# Biometric authentication using evoked potentials stimulated by personal ultrasound

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***Abstract*—In recent years, biometrics such as fingerprints and iris scans has been used in authentication. However, conventional biometrics is vulnerable to identity theft, especially in user management systems. As a new biometric without this vulnerability, we focused on brain waves. In this paper, we show that individuals can be authenticated using evoked potentials when they are subjected to ultrasound. We measured the electroencephalograms (EEGs) of 10 experimental subjects. Individual features were extracted from the power spectra of the EEGs using the principle component analysis and verification was achieved using the support vector machine. We found that for the proposed authentication method, the equal error rate for a single electrode was about 22-32 %. For a multi-electrode, the equal error rate was 4.4 % using the majority decision rule.**

***Index Terms*—biometrics; brain wave; EEG; ultrasound; evoked potential**

## I. Introduction

Biometrics has been studied as a method of authenticating people [1]. Modalities such as fingerprints and facial images have already been used in various applications. However, conventional biometrics is used in one-time-only authentication. Therefore, especially in user management systems, conventional biometrics have a vulnerability that unregistered users can access the system after a registered user has logged in. An effective way to prevent this type of identity theft is to implement continuous authentication. In this type of authentication, the biometric data should be presented unconsciously because the system should not be inconvenient to use. Also, conventional biometrics, such as fingerprints and facial image recognition, is based on information exposed on the surface of the body, so that there is a risk of identity theft. For example, a prosthetic produced from stolen biometric data could be used for authentication. Therefore, we focus on brain waves measured by electroencephalography (EEG), which records the electrical signals produced by an active human brain. The signals are always produced as long as the person is alive, so this information can be measured continuously. Besides, since brain waves are detectable only when the person is wearing a brain-wave sensor, it is not possible for others to steal the data covertly.

There are two types of brain waves. Spontaneous brain waves always occur and induced ones are evoked by any thoughts or external stimuli. We studied biometric authentication using spontaneous brain waves, but the accuracy was not sufficient [2]. Therefore, here we focus on the uniqueness of the induced brain waves evoked when someone is presented with sound stimuli. However, since audible sound stimulation is a conscious activity for the user, it is unsuitable for continuous authentication. The stimuli must be unrecognizable to the user. Therefore, we focus on ultrasounds. Ultrasounds are high-frequency sounds that are inaudible to human beings. The user is not distracted by this stimulus.

In recent years, to use the brain wave as biometrics has been actively studied [3], [4], [5]. However, almost all of them evaluated authentication performance using spontaneous brain waves when experimental subjects are relaxed with eye-closed. Such a situation is not assumable in practical applications. There are some researches which used visual stimulation [6]. However, visible stimulation is not suitable for continuous authentication. The idea to use induced brain waves evoked by inaudible stimulation as biometrics is our original.

In [9], we confirmed that the induced brain waves were evoked by the ultrasounds, which were common stimulation to all experimental subjects. In this paper, we introduce personal stimulation which is an ultrasound in a music which is memorable to each experimental subject. The personal stimulation is expected to induce more different response in a brain wave and improve authentication performance. We measure the EEGs of the subjects when personal ultrasonic stimulation are presented and examine authentication performance using a support vector machine (SVM) for each electrode. Furthermore, to improve the performance, the SVM results are integrated on the basis of the majority rule.

## II. Personal Ultrasound Stimuli

The frequency range audible to human beings is generally from 20 Hz to 20 kHz, and sounds beyond 20 kHz are inaudible and called ultrasonic. However, an evoked potential can occur when audible sounds are presented with ultrasounds [7]. This is called the hypersonic effect. It is known that the $\alpha$ band of brain waves is activated 20 s after the start of stimulus presentation. On the other hand, there is also a report that a similar phenomenon is caused only by ultrasounds [8], [9].

Stimuli that mean something to the person produce different evoked potentials compared with random stimuli [10], [11].

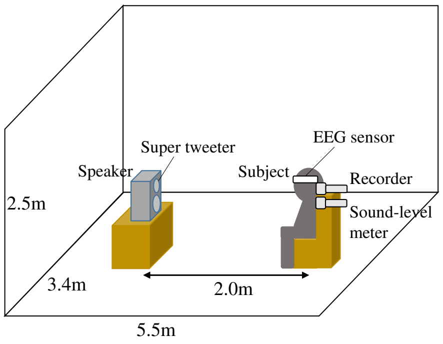


Fig. 1. The experimental environment.

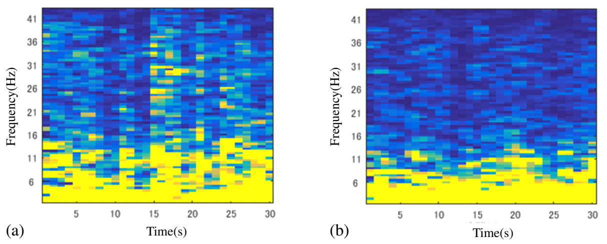


Fig. 2. Evoked responses for (a) personal ultrasonic stimulation and (b) unrelated ultrasonic stimulation.

In this paper, we use sounds that mean something to the individuals in order to generate more individuality in the evoked potentials. However, as far as we are aware, all the research into personal sound stimuli have used only audible sound. It is unknown what type of potential is evoked when personal stimuli are presented as ultrasound.

Therefore, we examined the EEGs of individuals when they were presented with personal ultrasound stimuli. For this, we used a memorable music for each individual. The memorable music was selected using a questionnaire to experimental subjects. The ultrasonic stimuli were made by filtering audible elements from high-resolution sounds, of which sampling rate was 96 kHz, and bit depth was 24 bits. The frequency range of the speaker used for stimulus presentation was 48 Hz to 100 kHz.

Figure 1 shows the experimental environment. We placed a recorder to confirm that the ultrasound stimuli were actually presented. The sound level meter was for adjusting the levels of the original sounds. To prevent artifacts due to eye blinking or other movement, the lights in the room were turned off and the subjects were instructed to keep still and to close their eyes. The brain-wave sensor was EMOTIVE's EPOC + premium, which had 14 electrodes and the sampling frequency was 128 Hz.

Figure 2 compares the evoked potentials caused by (a) personal and (b) unrelated ultrasonic stimulation. The EEGs from the F3 electrode on the right frontal lobe were processed with a fast Fourier transform (FFT) to obtain an EEG power spectrogram. This was normalized using the content ratio, which is the proportion of power spectral elements in a certain frequency band to that of all frequency bands. We identified evoked potentials in high-frequency bands, such as the $\beta$ and $\gamma$ bands (13-42 Hz), with personal ultrasonic stimulation but not with an irrelevant stimulus.

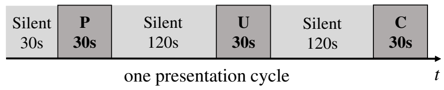


Fig. 3. A typical order of sound stimuli.

## III. Verification Performance

We created a verification system using SVM models and evaluated its performance. For this evaluation, we measured EEGs from 10 subjects 10 times.

### A. Measurement conditions

EEGs were measured in the same environment as Sect. II, and we created the ultrasound samples in the same way. Note that we presented three types of stimulation: personal stimuli created from high-resolution sounds selected by subjects, stimuli relevant to other subjects, and a stimulus common to all subjects. The stimuli relevant to other subjects were used to see what would happen with an identity imposter. The common stimulus was used for comparison. Figure 3 shows a typical order of sound stimuli. Each subject underwent 10 measurements, and the order of the stimuli was changed for each measurement.

### B. Pre-processing of EEG data

First, from the measured EEG data, we extracted a section of data for the 30 s from the start to the end of each stimulus. Then, the trend was found for each section using the approximate straight line calculated using the least-squares method. On the basis of visual observation, the sections that were regarded as being obtained by failure measurement were excluded from the database. Finally, the database consisted of 80 data (10 subjects $\times$ 8 sections).

### C. Feature extraction

The feature used for authentication was based on the power spectrum calculated by FFT. The window function was the Hamming window. The power spectrum obtained (960 elements) was divided into 24 partitions, and the average value was calculated for each partition. As a result, 40 average values were obtained, which were processed by principal component analysis (PCA). By extracting the top three principal components, the number of dimensions was reduced to 3, which were used as individual features. The cumulative contribution was 80-90 %. We also found that applying the log scale to the power spectrum improves the performance at some electrodes. As observed in Fig. 2, there are evoked responses in the higher frequency band, but they are weaker than those in the lower frequency band, so that it is hard to extract them using a normal power spectrum. The logarithmic transformation enhances weak power spectral elements while it suppresses large ones.

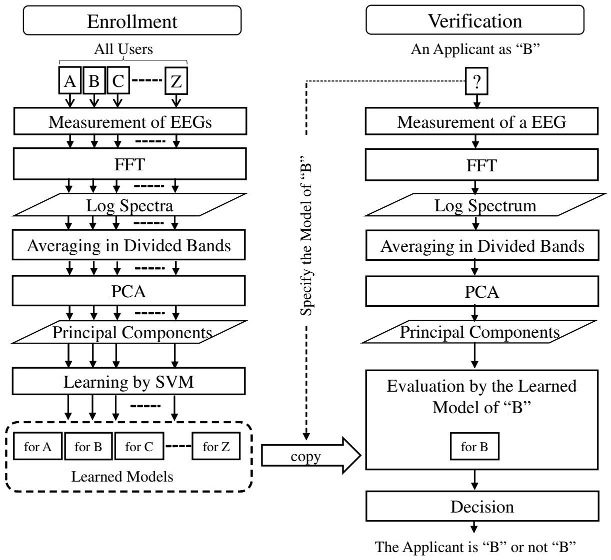


Fig. 4. Verification procedure.

### D. Classifier

In this study, we assume verification of users and used SVMs for the verification. The verification procedure is shown in Fig. 4. In the enrollment phase, we created a one-vs-all SVM model to distinguish a user from other ones. In the verification phase, an applicant is judged whether he/she is genuine by a SVM model relevant for him/her. When learning each SVM model, four genuine data and four imposter data were used. The remaining data were used to evaluate the method. The genuine data were the EEG data when personal stimuli were presented to genuine users. The imposter data were EEG data when the personal stimulus of each genuine user was presented to other ones. We used the tool kit SVM-light [12] developed by Cornell University to build the SVM models. To create an SVM model, it is necessary to set kernel functions (linear kernel, polynomial kernel, or radial basis function kernel) and parameters. We found the optimal settings with a grid search.

### E. Evaluation

In an authentication system, the false acceptance rate (FAR) that is the rate of accepting imposters and the false rejection rate (FRR) that is the rate of rejecting genuine users are used and there is a trade-off between these rates. Therefore, for performance evaluation, we use the equal error rate (EER), where FAR = FRR. In addition, in order to reduce the influence of selecting data for enrollment and verification stages, we introduce cross-validation into the selection based on a random sampling method. The number of random sampling is 10.

Table I shows the EERs for the 14 electrodes. Their averaged value was 26.2 %. The best performance was EER = 22.0 % for o2 and the EERs of o1 and o2 are relatively smaller than others. The o1 and o2 are located on the occipital lobe which mainly processes visual information. On the other hand, the

TABLE I
EERS (%) FOR THE 14 ELECTRODES.

| Left | | | | | | |
|---|---|---|---|---|---|---|
| AF3 | F7 | F3 | FC5 | T7 | P7 | O1 |
| 26.5 | 30.8 | 26.5 | 32.0 | 32.0 | 26.8 | 22.6 |
| Right | | | | | | |
| O2 | P8 | T8 | FC6 | F4 | F8 | AF4 |
| 22.0 | 24.9 | 25.2 | 23.6 | 25.9 | 25.2 | 22.3 |

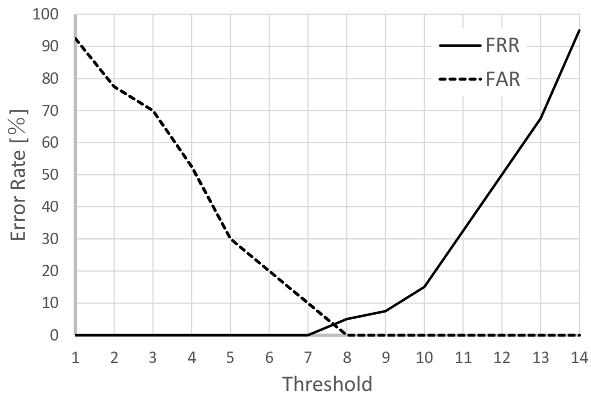


Fig. 5. Error rate curves when using the majority rule.

EERs of electrodes (o2, P8, T8, FC6, F4, F8, AF4) in the right hemisphere are relatively smaller than those (o1, P7, T7, FC5, F3, F7, AF3) in the left hemisphere. There is a knowledge that the right hemisphere is central for recognizing faces of known persons. The personal ultrasounds were also known to subjects. Such a condition might influence the above results but further considerations are necessary.

### F. Majority decision using multiple electrodes

The EERs obtained by individual electrodes are inadequate. Therefore, we introduce multichannel judgment using the results from all electrodes. There are some approaches to fuse multiple modalities for authentication: input-level fusion, feature-level fusion, score-level fusion, and so on. In this paper, we introduce the score-level fusion into the verification procedure as shown in Fig. 4 since it is easier to implement compared with other fusions, In score-level fusion, each modality is separately judged, and a final judgment is based on a logical operation of all judgment results. In this study, the most common verdict among the 14 electrodes (genuine or imposter) was adopted as the majority decision. Figure 5 shows the error rate curves when using the majority rule. The horizontal axis (threshold) is the number of electrodes needed to determine that the applicant is genuine. As a result, the EER was 4.4 %.

For your information, the EERs are 5.9 % and 11.0 % when using the results from electrodes in the right hemisphere and the results from top three electrodes, respectively. The verification performance was not improved. In this case, the robustness increase by using more electrodes may gain an advantage over the accuracy improvement by selecting electrodes with better performance.

## IV. CONCLUSION

The purpose of this study is to authenticate individuals using potentials evoked by ultrasound. We created personal stimuli using memorable sounds. In this paper, we created a verification system and evaluated its performance.

The feature used in the proposed system is the frequency power spectrum. However, since low-frequency components are more dominant than high-frequency ones in an EEG, it is hard to incorporate the potentials evoked by ultrasounds in feature extraction. Therefore, we introduced a logarithmic scale. SVM was used as the classifier. However, in SVM, if the number of features is larger than the number of learning data points, there is a risk of over-learning. For this reason, the dimension of the feature vector space was reduced to 3 using the average spectrum and principal component analysis. Finally, the verdicts for all electrodes were integrated and the final verdict was the majority decision. As a result, the EER of the proposed system was 4.4 %.

EER when using fingerprints as biometrics is less than 1 %; therefore, EER of 4.4 % is not great achievement. However, it is very important that biometric authentication using evoked potentials stimulated by personal ultrasound is feasible for the first time.

To improve performance further, we are planning to investigate better ways to integrate the results of the electrodes. In addition to score-level fusion, we will consider feature-level fusion. Furthermore, we need to measure the brain waves of more subjects. In addition, although music memorable to the users was used as the personal stimuli in this study, there is a risk that the same piece of music may be selected by some users. Therefore, we are considering using highly personalized stimuli, such as the person's name.

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