer a higher degree of multi-level protection. Additionally, the recognition system can be integrated into intelligent vehicle systems for purpose of achieving safer driving. For example, upon recognition of the driver by the system, a profile of the driver can be loaded from the system associative memory. Any deviation of the driver behavior from its norm can then be predicted and the necessary action taken accordingly.

Artificial Neural Networks has emerged as a powerful and practical computing tool over recent years, particularly in the field of pattern recognition/classification [6]. Some commonly used artificial neural networks include Multi-Layer Perceptron (MLP), Radial Basis Function (RBF) and Adaptive Resonance Theory (ART). Two limitations associated with most artificial neural networks are their long training process and finding an optimal boundary when handling real-life data due to the ambiguous nature of such data. Fuzzy logic was introduced as an approach to handling vagueness and uncertainty [7]. Fuzzy neural hybrid systems combine the two concepts by applying learning techniques of neural networks for fuzzy models parameter identification. These systems offer strong generalization ability and fast learning capability from large amount of data. Even though still not widely explored, fuzzy neural systems like the Evolving Fuzzy Neural Network (EFuNN) and Adaptive Network-based Fuzzy Inference System (ANFIS) have been applied in several recognition researches with high degree of accuracy [8,9]. In this research, the performance of EFuNN will be compared to MLP on driver recognition tasks. The work in [5] will also be implemented for comparison.

1.1 Resources

The driving data utilized in this research are from the In-car Signal Corpus hosted in Center for Integrated Acoustic Information Research (CIAIR), Nagoya University, Japan [10]. The In-car Signal Corpus is one of several databases hosted by CIAIR. This database contains multi-dimensional data collected in a vehicle under both driving and idling conditions. The purpose of setting up the database was to deal with 2 issues, namely noise robustness of speech and continual change of the vehicular environment. To date, the number of subjects involved in the data collection amounts to about 800 with a total recording time of over 600 hours. The multimedia data consists of speech, image, control (driving) and location signals, all synchronized with the speech recording. For this research, only the driving signals (accelerator pedal pressure & brake pedal pressure) were utilized.

Modeling and studies of driving behaviors began as early as in the 1950s. Many of the studies have been conducted with the objectives of increasing traffic safety or improving the performance of intelligent vehicle systems [11,12,13]. However, the utilization of driving behavior for personal identification is still not widely explored.

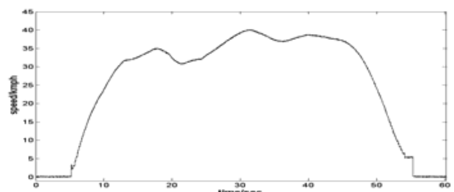
1.2 Driver Recognition

Driver Recognition, in the perspective of biometrics, is the general process of distinguishing individuals based on the analysis of their driving behaviors. In the research conducted by Igarashi et al, driving characteristics including accelerator pedal pressure and brake pedal pressure were utilized in the application of driver recognition. Differences were observed in the distribution plots of the pedal pressure signals among drivers. For example, the relative frequency of the accelerator pedal pressure is concentrated around different pressure values for different drivers. Experiments were conducted on a group of 30 drivers and both static and dynamic information of the pedal pressure data were used in the experiments. An identification rate of 73.3% and a verification equal error rate of 8.4% were achieved in the experiments. The results suggest considerable differences among drivers in the way they apply pressure to the pedals.

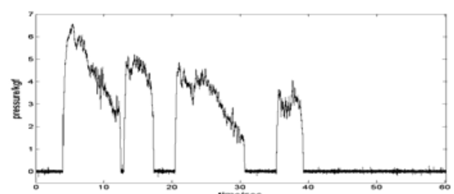
2. Data Analysis & Features Extraction

The vehicle control signals from the In-car Signal Corpus consist of accelerator pedal pressure, brake pedal pressure, steering angle, engine speed and vehicle speed. The first 3 are more driver-dependant traits while the latter 2 are more vehicle-dependant attributes. In this research, the focus was placed only on the driver-dependant traits and more specifically, the accelerator pedal pressure and brake pedal pressure signals since it was noted that there is considerable differences among drivers in the way they apply pressure to the pedals. The vehicle control signals were collected through analog channels, each sampled at 1.0 kHz with a 16-bit Little Endian format. The pedal pressure sensors can detect pressures ranging from 0 to 30 kgforce. This range is mapped to 0 – 5.0 V and linearly digitized in the range 0 to 32767.

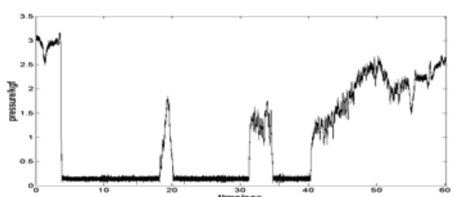
Segments known as stop & go regions were extracted from the original collected driving signals for the experiments conducted in [5]. These segments are also available in the In-car signal corpus. A stop & go region is defined as the period from when the vehicle moves off from a stationary position until when the vehicle comes to a complete halt. The motivation for using just the stop & go regions instead of the entire signals is instinctive since little or no information pertaining to driving behaviors is present when the vehicle is not in motion. Figure 1 show the associated vehicle speed, accelerator pedal pressure and brake pedal pressure signals of a stop & go region. At the start, the vehicle speed remains at 0 for a brief amount of time. This indicates that the vehicle is in a halted state.



(a) Vehicle Speed Signal



(b) Accelerator Pedal Pressure Signal



(c) Brake Pedal Pressure Signal

Figure 1 Associated Signals of a Stop & Go Region

It can be seen in the brake pedal pressure signal that the driver was applying pressure on the brake pedal during the period of time when the vehicle is stationary. Shortly after, the brake pedal pressure goes to zero and there is a sharp transition in the accelerator pedal pressure signal. The vehicle speed then increased quite constantly for about 15 seconds before a slight drop in the vehicle speed. This portion of the stop & go region is sometimes referred to as the initial-acceleration. The vehicle then maintains at an average speed of about 35 kmph for approximately 30 seconds. This region during which the vehicle travels at a constant speed can be referred to as the steady state in which there is no significant variation in the vehicle speed. Following that, the vehicle speed starts to decrease gradually until the vehicle comes to a complete halt indicated by the vehicle speed signal. This region can be referred to as the deceleration or stopping region during which no pressure is applied to the accelerator pedal. It was noted that at any one time, the driver can apply pressure on only 1 of the 2 pedals.

In many researches, often the focus is not placed only on the static data but also on the dynamics of the data as well. Dynamics of pedal pressure can be defined as the rate of change in pressure applied on the pedal by the driver. Intuitively, this offers additional information on top of the static signals. In the research conducted by Igarashi et al, it was found that dynamics improve the performance of driver identification compared to when only the static signals were being used. Figure 3.2 shows an accelerator pedal pressure signal and its dynamics respectively while Figure 3.3 shows a brake pedal pressure signal and its dynamics. The dynamics signal is a function of time with the pressure/s^2 as the y-axis. The value at any point represents the rate of change in pedal pressure. For example, a sharp positive-going transition (increase) in the accelerator pedal pressure is translated to a high positive rate of change value in the dynamics; a sharp negative-going transition (decrease) in the pedal pressure is translated to a high negative rate of change value in the dynamics.

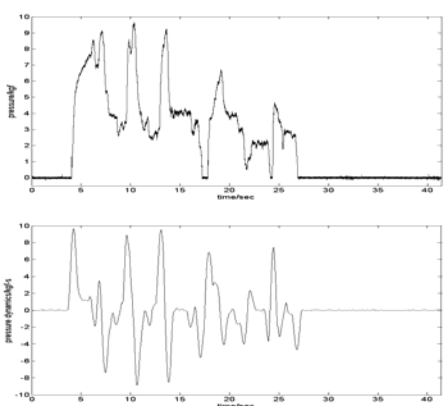


Figure 2 Accelerator Pedal Pressure Signal (top) and its Dynamics (bottom)

2.1 Feature Extraction

Reduction of data size is a critical step in the neural network approach to pattern recognition tasks. The use of pre-processing can often greatly improve the performance of a pattern recognition system. If a prior knowledge about the data is present, the performance can often be improved considerably by a selection of relevant features that can best characterize the data. In general, to obtain an appropriate model of the data and achieve faster learning, irrelevant information must be eliminated from the network training inputs.

2.2 Gaussian Mixture Models

Gaussian Mixture Model is a semi-parametric approach to density estimation [6]. Besides offering powerful techniques for density estimation, Gaussian mixture models provide important applications in the context of neural networks, in techniques for conditional density estimation, soft weight sharing and in the mixture-of-experts model. Gaussian mixtures are also well known for their ability to form smooth approximations to arbitrarily shaped densities. The use of Gaussian mixture models for modeling driver identity is motivated from the observed behavior that there is a general tendency for the driver to exert certain amounts of pressure on the pedals more frequently than others and in some distributions that can be represented by Gaussian components.

3. Experiments setup

The driver recognition task was compared on different implementations of the system using Gaussian Mixture Statistical Scheme (GMSS) and EFuNN. The training and testing methodology for the neural network-based implementation is first discussed. Features were extracted from the driving data (stop & go regions) of 30 drivers. For each driver, each set of features can be further classified into 4 sets corresponding to the signal type namely accelerator pedal pressure, brake pedal pressure, dynamics of accelerator pedal pressure and dynamics of brake pedal pressure. Each driver can be modeled by 1 up to 4 networks corresponding to the different signal types.

Generally, 2 types of data files were prepared as the sources of the networks namely training data files and testing data files. Training data files contain input features for the networks' training purpose and testing data files contain input features used to measure the performance of the networks after the training process. Identification is performed by presenting the testing data file(s) to the driver recognition system which is then presented to all the corresponding network(s) of all drivers. The networks' outputs are linearly combined for each driver and the driver with the highest combined network output is identified as the driver. For verification, the testing data file is fed to the asserted driver networks and the linearly combined output of the networks is compared with a decision threshold. If the output satisfies the pre-defined threshold level, the identity claim is verified otherwise the claim will be rejected.

Each driver is modeled by 1 up to 4 sets of GMM parameters corresponding to the different signal types. Each set of GMM parameters is computed for a single vector formed by appending the stop & go regions designated for training. In general, there would be a total of 10 driver templates of up to 40 sets of GMM parameters for each driver recognition system. For identification, the input signal(s) are presented to the driver recognition system where the likelihood is measured for each driver template and the driver template that gives the maximum likelihood is identified as the driver. For verification, the input signal is presented to the driver template for which the claim is asserted and the likelihood is computed. If the likelihood value satisfies a pre-defined threshold level, the identity claim is verified otherwise the claim will be rejected.

3.1 Validation Method

Experiments were conducted on 2 groups of drivers where each group consisted of 10 different drivers and the average number of input patterns for each driver is 16. The *N-Leave-One-Out* validation method is employed in the experiments. Given *N* cases (stop & go regions) for each driver numbered from 1 to *N*, the validation is performed as follows:

1. The n^{th} case for each driver is omitted from the training process.
2. The omitted cases are used in the testing process.
3. Steps 1 and 2 are repeated for each case of the data set.

3.2 Driver Identification Performance

In the first part the EFuNN based driver recognition system were trained and tested using the GMM-based features. The performances of these implementations were measured against GMSS. The identification results for 2 groups of drivers are presented below in Table 1 and 2.

Table 1 Group I Identification Results based on GMM Features using both the accelerator and Brake pedal pressure

Signals	Accelerator + Brake Pedal Pressure (Static & Dynamic)				Accelerator + Brake Pedal Pressure (Static)			
System Type	GMSS		EFuNN		GMSS		EFuNN	
Driver #	Accuracy [%]	Test time/s	Accuracy [%]	Test time/s	Accuracy [%]	Test time/s	Accuracy [%]	Test time/s
1	93.75	2.37	81.25	0.78	81.25	1.37	81.25	0.47
2	100	1.59	93.75	0.94	81.25	0.88	68.75	0.47
3	100	2.86	100	0.78	81.25	1.54	75	0.46
4	100	2.47	81.25	0.93	87.5	1.43	81.25	0.47
5	87.5	2.30	93.75	0.79	75	1.76	81.25	0.47
6	93.75	2.58	93.75	0.93	93.75	1.60	68.75	0.31
7	93.75	2.64	100	0.78	87.5	1.49	81.25	0.47
8	93.75	2.25	75	0.94	87.5	1.32	56.25	0.47
9	100	2.53	87.5	0.94	81.25	1.48	81.25	0.47
10	87.5	1.81	81.25	0.78	87.5	0.93	75	0.47
Average	**95.0**	**2.34**	**88.75**	**0.86**	**84.38**	**1.38**	**75.0**	**0.45**

Table 2 Group 2 Identification Results based on GMM Features using both the accelerator and Brake pedal pressure

Signals	Accelerator + Brake Pedal Pressure (Static)				Accelerator + Brake Pedal Pressure (Static & Dynamic)			
System Type	GMSS		EFuNN		GMSS		EFuNN	
Driver #	Accuracy [%]	Test time/s	Accuracy [%]	Test time/s	Accuracy [%]	Test time/s	Accuracy [%]	Test time/s
1	87.5	1.48	93.75	0.63	100	2.30	100	1.56
2	93.75	1.04	100	0.62	100	2.52	100	0.94
3	62.5	1.10	87.5	0.63	75	1.75	100	0.78
4	81.25	2.47	87.5	0.62	93.75	4.29	87.5	1.09
5	68.75	1.54	68.75	0.63	81.25	2.64	68.75	0.94
6	87.5	2.03	81.25	0.62	100	3.41	87.5	0.94
7	87.5	2.14	81.25	0.78	93.75	3.74	87.5	0.94
8	81.25	1.26	81.25	0.63	93.75	2.09	93.75	0.78
9	75	1.16	68.75	0.62	100	1.97	93.75	0.93
10	81.25	1.32	68.75	0.47	87.5	2.20	68.75	0.94
Average	**80.63**	**1.55**	**81.88**	**0.63**	**92.5**	**2.69**	**88.75**	**0.98**

It was observed from table 1 and 2 of the results obtained that the fuzzy neural systems performed comparatively well against GMSS in terms of identification rate. The driver identification performance is also consistent throughout the different tests. In all 2 groups of drivers, the highest accuracy was obtained when the combination of all signals was used. It can be seen that the average identification rate obtained from using ANFIS is very close to the rate obtained for GMSS. From the driver identification tests several observations were made. Firstly, the accuracy of the GMM-based systems is good and fairly consistent between the GMMSS and the EFuNN. It may be reasonable to infer from these results that the pressure distribution information can better characterize driving behavior. Additionally, driving behavior modeling based on the pressure distribution is a more natural and intuitive method.

In terms of processing time, the training for EFuNN takes less than 20s on the worst case and testing time is only a fraction of a sec. The average testing time for GMSS was much longer compared to EFuNN systems. The testing times in all the different implementations were generally low, therefore indicating that the identification task can be performed in a relatively short amount of time. It can also be noted that the training time of the ANFIS systems were significantly smaller in GMM-based systems.

In the feature extraction techniques and for both groups of drivers, the best performance was obtained when a combination of all the driving data was used. The same phenomenon was observed in the work by Igarashi et al indicating that the combination of these signals can characterize driving behavior to a higher degree than other combinations of the signals. From these results, a driver identification system with high accuracy and fast testing time can be implemented using EFuNN with the combination of static and dynamic accelerator and brake pedal pressure signals.

3.3 Driver Verification Performance

In the second phase of testing, a further evaluation on the performance of the driver recognition system using these 3 configurations was carried out. The driver verification performance in terms of the equal error rate was measured for the 2 groups of drivers. As can be seen from the above tables, despite some variations across the 2 groups of drivers, the equal error rates are low in all instances. This indicates a good performance since in verification, it is undesirable to reject any authorized access or accept any unauthorized access. An average error rate of 3.44% was obtained for GMSS and 5.02% for EFuNN. Comparing the timing performance for identification and verification application, the latter performs better in terms of testing time since there is no need to compare the input against the template of all the drivers but only against the driver for which the claim is asserted.

Table 3 Verification results of group 1 driver using the GMM features from the Accelerator + Brake Pedal Pressure (Static & Dynamic).

System Type	GMSS		EFuNN	
Driver #	EER [%]	Test time(s)	EER [%]	Test time(s)
1	2.5	0.24	2.5	0.078
2	0	0.16	0	0.094
3	0	0.29	2.5	0.078
4	0	0.25	2.5	0.093
5	7.5	0.23	0	0.079
6	2.5	0.26	0	0.093
7	2.5	0.26	0	0.078
8	3.125	0.23	2.5	0.094
9	0	0.25	10	0.094
10	7.5	0.18	2.5	0.078
Average	**2.5625**	**0.23**	**3.25**	**0.086**

Table 4 Verification results of group 2 driver using the GMM features from the Accelerator + Brake Pedal Pressure (Static & Dynamic).

System Type	GMSS		EFuNN	
Driver #	EER [%]	Test time(s)	EER [%]	Test time(s)
1	0	0.23	0	0.156
2	0	0.25	0	0.094
3	12.5	0.18	0	0.078
4	2.5	0.43	22.5	0.109
5	7.5	0.26	7.5	0.094
6	0	0.34	7.5	0.094
7	2.5	0.37	12.5	0.094
8	2.5	0.21	2.5	0.078
9	0	0.19	3.125	0.093
10	12.5	0.22	5.0	0.094
Average	**4.0**	**0.27**	**6.0625**	**0.098**

The performances of the 3 implementations are comparatively well in verification task and thus indicate the driver recognition system's ability to deter most unauthorized access. Despite the reasonably good performance, this may not be sufficient especially for strict access control or security systems since any false acceptance will result in serious consequences. Despite the ability of the GMM-based features to model driving behavior to a high degree of accuracy, the non-perfect verification results suggest that there is still some slight similarity in driving behaviors among drivers in terms of the way they apply pressure to the brake and accelerator pedals which requires more extensive investigation and research.

4. Conclusion & Recommendations

In this research, statistical, artificial neural network and fuzzy neural network techniques were implemented and compared in the application of driver recognition. Gaussian

Mixture Models was proposed and implemented and features were extracted from the accelerator and brake pedal pressure signals of 30 drivers. The features extracted were then used as inputs to fuzzy neural network-based driver recognition systems namely EFuNN. This system was compared against a statistical method, GMSS.

Extensive testing was carried out using Matlab and several observations were made. The use of the mean pressures (applied on the accelerator and brake pedals) obtained using the GMM-based extraction process as inputs to the fuzzy neural-network based driver recognition systems was found to achieve a high identification rate and low verification equal error rate. The stated results show that the use of only the means out of the entire set of GMM parameters is adequate to efficiently characterize driving behaviors. The combination of accelerator pedal, brake pedal pressures and the dynamics of both signals was also found to give the best performance among driver combinations of the signals. The fuzzy neural systems, EFuNN performed comparatively well against GMSS. EFuNN offer fast testing time.

The idea of utilizing driving behaviors in biometric identification may initially appear to be a bit far-fetched but it has been shown to be realizable. This biometric method will offer not only an added level of protection for vehicles but also a natural and secured identification of drivers. The system can be subsequently integrated into intelligent vehicle systems where it can be used for detection of any abnormal driver behavior for purpose of achieving safer driving. The area of driver recognition is a relatively new field of study which requires more research and investigations. Further exploration is required to refine and optimize the current system implementation.

5. References

[1] Barua S., "Authentication of cellular users through voice verification", Systems, Man, and Cybernetics, 2000 IEEE International Conference, Volume: 1, 8-11 Oct. 2000, Pages: 420 - 425

[2] Pottier I. & Burel G., "Identification and authentication of handwritten signatures with a connectionist approach", *Neural Networks*, IEEE World Congress on Computational Intelligence, 1994 IEEE International Conference, Volume: 5, 27 June-2 July 1994, Pages: 2948 – 2951

[3] Obaidat M.S. & Sadoun B., "Verification of computer users using keystroke dynamics", *Systems, Man and Cybernetics*, Part B, IEEE Transactions, Volume: 27, Issue: 2, April 1997, Pages: 261 - 269

[4] Reynolds D., "An overview of automatic speaker recognition technology", *Acoustics, Speech, and Signal Processing*, Proceedings ICASSP, IEEE International Conference, Volume: 4, 13-17 May 2002, Pages: 4072 – 4075

[5] Igarashi K., Takeda K., Abut H., Itakura F. et al., "Biometric Identification Using Driving Behavioral Signals", Graduate School Of Engineering, Nagoya University, 2003

[6] Bishop C., Neural Networks for Pattern Recognition, Oxford: Clarendon Press, 1995

[7] Zadeh L. A., "Fuzzy Logic", *Computer*, Vol. 1, No. 4, Pages: 83-93, 1988

[8] Zhang L., "Associative Memory and Fuzzy Neural Network for Speaker Recognition", *Honor Year Project Report*, School Of Computer Engineering, Nanyang Technological University, 2004

[9] Hui H., Li J.H., Song F.J. & Widjaja J., "ANFIS-based Fingerprint Matching Algorithm", *Optical Engineering*, SPIE-International Society for Optical Engine, Volume: 43, Issue: 8, Aug. 2004, Pages: 1814 – 1819

[10] Kawaguchi N., Matsubara S., Takeda K. & Itakura F., "Multimedia Data Collection of In-Car Speech Communication," Proceedings 7th European Conference on Speech Communication and Technology, Sep. 2001, Pages: 2027 – 2030

[11] Bengtsson J., Johansson R. & Sjogren, A., "Modeling of Drivers' Behavior", *Advanced Intelligent Mechatronics*, Proceedings. 2001 IEEE/ASME International Conference, Volume: 2, 8-12 July 2001 Pages: 1076 - 1081

[12] Ohno H., "Analysis and Modeling of Human Driving Behaviors Using Adaptive Cruise Control", *Industrial Electronics Society 2000*, IECON 2000. 26th Annual Conference of the IEEE, Volume: 4, 22-28 Oct. 2000, Pages: 2803 - 2808

[13] Chan M., Herrera A. & Andre B, "Detection of changes in driving behaviour using unsupervised learning", *Systems, Man, and Cybernetics*, 1994 IEEE International Conference on Humans, Information and Technology, Volume: 2, 2-5 Oct. 1994 Pages: 1979 - 1982