A Biometric-based Covert Warning System Using EEG

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Abstract

Covert Warning (CW) is a feature that allows an authorized person, when coerced, to secretly send out a warning message along with his/her personal identification. This concept was implemented in an identification system in this paper using brainwaves, i.e. Electroencephalogram (EEG), as the biometric modality. Our contribution is that we demonstrated clenching teeth producing robust signals, and proposed it as a novel CW solution to portable EEG-based biometric systems. When the volunteers were properly instructed, the CW messages were detected perfectly (i.e. 100% detection rate) in the new system. Meanwhile, the new system maintained its relatively high personal identification rate, when compared with the system without the CW feature.

1. Introduction

Covert Warning (CW) is a feature that allows an authorized person to secretly send out a warning message when he/she is coerced to pass a personal identification and authorization system. The important thing is how to do it unnoticeable and automatically. A simple implementation of the CW concept in a password-based authorization system can be, for example, to have two passwords for the system, with one as a normal password, and the other as a password associated with warning. However, password-based authorization system has its intrinsic weaknesses [1, 2], which can be addressed by personal identification systems based upon various human biometric modalities, such as fingerprint, face, and iris. Biometric-based personal identification systems constitute a strong and permanent "link" between a person and his/her identity, and these traits cannot be easily lost, forgotten, shared, or forged, which provides more security than password/token-based systems. Therefore, a biometric-based identification system combined with the CW feature would further enhance the system security [19]. For example, voice system can include panic words in the response, fingerprint systems can present multiple fingers and the multi-factor solution can combine the duress password/pin with biometrics.

This paper proposed an EEG-based personal identification system with a CW feature, since the approach to imbed extra information in more conventional biometric modalities (e.g. voice, fingerprint, face, and iris) is easier to be forged. EEG is a validated effective biometric modality with distinct advantages [3-16]. First, the active EEG must come from a living individual with a normal mental state. Second, EEG is hard to mimic. Finally, nowadays, advances in EEG recoding hardware dramatically simplified EEG acquisition procedure, and reduced the cost. In the past five years, EEG gradually emerged as a promising biometric modality to enhance the anti-spoofing capability of the existing biometric systems, and demonstrated some unique advantages in applications with high security requirements. That is, EEG has been recognized as an appealing complementary modality to the existing biometric modalities [3, 4, 10, 14-16].

An EEG-based personal identification system with the CW feature is implemented based upon a validated portable EEG-based identification system we developed in the past two years. In this new system, a robust CW message is proposed as three short bursts of muscle signals, which can be covertly produced by clenching the teeth three times during EEG recording. Adding CW message in EEG by clenching teeth is an innovative and convenient approach to imbed CW message in EEG signals. It is easy to be done covertly, and the generated CW message is so that it can be robustly detected. Experimental results show that, when the volunteers are properly instructed, the CW messages are detected perfectly (i.e. 100% detection rate) in the new system. Meanwhile, the new system maintained its relatively high personal identification rate, when compared with the system without the CW feature.

The rest of the paper is organized as follows. In section 2, an EEG-based personal identification system is described. Section 3 details an updated EEG-based personal identification system enhanced with a CW detection mechanism. Section 4 evaluates the enhanced EEG system with real world EEG data. Finally, conclusion is drawn in Section 5.

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2. EEG as a biometric modality

2.1. Related effort

Using EEG signals as a biometric modality to identify or authenticate individuals is relatively a novel method as compared to the other biometrics. There were several studies proposed to use brain waves, e.g. EEG, as a biometric modality in the past decade [3-16]. Related research can be classified into two categories, EEG-based [3-8] and Visual Evoked Potential (VEP)-based methods [9-13]. Poulos et al [3] used autoregressive (AR) modeling of EEG signals and Learning Vector Quantization network to classify an individual as distinct from other individuals with 72~80% success. In [4], AR modeling with discrimination analysis was applied to identify individuals with classification accuracy ranging from 49% to 85% depending on the model order. Markus et al. [5] validated the test-retest reliability of resting EEG spectra as a statistical signature of people using the generalized linear model (GLM). Chisei et al. [6] employed the variance of spectral power combined with the non-dominant region of the power spectra as the feature vector used in personal verification. A user claimed a unique identifier and then the EEG was measured. They obtained the maximum accuracy of 79% on a dataset of 23 subjects. Palaniappan [7] proposed a two-stage biometric authentication method using the mental task EEG data. The false reject rate ranged from 1.5%~0%, and the false accept rate was 0% for all 5 subjects. Brigham [8] investigated the potential of using electrical brainwave signals during imagined speech to identify which subject the signals originated from. VEP-based methods processed the responses when some mental tasks or stimuli were applied to the subject. In another paper, Palaniappan [9] analyzed the potential of dominant frequency powers in gamma band VEP signals as a biometrics. For 102 subjects, an average classification rate of 98.12% was achieved. Marcel [10] proposed the use of statistical framework based on Gaussian Mixture Models and Maximum a Posteriori model adaptation on motor imagery EEG signal.

Nearly all the published EEG data were collected by expensive medical equipments. With the advances in the development of EEG recording technology, portable EEG recording systems using dry electrodes without preparing human scalp before recording, were developed as the peripheral equipments to allow people to use their EEG to play computer games or control toys [17]. Su et al. [14-16] proposed to apply the single channel dry electrode portable EEG equipment for personal identification. Based on a well-designed EEG recording experiment, they demonstrated that the single channel EEG signal recorded by the portable equipment can be used for personal identification with average accuracy of 97.5% on a dataset of 40 subjects.

2.2. Building the EEG template database

All EEG signals used in this paper were recorded using HXD-I portable equipment[1] (see Figure 1), which collects signals from FP1 electrode without requiring any skin preparation or conductive pastes. The sampling rate is 200Hz, and the reference sensors are placed at both earlobes. Therefore, it is quite unobtrusive, fast and easy to place, which makes it possible to use EEG in personal identification.

Figure 1: Portable EEG recording equipment.

The EEG signals in the database including 40 volunteers (29 male and 11 female) were those collected one year ago described in [14]. The data were recorded in a quiet, normal temperature environment with daylight. After a standard instruction was read, a segment of five-minute restful EEG signal was recorded when the volunteer kept his/her eyes close and sat on a comfortable sofa. Each volunteer's EEG was recorded in two separate days, which was considered as two periods. In one period, a cup of pure water was drunk. In the other period, the same amount of coffee was drunk at the same time of the day. Here we use coffee to represent a diet that potentially has a big impact on EEG. In each period, 6 EEG sessions were recorded at different time points, including a pre-dose session and five post-dose sessions. Immediately after the pre-dose EEG recording session was finished, the volunteer was instructed to drink a cup of coffee or water, i.e. conducting the drinking event. Then, five post-dose sessions were recorded at 0.5 hour, 1 hour, 1.5 hours, 2 hours, and 2.5 hours after the drinking event. EEG recording was executed purposely at different time of day with different diet is to introduce more person's circadian and diet effect on EEG signal. Each five-minute recording is an EEG event here. There are totally 480 EEG events (i.e. 1 event per EEG session, 6 sessions per period, 2 periods per subject, and 40 subjects) stored as templates in our application.

2.3. Feature set and classifier

Through data collection, the information related to each person was constructed and stored in the database as the gallery template. And then the identification results were obtained by matching the probe and galley. The whole identification procedure can be viewed as a machine learning problem, in which feature extraction and classifier

[1] http://www.easymonitor.com.cn/

are two key points.

Unlike in [14], autoregressive (AR) coefficients were discarded here for they have a little contribution to the whole system performance, the performance of our system only decrease 1.5% without AR coefficients, but adding the burden of computation. Power Spectrum Density (PSD) via Burg's method [18] with full frequency range is only used as feature set. Because the PSD below 4Hz is frequently contaminated by ocular artifacts, and the PSD above 33Hz is affected by a system embedded specific notch filter, we finally decided to incorporate the PSD at certain frequency range from 5 to 32Hz into our feature set. Each frequency bin was presented by four points and concatenated to form the feature vector, whose dimension is 108 (27 frequent bins with four points per frequency).

Figure 2 shows the PSDs of two randomly picked volunteers, denoted by blue and red lines respectively. Each volunteer has 12 EEG events. It is obvious that different people present discriminant PSD properties.

Classification of the subjects was performed by using dual space LDA based on simple regularization and K-nearest neighbor (K-NN).

2.4. Recording factors evaluation

Some researchers questioned if EEG can be a practical biometric modality because the EEG signals are determined by many factors, such as diet, time of day, etc., and it is impossible to fully control all these factors in a practical personal identification system. The mechanism of how these factors affect the performance of an EEG-based biometric system was discussed in [16]. Considering that the diet and personal circadian are crucial factors affecting the EEG signals compared to other factors, the quantitative measures of the diet, person's circadian and both the diet and person's circadian effects on the EEG-based personal identification accuracy were addressed. Their experimental results showed that the EEG recording factors would diminish the accuracy of EEG-based personal identification to a certain extent. However, if more comprehensive training sets (like diverse samples) were included, a better system performance would be guaranteed. This study offers an instructive method on how to build representative training sets in real system building.

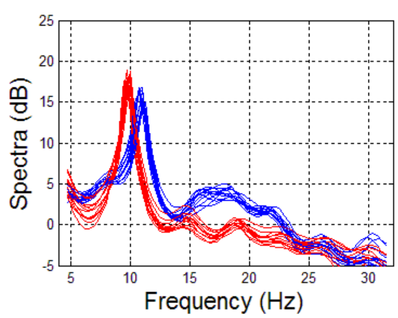


Figure 2: PSDs of samples from two subjects.

2.5. EEG-based personal identification system

The framework of EEG-based personal identification system is shown in Figure 3.

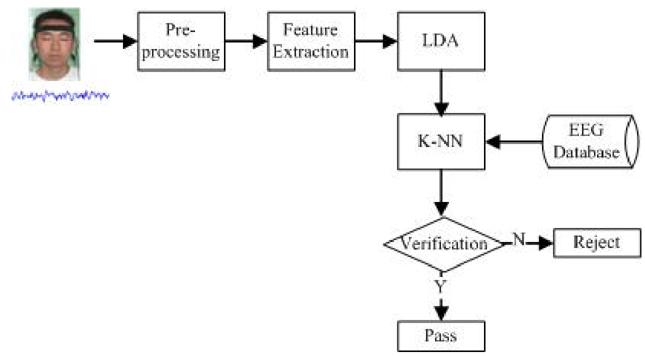


Figure 3: EEG-based personal identification system framework.

As described in Section 2.2, there are totally 40 subjects. In our experiments, for each subject, we randomly select 50 percent recordings for training, and use the remaining 50 percent recordings for testing. The system performance is estimated using a hold-out method, which evenly splits dataset to training and testing sets 100 times, and reports the average accuracy over 100 splits. Here, the results of total 12 EEG recordings and only half recordings (randomly choosing 6 EEG recordings) of each subject are reported in Fig.4. The results provide supporting evidence that EEG is a validated effective biometric modality, and if more diversity samples are included in modeling, the higher accuracy will be obtained.

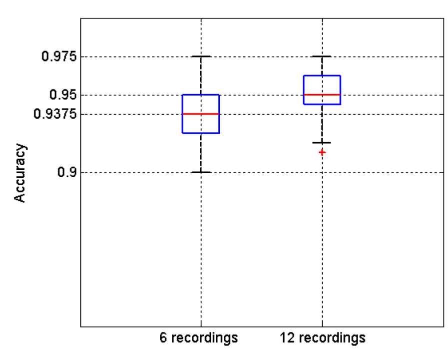
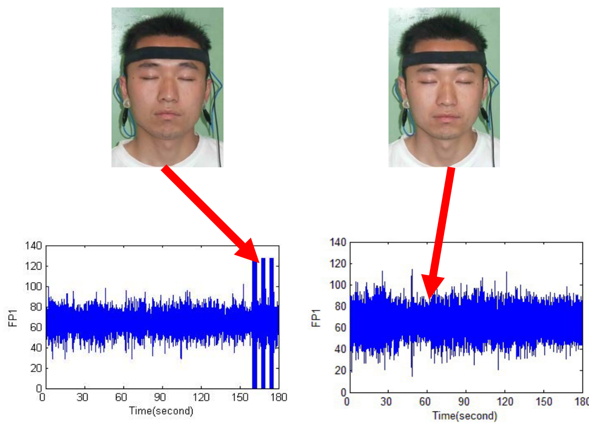


Figure 4: Box-plot of system accuracy.

3. An EEG-based personal identification system with covert warning

3.1. Using muscle signals to code CW message

A key contribution of this study is that we innovatively propose to use muscle signals, generated by clenching teeth, to code CW message during EEG recording. A robust CW message is proposed as three short bursts of muscle signals, which can be covertly produced by clenching the teeth three times during EEG recording. That is, the muscle activities here are treated as useful CW message, instead of artifacts.



(a) EEG signals acquired with clenching the teeth

(b) EEG signals acquired without clenching the teeth

Figure 5: Examples of EEG recording process.

Figure 5 illustrates the subject's facial expression during EEG recording processes with and without clenching the teeth, as well as the corresponding EEG signals recorded. The two pictures show that almost no noticeable difference on the subject's face can be observed between these two scenarios, whereas, it is obvious that the EEG signal with clenching the teeth is very different from the normal restful signals. .

3.2. The algorithm for CW pattern detection

Because the CW message is so strong, a simple method is sufficient to robustly detect CW message embedded in EEG signals. The details of the method are as follows:

Step 1: Define $s(n)$ as the sampled recorded EEG signal, where *n=1, … Num.* The total length of the signal is expressed by *Num*.

Step 2: Through observation, we found that when the volunteer clenched his/her teeth, EEG signals contain much higher frequency components than those in the acquired restful EEG signals. Therefore, the 10 order Butterworth high-pass filter with 20Hz cutoff frequency is used, and the filtered signal is expressed by $\hat{s}(n)$ here, where *n=1,…Num*.

Step 3: The initial part of the recorded EEG signal is considered to be the restful EEG without clenching the teeth. It is used to compute the average normal signal energy *Average_E*.

$$Average\_E = \frac{1}{C}\sum_{n=1}^{C}\hat{s}(n)^2 \tag{1}$$

In our experiment, the first 5-second signal is used for estimation, so C is a constant 1000.

Step 4: The left signal (except those 5-second for estimation in Step 3) is divided into a series of 1-second-duration window, and the average energy of each window is computed by using the following equation:

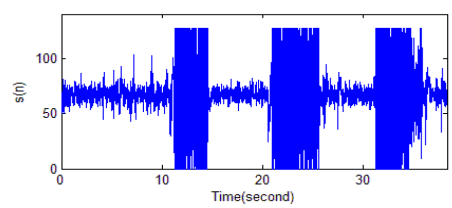
$$Window\_E(j) = \frac{1}{f_s}\sum_{n=fs\times(j-1)+1}^{fs\times j}\hat{s}(C+n)^2,\ j=1,\cdots(Num-C)/fs \tag{2}$$

where f_s is the sampling frequency, and j is the number of the window.

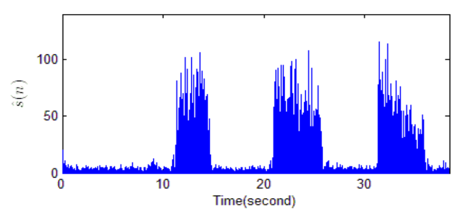
According to the relationship listed in Eq. (3) between *Windows_E(j)* and *Average_E*, the starting and ending time of clenching the teeth will be detected.

$$if\begin{cases} Windows\_E(j) > 20\times Average\_E, & starting\ time \\ Windows\_E(j) < 10\times Average\_E, & ending\ time \end{cases} \tag{3}$$

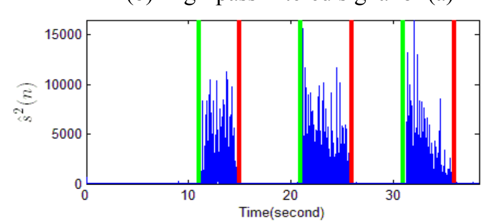
Figure 6 gives an example of the detail results in each step of our proposed EEG-based CW pattern detection method. In Figure 6 (c), the green line and red line represent the starting and ending time of clenching the teeth respectively.



(a) The original EEG signal with clenching the teeth



(b) High-pass filtered signal of (a)



(c) Detected starting and ending time of clenching the teeth

Figure 6: An example of each step result in the EEG-based CW detection method.

3.3. An EEG-based identification system with the CW feature

As we described above, considering the specificity of EEG, an updated system with the CW feature is implemented based upon a validated portable EEG-based identification system developed in section 2.5.

The flowchart of our proposed the updated EEG-based personal identification system with CW feature is shown in Figure 7. It is divided into two parts: EEG-based identification and CW detection.

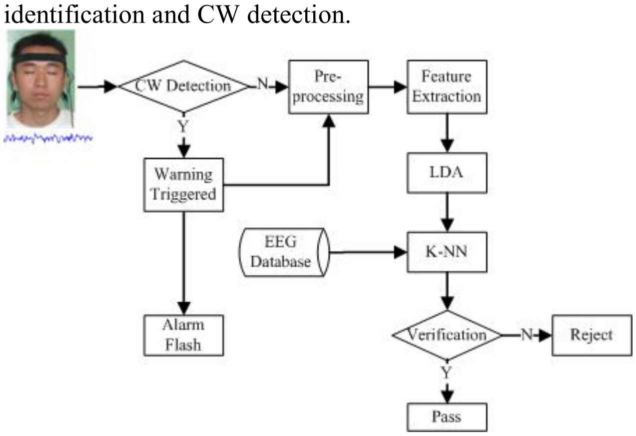


Figure 7: The block diagram of the system.

4. System performance evaluation

4.1. Data collection

To evaluate the whole system performance, data from a cohort of 24 volunteers' EEG signals were collected (15 male and 9 female) based on a well designed recording process. The recording environment is a quiet meeting room with normal temperature, and it is not the same room as those 40 volunteers' restful EEG signals in the database recorded one year before. The volunteer sits in a chair, and the EEG signal was recorded on the daylight or nightlight when the volunteer kept his/her eyes close. Each volunteer's EEG was recorded in two sessions. In each session, he/she was instructed to covertly clenching the teeth three times with random intervals after the approximately two-minute recording of restful EEG signals. The whole signal is about 3-minute length.

4.2. Covert warning detection results

For each EEG signal, the starting and ending time of clenching the teeth are detected using the algorithm described in 3.2, and compared with those time points labeled manually. In our experiment, the CW messages of one volunteer were detected failed in the beginning. Because the volunteer clenched teeth so gently in recording, leading to almost no differences between the recorded restful EEG signals and EEG signals with clenching teeth. When the volunteers were properly instructed, the CW messages were detected perfectly (i.e. 100% detection rate) for all 48 EEG signals with clenching the teeth from 24 volunteers in the new system.

4.3. Personal identification results

To further evaluate the impact of the extra CW feature on the EEG-based personal identification system, the overall personal identification accuracy rates with and without CW are compared.

For each volunteer, there are two recorded EEG signals with clenching the teeth. Therefore, $24 \times 2 = 48$ signals total act as the probe in the matching, and the templates are those 480 restful EEG signals recorded one year ago as described in Section 2.2.

In our experiments, to evaluate the performance of EEG-based personal identification, the first 2-minute restful EEG of each signal is used to simulate the scenario of without CW, and the last 2-minute EEG signal including the part of clenching the teeth are used to simulate the scenario of with CW feature. Through CW detection, artifacts removing, feature extraction, and feature dimension reduction, the matching results would be obtained. The results are listed in Table 1.

Table 1. Comparison of matching performances

Scenario	Accuracy Rate
With CW	90%
Without CW	93.7%

Figure 8 demonstrates one false matching sample. The blue lines, red lines and green lines represent the twelve PSD curves of the real template in the database, the probe PSD of same person, and twelve PSD curves of the false matched template, respectively.

The experimental results imply that there has a little

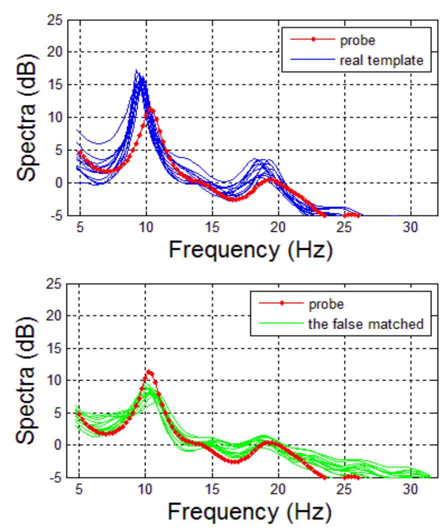


Figure 8: A mismatched example.

decrease of matching performance in the scenario with CW. This decrease is indeed not a surprise. For the same length of the original signal, after artifacts removing, the left effective signal is shorter in the scenario with CW than that without CW because the signals of clenching teeth are removed as artifacts before matching stage. The small amount of decrease in system identification rate is a reasonable tradeoff for a new feature of CW to enhance the whole system security. Alternatively, this decrease can be resolved by recording the EEG signal for a dozen of seconds longer.

Although the EEG templates used in our experience were recorded one year ago in different environments, the experimental result indicates that the identification accuracy is still fairly comparable with the original system performance, which was provided in Section 2.5. This again confirms that EEG modality can tolerate different recording environments and, can remain consistent across a fairly long period time.

5. Conclusion

Given the convenience of keyboards and mice, Brain Computer Interface (BCI), which uses EEG, has fortunately been an exciting research area in computer science. With EEG's wider applications (e.g. BCI, driver's drowsiness detection), its advantage as a biometric to provide continuous identification will become evident. An EEG-based personal identification system that can send out a covert warning (CW) message when necessary is introduced in this paper. Our contribution is that we demonstrated clenching teeth producing robust signals, and proposed it as a novel CW solution to EEG biometric systems. The novelty is that the bursts of muscle actions are proposed as the CW message, rather than artifacts. This is the first system with the CW feature implemented based upon a validated portable EEG-based identification system.

Following the idea of [16], in which a dual-biometric-modality identification system based on fingerprint and EEG was introduced, we can import our proposed the CW concept to the multi-modal biometric system aiming to improve the overall system accuracy. This represents one of our future effects in the development of biometric-based personal identification system.

Acknowledgement

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