Using Brain Waves as Transparent Biometrics for On-Demand Driver Authentication

Isao Nakanishi*

Graduate School of Engineering,
Tottori University,
4-101 Koyama-minami, Tottori 680-8552, Japan
E-mail: nakanishi@ele.tottori-u.ac.jp
*Corresponding author

Sadanao Baba

Graduate School of Engineering,
Tottori University,
4-101 Koyama-minami, Tottori 680-8552, Japan
He is now at JTEKT corporation.

Koutaro Ozaki

Faculty of Engineering,
Tottori University,
4-101 Koyama-minami, Tottori 680-8552, Japan
He is now at SUZUKI MOTOR corporation.

Shigang Li

Graduate School of Engineering,
Tottori University,
4-101 Koyama-minami, Tottori 680-8552, Japan
E-mail: li@ele.tottori-u.ac.jp

Abstract: Conventional biometric systems mainly assume one-time-only authentication. However, this technique is not used with user management applications. If a user is replaced by an imposter after the authentication has occurred, the systems cannot detect such a replacement. One solution to this problem is on-demand authentication, in which users are authenticated on a regular or nonregular schedule, as determined by the system. However, the on-demand-authentication technique requires that we present biometric data without regard to do so. In this paper, we focus on the use of brain waves as transparent biometric signals. In particular, we assume driver authentication and measure the brain waves of drivers when they are performing mental tasks such as tracing routes or using a simplified driving simulator as an actual task. We propose to extract the power spectrum in the α–β band as an individual feature and propose two verification methods based on the similarity of the features. In addition, we propose to divide the α–β band into either four or six partitions and to fuse the similarity scores from all the partitions. We evaluate the verification performance using 23 subjects and obtain an equal error rate of 20-25 %.

Keywords: brain wave; EEG; on-demand authentication; transparent biometrics; driver authentication; route trace; simplified driving simulator.

Biographical notes: Isao Nakanishi received his B. E., M. E., and Dr. E. degrees in Electrical Engineering from Osaka Prefecture University, Japan in 1984, 1986, and 1997, respectively. He is now an associate professor in the Graduate School of Engineering, Tottori University, Japan. His research interests are in digital signal processing and biometrics. He is a member of the IEEE, the Institute of Electronics, Information and Communication Engineers (IEICE) and the Information Processing Society of Japan (IPSJ).

Sadanao Baba received his B. E. and M. E. degrees in Electrical Electronic Engineering from Tottori University, Japan in 2007 and 209, respectively. In 2009, he joined JTEKT Corporation.

Koutaro Ozaki received his B. E. degree in Electrical Electronic Engineering from Tottori University, Japan in 2010. In 2010, he joined SUZUKI MOTOR Corporation.

Shigang Li received his B. E. degree in Electrical Engineering from Beijing Tsinghua University, China in 1985. He received his M. E. and Dr. E. from Osaka University, Japan in 1990 and 1993, respectively. After receiving his Dr. E., he worked at Osaka University as a Research Associate. He became an associate professor with the Faculty of Information Sciences, Hiroshima City University, Japan in 1995. In 2001, he joined to the Faculty of Engineering, Iwate University, Japan. He has worked as a professor with the Graduate School of Engineering, Tottori University, Japan, since Oct. 2007. His research interests include computer/robot vision, intelligent transportation system and mixed reality systems.

1 Introduction

In security systems, biometrics is expected to lead to better results than passwords or ID cards (Wayman et al., 2005). However, this approach is vulnerable. A few biometric authentication systems have been circumvented by artifacts; therefore, it is desirable that the biometric data are hidden within a person's body and authentication systems possess the function of liveness detection.

In addition, conventional biometric systems mainly assume one-time-only authentication technique such as access control, ATM-banking, and passport control. However, the one-time-only authentication method is not used with user

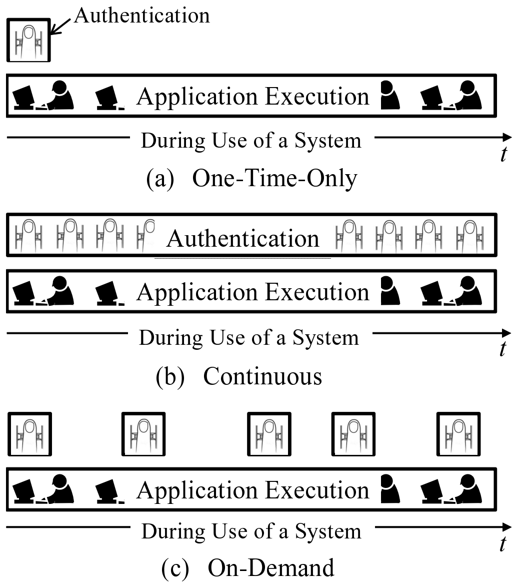


Figure 1 Authentication styles, (a): one-time-only, (b): continuous, and (c): on-demand authentication.

management applications. Once a genuine user is authenticated at the beginning of use a system, the system is unable to detect whether or not the user has been replaced by an imposter after authentication has occurred. This issue is illustrated in Fig. 1 (a) (Nakanishi et al., 2010), in which it is assumed that both the authentication and application processes are executed in a single system. The one-time-only authentication technique cannot detect spoofing after authentication, whereas authentication does not incur a large computational load on the system because it is performed only once when the execution of the application begins.

To overcome the above problem, continuous authentication (Altinok and Turk, 2003; Kwang et al., 2009) is found to be effective as illustrated in Fig. 1 (b). Security is always guaranteed while the application is being executed. However, continuous authentication increases the computational load on the system. For instance, Ref. (Kwang et al., 2009) reported that a computational overhead of 42 % was recorded in a continuous authentication system.

Therefore, we proposed an on-demand authentication, which is illustrated in Fig. 1 (c) (Nakanishi et al., 2010). Users are authenticated on both regular and nonregular schedules according to the authentication demand request received from the system. On-demand authentication is shown to be a solution to the trade-off problem between guaranteeing security and preventing system overload.

The fingerprint and iris are not suitable for continuous and on-demand authentication because they require users to present the biometric data whenever authentication is performed. In other words, continuous and on-demand authentication techniques require biometrics sources that can transparently present biometric data.

For transparent biometrics, the face, ear, voice, keystroke, and gait are possible options. However, the face and ear can easily be imitated using artifacts, and the voice, keystroke, and gait have limited applications.

On the other hand, the use of brain waves as biometrics has been proposed in several studies (Poulos et al., 1999a,b,c; Paranjape et al., 2001; Ravi and Palaniappan, 2005; Palaniappan, 2005; Mohammadi et al., 2006; Ravi and Palaniappan, 2006; Singhal and Ramkumar, 2007; Marcel and Millan, 2007; Palaniappan and Mandic, 2007; Riera et al., 2008). Brain waves are generated by the neural activities in the cerebral cortex; therefore, it is hidden in the body and cannot be bypassed. The brain wave is useful for the function of liveness detection because it is generated only by alive human beings. Moreover, brain waves are generated naturally; therefore, it enables on-demand authentication. Conversely, the brain wave is unsuitable for one-time-only authentication because users are required to put sensors on their scalp whenever they are being authenticated.

In authentication applications, there exists a trade-off between the degree of security and the usability. From a basic research standpoint, it is important to evaluate complex models/methods for feature extraction and verification in order to obtain higher security degree. In such cases, for instance, users have to put a lot of electrodes on their scalp; thus, the usability is degraded. In addition, a high performance system is required for coping with a heavy computational load. On the other hand, for a practical use, the usability sometimes has higher priority. It is better to execute authentication in the easy manner possible, for instance, using single sensor and simple methods for feature extraction and verification as they should be processed in a low-cost embedded system.

We have studied brain waves as biometrics based on the latter standpoint (Nakanishi et al., 2009, 2010, 2011a; 2011, b; Nakanishi et al., 2012a,b). Moreover, to verify the performance of brain waves, we assumed five steps based on the user's physical and mental conditions: 1) eye-closed and relaxed condition, 2) eye-closed and mentally-burdened (using mental energy to perform tasks) condition, 3) eye-opened and relaxed condition, 4) eye-opened and mentally-burdened condition, and 5) eye-opened and performing-actual-task condition (Nakanishi et al., 2012b).

We consider that operator verification for systems such as computers and vehicles are suitable applications, in which authentication using brain waves may be used. The operator wears a brain wave sensor, and he/she is verified on demand while using the system. However, it is assumed that the operator is replaced by the other when he/she is not in operation but in stoppage. It is necessary to perform authentication whenever the operation is re-started; thus, in such a situation, on-demand authentication is suitable.

In Ref. (Nakanishi et al., 2012b), by assuming authentication of computer users, we examined the first three steps as mentioned above. The verification rate was approximately 15%, which was unsatisfactory. However, it is confirmed that brain waves can be utilized as a biometric modality even by using a simple approach.

In this study, we verify performance of the brain wave for the last two conditions, that is, the eye-opened and mentally-burdened conditions, and eye-opened and performing-actual-task conditions. More precisely, to perform driver authentication, we examine verification performance of the brain waves of users (drivers) who are tracing routes (mental task) or driving virtually (actual task).

In this study, we focus on driver authentication because if sleeping and/or intoxicated drivers can be detected using brain waves, this technique can be integrated with a driver's on-demand authentication system and it will become a valuable tool to reduce the frequency of vehicle accidents.

2 Verification Using Brain Waves

2.1 Brain Wave

Electrical changes that are due to a large number of synapses (neurons) in the cerebral cortex are accumulated and are then detected as brain waves on scalp using an electrode. Because of the spatiotemporal dispersiveness of the neurons, there are generally no synchronized patterns in the electroencephalogram (EEG) signals. However, when the activity of the cerebral cortex decreases, the brain wave becomes partially synchronous, and distinct waves are observed. Waves such as δ (0.5–3Hz), θ (4–7Hz), α (8–13Hz), and β (14–30Hz) are well known and are usually detected when humans are in a deep sleep, sleepy, relaxed with closed eyes, and involved in some mental activity, respectively. In particular, the α and/or the β waves are applicable for authentication of persons.

2.2 Feature Extraction and Verification

The approach used to perform authentication using EEG is the same as that in conventional studies (Nakanishi et al., 2009, 2010, 2011a; 2011, b; Nakanishi et al., 2012a,b); that is, the architecture for feature extraction and verification must be as simple as possible.

In Ref. (Nakanishi et al., 2012b), for the individual feature, we proposed the use of spectral variance and the maldistribution in the α band and the difference between the spectra under relaxed and mentally-burdened conditions in the β band. In particular, the former two are based on the assumption that the EEG power spectral elements are normally distributed in the α band. However, the EEG spectrum in the α band is suppressed in the tasked condition; therefore, the conventional feature becomes ineffective. Thus, by extending the concept of feature extraction in the β band in the conventional study, in this paper, we propose to extract the power spectrum in the α–β band as an individual feature. Verification is achieved on the basis of the difference between the mean value of the power spectrum in the tasked condition and that in relaxed condition.

It should be noted that in the eye-opened condition, it is well known that the EEG is affected by blinking of the eye. Therefore, we examined the effect of eye-blinks in advance. The results confirmed that the spectral elements of the EEG during eye-blinks were distributed under the α band and did not overlap with the spectrum used in feature extraction described later in the text. As long as individual features are extracted from the EEG spectrum, we believe that to prevent it from having an impact, it is unnecessary to detect or filter the eye-blink.

Furthermore, we divide the α–β band into several partitions and merge the scores from all partitions. This is because distribution of the spectral elements in

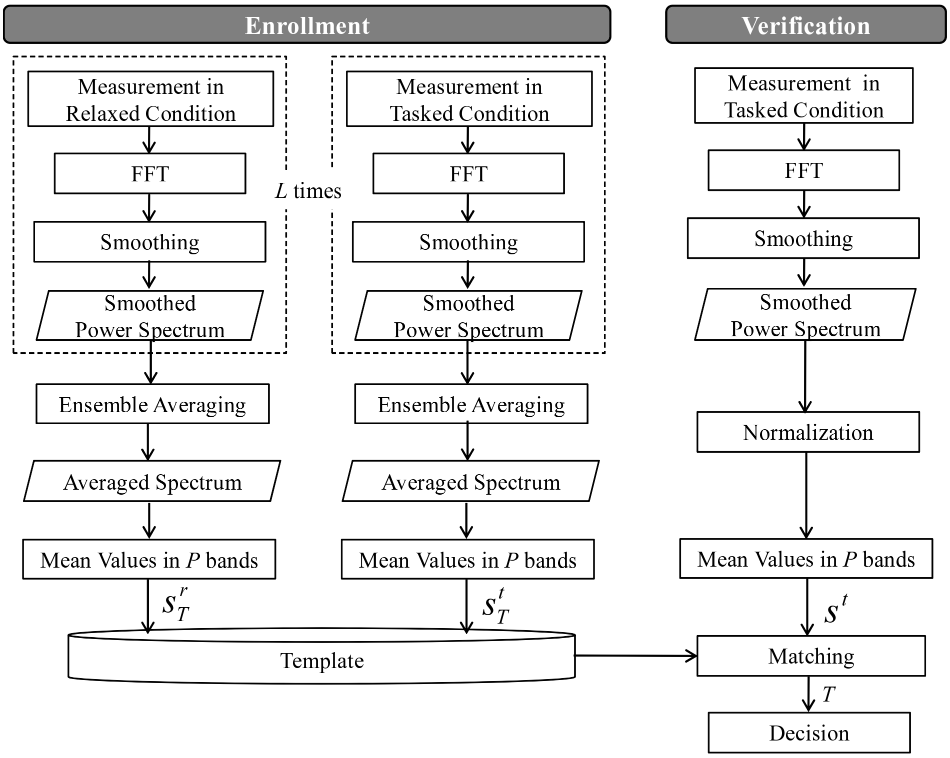


Figure 2 Block diagram of the verification method (I).

the α–β band depends on an individual; therefore, each partition has a different effect on the verification.

The block diagram of the verification method is described in Fig. 2. Prior to the verification, the templates are enrolled. There are two stages. First, EEGs for all users are measured in the relaxed condition. Then, their power spectra are calculated using FFT. Spectral elements in each spectrum are smoothed using the moving average with a window size of five. This process is repeated L times for each user, and by using the L power spectra, an ensemble-averaged spectrum is obtained. All spectral elements of the averaged spectrum are simply divided into several partitions (groups), and the mean value of the power spectral elements in each partition is calculated and stored as a template s_T^r.

Next, similar measurements and calculations are performed in the tasked condition. The resulting values of power spectral elements in all partitions for all users are stored as templates s_T^t.

In verification, the EEG of an applicant is measured in the tasked condition, and after smoothing and normalization, the mean values of power spectral elements s^t are obtained in all partitions. The verification score T is calculated by

$$T = \sum_{p=1}^{P} ||s_T^r - s_T^t| - |s_T^r - s^t||_p \qquad (1)$$

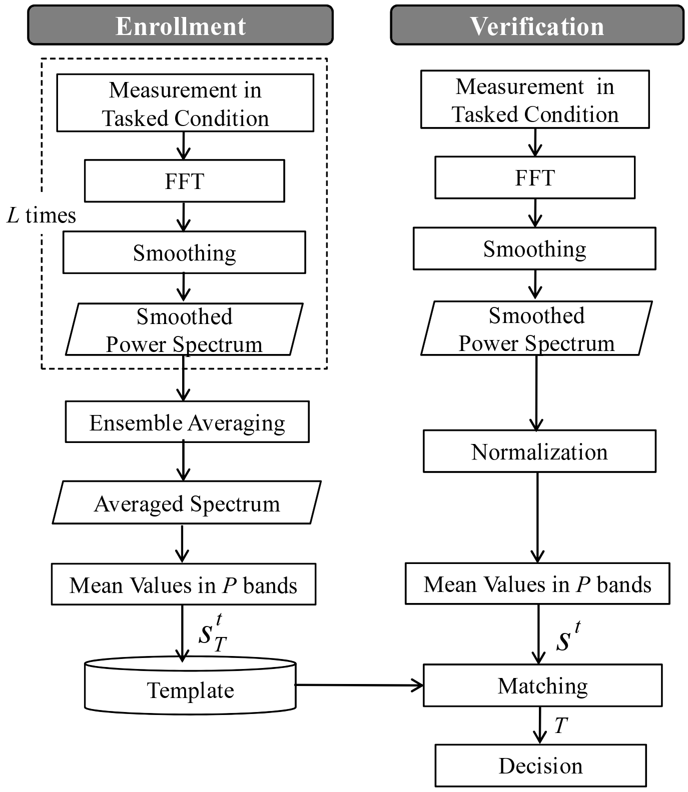


Figure 3 Block diagram of the verification method (II).

where P is the number of partitions.

For normalization, each power spectral element of s^t is multiplied by the ratio of the mean value of all power spectral elements of the template: s^t_T to that of s^t. The mean power spectrum of s^t is equalized to that of the template: s^t_T. This method is called as Method (I) for convenience.

In this paper, we propose another verification method, in which the mean power spectra: s^t_T and s^t are directly compared. In this method, measurement in the relaxed condition becomes unnecessary, and the two stages for the enrollment required in Method (I) can therefore be reduced to one, as described in Fig. 3.

The score T is given by

$$T = \sum_{p=1}^{P} |s^t_T - s^t|_p. \tag{2}$$

We call this Method (II).

In both methods, if T is less than the threshold, the applicant is authenticated as being genuine. If not, the applicant is rejected as an imposter. The threshold is determined in the tradeoff between ”security” and ”usability”. A small threshold results in higher degree of security while degrading the usability. The decision depends on which of the two has a higher priority in practical applications.

3 Simplified Driving Environments

By using the proposed feature extraction and verification, we verified the performance of EEGs for driver authentication. However, experiments that are performed while driving are at risk of causing accidents. Therefore, in our laboratory, we prepared two experimental environments that simulate driving. One is a mental task called route trace (Nakanishi et al., 2011a), and the other is an actual task using a simplified driving simulator (2011, b).

3.1 Route Tracing

Drivers use four limbs to control their cars on the basis of audio-visual information that is received. In addition, such a process occurs quickly, so it is difficult to extract mental tasks that occur while performing all possible tasks during practical driving. Furthermore, if actual tasks are different from the mental ones, drivers will not progress to the next actual task, and they will then be required deliberately perform the mental ones purposely every time authentication is executed. This is inconvenient for drivers. To realize transparent authentication, mental tasks should be related to the actual tasks being carried out.

In this study, we select a mental task, in which drivers are comparing the landmarks in their field-of-view with the landmarks in their memory. This is hereafter called route tracing. Route tracing is a realistic task for drivers; therefore, it enables transparent authentication.

To build an environment for the route trace, we captured driving scenes using a digital video camera, which was placed on the dashboard in the direction of movement in a car. As the car was being driven, it turned at as many intersections as possible to provide the subjects with a heavy mental load.

The captured scenes are loaded in a computer, and the scenes with poor visibility and/or out-of-focus ones are eliminated. As a result, a three minutes long driving scene was prepared. Still images of the driving scene are shown in Fig. 4.

3.2 Simplified Driving Simulator

We desired to measure brain waves in a more practical environment by introducing a special training simulator for driving, but it was not possible due to the associated cost. Thus, we composed a simplified driving simulator using home-use gaming machines.

Driving scenes were generated using the PlayStation 3 (PS3) as a hardware and the Gran Turismo 5 Prologue (GT5P) as a software. Both were produced by Sony Computer Entertainment Inc. However, GT5P is basically a racing game, and so, the following settings were selected to convert it into a driving simulator. The maximum possible speed of a car was limited to 65 km/h by holding the first gear in the manual transmission. The driving course was selected to be an urban road in London to simulate normal driving conditions. The driving mode used was the time trial (solo drive) to avoid accidents with other cars. Figure 5 shows still images of the driving scene.

Figure 4 Still images of the driving scene captured for the route trace.

Figure 5 Still images of the driving scene produced by the simplified driving simulator.

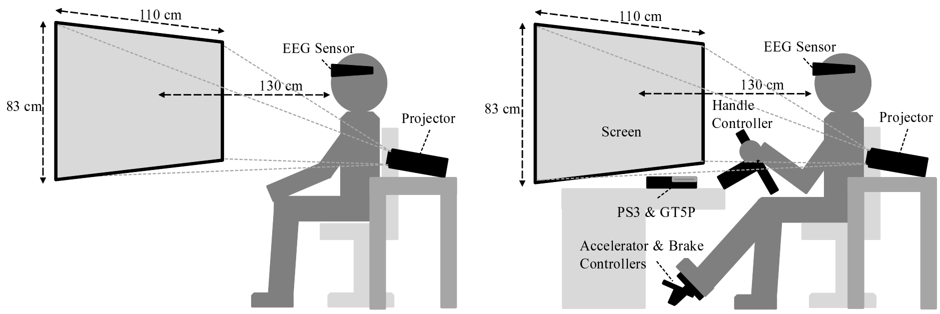
3.3 Measurement of Brain Waves

For the brain wave sensor, we also used a single-channel consumer electroencephalograph produced by Brain Function R&D Center. A single electrode was set on the frontal region of the head using a headband. This region corresponds to the frontal pole (Fp1), which is defined by the 10/20 method, an international standard. Table 1 shows the specifications of the sensor.

The driving scenes were displayed on a 60 inch screen with a size of 1100 mm $\times$ 830 mm. The distance between the screen and the subject was 1300 mm. In preliminary experiments using nine subjects, we determined these factors on the

Table 1 Specifications of the brain wave sensor.

Frequency Range	1–24 Hz
Minimum Voltage	5 μV_{p-p}
Maximum Voltage	80 μV_{p-p}
Sampling Frequency	128 Hz



(a) Route Tracing (b) Simplified Driving Simulator

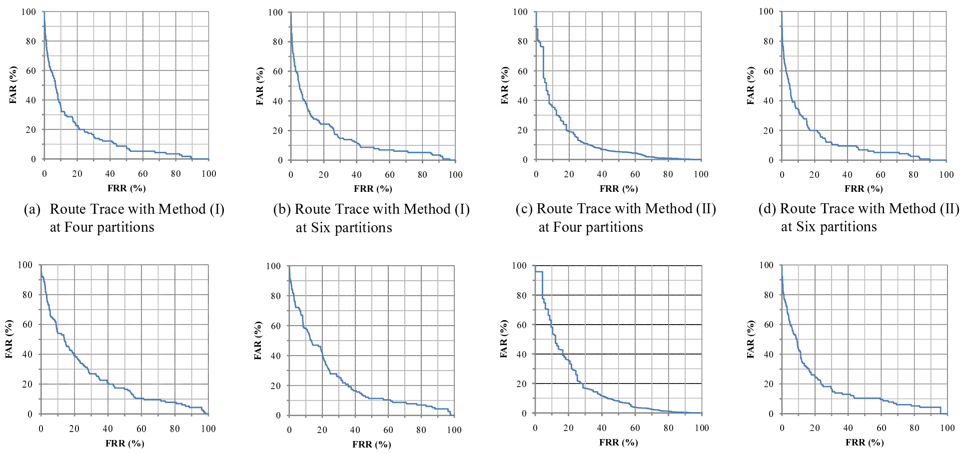
Figure 6 Layouts for (a): route tracing and (b): simplified driving simulator.

basis of a comparison of the similarity of the view from the subjects with the real one [1]. Layouts for the measurements are illustrated in Fig. 6.

There were 23 male subjects around 20 years old, and each had a driver's license. Prior to measuring the brain waves in the tasked condition, we measured the brain waves in relaxed and eye-opened conditions to establish control for Method (I).

In the route trace, the subjects were first presented with driving scenes twice, and they were requested to memorize the landmarks in the scenes. Next the subjects wore the brain wave sensor, and the same driving scenes were again presented. While measuring brain waves, the subjects were requested to trace a route by checking the landmarks. After the measurements, to confirm whether or not the subjects had traced the route, they were presented with printed images of certain intersections, and they were then asked the direction, in which the car had been moving. If they made a mistake, that is, forgot the route, measurement was cancelled and retaken.

In case of the simplified driving simulator, before the measurements, the subjects were required to make two rounds to get adapted to the feeling of maneuvering. After the practice, the subjects wore the sensor, and their brain waves were then measured while handling the controllers depending on the driving scenes. If there was an accident, for instance, the car hit against a wall, measurement was retaken.



(a) Route Trace with Method (I) at Four partitions
(b) Route Trace with Method (I) at Six partitions
(c) Route Trace with Method (II) at Four partitions
(d) Route Trace with Method (II) at Six partitions
(e) Driving Simulator with Method (I) at Four partitions
(f) Driving Simulator with Method (I) at Six partitions
(g) Driving Simulator with Method (II) at Four partitions
(h) Driving Simulator with Method (II) at Six partitions

Figure 7 ROC curves in various conditions.

Each measurement lasted three minutes. The measurement was performed once a day, and it was repeated ten times (for ten days) in intervals of at least one week. As a result, ten EEGs were obtained from each subject.

4 Verification Experiments

The middle one-minute data of each EEG measured were used in the verification experiments[2]. The average number L was set to five, that is, five EEGs from each subject were used to generate his/her templates. The remaining five sets of data for each subject were used for verification, and all other subjects' data were considered to be of imposters. In this experiment, spectral elements at 8–20 Hz were used to extract individual features.

4.1 Results

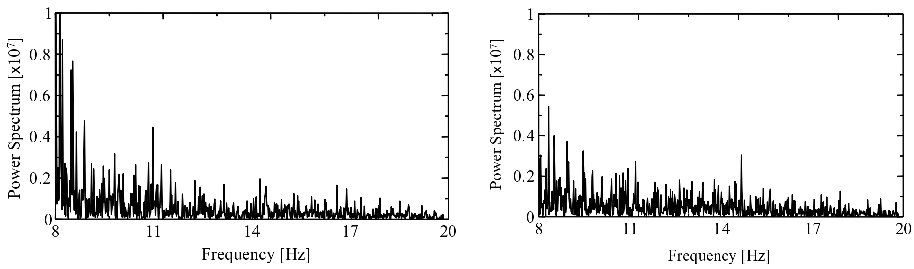
Figure 7 shows ROC curves in the route trace and the simplified driving simulator obtained using Methods (I) and (II) with four and six partitions. The performance is verified using an equal error rate (EER), where a false acceptance rate is equal to the false rejection rate. The threshold T is determined to obtain each EER. EERs in all conditions are summarized in Table 2.

4.2 Comparison of two tasks

By comparing EERs of two tasks, it was confirmed that the verification performance in the driving simulator was degraded. The movement of limbs in the simulator may have caused the variation of EEG spectra as individual features, thereby resulting in degradation.

Table 2 Verification performance.

	EER (%)	
Route Trace	Four partitions	Six partitions
Method (I)	21	23
Method (II)	19	19
Driving Simulator	Four partitions	Six partitions
Method (I)	28	28
Method (II)	23	20



(a) Relaxed condition (b) Tasked condition

Figure 8 Spectral distribution at α–β band.

It is well known that EEGs will be greatly contaminated by the movement and it is impossible to remove such an artifact from the EEG. The brain waves measured in the driving simulator are close to those obtained during practical driving. Therefore, to prevent the verification performance from being degraded in practical driving, it is necessary to detect the movement of limbs and to avoid measuring brain waves while the limbs' moving.

On-demand authentication is better suited for such a case. If the movement of limbs can be detected using sensors in the steering wheel, accelerator, and brake, it is possible to perform authentication only when limbs are not moving.

4.3 Comparison of two verification methods

A Comparison of two verification methods shows that the performance of Method (II) was slightly superior to that of Method (I). Figure 8 shows the spectral distribution in the α–β band in (a) relaxed and (b) tasked conditions. In the relaxed condition, there are many large peaks in the α band. We proposed the extraction of individual features, assuming that the spectral elements in the α band are normally distributed (Nakanishi et al., 2012a). On the other hand, the spectral distribution in the β band is not distinct; therefore, we used as related features the difference between the mean value of the power spectrum in the

Table 3 EER at each partition.

	EER (%)	
Four partitions (Hz)	Route Trace	Driving Simulator
8–11	27	36
11–14	27	29
14–17	30	28
17–20	33	27
Six partitions (Hz)	Route Trace	Driving Simulator
8–10	29	37
10–12	27	34
12–14	30	30
14–16	33	30
16–18	33	27
18–20	35	27

relaxed condition and that in the tasked condition (Nakanishi et al., 2012b). In this study, we extended the concept to the α band and used the difference between the mean value of the power spectrum in α–β band in relaxed conditions and that in tasked conditions in Method (I). However, the result for which Method (II) is better than Method (I) suggests that the mean value of the power spectrum in the α–β band in tasked condition, that is, the absolute feature is better than the relative one. Therefore, the spectrum in the β band appears to possess more effective characteristics for verification, whereas it does not have a distinctive pattern in its spectral distribution, as shown in Fig. 8.

An advantage of Method (II) is that simpler verification results in better verification. In addition, the procedure for making templates becomes simpler.

4.4 Comparison of two partition cases

From a comparison of the results for two partition cases, it is difficult to determine whether four or six partitions are better. Therefore, we examined EER at each partition in case of Method (II), and the results are summarized in Table 3.

For the route trace, it is evident that EERs at lower frequency partitions are smaller. That is, the verification performance is better than that at higher frequency partitions. This is because the subjects were required to check the landmarks in the screen using those memorized in the route trace. However, we used the same driving scenes each time. Therefore, the mental task was more easily for the subjects, and it caused them to be relatively relaxed during the measurements. As a result, the α wave was not suppressed, and verification using lower frequency partitions that are included in the α band was more effective.

On the other hand, in the driving simulator, EERs in higher frequency partitions are relatively small. The mental task performed while using the driving simulator was difficult, and mental activity became higher than that in the route tracing activity. Therefore, the α wave was suppressed, whereas the β

wave became detectable. According to our results, the verification using higher frequency partitions corresponding to the β band was more efficient.

A similar issue was discussed in Ref. (Nakanishi et al., 2010). The verification performance while subjects were performing mental arithmetic tasks was superior to that while they were mentally making sentences. This is because the degree of mental activity, that is, the nature of the mental task influenced the performance. In mental arithmetic, the contents were clearly defined, and it was relatively difficult for the subjects to perform the arithmetic. On the other hand, in case of the mental composition, several themes were provided as rough guidelines, but actual contents created during the measurement depended on the subjects. A few subjects may form simple sentences, which were not as difficult as mental tasks. As the mental task becomes more difficult, the verification performance improved.

As mentioned in Section 4.2, it is conceivable that brain waves during actual driving are similar to those in the driving simulator. The use of scores from partitions corresponding only to the β band may prevent degradation of the verification performance during practical driving. This must be studied in more detail.

5 Conclusions

In the application of biometrics for user management, one-time-only authentication is not used, and therefore, continuous or on-demand authentication is necessary. In particular, on-demand authentication is effective at reducing the computational load of authentication systems, thereby maintaining relatively high degree of system security. However, on-demand authentication requires transparent biometrics.

We have studied the use of brain waves as transparent biometrics. In this study, we evaluate the verification performance of the brain wave under eye-opened and mentally-burdened conditions and the condition with eyes-opened while performing actual tasks. In particular, to authenticate drivers, we measured their brain waves as they performed the mental task of tracing routes or the actual task using a simplified driving simulator. We extracted the power spectrum in the α–β band as an individual feature and proposed two verification methods based on the similarity of the feature. One method was to examine the similarity between the mean value of the power spectrum in the α–β band in tasked and relaxed conditions. The other method was to directly compare the mean power spectrum in the α–β band and its template. In addition, we proposed division of the α–β band into four or six partitions and merging the similarity scores from all partitions.

From the experimental results obtained using 23 subjects, an EER of approximately 20 % was obtained for route tracing. On the other hand, EER was approximately 25 % for the case of simplified driving simulator, which is similar to practical driving. The slight degradation of the performance may be due to the movement of limbs. To prevent such performance degradation of performance during practical driving, brain waves should be measured while the limbs are not moving, thereby enabling on-demand authentication to become effective.

There are many other problems to be studied since to use the brain wave as biometrics is an emerging technology.

Our approach is based on the assumption that the EEG patterns are unique for each individual. However, the results in this study did not completely demonstrate accuracy of the assumption. We will address this problem in future. The verification performance is not high enough to conclude that the brain wave is applicable to driver authentication on the basis of our simple approach. We are currently attempting to introduce a more powerful verification method such as a support vector machine (SVM) to improve the performance. We also hope to increase the number of subjects for the experiments to achieve a more reliable evaluation of the proposed methods.

There have been attempts to use the brain waves in responded to visual or audio stimuli as biometrics (Ravi and Palaniappan, 2006; Singhal and Ramkumar, 2007). In the literature, it is mentioned that the gamma band is related to higher order processing of visual images and contains useful information for biometric applications. However, those approaches are not suitable for scenarios requiring transparent biometrics because the stimuli are provided every time authentication task is performed. If the presentation of the stimuli to users of a system for authentication does not disturb their continuous usage of the system, these methods can be applied to on-demand authentication.

Stability of the EEG spectrum is also an important issue. A report states that the EEG can change over a period of a few months (Palaniappan and Revett, 2012). If this is the case, methods for dealing with the instability, (for instance, incremental enrollment (additional learning) of templates) will be required.

In the future, we plan to develop an on-demand authentication system using brain waves and to evaluate its verification and usability. We would also like to do detailed evaluation using more accurate analyzing equipment.

References

Wayman J., Jain A., Maltoni D. and Maio D. (2005) *Biometric Systems*, Springer, London.

Nakanishi I., Baba S., and Miyamoto C. (2010) 'On-Demand Biometric Authentication of Computer Users Using Brain Waves', in Zavoral F. et al. (Eds.), *NDT2010*, Part I, CCIS 87, Springer, pp. 504–514.

Altinok A. and Turk M. (2003) 'Temporal Integration for Continuous Multimodal Biometrics', *Proc. of 2003 Workshop on Multimodal User Authentication*, pp. 131–137.

Kwang G., Yap R. H. C., Sim T. and Ramnath R. (2009) 'An Usability Study of Continuous Biometrics Authentication', in Tistarelli M. and Nixon M. S. (Eds.), *ICB2009*, LNCS 5558, Springer, pp. 828–837.

Poulos M., Rangoussi M., Chrissikopoulos V. and Evangelou A. (1999a) 'Person Identification Based on Parametric Processing of the EEG', *Proc. of the 9th IEEE International Conference on Electronics, Circuits and Systems*, vol. 1, pp. 283–286.

Poulos M., Rangoussi M. and Alexandris N. (1999b) 'Neural Networks Based Person Identification Using EEG Features', *Proc. of 1999 International Conference on Acoustic Speech and Signal Processing*, pp. 1117–1120.

Poulos M., Rangoussi M., Chissikopoulus V. and Evangelou A. (1999c) 'Parametric Person Identification from the EEG Using Computational Geometry', *Proc. of the 6th IEEE International Conference on Electronics, Circuits and Systems*, pp. 1005–1008.

Paranjape R. B., Mahovsky J., Benedicent L. and Koles Z. (2001) 'The Electroencephalogram as a Biometric', *Proc. of 2001 Canadian Conference on Electrical and Computer Engineering*, vol. 2, pp. 1363–1366.

Ravi K. V. R. and Palaniappan R. (2005) 'Recognising Individuals Using Their Brain Patterns', *Proc. of the 3rd International Conference on Information Technology and Applications*.

Palaniappan R. (2005) 'Identifying Individuality Using Mental Task Based Brain Computer Interface', *Proc. of the 3rd International Conference on Intelligent Sensing and Information Processing*, pp. 239–242.

Mohammadi G., Shoushtari P., Ardekani B. M. and Shamsollahi M. B. (2006) 'Person Identification by Using AR Model for EEG Signals', *Proc. of World Academy of Science, Engineering and Technology*, vol. 11, no. 2, pp. 281–285.

Ravi K. and Palaniappan, R. (2006) 'Neural Network Classification of Late Gamma Band Electroencephalogram Features', *Soft Computing*, vol. 10, no. 2, pp. 163–169.

Singhal G. K. and Ramkumar P. (2007) 'Person Identification Using Evoked Potentials and Peak Matching', *Proc. of 2007 Biometric Symposium*.

Marcel S. and Millan J. R. (2007) 'Pearson Authentication Using Brainwaves (EEG) and Maximum A Posteriori Model Adaption', *IEEE Trans. on Pattern Analysis and Machine Intelligence*, vol. 29, no. 4, pp. 743–748.

Palaniappan R. and Mandic D. P. (2007) 'Biometrics from Brain Electrical Activity: A Machine Learning Approach', *IEEE Trans. on Pattern Analysis and Machine Intelligence*, vol. 29, no. 4, pp. 738–742.

Riera A., Soria-Frish A., Caparrini M., Grau C. and Ruffini G. (2008) 'Unobtrusive Biometrics Based on Electroencephalogram Analysis', *EURASHIP Journal on Advances in Signal Processing*.

Nakanishi I., Baba S., and Miyamoto C. (2009) 'EEG Based Biometric Authentication Using New Spectral Features', *Proc. of 2009 IEEE International Symposium on Intelligent Signal Processing and Communication Systems*, pp. 651–654.

Nakanishi I., Baba S. and Li S. (2011a) 'Driver Authentication Using Brain Waves While Route Tracing as a Mental Task', *Proc. of the 6th International Conference on Security and Cryptography*, pp. 90–96.

Nakanishi I., Baba S. and Li S. (2011b) 'Evaluation of Brain Waves as Biometrics for Driver Authentication Using Simplified Driving Simulator', *Proc. of 2011 International Conference on Biometrics and Kansei Engineering*, pp. 71–76.

Nakanishi I., Baba S., Miyamoto C. and Li S. (2012a) 'Person Authentication Using a New Feature Vector of the Brain Wave', *Journal of Communication and Computer*, vol. 9, pp. 101–105.

Nakanishi I., Miyamoto C. and Li S. (2012b) 'Brain Waves as Biometrics in Relaxed and Mental Tasked Conditions with Eye-Closed', *International Journal of Biometrics*, vol. 4, no. 4, pp. 357–372.

Palaniappan R. and Revett K. (2013) 'PIN generation using EEG: A stability study', *International Journal of Cognitive Biometrics*, (in press).