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Exploring EEG based Authentication for Imaginary and Non-imaginary tasks using Power Spectral Density Method

Tze Zhi Chin[1]**, A Saidatul**[1] **and Z Ibrahim**[2]

[1] Biosignal Processing Research Group (BioSIM), School of Mechatronic Engineering, Universiti Malaysia Perlis, Arau, Perlis, Malaysia
[2]Faculty of Technology, University of Sunderland, St Peter's Campus, Sunderland, SR6 0DD, United Kingdom

Abstract. Biometric technology has swiftly emerged as a go-to solution for improving cyber security especially in financial fraud and security threats. EEG based-authentication is best of security in cyber security application as it is unique and cannot be replicated. The aim of this study is to investigate the possibility of adopting imaginary or non-imaginary task for human authentication. In this study, twenty subjects were recruited from undergraduate students with age ranging from 19 to 30 years old. The subject must be healthy and right-handed. The subjects were required to perform non-imaginary task (left hand or right hand movement) and imaginary task (just need to imagine the movement of left hand or right hand). Duration for each task is 1 minute and take rest for 1 minute between the tasks. Truscan EEG device (Deymed Diagnostic, Alien Technic, Czech Republic) with 19 channels were used to collect EEG data with 1024 Hz frequency sampling and the impedance is kept below 5 kOhm. Bandpass filter was used in pre-processing to extract alpha (8-13Hz) and beta (14-30Hz) waves. The signal was segmented and the power spectral density were calculated by Welch's method and Burg's method. The statistical features (mean, median, mode, variance, standard deviation, minimum and maximum) were obtained from PSD were used as input of classifier. K-nearest neighbour classifier (KNN) and Linear Discriminant Analysis (LDA) were applied for classification. In conclusion, Welch method gives the highest classification accuracy which is 98% for beta waves from channel C4 with the K-nearest neighbour classifier. Imaginary task shows the higher classification accuracy which is 98.03% instead of non-imaginary task which is 94.95%. Thus, imaginary task is more suitable for authentication.

1. Introduction
Biometric technology has swiftly emerged as a go-to solution for improving cyber security especially in financial fraud and security threats. Biometric approaches have obtained energetically rising interest for individual authentication and identification as they are associated with physiological as well as behavioural of individual [1]. Biometric authentication systems presently in use have some vulnerabilities. For instance, iris recognition can be cheated by high resolution images while palm-prints and fingerprints can be replicated. Thus, it is greatly desired to find robust biometric approaches that can probably overcome aforementioned weaknesses [2]. In the drive to improve highest level of security, EEG signal is one of the alternative method to replace conventional biometric system.

Electroencephalogram (EEG) is a non-invasive method that records the electrical activity of brain by measuring the small voltage fluctuations with placement of the electrodes on the scalp surface [3]. The communication of brain cells will generate electrical impulse and active the whole time [4]. Brain signals can be influenced by individual's mental state which makes them very hard to be collected under

coercion and force. If a mental state is chosen for authentication, it can be inhibited by a user in threatening situation [5]. Moreover, brain signals are related to the genetic information of individuals so it is unique for each individual and stable over time [6].

EEG based authentication is measuring and statistical analysis of bio signal characteristics of individual. It is important to proof individual's unique identity especially in security purpose [7]. In most EEG-related studies, features are extracted from the frequency bands of the signal. Five main frequency bands have been recognised. They are arranged in increasing order which are called delta (δ), theta (θ), alpha (α), beta (β) and gamma (γ). The amplitudes and frequencies of signals change from one state to another [2].

The goal of this research is to investigate the possibility of adopting imaginary or non-imaginary task for human authentication. Motor and motor imaginary activities will generate electrical signals on the motor cortex on the brain [8]. Due to the artifact and complexity of signals, advanced signal processing is needed to improve the EEG signals. Pre-processing, feature extraction and classification are the three major stages of signal processing [9].

2. Data Acquisition

A total number of twenty subjects were recruited from undergraduate students with the range of age from 19 to 30 years old. The subject must be healthy and right-handed. All subjects are free from mental injury or mental disorder. Before conducting the experiment, the subject was requested to fill in the Consent Form to let subject understands what it means to be in the study and get approval from subject to take part in it. Next, Demographic Information Form was filled by subject to know the general background of subjects.

After that, the EEG cap is placed correctly on the subject's scalp. This device captures EEG signals across 19 channels with 1024Hz sampling rate and 256 data are collected per second. The voltage is set as 70uV and frequency range from 1 to 80 Hz to get the EEG signals frequency bands for analysis. The electro gel is injected into every electrodes to reduce impedance below 5 kΩ. Then the subject adjusts to a comfortable position and close the eyes for whole process.

There are four tasks in the experimental protocol which are left hand movement, imaginary left hand movement, right hand movement and imaginary right hand movement. Duration for each task is 1 minute and take rest for 1 minute between the tasks. Subject should open and close the hand according to the metronome track at 60 BPM as well as imagine open and close the hand to ensure that subject moves and imagines at constant speed. The duration of each task is 2 minutes while for the whole process is 10 minutes.

3. EEG Signal Processing

EEG signal is complex, random and not stationary in nature, it is unable to interpret signal by visual inspection. Thus, advanced signal processing is required to investigate the EEG signals by extracting hidden information from the brain signal [10]. The EEG signal processing aid separated into three stages including pre-processing, feature extraction and classification.

3.1 Pre-processing

The raw signals generated from non-cerebral system are filtered and removed unwanted frequencies to enhance the embedded information in the brain signals [11]. Butterworth bandpass filter was used as the pass band is maximally flat with no ripple [9][12]. To obtained the two desired frequency which are alpha wave (8 -13Hz) and beta wave (13-30Hz), raw signals required to filter through Butterworth band pass filter.

3.2 Feature Extraction

Feature extraction is a vital part of signal processing as accuracy of classification is determined by quality selection of the features [12].

3.2.1. Welch Method. Welch's method is a non-parametric method. It is usually used to estimate the power spectrum of a given time sequence [13][14]. The sequences are allowed to overlap and windowed each data segment. Thus, the SNR for Welch method is high.

3.2.2. Burg Method. Burg method is depended on reducing forward and backward prediction errors whilst fulfilling the Levinson-Durbin recursion. By using this method, reflection coefficients are estimated straight away instead of calculating auto correlation. The benefits of this method are resolving nearly spaced sinusoids in low noise levels signals and estimating short data records as AR PSD estimates are proximate to the true values. Moreover, the Burg method confirms that a stable AR model and is computational efficiently. The accuracy of this method is reduced for high-order models, long data records and high SNR as it can cause line splitting or generate irrelevant peaks in the spectrum estimate. The spectral density estimate computed by the Burg method is also influenced by frequency shifts which relative to the true frequency resulting from the initial phase of noisy sinusoidal signals. This effect is enhanced when analysing short data sequences [13][15].

3.3 Classification

Classification is the final stages of EEG signal processing. The statistical features (mean, median, mode, variance, standard deviation, minimum and maximum) were obtained from output of feature extraction were used as input of classifier.

3.3.1. k-Nearest-Neighbors (k-NN). K-Nearest-Neighbors (k-NN) is a non-parametric, non-linear and supervised learning algorithms that used for classification. Among several types of supervised statistical learning algorithms, k-NN algorithms obtains typically high performance without any assumptions about the distributions from which the training examples are drawn [16].

The minimum distance from the signal to the training set is decided to find the k-NN category of the training dataset. Distance metrics are an approach to investigate the distance between a new data point and existing training dataset. The distance based on correlation is a measure of statistical dependence between two vectors [17]. The correlation distance is calculated as follow:

$$d_{st} = \left(1 - \frac{(x_s - \bar{x}_s)(y_t - \bar{y}_t)}{\sqrt{(x_s - \bar{x}_s)(x_s - \bar{x}_s)'}\sqrt{(y_t - \bar{y}_t)(y_t - \bar{y}_t)'}}\right) \tag{1}$$

$$\bar{x}_s = \frac{1}{n}\sum_j \bar{x}_{s_j}$$

$$\bar{y}_t = \frac{1}{n}\sum_j \bar{y}_{t_j}$$

3.3.2. Linear Discriminant Analysis (LDA). Linear Discriminant Analysis (LDA) is one type of statistical classification that used in machine learning and pattern recognition to get the features that linearly combined more than two classes of objects [18]. It is a linear transformation techniques that are commonly used for dimensionality reduction. LDA is supervised learning algorithm and computes the directions that will represent the axes that maximize the separation between multiple classes [19].

4. Result and Discussion

4.1 Determination of Most Informative Electrode for EEG based Authentication

There are two electrodes were selected for comparison, the electrodes are located on motor cortex area which related to our imaginary and non-imaginary activities[8].

Table 1. Classification Result based on Channel

Frequency band	C3	C4	Combination C3 and C4
Alpha	89.5%	**96.98%**	95.33%

From Table 1, by comparing the alpha frequency band, it can be shown that C4 is the most informative electrode with highest accuracy of 96.98% and followed by combination C3 and C4 with 95.33% and the last is C3 electrode with accuracy of 89.5%.

4.2 Determination of Best Feature Extraction for EEG based Authentication

There are two types of feature extraction that used for analysis. The feature extracted are based on one second segmentation time of filtered signal.

Table 2. Classification Result based on Feature Extraction

Feature	Frequency band	Result
Welch	Alpha	96.4%
	Beta	**97.94%**
	Combination of alpha and beta	87%
Burg	Alpha	96.98%
	Beta	95.15%
	Combination of alpha and beta	94.15%

As shown in Table 2, Welch method with beta features show the highest accuracy which is 97.94% compared to Burg method with beta frequency is 95.15%.

4.3 Determination of Best Task for EEG based Authentication

Table 3. Classification Based on Task

Channel	Non-imaginary task	Imaginary task
C4	95.22%	97.63%
	96.4%	98.17%
	94.91%	98.95%
	92.45%	97.36%
Average	94.75%	**98.03%**

From Table 3, imaginary task shows the highest accuracy with 98.03% while non-imaginary tasks shows only 94.75%.

5. Conclusion

In conclusion, Welch method gives the highest classification accuracy that almost 98% for beta waves from channel C4 with the K-nearest neighbour classifier. Imaginary task shows the higher classification accuracy which is 98.03% instead of non-imaginary task which is 94.75%. Thus, imaginary task is more suitable for biometric authentication.

Acknowledgments

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