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PRELIMINARY STUDY FOR PERSONAL IDENTIFICATION BY STEADY STATE VISUAL EVOKED POTENTIALS

Tadanori Fukami[1], Takahiro Narutaki[1], Takamasa Shimada[2] and Fumito Ishikawa[3]

[1]Department of Informatics
Yamagata University
4-3-16 Jonan, Yonezawa, Yamagata 992-8510, Japan
fukami@yz.yamagata-u.ac.jp; tke83312@st.yamagata-u.ac.jp

[2]Faculty of Information and Environment
Tokyo Denki University
2-1200 Muzaigakuendai, Inzai, Chiba 270-1382, Japan
tshimada@mail.dendai.ac.jp

[3]Neuropsychiatry
Hotokukai Utsunomiya Hospital
4-6-34 Yonan, Utsunomiya, Tochigi 320-8521, Japan
fumitoi@hotmail.com

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Abstract. *In this study, we examined an appropriate feature vector for classification and the best classifier for the development of a biometrics authentication system using steady state visual evoked potentials (SSVEPs). We classified a participant based on feature vectors extracted from the frequency power spectrum in 10-second measurements using three kinds of classifiers: Fisher linear discriminate analysis, random forest, and support vector machine. Six healthy participants were classified using the difference in power in all combinations of two electrodes extracted from four electrodes (P_3, P_4, O_1, O_2) for five SSVEP frequency components (fundamental and second to fifth harmonics). Our highest accuracy was 97.5% using the random forest classifier. A feature vector consisted of the difference in power in combinations of two electrodes and random forest classifier will be useful for personal identification by SSVEP.*
Keywords: Personal identification, Electroencephalography (EEG), Steady state visual evoked potentials (SSVEPs)

1. **Introduction.** In recent years, biometrics authentication has been an area of active research. Authentications using fingerprints, iris scans and palm veins have already been put to practical use.

In this study, we focused on authentication using EEG. This modality has several advantages: it is confidential, difficult to mimic, and impossible to steal [1]. There are some previous studies regarding personal identification and biometrics authentication using EEG at rest [2], mental tasks with thought activities [1,3], and visual evoked potentials (VEPs). In reports using VEPs, Das et al. employed a difficult visual perceptual task using images contaminated with noise and performed classification based on amplitude differences between the different stimuli within a few hundred milliseconds after presentation [4]. Studies on VEPs with a cognition task in which participants had to remember the picture being presented [5] and gamma wave analysis within VEPs [6] have also been reported.

Though there have been a few studies using EEG so far, most reports record EEGs while participants execute mental tasks or VEPs. However, EEGs depend on participants' mental and physical condition because they are generated from an actively-executed task.

Accordingly, EEGs vary widely, which means that the repeatability and accuracy of authentication decreases. Moreover, the biggest weak point common to currently used systems is that it is difficult to ensure the safety through the course of a lifetime if security features, for example a password, are leaked once. Therefore, to strengthen the authentication system, not fixed biological information but a system that enables the password to be changed will be needed. SSVEPs are not affected by psychological factors and can be easily changed by stimulus frequency. We, therefore, investigated what feature vector in classification is needed and which classifier is appropriate for personal identification by SSVEPs in a small number of participants.

The final goal of our research is to realize the personal identification system by SSVEP with changeable biological password. We first described about the method including the explanation of SSVEP in Section 2. And then we showed the results in Section 3 and discussed them in Section 4. We finally presented conclusions.

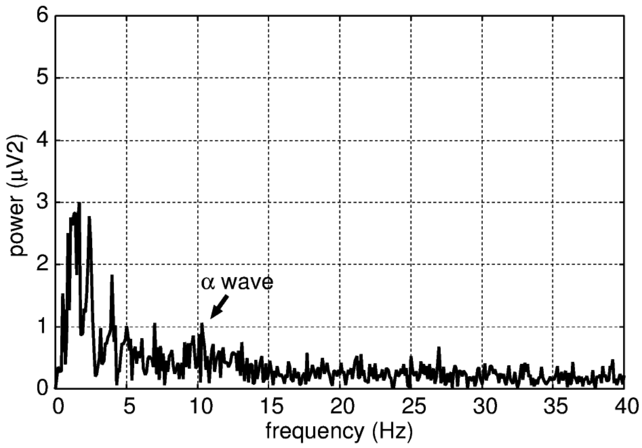
2. **Methods.** EEG signals were digitized at a sampling frequency of 400 Hz by the electroencephalograph (Comet; Grass Technologies, Warwick, USA). The visual stimuli were generated by a photic stimulator (FLC-40/B; Astro-Med, Inc., Warwick, USA). The flash intensity was approximately 0.7 joules, flash duration was 10 μs, and the equipment was placed 30 cm in front of the participants. Electrodes at which EEG data were measured for personal identification were P_3, P_4, O_1, and O_2 according to the international 10/20 system with monopolar derivation from bilateral reference electrodes attached to the corresponding earlobes. These electrodes were chosen because SSVEPs appear prominently around the occipital region. SSVEPs were measured for 10 seconds with 5 Hz stimulus frequency. We define a 10-second measurement as one trial and 24 trials are performed for each participant.

In this study, we measured EEG four times from six healthy participants (all were male, age = 23.0 $\pm$ 1.0 years old) as preliminary evaluation. The interval between experiments was 3 months. In total, 24 (6 participants $\times$ 4 measurement sessions) trials were obtained. Participants were recorded during a state of relaxed wakefulness with closed eyes and sitting still so as to suppress artifacts based on body motion as much as possible. This EEG experiment was approved by the university ethics committee, and all data reported in this study were recorded after obtaining informed consent.

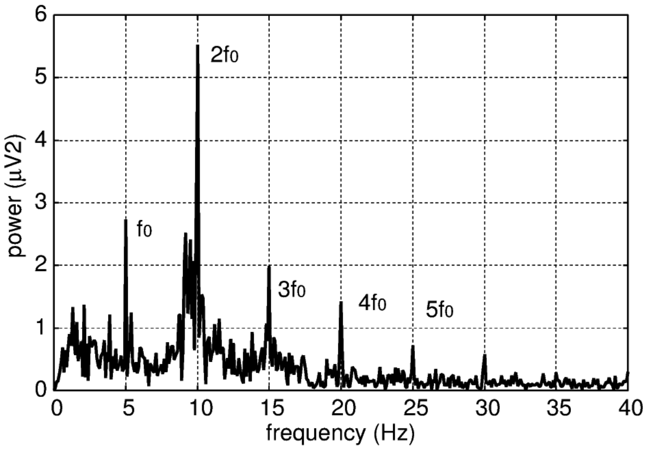
2.1. **SSVEP.** The SSVEP is a visual evoked potential generated in the visual cortex by periodic visual stimuli. It consists of the elicited rhythmic activity based on stimulus repetition. In the activity, two types of frequency components, the fundamental driving component for which the frequency is equivalent to the stimulus frequency (f_0), and the harmonic driving component for which the frequency is nf_0 ($n \geq 2$), are included in frequency spectrum obtained via Fourier transform. We show the EEG frequency spectrums at rest and during 5 Hz visual stimulation in Figure 1. We can see a prominent alpha wave around 10 Hz at rest (Figure 1(a)). In contrast, the fundamental driving at 5 Hz and the harmonic driving at multiples of 5 Hz except fundamental driving can be detected by visual stimulation (Figure 1(b)). We use these fundamental and harmonic driving components with clearly visible for personal identification.

2.2. **Extraction of feature vector for personal identification.** In personal identification, we classified the personal EEG data into any one of the six participants. Other participants who were not included in the EEG experiment were not included in the classification data. In this study, five frequency components, the fundamental wave (f_0) and four harmonics ($2f_0$, $3f_0$, $4f_0$, $5f_0$), were used for the classification. Here, we set the following four kinds of feature vectors.

(FV1) Original values of power at two occipital electrodes (O_1, O_2) for five SSVEP frequency components (10-dimensional feature space)



(a) At rest



(b) During 5Hz visual stimulation

FIGURE 1. Frequency spectrum

(FV2) Original values of power at all (four) electrodes for five SSVEP frequency components (20-dimensional feature space)

(FV3) Difference in power at bilateral electrodes (P_3-P_4, O_1-O_2) for five SSVEP frequency components (10-dimensional feature space)

(FV4) Difference in power at all combinations of two electrodes extracted from four electrodes (P_3-P_4, P_3-O_1, P_3-O_2, P_4-O_1, P_4-O_2, O_1-O_2) for five SSVEP frequency components (30-dimensional feature space)

The SSVEP is a passive response to visual stimuli and is not susceptible to psychological conditions compared with spontaneous EEG. It is considered to be relatively stable in comparison with spontaneous EEG. Vialatte et al. also reported that the amplitude distribution of the spectral content of the SSVEP, with characteristic SSVEP peaks, remains stable over time [7]. For these reasons, we assume that we can stably derive individual differences from the original power. We, therefore, used the original power as an element in the feature vector.

On the choice of feature vectors, we considered the prominent SSVEP appearance in parietal and occipital regions and the use of ipsilateral and bilateral differences. Here, we focused on finding the appropriate feature vector to obtain the highest classification accuracy without restricting the dimensions of the feature vector.

2.3. **Classification.** We tried to classify EEG data using three classifiers, Fisher linear discriminant analysis (FLDA), random forest (RF), and support vector machine (SVM), which are all widely used in EEG analysis. We used multi-class LDA which can be formulated as an optimization problem to find a set of linear combinations that maximizes the ratio of the between-class scattering to the within-class scattering in FLDA. In RF, we generated 100 pairs of subsample with random sampling and then constructed 100 pairs of decision tree. By majority voting, classification was performed. Here, the Gini coefficient was used for branching in tree generation. Though SVM originally separates the binary classes, we used multi-class SVM to classify an EEG feature vector into one among all subjects. In this study, we used multi-class SVM function of e1071 package in statistical software R. A Gaussian kernel was used as a kernel function. Evaluation of classification accuracy was performed by 3-fold cross-validation. Two-thirds of the data were used for training, and the remaining data were used for the test. The 24 trials were divided into three parts randomly. Accordingly, 16 trials are used for training and 8 trials are used for the test. We then calculated classification accuracy as the average of 10 repetitions. The average is collected from all subjects. A grand average for all subjects and a standard deviation among all subjects are calculated.

3. **Results.** We show the accuracy rate results in Figure 2. There was no significant difference among classifiers. However, FLDA, which is a linear classifier, showed a relatively low accuracy rate as a whole. Observing the result from the opposite side, using the value of power, we can say that even linear classification can obtain good results of more than 80% on average. However, the nonlinear discriminant functions showed higher classification rates in our experiment and stable classification performance (small variations in accuracy rate). Regarding feature vectors, the original values of power at two occipital electrodes (FV1) and the difference in power at bilateral electrodes (FV3) were relatively low among the four feature vectors we chose.

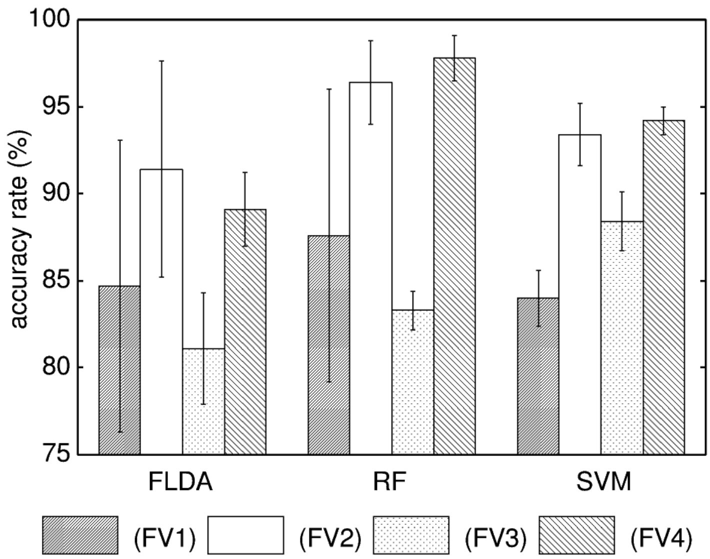


Figure 2. Accuracy rate for personal identification using three kinds of classifiers

4. **Discussions.** In all classifiers, classification error occurred without bias toward any particular participant, likely caused by outliers generated by artifacts. Regarding feature vectors, accuracy rate tends to be higher with the increase of dimension of a vector space. Comparing the original power at each electrode ((FV1), (FV2)) with the difference between two electrodes ((FV3), (FV4)), the standard deviation of accuracy rate using the difference showed lower values. It is known that subtraction can suppress the variation in classification. The difference between two electrodes extracted from four electrodes (FV4) gave better results than the difference between left and right electrodes (FV3). Though

the number of feature vector dimensions is different, not only the ipsilateral relationship but also the bilateral relationship may be important for personal identification.

On the whole, accuracy rate exceeded 85% for all classifiers with the highest classification at 97.5% when using RF. We considered that SSVEPs have the potential to be used for biometrics authentication from the points of reproducibility and specificity.

5. **Conclusions.** In this study, we performed personal identification using SSVEP for six healthy participants as a first step in the development of a biometrics authentication system with a large number of individuals. In the experiment, we classified a participant based on feature vectors extracted from the SSVEP frequency spectrum. Here, we set four kinds of feature vectors using five power values at the fundamental and four harmonic frequencies. Elements constituting these vectors are the following: original values of power at two occipital electrodes for five SSVEP frequency components, original values of power at all four electrodes for the five frequency components, difference in power at bilateral electrodes for the five frequency components, and difference in power at all combinations of two electrodes extracted from four electrodes for the five frequency components. We performed the classification using three kinds of classifiers: FLDA, RF, and SVM. The results showed that using difference in power at all combinations of two electrodes extracted from four electrodes for five SSVEP frequency components gave the best classification performance. Accuracy rate exceeded 85% for all classifiers with the highest classification accuracy at 97.5% when RF was used. From these results, we suggest that SSVEP has the potential to be used for biometrics authentication though we cannot say sure that SSVEP can be used because of the result for only 6 subjects. In this study, we could obtain the information about an appropriate feature vector for classification and the classifier.

In future research, we need to investigate whether the accuracy rate remains at a high level when increasing the number of participants. Unregistered people should be excluded from authentication in actual situations, though we assume that the SSVEP data belongs to the participants of this study. The classifier should also be changed to make it possible to correspond to one-to-others classification because currently identification requires the classifier to obtain the discriminant function for the addition of every new participant. In the final authentication system, we will have to evaluate the false rejection rate in which a person who should be certified is rejected, and the false acceptance rate in which a person who should not be certified is accepted.

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