タイトル Title	Introduction of a Mutual Feature between Electrodes into Support Vector Machine Based Person Verification Using Evoked Electroencephalogram by Ultrasound
著者 Auther(s)	Nakanishi, Isao; Mukai, Kotaro
掲載誌・巻号・ページ Citation	Proceedings of 2022 IEEE Symposium Series on Computational Intelligence (SSCI 2022) : 171 - 177
刊行日 Issue Date	2023-01-30
資源タイプ Resource Type	会議資料 / Conference Paper
版区分 Resource Version	著者版 / Author
権利 Rights	(C) 2022 IEEE
DOI	10.1109/SSCI51031.2022.10022272
URL	https://repository.lib.tottori-u.ac.jp/14634

Introduction of a Mutual Feature between Electrodes into Support Vector Machine Based Person Verification Using Evoked Electroencephalogram by Ultrasound

1st Isao Nakanishi
Faculty of Engineering
Tottori Univerisity
Tottori, Japan
0000-0001-9533-9987

2nd Kotaro Mukai
Faculty of Sustainable Sciences
Tottori University
Tottori, Japan

***Abstract*—In user management, to realize continuous user authentication, we study the use of an electroencephalogram (EEG) evoked by ultrasound as biometrics. In previous studies, using a spectrum and four nonlinear quantities in EEG as individual features and a support vector machine (SVM) as a verification method achieved an equal error rate (EER) of 0 %. However, it required a large number of SVM models, wherein considerable amount of computation regarding learning was consumed. In this study, we introduce a mutual feature between electrodes and confirm its effectiveness in achieving EER = 0 % with a smaller number of SVM models.**

***Index Terms*—biometrics, SVM, ultrasound, evoked brain wave, mutual feature between electrodes, reduction of SVM models**

I. Introduction

Unlike conventional passwords and ID cards, biometrics is a convenient user authentication method, which does not require users to remember or to have anything. Fingerprints, irises, and faces are well-known typical biometrics. However, these are exposed body parts. Hence, there is high risk that their information be stolen by an imposter and then an authentication system be deceived by using imitated biometrics made by the stolen information. In addition, these biometrics often consider one-time-only authentications, whereby the authentication is executed only at the beginning of system use. Consequently, they cannot detect user replacement after authentication (spoofing). Here, continuous authentication is required to prevent spoofing.

In this study, we focused on a brain wave, which is not exposed on the body surface. It is highly confidential and suitable for contentious authentication. Particularly, we proposed verifying users with brain waves evoked by ultrasound. We expected that individual differences existed between stimulation responses and they were further increased owing to individually related stimulation. In previous studies, the verification performance was evaluated using a spectrum and three nonlinear values (sample entropy, maximum Lyapunov exponent, and permutation entropy) in brain waves as individual features. Additionally, a support vector machine (SVM) as a verification method was used. An error rate of 0 % was achieved by the majority voting of all features and electrodes [1]. However, majority voting required 56 SVM models (4 features$\times$14 electrodes), which required a long learning period (computational time). Consequently, reducing the number of SVM models needed to be solved. In Ref. [2], the fractal dimension nonlinear feature was introduced. Provided the electrodes used in each feature were identical, all combinations of features and electrodes were examined. Consequently, the number of SVM models were reduced to 24 while maintaining an error rate of 0 %.

In this study, a mutual feature between electrodes was introduced. It is considerably different from conventional features and further reduces the number of SVM models.

II. SVM Based Person Verification Using Evoked EEG by Ultrasound

In this section, we introduce a person verification method based on SVM using an evoked electroencephalogram (EEG) generated by ultrasound [1], [2].

The continuous authentication of the system user is necessary to prevent spoofing. However, if the stimulation for inducing the brain wave is perceptible, it obstructs the original work. When a person is working with a system, if perceptible stimulation is provided to him/her, it interferes with the original work. Thus, we focused on ultrasound because it is not perceptible to human beings. The human ear audible range stands at 20 Hz$\sim$20 kHz and sounds higher than that are considered to be ultrasounds. Ultrasounds are not perceptible. However, there are hypersonic effects whereby brain waves are activated in the α waveband by sounds, including ultrasounds [3]. It has been reported that responses in the brain wave to voices calling their own names and familiar voices differ from unrelated voices [4]. Thus, in experiments that use subjects, a familiar sound to each subject was used and called personal ultrasound.

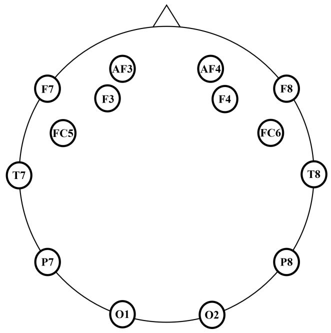

Fig. 1. Electrode position

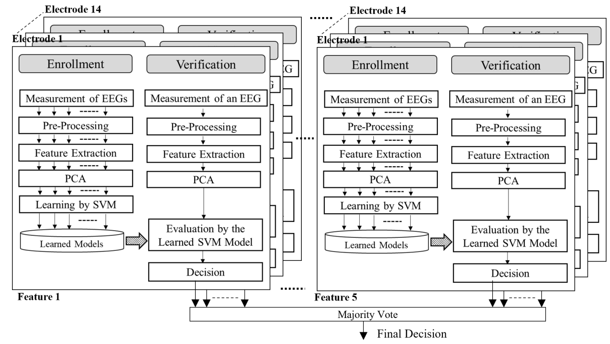

Fig. 2. Verification process.

Before the experiments, the memorable sounds of all subjects were investigated and personal ultrasounds were created by eliminating frequency elements under 20 kHz from high-resolution (192 kHz/24 bit) sources of the memorable sounds using a sound editing software. The personal ultrasounds were presented to the subjects who sat in a relaxed state with their eyes closed, and their EEGs were measured for 120 s, eight times per subject. The subjects were 10 university students aged between 22 and 24 with no hearing abnormalities. We confirmed whether they had enough sleep by interviewing in advance. To reduce the influence of environmental sounds on the EEG, the measurements were performed in a room at the university. The room didn't have many people in the corridor; therefore, it was relatively quiet. To measure EEG, a consumer brain wave sensor, Epoc+ produced by Emotive, had 14 electrodes: AF3, F3, F7, FC5, T7, P7, O1, O2, P8, T8, FC6, F8, F4, AF4 as shown in Fig. 1.

After pre-processing (eliminating a trend and spike noises, bandpass filtering, and normalizing) the measured EEGs, individual features were extracted. A total of five features were extracted: a spectrum (SP), four nonlinear values (sample entropy (SE)), maximum Lyapunov exponent (ML), permutation entropy (PE), and fractal dimension (FD)). However, nonlinear features are originally one-dimensional; however. it is not suitable for classification. Thus, the EEG was divided into several regions in the time domain or six bands in the frequency domain and the nonlinear values in the regions or bands were used as multidimensional features. Verification was performed using SVM [5], which is a two-class classifier based on learning aimed at achieving high verification performances. In this study, SVM^{light} [6] was used. The most preferred kernel function was selected from the linear, polynomial, and radial basis function kernels. Other parameters were determined via a grid search (brute forcing).

The verification process is illustrated in Fig. 2. In the enrolment stage, EEGs from all users (subjects) were measured. Pre-processing, feature extraction, and principal component analysis (PCA) were performed on the measured EEG and SVM models were created using learning extracted features for all electrodes.

SVM is a two-class classifier; therefore, each SVM model is learned to distinguish a user form another user. Consequently, the number of SVM models required depends on the number of users. Let the number of users m $(m \times m-1)$ SVM models be required for each feature and electrode. However, to discuss the independent number of SVM model of users in this study, it is assumed that one SVM model is prepared for each feature and electrode.

In the verification stage, EEG is measured from an applicant who claim to be a regular user, and his features are extracted similarly to the processing in the enrolment stage. Using each extracted feature, the applicant is verified as genuine using learned SVM models, which are related to the regular user. If the number of SVM models that deem an applicant as genuine is larger than a threshold, the applicant is regarded as genuine. A verification result is obtained for each feature and electrode. The final decision is performed by majority voting of all verification results.

In this study, an equal error rate (EER) was used to evaluate verification performances. In biometrics, there are two errors: genuine users be rejected and non-genuine users be mistakenly accepted. The former is evaluated using the false rejection rate (FRR), which is the ratio of rejected data of genuine users to all genuine users' data and the latter is evaluated as a false acceptance rate (FAR), which is the ratio of accepted non-genuine users' data to all non-genuine users' data. The FRR and FAR have a trade-off relationship. Thus, when plotting them in a vertical axis with the threshold in a horizontal axis, their curves intersect at one point; that is, the FRR is equal to the FAR, which is called EER. A smaller EER implies higher verification performance.

EERs by the majority voting of 14 electrodes for each of the five feature and those by the majority voting of 14 electrodes and all features are summarized in Table I. When majority

TABLE I
EERs [%]

Feature	EER
SP	4.4
ML	3.1
SE	5.1
PE	4.3
FD	5.3
All	0.0

voting was used for all electrodes and features, that is, 70 SVM models (5 features$\times$14 electrodes), an EER of 0 % was achieved.

However, learning 70 SVM models is a heavy computational (processing) load for authentication systems. In fact, $(m \times m - 1)$ times, as many models were required. Consequently, the reduction in SVM models (features and electrodes) was a problem that had to be solved.

The most reliable method is to examine the verification performance in all combinations of features and electrodes and determine that which has the least SVM models while maintaining an EER of 0 %. However, the number of combinations is large, and learning SVM models in all combinations requires unrealistic computational time. Hence, it is impossible to do so. Thus, by accepting several conditions that could reduce the number of combinations, the verification performance of all the combinations was evaluated. Consequently, under the condition that identical electrodes are used for each feature, the number of SVM models was reduced to 24 while maintaining an EER of 0 % [2].

III. Introduction of Mutual Feature between Electrodes

To make the classification easier brings to effectively further reduce SVM models. In general, increasing the number of features increases the number of dimensions in the classification space, thereby facilitating classification. However, at the extreme, even if the same feature is introduced, the number of dimensions increases, but classification does not become easier.

In previous studies, a spectrum and four nonlinear features extracted from the EEG for each electrode were used. Brain waves arise from the activity of many nerve cells and interact with each other. If such a relation is represented as a feature, a different feature from conventional ones is obtained. Fusing the feature with conventional ones can further reduce SVM models.

A. Mutual Feature

Recently, studies on quantifying connectivity between electrodes and regarding them as nodes have been actively conducted and applied for estimating diseases, such as epilepsy and schizophrenia [7], [8], as well as person authentication [9].

The basic analysis procedure is as follows. The relationship between the electrodes is quantified as a correlation value using EEGs from N electrodes; subsequently a square matrix of $N \times N$ is obtained. When assessing if there is a relationship between electrodes (brain regions), the quantified values are binarized using a threshold. The network metrics are calculated from the matrix.

In this study, mean phase coherence (MPC) was used to quantify the relationship between electrodes, and eigenvector centrality (EC) was used as a network metric.

1) MPC: Mean phase coherence (MPC) is a scale used to measure the degree of synchronization between signals [10]. The calculation of MPC is as follows: Let the two signals be $x_a(t), x_b(t)$ with the number of sampled data N, and their phases $\phi_a(t), \phi_a(t)$ are defined as:

$$\phi_a(t) = \arctan \frac{\tilde{x_a}(t)}{x_a(t)}, \tag{1}$$

$$\phi_b(t) = \arctan \frac{\tilde{x_b}(t)}{x_b(t)}, \tag{2}$$

where $\tilde{x_a}(t)$ and $\tilde{x_b}(t)$ are obtained using the Hilbert transform of x_a and x_b, respectively. The phase difference $\Delta\phi(t)$ at t is presented as:

$$\Delta\phi(t) = \phi_a(t) - \phi_b(t) \tag{3}$$

MPC is defined as the average phase difference given by

$$\text{MPC} = \left| \frac{1}{N} \sum_{t=0}^{N-1} e^{i\Delta\phi(t)} \right|. \tag{4}$$

Finally, by calculating the MPCs between all electrodes, a square matrix of $N \times N$ is obtained. In the matrix, the diagonal components are zero, assuming there is no influence between similar electrodes.

2) EC: EC is an index for evaluating the importance of each node (electrode) [11]. Let the component of ith column and jth row be $a_{i,j}$ in matrix $\boldsymbol{A}$, and the EC of ith column would be defined as:

$$C_i = \frac{1}{\lambda} \sum_{j=1}^{N} a_{i,j} e_j, \tag{5}$$

where λ is the maximum eigen value of the matrix $\boldsymbol{A}$ and $e_j (j = 1, \cdots, N)$ are eigen values.

3) Multi-dimensionalization: The EC is an index (feature) of one dimension. When using EC in pattern classification, it is necessary to multi-dimensionalize the EC. Thus, in addition to the multi-dimensionalization of nonlinear features [1], EEG is divided into several regions in the time domain or six bands in the frequency domain and EC is calculated in each region or band. ECs obtained in all regions or six bands are regarded as multidimensional features. In this study, $1 \sim 10$ divisions were examined in the time domain. In the frequency domain, six bands, δ, θ, α, low β, high β, γ, were examined. Subsequently, the verification results were compared, and the suitable division and domain was determined.

By using Euclidean distance matching rather than SVM, the verification performance using multi-dimensionalized features was evaluated. Table II summarizes the EERs of all electrodes and their mean when using each multi-dimensionalization. where T and F are the division methods in the time and frequency domains, respectively. The values in parentheses are the number of divisions.

When the number of divisions was changed in the time domain, EER remained almost unchanged. EER by six divisions in the frequency domain was slightly superior to that

TABLE II
EERS [%] OF ALL ELECTRODES AND THEIR MEAN WHEN USING EACH MULTI-DIMENSIONALIZATION

Method	Electrode														Ave.
	AF3	F7	F3	FC5	T7	P7	O1	O2	P8	T8	FC6	F4	F8	AF4	
T(1)	42.6	46.6	46.7	49.4	46.8	49.5	47.8	47.9	51.0	44.9	44.8	44.3	46.6	45.8	46.7
T(2)	43.8	47.3	45.8	48.6	47.0	48.1	46.3	45.1	47.8	46.5	47.3	43.9	45.9	45.8	46.4
T(3)	43.4	45.3	46.4	48.7	43.6	48.4	50.6	45.8	46.6	47.4	44.9	44.2	45.0	45.6	46.1
T(4)	43.6	45.6	47.5	50.3	48.8	48.4	51.8	46.4	47.4	48.8	47.4	43.6	45.6	45.3	47.2
T(5)	41.4	43.1	45.9	49.6	45.1	52.1	54.3	48.1	51.5	47.8	45.1	44.9	43.4	44.1	46.9
T(6)	42.6	46.9	47.9	47.3	45.4	49.5	53.6	47.3	49.9	49.1	44.3	44.8	44.3	43.4	46.9
T(7)	42.8	41.3	46.8	47.9	45.6	49.0	50.5	47.8	47.8	49.8	45.9	44.3	42.8	43.5	46.1
T(8)	45.6	44.0	45.8	50.0	40.7	50.0	53.1	46.6	47.9	50.7	45.7	43.8	43.4	42.4	46.4
T(9)	42.2	48.0	46.7	48.0	42.8	47.3	48.8	48.6	49.8	49.1	44.2	42.8	46.2	44.8	46.4
T(10)	44.2	45.4	46.7	47.9	45.6	50.9	47.7	45.6	48.5	48.5	45.6	43.8	46.1	43.9	46.5
F(6)	38.2	36.7	41.1	41.2	39.6	39.1	44.8	49.4	50.1	43.6	41.3	43.6	43.6	41.3	42.4

in the time divisions. Hence, we decided to apply multi-dimensionalization in the frequency domain, as follows.

Next, the multi-dimensionalized EC feature in the frequency domain was examined using SVM. The results are shown in III, wherein the results of the majority voting of all electrodes are also presented. Compared with EERs presented in Table I, it is confirmed that the verification performance of the EC feature is equivalent to that of conventional features.

4) Wavebands for Feature: Furthermore, we investigated the individualities of each band because induced responses were believed to be caused in some specified wavebands, as the hypersonic effect activated the α waveband. Particularly, the difference between variance in the data of all subjects (inter-class variation) and that of each subject (intra-class variation) was calculated. A difference of negative value suggests that intra-class variations is larger than the inter-class variations. Hence, the waveband with the difference is not suitable for verification.

The results are listed in Table IV, where the values are multiplied by 10^4 for convenience. Wavebands with positive values are suitable for verification. For instance, wavebands of more than five are shown in bold and are found for AF3, F7, F3, FC6, F4, F8, AF4. These electrodes are localized at the forehead. Thus, in future, the verification performance will be improved by using only these electrodes.

In contrast, yellow-colored cells indicate that the differences had negative values and are not suitable for verification. There were several yellow-colored cells in δ waveband. Thus, the verification performance was re-evaluated using five wavebands, excluding the δ waveband, and Euclidian distance matching. These results are presented in Table V. Compared to EERs using six wavebands, the average EER decreased, while others increased.

Despite reducing the number of feature dimensions, the verification performance was improved. Consequently, excluding the δ waveband was effective in improving the verification performance. In the following, we use five wavebands, excluding δ waveband, as an individual feature.

5) Normalization: The results presented in Table IV show that the EC variance for each waveband is not equivalent. If dimensions with wide variances are fused into a multi-dimensional feature, they will become dominant and impair the effect of multi-dimensionalization.

Thus, we proposed fusing ECs at five wavebands after normalization. By applying the min-max method to EC data for creating templates, all ECs were normalized within $0 \sim 1$. The verification performance was evaluated after using normalized ECs.

The results are summarized in Table VI. Compared to the results presented in Table V, all EERs were reduced. Consequently, the effect of normalizing ECs in wavebands was confirmed.

Further, the verification performance was evaluated using SVM. EERs are shown in VII, where EER by the majority voting of all electrodes is described. Compared to the EERs presented in Table III, although some EERs increased, the EER by majority voting decreased. Thus, the effects of excluding δ wavebands and normalization were confirmed.

IV. Verification Using Fused Features

In this section, we evaluate the verification performance of the multi-dimensionalized and normalized EC features fused with conventional features. However, the normalization of dimensions, which was essential in the previous section, was not introduced into the conventional features.

A. Applying Normalization to Conventional Features

Thus, normalization into the conventional features was introduced and their verification performances were evaluated.

The results are summarized in Table VIII For reference, the results without normalization are also shown. Features with (N) depict normalized cases. The verification performances of the conventional features were also improved using normalization, whereas the EER in ML increased.

B. Fusing Features

The normalized EC feature was fused with the normalized conventional features and used for user verification using SVM and majority voting. The number of SVM models was 84 (6 features$\times$14 electrodes).

The FAR–FRR curves are shown in Fig. 3, where a threshold in a horizontal axis is for determining the number of

TABLE III
EERs [%] BY MULTI-DIMENSIONALIZED EC FEATURE FOR EACH ELECTRODE

Electrode														Majority Voting
AF3	F7	F3	FC5	T7	P7	O1	O2	P8	T8	FC6	F4	F8	AF4	
27.8	30.5	27.1	26.9	31.7	29.7	27.6	27.3	32.6	30.9	26.8	28.1	31.2	27.0	3.9

TABLE IV
DIFFERENCE BETWEEN INTER-CLASS VARIATION AND INTRA-CLASS VARIATION

Waveband	Electrode													
	AF3	F7	F3	FC5	T7	P7	O1	O2	P8	T8	FC6	F4	F8	AF4
δ	4.4	-0.1	0.2	-0.8	-0.1	-1.6	-0.1	-0.4	2.1	-2.0	1.1	0.0	3.8	**6.3**
θ	**13.3**	2.5	**7.1**	0.8	0.5	0.6	0.3	0.1	1.6	0.6	**7.0**	**8.3**	4.6	2.2
α	**15.3**	**11.4**	**10.6**	**7.8**	1.7	2.6	2.1	2.7	-0.1	4.3	**7.4**	**8.7**	2.2	**6.8**
Lowβ	2.9	0.7	1.8	1.0	0.5	0.4	0.0	0.6	03	0.4	**6.5**	**8.3**	2.2	0.9
Highβ	1.0	0.6	1.4	1.0	0.4	0.9	0.6	0.9	0.0	-0.1	**12.7**	**10.8**	**6.7**	1.3
γ	0.1	0.1	0.4	0.1	0.3	0.4	0.2	0.2	0.3	0.1	2.4	3.2	3.3	-0.4

TABLE V
EERs [%] OF EC IN 5 AND 6 WAVEBANDS USING EUCLIDIAN DISTANCE MATCHING

Number of Wavebands	Electrode														Ave.
	AF3	F7	F3	FC5	T7	P7	O1	O2	P8	T8	FC6	F4	F8	AF4	
5	36.5	37.2	38.6	39.8	40.9	39.9	43.1	44.3	44.7	37.5	38.0	45.2	40.1	42.5	40.6
6	38.2	36.7	41.1	41.2	39.6	39.1	44.8	49.4	50.1	43.6	41.3	43.6	43.6	41.3	42.4

TABLE VI
EERs [%] USING NORMALIZED ECs AND EUCLIDIAN DISTANCE MATCHING

Electrode														Ave.
AF3	F7	F3	FC5	T7	P7	O1	O2	P8	T8	FC6	F4	F8	AF4	
32.0	39.8	37.3	34.8	39.6	38.5	37.9	41.6	37.3	33.8	34.3	37.6	33.9	36.8	36.8

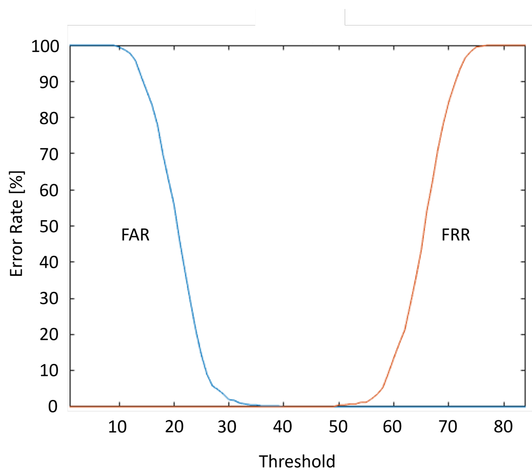

Fig. 3. FAR-FRR curves when fusing 6 features and using SVM and majority voting

majority. It is natural that EER = 0 % is achieved as the number of features increases. Additionally, the threshold range for achieving EER = 0 % expanded to 40 $\sim$ 49 and the number of thresholds considerably increased to 10 compared to 3 in conventional fusing of five features [2]. This is due to the introduction of the EC feature, which is independent of conventional features.

V. REDUCTION OF SVM MODELS

In this section, we investigated how many SVM models could be reduced while maintaining EER = 0 % using a method wherein the electrodes used are identical for all features [2].

Consequently, the number of SVM models reduced to 16 (4 features$\times$4 electrodes). Their combinations are shown in Table IX. In Ref. [1], EER = 0 % was achieved using the results from all features and electrodes (4 features$\times$14 electrodes=56). In Ref. [2], a new nonlinear feature was introduced and EER = 0 % was naturally achieved. In addition, the threshold range for achieving EER = 0 % was expanded. When using all features and electrodes, to increase the number of features leads to facilitating the verification and expanding the threshold range. However, the minimum number of SVM models while maintaining EER = 0 % was the same as before the introduction of the new feature [2]. To achieve EER = 0 % using the minimum number of SVM models, redundancy must be eliminated and equivalent verification performance achieved with a smaller number of SVM models (features and electrodes). This must be an efficient fusion, not just an increase in the number of features. The introduced EC feature was based on the information between the electrodes, which is different from and independent of the conventional spectrum

TABLE VII

EERS [%] OF NORMALIZED EC USING SVM

Electrode														Majority Voting
AF3	F7	F3	FC5	T7	P7	O1	O2	P8	T8	FC6	F4	F8	AF4	
27.1	30.5	25.9	27.1	27.6	26.6	28.1	25.2	29.0	27.9	30.1	28.3	28.3	29.0	2.5

TABLE VIII

EERS [%] OF NORMALIZED CONVENTIONAL FEATURES USING SVM.

Feature	Electrode														Majority Voting
	AF3	F7	F3	FC5	T7	P7	O1	O2	P8	T8	FC6	F4	F8	AF4	
SP	26.5	30.8	26.5	32.0	32.0	26.8	22.6	22.0	24.9	25.2	23.6	25.9	25.2	22.3	4.4
SP (N)	22.5	26.3	23.0	29.5	24.0	27.6	24.8	23.4	25.2	21.1	16.0	23.5	23.0	24.5	2.5
ML	30.7	32.3	26.1	28.7	31.1	30.0	34.3	29.3	33.5	30.9	29.5	30.7	32.1	28.3	3.1
ML (N)	30.4	30.7	25.8	28.3	28.8	30.2	29.9	29.0	29.5	31.8	28.1	31.2	30.5	27.6	4.3
SE	32.8	27.9	30.6	35.0	29.5	28.8	30.5	30.3	27.6	28.6	32.3	30.1	32.4	27.1	5.1
SE (N)	22.9	22.0	29.5	20.8	28.5	22.8	23.7	28.3	25.4	25.2	23.5	28.5	23.3	25.2	2.4
PE	35.5	32.8	30.0	32.8	30.2	27.1	29.7	29.0	34.3	29.3	31.2	32.8	30.0	32.1	4.3
PE (N)	25.7	27.7	26.6	32.0	30.7	28.5	28.5	27.8	30.2	27.3	27.3	30.0	28.5	29.0	3.0
FD	30.3	28.7	25.8	33.5	31.3	29.4	30.2	29.7	27.8	26.4	30.2	29.2	33.7	27.1	5.3
FD (N)	23.2	30.1	27.1	30.0	31.0	26.8	27.1	29.2	25.8	23.7	26.6	28.8	29.7	23.5	4.3

TABLE IX

COMBINATIONS OF FEATURES AND ELECTRODES WHEN USING 16 SVM MODELS

Features	Electrodes
SP, SE, PE, EC	AF3, F3, P7, O2
SP, SE, PE, EC	F7, P8, T8, F8

and nonlinear features. The minimum number of SVM models was 24 even when the number of features increased from four to five [2]. However, it could be reduced to 16 when EC was introduced. Despite the increase in the number of features, the minimum number of SVM models decreased. When fusing features, fusing independent features was effective.

Let us consider the reason for taking the majority vote in our daily lives as an example. In the majority vote, it is meaningless if several people have similar opinion. In extreme cases, if everyone has similar opinions at each judgement, it is considered as one opinion. This never degrades the judgement accuracy; however, it makes no sense to hear from many people. The majority vote is not to improve the accuracy of the judgement but to improve robustness. In the majority vote, it is important that numerous people have different opinions. If some people give a wrong opinion, others, who give the right one, prevent from making a wrong decision. It is important that individuals think independently without being influenced by others. From the above, in this study (where majority voting was performed at the decision level fusion), fusing independent features improved the robustness of the decision, thereby reducing the minimum number of SVM models.

VI. CONCLUSIONS

In SVM based person verification using evoked EEG by ultrasound, reducing the number of SVM models while maintaining EER = 0 % was challenging. Introducing a different feature from the conventional ones was expected to effectively solve the problem. Brain waves arise from the activity of several nerve cells that interact with each other. To represent such a relation as a feature, the EC feature was introduced. This was obtained from the information between the electrodes. However, the original EC was a one-dimensional feature. Hence, the EC was multi-dimensionalized in the time and frequency domains. By evaluating their verification performance, multi-dimensionalization in the frequency domain was confirmed to be effective. Furthermore, by investigating the relationship between the intra- and inter-class variations of EEG in the frequency domain, it was confirmed that excluding δ wave-band was effective in person verification. In addition, it was confirmed that normalization in multi-dimensionalization as regard introducing EC and conventional features was effective in improving the verification performance. Finally, it was confirmed that the minimum number of SVM models could be reduced to 16, while maintaining EER = 0 %. This suggests that fusing independent features in decision-making based on majority voting is effective.

Based on the aforementioned concept, we intend on introducing another feature. For example, finding out how statistical values in EEG, such as the mean, standard deviation, and median, can further reduce the number of SVM models while maintaining EER = 0 %.

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