Correlation Analysis of Features for Fusing in User Verification Using EEG Evoked by Ultrasound

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***Abstract*—In user verification using electroencephalograms (EEGs) evoked by ultrasound, an error rate of 0% was achieved. However, to achieve this, the classifiers for the number of features multiplied by the number of electrodes must be learned. Therefore, reducing the number of classifiers is crucial and must be achieved. This study confirmed that the random selection of features and electrodes facilitates further reduction in the number of classifiers. Random selection is equivalent to evenly selecting electrodes for each feature and electrode position. Consequently, the effectiveness of even selection was statistically confirmed. Furthermore, even selection resulted in the fusion of uncorrelated features. Thus, four statistical values of an EEG were introduced, and the effectiveness of fusing uncorrelated (independent) features was confirmed.**

***Index Terms*—biometrics, evoked brain wave, reduction of classifiers, statistical values of brain waves, support vector machine, ultrasound**

I. Introduction

Biometrics has attracted attention as one of the most convenient user authentication methods because it does not require the user to remember information such as a password or to carry identification documents such as an ID card. Generally, fingerprints, iris images, and facial images are commonly used in biometric authentication. However, these features are exposed, as they exit on the surface of the human body; therefore, they are susceptible to identity theft. Moreover, the use of such features in biometric systems assume one-time-only authentication wherein users are only authenticated when they start using the system. However, users can be replaced by others after authentication, which is referred to as spoofing; one-time-only authentication cannot prevent spoofing. Continuous authentication is necessary to solve spoofing problems.

Therefore, researchers have focused on using brain waves for continuous authentication, which are not exposed on the body surface and have high confidentiality. In particular, the use of brain waves evoked by ultrasound, which is imperceptible to humans was studied. Imperceptible stimulation does not hinder users working on a system; however, it induces responses in brain waves.

We proposed the use of a spectrum and three nonlinear values (sample entropy, maximum Lyapunov exponent, and permutation entropy) in brain waves as individual features and a support vector machine (SVM) as a verification method; they achieved a verification error rate of 0% by a majority vote of the results from all features and all 14 electrodes [1]. However, to achieve this, 56 (features$\times$14 electrodes) SVM models were required. Consequently, learning them requires a significant amount of time. Therefore, reducing the learning time (the number of SVM models) is a problem yet to be solved.

II. User Verification Using Brain Waves Evoked by Ultrasound

This section briefly outlines the findings of previous studies on user verification using brain waves (electroencephalograms, EEGs) evoked by ultrasound [1]–[4].

A. Conventional Studies

Sound with a frequency of over 20 kHz is referred to as ultrasound, and such sounds cannot be perceived by human beings. However, by presenting sounds comprising numerous ultrasounds, spectral elements in the α waveband (8-13 Hz) of an EEG can be activated [5]. It has been reported that such an effect is caused only by ultrasound [6], which has also been confirmed in [4]. Moreover, individual stimuli were prepared via the extraction of ultrasound elements from high-resolution sounds memorable to experimental subjects to enhance the individualities in induced brain waves. EEGs were measured when stimuli were presented to the corresponding subjects. From the measured EEGs, individual features were extracted and compared with templates that are features and have been enrolled in an authentication system in advance to determine whether the subjects were genuine. A schematic of the verification system is displayed in Fig. 1. In this system, an applicant who wants to use applications in a system specifies or claims that he/she is a regular user; his/her features are then compared with a template of the specified user. Consequently, the genuine nature of the user is verified. For verification, SVM, which is a learning-based two-classifier, was used. Furthermore, a spectrum (SP) and four nonlinear values (sample entropy (SE), maximum Lyapunov exponent (ML), permutation entropy (PE), and fractal dimension (FD)) of the EEG were used as individual features. The number of dimensions of the spectrum feature was reduced to 24 by dividing the frequency band into several regions and averaging

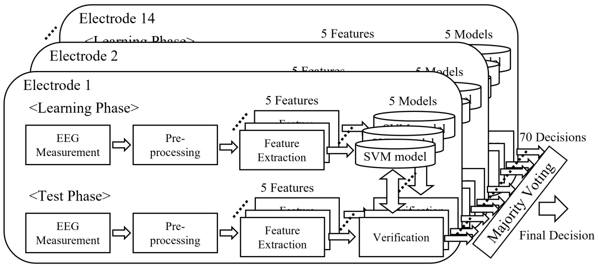

Fig. 1. Schematic of the verification system

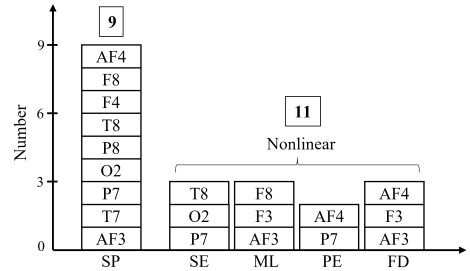

Fig. 2. Features and their numbers obtained using the random reduction method

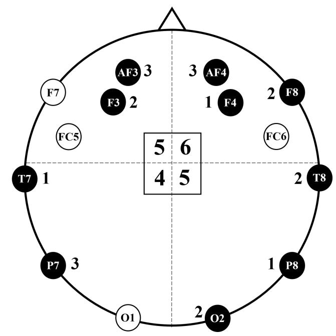

Fig. 3. Electrode positions obtained using the random reduction method

the spectral elements in each region. Originally, the dimension of nonlinear features was one; however, it was increased by division into the time and frequency domains. In the time domain, EEG data were divided into several regions, a nonlinear value was extracted from each region, and the obtained values were used as a feature. By contrast, in the frequency domain, the waveband (0–43 Hz) of the EEG was divided into δ, θ, α, $low\beta$, $high\beta$, and γ wavebands. Subsequently, the nonlinear values were extracted from these wavebands. The number of dimensions of all features was reduced to three via principal component analysis (PCA). Epoc+ produced by Emotive with 14 electrodes (AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, and AF4) was used to measure the brain waves. The number of experimental subjects was ten. Subsequently, verification was performed for each feature and electrode, and the final decision (fusion) was made by majority voting of all verification results, resulting in an equal error rate (EER) of 0% [1]. Verification was performed by comparing the obtained final score with a threshold, that is, the number of majorities. However, there are misjudgments, that is, regular users are rejected or nonregular users are accepted. These rates are referred to as the false rejection rate (FRR) and false acceptance rate (FAR) and have a trade-off relationship. Additionally, when the FRR is equal to the FAR, the rate is referred to as EER; the smaller the EER, the better is the performance.

Table I lists the EERs when using each individual feature and fusing the five features listed [1], [3].

TABLE I
EERs (%) WHEN USING EACH INDIVIDUAL FEATURE AND FUSING FIVE FEATURES [1], [3]

SP	ML	SE	PE	FD	Fusion
4.4	3.9	5.1	4.3	5.3	0.0

B. Reduction of the number of SVM Models

However, 70 (5 features $\times$ 14 electrodes) SVM models are required to achieve an EER of 0%. SVM is a learning-based two-classifier (one versus one verification); therefore, an SVM model is learned using the data of two users, one is as a genuine user and the other is as an imposter of the user. When the number of regular users is m, $m \times (m-1)$ SVM models are required for each feature and electrode. In total, $70 \times m \times (m-1)$ SVM models are needed, and they require a significant amount of computational time for learning. Therefore, reducing the number of SVM models remains an urgent problem.

In the following sections, to consider the independent number of SVM models for the number of users, the number of SVM models is considered as one for each feature and electrode.

1) Conventional Reduction Method: The most accurate method involves the evaluation of the verification performance under all combinations of features and electrodes; however, this is impossible because significant learning time is required for learning $70 \times m \times (m-1)$ SVM models.

In Ref. [2], under a condition where identical electrodes were used for each feature, the extent to which the number of SVM models could be reduced was examined. In total, 56 (4 features$\times$14 electrodes) SVM models were required. Consequently, it was determined that the number of SVM models could be reduced to 24 while maintaining an error rate of 0%. In Ref. [3], another nonlinear feature, the fractal dimension, was introduced, and an attempt was made to further reduce the number of SVM models using five fused features under the same condition; however, the required number of SVM models was still 24.

2) Random Reduction Method: The number of SVM models was reduced to 24; however, it was not guaranteed to be minimal. Thus, the verification performance was examined via the random selection of features and electrodes.

Consequently, we identified a combination wherein EER = 0% was achieved using 20 SVM models. However, we are

TABLE II
EERs (%) OF A STATISTICAL FEATURE USING SVM

AF3	F7	F3	FC5	T7	P7	O1	O2	P8	T8	FC6	F4	F8	AF4	Majority Vote
27.2	22.7	25.2	17.5	20.6	22.8	24.2	19.2	15.8	25.7	30.4	29.7	29.5	23.0	2.5

uncertain if this is the smallest; further reduction may be possible. Figure 2 illustrates the features and their numbers. The number of spectrum features and nonlinear features is given by the numerical values surrounded by a square. Indeed, the total is 20. The electrode positions are depicted in Fig. 3, where black and white circles indicate used and unused electrodes, respectively. The value for each electrode represents the number of features used for the electrode. The total is 20. Additionally, the brain region was divided into four quadrants, as illustrated in the figure, and the number of features surrounded by a square in each quadrant is presented.

C. Uniform Selection Method

The results illustrated in Fig. 2 indicate that the number of spectrum features used is equivalent to that of nonlinear features. Moreover, it is evident that electrodes were selected almost uniformly from the four quadrants. Based on these findings, we hypothesize that uniformly selecting features from the spectra, including nonlinear features, and uniformly selecting electrodes from the four quadrants may be effective for reducing the number of SVM models.

To validate this hypothesis, the average EER over 1000 evaluations in the case of uniform selection was compared with that in the case of nonuniform selection. To equalize the conditions, the number of SVM models was set to 20. In the case of uniform selection, from the 20 electrodes, 10 were used for the spectrum feature, and the remaining were used for nonlinear features. Furthermore, four nonlinear features were randomly selected. Thereafter, five electrodes were placed in each quadrant. In the case of nonuniform selection, features were only selected from nonlinear features, and electrodes were selected from upper two quadrants. For reference, the random reduction (selection) method presented in the previous subsection was evaluated under the condition that the number of SVM models was 20.

The average EERs over 1000 evaluations for the uniform, random, and ununiformly selection methods were 1.51, 1.66, and 2.14, respectively. It is evident that the average EER of uniform selection was lowest, whereas that of nonuniform selection was highest. Therefore, the proposed uniform selection effectively reduces the number of SVM models. The random selection method is superior to the nonuniform selection method; however, it is inferior to the uniform selection method.

III. Statistical Value of Brain Waves

Uniform feature selection corresponds to the selection of independent features. It has been reported that verifiers must be sufficiently different (various) to improve the verification accuracy in majority voting [7].

In this section, the number of SVM models is further reduced by introducing an independent feature from the conventional ones.

A. Verification Performance

The introduced feature comprises statistical values of the brain waves. Specifically, the mean, standard deviation, median, and average of the local maxima were extracted from an EEG. The spectrum feature is a distribution of EEG spectral elements, and the nonlinear features represent the nonlinearities of an EEG; therefore, the introduced feature based on statistical values is independent of conventional features. For multi-dimensionalization, four statistical values were combined into one feature. However, each value must be normalized before combining the values. If there is a large difference between the statistical values, the large values exhibit dominant behavior in a combined feature, and the effect of multi-dimensionalization is lost. In this study, the min–max method was employed for normalization. Each statistical value was normalized to $0 \sim 1$.

The verification performance of the statistical feature was evaluated. The EERs at 14 electrodes are listed in Table II. In majority voting, the EER was 2.5% in the case of the new feature, whereas those of each conventional feature were in the range of 3%∼5%. Thus, the verification performance was equal to or better than that of the conventional method.

B. Verification Performance Evaluation by Uniform Selection

We examined whether the number of SVM models can be further reduced by fusing independent features. This was done by the fusion of the introduced statistical feature with conventional spectrum and nonlinear features and use of the uniform selection method proposed in Sect. II-C.

The conditions are identical to those provided in Sect. II-C. The number of SVM models was 20, and the average EER over 1000 evaluations was used as an evaluation index. Combinations of two features from the three were examined; these were (1) spectrum and nonlinear, (2) spectrum and statistical, and (3) nonlinear and statistical features. Additionally, (4) represents the case involving the fusion of all three features. One nonlinear feature was randomly selected from the four nonlinear features.

TABLE III
AVERAGE EERs (%) BY UNIFORM SELECTION

	Number of features	Average EER
(1)	10+10	1.52
(2)	10+10	1.08
(3)	10+10	0.86
(4)	7+6+7	0.80

TABLE IV
FEATURES AND ELECTRODES WHEN USING 14 SVM MODELS

	AF3	F7	F3	FC5	T7	P7	O1	O2	P8	T8	FC6	F4	F8	AF4	Subtotal
Spectrum	0	0	1	0	0	0	0	1	0	1	0	0	1	1	5
Nonlinear	0	0	1	0	1	2	0	0	0	1	0	0	0	0	5
Statisical	1	0	1	1	1	0	0	0	0	0	0	0	0	0	4

The results are presented in Table III. The highest verification performance was obtained when three features were uniformly fused. In evaluations using individual features, the verification performance of the statistical feature was highest, which was followed by that of the nonlinear feature. Therefore, if two features are combined, fusing nonlinear and statistical features of (3) could most likely provide the best performance; using the statistical feature of (2) might be the second best, while fusing the spectrum and nonlinear features (not fusing the statistical feature) of (1) might be the worst.

If the verification performance during the fusion of features is determined by that of each feature, those of (2) and (3), where 10 statistical features with the highest verification performance were used, should be higher than that of (4), where seven statistical features were used; however, the result obtained was opposite. Although the number of statistical features that achieve the highest verification performance was reduced from 10 to 7, the verification performance for the fusion of three types of features was higher than that for two types of features. This suggests that fusing uncorrelated features results in a higher verification performance.

C. Reduction of the Number of SVM Models

In the case of (4) in the previous subsection, the number of SVM models is further reduced. The smallest number of SVM models was 20, which was obtained using the random reduction method detailed in Section II-B2. Accordingly, the number of SVM models was sequentially reduced starting from 19 by adjusting the numbers of spectrum, nonlinear, and statistical features to be uniform and by investigating whether EER = 0% could be maintained.

It was found that EER = 0% was achieved even when the number of SVM models was reduced to 14. Table IV lists the combinations of the features and electrodes. The used and unused electrodes are denoted as 1 and 0, respectively. The number of features used is presented in the subtotal column. Of the existing four, the nonlinear feature to be used was dependent on the electrode. When fusing the two types of features, the smallest number of SVM models was 20. The number was reduced to 14 by increasing the number of types to three. Thus, the fusion of uncorrelated features is effective for reducing the number of SVM models, which in turn improves the verification performance.

IV. CONCLUSIONS

User verification using EEGs evoked by ultrasounds achieved an EER of 0% when a final decision was made based on majority voting of the verification results by SVMs using all features for all electrodes. However, SVM is a learning-based classifier; therefore, learning numerous SVM models required significant computational time, and hence, reducing the number of SVM models was crucial.

In this study, a combination of features and electrodes that achieved EER = 0% with 20 SVM models was determined using a random reduction method. Regarding the result, it can be proposed that reducing SVM models via the uniform selection of features from the spectrum and nonlinear features, and uniform selection of electrodes from those in four quadrants of electrode position was possible. The concept was confirmed to be effective by examining the verification performance in 1000 selected combinations of features and electrodes compared with those selected ununiformly and randomly. Furthermore, this concept led to another, which involved using features that were uncorrelated with each other. Accordingly, a statistical feature that is independent of the conventional spectrum and nonlinear features was introduced. The verification performance of fusing the statistical feature with conventional features was evaluated by adopting a uniform selection method, and the effect of fusing uncorrelated features was confirmed. Moreover, the reduction in the number of SVM models was examined using the random reduction method while maintaining an EER of 0%; consequently, the number of SVM models was reduced to 14.

In future, other features that are independent of the features used in this study, such as mutual features between electrodes, will be introduced to further reduce the number of SVM models.

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