Non Linear Features Analysis between Imaginary and Non-imaginary Tasks for Human EEG-based Biometric Identification

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Non Linear Features Analysis between Imaginary and Non-imaginary Tasks for Human EEG-based Biometric Identification

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Abstract. Electroencephalogram (EEG) is a signal contains information of brain activities. Nowadays, many types of research regarding EEG have been done such as neuromarketing. The human brain is very complicated but it contains a lot of information. EEG signal is a non-stationary signal, it changes over time and it also depends on human's emotion, thinking and activities. Due to the uniqueness of the EEG signal, the EEG signal has the potential to be used in the human authentication system. In this paper, an imaginary task and a non-imaginary task were studied to find out which type of task is possible to be used in authentication system. In preliminary study, five subjects were volunteered and performed the motor imagery and motor execution tasks. EEGO^{TM} sports device (ANT Neuro, Enschede, Netherlands) with 32 channels was used to record the EEG signal and the sampling frequency is set to 512 Hz. The EEG signal was analysed by using EEG signal processing namely pre-processing, feature extraction and classification. Power line interference was removed by using a notch filter. Daubechies 8 wavelet family with 5th level decomposition has been applied to remove baseline wander noise. The performance of non-linear features such as Empirical Mode Decomposition (EMD), Hurst Exponent and Entropy were examined. Random forest gives good classification accuracy for imaginary task and non-imaginary task which are 83.53% and 87.06% respectively, thus, it shows non-linear features is possible to be employed in biometric identification.

1. Introduction

A signal that contains information of brain activities is known as electroencephalogram. It is defined as electrical activity of an alternating type recorded from scalp surface [1]. Electroencephalography (EEG) is a way to measure the electroencephalogram. Recently, research on EEG is getting more and more. Many types of research regarding EEG have been done such as neuromarketing [2]. The human brain is very complicated but it contains a lot of information. EEG signals are electrical activities generated from activities in the neurons. Local current flows when neurons activated. During synaptic excitations of dendrites of many pyramidal neurons in the cerebral cortex, the currents flow mostly measured by EEG [3].

Human brain contains of 4 lobes namely frontal lobe, temporal lobe, occipital lobe and parietal lobe. Each lobe has its specific function. Frontal lobe is used for movement, planning and problem solving. Temporal lobe is used for auditory, memory and speech signal. Occipital lobe is used for visual processing. Parietal lobe is used for sensing, perception, spelling and arithmetic [4]. Figure 1 shows basic structural of a neuron and figure 2 shows the picture of brain.

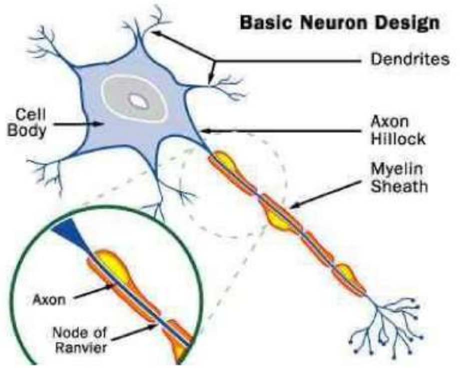

Figure 1. Basic structural features of a neuron [3].

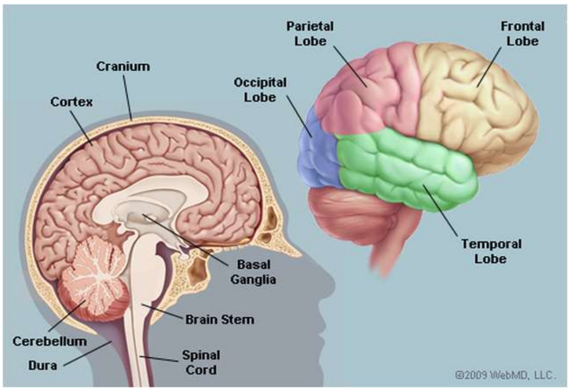

Figure 2. Picture of brain [5].

EEG signal is a non-stationary signal, it changes over time and it also depends on human's emotion, thinking and activities. Due to uniqueness of the EEG signal, the EEG signal has the potential to be used in the human authentication system. In this paper, an imaginary task and a non-imaginary task were studied in order to find out which type of task is possible to be used in authentication system.

2. Data Acquisition

Five healthy and right-handed subjects were volunteered in this preliminary study. They are students from Universiti Malaysia Perlis (UniMAP) with age 20 to 30 years old. Before the experiment start, the subjects required to sign the informed consent form, answer the questionnaire and take part in Standardized Mini-Mental State Examination (SMMSE). The informed consent form is to prove that the subjects willing to volunteer in this study and give confidence to the subjects about the safety issues. The questionnaire and the Standardized Mini-Mental State Examination (SMMSE) is to obtain the background of the subjects and make sure the subjects are in healthy mental condition with no neurological disorder respectively [6].

The subjects were asked to sit comfortably on the chair. The environment of the room was quiet. EEGO^{TM} sports device (ANT Neuro, Enschede, Netherlands) with 32 channels was used to acquire EEG signal and the sampling frequency was set to 512 Hz. The EEG cap was placed on the scalp and the gel was inserted in all channels to reduce the impedance. The impedance kept below 5 kΩ to minimise the noise. The EEG cap was connected to amplifier and tablet with EEGO64 software.

After experimental set up, the subjects were asked to relax, close eyes and avoid body movement. Then, they were performed motor imagery and motor execution tasks according to the sound of 60 Beats Per Minute (BPM). During motor imagery task, the subjects required to imagine opening and closing left fist for 1 minute, right fist for 1 minute and followed by both fist for 1 minute. After performing the imaginary task, the subjects were asked to rest for 30 seconds and took part in non-imaginary task. For non-imaginary task which is motor execution, the subjects were asked to open and close their fists instead of imagine. The procedures similar with motor imagery task. Figure 3 and figure 4 shows the photo during data collection.

3. EEG Signal Processing

There are 3 key stages namely pre-processing, feature extraction and classification to analyse he raw EEG signals [7].

3.1. Pre-processing
Pre-processing is the stage of remove unwanted noises. Notch filter was used to remove power line interference. The power line interference in Malaysia is at 50 Hz [8]. Therefore, the notch filter was set to filter the frequency at 50 Hz [1], [9], [10], [11]. This filter is to minimize the possibility of power line interference. Baseline wander noise was de-noise by using Daubechies 8 wavelet family with 5th level decomposition. Daubeches of db8 is the most effective Daubechies among others. It performed de-noise effectively [12], [13].

3.2. Feature Extraction
Non-linear feature was used in this study due to EEG signal is a non-stationary signal. EEG signal changes over time. In this preliminary study, 4 different methods of non-linear feature were compared. First, Empirical Mode Decomposition (EMD) was applied to decompose the signal and Hilbert transform forms the Intrinsic Mode Functions (IMF) components from EMD. Then Hurst Exponent and Approximate Entropy were applied to extract the features of IMF component respectively. Hurst Exponent and Approximate Entropy also applied to extract the features of original signal after filtered directly.

3.2.1. Empirical Mode Decomposition (EMD). Empirical Mode Decomposition (EMD) decomposes the signal into small function which is known as Intrinsic Mode Functions (IMF). IMF is a significant function. Hilbert transform is useful in calculating instantaneous frequency and amplitude. In this preliminary study, it has been used to form IMF components which are instantaneous frequency and instantaneous amplitude respectively [14]. The IMF components were used to extract features of Hurst Exponent and Approximate Entropy.

3.2.2. Hurst Exponent. Hurst Exponent is a measure of long range correlation in a time-series. It is popular due to its capability of as a measure of the smoothness of a fractal time-series based on asymptotic behavior [14].

3.2.3. Entropy. Approximate Entropy is a measure that quantifies the complexity or irregularity of a time-series data [15], [16]. Larger value of Approximate Entropy will have more complexity and irregularity of the signal [17].

3.3. Classification
Random Forest is also known as random decision tree. It is capable to work with large data sets. It does not required normalization. It only required simple and little features parameter [18]. The accuracy based on class is calculated using equation (1) and the overall accuracy is calculated using equation (2).

$$A = \frac{T_P + T_N}{T_P + T_N + F_P + F_N} \tag{1}$$

$$TA = \frac{Total\ correct}{Total\ of\ predicted\ values} \tag{2}$$

A denotes the accuracy based on class, TA denotes the overall accuracy, T_P denotes the number of true positives, T_N denotes the number of true negatives, F_P denotes the number of false positives and T_N denotes the number of true negatives.

4. Results and Discussions
The classification accuracy for different method of non-linear features were examined. The non-linear features that used in this preliminary study were Empirical Mode decomposition (EMD), Hurst

Exponent and Approximate Entropy. The features of 32 channels were extracted and the EEG signals had divided into 170 segments.

The classification accuracy using different method of non-linear features were analysed. EMD followed by HE is extracted the filtered EEG signal using EMD then extracted the features of EMD using Hurst Exponent. EMD followed by ApEn is extracted the filtered EEG signal using EMD then extracted the features of EMD using Approximate Entropy. HE is used only Hurst Exponent to extract the features of filtered EEG signal. ApEn is used only Approximate Entropy to extract the features of filtered EEG signal. Table 1 and table 2 show the classification result for motor imagery task and motor execution task using different method of non-linear features. Random Forest is the method of classification that had been used in this preliminary study. The subject is referred to class.

Table 1. Classification result for motor imagery task using different method of non-linear features.

	Subject 1	Subject 2	Subject 3	Subject 4	Subject 5	Overall
EMD followed by HE	60.00	60.38	65.31	74.42	62.75	37.65
EMD followed by ApEn	71.64	75.41	75.81	96.00	84.48	57.65
HE	89.71	93.94	89.04	95.39	97.06	77.65
ApEn	92.21	93.33	91.03	100.00	100.00	83.53

Table 2. Classification result for motor execution task using different method of non-linear features.

	Subject 1	Subject 2	Subject 3	Subject 4	Subject 5	Overall
EMD followed by HE	58.49	58.33	60.47	61.22	60.47	36.47
EMD followed by ApEn	78.38	84.06	84.06	90.48	93.55	68.24
HE	88.89	96.97	88.00	95.89	95.89	82.35
ApEn	89.16	97.37	88.46	100.00	100.00	87.06

As shown in table 1 and table 2, the classification accuracy for both tasks using Approximate Entropy is the highest among others. On the other hand, the classification accuracy is low when using Empirical Mode Decomposition. The accuracy based on class only calculated the predicted values within the class, it does not consider predicted values of other classes. Overall accuracy consider all predicted values. Therefore, the accuracy based on class is higher than overall accuracy. From table 1 and table 2, the classification accuracy based on class and overall between motor imagery task and motor execution task not much different.

5. Conclusion

From this study, Approximate Entropy is most suitable to be used in human authentication system among others. Empirical Mode Decomposition (EMD) is not suitable in this case because it limited the features of EEG signal although the extracted features is significant. The classification accuracy for both tasks not much different and it is above 80%. Therefore, this can concluded that motor imagery and motor execution are suitable for human authentication system. In future, fusion features between time frequency domain analysis and non-linear method are expected can perform in a more effective way for human authentication system. The recognition accuracy process need to further enhance by developing new algorithm.

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