Reduction of Computational Amount in Person Verification Based on SVM Using Evoked Brain Wave by Ultrasound

Isao Nakanishi
Faculty of Engineering, Tottori University, Tottori, Japan
Email: nakanishi@tottori-u.ac.jp (I.N.)

Kouki Kawakami
School of Engineering, Tottori University, Tottori, Japan
Email: b19t2027k@edu.tottori-u.ac.jp (K.K.)

***Abstract*—For realizing continuous authentication of users, we have studied to use an electroencephalogram (EEG) evoked by ultrasound as biometrics. Users are presented only the ultrasound of their memorable music and verified whether genuine or not using the induced components of EEG. In our previous studies, the verification error rate of 0 % was achieved using multiple quantities in EEG as individual features and a support vector machine (SVM) as a verification method; however, it required a large amount of computation for processing SVM models. Thus, we reduce the number of SVM models by applying two selection methods of features and electrodes, which have been previously introduced. Furthermore, we examine the usage rates of features and electrodes in the reduced SVM models. By using only the electrodes with high usage rates, the verification error rate of 0 % is guaranteed with a small amount of computation.**

***Index Terms*—biometrics, electroencephalogram, ultrasound, support vector machine, computational amount reduction**

I. INTRODUCTION

With the spread of information devices, such as smartphones, leakage of personal information and spoofing have emerged as modern problems, and the importance of person authentication is increasing. IC cards and password input are used as general authentication methods; however, there is a risk of loss or forgetting. Therefore, biometrics is attracting attention.

As typical biometrics, there are fingerprints as well as face and iris images. These are static biometrics; thus, high authentication accuracy is achieved. However, there is a risk of biometric data leakage because they are exposed on the body surface. In addition, when using them in system-user management, it is difficult to prevent the replacement of users (spoofing) because authentication is performed only once when users begin to use a system. To solve this problem, continuous authentication where users are always authenticated while using a system is required; however, the system usage should not be hindered by actions for authentication.

Thus, employing brain waves as biometrics has been proposed [1]. The brain wave is not exposed on the body surface; therefore, the risk of data leakage is low. In addition, the brain wave is passively (unconsciously) detectable; thus, to detect the brain wave never prevent users from using a system. In particular, ultrasound is used as imperceptible stimulation in this study. This study aims to verify users using brain waves evoked by ultrasound.

In the previous studies, we measured evoked brain waves by ultrasound at multiple electrodes, extracted spectral and nonlinear features for verifying individuals from the brain waves, verified individuals using a SVM at each feature and electrode, and performed final decision based on majority voting using verification results from all features and electrodes. The SVM is one of machine learning and makes a model for verifying individuals based on learning. An error rate of 0 % was achieved in [2].

However, obtaining SVM models for all features and electrodes is cumbersome, which is not realistic; thus, we reduced the number of SVM models while maintaining the error rate of 0 % [3]. Furthermore, the number of SVM models was reduced by increasing the number of features [3–5]. Larger number of features makes verification easier. Thus, we first evaluate the reduction methods of SVM models, which were not applied yet in [4, 5]. Subsequently, we reduce the number of SVM models when fusing all the features introduced. Finally, we obtain the tendency of the electrodes used in the results and consider the relationship with the information processing mechanism of the brain.

Manuscript received June 19, 2023; revised August 10, 2023; accepted September 10, 2023.

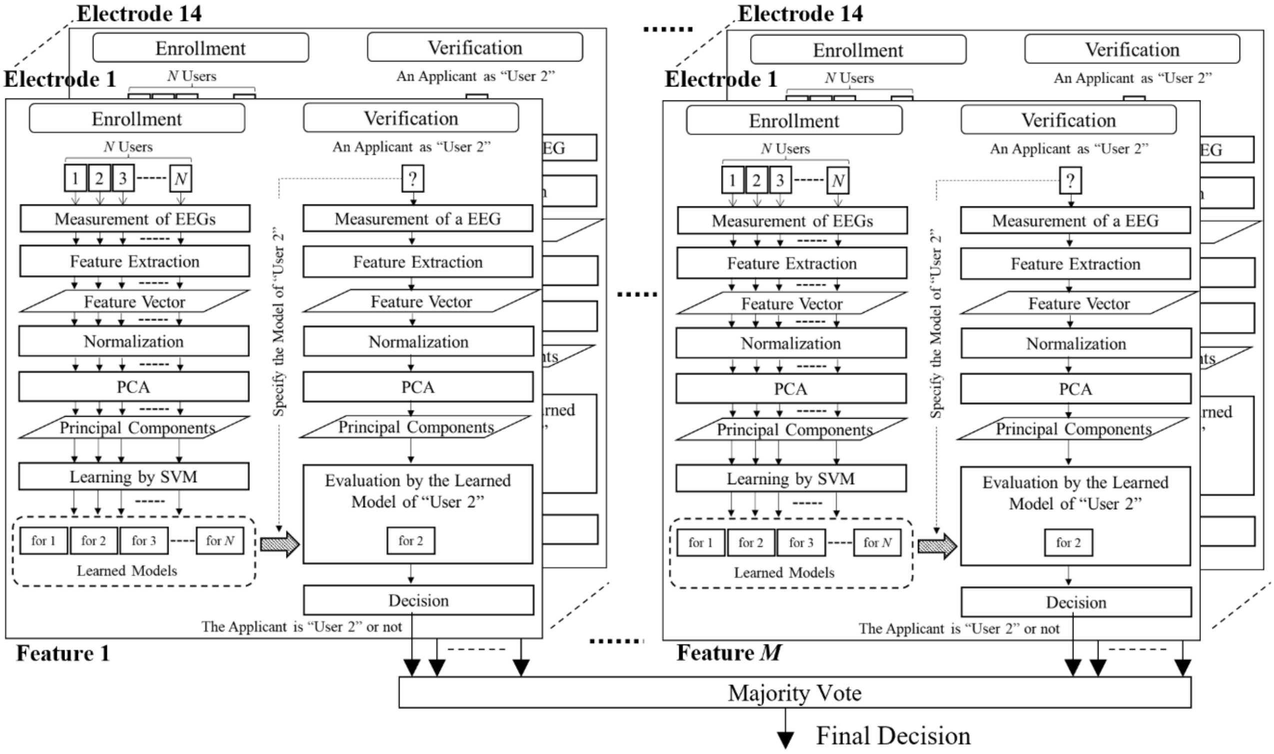


Figure 1. Verification system fusing M features.

II. Person Verification Using Evoked Brain Waves by Ultrasound

Please refer to [2–5] for the details of the previous studies. Ultrasound was extracted from high-resolution (192 Hz / 24 bit) music, which was memorable for each experimental subject, using a digital filter with a cut-off frequency of 20 kHz, presented to a subject sitting at rest with closed eyes as an inaudible stimulus during 30 s and his/her brain wave (electroencephalogram: EEG) was measured. No noise reduction was performed. The number of experimental subjects was N = 10. The electroencephalograph was of a wireless connection type, and had 14 electrodes (AF3, F3, F7, FC5, T7, P7, O1, O2, P8, T8, FC6, F8, F4, AF4). As features for verifying individuals, the spectrum of EEG (SP) and nonlinear values of EEG, such as sample entropy (SP), maximum Lyapunov component (ML), and permutation entropy (PE) were used in [2]. In [3], the fractal dimension value of EEG (FD) was added to the features. Furthermore, the eigenvector centrality (EC) based on mutual values between electrodes and statistical values of EEG (ST) were added as features in [4] and [5], respectively. For suppressing the influence of different magnitude values, each feature was normalized using all data at the enrollment stage. The normalized features were processed in principle component analysis (PCA), and the number of features was reduced to three. SVM is a two-classifier, which examines whether the user is the person himself/herself, was used as a verification method. The verification system is described in Fig. 1. In the verification stage, an applicant who wants to use a system

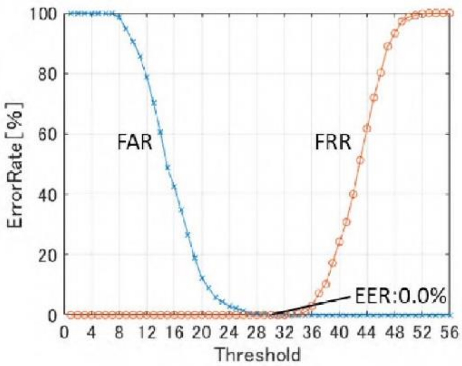


Figure 2. Error curves [2].

is verified to determine whether he/she is a regular user at each feature and electrode using a corresponding SVM model, which is already built using his/her data and others' data in the enrollment stage, and the final decision is done based on majority voting of all verification results (SVMs).

The error curves when using 4 features (SP, SE, ML, PE) and 14 electrodes are presented in Fig. 2 [2]. The threshold corresponds to the number of majority votes in the final decision. If the threshold is set higher, the false rejection rate (FRR) increases, and inversely, the false acceptance rate (FAR) decreases, where FRR is the ratio of the number of mistakenly rejected regular users' data to all regular users' data and FAR is the ratio of the number of mistakenly accepted non-regular users' (others') data to all non-regular users' data. Therefore, these rates always have a trade-off relationship. When the FRR equals with the FAR, the rate is called equal error rate (EER), which is used as an index for evaluating

TABLE I. FEATURES AND ELECTRODES IN 16 SVM MODELS OBTAINED BY THE IDENTICALLY SELECTION WHEN FUSING 6 FEATURES [4]

Feature	Electrode													
	AF3	F7	F3	FC5	T7	P7	O1	O2	P8	T8	FC6	F4	F8	AF4
SP, SE, PE, EC	○		○		○		○							
SP, SE, PE, EC		○						○	○				○	

verification performance. Smaller EER means better verification performance. In this case, EER = 0 % was achieved when the threshold was set to 30.

III. REDUCTION OF SVM MODELS

However, for achieving EER = 0 %, 56 SVM models (4 features X 14 electrode) were needed, and that requires huge computational amount. The appropriate method to reduce the computational amount, that is, the number of SVM models is to examine whether EER = 0 % can be achieved in all combinations of features and electrodes, and then find a combination with the least number of SVM models. However, the number of all combinations of 56 SVM models is expressed as

$$\sum_{r=1}^{56} {}_{56}C_r \approx 7.2 \times 10^{16}\,, \qquad (1)$$

and these examinations are time consuming and unrealistic [2].

A. *Identical Electrodes Selection*

Thus, we assumed the condition where the electrodes used was identical for all features and found the smallest number of SVM models while maintaining EER = 0 % under that condition [2]. This condition was assumed because it is unnecessary to wear all electrodes, which is more convenient for users. Even if the number of electrodes is reduced, if the combination of electrodes is different for each feature, the user will eventually have to wear all the electrodes. The total number of combinations investigated by this selection could be evaluated in a realistic time. This process is called identically selection. Consequently, the smallest number of SVM models was 24 [2].

Next, we considered that increasing the number of features improved the verification performance, and then further reduced the number of SVM models. Specifically, we introduced FD as a new nonlinear feature, fused it with conventional 4 features (SP, SE, ML, PE), and tried to reduce the number of SVM models using the identically selection. In particular, 70 (5 features X 14 electrodes) SVM models could be reduced to 24 [3]; however, it remained the same as before increasing the number of features. The number of SVM models could not be reduced because the introduced FD feature was a nonlinear feature, and not independent of conventional nonlinear SE, ML and PE features. For extreme cases, even if the number of features is increased by fusing the

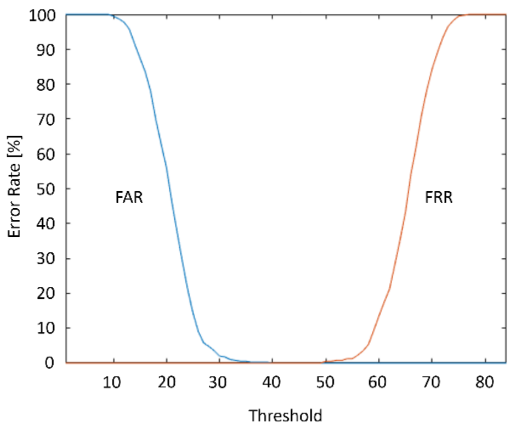


Figure 3. Error curves when fusing six features [4].

same features, the verification performance does not improve.

Thus, we introduced another feature, eigenvector centrality (EC) that was a mutual feature between electrodes and independent of the above five features [4]. In addition, the EC feature is typically one-dimensional, that is unsuitable for pattern classification. Thus, an EEG was processed through bandpass filters of which wavebands were δ, θ, α, lowβ, highβ, and γ. An EC value was extracted from each band, and the extracted 6 EC values were combined after normalization as an EC feature of 6 dimensions. The number of total SVM models was increased to 84 (6 features X 14 electrodes).

The verification performance was evaluated, and the error curves is shown in Fig. 3. EER = 0 % was achieved because the number of features was increased to 6. Note that the number of thresholds that achieved EER = 0 % was increased to 10 from 3 when fusing 5 features [3], and it was only one when fusing 4 features (Fig. 2). By using the identically selection method, the number of SVM models could be reduced to 16 [4]. This result suggests that fusing independent features makes verification easier and improves verification performance; it results in further reduction of SVM models. Table I shows two combinations of features and electrodes in 16 SVM models.

B. *Random Selection*

The smallest number of SVM models was 24 in [2]; however, it was not guaranteed to be minimal. Thus, while reducing the number of models one by one from 23, we randomly selected combinations of features and electrodes corresponding to the number of SVM models and examined whether EER = 0 % could be achieved. If there was one combination that could achieve EER = 0 %,

TABLE II. A COMBINATION OF FEATURES AND ELECTRODES IN 14 SVM MODELS OBTAINED BY THE UNIFORMLY SELECTION WHEN FUSING 6 FEATURES [5]

Feature	Electrode													
	AF3	F7	F3	FC5	T7	P7	O1	O2	P8	T8	FC6	F4	F8	AF4
SP			○					○		○			○	○
SE														
ML			○			○								
PE					○	○								
FD														○
ST	○		○	○	○									

TABLE III. FEATURES AND ELECTRODES BY THE IDENTICALLY SELECTION WITH 6 FEATURES INCLUDING ST

Feature	Electrode													
	AF3	F7	F3	FC5	T7	P7	O1	O2	P8	T8	FC6	F4	F8	AF4
SE, ML, ST		○		○	○	○								○
		○		○	○								○	○
SP, ML, ST	○		○	○				○			○			
SP, SE, ST	○		○	○				○		○				
	○				○			○	○	○				
	○				○			○	○			○		
				○	○				○		○			○

the number of SVM models was further reduced by one. This searching was stopped within a realistic time. This process is referred to as random selection. There was no guarantee that the number of SVM models obtained was minimal; however, we believed that some knowledge could be obtained from the selected features and electrodes.

After searching, we found a combination of features and electrodes that achieved EER = 0 % using 20 SVM models. This suggested that 24 SVM models found by the identically selection was not minimum. The condition where electrodes are identically selected in all features is severer than the condition where electrodes are randomly selected; therefore, the smallest number of SVM models by the identically selection is larger than that by the random selection.

C. *Uniformly Selection*

By examining the combination of features and electrodes found by the random selection, which achieved the smallest number of SVM models, we found that features were almost uniformly selected from five features and electrodes were selected almost uniformly from four quadrants of the brain. This corresponds to the knowledge that fusing independent features improves verification performance obtained in III-*A*. Uniform selection corresponds to independent selection. Thus, we proposed a method to uniformly select features from five features and electrodes from four quadrants of the brain [5]. This method is called uniformly selection. In addition, we introduced statistical values of EEG (ST) as a new feature, which was independent of conventional five features in [3]. Specifically, mean, standard deviation, median, and average of the local maxima were extracted from EEG, and combined as a feature of four dimension after normalization using registered data from all users. The number of total SVM models was 84 (6 features X 14 electrodes).

By using the uniformly selection, the 84 SVM models could be reduced to 14 [5]. Table II indicates a combination of features and electrodes in 14 SVM models. The SP was selected five times, the nonlinear features, SE. ML, PE, and FD were selected five times, and the ST was selected four times. As with the EC in Sec. III-*A*, introducing the ST feature that was independent of other ones improved verification performance, and then reduced the number of SVM models while maintaining EER = 0 %.

Furthermore, the condition that features and electrodes are uniformly selected is looser than the condition that identical electrodes are selected in all features; therefore, the smallest number of SVM models was further reduced to 14 by the uniform selection compared with 16 by the identically selection.

IV. FURTHER REDUCTION OF SVM MODELS

In this section, we examine the reduction of SVM models by the identically selection with 6 features, including ST and the uniformly selection with 6 features, including EC, which have not been examined.

A. *Identically Selection with 6 Features Including ST*

First, we applied the identically selection to reduction of SVM models in 6 features, including ST. Consequently, the number of SVM models could be reduced to 15 while maintaining EER = 0 %. Seven combinations of features and electrodes in the 15 SVM models are listed in Table III. When using the uniformly selection, the number of SVM models in 6 features, including ST, could be

TABLE IV. A COMBINATION OF FEATURES AND ELECTRODES BY THE UNIFORMLY SELECTION WITH 6 FEATURES, INCLUDING EC

Feature	Electrode													
	AF3	F7	F3	FC5	T7	P7	O1	O2	P8	T8	FC6	F4	F8	AF4
SP	○		○	○				○				○		
SE	○			○										
ML														
PE	○													
FD									○	○				
EC				○		○			○	○				○

TABLE V. FEATURES AND ELECTRODES OF 15 SVM MODELS USING THE IDENTICALLY SELECTION IN 7 FEATURES

Feature	Electrode													
	AF3	F7	F3	FC5	T7	P7	O1	O2	P8	T8	FC6	F4	F8	AF4
SE, EC, ST	○		○		○		○							○
SE, ML, ST		○		○	○	○								○
		○		○	○								○	○
SP, ML, ST	○		○	○				○			○			
SP, SE, ST	○		○	○				○		○				
	○				○			○	○	○				
	○				○			○	○			○		
				○	○				○		○			○

TABLE VI. A COMBINATION OF FEATURES AND ELECTRODES IN 13 SVM MODELS USING THE UNIFORMLY SELECTION IN 7 FEATURES

Feature	Electrode													
	AF3	F7	F3	FC5	T7	P7	O1	O2	P8	T8	FC6	F4	F8	AF4
SP	○				○						○			
SE		○												
ML											○			
PE														○
FD														○
EC				○		○							○	
ST		○		○										○

reduced to 14 [5]. The reduction using the identically selection could not reach that result because the condition that identical electrodes were selected in all features was severer.

B. *Uniformly Selection with 6 Features Including EC*

We applied the uniformly selection to reduction of SVM models in 6 features, including EC. The number of SVM models could be reduced to 15 while maintaining EER = 0 %. Table IV shows a combination of features and electrodes in the 15 SVM models. When using the identically selection, the reduced number of SVM models was 16. Therefore, the uniformly selection, which is looser than the identically selection, could further reduce the number of SVM models.

C. *Reduction in Fused 7 Features*

Fusing independent features can spread feature space and improve verification performance. Consequently, further reduction of SVM models can be achieved. Thus, we examined the verification performance using 7 features, including both EC and ST, which were previously examined individually. The total number of SVM models becomes 98 (7 features Ｘ 14 electrodes).

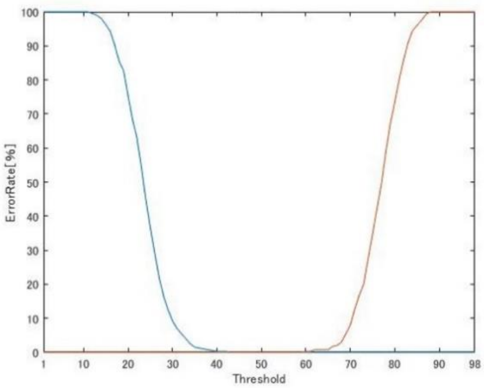
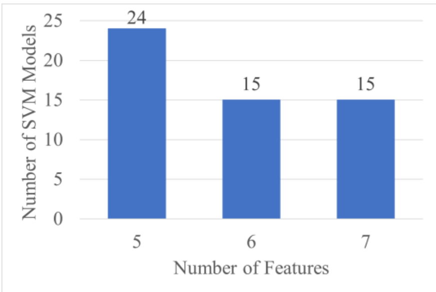


Figure 4. Error curves when fusing 7 features.

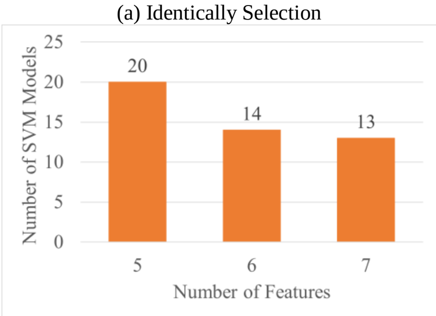
Figure 4 indicates the error curves. EER = 0 % was achieved because the number of features was increased. Note that the number of thresholds for achieving EER = 0 % was increased to 17 (43~59) from 10 when fusing 6 features.

TABLE VII. USAGE RATES (%) OF ELECTRODES IN EACH SELECTION METHOD

Selection Method	Electrode													
	AF3	F7	F3	FC5	T7	P7	O1	O2	P8	T8	FC6	F4	F8	AF4
Identically	51.3	24.5	53.0	41.8	46.9	29.0	24.4	50.4	34.5	30.0	28.1	16.6	33.5	35.9
Uniformly	86.0	82.0	83.0	88.0	91.0	80.0	74.0	80.0	76.0	87.0	77.0	82.0	76.0	78.0



(a) Identically Selection



(b) Uniformly Selection

Figure 5. Minimum number of SVM models in two selection methods.

1) Reduction using identically selection

We examined the identically selection of electrodes in fused 7 features and investigated the minimum number of SVM models while maintaining EER = 0 %. Consequently, the minimum number of SVM models was 15 (3 features X 5 electrodes). Eight combinations of features and electrodes in the 15 SVM models are shown in Table V. The reduced number is less than that of 6 features including EC, but equivalent with that of 6 features including ST.

2) Reduction using uniformly selection

We reduced the number of SVM models by using the uniformly selection and found that the minimum number of SVM models was 13. Table VI shows their features and electrodes. Comparing with 14, which was the smallest number of SVM models when fusing 6 features, it was confirmed that further reduction could be achieved.

D. Considerations

Figure 5 shows the minimum numbers of SVM models found when fusing 5, 6, and 7 features in two selection methods, (a) identically selection and (b) uniformly selection, where only the case of 5 features in (b) is by the random selection. When increasing the number of features from 6 to 7, the effect of reduction in the number of SVM models is low. Therefore, it is difficult to further reduce the number of SVM models even if the number of features is further increased.

Let us consider the number of thresholds that achieved EER = 0 %. It was only one for 4 features (the maximum number of SVM models was 56) [2], 3 for 5 features (70) [3], 10 for 6 features (84), and 17 for 7 features (98). However, it is unnecessary to discuss the number of thresholds because the maximum number of SVM models was increased according to the number of features. Thus, the number of thresholds is normalized by the maximum number of SVM models. The normalized number of thresholds is 0.017, 0.043, 0.12, and 0.17 for 4, 5, 6, and 7 features, respectively. Furthermore, expressing the increment as a ratio, the ratio is 2.5 from 4 to 5, 2.8 from 5 to 6, and 1.4 from 6 to 7. The increment ratio from 6 to 7 was approximately half compared to other cases; therefore, it is considered that further reduction of the number of SVM models by increasing the number of features cannot be expected.

V. KNOWLEDGES FROM SELECTED ELECTRODES

In the proposed verification system using EEG evoked by ultrasound, huge computational amount is required for building many SVM models; thus, we worked on reducing the number of SVM models while maintaining the verification performance. However, the minimum number of SVM models cannot be determined unless reduction based on some rule, such as the identically or uniformly selection in this study, which is inconvenient in practical applications.

A. Use Rate of Electrodes

We acquire some knowledge or generality from the SVM models reduced, that is, the combinations of features and electrodes. In particular, we investigated the usage rate of electrodes that achieved EER = 0 %, where the number of SVM models was assumed to be 20 (4 features and 5 electrodes) because the number of combinations of features and electrodes was few for calculating the rate in the minimum number of SVM models. There were 100 and 1085 combinations that achieved EER = 0 % using the uniformly selection and the identically selection, respectively. In these combinations, we calculated the usage rate of electrodes, which indicates how much each electrode was used. The results are shown in Table VII.

The usage rates by two selection methods are different as follows. The number of selected electrodes was 4 when using the identically selection in 6 features as shown in Table I while the other one was 9 when using the uniformly selection as shown in Table II. The number of selected electrodes in each combination using the identically selection is relatively few, and it results in low usage-rate of electrodes while that using the uniformly selection is relatively large, and it leads to increase of

TABLE VIII. USAGE RATES (%) OF THE COMBINATIONS OF FEATURES AND ELECTRODES SELECTED BY THE IDENTICALLY SELECTION

Feature	Electrode													
	AF3	F7	F3	FC5	T7	P7	O1	O2	P8	T8	FC6	F4	F8	AF4
SP	37.1	15.8	42.2	30.7	36.5	18.1	15.2	40.1	28.9	25.0	23.0	15.0	25.6	27.8
SE	34.4	17.6	34.1	29.1	27.6	22.0	19.2	37.1	22.5	19.9	18.4	11.7	26.6	26.8
ML	16.0	7.5	16.0	16.1	17.5	7.7	6.2	16.6	12.4	6.0	11.6	4.4	8.7	13.2
PE	34.1	16.3	35.2	22.2	30.5	19.9	15.5	36.8	21.7	20.9	19.9	10.0	21.9	21.4
FD	8.9	4.5	10.1	5.3	10.8	4.5	6.0	7.0	4.8	4.2	5.4	3.5	5.3	3.2
EC	32.3	13.7	29.8	26.6	23.6	22.0	15.2	24.0	16.7	20.5	11.5	9.6	22.0	22.4
ST	42.5	22.7	44.5	37.3	41.2	21.9	20.5	40.2	30.9	23.4	22.6	12.2	23.7	28.9

TABLE IX. FOUR FEATURES AND FIVE ELECTRODES WITH HIGHER USAGE-RATES

Feature	Electrode
SP, SE, PE, ST	AF3, F3, FC5, T7, O2

usage-rate of electrodes. Therefore, it is unnecessary to discuss this difference.

However, it can be observed that there are some tendencies in the selected electrodes, especially for using the identically selection. Thus, for further investigation, we calculated the usage rate of SVM models that corresponds to the combinations of features and electrodes under the same condition as before.

The results are presented in Table VIII. From these results, there is a large difference in the usage rate for each combination. The combinations with high usage rates is considered to contribute for achieving EER = 0 %: high verification performance and inversely the combinations with low usage rates have slight influence on the verification performance.

Thus, we believe that by using only the combinations (SVM models) with high usage rates, we would not have to reduce the number of SVM models using any electrode selection method. Table IX presents 4 features and 5 electrodes of the combinations with higher usage-rates in Table VIII.

To verify the above hypothesis, we evaluated the verification performance using the features and electrodes in Table IX. Consequently, it was confirmed that EER = 0 % was achieved by this combination. Therefore, it is sufficient to use the features and electrodes in Table IX without reducing the number of SVM models each time an authentication system is constructed.

B. Relationship with Information Processing of the Brain

Let us consider the relationship of the selected electrodes with information processing mechanism of the brain. The positions of five electrodes in Table IX are indicated in Fig. 6. Electrodes, AF3, F3, FC5, and T7 are located on from the front to the side of the left brain. In this study, ultrasound extracted from memorable music for experimental subjects was used as inaudible stimuli. The temporal lobe of the brain is activated when recalling memories [6]. In addition, the primary auditory cortex, which performs auditory information processing, is

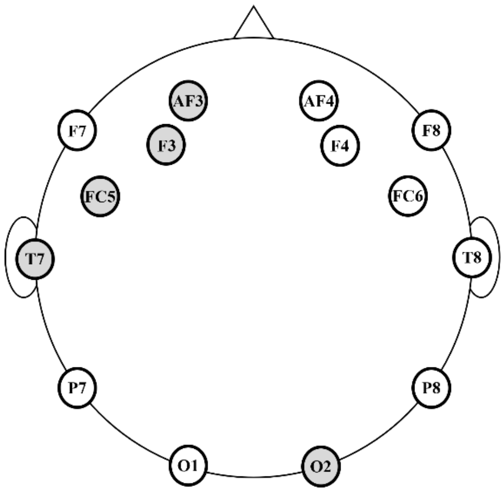


Figure 6. Positions of electrodes with high usage-rates.

located in the temporal lobe. AF3, F3, FC5, and T7 were selected owing to the above information.

However, the usage rates of electrodes, AF4, F4, FC6, and T8, which are located on the side of the right brain, are low in Table VIII. There is a clear difference depending on the electrode position. In human beings, language comprehension is processed in the left-brain; therefore, the words voiced in music, even if only in ultrasound, might effect on this difference.

The usage rate of electrode O2 located on the back of the head was high. The occipital lobe is a region related to visual information processing. However, EEG measurement was performed with the eye-closed condition in this study; therefore, there was no visual stimulus. In addition, there is an obvious difference between the usage rates of O1 and O2, which are located on the back of the head together. The reason why the usage rate of only O2 electrode was high is unclear.

VI. CONCLUSIONS

This study aims to verify individuals using EEG evoked by ultrasound, where many SVMs are used as a verification methods. However, large computational amount is required to build many SVMs. Thus, the reduction of the number of SVM models is an issue.

We examined the reduction of SVM models by the identically selection with 6 features, including ST, and the uniformly selection with 6 features, including EC, which had not been examined. Furthermore, we examined the reduction of SVM models using both selection methods when fusing 7 features. Consequently, the number of SVM models could be reduced to 13 while maintaining EER = 0 %, that is the lowest ever. In addition, we calculated the usage rates of SVM models, and found that some electrodes had high usage rates and others had low ones. By using only the electrodes with high usage rates, it is unnecessary to reduce the number of SVM models using any electrode selection method. If the features and electrodes found is used, EER = 0 % is achieved with a small amount of computation. Finally, we examined the relationship between the results obtained and the information processing mechanism of the brain.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

IN devised the project, the main conceptual ideas and proof outline; KK carried out the experiments; IN wrote the paper; all authors had approved the final version.

ACKNOWLEDGMENT

This study has been approved by the non-medical research ethics committee of the Faculty of Engineering, Tottori University.

REFERENCES

[1] Q. Gui, M. V. Ruiz-Blondet, S. Laszlo, and Z. Jin, "A survey on brain biometrics" *ACM Computing Surveys*, vol. 51, no. 6, pp. 1–38, 2019.

[2] I. Nakanishi and T. Maruoka, "Biometrics using electroencephalograms stimulated by personal ultrasound and multidimensional nonlinear features," *Electronics*, vol. 9, issue 1, no. 24, pp. 1–18, 2020.

[3] K. Mukai and I. Nakanishi, "Introduction of fractal dimension feature and reduction of calculation amount in person authentication using evoked EEG by ultrasound," in *Proc. of 2020 IEEE R10 Conference*, 2020, pp. 567–572.

[4] I. Nakanishi, and K. Mukai, "Introduction of a mutual feature between electrodes into support vector machine based person verification using evoked electroencephalogram by ultrasound," in *Proc. of the 2022 IEEE Symposium Series on Computational Intelligence*, 2022, pp. 171–177.

[5] I. Nakanishi, Y. Ishikawa, and K. Mukai, "Correlation analysis of features for fusing in user verification using EEG evoked by ultrasound," in *Proc. of 2022 Tenth International Symposium on Computing and Networking Workshops*, 2022, pp. 388–391.

[6] M. Takeda, K. W. Koyano, T. Hirabayashi, Y. Adachi, and Y, Miyashita, "Top-down regulation of laminar circuit via inter-area signal for successful object memory recall in monkey temporal cortex," *Neuron*, vol. 86, no. 3, pp. 840–852, 2015.