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AUTHENTICATION SYSTEM PREVENTING UNAUTHORIZED ACCESS OF A THIRD PERSON BASED ON STEADY STATE VISUAL EVOKED POTENTIALS

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Abstract. *In this study, we constructed an authentication system using steady state visual evoked potential (SSVEP), which is an electroencephalography (EEG) evoked by sensory stimuli. We consider authentication that can include the authentication of an individual who is not registered in the authentication database, which is closer to a realistic scenario. We calculated five amplitudes of the fundamental frequency and four harmonic frequencies at four parietal and occipital electrodes given a stimulus frequency and then extracted the feature vectors for authentication after reducing the number of dimensions using principal component analysis (PCA). The recorded data were split into training and test data. The distribution for an individual person was found using the training data. Changing the PCA dimensions and the threshold for the Mahalanobis distance between the test data and an individual distribution, we evaluated the method. SSVEP-based authentication without considering unregistered individuals obtains the lowest false rejection rate of 5.0% when four PCA dimensions are used. For identification considering unregistered individuals, the best equal error rate is 9.0% when one out of six subjects is an unregistered individual. The average equal error rate for all subjects is 20.3% when four PCA dimensions are used.*
Keywords: SSVEP, Authentication, Mahalanobis distance, Unregistered individual

1. **Introduction.** In recent years, research on biometric authentication systems has been actively conducted. A biometric-based identity is fundamentally more difficult to impersonate in principle than a simple sequence of numbers and letters. Biometric authentications using fingerprints, voiceprints, retinas, irises, and veins have been developed. Fingerprints, irises, and palm veins, which are relatively easy to use, are currently in practical use, but many disadvantages of these systems have also been reported such as replication using residual fingerprints [1]. Therefore, personal authentication using EEG, which cannot be easily duplicated, has attracted attention.

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EEG is classified into two categories: spontaneous EEGs and evoked potentials. In this study, we focus on SSVEPs, which are potentials evoked by steady visual stimuli. Recently, SSVEP has not only been studied in clinical diagnosis [2, 3] but also used in the field of brain-computer interfaces [4, 5]. Spontaneous EEG depends on various human conditions, but SSVEP can be measured stably because it is a passive response to a visual stimulus [6]. However, few studies regarding biometric authentication using SSVEP have been reported so far, even though many reports regarding spontaneous EEGs or event-related potentials categorized in evoked potentials can be found [7, 8]. Piciucco et al. analyzed SSVEP and performed authentication using two discriminative features: mel-frequency cepstral coefficients and autoregressive reflection coefficients [9]. Falzon et al. used normalized variances of the signals after applying narrowband filters at the fundamental and harmonic frequencies up to the fifth harmonic [10]. Phothisonothai investigated the optimal frequency bands for features in individual classification using the k-nearest neighbor algorithm [11].

Generally, recorded data are divided into two sets: training and test datasets. The training data is used for constructing individual distributions and these distributions are registered in the authentication database. The authentication system evaluates an identity by determining whether or not a test sample is included in the distribution of an individual. Conventional reports on authentication based on SSVEP used test data obtained from persons registered in the authentication database. Hence, individuals who are not registered in the database were not considered. This case is unrealistic in practice. To address this problem, SSVEP authentication may be an option for a biometrics-based authentication system because it has a high signal-to-noise ratio (the ratio between SSVEP and spontaneous EEG) and stable spectrum. We therefore evaluated the authentication performance using registered and unregistered individuals. To realize such a system, it is important to determine the features needed for personal identification. Moreover, a feature vector with a lower dimensionality is preferrable to shorten the time required for authentication. Therefore, in this study, using frequency power, which is a basic feature in EEG analysis, we investigated the relationship between the order of the PCA dimension and authentication performance. We believe that our fundamental investigation contributes to the development of an SSVEP authentication system.

In this paper, we explain SSVEP measurement, determination of the feature vector, the authentication method and evaluation of authentication performance in Section 2. In Section 3, we first show the detection results when unregistered individuals are not considered for comparison, as in conventional studies performed by other researchers. We then show the results obtained by our proposed method when unregistered individuals are considered. Subsequently, we discuss the relationship between the performance and parameters required for authentication in Section 4. In Section 5, we summarize our study and describe tasks for future research.

2. **Method.**

2.1. **EEG acquisition.**

SSVEP was recorded at a sampling frequency of 400 Hz by an electroencephalograph (Comet; Grass Technologies, Warwick, USA). The visual stimuli were generated by a photic stimulator (FLC-40/B; Astro-Med, Inc., Warwick, USA) at a frequency of 5 Hz. The flash intensity was approximately 0.7 J and its duration was 10 s. The flashing equipment was placed 30 cm in front of the participants. Electrodes were attached at P3, P4, O1, and O2 according to the international 10/20 system.

In this experiment, we measured EEG from six healthy participants (all male, aged 23.0 $\pm$ 1.0 years). We defined a 10-s measurement as one trial and 20 trials were performed for each participant. Here, five trials were recorded over four sessions with a three-month interval between each session. We therefore obtained 20 data samples for each participant. Participants were recorded while sitting still during a state of relaxed wakefulness with closed eyes to suppress artifacts caused by eyeblinks as much as possible. This experiment was approved by Yamagata University's ethics committee, and all data reported in this study were recorded after obtaining informed consent.

2.2. **Feature vector for authentication.** SSVEP consists of rhythmic activity elicited by a stimulus repeated at constant time intervals. It has two frequency components: the fundamental driving component, which is equivalent to the stimulus frequency (f_0), and the harmonic driving component, with frequency nf_0 ($n \geq 2$). Figure 1 shows an example of an EEG frequency spectrum during a 5 Hz visual stimulation. The fundamental driving frequency is at 5 Hz and the harmonic driving frequencies are at multiples of 5 Hz. We calculated the frequency spectrum for 10-s EEG data using the Fourier transform. We then extracted five frequency components, the fundamental wave (f_0) and four harmonics ($2f_0$, $3f_0$, $4f_0$, and $5f_0$), to compose the feature vector for authentication. We constructed 20-dimensional vector consisting of the amplitudes at four electrodes (P3, P4, O1, and O2). We then performed PCA on all training data samples of all participants to reduce the dimensions from 20 to n_{dim} ($n_{dim} < 20$).

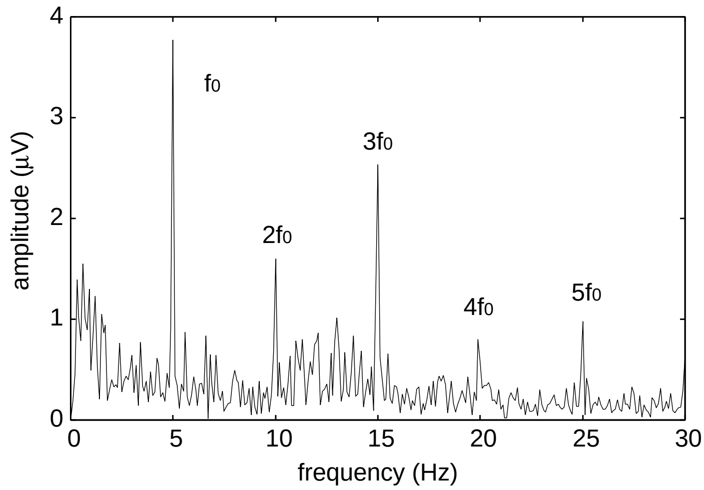


FIGURE 1. Example of an SSVEP frequency spectrum

2.3. **Authentication method.** In this study, we performed a simple authentication method to discriminate individuals. Here, we constructed the distribution of an individual's feature vector based on samples of training data. The sample is expressed as $\boldsymbol{x}$ and consists of principal components, that is, $\boldsymbol{x} = (x_1, x_2, \dots x_{n_{dim}})^T$, where x_k is the k-th principal component. For person i, we measure the distance ($D_M^i(\boldsymbol{x})$) from the center of the distribution ($\boldsymbol{\mu}^i$) to a sample ($\boldsymbol{x}$) calculated by the Mahalanobis distance, as follows:

$$D_M^i(\boldsymbol{x}) = \sqrt{(\boldsymbol{x} - \boldsymbol{\mu}^i)^T \, \Sigma^{-1} \, (\boldsymbol{x} - \boldsymbol{\mu}^i)}, \tag{1}$$

where $\boldsymbol{\mu}^i$ is the average of all samples included in the training data: $\Sigma^{-1} = E\big[(\boldsymbol{x} - E[\boldsymbol{x}])(\boldsymbol{x} - E[\boldsymbol{x}])^T\big]$.

Person j minimizing $D_M^i(\boldsymbol{x}_T)$ is searched for among the individuals registered in the authentication database using the following equation, where $\boldsymbol{x}_T$ is the test sample.

$$j = \operatorname*{argmin}_i D_M^i(\boldsymbol{x}_T). \tag{2}$$

If the distance for test sample $\boldsymbol{x}_T$ does not exceed a threshold (d_{th}), $D_M^j(\boldsymbol{x}_T) \le d_{th}$, we determine that the sample belongs to person j. Conversely, when the distance is more than threshold $\left(D_M^j(\boldsymbol{x}_T) > d_{th}\right)$, the sample must belong to an unregistered individual. If the test sample is included in several distributions, as shown in Figure 2, the sample is authenticated as belonging to the person with the minimal distance. In the scenario shown in the figure, we determine that test sample $\boldsymbol{x}_T$ belongs to Subject B because $D_M^B(\boldsymbol{x}_T)$ is smaller than $D_M^A(\boldsymbol{x}_T)$. In this study, we assumed that one subject out of six is an unregistered individual and obtained the average of the results for six combinations by changing the unregistered individual.

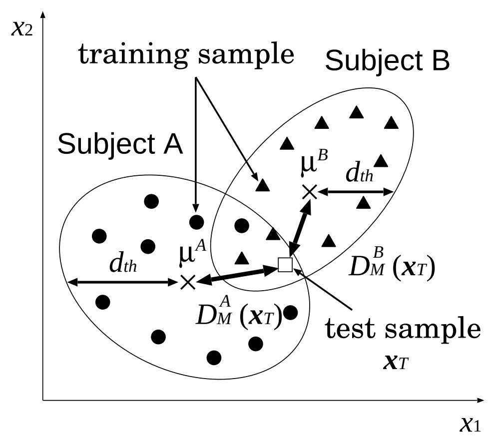


FIGURE 2. Authentication based on the Mahalanobis distance ($n_{dim} = 2$). Samples of Subjects A and B are respectively indicated as '●' and '▲'. '□' and '×' indicate a test sample and the center of a distribution, respectively.

To compare our results with those of conventional studies, we also investigated the case in which unregistered individuals are not considered. In this case, d_{th} is set at $+\infty$ and the test sample is authenticated to be one of the registered persons. In this case, because we do not need an unregistered individual, the six data distributions for all subjects were calculated from the training data.

2.4. **Performance evaluation of our authentication method.** In this study, we evaluated the authentication performance of our method using the following three indices.

- **FRR (false rejection rate):** the probability that the system fails to detect the SSVEP as the EEG of an identical person.
- **FAR (false acceptance rate):** the probability that the authentication system incorrectly recognizes the SSVEP as an EEG of another person.
- **EER (equal error rate):** the probability of the intersection between FAR and FRR. This value is introduced to evaluate above two indices together because they have a trade-off relationship.

We performed leave-one-out cross validation to obtain the above indices. This means that 19 out of 20 samples were used as training data for constructing a personal distribution. The remaining sample was a test sample, and the indices can be obtained as an average of 20 trials by changing the sample used for testing.

3. **Results.** We first present the results when unregistered individuals are not considered. We tabulated the best FRR and its n_{dim} for each subject in Table 1. The FRR when n_{dim} is varied for all subjects is shown in Figure 3. The minimum score is 5.0% at $n_{dim} = 4$. This value corresponds to a 95.0% authentication rate.

TABLE 1. Detection results for each subject when unregistered individuals are not considered

Subject	PCA Dimension (n_{dim})	FRR (%)
A	4	15.0
B	$3 \sim 6$	10.0
C	$4 \sim 5$	0.0
D	4	0.0
E	$4 \sim 5$	5.0
F	$4 \sim 7$	0.0

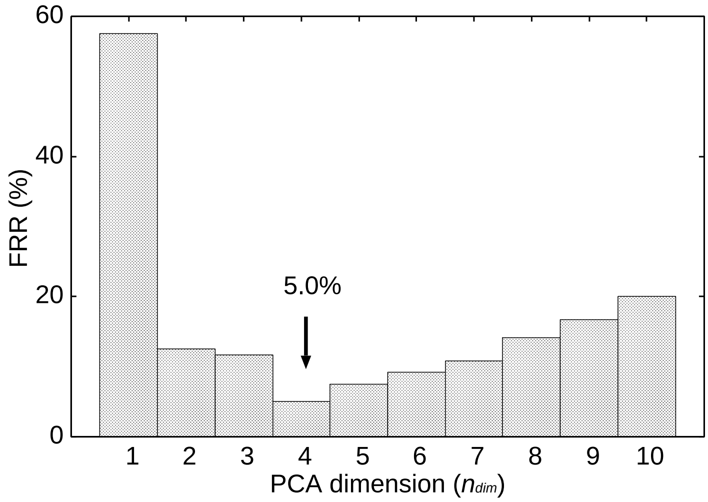
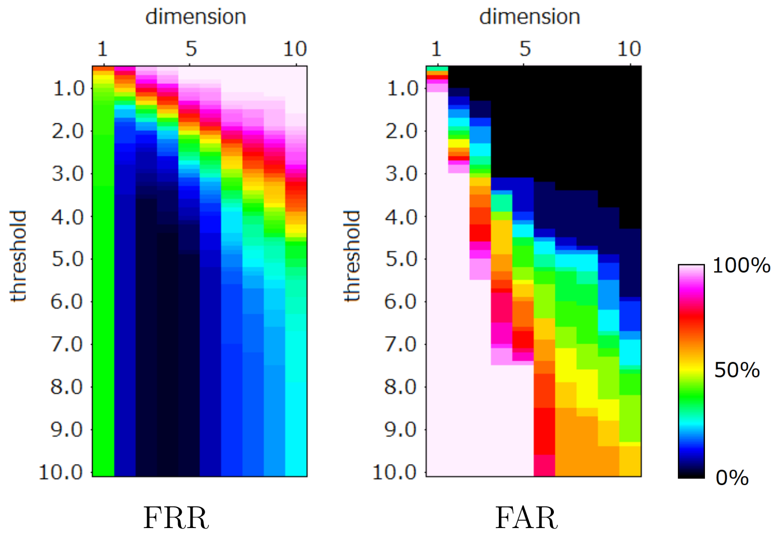


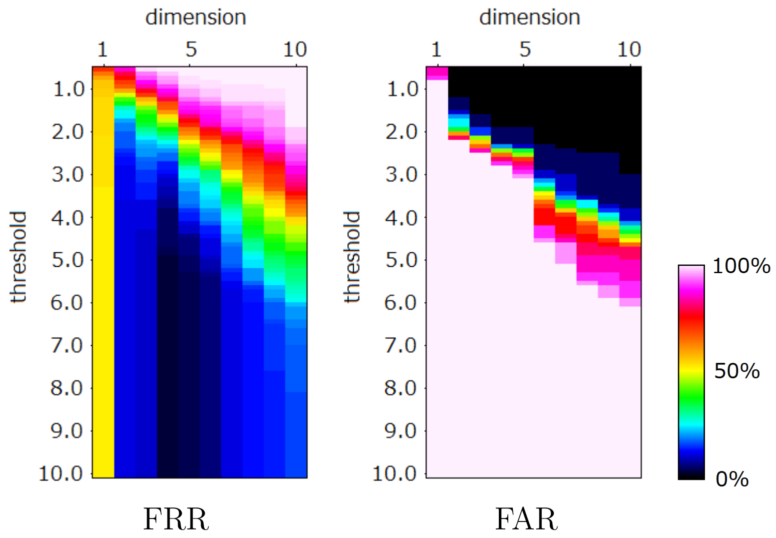
FIGURE 3. Relationship between FRR and PCA dimension when unregistered individuals are not considered

We next show the results when unregistered individuals are considered. In this case, the indices are affected by two parameters: n_{dim} and d_{th}, which determine a personal distribution. We calculated the FRR and FAR for various combinations of these two parameters. Figures 4(a)-4(c) respectively show the results for the subjects with the best and worst EERs as well as the average of all subjects. The FRR tends to increase when n_{dim} increases and d_{th} decreases. Inversely, FAR tends to increase when n_{dim} decreases and d_{th} increases. Thus, FRR and FAR have a trade-off relationship. Here, it is difficult to find the best EER from Figure 4. We therefore show the relationship between FRR and FAR at n_{dim} in Figure 5. This figure includes the results for the subjects with the best and worst EERs as well as the average of all subjects. The parameter values for each subject when the best EER is obtained are summarized in Table 2. Moreover, we show the average EER for all subjects at each dimension in Figure 6.

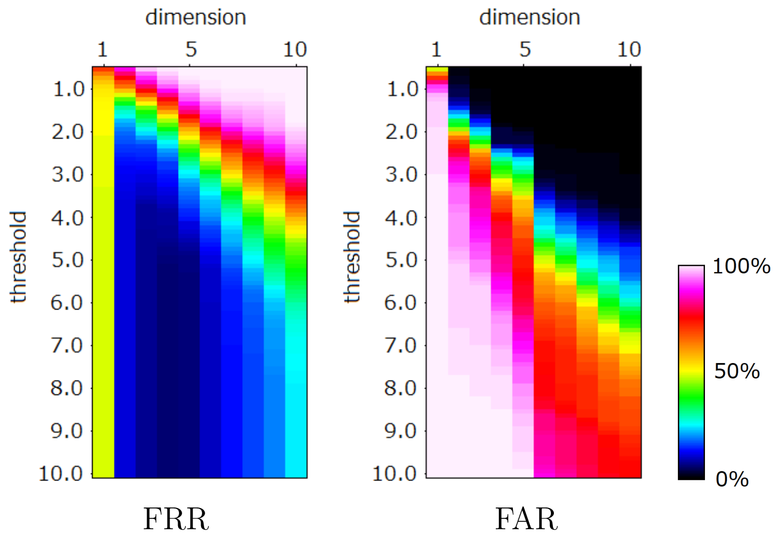
4. **Discussion.** When classifying six subjects without considering an unregistered individual, the highest FRR of 57.5% is obtained when n_{dim} is one. Because the contribution rate of the first principal component is 55.2%, it is considered that n_{dim} is too small to express the characteristics of an individual's data to discriminate it from that of other individuals. In contrast, the best FRR result was 5.0% (corresponding to an authentication rate of 95.0%) and was obtained when n_{dim} was 4. These results are comparable to those of a previous study [9], demonstrating that SSVEP may be viable as a tool for authentication. The cumulative contribution rate up to the fourth principal component



(a) The best case (Subject D)

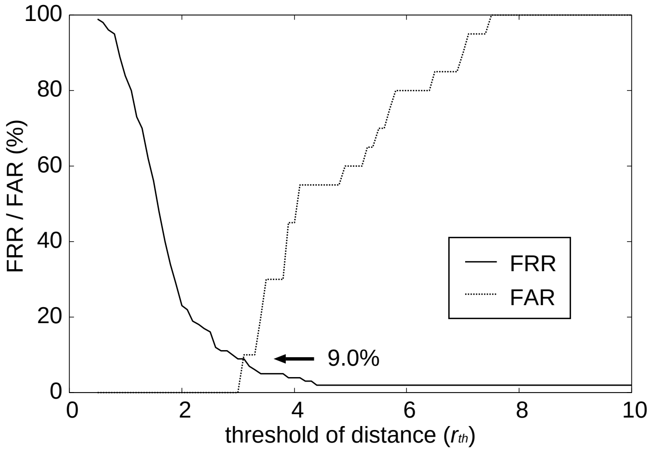


(b) The worst case (Subject A)

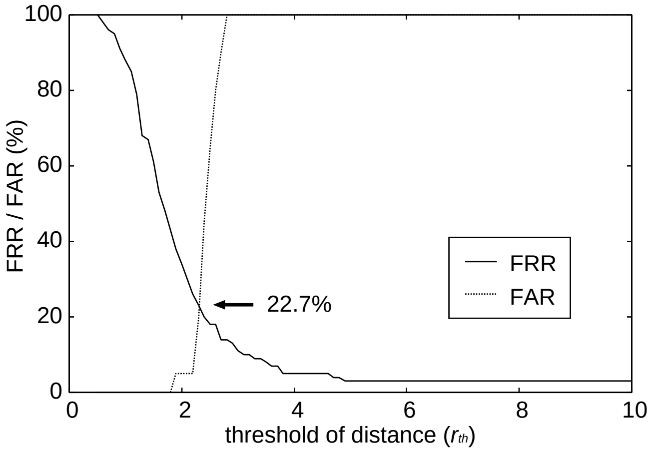


(c) Average of six subjects

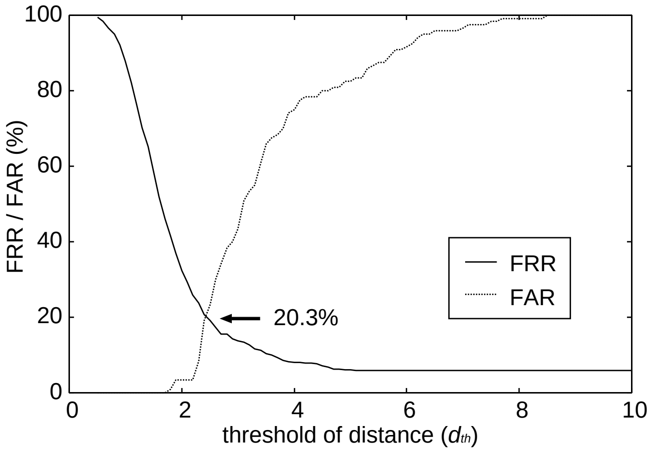
FIGURE 4. (color online) FRR and FAR for various combinations of PCA dimensions and Mahalanobis distance thresholds



(a) Best case (Subject D) ($n_{dim} = 4$)



(b) Worst case (Subject A) ($n_{dim} = 4$)



(c) Average of six subjects ($n_{dim} = 4$)

FIGURE 5. FRR and FAR at the best dimension

was 92.2%. However, if n_{dim} is more than 5, the FRR increases, even though the cumulative contribution ratio of the principal components increases. This demonstrates that an optimal dimension for authentication exists. Focusing on the FRR of each subject in Table 1, three subjects (Subjects C, D, and F) obtained an FRR of 0.0% and Subject A obtained the worst FRR value. From the distribution of each subject's feature vector when n_{dim} is 3, as shown in Figure 7, it is clear that the plots of Subject A's distribution

Table 2. Detection results for each subject when unregistered individuals are considered

Subject	PCA Dimension (n_{dim})	EER (%)	Threshold of Mahalanobis Distance (d_{th})
A	4	22.7	2.31
B	6	15.0	5.30
C	4	13.6	2.84
D	4	9.0	3.09
E	9	18.3	5.87
F	5	10.0	4.00

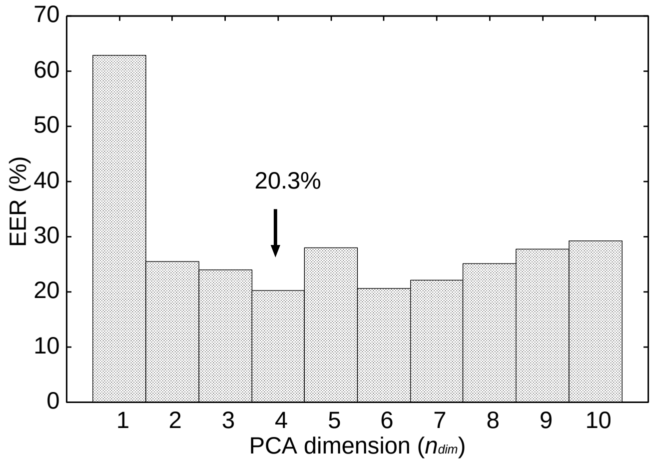


Figure 6. Relationship between EER and PCA dimension when unregistered individuals are considered

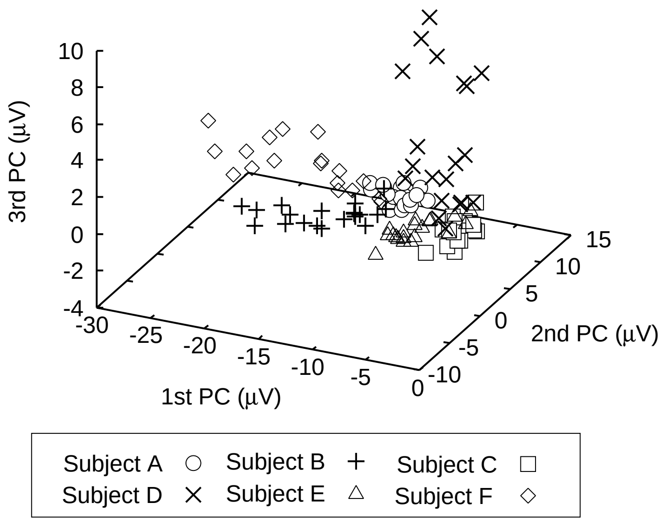


Figure 7. Distribution of training data for all subjects ($n_{dim} = 3$)

overlap with those of other subjects, even though the best number of dimensions was approximately 4 for all subjects. It is necessary to determine the optimal number of dimensions to improve the authentication rate. In this study, we analyzed the EEGs at four electrodes that are close to each other. However, these have relatively high correlation because the electric signals are transmitted from a source to the whole brain. We have to determine the optimal number of dimensions by considering the independence of the measurements at different electrodes.

When considering unregistered individuals in the authentication evaluation, we must examine two parameters, n_{dim} and d_{th}. As shown in Figures 4 and 5, although FRR has a similar value for all subjects, their FAR values vary widely. It is believed that FAR increases because the sample of unregistered individuals is close to the distributions of the registered individuals. FRR tends to decrease as d_{th} increases. However, FRR does not decrease when n_{dim} exceeds a certain value. In this study, we defined a test sample to be authenticated as the subject with the shortest distance when the sample is included in several subjects' distributions. Thus, the Mahalanobis distance from a test sample to the distribution of a person who is supposed to be authenticated is considered to be larger than the distance to those of other registered individuals. In this case, we could not decrease the FRR by adjusting d_{th}. To overcome this problem, we have to increase the dimensionality of the feature vector such as by increasing the number of electrodes and kinds of stimulus frequencies. Regarding parameter n_{dim}, a locally increased EER was yielded at a value of 5 in Figure 6. The FAR shows a rapid change between 5 and 6, unlike the FRR, as shown in Figure 4(c). The result depends on various factors such as d_{th} and the distribution of the feature vector of unregistered individuals. More investigation will be required to determine the optimal n_{dim}.

The best EER when unregistered individuals are considered is much larger than that when unregistered individuals are not considered. We recognize that authentication considering unregistered individuals is much more difficult than when they are not considered.

5. **Conclusions.** In this study, we constructed an authentication system using SSVEP, which is an EEG evoked by sensory stimuli. Experiments were performed by first extracting feature vectors from the frequency spectra of SSVEP and then using them for authentication. To extract the feature vector, the signal amplitudes at four parietal and occipital electrodes for fundamental and four harmonic frequency components (a feature space of 20 dimensions) were reduced by PCA. Our method was evaluated by leave-one-out cross validation.

Classification without considering unregistered individuals yielded the lowest FRR of 5.0% when n_{dim} is 4. In authentication considering unregistered individuals, the best EER was 9.0% when one out of six subjects was assumed to be an unregistered individual. We obtained an average EER for all subjects of 20.3% when four PCA dimensions were used.

In the future, we would like to improve the authentication accuracy by increasing the dimensionality of the feature vector, such as by increasing the number of electrodes and kinds of stimulus frequencies used in the SSVEP measurement.

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