

# Analysis of the EEG Signal for a Practical Biometric System

Muhammad Kamil Abdullah, Khazaimatol S Subari, Justin Leo Cheang Loong and Nurul Nadia Ahmad

**Abstract**—This paper discusses the effectiveness of the EEG signal for human identification using four or less of channels of two different types of EEG recordings. Studies have shown that the EEG signal has biometric potential because signal varies from person to person and impossible to replicate and steal. Data were collected from 10 male subjects while resting with eyes open and eyes closed in 5 separate sessions conducted over a course of two weeks. Features were extracted using the wavelet packet decomposition and analyzed to obtain the feature vectors. Subsequently, the neural networks algorithm was used to classify the feature vectors. Results show that, whether or not the subjects' eyes were open are insignificant for a 4-channel biometrics system with a classification rate of 81%. However, for a 2-channel system, the P4 channel should not be included if data is acquired with the subjects' eyes open. It was observed that for 2-channel system using only the C3 and C4 channels, a classification rate of 71% was achieved.

**Keywords**—Biometric, EEG, Wavelet Packet Decomposition, Neural Networks

## I. INTRODUCTION

A HUMAN identification system uses the unique features of an individual as an identifier. Existing technologies mostly use fingerprints, speech, facial features, iris and signatures as a base for an authentication or an identification system. These traits however, are known to be vulnerable to falsification as it is possible to forge or steal. Therefore, new types of physiological features that are unique and cannot be replicated are proposed for an identification system. This paper focuses its attention to the electroencephalogram (EEG) signal as a biometric.

The EEG is the summation of electrical activity of billions of nerve cell connections in the brain cortex [13]. It is measured using electrodes that are placed on several locations on the scalp. The main advantage of using EEG is its uniqueness; the electrical activities were observed to be different for each person and cannot be faked or duplicated [2], [8], [10], [11], [17]. Therefore, it is very unlikely that a person's identity can be forged or stolen. However, there is one disadvantage of using the EEG signal that cannot be overlooked; and that is the difficulty in setting up the subject for the signal acquisition process.

When prepping the subject for EEG data collection, a cap has to be placed on the subject securely. The electrodes that are placed onto the scalp (two for each point location in a dipole configuration) goes through a rigorous process; first the subject's hair needs to be parted, secondly, the electrodes

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are smeared with gel and then screwed onto the cap, ensuring that the copper bands on the bottom part of the electrodes come into contact with the scalp. The whole process takes approximately 15 minutes to complete, a procedure that is impractical for an identification system where the identity of the subject at an almost immediate rate is preferred.

Another question that arises is how can the thoughts of the subject be controlled for each measurement, since the EEG signal varies from person to person and dependant on the state of the subject's thoughts. Many studies have reported excellent results using visual evoked potentials (VEP) (e.g., [10], [11]), but this again requires the subject to undergo several tasks that is impractical for an identification system.

In this paper, a biometrics identification system was analyze using 2 and 4 electrode configurations. No VEP were used while the signals were recorded; the subjects were only asked to clear their minds. The signals were recorded for the subjects with eyes closed and eyes opened. The features were extracted using the wavelet packet decomposition tool and classified using neural networks.

## II. EEG IDENTIFICATION AND AUTHENTICATION STUDIES

A study by Paranjape et al. (2001) suggests that EEG has biometric potential as they were able to discriminate between 40 subjects with 8 channels using autoregressive models with a correct classification rate of 82% [13]. Poulos et al. (1999) collected 1 channel of EEG from 75 subjects in one session and obtained a classification rate of 91% thus corroborating the evidence that the EEG signal carries genetically specific information and suitable for person identification [14].

Ravi and Palaniappan (2005) used a total of 61 channels to record VEP EEG signals from 20 subjects [16]. They were able to authenticate subjects with the best classification performance of 95%. Palaniappan and Mandic (2007) also using VEP were able to achieve an accuracy of 98% for 40 individuals using 61 channels [11]. Shiliang Sun (2008) used the signal from 15 electrodes of 9 subjects imagining movements to a visual cue with a success rate of 94% [22].

More research on biometrics identification systems are summarized here. Poulos et al. (1999a) and Poulos et al. (1999b) recorded EEG signals from 1 channel of 4 subjects resting with eyes closed [15], [14]. They applied parametric processing and computational geometry and achieved 84% and 91% respectively.

Some researches have also used EEG as an authentication tool. Riera et al. (2008) collected data from 51 subjects and

36 intruders [17]. The EEG were recorded from 2 channels while subjects were sitting with eyes closed for 1 minute. They obtained a true acceptance rate of 96.6% and false acceptance rate of 3.4%. Hema et al. (2008) recorded EEG signals from 3 channels of 6 subjects and achieved an average authentication rate of 97% [5]. Jiang Feng Hu (2009) were able to achieve accuracy ranging from 75% to 80% for subject authentication and 75% to 78.3% for identification using 6 channels [7]. In the study, subjects were asked to imagine left and right hand movement, tongue and foot movement.

### III. WAVELET PACKET DECOMPOSITION AND NEURAL NETWORKS FOR EEG ANALYSIS

Wavelet packet decomposition was selected because of its ability to provide information in time and frequency domain of a non-stationary signal. It divides the signal into its low frequency and high frequency components and the frequency is downsampled at every level resulting in a complete wavelet packet tree for a comprehensive signal analysis.

Studies using wavelet packet decomposition to analyze EEG signals were able to obtain the four brain rhythms: alpha, beta, theta and delta [9], [21]. Ting et al. (2008) used the wavelet packet decomposition as feature extraction method for classifying EEG during motor imagery tasks [24].

Neural networks has been used by many researchers to classify the EEG signal [1], [4], [5], [6], [19], [23]. Subasi et al. (2005) used neural networks to classify between normal and epileptic EEG and were able to achieve an accuracy of 92% [20]. Jahankhani et al. (2006) achieved 97% accuracy in classifying EEG signals for a study on epileptic seizure detection [6].

### IV. METHODOLOGY

In this paper, the use of wavelet packet decomposition was proposed as the feature extraction method and neural networks for classification. The potential of EEG signals which were recorded while participants were resting with eyes closed and eyes open will be discussed in detail. The possibilities of using lesser number of channels for the practicality of a biometric system will also be looked into. The following subsections will explain in detail the experimental setup, preprocessing, feature extraction and classification of the EEG signal.

#### A. Experimental Setup

EEG signals were recorded using a gMobilab+ console by Guger Technologies that was connected to a laptop and captured using the Matlab Data Acquisition Toolbox with a sampling frequency of 256 Hz. Eight electrodes were placed on the scalp at positions FC3 and CP3, P1 and P5, FC4 and CP6 and P2 and P6 to record the bipolar EEG signal at points C3, P3, C4 and P4 respectively. The electrodes were placed according to the standard 10–20 international system. Figure 1 shows the position of the electrode placement for the bipolar EEG recording.

Data were collected from 10 subjects, in 5 separate recording sessions over a course of 2 weeks. All subjects were male students from the Faculty of Engineering, Multimedia

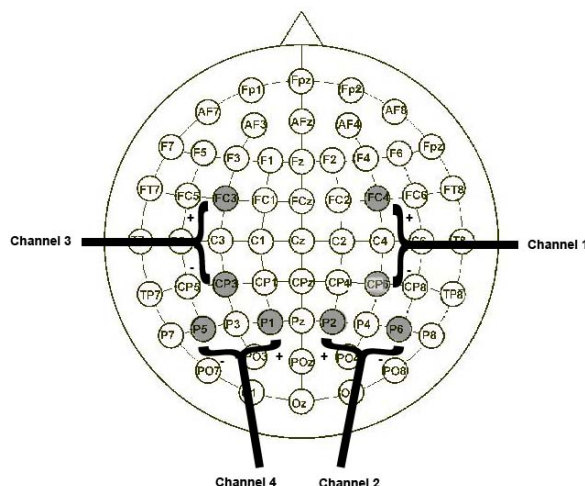


Fig. 1. Position of electrode placements for bipolar EEG recording.

University, whose age ranged from 22 to 28 years old. Subjects were required to sit on a reclining chair and remain calm and relaxed throughout the whole recording procedure. Each session consisted of 5 trials where each trial consisted of 5 tasks: eyes open, eyes closed, imagining right index finger movement, imagining left leg movement and puzzle solving. Only the results of the first two tasks (i.e., eyes open and eyes closed) are presented here. They were also required to minimize any movements to avoid any contamination to the EEG signal. During signal acquisition, subjects were asked to clear their minds of any thoughts and relax.

#### B. Preprocessing

Prior to the feature extraction stage, the signal is low-passed filtered using an elliptic filter with a cut-off frequency of 45 Hz to remove noises that may be caused by body or hand movements and noise produced by alternating current at 50 Hz generated by the recording console. The EEG signals are then segmented into 5 second frames before the feature extraction process.

#### C. Feature Extraction

The signal  $x(t)$  is decomposed into different scales as follows:

$$x(t) = \sum_{j=1}^K \sum_{k=-\infty}^{\infty} d_j(k) \psi_{j,k}(t) + \sum_{k=-\infty}^{\infty} a_K(k) \phi_{K,k}(t) \quad (1)$$

where  $\psi_{j,k}(t)$  are discrete analysis wavelets and  $\phi_{K,k}(t)$  are discrete scaling functions.  $d_j(k)$  are the wavelet coefficients at scale  $2^j$  and  $a_K(k)$  are the scaling coefficients at scale  $2^K$ . The discrete wavelet transform can be implemented by the wavelet and scaling filters

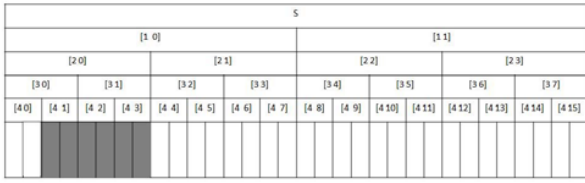


Fig. 2. Complete wavelet packet tree.

$$h(n) = \langle \phi(t), \phi(t - n) \rangle, \quad (2)$$

$$g(n) = \langle \psi(t), \phi(t - n) \rangle, \quad (3)$$

$$= (-1)^{1-n} h(1 - n)$$

being quadrature mirror filters (QMS) [3]. If the scaling function is define as  $x_0(t) = \phi(t)$  and the wavelet function  $x_1(t) = \psi(t)$ , then the functions  $x_i(t)$ ,  $i = 0, 1, 2, \dots$ , can be expressed as

$$x_{2i}(t) = 2 \sum_{n=0}^{2N-1} h(n)x_i(2t - n) \quad (4)$$

$$x_{2i+1}(t) = 2 \sum_{n=0}^{2N-1} g(n)x_i(2t - n) \quad (5)$$

where  $j$  is the scale parameter,  $n$  is the time-localization parameter and  $i$  is the number of cycles included in the oscillating waveform.

The EEG signals were then applied a five-level wavelet packet decomposition as shown in Figure 2. Coefficients from nodes (5 2), (5 3), (5 4), (5 5), (5 6) and (5 7), highlighted in Figure 2, which represents frequencies from 8 Hz to 32 Hz were extracted for further processing.

The mean,  $\mu_x$ , standard deviation,  $\sigma_x$ , and entropy,  $\epsilon(x)$ , values of each coefficient vector were then calculated according to the following equations to obtain the feature set,  $\bar{v}$ , of a single person:

$$\mu_x = \frac{1}{n} \sum_{i=1}^n x_i \quad (6)$$

$$\sigma_x = \sqrt{\frac{1}{n} \sum_{i=1}^n (x_i - \mu_x)^2} \quad (7)$$

$$\epsilon(x) = - \sum_t x^2(t) \log(x^2(t)) \quad (8)$$

In total there are 21 feature coefficients for a single channel per person. Before processing, all feature vectors are normalized to a mean and standard deviation of 0 and 1 respectively using the following equation:

$$\bar{v}_n = \frac{\bar{v} - \mu_v}{\sigma_v} \quad (9)$$

where  $\mu_v$  is the mean and  $\sigma_v$  is the standard deviation of all feature vectors.

TABLE I  
CRR OF 4 CHANNELS AND 2 CHANNELS

Channels	Eyes Opened	Eyes Closed
	CRR(%)	CRR(%)
C3, C4, P3, P4	78	81
C3, C4	71	65
P3, P4	54	65
C3, P3	62	64
C4, P4	62	68

TABLE II  
STATISTICAL ANALYSIS FOR EYES-OPEN AND EYES CLOSED. LEVEL OF SIGNIFICANCE IS SET AT 0.05 TO REJECT THE NULL HYPOTHESIS,  $H_0$

Test Data		Probability	Conclusion
Eyes Opened	Eyes Closed		
C3, C4, P3, P4	C3, C4, P3, P4	0.63	Fail to reject $H_0$
C3, C4	C3, C4	0.015	Reject $H_0$
P3, P4	P3, P4	0.000	Strong reject
C3, P3	C3, P3	0.528	Fail to reject $H_0$
C4, P4	C4, P4	0.002	Reject $H_0$

D. Classifications

The data collected were randomly divided into training and testing sets everytime the system was executed; 90% of the data is used for training and the remaining 10% for testing. Extracted features were then defined as input layers to the neural network algorithm. Two hidden layers were used with 100 nodes on each layer. The training function used was the scaled conjugate gradient. The minimum performance gradient was set to  $1.00e^{-18}$  and training will stop when any one of these conditions are met:

- 1) the maximum number of epochs reaches 3000;
- 2) the mean square error reaches 0.01; or
- 3) the performance gradient falls below  $1.00e^{-18}$ .

V. RESULTS AND DISCUSSION

The results of this experiment will be based on the correct recognition rate (CRR) of the system which is calculated according to the following equation:

$$CCR = \frac{1}{10} \sum_{i=1}^{10} \frac{C_n}{T_n} \times 100\% \quad (10)$$

where  $C_n$  is the number of correct classifications and  $T_n$  is the total number of testing samples. Since samples used for training and testing are randomized everytime the system is executed, the CCR is computed over an average of 10 executions.

Table I shows the results for eyes-closed and eyes-open using 2 and 4 channels. It was observed that eyes-closed produced higher identification rates than eyes-open for 4 channels. The CRR was speculated to be high was due to the fact of the open-eyes signal being contaminated with eye blinks. However, statistical analysis shows that the differences between the CRR values of eyes closed and eyes-open are not significant ( $P = 0.314$ , for  $\alpha = 0.05$  level of significance).

TABLE III

STATISTICAL ANALYSIS FOR CHANNELS PLACED ON THE CENTER VERSUS POSTERIOR REGION. LEVEL OF SIGNIFICANCE IS SET AT 0.05 TO REJECT THE NULL HYPOTHESIS,  $H_0$

Test Data	Channels	Probability	Conclusion
Eyes Closed	C3, C4 vs P3, P4	0.686	Fail to Reject $H_0$
Eyes Opened	C3, C4 vs P3, P4	0	Reject $H_0$

Therefore, is trivial whether the subjects' eyes were open or closed during signal acquisition.

Table II compares the CRRs of different combinations of channels for eyes–open and eyes–closed. It is observed that the P4 channel signal is consistently different between eyes–open and eyes closed which significantly affected the results of the identification algorithm. This is in agreement with the literature where the right posterior area of the brain plays an active part in dealing with visual information. Therefore, it may be useful to not include this channel when acquiring data with eyes–open. This is proven by the fact that the C3 and C4 channels achieved a CRR of 71%, which is relatively high for a 2–channel biometrics system. Further analysis was done as shown in Table III where the CRR of the front and back channels were tested for significance. It is observed that with eyes–open, the EEG signal was significantly different between the posterior and the frontal part of the brain which affected the results.

A final test was done between left versus right brain for 2 channels shown in Table IV. It is observed that there is no significant difference between the left and right brain for eyes–open and eyes–closed.

The results that are found here are significant as previous studies have achieved higher classification rates for data that was collected in the same session (e.g., [14]), using a significantly higher number of electrodes (e.g., [12], [11], [16]), had fewer subjects (e.g., [7], [22]) as well as different stimulus while the EEG data was obtained (e.g., [18], [25], [12]). This study focuses on a practical biometrics system with the least number of electrodes and no stimulus.

## VI. CONCLUSION

From the results obtained, the classification rates using 4 channels of eyes–closed EEG is slightly better than eyes–open, probably due to less artifacts in the signal. However, whether or not the subjects' eyes were closed is not significant when 4–channels are used to identify the subject. Indeed, a good classification rate of approximately 80% can still be achieved. In an effort to reduce the number of electrodes for a practical implementation of a biometrics system, 2–channels may be sufficient. Based on the findings, that for the creation of a 2–channel biometrics system, that channel P4 should not be included if the signal is acquired with the subjects' eyes–open. Further enhancement of the system is necessary in order to achieve higher classification rates. However, the preliminary results that are seen here are promising.

TABLE IV

STATISTICAL ANALYSIS FOR CHANNELS PLACED ON THE LEFT VERSUS RIGHT REGION. LEVEL OF SIGNIFICANCE IS SET AT 0.05 TO REJECT THE NULL HYPOTHESIS,  $H_0$

Test Data	Channels	Probability	Conclusion
Eyes Closed	C3, P3 vs C4, P4	0.206	Fail to reject $H_0$
Eyes Opened	C3, P3 vs C4, P3	0.847	Fail to reject $H_0$

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