Validation of EEG Personal Authentication
with Multi-channels and Multi-tasks

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Abstract - We investigate a feature extraction method that is effective for biometric identification using brain waves in this paper. We extract power spectrums of theta waves, alpha waves, beta waves and gamma waves for the quantity of personal characteristic. We measure brain waves with five tasks and multi-channel electroencephalograph to analyze each error rate. As a result, the error rate of the alpha wave is the lowest; the authentication rate by a single channel / a single task, sixteen channels / a single task, and sixteen channels and five tasks are 90%, 92%, and 97%, respectively.

Keywords: biometric authentication, brain wave, image task, power spectrum

1 Introduction

As the spread of Internet infrastructure in recent years, various social networking services such as on-line shopping are provided for the information society. According to the increase of usability, crimes using the Internet are increasing rapidly, and the importance of authentication technologies to prevent such unauthorized access is required more than ever. While personal authentication by ID and password has been used mainly in the social networking services available at the time, it would have been forged easily against prying eyes or brute-force authentication attempts. As just described, conventional authentication technologies cannot be said to be reliable means necessarily in terms of safety, and biometric authentication is getting a lot more attention recently.

The biometric authentication refers to the personal authentication using biometric information. The biological information for the authentication includes fingerprint, iris, face, voiceprint, and handwriting, where plagiarism is difficult as compared with the traditional password-based authentication. In particular, iris or fingerprint based authentication does not provide high recognition rates but also be used in practical applications, but there are also reports that some authentication systems are forged [1]. Since the biological information is exposed to the outside at all times, it can be acquired for forgery on the basis of the biometric information. A vein based authentication system that uses in-vivo (not exposed to the outside) information is introduced while there is a report that spoofing is possible even for the vein authentication system. Conventional biometric authentication methods have a problem that it is impossible to change the biometric information right after succeeding the authentication once. It is considered that changeable biometric information is applicable to the biometric authentication so that it is to be updated if the biometric information is plagiarized. For these reasons, updatable in-vivo biological information is required.

In this paper, a biometric authentication using brain waves as the biometric information is proposed. EEG is in-vivo information and superior to confidentiality because it is measured neuronal activity of a number of cerebral cortices and not measurable without wearing an electroencephalograph. Also it shows different characteristics depending on the individual, and can be used to intentionally change the own brain waves by changing what he/she images. The concept of personal authentication using the EEG and images has been proposed as pass-thoughts [2]. By making an efficient use of this feature, the biological information is possibly updated on a regular basis, and the safety is enhanced.

Studies utilizing brain waves for authentication are already underway by various researchers. For example, EEGs of forty examinees during open-eye-closed-eye are measured for personal identification to get an accuracy of 80% is reported in [3], and EEG rhythms of four examinees during closed-eye are analyzed to get an accuracy of 90% or more [4]. Other studies include personal authentication by visual evoked potential [5] and verbal recall problems and/or potential recall movement [6]. In such previous studies, auto-regressive (AR) models [3] [4] [7] or neural networks [5] [6] [8] for feature extraction have been proposed, but their computational costs are too expensive while the authentication performances are improved more than 90%. In this paper, we propose a personal authentication method with light computational cost as well as good authentication performance using frequency distribution of the target power spectrum as feature values.

The rest of the paper is organized as follows. In section 2, we introduce two types of related works. According to the existing research results, we propose an extension of the previous methods in section 3. The proposed method is validated with some experiments in section 4.

2 Related works
2.1 EEG personal authentication based on the
average power spectrum

We introduce a study for EEG personal authentication with light computational cost using average power spectrum as feature values [9]. In this study, a method of personal authentication by EEG brain waves during virtual driving operation, which means a simple driving simulator with tracing route, is proposed.

Electroencephalograph to be used is a single electrode of the frontal lobe Fp1 (International 10–20 system) with the sampling frequency of 128Hz. Spectral analysis by Fourier transform for the extraction of individual feature is adopted based on the fact that there are individual differences in brain wave spectrum in the α-β wave band. Exactly saying, the α and the β wave bands are divided into α1-α4 and β1-β4 regions, respectively. In each region, the average of power spectrums as individual feature is evaluated for authentication.

The flow of authentication process is as follows. First, the personal data is registered in advance to perform authentication. The brain waves during virtual driving operation are measured to calculate the power spectrum by FFT. The measured EEG spectrum is smoothed with five points moving average process. The process is performed L times for each examinee to generate L spectrums, which are spatially averaged. The α-β wave band parts of the obtained averaged spectrums are divided into several regions and the average value is calculated for each region. The average value is the template.

In collation process, examinee’s brain waves in the virtual driving operation environment are measured once to calculate the spectrum as in the template and perform smoothing and normalization. Note that the normalization is a process to align the average spectrum used in the template calculation with the average spectrum for collation. To be compared with the template, if it is smaller than a predetermined threshold, it is authenticated as the right person.

For the authentication experiment, thirty examinees are employed. Measurement time is three minutes, and ten sets of brain waves data are taken from each examinee: five sets of data are used for generating templates, and the rest of five sets are for authentication. Evaluating experimental results by equal error rate (EER), the tracing route and driving simulator record 0.35 and 0.36, respectively. Furthermore, EERs are 0.51 and 0.22 in the case of B1 region and B3 region, respectively. In this way, a remarkable difference in each area is observed.

2.2 EEG personal authentication using multiple tasks

While the previous sub-section describes a study aiming at EEG measuring and its authentication during unconscious states, this sub-section describes another study for personal authentication of the EEGs that are measured with selecting own password thoughts (Pass-thoughts) [10].

They use the MindSet of NeuroSky Inc. as an electroencephalograph with 200Hz sampling frequency at frontal lobe Fp1 by a single channel. The following seven tasks are used for measuring brain waves: Deeply breathe (breathing), Image moving own fingers up and down (finger), Image doing a favorite sport (sport), Image singing a favorite song (song), Listen to a mechanical sound, then gaze at one point (audio), Select a color among red, green, blue and yellow, then count the number of the selected color on a displayed picture (color), Image a favorite password (pass). In audio, the examinee listens to a mechanical sound for five seconds, then gazes at one point for five seconds while his/her brain waves are measured for the total of ten seconds. In color, the examinee counts the number of selected color on a picture with measuring his/her brain waves for five seconds. Since the number of pictures is six, the total time for measuring examinee’s brain waves is thirty seconds in total. In the rest of five tasks, the examinee imagines the tasks while his/her brain waves are measured for ten seconds.

In the authentication method, an STFT (short-time Fourier transform) is first applied to the recorded sample data as a pre-processing, and time-frequency analysis is performed. The frequency bands of the α and the β waves are cut out to calculate the median of the power spectrum for each frequency band. The resultant data is used as one-dimensional feature vector. Then, to calculate the degree of similarity between the one-dimensional vectors obtained from the sample data, the cosine similarity method is applied. From the above calculated self-similarity and cross-similarity, an optimal threshold value for authentication is estimated. The authentication is evaluated by the HTER (Half Total Error Rate), which is the average of the FAR (False Acceptance Rate) and the FRR (False Rejection Rate) calculated from each similarity.

In experiments with fifteen examinees, when evaluated using a common threshold to the examinees, the HTER is 0.32-0.43. However, when changing the task and the threshold for each examinee, the HTER decreased up to 0.011

3 Analysis of personal authentication using a multi-channel electroencephalograph

In this paper, we perform personal authentication using a multi-channel electroencephalograph based on the above related works, and analyze the results for several factors.

3.1 Measuring EEG

We use the BioSemi as the multi-channel electroencephalograph, of which the maximum sampling rate is 2,048Hz and the maximum electrode number is 256. A bipolar lead method is used for deriving the reference electrode. In this paper, we use a BioSemi with the maximum
sampling rate of 2,048Hz and 16 electrodes. The electrodes are placed as shown in Fig.1 based on International 10–20 system. Figure 2 shows mounting a BioSemi and measuring EEGs in the left and right, respectively.

### 3.2 Authentication method

We use an authentication method as described in subsection 2.1 and 2.2 to be extended. First, a template for individual is generated using $L$ trial data sets. Each data set is processed as following. We apply STFT to the data to calculate the power spectrum by time, and perform a median filter on successive five values. In subsection 2.1, 8-29Hz brain waves ($\alpha$ and $\beta$ waves) are partitioned into seven regions to calculate the average of each power spectrum as feature values. As a result, it is reported that the authentication rate at B3 $\beta$-wave region is good, but this is likely because some differences are observed in the $\beta$ wave EEG that usually evokes concentration during virtual driving operations. In this paper, we use 4-40Hz brain waves ($\theta$ to $\gamma$ waves) to get more information. Since the brain waves less than 3Hz contain considerable EOGs (electrooculography), we do not use them in this paper. Figure 3 shows an example $\theta$-$\gamma$ wave bands partition. The $\theta$-$\gamma$ wave bands are partitioned into two, three, five and three regions of $\theta1$-$\theta2$, $\alpha1$-$\alpha3$, $\beta1$-$\beta5$ and $\gamma1$-$\gamma3$, respectively. The average power spectrum for each region by time is calculated to be used as feature values. The calculated feature values are averaged by each examinee to generate the template $S = \begin{pmatrix} \theta1,1 & \theta2,1 & \cdots & \gamma3,1 \\ \theta1,2 & \theta2,2 & \cdots & \gamma3,2 \\ \vdots & \vdots & \ddots & \vdots \\ \theta1,t & \theta2,t & \cdots & \gamma3,t \end{pmatrix}$, where $t$ represents time.

The authentication is performed using each feature value in the template and its cosine similarity. If the similarity is larger than a pre-defined threshold, the examinee is accepted. Otherwise, the examinee is rejected as a personator. The threshold is selected as the minimum EER that is the intersection of graphs FAR and FRR. The minimum EER is also used for evaluating the authentication accuracy performance.

### 4 Experiments

#### 4.1 Experiment method

The examinees are ten healthy women in their 20s. To measure their brain waves, we adopt five tasks except color and audio described in subsection 2.2. Since tasks of color and audio require an open-eye state, we think they increase noises. We abbreviate tasks breathing, finger, pass, song and sport to B, F, P, So and Sp, respectively. Figure 4 shows the flow of a trial. We measure ten seconds for each of five tasks with taking a break of five seconds between each task, which is a trial. Each examinee performs ten trials. The learning data, namely templates are from the measured data of five examinees, and the rest of five examinees data are used for authentication tests. In other words, the number of authentication test data is fifty.

We perform the experiments for three different purposes. Experiment 1, 2 and 3 are to validate the equal error rate (EER) for each frequency band, each measuring position and
task combinations, respectively. We randomly select five learning data sets from the ten measured data sets and the rest of five data sets are used as authentication test data so that we have ten kinds of learning-test data set combination. The resultant ten EERs are averaged for the validation.

4.2 Experiment 1: Validate EER for each frequency band

We investigate the difference in EERs when changing the frequency band of the EEGs used for authentication.

In Experiment 1a, we get the EER of each frequency band in each task. The frequency bands consist of θ wave (4-8Hz), α wave (8-14Hz), β wave (14-26Hz) and γ wave (26-40Hz). From the EEGs for each task with changing the frequency band of the feature, we calculate the EER for each channel to obtain the average value of the 16 channels. Figure 5 shows the plots of the experiment results. The average EERs of θ, α, β and γ waves are 0.44, 0.28, 0.40 and 0.45, respectively. The authentication by α wave achieves the highest preciseness. It is also confirmed by Fig.5 that the authentication by α wave is more accurate for all tasks, and the difference to the second accurate authentication by β wave is more than 0.1. Investigating the results by task, pass and sport provide better accurate authentication while other tasks provide worse. This trend is true for all frequencies. Looking at α wave, sport is the best (0.27) and song is the worst (0.29).

In Experiment 1b, we get the EER of each frequency at each electrode position. Similar to Experiment 1a, the EER for each electrode position is calculated from the EEGs for each task with changing the frequency band of the feature. The obtained EERs are averaged by task for the validation as shown in Fig.6. As shown in the graph, the authentication accuracy by α wave is the best in all channels. In the case of α wave, the authentication performances from P4 to O2 are better than from Fp1 to T8. In the cases of θ wave and β, wave, the performances from P4 to O2 are relatively good. The performances of θ-β waves on occipital area are better than frontal area. However, in the case of γ wave, no prominent differences for the EERs on any channels are confirmed.

From the results of Experiment 1a and 1b, the authentication accuracy is good in the order of α, β, θ and γ wave. Particularly, the authentication accuracy by α wave is outclassing. Although there are differences in the authentication accuracy by task, the performances of α and β waves are well for all tasks. Furthermore, focusing on the channels, the authentication accuracy of occipital α, β and θ waves is better than frontal. We think that the reason of the above trend is that the noises of eye movement are included in the frontal α, β and θ waves. Therefore, no influence is observed in the frontal γ wave that has a relatively high frequency.

4.3 Experiment 2: Validate EER for each measuring position

In Experiment 1b, we get the EER of each frequency at each electrode position. Similar to Experiment 1a, the EER for each electrode position is calculated from the EEGs for each task with changing the frequency band of the feature. The obtained EERs are averaged by task for the validation as shown in Fig.6. As shown in the graph, the authentication accuracy by α wave is the best in all channels. In the case of α wave, the authentication performances from P4 to O2 are better than from Fp1 to T8. In the cases of θ wave and β wave, the performances from P4 to O2 are relatively good. The performances of θ-β waves on occipital area are better than frontal area. However, in the case of γ wave, no prominent differences for the EERs on any channels are confirmed.
We investigate the difference in EERs due to the combination of electrode positions to be used for authentication. In Experiment 2a, we get the EER at each electrode position calculated from the EEGs for each task using the frequency band of 4-40Hz. Figure 7 shows the results. There is little difference between the authentication rates of all tasks. Although they are also affected by the kind of tasks, the channel with good authentication rates are Fz, P4, and Pz. The combination of a task and a channel with the best authentication rates is sport/Pz with the EER of 0.12. From the experiment results, we confirm that about 90% authentication rate is obtained using all the 4-40Hz frequency with single channel and single task. Since pass is the task that is individual-changeable, EEGs with pass are expected as a pass-thought. The channel with bad authentication rates is Cz. The EER of the best channel P4 with pass is 0.15 while the EER of the worst channel Cz is 0.30. The results indicate that the authentication performance differs by electrode position so much.

In Experiment 2b, we generate a set of patterns by combining several channels, and use them to calculate EERs for each task on the electrode position to validate the patterns with good authentication performance. Figure 8 shows the patterns for the combined positions. The details of the patterns are shown in Tab.1. We investigate twenty-one combination patterns for each electrode position in this paper. Figure 9 shows the EER for the pattern 1-21 by task. Focusing on tasks, there is little difference between the authentication rates of all tasks. Focusing on patterns with accurate authentication, the pattern 21 for all tasks on all of 16 channels achieves the best EER. On the pattern 21, the task with best authentication performance is finger with EER 0.071. In Experiment 2a, while the authentication rate for the task pass on a single channel is about 85%, it increases up to about 92% on all of the 16 channels. The next best patterns include the pattern 16 occupying the left hemisphere for the tasks breathing, finger and pass, the pattern 15 occupying the left hemisphere and the pattern 3 passing through the center of the midline hemisphere for the task song. On the contrary, the patterns with poor authentication rates include the pattern 6 through the frontal pole and the pattern 10 through the occipital area. The experiment results indicate that different tasks give different electrode positions to each examinee. In particular, it turns out that the authentication performance using either hemisphere according to given tasks is better than using both hemispheres of the brain.

In Experiment 2c, we obtain the EERs on the electrode positions within the left, right and midline of hemisphere for
all tasks as shown in Fig.10. Apparently, the electrode positions in the right of hemisphere give a little better authentication performance than the left. Especially, the electrode positions T and C within the right of hemisphere provide better authentication performance than the left/midline 0.03. The electrode positions of the midline hemisphere have a large difference between good authentication rates (T, C) and poor authentication rates (F, P). Furthermore, the electrode position P achieves the best authentication performance within any parts of hemisphere.

4.4 Experiment 3: Validate EER for the combination of tasks

We investigate the difference in EERs due to the combination of tasks to be used for authentication. In Experiment 3a, we generate all combinations of one to five tasks to be used for the authentication and calculate each EER. In this paper, we present the pattern 21 (all channels) that gives the best authentication performance in Experiment 2b to calculate its EER. Figure 11 and 12 show the cases that the number of tasks to be combined is 1-2 and 3-5, respectively.

In the case of a single task, the task breathing gives good authentication performance. On the contrary, the task song gives the worst authentication performance of EER 0.084. In any case, the EER of each task is less than 0.09, which means a single task achieves good authentication of more than 92%.

The number of two task combinations is 10. The combinations of tasks including breathing which provide good authentication when used as a single task, achieve authentication performance of 95%. The combination of breathing/song provides the best authentication of EER 0.040.

The number of three task combination is 10, too. They all provide less than 0.05. Among the three task combinations, breathing/pass/song provides the best authentication of 0.031.

The number of four task combination is 5 and all combinations achieve good authentication of 0.03 to 0.04. Using all tasks, the authentication performance is the best 0.029.

In Experiment 3b, we investigate the difference of EERs with varying the number of tasks for the task combination. Figure 13 shows the average EERs by the number of tasks. The average EERs are 0.076, 0.051, 0.040, 0.036 and 0.029.
as the number of tasks increases from 1 to 5. Namely, the larger the number of tasks for the task combination is, the better the average EERs are.

5 Conclusions

In this paper, we investigate EEG personal authentication with a 16-channel electroencephalograph. We adopt averaged power spectrums calculated by STFT for each frequency band of \( \theta \), \( \alpha \), \( \beta \) and \( \gamma \) waves as feature values for individuals. When EEGs are measured, the examinees perform five kinds of tasks: breathing, finger, pass, song and sport. Using the above data, we performed three types of experiments to validate EERs for each frequency band, EERs for electrode positions and EERs for the combination of tasks. From the experiment results of EER validation for each frequency band, we confirm that \( \alpha \) waves provide the best authentication performance followed by \( \beta \), \( \theta \) and \( \gamma \) waves. It means that the \( \alpha \) wave band is the most effective frequency of EEGs for personal authentication. From the experiment results of EER validation for electrode positions, about 85% authentication rates are observed with the task pass and the electrode position Pz, and we also observe that the authentication rates increase up to about 92% with all of 16 channels. Finally, from the experiment results of EER validation for the task combination with 16 channels, we confirm that the larger the number of task combinations is, the better the authentication performance is. Using all of five tasks, the EER achieves the best 0.029 that means the authentication rate of more than 97%.

Our future work includes investigating optimal tasks, electrode positions and frequency band with more examinees to get better authentication performance. We believe that power spectrum of EEGs is insufficient. So we should develop a new feature for individual authentication rather than power spectrum.

6 References


