PAPER

User Verification Using Evoked EEG by Invisible Visual Stimulation

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SUMMARY Person authentication using biometric information has recently become popular among researchers. User management based on biometrics is more reliable than that using conventional methods. To secure private information, it is necessary to build continuous authentication-based user management systems. Brain waves are suitable biometric modalities for continuous authentication. This study is based on biometric authentication using brain waves evoked by invisible visual stimuli. Invisible visual stimulation is considered over visual stimulation to overcome the obstacles faced by a user when using a system. Invisible stimuli are confirmed by changing the intensity of the image and presenting high-speed stimulation. To ensure invisibility, stimuli of different intensities were tested, and the stimuli with an intensity of 5% was confirmed to be invisible. To improve the verification performance, a continuous wavelet transform was introduced over the Fourier transform because it extracts both time and frequency information from the brain wave. The scalogram obtained by the wavelet transform was used as an individual feature and for synchronizing the template and test data. Furthermore, to improve the synchronization performance, the waveband was split based on the power distribution of the scalogram. A performance evaluation using 20 subjects showed an equal error rate of 3.8%.

key words: *EEG, event-related potentials, wavelet transform, invisible visual stimuli*

1. Introduction

In recent years, with the development of modern technology, many people are using personal computers and smartphones daily. This has led to problems such as private data leaks and impersonation. Therefore, it has become necessary to strengthen the security technology. Currently, three major security technologies are widely used for person authentication: authentication based on knowledge, such as passwords and pattern locks; authentication based on possessions, such as integrated circuit (IC) cards; and authentication based on biometrics, such as fingerprints and faces [1]. However, simple spoof attacks can easily forge conventional knowledge- and possession-based authentication systems. Therefore, person authentication using biometric information has recently become increasingly popular.

Biometric authentication is employed to identify or verify a person on account of his physiological and/or behavioral characteristics. However, conventional biometric authentication techniques assume one-time authentication, where the authentication is performed only once when a user starts to use a system. However, if the user is replaced by another one, the one-time authentication cannot detect the user change after authentication.

To address spoofing, continuous authentication, in which the user is always authenticated, is essential [2], [3]. Therefore, it is worthwhile to explore unique bio-electrical signals for continuous biometric authentication.

To overcome this, an electroencephalogram (EEG) is considered as a potential user authentication technique as it offers the advantages of being difficult to fake, continuously generated, and requiring live person recording [4]–[8]. The brain wave is not exposed on the body surface unlike fingerprints and face images; thus it is difficult for others to capture an EEG without user consent. That makes it resistant to spoofing. EEG is continuously generated; hence, it can be used as a continuous real-time authentication system without requiring user cooperation. Unconsciously recordable personal data is desirable for real-time authentication. In addition, the EEG signal cannot be recorded from a dead person; therefore, the possible threat of misuse of the dead person's information is resolved.

The purpose of our research is to realize person authentication using brain waves evoked by invisible visual stimuli. The evoked brain waves are used as confidential biological information. In addition, visible stimulation is an obstacle to users when using a system; therefore, invisible visual stimuli were considered rather than visual stimuli [9]. In Refs. [10], [11] a scalogram was obtained using wavelet transformation as an individual feature. The wavelet transformation is one of the time-frequency transformation, which contains both time and frequency information [10]–[12]. We introduced a synchronization method using correlation for matching scalograms and evaluated the verification performance based on the Euclidean distance method [10]. Initially, the correlation value in the entire band (1–43 Hz) of the scalogram was used for synchronization; however, there may be a specified band that is more effective for calculating the correlation within the waveband.

Thus, in this study, we focus on α-waveband of the scalogram considering that the power of the α-waveband is dominant when the invisible stimuli are presented. Furthermore, we split the α-waveband into three sub-bands, low α-waveband (8–9 Hz), mid α-waveband (9–12 Hz), and fast α-waveband (12–14 Hz) and proposed the synchronization scalograms and extraction of features in a sub-band. To further improve synchronization and feature extraction, we

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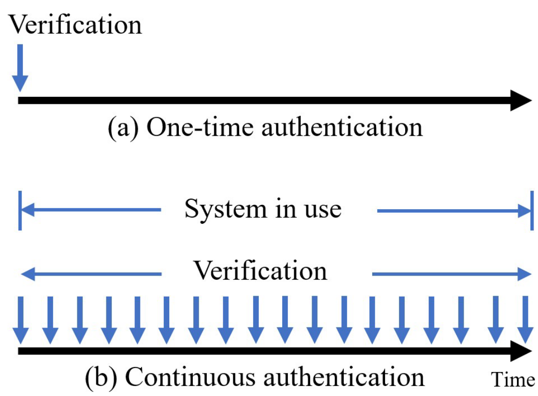


Fig. 1 One-time vs continuous authentication.

introduced another sub-band (8–10 Hz) and confirmed that the verification rate was increased in the sub-band.

2. Basis Knowledge

2.1 Necessity of Continuous Authentication

Conventional authentication using fingerprints, facial images, passwords, and IC cards is currently being used as a one-time authentication system. In conventional methods, it is possible to verify the user at the beginning of the authentication procedure; however, once the procedure has been completed, the identity is not guaranteed. Figure 1 shows the difference between (a) one-time authentication and (b) continuous authentication. In the case of one-time authentication, the authentication takes place only when a user starts using a system; therefore, it is impossible to respond to the replacement of users after the completion of the authentication procedure. However, in the case of continuous authentication [9]–[11], [13], in addition to the sign-in at the start of using a system, authentication is performed even when using the system, such that other users cannot impersonate while using the system. Therefore, identity is always guaranteed when the system is being used.

2.2 EEG

An EEG is a record of the electrical activity of the brain captured by electrodes [14]. The EEG is the aggregate of electrical activities of many cells and is recorded from the outside of the conductive living tissue (brain, cerebral spinal fluid, blood vessels, skull, and scalp) indirectly surrounding the source, as shown in Fig. 2. There is a small potential difference between the two electrodes attached to the scalp. The magnitude of the signal is μV, and after amplifying the signal, it can be observed as a rhythmic wave.

As an EEG can only be recorded by wearing an electroencephalograph, it is highly resistant against spoofing. In addition, by attaching an electroencephalograph, EEG can be acquired continuously even when people are sub-conscious to wear EEG sensor.

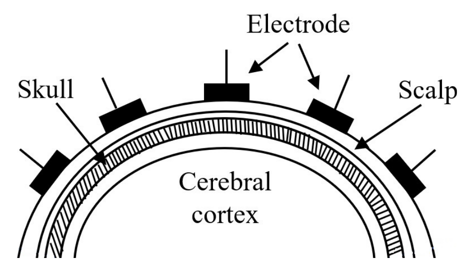


Fig. 2 Schematic of the cortex and electrode.

To perform continuous biometric authentication, sequential biometric information of the user is required. Furthermore, it should be ensured that while recording the biometric information, the recording process does not interfere with the actual work being performed by the user. We have considered an EEG to be the biological information that satisfies the above requirement [9]–[11].

3. Related Works

3.1 EEG Evoked by External Stimuli

There are two types of brain waves: spontaneous brain waves that are constantly generated even when unconscious, and evoked brain waves that are generated by external stimuli, such as light, sound, and psychological changes, such as the meaning and attention of the stimuli. Brain waves depict electrical activity of the brain that occurs in response to stimuli, and these brain waves are called event-related potentials (ERP) or event-related brain potentials [15]–[18]. The captured potential difference is μV. Conventional techniques [19], [20] of person verification using brain waves, both spontaneous and induced, have been studied.

Conventional authentication using brain waves has already achieved a high authentication rate. However, conventional studies impose perceptible stimulus presentation and image tasks, which hinder the use of the authentication system. Therefore, it is necessary to realize a continuous authentication method that does not obstruct the use of the authentication system. In Ref. [21], the imperceptible stimulation and verification performance of ultrasounds was evaluated. Consequently, an EER† of 0% was achieved based on majority of the results obtained using spectrum and nonlinear features. However, there may be some people to whom such a verification method may not be applied; therefore, it is necessary to give them alternative methods. One of them is the proposed method utilizing a visual function. On the other hand, it is interesting to fuse biometrics based on five senses. Multi-biometrics using EEGs evoked by invisible and inaudible stimuli may improve the verification performance using either stimulus.

†An EER is the cross-point between the false acceptance rate and false rejection rate, which indicates the performance of a biometric authentication system. A system with a minimum value of EER is regarded as having a high accuracy.

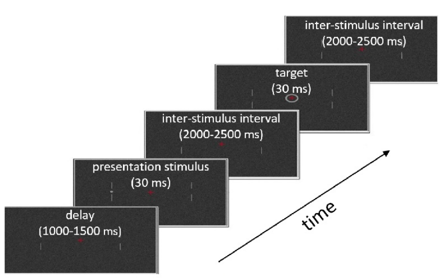
3.2 Creation of Invisible Visual Stimuli

There are several popular methods for creating imperceptible stimuli. The reason why the visual function is targeted is vision is as important as hearing.

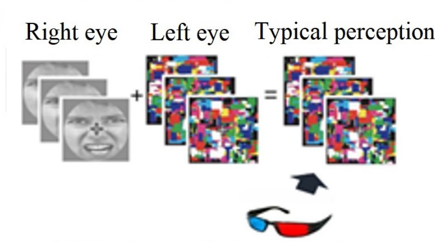
(1) The simplest method is to present the target stimulus on the display at a high speed and then change the contrast of the stimulus to realize the subliminal stimulus [22] as shown in Fig. 3(a), the circular figure, which is the target stimulus that was presented only for a short duration of 30 ms.

(2) A method called continuous flash suppression [23], in which each eye is made to observe separate stimuli and the target stimulus is masked by an image (mask image). In Fig. 3(b), the face image, which is the target stimulus, is presented to the right eye, and the mosaic image, which is the mask image, is presented to the left eye. The displayed image is a combination of the observations of both eyes; however, by wearing 3D glasses, it is presented separately for each eye. Normally, the mask image has a higher contrast than the target stimulus; therefore, the person viewing the image tends to be more conscious of the mask image presented to the left eye, and the target stimulus presented to the right eye becomes a subliminal stimulus.

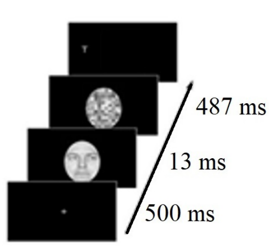
(3) By masking the preceding stimulus to consciousness with the subsequent visual stimulus using a method called back-masking [18], [24]–[26], the initially presented stimulus becomes a subliminal stimulus. In Fig. 3(c), a mosaic image is presented after the face image, which is the target stimulus.



(a) High-speed presentation



(b) Continuous flash suppression



(c) Back masking

Fig. 3 Presentation method of sub-threshold visual stimulus, (a) high-speed presentation, (b) continuous flash suppression, and (c) back masking.

4. Invisible Visual Stimulation

In Ref. [9], invisible stimuli were created by adjusting the two parameters of "stimulus presentation speed" and "contrast". We selected the method (a) in Fig. 3 since it was the simplest. The stimulus was presented at 120 frames per second (fps), which can present fast stimuli on commercially available computers and displays. However, a stimulus that could not be perceived was made by creating several patterns of moving images in which the contrast of the stimulus was adjusted to confirm whether the experimental subject could perceive it or not.

4.1 Equipment

A high-configuration computer and display were used in this study to display a 120 fps stimulation video. A computer (CPU-Intel core i7-4790K, 4.00 GHz, GeForce GTX750, 16 GB memory) with a display (iiyama ProLite GB2488HSU, 24 inch, 144 Hz) was used to play the higher refresh rate stimulus video.

4.2 Stimulation Content

The stimuli to be presented was in the shape of "○". Further, as shown in Fig. 4, the following four types of stimulus images were created by changing the contrast of the target stimuli:

- "White (color model R: 255, G: 255, B: 255)" In the following, the stimulation intensity is shown as 0%.
- "White + 5% basic color (color model R: 242, G: 242, B: 242)" The stimulus intensity is shown as 5%.
- "White + 10% basic color (color model R: 220, G: 220, B: 220)" The stimulus intensity is shown as 10%.
- "White + 100% basic color (color model R: 0, G: 0, B: 0)" The stimulus intensity is shown as 100%.

The size of each stimulus image was 23 × 30 cm, as shown in Fig. 5. The gaze point is a red cross with a vertical dimension of 0.5 cm and horizontal dimension of 0.8 cm, and

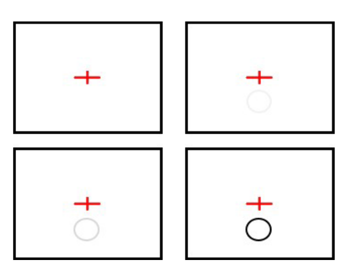


Fig. 4 Stimulation intensity 0% (Upper left), 5% (Upper right), 10% (Lower left), and 100% (Lower right).

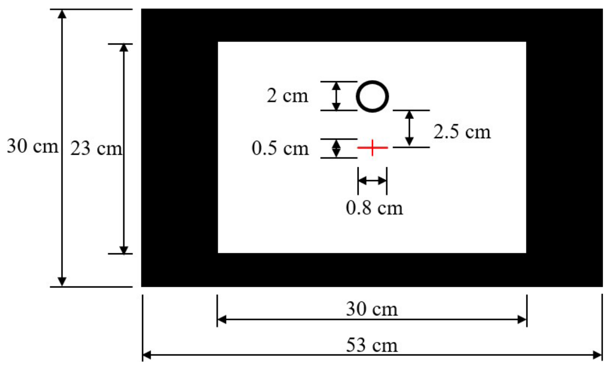


Fig. 5 Magnitude of the stimulus presented.

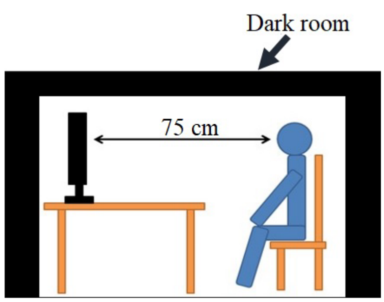


Fig. 6 Measurement environment.

the stimulating circle ("○") has a diameter of 2.0 cm and appears 2.5 cm above or below the red gaze point.

4.3 EEG Measurement by Invisible Visual Stimulation

Measurements were performed on 20 subjects between 20 and 26 years of age. The subjects were asked to sit in a simple dark room at a distance of 75 cm from the display on which the stimulus was presented, and they remained in a resting state, as shown in Fig. 6. Four types of stimuli (stimulation intensity 0, 5, 10, and 100%) were used to create a moving image presented at 120 fps. The EEG measurements were performed by EMOTIV EPOC (14 electrodes, sampling rate: 128 Hz, bandwidth: 0.2–45 Hz).

The flow of the stimuli is shown in Fig. 7. A red colored cross-mark was placed to gaze at the center point of the white background. To implement the visual stimulation, a black circle was presented above or below the gaze. By increasing the frame rate to 120 fps and lowering the intensity, invisible visual stimulation was achieved. The stimulus intensities were 0, 5, 10, and 100%, as described in Sect. 4.2. The 0% were considered to indicate no stimulation. Initially, only the colored cross-mark was presented for 5000 ms, and then the target stimuli were applied for approximately 8 ms. Subsequently, only the gazing figure was implemented for 992 ms. This completed one set; the experiment was repeated for 55 sets.

Moreover, to prevent the subject from predicting the next stimulus, the stimulus was presented irregularly, above or below the gaze point. The irregular presentation of the

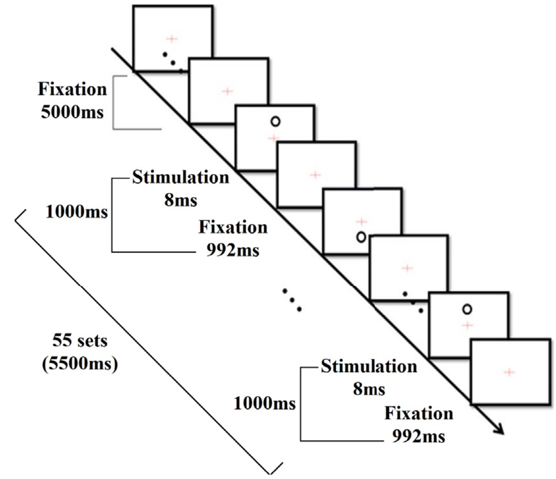


Fig. 7 Stimulus presentation flow.

stimulus was 50%; thus, the probability of the stimulus appearing above or below was not biased. Measurements were performed 10 times per subject.

The detailed results were presented in Ref. [9]; therefore, they are omitted here but the 5% stimulation intensity was not recognized by any subject; thus, it was considered an invisible stimulus in this study.

5. Person Verification Using Evoked EEG

5.1 Verification System

The flow of the verification system is shown in Fig. 8. The average amplitude of the recorded EEG data of more than $\pm 100\,\mu$V was regarded as noise and excluded from the EEG signal. An EEG recorded for a 55 s duration was divided into 55 data points of 1 s each, and the 55 data points were ensemble-averaged to obtain a one-second EEG.

Furthermore, a continuous wavelet transform (CWT) was performed which is a time–frequency analysis method for feature extraction. One second of EEG was converted into a scalogram of 1–43 Hz using CWT as shown in Fig. 9, where mother wavelet was Morlet. Data for the α-waveband (8–13 Hz), low β-wave (13–20 Hz), high β-wave (20–30 Hz), and γ-wave (30–43 Hz) bands were extracted from the scalogram.

Furthermore, we performed z-score normalization to ensure that all data were in a similar range and to make the synchronization process robust. After normalization, a scalogram with an average power of zero and standard deviation of one was used as the template and test data. The scalograms include temporal information; therefore, for comparing them, it is necessary to synchronize them. However, in our measurement environment, the electroencephalograph and the device for stimulus presentation were not synchronized. Thus, we utilize the condition that the visual stimulation is presented every one second. It is certain that EEG data for one second include one evoked response. Based on the scalogram of a template, the scalogram for verifica-

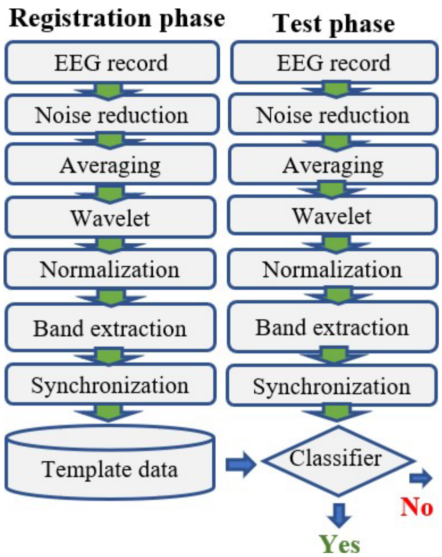


Fig. 8 Flow of verification system.

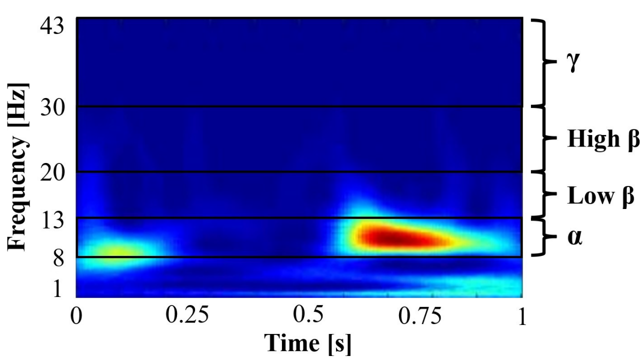


Fig. 9 A scalogram with divided four frequency bands.

tion is cyclically shifted in time direction and the correlation value is calculated at each shift. After evaluating all shifts, the shift value with the maximum correlation value is taken as a synchronization point. Finally, the template scalogram is compared with the scalogram obtained by test data and shifted by the synchronization point.

In the experiment, eight EEG recordings were obtained for each subject. The EEG data of each subject were divided, and four of them were used as test data, and the rest were used as a template. A template was obtained for each subject by averaging the scalograms of the EEG data. Cross-validation was performed ten times. Verification was performed using Euclidean distance matching between the features in the template and test data. Test data with a distance less than or equal to the predefined threshold were regarded as genuine and otherwise rejected.

5.2 Effect of Introducing Time-Frequency Analysis

Synchronization was performed in the frequency bands for feature extraction. To verify the effectiveness of introducing temporal information into feature extraction, the time do-

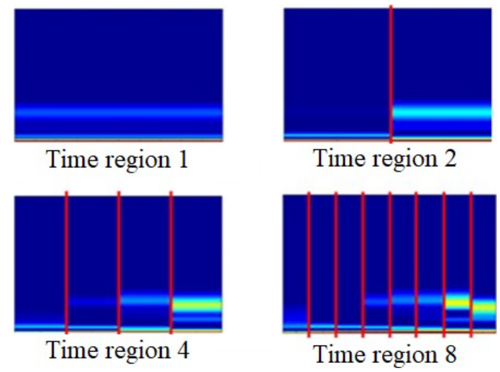


Fig. 10 Averaged scalograms corresponding to different time regions (n = 0, 1, 2, 3).

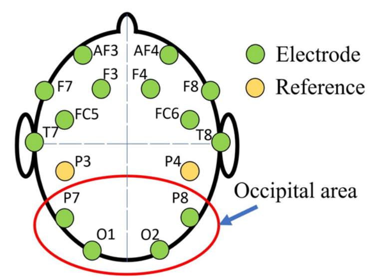


Fig. 11 Electrode position.

Table 1 EER (%) in each time region and each band for O1 electrode.

Time Region	α (8–13 Hz)	low β (13–20 Hz)	high β (20–30 Hz)	γ (30–43 Hz)
1	25.2	38.5	45.1	45.3
2	11.1	32.1	46.3	47.7
4	13.1	31.1	47.9	44.2
8	12.4	29.3	46.6	49.3
16	9.4	32.2	45.7	46.1
32	11.8	31.7	45.2	46.6
64	12.4	32.1	44.3	44.9
128	11.2	29.4	46.8	44.3

main in a scalogram was divided into several regions, and the values in a frequency bin were averaged in the same region. The number of time regions was 2^n(n=0, 1, $\cdots$, 7). A scalogram with n = 7 was the original. Examples of scalograms averaged in the time direction are shown in Fig. 10.

The EERs of α, low β, high β, and γ wavebands in each time region were evaluated for O1, O2, P7, and P8 electrodes [10], [11]. These electrodes were chosen because they were positioned in the occipital area, as shown in Fig. 11, which are primarily responsible for visual processing. The results for O1 electrode are summarized in Table 1 as the best case in four electrodes. The best frequency and time region for other electrodes were approximately equal with those for O1. The number of times region 1 corresponds to the Fourier transform, which has no temporal information. EERs in more than two time regions were greatly reduced compared to EERs in time region 1. Similar characteristics are found in other electrodes. By introducing temporal information, the

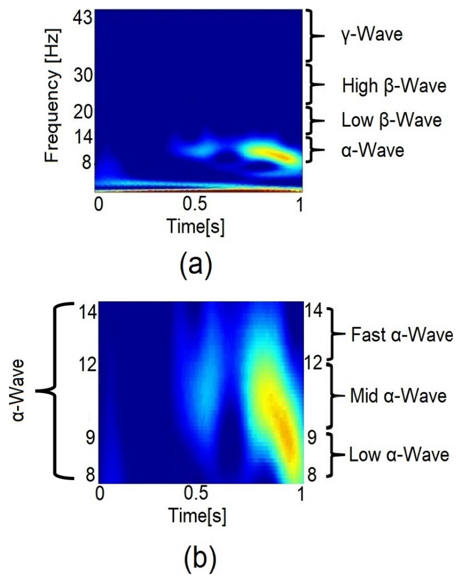


Fig. 12 Scalogram in (a) EEG band and (b) Enlarged version of (a) in α-band.

EER decreased, particularly in the α-waveband. Therefore, the effect of introducing the time-frequency analysis was confirmed. The EER was 9.4% in α-waveband when the number of time regions was 16 [11].

5.3 Effect of Specifying Wave Band

In Fig. 12(a), an example of the power distribution of EEG data is shown. Blue (dark) indicates a non-significant area of power distribution, and red (light) indicates the most significant power distribution. If the color is changed from blue to red in the scalogram, it is considered that the amount of power is increased. As confirmed in the previous section, verification performance using only α-waveband is preferred over that using other wavebands. Previous research has confirmed that the amount of power in the α-waveband increases in the occipital region when an imperceptible stimulus is applied [10]. However, as illustrated in Fig. 12(b), there are differences in the response, even in α-waveband. Therefore, to improve the verification performance, we propose to further divide the α-waveband, which has a large amount of power in the scalogram and use each sub-band for synchronizing and feature extraction.

The main focus is to determine the sub-band with the most significant power distribution in the α-waveband. Thus, we split α-waveband into three different sub-bands, which are defined in the brain wave research shown in Fig. 12(b). The three sub-bands were considered to be a low α-waveband (8–9 Hz), mid α-waveband (9–12 Hz), and fast α-waveband (12–14 Hz).

The verification performance at O1, O2, P7, and P8 electrodes was re-evaluated in the three bands. The other verification procedure was the same as that in the previous sections. Table 2 lists the average EER of α-waveband and the three sub-bands for O2 electrode as the best case in four electrodes. The smallest EER was 4.4% in the low α-waveband when the number of time regions was 64. The best result was found for 64 time regions; however, considering all wave-band results, the EER (%) decreases when the number of time regions increases. The results for other electrodes were approximately equal with those for O2. The verification performance significantly improved after splitting the α-waveband. The EER was less than half of that of the full α-waveband. Similar characteristics are found in other electrodes. It was confirmed that splitting the α-waveband for synchronization and feature extraction is effective in improving verification performance.

Table 2 EER (%) in α-waveband and three sub-bands for O2 electrode.

Time Region	α (8–13 Hz)	low α (8–9 Hz)	mid α (9–12 Hz)	fast α (12–14 Hz)
1	30.6	7.3	8.2	11.2
2	13.6	6.5	7.9	9.9
4	15.4	5.9	6.8	6.8
8	15.0	5.3	5.8	5.0
16	13.4	4.8	5.3	4.8
32	16.1	4.5	5.2	4.6
64	15.5	4.4	5.5	4.8
128	15.0	4.9	4.6	4.7

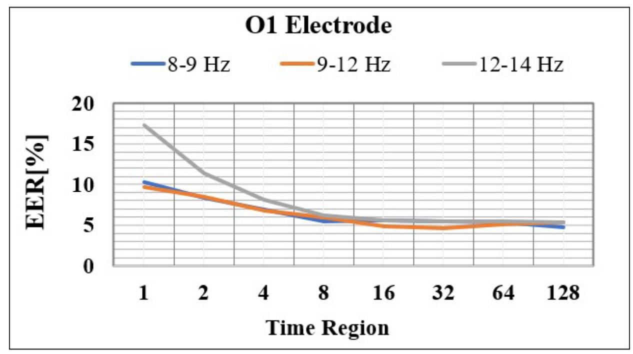


Fig. 13 Variation of EER according to the number of time-regions for O1 electrode.

Figure 13 shows the variation in EERs according to the number of time regions for O1 electrode. As the number of time regions increased, the EERs decreased, but converged above 16 time regions as well as Table 2. Therefore, to simplify the processing, we selected the maximum time region to evaluate the verification performance using the time region 128, that is, directly using the scalogram.

In the previous evaluation, we used categories for brain wavebands: low α, mid α, and fast α. However, it is not guaranteed that such categories are suitable for synchronization and individual features. Thus, we considered another sub-band (8–10 Hz). This band was selected as a sub-band because the most significant power distribution area was within this bandwidth, as determined by detailed visual inspection of the scalogram. To confirm the visual inspection, we assume the other two sub-bands (8–11 Hz) and (9–11 Hz). Using these sub-bands, we re-evaluated the verification performance. The results are presented in Fig. 14. The best result was obtained for (8–10 Hz) at the P8 electrode, with

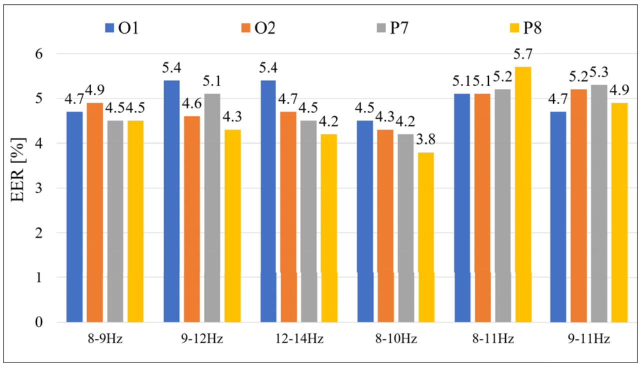


Fig. 14 EER (%) for sub-bands.

an EER of 3.8%. The verification performance was slightly improved using the sub-band.

6. Conclusions

Considering the continuous authentication of users using EEG evoked by an external stimulus, it is desirable that an external stimulus that cannot be perceived by the user should be presented. Based on this technical background, this study focused on invisible visual stimulation and aimed to realize person verification using evoked EEG when visual stimuli that the user cannot recognize were presented.

We created invisible visual stimulation by inserting a target image with low intensity into a moving picture with a fast frame rate. Using this stimulation, we measured EEGs from 20 subjects. We also introduced CWT for feature extraction based on the fact that users had different time-frequency responses (scalograms) depending on the given stimuli and made them individual characteristics. Next, four types of bands were extracted as features from the scalogram: α, low β, high β, and γ wavebands. The verification performance of these bands was evaluated using Euclidean distance-matching. The effect of introducing the time-frequency analysis was confirmed, but the best result was 9.4%, which was insufficient for practical use.

To improve the verification performance, we divided the α-waveband into three sub-bands: low α-waveband, mid α-waveband, and fast α-waveband, which had a large amount of power in the scalogram, and evaluated the verification performance using each waveband. Consequently, the best EER was improved to 4.4%. For further improvement, we introduced another new sub-band (8–10 Hz) and confirmed that the verification performance was improved with an EER of 3.8%.

The verification performance was still not suitable for practical use of this method. In the future, it will be necessary to introduce individual-related stimuli such that we can obtain higher evoked responses than those obtained using the common stimuli used in this study. It is also necessary to consider increasing the number of subjects and databases to improve the reliability of the verification accuracy.

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