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PERSONAL IDENTIFICATION BY STEADY-STATE VISUAL EVOKED POTENTIALS BASED ON VOTING PROCESS BY MAHALANOBIS DISTANCE

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Abstract. *In this study, we attempt personal authentication using steady-state visual evoked potentials (SSVEPs), a type of evoked electroencephalographic brain activity generated by external visual stimuli. We recorded SSVEPs induced by a 5-Hz light stimulus from 16 participants. Recordings were from four electrodes, and multivariate autoregressive coefficients were used as features for authentication. Subsequently, classification based on the Mahalanobis distance was performed using the multivariate autoregressive coefficients. The authentication was performed under two conditions: 1) considering only those registered in the database and 2) considering unregistered third persons. Furthermore, we examined the effectiveness of the voting process, in which the person is authenticated on the basis of voting on multiple test samples. When authentication proceeded using only registrants, accuracy was higher when four electrodes were used than when two electrodes were used, and the voting process improved identification accuracy to 96.4%. Authentication using unregistered third persons was also more accurate with four electrodes than with two electrodes. The accuracy was 75.8% when voting was not applied and reached 90.4% when voting was applied. Our method, which can authenticate an individual in just a few seconds, is considered effective for realizing personal authentication by SSVEP.*
Keywords: Personal identification, Steady-state visual evoked potential (SSVEP), Electroencephalogram (EEG), Voting process, Mahalanobis distance

1. **Introduction.** Biometric authentication has become a widely used security measure in recent years. Authentication requires highly specific biometric features related to a person's body that are unique to the individual. Representative biometric features include fingerprints, voiceprints, and retina, iris, and vein patterns. In principle, authentication using these features is thought to be difficult to fake. However, biometric authentication currently in practical use makes it difficult to ensure security once the features are leaked.

In recent years, biometric authentication using electroencephalograms (EEGs) has attracted some attention because feature extraction is complicated and there is little possibility of leakage. EEGs can be spontaneous (appearing regardless of specific events) or evoked (induced by sensory stimulation). There have been several reports on biometric authentication using both types of EEG.

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Some studies have reported authentication based on spontaneous EEGs under resting-state eyes-open or eyes-closed conditions [1, 2, 3] while listening to music [4], during mental imagery such as motor imagery tasks [1], and when imagining words [5]. In contrast, studies of authentication using evoked EEGs focus mainly on visual evoked potentials obtained by presenting simple figures, objects, and faces [6, 7, 8, 9].

The steady-state visual evoked potentials (SSVEPs) that we use are a type of evoked potential that is generated by repeatedly presenting visual stimuli at a constant interval. Characteristically, SSVEPs have two frequency components: a fundamental component that is equivalent to the stimulus frequency (f_0), and a harmonic component with a frequency of nf_0 ($n \geq 2$), as shown in Figure 1 [10]. This means that the characteristics of SSVEPs can be altered by adjusting the stimulation frequency. From a security perspective, this capability is useful because the password corresponding to the stimulus frequency can be easily changed. SSVEPs are passive responses to visual stimuli that do not require the user to perform a task. Therefore, SSVEPs have the advantage of being virtually unaffected by human physical and mental conditions. However, at present, very few authentication systems are based on SSVEPs. Phothisonothai performed SSVEP-based personal identification based on the logarithm of the maximum power at each of four frequency bands (δ, θ, α, and β). SSVEPs were recorded at two occipital electrodes with stimulus frequencies varying from 6 to 9 Hz. The SSVEPs showed the true acceptance rate of 60% to 100% approximately using the k-nearest neighbor algorithm [11]. Using mel-frequency cepstral coefficients calculated from EEGs at 19 electrodes and four frequency stimuli, Piciucco et al. obtained a 100% correct recognition rate. They then reduced the number of electrodes to five and obtained a recognition rate of 96.0% [12]. Falzon et al. performed personal identification using normalized variances of SSVEPs after applying narrowband filters at the fundamental and harmonic frequencies up to the fifth harmonics. SSVEPs were acquired from 32 electrodes on six types of stimulus frequencies. They obtained a true acceptance rate of 91.7% [13]. In a practical application, the length of time until the start of the EEG measurement is proportional to the number of electrodes and the measurement time is proportional to the number of stimulation frequencies. In the above studies, the number of electrodes was relatively large, except for that in the report by Phothisonothai. Additionally, all studies required long measurement times of more than tens of seconds for authentication.

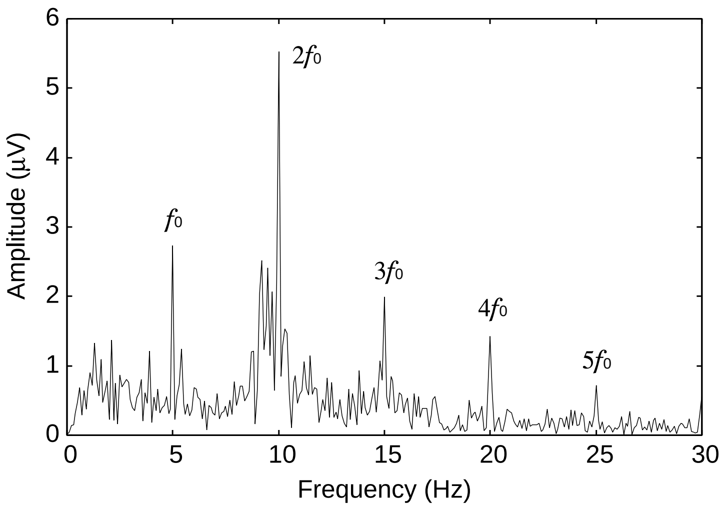

Figure 1. Example of the frequency spectrum for an SSVEP

In the field of brain-computer interface (BCI), the method of extracting one candidate intended by the user as an output from multiple candidates is applied. This means that test data are classified into one of multiple classes using clustering [14]. However, authentication requires a mechanism to reject the authentication of user data that do not belong to any class that is not registered in the authentication database. Piciucco et al. and Falzon et al. did not consider rejection. Phothisonothai rejected authentication on the basis of the threshold value, but the details of the definition were not described.

In our previous paper, we obtained the amplitudes at specific frequencies from 1-second SSVEPs at each electrode and used them as features for authentication, but the identification accuracy was only 79.7% for six subjects [15]. In the present study, the performance was significantly improved by changing the features into multidimensional autoregressive (MAR) coefficients and incorporating a voting process to authenticate the results of multiple test samples, even though the number of subjects was doubled or more. We therefore report our new authentication method.

In this manuscript, we describe the methods in the next chapter, including SSVEP measurement, acquisition of features of MAR coefficients, the definition of the distance in feature space, and authentication. In Section 3, we show the evaluation of the authentication performance of our method. Additionally, we discuss the results in Section 4, and provide a conclusion in the final section.

2. Methods.

2.1. EEG measurement.

EEG measurements were performed using an electroencephalograph (Comet; Grass Technologies, Warwick, USA) and a photic stimulator (FLC-40/B; Astro-Med, Inc., Warwick, USA). SSVEPs evoked by the 5-Hz visual stimulus presentation were measured at four electrodes (P_3, P_4, O_1, and O_2 in the international 10/20 system) at which SSVEPs appear prominently. One session comprised 10 seconds of data sampled at 400 Hz. Each of 16 participants completed 10 sessions (15 men and 1 woman, mean age = 22.1 ± 1.12 years). Thus, 100 seconds of SSVEP data were obtained for each person. During the measurement, participants sat at rest about 30 cm in front of the light stimulator and kept their eyes closed. These actions reduced the chance of artifacts such as blinks and body movements. This study was approved by the ethics committee of the Faculty of Engineering at Yamagata University.

2.2. Acquisition of features for personal identification.

SSVEPs are visual evoked potentials generated in the visual cortex after viewing repetitive visual stimuli. Because the stimuli are presented at a constant interval, SSVEPs have a highly stationary waveform that includes two kinds of frequencies: a fundamental wave with the same frequency as the stimulus and harmonic frequencies that are multiples of the fundamental frequency (Figure 1).

In this study, we calculated MAR coefficients for the SSVEP waveforms and used them as features for differentiating SSVEPs. Personal identification was performed using Mahalanobis distances that were based on the MAR coefficients. Finally, we evaluated authentication accuracy. Details of each process are described below.

We applied an MAR model to the EEGs obtained from four channels (P_3, P_4, O_1, O_2) because SSVEPs predominantly appear in the occipital region where the visual cortex is located. The resulting coefficients were then used as individual features. The MAR model is given by the following equation.

$$\boldsymbol{y}(t) = \sum_{m=1}^{M} \boldsymbol{A}(m)\boldsymbol{y}(t-m) + \boldsymbol{\varepsilon}(t) \tag{1}$$

Here, $\boldsymbol{y}(t)$ is a four-dimensional vector comprising the potentials of the four electrodes at an arbitrary time t, M is an MAR order, and $\boldsymbol{A}(m)$ is an autoregressive coefficient matrix whose size is $N \times N$ when N is the number of electrodes. $\boldsymbol{\varepsilon}(t)$ is the residual vector, and each element follows a Gaussian distribution. The $M \times N^2$ MAR coefficients are calculated over a 1-second analysis window and then used as features for personal identification.

2.3. **Personal identification method.** The region for each individual in the $M \times N^2$ dimensional feature space is determined. Here, it was determined as the region in which the Mahalanobis distance from the center was below a threshold. Test sample $\boldsymbol{x}_t$ is authenticated as person i when it satisfies the inequality:

$$d_i(\boldsymbol{x}_t) = \sqrt{(\boldsymbol{x}_t - \boldsymbol{\mu}_i)\Sigma^{-1}(\boldsymbol{x}_t - \boldsymbol{\mu}_i)^T} \leq D \tag{2}$$

where Mahalanobis distance from the center of a person $i(\boldsymbol{\mu}_i)$ is $d_i(\boldsymbol{x}_t)$, the threshold is D, and Σ is $E\left[(\boldsymbol{x} - E[\boldsymbol{x}])(\boldsymbol{x} - E[\boldsymbol{x}])^T\right]$, calculated by all samples of person i in the training data.

Among all registered persons, a person j having the minimum Mahalanobis distance $d_j(\boldsymbol{x}_t)$ is obtained, and if Equation (2) is satisfied, $\boldsymbol{x}_t$ is authenticated as person j. When D is set at $+\infty$, $\boldsymbol{x}_t$ is authenticated to be one of the registered persons.

2.4. **Method performance evaluation.** Because each sample was set to 1 second of EEG data, we were able to extract 100 samples per person. For these 100 samples, n samples were used as test data, and the remaining $100 - n$ samples were used as training data. Here, the person is authenticated on the basis of voting on n test samples. This method authenticates the person with the largest number of votes. However, if one person cannot obtain the majority of votes, authentication fails and no one is authenticated.

In this study, we considered two cases: the case in which only registrants are considered in the authentication system and the more realistic case in which unregistered third persons are considered in the system. In the case 1, because the number of participants was 16, when the number of votes was n, performance was evaluated from $16\times \left[\frac{100}{n}\right]$ authentication trials, where $[x]$ was the largest integer not exceeding x. When n is 1, the evaluation method is equivalent to leave-one-out cross-validation. In case 2, one of the 16 participants was assigned to an unregistered third person and the others were used for training data. The number of authentication trials was the same as in case 1. We set a threshold for the Mahalanobis distance to prevent third persons from being authenticated. When the minimum Mahalanobis distance is less than or equal to the threshold, the sample is authenticated as the person who minimizes the distance. Otherwise, the sample is determined to belong to a third person and the authentication is rejected.

We used the following three indices to evaluate authentication accuracy.

- **False rejection rate (FRR):** error rate when a registrant is identified as another registrant or is excluded from authentication as a third person. The higher the threshold, the more easily registrants will get through the system, and the lower the FRR.
- **False acceptance rate (FAR):** error rate at which a third person passes through the authentication system and is identified as one of the registrants.
- **Equal error rate (EER):** error rate at the Mahalanobis threshold for which FAR and FRR are the same value. Because FRR and FAR have a trade-off relationship, EER is a measure of the authentication system's accuracy. The smaller the value, the higher the accuracy.

3. Results.

3.1. Case 1: Identification accuracy when only registrants are considered in the authentication system.

In case 1, because unregistered third persons are not considered, only FRR was evaluated. The FRR was calculated as the percentage of test data (1600 samples: 16 persons $\times$ 100) misidentified as other registrants. FRR was calculated for 16, 32, 48, and 64 feature dimensions using MAR coefficients at either all four electrodes or at two electrodes. The FRRs without voting for the varying numbers of feature dimensions are shown in Table 1. FRR was lower when using four electrodes than when using two electrodes, and the minimum FRR was 10.1% when using 48 feature dimensions.

TABLE 1. FRR (%) for two or four electrodes and varying numbers of feature dimensions obtained without voting. (Bold letters indicate the minimum value. M and N are MAR order and the number of electrodes, respectively.)

Electrodes	The number of feature dimensions ($M \times N^2$)			
	16	32	48	64
P_3, P_4, O_1, O_2	20.9	10.6	**10.1**	10.5
P_3, P_4	31.3	28.6	29.6	29.5
O_1, O_2	38.9	38.9	40.8	40.7
P_3, O_1	43.1	41.4	39.7	39.2
P_4, O_2	27.9	30.7	30.4	31.3

We then investigated the relationship between inter-participant variability in data distribution and the FRR. Figure 2 shows the relationship between FRR and the ratio between average within-class (intra-participant) and between-class (inter-participant) variance for the distributions of two participants in 48-dimensional space at four electrodes. The analysis shows that the larger the ratio, the lower the FRR.

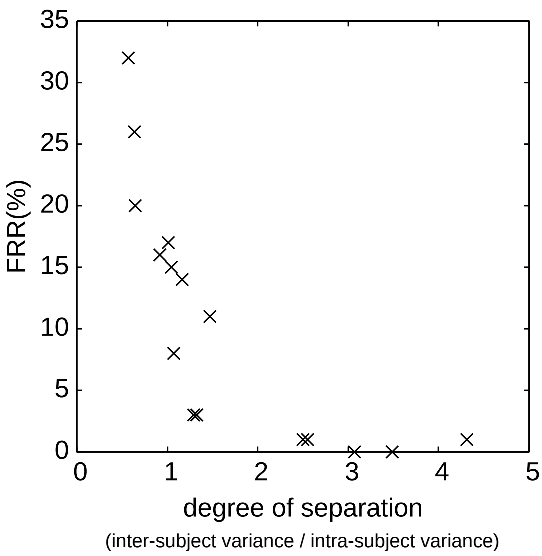

FIGURE 2. The relationship between FRR and the average ratio between within-class and between-class variance for the distributions of two participants in 48-dimensional space at four electrodes

Next, we performed the identification by introducing a voting process to the MAR coefficients at the four electrodes. The resulting FRR (averaged over 16 participants) is shown in Table 2. The identification error rate was lower with voting than without voting.

Table 2. FRR (%) for four electrodes and varying numbers of feature dimensions with voting. Here, only registrants were considered and voting was applied to MAR coefficients for four electrodes. (Bold letters indicate the minimum value. M and N are MAR order and the number of electrodes, respectively.)

The number of votes	The number of feature dimensions ($M \times N^2$)			
	16	32	48	64
3	18.4	7.0	5.6	5.9
4	17.5	8.0	7.2	7.5
5	15.3	5.6	5.3	5.5
6	16.0	6.3	4.3	6.3
7	14.3	5.8	**3.6**	5.7
8	13.8	4.7	3.7	5.2
9	13.4	5.0	3.7	4.9
10	14.3	5.6	4.2	5.3
11	17.7	5.8	4.7	5.8
12	17.9	7.3	5.1	6.6

3.2. **Case 2: Identification accuracy when unregistered third persons are considered in the authentication system.** We evaluated identification accuracy considering third persons using the EER, calculated from the FRR and FAR. Here, we calculated the three error values assuming that one of the 16 participants was an unregistered third person (and the others were registrants). Excluding samples from the registrant set as the third person, FRR was calculated as the percentage of test data (1500 samples: 15 persons $\times$ 100) misidentified as other registrants, excluded as a third person, or was unrecognizable data. FAR was the percentage test data misidentified as registrants out of 1600 samples from unregistered participants (16 participants $\times$ 100). Because EER changes depending on the threshold for Mahalanobis distance, Table 3 presents results

Table 3. Minimum EER (%) without voting using two or four electrodes and varying numbers of feature dimensions when unregistered third persons were considered. (Bold letters indicate the minimum value. M and N are MAR order and the number of electrodes, respectively.)

Electrodes	The number of feature dimensions ($M \times N^2$)			
	16	32	48	64
P_3, P_4, O_1, O_2	37.1	24.8	**24.2**	25.3
P_3, P_4	64.2	63.1	63.5	63.3
O_1, O_2	70.9	70.8	76.5	76.8
P_3, O_1	74.8	73.2	72.1	71.6
P_4, O_2	60.5	62.3	64.9	65.3

for the threshold that minimized the EER. The table shows the EER for 16, 32, 48, and 64 feature dimensions using two or four electrodes.

Figure 3 shows the FRR/FAR curves obtained by averaging the error rates for all 16 participants when 48 feature dimensions at four electrodes were used for identification. As the threshold increases, FRR decreases and the FAR increases, and they intersect at a certain threshold. Using this threshold, we tested identification with voting when considering third persons. Table 4 shows the EER obtained by averaging data from all 16 participants when MAR coefficients at four electrodes were used. Compared with (3.6% in Table 2) or without voting (10.1% in Table 1), identification using voting produced a lower error rate than classification without voting.

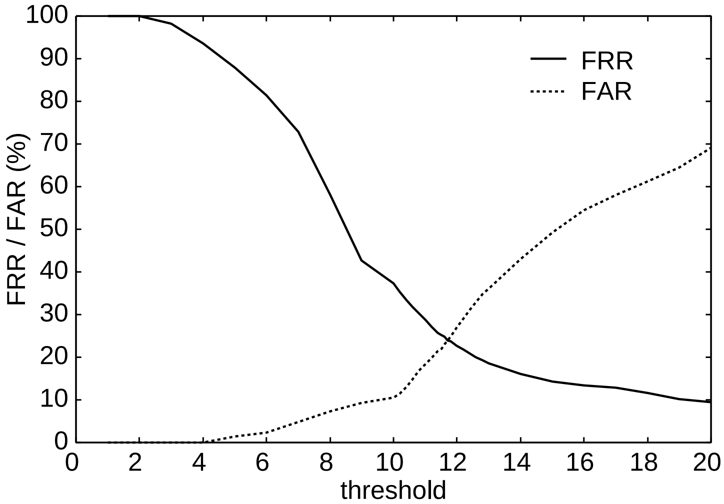

Figure 3. Averaged FRR and FAR for 16 participants as the threshold changed

Table 4. EER (%) for varying numbers of votes and numbers of feature dimensions when unregistered third persons were considered. (Bold letters indicate the minimum value. M and N are MAR order and the number of electrodes, respectively.)

The number of votes	The number of feature dimensions ($M \times N^2$)			
	16	32	48	64
3	26.8	28.2	17.5	18.3
4	29.3	19.6	19.1	20.0
5	20.0	13.3	13.0	13.6
6	21.1	14.1	12.1	13.4
7	17.5	11.7	10.8	11.5
8	15.2	10.4	9.8	10.8
9	15.0	10.2	**9.6**	10.6
10	16.1	10.2	11.5	11.5
11	15.9	11.5	10.6	11.7
12	17.3	11.9	14.3	13.5

4. Discussion.

4.1. Identification accuracy when only registrants are considered in the authentication system.

In case 1, we found an optimal number of feature dimensions that minimized FRR depending on the choice of electrodes (Table 1). Identification accuracy was higher when using four electrodes than when using two electrodes. This indicates that collecting EEGs from a larger spatial region on the scalp leads to more accurate discrimination.

We found that the smallest FRR (10.1%) was obtained when the number of feature dimensions at four electrodes was set to 48. This is equivalent to the values obtained in other studies by taking measurements for several tens of seconds to several minutes [11, 12, 13]. Our method, which can authenticate an individual in just a few seconds, is considered effective for realizing personal authentication by SSVEP. Because of the large difference in authentication accuracy among participants, we focused on the degree of separation (the intra-subject to inter-subject ratio in variance) between the distribution of two participants in the 48-dimensional space of the MAR coefficients. As shown in Figure 2, the larger the degree of separation, the lower the FRR value. This indicates that a high degree of separation is required to obtain high identification accuracy. Thus, overlapping the data distributions between participants decreases the degree of separation and increases the FRR.

We found that the minimum error rate when voting was included in the authentication process was 3.6% if the number of votes was 7 and the number of electrodes was 4, which was 6.5% lower than the error rate without voting. This suggests that even if the appearance of SSVEPs fluctuates and identification is incorrect in a small number of cases, taking the majority by voting led to a stable and more accurate decision. Therefore, the error rate will decrease as the number of votes increases. However, measurement time also increases with the number of votes. Therefore, when setting the optimal number of votes, identification accuracy and practical use must both be considered. Table 2 shows that the error rate tends to be slightly lower when the number of votes is odd than when it is even. We found that when multiple participants received maximum votes, the identification result becomes "unable to authenticate" when the number of votes was even.

4.2. Identification accuracy when unregistered third persons were considered in the authentication system.

In case 2, we found that authentication performance decreased when third persons were considered. This is because there were two types of errors: 1) registrant misidentified as a third person and 2) a third person misauthenticated as a registrant.

In the FRR/FAR curve seen in Figure 3, the FRR decreases as the threshold increases, but the degree of the decrease becomes smaller at a certain threshold. This lower limit is the error rate for incorrectly identifying one registrant as another registrant when the Mahalanobis distance between the center of another registrant and the test data is shorter than the distance between the registrant's center and the test data. Because reducing erroneous identification of registrants as other registrants is impossible using only the threshold value, it is necessary to increase the degree to which distributions of other registrants are separated, such as by increasing the number of dimensions of the feature space.

When authenticating with voting, the minimum EER of 9.6% was obtained with four electrodes when the number of votes was 9 (Table 4), and the error rate 14.6% less than when voting was not included. Regardless of the presence of third persons, because the error rate was reduced when voting was included, applying voting to the identification is considered will improve authentication performance.

In this study, the number of male and female data used was unbalanced. Because we focused on increasing the number of subjects, the cooperation of many male participants caused an imbalance. Regarding the gender difference of SSVEP, in the BCI experiment of inputting characters to a computer using SSVEP generated by blinking characters on the display, Allison et al. reported that women tend to have better input performance, but no statistical significance between men and women could be seen. Therefore, we do not believe that the imbalance in this study had a great influence on the authentication accuracy, but to implement a more practical system, it is necessary to reduce the imbalance between male and female participants [16].

5. **Conclusions.** In this study, we attempted personal authentication in just a few seconds using SSVEP, a type of evoked EEG generated by external visual stimuli. In the experiment, we generated SSVEPs by presenting a 5-Hz light stimulus to 16 people and used MAR coefficients as features for authentication. Classification based on the Mahalanobis distance was performed using the MAR coefficients obtained at either two or four electrodes. Authentication was performed when only registrants were considered and when unregistered third persons were considered. When we examined the effectiveness of the voting process, we found that when third persons were not considered, authentication accuracy was higher when using four electrodes than when using two electrodes. When a voting process was not applied, the minimum FRR was 10.1%, which is equivalent to 89.9% identification accuracy. Voting improved the minimum FRR to 3.6%, which corresponds to 96.4% accuracy. Authentication with four electrodes was also more accurate than authentication with two electrodes when considering unregistered third persons. In this case, accuracy was 75.8% (24.2% EER) without voting and a maximum of 90.4% (9.6% EER) when voting was applied. This result suggests that voting is effective for improving authentication accuracy. In the future, it will be necessary to not only improve identification accuracy but also verify whether the authentication accuracy can be maintained even if the number of participants is further increased. Moreover, it is necessary to eliminate the bias in the number of data for male and female participants.

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