

Personal Authentication Using New Feature Vector of Brain Wave

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Abstract: Conventional person authentication methods using the brain wave: electroencephalogram (EEG) have a problem that they require heavy computational load. In this paper, we propose a new feature vector with light computational load, which consists of maximum spectral powers, their frequency values, and accumulated spectral powers which are greater than a threshold. The verification performance is examined in authentication experiments using 23 subjects and as a result the verification performance of 72% is obtained.

1. Introduction

Recently, as the information-oriented society progresses, more effective authentication method is needed in order to prevent incidents of information leaks or spoofing. The biometrics is to authenticate human beings by biometric features: fingerprint, iris, signature, voice and so on [1]. However, almost of them require a user to indicate physical or behavioral features consciously, so that they are not suitable for continuous authentication. Additionally, they have vulnerability that biometric features can be mimicked by imposters since they are exposed on the body or given out from the body. Moreover, the absence of physical body parts which include biometric features causes the problem of accessibility.

In order to cope with such problems, we consider that the brain wave: Electroencephalogram (EEG) is feasible for the biometrics. The EEG can be detected unconsciously; therefore, it makes continuous authentication possible. In addition, the EEG is not exposed on the body, so that it is difficult to make its mimic. Several methods for the authentication using the EEG have been proposed [2-7].

The authentication methods using the EEG are divided into two approaches. One is to use the alpha rhythm which is detected when a subject closes eyes and is relaxed [2][3] and the other is to utilize some response when some mental tasks and/or stimuli are given to the subject [4][5]. In this paper, we utilize the alpha rhythm, too.

However, in the conventional methods using the alpha rhythm, it has not been considered to use them in practical applications. In [3], a lot of channels (electrodes) were required for extracting features from the EEG but they are inconvenience for users. Additionally, the data from a lot of channels make computational load heavy. The AR modeling for extracting features [3][6][7] and the neural networks for identification [2][6][7] were introduced but these also require heavy computational load.

We consider that the following terms should be realized in order to make the authentication using the EEG more practical.

- Measuring with one channel
- Feature extraction and verification with light computational load



Figure 1. the Brain Builder Unit.

- Measuring in short time
- Measuring with opened eyes

In this paper, we focus on the realization of the former two terms. Especially, we propose a new method for extracting features of the alpha rhythm. The proposed method is examined in experiments using 23 subjects.

2. Extracting Brain Wave

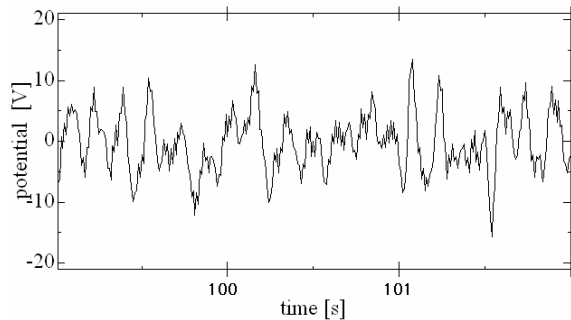
In the measuring system of the EEG, we use one electrode in a head band in order to realize the measuring with one channel. Figure 1 shows a photo of our used measuring system: the Brain Builder Unit produced by Brain Function Research Center in Japan. Table 1 shows The specifications of this system.

Table 1. Specifications.

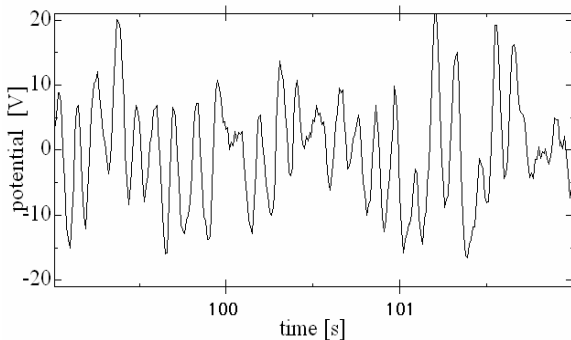
Frequency Range	1~24Hz
Minimum Voltage	5 μ Vpp
Maximum Voltage	80 μ Vpp
Sampling Frequency	128Hz

This product is for nonmedical purpose; therefore, the detection accuracy of the EEG is not all that high. In this system, the electrode is placed on forehead, that is, Fp1 or Fp2 defined by the 10-20 system. To set the electrode on forehead is not disturbed by hair. This is also important to make the authentication using the EEG practical.

Subjects are seated at rest with closed eyes in a silent room. These conditions make it easier to yield the alpha rhythm (7.8-13.3Hz). In addition, the reason why the subjects are requested to close their eyes is that eye blink artifacts contaminate the EEG signals. On each subject, the



(a) Subject A



(b) Subject B

Figure 2. Examples of EEG.

EEG data are recorded during three minutes. Figure 2 (a) and (b) show EEGs of two subjects. There may be some difference between two signals. However, it is difficult to discriminate the EEGs in time domain. It is needed to introduce some transformation for extracting individual features from the EEG.

3. EEG in Frequency Domain

In order to extract individual features from the EEG, we introduce the spectral analysis using fast Fourier transform (FFT). Figure 3 shows examples of the EEG power spectrum of two subjects. The spectral analysis has long been introduced into automated analysis of the EEG [8][9] and also utilized in personal identification using the EEG [3][4].

In our previous work [10], we found that the verification rate using a feature vector which was consist of the maximum spectrum and its frequency value was superior than that based on spectral matching where each spectrum was compared with stored one as a template. The reason is that too much features cause the increase of the intra-class variation. This is common to the fact that the AR modeling with less 20 order is adopted in several methods [2][6][11], though it requires heavy computational load.

4. Authentication System

The authentication system consists of two phases. One is the enrollment phase and the other is the verification one. In advance of the verification phase, the enrollment phase is achieved for obtaining the template. Concretely, EEG spectral data of a user are averaged at the same spectral bin and then all spectral data stored as a template for the user. In the verification phase, a user claims a unique identifier

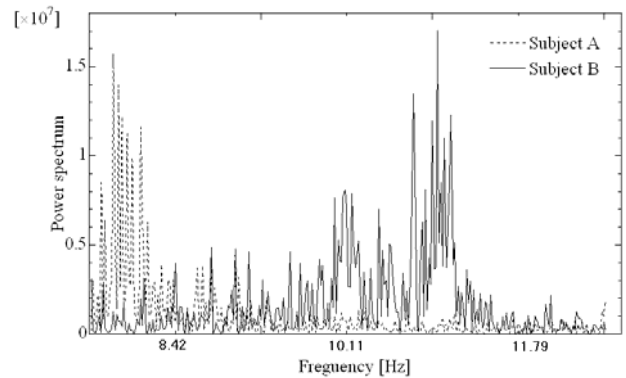


Figure3. Examples of EEG power spectrum

and then the input feature vector based on the spectrum of the user is compared with that of the template corresponding to the identifier. If the difference between the input and the template feature vectors is smaller than a threshold, the user is recognized as genuine.

5. Verification Experiments

The number of subjects was 23. All were healthy male around twenty. 10 EEG signals were recorded from each subject on the same day. We confirm that the EEG spectrum does not vary even after one year. Moreover, in each EEG signal for continuous three minutes, the data for the last one minute were used in this experiment, which corresponds to 7680 samples. Among of 10 EEG data, five data were used for obtaining the template and the rest five data were used in verification. As a result, total number of EEG data for verification were 115: 5 were genuine data and 110 were imposter data for each user. In this experiment, we used the spectra corresponding to the alpha rhythm band (8.4-11.8Hz). Therefore, the number of spectral bins was 203.

First, we examined the verification performance by using the feature vector in our previous work [10], which consisted of the maximum spectrum and its frequency value. The dimension of the feature vector was two. The verification score VS is defined as

$$VS_{conv} = x_1(s - s_t) + x_2(f - f_t) \quad (1)$$

where s and f are the maximum spectrum power and its frequency value and s_t and f_t are their template data, respectively. x_1 and x_2 are the coefficients for connecting two features. In [10], it was found that $x_1 = 0.2$ and $x_2 = 0.8$ was the best matching. When the VS_{conv} is smaller than a threshold, the user is regarded as genuine.

Using conventional feature vector, we obtained the verification rate of 64%. Comparing with the verification rate: 85% in our previous work[10], the verification performance was degraded. The reason was that the number of subjects was increased. Our conventional feature vector was not robust enough to discriminate many subjects.

6. New Feature Vector

In order to cope with the increase of the number of subjects, we propose to increase the number of maximum

spectra for obtaining the feature vector. The verification score is defined by

$$VS_{\max} = x_1 \cdot \left\{ \frac{1}{N} \sum_{i=1}^N (s^i - s_t^i) \right\} + x_2 \cdot \left\{ \frac{1}{N} \sum_{i=1}^N (f^i - f_t^i) \right\} \quad (2)$$

where s^i ($i=1,2,\dots,N$) is i^{th} maximum spectrum and f^i ($i=1,2,\dots,N$) is its frequency value. N is the number of maximum spectra. Each maximum spectrum power and its frequency are compared with those of the template individually and then the differences at N maximum spectra are averaged. x_1 and x_2 are the coefficients for connecting two features: the maximum spectral power and the frequency value and they are set to 0.2 and 0.8, respectively. Table 2 shows the variation of the verification rate as the number of maximum spectra is increased. These results show that the verification rate was 70% and the best when the number of maximum spectra was three.

Table 2. Verification rate using VS_{\max} number of maximum spectra.

N	Verification Rate(%)
1	65.0
2	66.0
3	70.0
4	67.0
5	66.5

On the other hand, it was also confirmed that there is limitation in performance improvement even if the number of maximum spectra was increased. In order to improve the verification rate further, we need another features. In this paper, we propose to utilize frequency values over a threshold. Such frequency values are accumulated and then used a feature. This feature indicates where dominant spectra are. The verification score is defined as

$$VS_{acc} = \sum_j^M f^j - \sum_j^L f_t^j \quad (3)$$

Where f^j is the frequency value over the threshold and f_t^j is that of the template. The number of f^j in an input EEG is not always equal to that of f_t^j ; therefore, they are defined as M and L , respectively. The threshold value is determined proportionally to the average of all spectral powers.

For reference, we examined the verification performance based on only VS_{acc} . Verification rates at several threshold values are summarized in Table 3. From these results, we confirmed that the best verification rate of 69 % was obtained when the threshold was set to 1.5 times average of spectral power.

Table 3. Variation of verification rate using VS_{acc} . the threshold

Threshold	Verification Rate(%)
Average of all spectral power	68.0
1.5 times average of all spectral power	69.0
Twice average of all spectral power	66.0

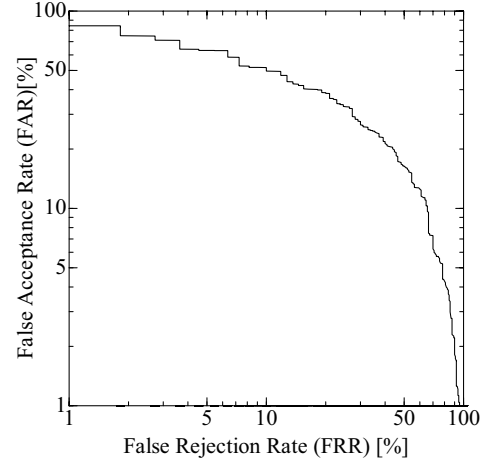


Figure 4. ROC curve.

Next, we fuse the previous features as a new feature vector. The new feature vector consists of three features; the maximum spectra, their frequency values and the accumulated spectral power. The dimension of the feature vector is increased to three. Verification score is defined as

$$VS = z_1 \cdot VS_{\max} + z_2 \cdot VS_{acc} \quad (4)$$

where z_1 and z_2 are coefficients for connecting the VS_{\max} with VS_{acc} . Table 4 shows the verification rates in several combinations of the coefficients. From these results, we obtained the verification rate of 72% at $z_1 = 0.3$ and $z_2 = 0.7$. Comparing with the result in Sect. 5, the verification rate was improved by 7%. Figure 4 shows the verification performance at $z_1 = 0.3$ and $z_2 = 0.7$. The proposed method is mainly based on comparison operation; therefore, it does not require much computational road comparing with the methods based on the AR modeling and/or the machine learning.

Table 4. Verification rates of the proposed method VS . combination of coefficients .

$z_1 : z_2$	Verification Rate(%)
0.1 : 0.9	70.0
0.2 : 0.8	71.0
0.3 : 0.7	72.0
0.4 : 0.6	71.0
0.5 : 0.5	70.0
0.6 : 0.4	69.0

In addition, it was confirmed that the verification performance was improved as the number of features increased. By adding the statistical characteristics, for example, the mean value, the variance and so on to the feature vector, more improvement of the verification performance is expected. This is our next work.

7. Conclusions

In this paper, in order to make the person authentication using the EEG signal practical, we proposed a new feature vector with light computational load, which consists of maximum spectral powers, their frequency values, and accumulated spectral powers over a threshold. As a result,

verification rate of 72% was achieved based on the measurement of the EEG with one channel and 23 subjects. In addition, it was confirmed that the verification performance was improved as the number of feature vector elements was increased. We are now trying to add some statistical values to the feature vector. To make the authentication using the EEG more practical, we must examine the verification performance with measuring in shorter recording time and with opened eyes.

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