

Chapter 2

DRIVER RECOGNITION SYSTEM USING FNN AND STATISTICAL METHODS

Abdul Wahab¹, Tan Chin Keong¹, Hüseyin Abut², and Kazuya Takeda³

¹School of Computer Engineering, Nanyang Technological University, Nanyang Avenue, Singapore (639798); ²ECE Department, San Diego State University, San Diego, CA 9218, USA and Sabanci University, Istanbul, Turkey; ³School 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 currently on electronic alarm or smart card systems. A biometric driver recognition system utilizing driving behavior signals can be incorporated into existing vehicle security system to form a multimodal identification system and offer a higher degree of protection. The system can be subsequently integrated into intelligent vehicle systems where it can be used for detection of any abnormal driver behavior with the purposes of improved safety or comfort level. In this chapter, we present features extracted using Gaussian Mixture Models (GMM) from accelerator and brake pedal pressure signals, which are then employed as input to the driver recognition module. A novel Evolving Fuzzy Neural Network (EFuNN) was used to illustrate the validity of the proposed system. Results obtained from the experiments are compared with those of statistical methods. They show potential of the proposed recognition system to be used in real-time scenarios. A high identification rate and the low verification error rate were indicated considerable difference in the way different drivers apply pressure to the pedals.

Key words: driving profile, behavioral modeling, verification and identification, soft computing, accelerator and brake pressure, dynamic driver profiling

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 characteristics are

relatively stable physical features, such as fingerprint, iris, facial features or hand geometry¹⁻⁴ while behavioral characteristics are affected, usually in a complex fashion, by the individual's mental status and they include voiceprint, hand-written signature or keystroke dynamics¹⁻³. The first class of biometrics, in particular fingerprint, has been widely used in forensics and now being evaluated in banking transactions. The second class of biometrics is gaining prominence in recent years with speaker/face/gait recognition garnering the most attention⁴.

In a recent work, driving characteristics, in particular, the amount of pressure a driver applies on the accelerator pedal and/or the brake pedal have been utilized in personal identification⁵. Encouraging experimental results indicate that there is uniqueness in driving behavior among individuals. The utilization of driving behavioral signals can blend nicely with the existing vehicle security systems and offer a higher degree of multi-level protection. Additionally, the recognition system can be integrated into intelligent vehicle systems with 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 identified and necessary actions could be taken accordingly.

Artificial Neural Networks has emerged as a powerful and practical computing tool over recent years, particularly in the field of pattern recognition/classification⁶. 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/ever changing nature of such data. Fuzzy logic was introduced as an approach to handling vagueness and uncertainty⁷. 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 for large amount of data. Even though still not widely explored, fuzzy neural systems like the Evolving Fuzzy Neural Network (EFuNN) have been applied in several recognition studies with high degree of accuracy^{8,9}. In this study, the performance of an EFuNN will be compared to Gaussian Mixture Statistical Scheme (GMSS) on driver recognition tasks. The prior work by Igarashi and others⁵ will also be implemented for comparison.

1.1 Resources

Driving data utilized in this research are subset of the In-car Signal Corpus collected by the Center for Integrated Acoustic Information Research (CIAIR), Nagoya University, Japan¹⁰. 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 primarily with the following two issues: noise robustness of speech and continual change of the vehicular environment. To date, the number of subjects involved in the data collection is more than 800 (men and women) 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 channels. For this research, only the driving signals (accelerator pedal pressure and 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.

2. DATA ANALYSIS AND FEATURE EXTRACTION

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 three are more driver-dependent traits while the latter two are more vehicle-dependent attributes. In this research, the focus was placed only on the driver-dependent 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 resolution. The pedal pressure sensors can detect pressures ranging from 0.0-30.0 kgforce/cm². 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 driving signals used in the experiments conducted by Igarashi and others⁵. These segments are also available in the In-car signal corpus. A stop&go region is defined as the period the vehicle starts moving it 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. Figures. 2.1-2.3 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.

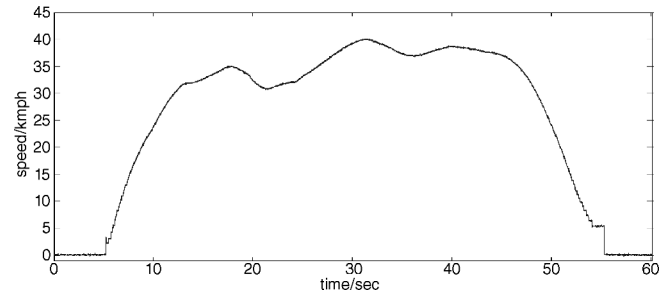


Figure 2-1. Signal trajectory of a stop&go region for the vehicle speed.

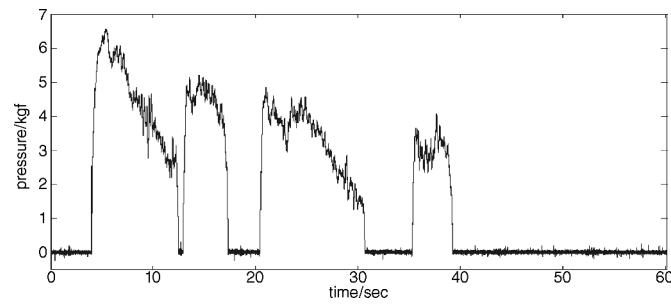


Figure 2-2. Signal trajectory of a stop&go region for the accelerator pedal pressure.

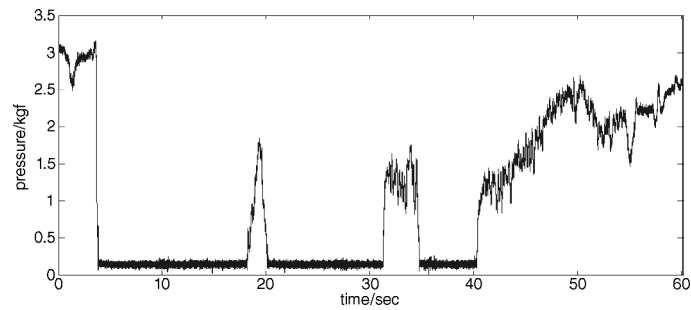


Figure 2-3. Signal trajectory of a stop&go region for the brake pedal pressure.

It can be seen from the brake pedal pressure signal plots 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 kmh 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. As expected, at any given moment, the driver can apply pressure on only one of the pedals.

In studies, often the focus is not placed only on the static data but not 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 2-4 shows an accelerator pedal pressure signal and its dynamics respectively. The dynamics signal is a function of time with the pressure/s² 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.

2.1 Feature Extraction

Reduction of data size is a critical step in the neural network approach to pattern recognition tasks. 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 data.

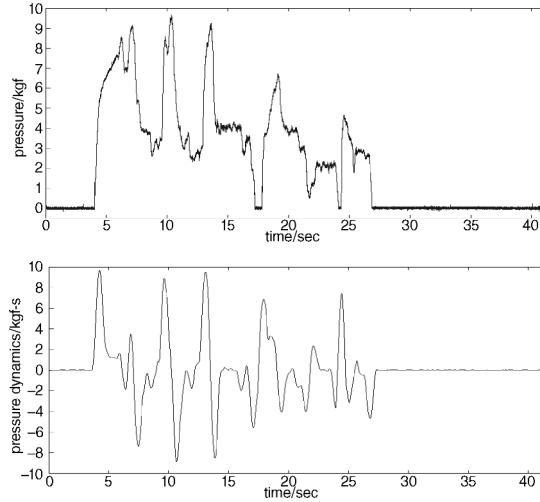


Figure 2-4. Accelerator Pedal Pressure Signal (top) and its Dynamics (bottom).

2.2 Gaussian Mixture Models

Gaussian Mixture Model is a semi-parametric approach to density estimation⁶. 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. EXPERIMENTAL SETUP

The driver recognition task was compared on different implementations of the system using 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 four sets corresponding to the signal under study, namely, the accelerator pedal pressure, brake pedal pressure, dynamics of accelerator pedal pressure

and dynamics of brake pedal pressure. Each driver can be modeled by a single or up to four networks corresponding to the different signal types.

Generally, two types of data files were prepared as the source for the networks: training data set and the test data. 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 network and a linearly combined output of the network 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 up to four sets of GMM parameters. 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 ten driver templates corresponding to forty 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 two 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 set of experiments, the EFuNN-based driver recognition system was trained and tested using the GMM-based features. The performances of these implementations were measured against GMSS. The

identification results for two groups of drivers are presented below in Tables 2-1 and 2-2.

Table 2-1. Group I Identification Results based on GMM Features using both the accelerator and Brake pedal pressure.

Signals	Accelerator + Brake Pedal Pressure (Static & Dynamic)			
System Type	GMSS		EFuNN	
Driver	Accuracy [%]	Test time/s	Accuracy [%]	Test time/s
1	93.75	2.37	81.25	0.78
2	100	1.59	93.75	0.94
3	100	2.86	100	0.78
4	100	2.47	81.25	0.93
5	87.5	2.30	93.75	0.79
6	93.75	2.58	93.75	0.93
7	93.75	2.64	100	0.78
8	93.75	2.25	75	0.94
9	100	2.53	87.5	0.94
10	87.5	1.81	81.25	0.78
Average	95.0	2.34	88.75	0.86

Signals	Accelerator + Brake Pedal Pressure (Static)			
System Type	GMSS		EFuNN	
Driver	Accuracy [%]	Test time/s	Accuracy [%]	Test time/s
1	81.25	1.37	81.25	0.47
2	81.25	0.88	68.75	0.47
3	81.25	1.54	75	0.46
4	87.5	1.43	81.25	0.47
5	75	1.76	81.25	0.47
6	93.75	1.60	68.75	0.31
7	87.5	1.49	81.25	0.47
8	87.5	1.32	56.25	0.47
9	81.25	1.48	81.25	0.47
10	87.5	0.93	75	0.47
Average	84.38	1.38	75.0	0.45

It was observed from these tables that the fuzzy neural systems performed comparatively well against GMSS in terms of identification rate. The driver identification performance is also consistent among different tests. Among these two 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 a version of Hui's ANFIS system⁹ is very close to the rate obtained for GMSS. From the driver identification tests

several observations were made. 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.

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

Signals	Accelerator + Brake Pedal Pressure (Static)			
System Type	GMSS		EFuNN	
Driver	Accuracy [%]	Test time/s	Accuracy [%]	Test time/s
1	87.5	1.48	93.75	0.63
2	93.75	1.04	100	0.62
3	62.5	1.10	87.5	0.63
4	81.25	2.47	87.5	0.62
5	68.75	1.54	68.75	0.63
6	87.5	2.03	81.25	0.62
7	87.5	2.14	81.25	0.78
8	81.25	1.26	81.25	0.63
9	75	1.16	68.75	0.62
10	81.25	1.32	68.75	0.47
Average	80.63	1.55	81.88	0.63

Signals	Accelerator + Brake Pedal Pressure (Static & Dynamic)			
System Type	GMSS		EFuNN	
Driver	Accuracy [%]	Test time/s	Accuracy [%]	Test time/s
1	100	2.30	100	1.56
2	100	2.52	100	0.94
3	75	1.75	100	0.78
4	93.75	4.29	87.5	1.09
5	81.25	2.64	68.75	0.94
6	100	3.41	87.5	0.94
7	93.75	3.74	87.5	0.94
8	93.75	2.09	93.75	0.78
9	100	1.97	93.75	0.93
10	87.5	2.20	68.75	0.94
Average	92.5	2.69	88.75	0.98

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.

For both groups of drivers, the best performance was obtained when a combination of all of the driving data was used. The same phenomenon was observed in the work by Igarashi et al⁵ indicating that the combination of these signals can characterize the 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 three configurations was carried out. The driver verification performance in terms of the equal error rate was measured for these two groups of drivers.

Table 2-3. 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 2-4. 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 three implementations are comparatively respectable in the verification task and thus indicate the driver recognition system's ability to deter most unauthorized access. Despite a 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, moderate verification results suggest that there is 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 AND RECOMMENDATIONS

In this research, statistical, artificial neural network, and fuzzy neural network techniques were implemented and compared in the framework of driver recognition. Gaussian Mixture Models was proposed and implemented. Features were extracted from the accelerator and brake pedal pressure signals of 30 drivers. These features were then used as input to a class of fuzzy neural network-based driver recognition systems, namely EFuNN. This system was compared against a well known 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. These experimental results show that the use of the means solely out of the entire set of GMM parameters is adequate to efficiently characterize driving behavior. The combination of the accelerator pedal and brake pedal pressures and their dynamics was also found to give the best performance among driver combinations of the signals. Fuzzy neural systems, EFuNN performed comparatively well against GMSS. EFuNN offer fast testing time.

The notion 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 the purpose of achieving safer driving experience. The field 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.

REFERENCES

- [1] S. Barua, "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] I. Pottier and G. Burel, "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] M.S. Obaidat B. Sadoun, "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] D. Reynolds, "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] K. Igarashi, K. Takeda, F. Itakura and H. Abut, "Biometric Identification Using Driving Behavioral Signals", Chapter 17 in *DSP for In-Vehicle and Mobile Systems*, Springer Science, Publishers, New York, 2005.
- [6] C. Bishop, *Neural Networks for Pattern Recognition*, Oxford: Clarendon Press, 1995
- [7] L. A. Zadeh, "Fuzzy Logic", *Computer*, Vol. 1, No. 4, Pages: 83-93, 1988
- [8] L. Zhang, "Associative Memory and Fuzzy Neural Network for Speaker Recognition", Unpublished Honor Year Project Report, School of Computer Engineering, Nanyang Technological University, Singapore 2004

- [9] H. Hui, J.H. Li, F.J. Song, and J. Widjaja, "ANFIS-based Fingerprint Matching Algorithm", *Optical Engineering*, SPIE-International Society for Optical Engine, Volume: 43, Issue: 8, Aug. 2004, Pages: 1814 – 1819
- [10] N. Kawaguchi, S. Matsubara, K. Takeda, and F. Itakura, "Multimedia Data Collection of In-Car Speech Communication," *Proceedings 7th European Conference on Speech Communication and Technology*, Sep. 2001, Pages: 2027 – 2030
- [11] J. Bengtsson, R. Johansson, and A. Sjogren, "Modeling of Drivers' Behavior", *Proceedings of Advanced Intelligent Mechatronics. 2001 IEEE/ASME International Conference*, Volume: 2, 8-12 July 2001 Pages: 1076 - 1081
- [12] H. Ohno, "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] M. Chan, A. Herrera, and B. Andre, "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

Advances for In-Vehicle and Mobile Systems

Challenges for International Standards

Abut, H.; Hansen, J.; Takeda, K. (Eds.)

2007, XVI, 284 p., Hardcover

ISBN: 978-0-387-33503-2