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Biometric Authentication using Evoked EEG by Invisible Visual Stimulation

- Feature Extraction Based on Wavelet Transform -

Nozomu Kinjo*, and Isao Nakanishi*
*Tottori University, Japan

***Abstract*— In this study, we aim at the realization of authentication using evoked electroencephalogram (EEG) when presenting invisible visual stimulation as biometrics authentication towards safer and continuous authentication. In the previous researches, the measured EEG signal was processed by fast Fourier transform (FFT), and the power spectrum obtained was used as an individual feature, but the equal error rate (EER) representing the verification rate was about 43%. Therefore, in this paper, we introduce wavelet transform, which is a time-frequency analysis method, and extract a new individual feature including temporal information to improve the verification rate. As a result of evaluating the verification performance, in the case of presenting an invisible visual stimulation, the verification rate averaged over all electrodes tends to be improved as temporal information is included. In addition, as a result of evaluating the verification performance with data in which the start time of presenting stimulation is synchronized, the EER is the best at 14.0%, which is greatly improved compared to the conventional verification rate.**

I. INTRODUCTION

Recently, biometrics information (fingerprint, face, iris, etc.) has attracted attention as a means of person authentication when using smartphones and ATMs. However, because biological information such as fingerprints and faces are exposed on the body surface, it is easy for other people to steal the information. Once stolen, it cannot be changed or reissued like a password. In order to prevent this, it is necessary to use the information that exists in the body such as a vein. In addition, when a user uses a system, widely used biometrics authentication technology cannot cope with user's change after authentication because it assumes only one-time authentication. To achieve higher security against the above problem, it is desirable to continue authentication while using the system. To realize the continuous authentication, it is necessary to continuously acquire user's biometric information. Therefore, likely the biometric information that the user has to consciously present every authentication becomes less convenient. Hence, it is desirable that biological information can be presented unconsciously.

Recently, researches using electroencephalogram (EEG) signals as biometrics have been actively conducted [1-7]. EEG is a variation in electric potential acquired by an electrode attached to the scalp and always occurred unconsciously from human beings as long as they live. Therefore, it is superior in data security.

There are two kinds of EEG, one is EEG that responds to external stimulation such as light and sound, and the other is EEG that is constantly generated in the unconscious state [8]. Researches on EEG recognition using EEG induced by external stimulation focus mainly on event-related potentials (ERPs) and visual-evoked-potentials (VEPs). However, the stimulation is perceptible to users [1,2,6,7]. To realize continuous authentication, it is considered that the visible stimulation is an obstacle to the user when using a system. The stimulation needs to be invisible to the user. Nakanishi et al. [9] conducted a research on person identification using evoked EEG with invisible visual stimulation, but the error rate was 43% which was not a high authentication rate. Therefore, this study aims to improve the verification rate when using evoked EEG by invisible visual stimulation.

The boundary at which a person can or cannot perceive a stimulation is called threshold and the unperceivable area is called subthreshold [10]. The researches of subthreshold stimulation have been mainly conducted to explore the perceptual threshold [11-15]. Focusing on visual stimulation, there are three ways to generate subthreshold stimulation: the first is a method of generating subthreshold stimulation by a high-speed frame rate and contrast change of the stimulation on a display [16]. The second is a method called continuous flash suppression (CFS). By presenting a different image to each eye, the subject image is masked by the other image and thus it becomes subthreshold stimulation [17]. The third is a method called posterior masking. The consciousness of the preceding stimulation is masked by the following stimulation and as a result the preceding stimulation becomes subthreshold stimulation [18]. By generalizing the findings from the above studies, ERP is not confirmed at the perceptual threshold, and the power spectrum in the alpha wave band (8-13 Hz) increases when an invisible stimulation is given especially in the area around the occipital region [16-19].

II. PREVIOUS RESEARCH

The outline of the previous research [9] of the person verification using the EEG induced by invisible visual stimulation is described below.

EEG measurement was conducted with 20 subjects and 10 times per subject. As shown in Fig. 1, a red fixation point was placed at the center of the white background. As visual stimulation, a black circle was presented above or below the point. The contrast of the visual stimulation was adjusted and

the display time of the stimulation was about 8 ms. Figure 2 shows the flow of stimulation presentation. First, an image with only the fixation point is presented for 5 seconds, and then a presentation cycle of 1 second (this is one set) in which there was an image with a black circle of 8 ms and images with only fixation point of 992 ms was repeated 55 times. The subjects remained at rest in a dark room. The EEG sensor used for the measurement was EMOTIV EPOC (14 electrodes, sampling rate: 128 Hz, bandwidth: 0.2-43 Hz). In addition, four stimuli with different contrasts were created. After the measurement, the subjects were asked whether the black circle was observable. Figure 1 shows four stimulation images of intensity 0%, 5%, 10% and 100%. In the study, the stimulation with stimulation intensity 5%, which were invisible to all subjects was regarded as an invisible visual stimulation.

In feature extraction, the EEG data were processed by fast Fourier transform (FFT), and the power spectra in 8-13 Hz (α), 13-20 Hz (low β), 20-30 Hz (high β) and 30-43 Hz (γ) were obtained. Euclidean distance was used for verification. As the verification performance evaluation, the false rejection rate (FRR) and the false acceptance rate (FAR) were obtained, and their intersection: equal error rate (EER) was obtained. The smaller the EER, the better the verification performance. Figure 3 shows FRR, FAR, and EER. As a result, even the best EER was 43% in alpha wave band, and high verification performance was not obtained.

III. Introduction of Time Frequency Analysis

In the previous research [9], the power spectra of the EEG signal obtained by FFT was considered as an individual feature. However, since the temporal change of frequency components cannot be analyzed by FFT, the temporal information was lost. So, in this study, we examine a new feature which includes temporal information by wavelet transform, which is well-known as a time-frequency analysis method.

A. *Continuous Wavelet Transform (CWT)*

A wavelet basis is defined as Eq. (1) by scaling and translating a localized basis wave $\Psi(t)$ called analyzing wavelet or mother wavelet [20].

$$\Psi_{a,b}(t) = \frac{1}{\sqrt{a}}\Psi\left(\frac{t-b}{a}\right) \tag{1}$$

The continuous wavelet transform is defined as Eq. (2) by convolving the signal $x(t)$with the wavelet basis

$$\tilde{x}(a,b) = \int_{-\infty}^{+\infty} x(t)\frac{1}{\sqrt{a}}\Psi^*\left(\frac{t-b}{a}\right)dt \tag{2}$$

where a is called a scale parameter which corresponds to the inverse of a frequency and b is a shifting parameter which is a time index. The wavelet base is scaled by changing the value of a and translated by changing the value of b. The wavelet coefficients $\tilde{x}(a,b)$ are squared to obtain a scalogram which

Fig. 1. Stimulation images (stimulation intensity 0%, 5%, 10%, 100% from the left)

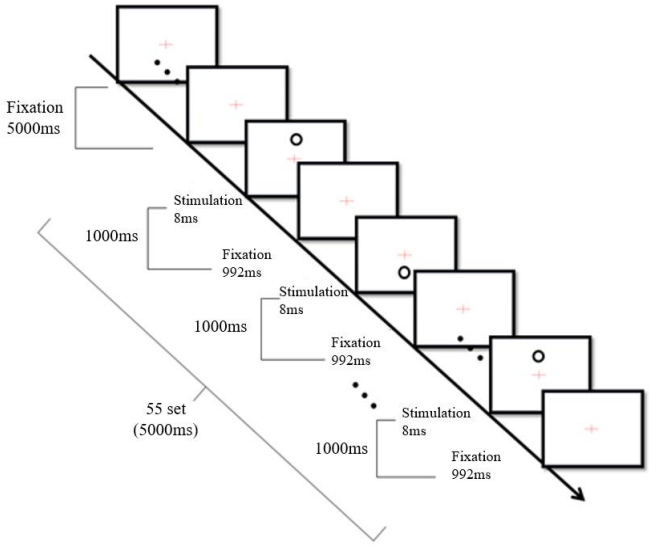


Fig. 2. Flow of stimulation presentation

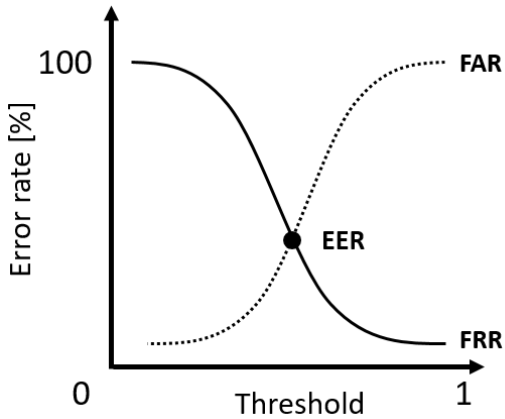


Fig. 3. Definition of FRR, FAR, and EER

is used as a time-frequency feature with the time axis: b and the frequency axis: $1/a$. When the scale parameter a is increased, the frequency resolution becomes finer but the time resolution becomes coarser and vice versa. In this way, CWT always makes the time and frequency resolution optimal according to a frequency band.

B. *Synchronization of scalograms*

Scalograms as individual feature include temporal information; therefore, To compare scalograms it is necessary to synchronize the presentation instants of visual stimulation. In this study, EEGs measured in Ref. [9] were used but in this data set, the electroencephalograph and the device for stimulation presentation were not be strictly synchronized.

Therefore, we need to synchronize the moments of presenting visual stimulation. As described in Sec. II, the visual stimulation is presented every one second. Therefore, it is certain that EEG data for one second include one evoked response. From a one-second EEG, a one-second scalogram is extracted. Based on a scalogram as a template, a scalogram of a verification EEG is cyclically shifted in the time direction and the correlation value is calculated at each shift. The correlation value is determined by the following equation. The shift value with the maximum correlation value is taken as a pseudo synchronization point.

$$R_k = \frac{\sum_{i=1}^{I}\sum_{j=1}^{J}(f_{i,j}-\bar{f})(g_{i,j+k}-\bar{g})}{\sqrt{\sum_{i=1}^{I}\sum_{j=1}^{J}(f_{i,j}-\bar{f})^2}\sqrt{\sum_{i=1}^{I}\sum_{j=1}^{J}(g_{i,j+k}-\bar{g})^2}} \quad (3)$$

where f and g are the power of two scalograms, I is the frequency range, J is the time range, and k is the shift sample value.

Since this synchronization method does not require strict synchronization between the electroencephalograph and the stimulus presentation, it can be implemented in a simple measurement environment. On the other hand, since this method only calculates a shift value that gives the most similar distribution in two scalograms, accurate synchronization cannot be always achieved.

IV. FLOW OF VERIFICATION

Figure 4 shows the follow of verification. We used EEGs measured in the previous study [9]. However, EEGs which obviously include spike noise were excluded and as a result, eight EEGs were used per subject. Each EEG was divided into multiple one-second data, and all one-second data were ensemble averaged to obtain a one-second EEG. The one-second averaged EEG was converted to a scalogram of 1-43 Hz by CWT (Mother wavelet: Morlet, Center frequency: 1.0 Hz) and normalized. The normalization is performed by adjusting the average of the total power amount to 0 and the standard deviation to 1.

Next, the synchronization processing described in Sect. III is performed. After synchronization, α (8-13 Hz), low β (13-20 Hz), high β (20-30 Hz), and γ (30-43 Hz) wavebands were extracted as an individual feature. Furthermore, to show the superiority of introducing temporal information, scalograms averaged in the time direction in four different resolutions were compared with an original scalogram. Those scalograms averaged in the time direction are shown in Fig. 5. Each frequency band of scalograms averaged at this time resolution was evaluated as a feature. Verification performance calculated Euclidean distance between the average of the template and the test data. A threshold is set, the test data with smaller distance than the threshold are regarded as genuine and otherwise are reject.

V. RESULTS AND DISCUSSION

A. Results of Verification performance evaluation

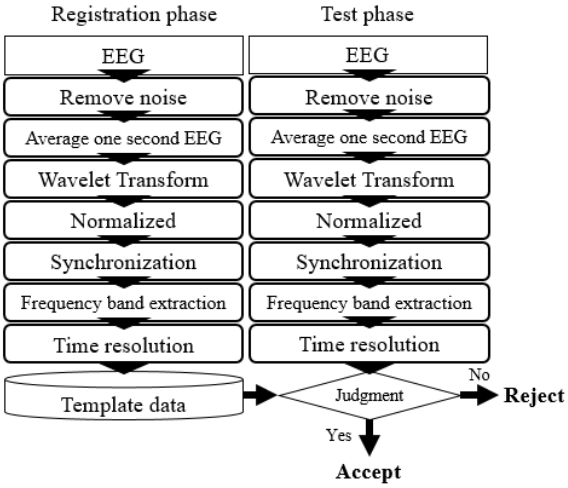


Fig. 4. Flow of verification

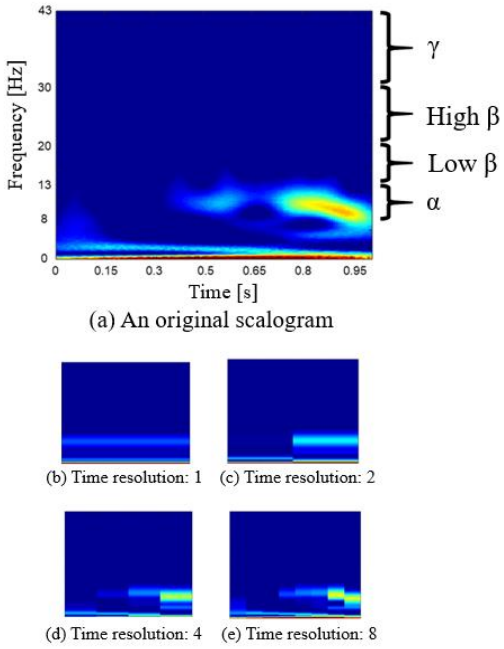


Fig. 5. Scalograms, an original one (a) and four different time-resolution ones (b)-(e).

Among eight EEG data per subject, four were used for making a template and the remaining four as test data. A template was created by ensemble-averaging four scalograms synchronized to one of them. Figure 6 shows the evaluation results of the verification performance obtained by averaging EERs of all electrodes in the α (8-13 Hz) waveband at each stimulation intensity. When the stimulation intensity is 5%, that is, when invisible visual stimulation was presented, the EER decreased as the number of time resolutions increased. This means that the verification rate was improved by introducing temporal information. However, such improvement was about a few percent and insufficient. In addition, the increase in the number of time-resolutions did not improve the verification rate except at a stimulation intensity of 5%. The reason is considered as follows. There is

no visual stimulation when the intensity was 0%, so there was no evoked response; therefore, there was no feature difference in individual responses even when the number of time resolutions was increased. In the cases of stimulation intensity 10% and 100%, the stimulation could be perceived by several and all subjects, respectively. In this study, the spectrum in the α wave band which is effective in the case of presenting invisible stimulation was used as individual feature. Therefore, it was not effective in the case of visible stimulation. Moreover, in the case of low β, high β, and γ wavebands, the improvement of the verification rate by the increase in the number of time resolutions was not obtained.

The EER of each electrode at intensity 5% is shown in Fig. 7. EERs of time resolution 8 is smaller than those of time-resolution 1 at thirteen electrodes. Therefore, the effect of introducing the time-frequency analysis was confirmed.

B. *Excluding of EEGs which could not be synchronized*

The verification performance was improved by including temporal information in the case of invisible visual stimulation, but it was still over 40%. This may be due to miss-synchronization before feature extraction. In this study, the synchronization of two scalograms compared is performed by calculating their correlation value in the time direction and sifting either scalogram by a value with the maximum correlation in a time-axis. However, this method cannot always perform complete synchronization. Therefore, we tried to achieve the synchronization of scalograms by our visual observation. As a result, there were several scalograms which could not be synchronized even by the visual observation. Examples of such scalograms are shown in Fig. 8 comparing with those in which synchronization by the visual observation is possible. Thus, after removing such scalograms, that is, EEGs, we re-evaluated verification performance using six EEGs per subject. Three data were used for making a template, and the remaining three data were used in the tests. Figure 9 shows EERs in different time-resolutions at an intensity of 5% and electrode O2. EER is improved by about 10~20% as compared with those at the electrode O2 in Fig. 7. Especially, EER is the smallest at 14.0% when the time resolution is 2. Therefore, the verification performance was improved to 80%~85%. It is suggested that scalograms obtained by time-frequency analysis are more appropriate for verification than spectral features. In this study, we focused on only O2 because its position corresponds to the back of the head, which is considered to have the largest influence on EEGs by visual stimulation. However, the investigation using only O2 is not sufficient, so it is necessary to examine the results with other electrodes in the future.

VI. Conclusions

In this study, we aim at the realization of authentication using evoked EEG when presenting invisible visual

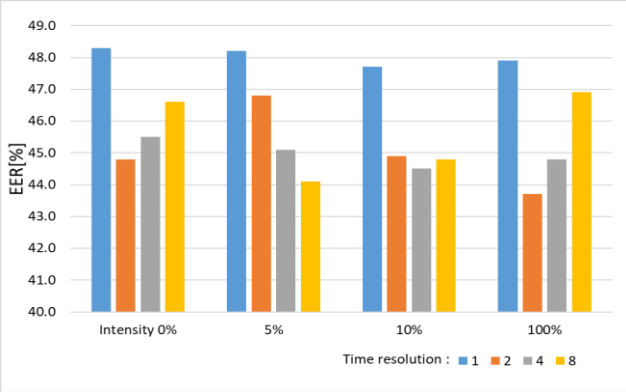


Fig. 6. EERs in four time-resolutions at each stimulation intensity

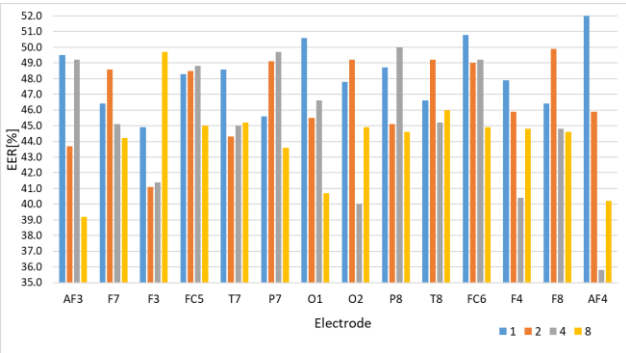
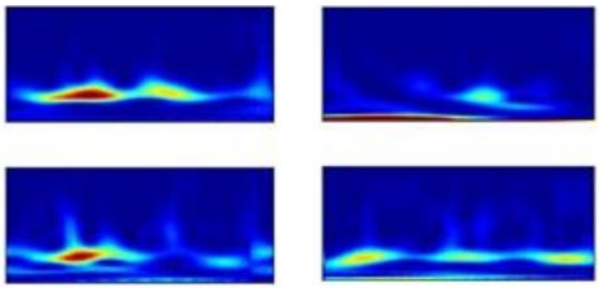


Fig. 7. EERs in four time-resolutions at each electrode in the case of stimulation intensity 5%



(a) Data that could be synchronized (b) Data that could not be synchronized

Fig. 8. Examples of scalograms which could be synchronized: (a) and could not be synchronized: (b)

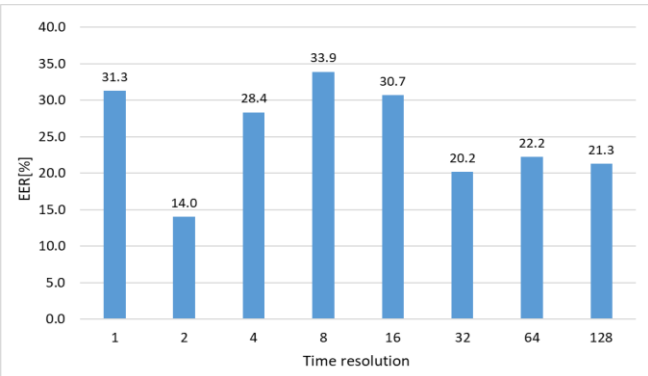


Fig. 9. EERs when excluding scalograms which were unable to be synchronized

stimulation as biometrics towards safer and continuous authentication. In the previous research, power spectra were extracted as an individual feature, but a high verification rate was not obtained. In this paper, we introduced time-frequency analysis and evaluated the verification performance with features including temporal information. As a result, in case of presenting an invisible visual stimulation, the verification performance averaged over all electrodes was improved. However, the improvement of the verification rate was about several percents. Therefore, we eliminated scalograms which are difficult to synchronize by our visual observation, and then re- evaluated verification performance. As a result, EER of 14.0% was achieved when the number of time-resolution was 2. This suggests that more accurate synchronization of scalograms leaves the room of much improvement of verification performance. On the other hand, it is necessary to construct a measurement environment for scalograms can be always synchronized in the future. In addition, we select the stimulation that induces a specific response to the individual. It may increase the individualize of a feature and improve the verification performance.

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