Trans Jpn Soc Med Biol Eng
50(1) : 162–167, 2012

CONTRIBUTION

Brainwave Biometrics: A New Feature Extraction Approach with the Cepstral Analysis Method

Koji Tsuru,* Gert Pfurtscheller**

Abstract Biometric personal authentication is an emerging technology in information security. One resulting problem has been a recent increase in fraud based on falsified biometric data concerning biological information. Brainwave-based identification is a promising biometric tool to prevent impostor attacks. Many researchers have reported biometric results using electroencephalogram (EEG) activity. The brainwave features of each individual are unique and have the potential for use in biometric authentication. Security can be enhanced by employing as many EEG features of an individual as possible. Although it takes time to measure brain waves at present, this authentication method can potentially be used for special security areas in the future. There are several approaches to brainwave biometrics using cognitive processes. We investigated the motor imagery for movements of the left hand, right hand, tongue, and both feet for brainwave biometrics. The nature of brain signal analysis parallels voice signal analysis in some respects. Hence, we applied the cepstral analysis method, which is commonly used in speech recognition, for feature extraction for brainwave biometrics. In our results, we identified almost all nine of the subjects correctly. We tested the performance of our biometric system using the Mahalanobis distance as the threshold and estimated the equal error rate (EER) value to be 0.17.

Keywords : biometric, authentication, EEG, cepstral analysis.

1. Introduction

This paper reports on secure electroencephalogram (EEG)-based personal identification. Recently, a series of cases of personal information leakage has been reported. Hence, there is increasing interest in using biometrics to protect the security of personal and other data. Current biometric methods include recognition based on fingerprints, the iris, the face, *etc.* These methods have been embedded in some computer devices and placed on many doors and security gates. Nonetheless, the fraud and imitation of personal biometric data have become such serious problems [1] that a new biometric method is required.

Brainwave biometrics have two advantages over prevailing biometric methods. One is the difficulty in eavesdropping on personal brainwave data. Since brainwave potentials are very weak, brainwave data must be measured by specialized equipment in contact with the outer surface of the scalp. Therefore, collecting data for fraudulent purposes is more difficult than doing so for traditional biometric methods based on image pattern matching. The second advantage is that the brainwaves can reflect individual mental activities. This property leads to many possibilities for diverse biometrics. The traditional biometric methods are based on image pattern matching to identify people using single fixed templates. In contrast, brainwave biometrics can identify people on the basis of templates that reflect different brain activities such as a cognitive process. We believe that this authentication method will be used for special security areas in the future, although brainwave biometrics require considerable time and effort to measure, at present.

The brainwave biometric approach is divided into three principal methods. The first method assesses resting brainwaves. Poulos *et al.* [2] first tried to identify individuals based on the EEG. They analyzed the α waves of four subjects' EEG using a neural network classification method. Paranjape [3] used brainwave data based on α waves when eyes were open/closed for biometric analysis. These and other results [4–6] based on the α wave reported good classification results. In addition, this method only requires a few electrodes, which is an important advantage when developing a practical device. However, subjects were required to sit quietly for a relatively long time. The second method utilizes the event-related potential from a cognitive human brain process. Palaniappan and Mandic [7] investigated the γ wave band of the visual evoked potential elicited during a mental task for personal identification. Thorpe [8] and Touyama [9] investigated biometric methods of extracting the P300-evoked potentials during image retrieval. The amplitude, latency, and scalp distribution of the P300 and related components are affected by cognitive processes, including attention and memory [10, 11]. Another cognitive process that has been assessed for brainwave biometrics is motor imagery. Mercel and Millan [12] studied the personal-authentication-based motor images of left or right hand movements as well as

Presented at the Symposium on Biomedical Engineering 2011, Nagano, September 2011.
Received July 29, 2011; revised October 29, 2011, November 22, 2011.
* Department of Computer and Control Engineering, Oita National College of Technology
** Laboratory of Brain-Computer Interfaces, Institute for Knowledge Discovery, Graz University of Technology

word generation. Bao [13] and Hu [14] investigated a biometric-method-based analysis of signal properties for four types of motor imagery. The last method involves the use of the brainwave biometrics in near infrared spectroscopy (NIRS), which is a noninvasive optical method to observe hemodynamic change in tissue. Pfurtscheller *et al.* studied the phase shift measured by NIRS signals for its suitability to use in brainwave biometrics.

While all of these approaches can yield promising results, the brainwave-based biometric technology is still inaccurate. In order to enable the use of an authentication method by anybody without the use of his or her own memory or a special practice, we decided to choose the brain waves of the motor imagery approach for brain wave authentication. We employed a cepstral analytical method for EEG feature extraction. The cepstral analysis is commonly used in speech recognition research [15]. The phoneme, which is a basic feature of speech, is extracted in the cepstral analysis. This analysis is effective in extracting and identifying the phoneme because the spectrum of the human voice can be compressed effectively by the discrete cosine transform (DCT). We applied this approach to brainwave analysis to extract the best individual feature. The use of cepstral analysis in brainwave research has been reported elsewhere for different purposes. Rauner *et al.* utilized it to remove artifacts [16]. Abdul and Wong [17] reported that they extracted the best brainwave feature for identifying motor actions of the limbs by using the cepstral method with a Mel filter bank. They reported that the cepstral method is a good method for feature extraction and classification of limb motions.

In this study, we investigated brainwave biometrics using the cepstral analysis method, which has not previously been applied for this purpose. We attempted to classify nine healthy subjects by the extracted cepstral data.

2. Experiment

2·1 Data description

All brainwave data in this paper were obtained from the dataset supplied by the Graz University of Technology at brain computer interface (BCI) Competition IV [18]. This dataset consists of two EEG data sessions from nine healthy subjects on two different days; the two data sessions are designated as datasets 1 and 2. These EEG data are composed of four motor imagery tasks: imagining the movement of the left hand, right hand, both feet, and tongue. As each dataset has 288 trials with short breaks, each motor imagery task has 72 trials. Each trial consisted of four stages: an instruction period lasting 2 s, cue for 1 s, motor imagery task for 3 s, and a short break for about 1 s. Twenty-two electrodes were attached to the top of head corresponding to the International 10–20 system. The sampling frequency of the brainwave signals was 250 Hz.

2·2 Preprocessing

Since brainwave signals are usually contaminated with various artifacts, some techniques were applied to improve the signal properties. The brain signals of the datasets were already filtered from 0.5 to 100 Hz by a band-pass filter with a 50 Hz notch filter. As these datasets include a list of trials containing eye movement artifacts, we removed these trials from our dataset. Therefore, the number of trials for each movement decreased slightly. For each trial, we extracted the first 6 s of data from instruction to the end of the motor imagery. As the readiness potential is used for individual qualities, we collected the EEG data before the motor imagery. To show that our approach can be applicable to a real-world system with few electrodes, we selected four electrodes for feature extraction out of the 22 electrodes in the dataset. The four electrodes—over locations Fz, C3, C4, and Pz—were chosen *a priori* because they typically reflect the motor activity [19]. C3 and C4 took measurements over the left and right sensorimotor cortices. Motor execution imagery produces lateralized amplitude suppression and then enhancement of β and μ waves over the sensorimotor cortices [20].

A general scheme is depicted in **Fig. 1**, with components that are explained in the following sections.

2·3 Feature Extraction

After the brainwave signals were preprocessed, important features describing the discriminative properties of the brainwaves were extracted in the feature extraction process. We applied the new feature extraction method based on cepstral analysis as follows. First, we applied a Hamming window and a rectangular window to each trial data because these windows provide good frequency resolution. Each window length was 1500 points corresponding to 6 s. Next, the discrete Fourier transform (DFT) algorithm was applied to each trial data to acquire the frequency spectrum. The strength of the spectrum was plotted on a logarithmic power scale up to 40 Hz. This frequency band included α wave (8–13 Hz), β wave (14–30 Hz), and μ wave (12–18 Hz) activities. These waves have distinctive characteristics that reflect motor imagery [20, 21].

Next, we prepared a small number of features extracted from the spectrum power of the brainwave data. With the reduced data, we calculated the sum of every 2 Hz of the spectrum power band from 0 Hz to 40 Hz. The reduced spectrum data were converted to cepstral data by the DCT. We obtained most features from the lower range of the cepstral data because the spectrum information was concentrated in the low-quefrency part of the cepstral

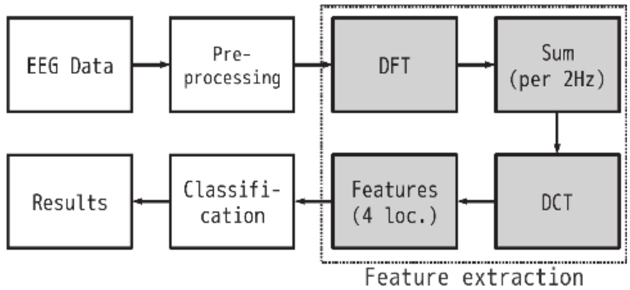

Fig. 1 Principal scheme for brainwave biometrics. The gray boxes show the feature extraction process.

data. For the four electrodes, we selected the first to seventh cepstral values as the feature amounts. All features at the four electrodes were put into one data set. Thus, we extracted 4–28 features per trial.

2・4 Classification

The next step is the classification block, which is shown in Fig. 1. The purpose of this stage is to separate the input data into multiple classes. In other words, one subject of the group is identified by the brainwave data of an unknown subject. The various classification methods have many different ways of implementation in BCI research. Here, we selected two fundamental classifiers: linear discriminant analysis (LDA) and quadratic discriminant analysis based on Mahalanobis distance (MD). The probability of person identification was called the identification rate. We used dataset 1 for training data, as mentioned 2.1, and we used dataset 2 for testing purposes only to create a situation analogous to practical use.

3. Results

Fig. 2 indicates the identification rate based on the features extracted with the logarithmic power scale data. The rate is the average of the nine subjects. The LDA classifier and MD classifier were used with Hamming and rectangular windows. The LDA classifier with a Hamming window produced a good result. The identification rate increased above 0.8 around the 20 features, with five features each from the four electrodes. Feature reduction using the DCT method was effective for classification. On the other hand, the MD identification rate was better with a rectangular window than with a Hamming window. Hence, we provided the LDA and MD classifiers with Hamming and rectangular windows, respectively.

Fig. 3 shows the identification rate of four motor imagery tasks depending on the number of features. Each motor imagery task suggested the same trend. Both the feet and the tongue motor imagery produced slightly higher identification rates than the others. All motor imagery plots improved the identification rate to closer to 0.8 at around 24 features and saturated the value. The classification rate was no different between the four motor imagery tasks.

Fig. 4 shows the identification rate of individual subjects for 4–24 selected features. The x-axis in this figure reflects individuals in the subject pool. With fewer features, the identification rate varied greatly. The rates without subject No. 2 reached a constant high rate when over 20 features were used. However, subject No.2 was difficult to identify. Hence, people who cannot be identified by our brainwave biometrics tools may exist [22].

Fig. 5 shows the identification rate across different numbers of selected features that were extracted from the averages of the four motor tasks with one, two, or four electrodes. The four electrodes were located at Fz, C3, C4, and Pz. Using two electrodes, we examined all combinations and calculated the average of all of them. As a result, the identification rate with two electrodes was about the same as with four electrodes. In all different combinations

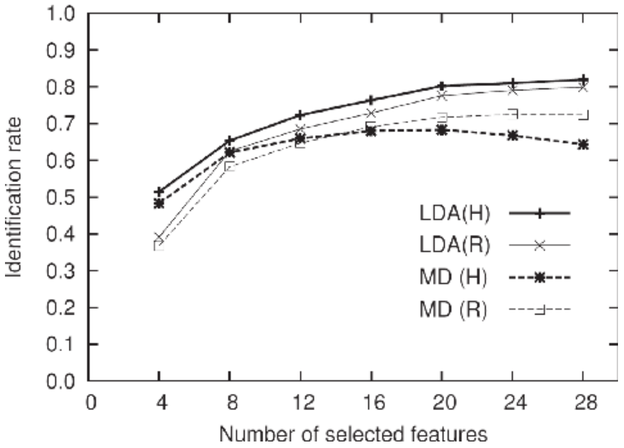

Fig. 2 Identification rate based on the number of features extracted from the cepstral data. The LDA classifier and MD classifier were employed with Hamming (H) and rectangular (R) windows, respectively.

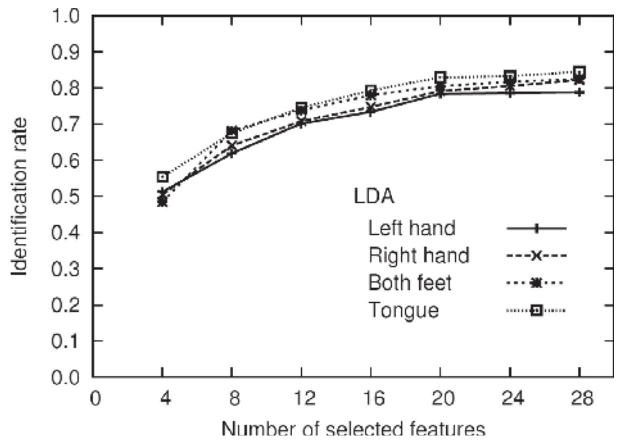

Fig. 3 Identification rate of four motor imagery tasks depending on the number of features. We obtained these rates using the LDA classifier.

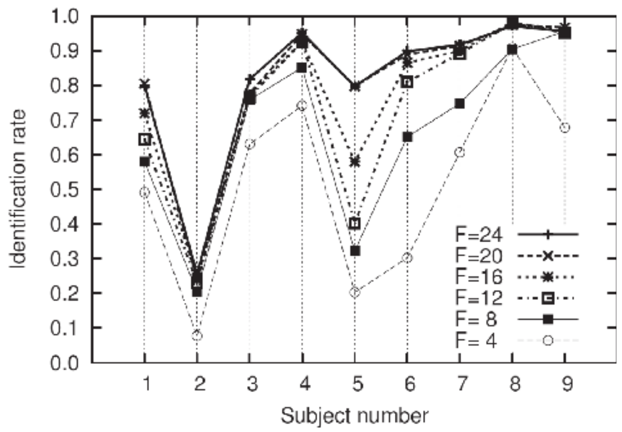

Fig. 4 Identification rate of individual subjects depending on selected features (F) from the LDA classifier. The x-axis indicates the subject identification number of Nos. 1–9.

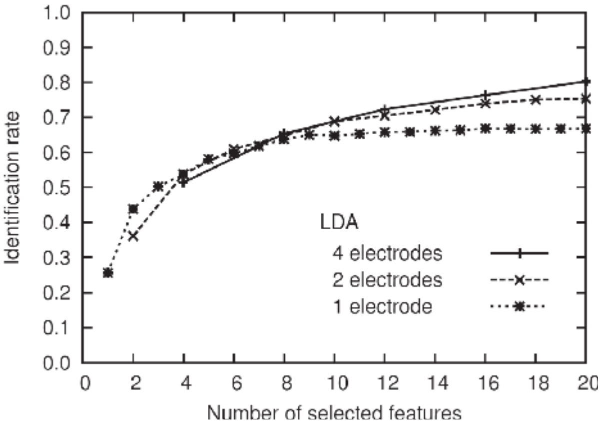

Fig. 5 Identification rate across different numbers of selected features that were extracted from the averages of the four motor tasks with one, two, or four electrodes. These rate were estimated by the LDA classifier.

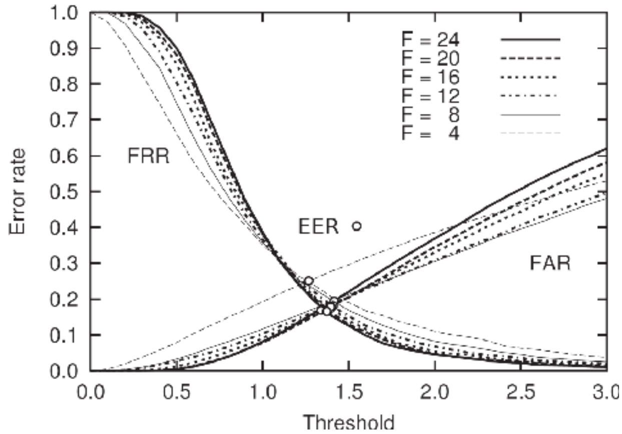

Fig. 6 Error rate depends on the threshold normalized by the average of the Mahalanobis distance from the correct dataset. Between 4 and 24 features (F) were used. EERs are indicated by open circles.

with two electrodes, rates were slightly better when the Pz-electrode site was included.

4. Discussion

This paper describes the brainwave biometric method that was applied to the feature extraction mechanism based on the cepstral analysis method. Our study revealed that this brainwave biometric approach yields good results based on relatively few features extracted from the cepstrum. After DCT, the spectrum information concentrates the low-quefrency part of the cepstrum; therefore, the cepstrum features are suitable for identifying individuals. We also performed experiments on the identification rate without this feature extraction. In the results, the rates were equivalent when more than 24 features were used. However, the rate with this feature extraction was better than the rate without it when less than 16 features were used [23]. The cepstral analysis method was useful for personal authentication from brainwave data, and these results suggest that brainwave propagation though the cranial bone is similar to voice propagation from the vocal-tract model in some respects. In this work, we did not use a filter bank such as the Mel filter, which is widely used in speech recognition. As the specific filter banks in relevant waves such as the α, β, and μ wave are employed in brainwave biometrics, there is a possibility that fewer features are necessary for the identification of individuals.

The identification rate was greater than 0.8 with 24-dimension parameters based on six cepstrum features extracted with four electrodes by the LDA classifier. Increasing the number of electrodes can potentially improve the identification rate. However, in terms of practical application, brain waves should be measured by as few electrodes as possible.

The results of the identification rate suggest the distinct clustering of each subject in the dimensions studied. Therefore, the classification must be confined to within a certain Mahalanobis distance to detect outliers. We calculated the error rate of the false rejection rate (FRR) and false acceptance rate (FAR) using the Mahalanobis distance as a threshold. The FRR and FAR are classification parameters often used to examine the biometric system. FRR is defined as the fraction of the number of rejected trials of a true subject divided by the total number of trials of the true subject. The FAR is defined as the fraction of falsely accepted subject trials divided by the number of all impostor trials. In this case, an impostor is defined as all subjects who are not a target subject. Assuming the Mahalanobis distances of the target subject should always be closer than the distances of impostors, we could use a certain threshold separating the two groups of distances to distinguish between the target subject and the impostors. The Mahalanobis distances depend on the dimensions of the feature; therefore, we used normalized distances divided by the average of the Mahalanobis distance of the correct data including the test dataset.

Fig. 6 shows the error rates of FRR and FAR when 4–24 features are used. The error rates are the average of the error rates across the four motor imagery tasks. The error rates of FRR and FRA were improved when the number of features was increased. The Mahalanobis distances were found to be suitable for person classification using brainwave biometrics. The intersection point between the FRR and FAR curves is usually called the equal error rate (EER), as shown by the open circles in Figure 6. The EER values gradually converged at 1.4 of the threshold. This means that if the threshold was set at 1.4 times the average of the Mahalanobis distances for 24 features, 0.17 of the true subjects would be rejected and 0.17 of the false subjects would be accepted by this biometric system. This EER value is higher than or comparable to that obtained using biometric methods based on the analysis of signal properties. The EER of a biometric system can be used to measure the performance independent of the threshold. A low EER value generally denotes good performance of the biometric system. The EER in this work was in the middle range of other reports on brainwave biometrics, which range from 0.03 to 0.3 [6, 4, 14]. For example, the EER values of fingerprint biometrics [24, 25] were about half to one-tenth of the EER values from brainwave biometrics. However, it is difficult to estimate the EER value correctly from the low number of subjects [26]. The more subjects we examine by our brainwave biometric approaches, the more reliable the EER value becomes. In addition, the demonstration of the superiority of the feature extraction methods used in this study for other event-related potentials, such as evoked potential by external stimulation, is an important research topic for brainwave personal identification.

5. Conclusion

We investigated a brainwave biometric approach using a new feature extraction based on the cepstral analysis method. The results indicate that brainwave biometrics are promising tools for personal authentication. The cepstral analysis method can be useful for extracting features. This method identified almost all of the nine healthy subjects accurately. We estimated the EER values of 0.17 using a Mahalanobis distance classifier to determine the threshold.

Acknowledgments

The authors thank Clemens Brunner, Josef Faller, Petar Horki, and Teodoro Solis Escalante for their suggestions regarding data processing. They also thank Alois Schlögl for technical suggestions regarding programming. Special thanks go to Brendan Z. Allison for his valuable comments and corrections. This work is supported by the grant for the Overseas Research Program from the Institute of National College of Technology, Japan.

References

1. Matsumoto T: Gummy and conductive silicone rubber fingers importance of vulnerability analysis. Advances in Cryptology ASIACRYPT 2002 (Lecture Notes in Computer Science vol. 2501), 2002, pp. 59–65.
2. Poulos M, Rangoussi M, Chrissikopoulos V, Evangelou: Person identification based on parametric processing of the EEG, Electronics. Circuits and Systems, . Proceedings of ICECS '99. The 6th IEEE International Conference on vol 1, 1999, pp. 283–286.
3. Paranjape RB, Mahovsky J, Benedicenti L, Koles'Z: The electroencephalogram as a biometric. Proc. Canadian Conf. Electrical and Computer Engineering vol. 2, 2001, pp. 1363–1366.
4. Miyamoto C, Baba S, Nakanishi I: Biometric person authentication using new spectral features of electroencephalogram (EEG). Proc. Int. Symp. Intelligent Signal Processing and Communications Systems ISPACS 2008. 2009, pp. 1–4.
5. Su F, Xia L, Cai A, Ma J: Evaluation of recording factors in EEG-based personal identification: A vital step in real implementations. Proc. IEEE Int. Systems Man and Cybernetics (SMC) Conf. 2010, pp. 3861–3866.
6. Riera A, Soria-Frisch A, Caparrini M, Grau C, Ruffini G: Unobtrusive biometric system based on electroencephalogram analysis. EURASIP J. Adv. Signal Process. 2008, pp. 1–8.
7. Palaniappan R, Mandic DP: Biometrics from brain electrical activity: A machine learning approach. Pattern Analysis and Machine Intelligence. IEEE Transactions on. **29**: 738–742, 2007.
8. Thorpe J, van Oorschot PC, Somayaji A: Pass-thoughts: authenticating with our minds. Proceedings of the 2005 workshop on New security paradigms NSPW '05 (New York, NY, USA: ACM), 2005, pp. 45–56.
9. Touyama H, Hirose M: The use of photo retrieval for EEG-based personal identification. Computer-Human Interaction. Lecture Notes in Computer Science vol. 5068, 2008, pp. 276–283.
10. Donchin E, Coles MGH: Is the P300 component a manifestation of context updating? Behavioral Brain Sci. **11**: 357–427, 1988.
11. Polich J: Updating P300: An integrative theory of P3a and P3b. Clin Neurophysiol. **118**: 2128–2148, 2007.
12. Marcel S, Millan J: Pattern Analysis and Machine Intelligence. IEEE Transactions on. **29**: 743–752, 2007.
13. Bao X, Wang J, Hu J: Method of individual identification based on electroencephalogram analysis. Proc. Int. Conf. New Trends in Information and Service Science NISS '09, 2009, pp. 390–393.
14. Hu J: New biometric approach based on motor imagery EEG signals. Proc. Int. Conf. Future BioMedical Information Engineering FBIE 2009, 2009, pp. 94–97.
15. Bogert B, Healy M, Tukey J: The quefrency analysis of time series for echoes: Cepstrum, Pseudo-Autocovariance, Cross-Cepstrum and Saphe Cracking, Proc. Symp. on Time Series Analysis, 1963, pp. 209–243.
16. Rauner H, Appel U, Wolf W: Application of a cepstral distance measure in evoked potential processing. Proc. IEEE Int. Acoustics, Speech, and Signal Processing Conf. ICASSP '83, 8, 1983, pp. 280–283.
17. Abdul W, Wong J W: Cortical activities pattern recognition for the limbs motor action, Proc. IET 4th Int. Intelligent Environments Conf., 2008, pp. 1–7.
18. Brunner C, Leeb R, Müller-Putz G, Schlögl A, Pfurtscheller G: BCI competition iv: Data sets 2a, http://www. bbci.de/competition/iv/, 2008.
19. Pfurtscheller G, Neuper C: Motor imagery activates primary sensorimotor area in humans. Neurosci Lett. **239**: 65–68, 1997.
20. Pfurtscheller G, Neuper C: Future prospects of ERD/ERS in the context of brain-computer interface (BCI) developments, Event-Related Dynamics of Brain Oscillations (Progress in Brain Research vol. 159), 433–437, 2006.
21. Pfurtscheller G, Neuper C: Motor imagery and direct brain-computer communication, Proceedings of the IEEE. **89**: 1123–1134, 2001.
22. Allison B, Luth T, Valbuena D, Teymourian A, Volosyak I, Graser A: BCI demographics: How many (and what kinds of) people can use an SSVEP BCI? Neural Systems and Rehabilitation Eng. IEEE Transactions on. **18**: 107–116, 2010.
23. Tsuru K: A proposal for brainwave biometrics with the cepstral analysis method. Proc. of FIT 2011, Hakodate, L-028, 2011, pp. 239–240.
24. Maio D, Maltoni D, Cappelli R, Wayman JL, Jain AK: Third fingerprint verification competition. Biometric Authentication (Lecture Notes in Computer Science vol 3072), 1–5, 2004.

25. Cappelli R, Maio D, Maltoni D, Wayman J, Jain A: Performance evaluation of fingerprint verification systems. Pattern Analysis and Machine Intelligence. IEEE Transactions on. **28**: 3–18, 2006.
26. Schuckers ME, Hawley A, Livingstone K, Mramba N: A comparison of statistical methods for evaluating matching performance of a biometric identification device. Proc. SPIE, 5404, 2004, pp. 144–155.

Koji TSURU

Koji TSURU received his MS and PhD degrees in physics from Kyushu University, Fukuoka, Japan. He worked in the R & D department of Nippon Telegraph and Telephone Corporation from 1988 to 2003. He has worked in the Department of Computer and Control Engineering at Oita National College of Technology, Oita, Japan, since 2004. He is currently a Professor. In 2010, he studied at the Brain Computer Interface Laboratory at the Graz University of Technology, Graz, Austria, as a Visiting Professor. His research interests include information security, analysis of biomedical data, and brain-computer interfacing based on EEG. He is a member of The Institute of Electronics, Information and Communication Engineers.

Gert PFURTSCHELLER

Gert PFURTSCHELLER received his MS and PhD degrees in Electrical Engineering from the Graz University of Technology, Graz, Austria. He was Full Professor of Medical Informatics and Professor of Brain Computer Interfaces at the Graz University of Technology (TUG), visiting Professor at Cape Town University and Vancouver University and is Emeritus Professor at TUG since October 2009. He was Head of the Institute of Biomedical Engineering, Director of the Ludwig Boltzmann Institute for Medical Informatics and Neuroinformatics and is Founding Director of the Brain-Computer Interface Laboratory (BCI-Lab) at the TUG. He has authored more than 300 publications in peer-reviewed journals and published 4 books. He was honoured by election as a member of the Austrian Academy of Science.