

## EEG Based Biometric Identification Using Correlation and MLPNN Models

<https://doi.org/10.3991/ijoe.v15i10.10880>

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**Abstract**—This study investigates the capability of electroencephalogram (EEG) signals to be used for biometric identification. In the context of biometric, recently, researchers have been focusing more on biomedical signals to substitute the biometric modalities that are being used nowadays as the signals obtained from our bodies is considered more secure and privacy-compliant. The EEG signals of 6 subjects were collected where the subjects were required to undergo two baseline experiments which are, eyes open (EO) and eyes closed (EC). The signals were processed using a 2nd order Butterworth filter to eliminate the unwanted noise in the signals. Then, Daubechies (db8) wavelet was applied to the signals in the feature extraction stage and from there, Power Spectral Density (PSD) of alpha and beta waves was computed. Finally, the correlation model and Multilayer Perceptron Neural Network (MLPNN) was applied to classify the EEG signals of each subject. Correlation model has yielded great significant difference of coefficient between autocorrelation and cross-correlation where it gives the coefficient value of 1 for autocorrelation and the coefficient value of less than 0.35 for cross-correlation. On the other hand, the MLPNN model gives an accuracy of 75.8% and 71.5% for classification during EO and EC baseline condition respectively. Therefore, these results support the usability of EEG signals in biometric recognition.

**Keywords**—Biometric, EEG, Correlation and MLPNN

### 1 Introduction

Biometrics is means to recognize individuals based on the high basis of one or more physical or behavioural criteria's such as fingerprint, retinal pattern and DNA [1]. The biometric system is fundamentally a pattern recognition system that operates constructed on three main stages which are enrollment stage - acquiring an individual's biometric data, excerpting a feature set from the secured data and matching the feature set with the template set in the gallery. This offers a substitute to username and password as well as smart cards [1]. Therefore, biometric systems have been widely deployed in wide-ranging areas such as in criminal investigation, health care

screening, commercial and government applications. For instance, fingerprint, signature, gait and iris as shown in Figure 1 are amongst the several biometric modalities that have been suggested for the past few years. Nevertheless, not all biometrics do not offer satisfactory recognition rates [1]. Fingerprints, for example, can be faked or can be obtained by force whereas the most unique biometric which is deoxyribonucleic acid (DNA) is easily contaminated and not really accepted by the society since it can give information about susceptibilities of a person to certain diseases. Besides that, some individual may not possess these biometric attributes due to mishap or disabilities. Hence, the use of EEG signals in biometric recognition has sparked interest of researchers in this area because of the ability to give excellent results as this signal is much closer to human brain which controls our actions and reactions.



**Fig. 1.** Different types of biometric modalities

EEG is defined as an alternating type electrical activity which was obtained by the metal electrodes assigned on human's scalp [2]. Like other biometric attributes, EEG signals also provide related information concerning individual dissimilarities related to brain anatomical and functional traits [3]. Due to distinctness of each brain configurations, it is presumed that each individual has their own brain patterns. This signal is considered more safe and privacy-compliant than traditional biometric identifiers. Furthermore, EEG based biometric systems offer open access to everyone including people with certain physical abilities such as missing fingers or absence of the iris. Therefore, the purpose of this study is to propose an EEG based biometric recognition system and to assess the performance of the proposed system.

## 2 Literature Review

Palaniappan [4] presented a two-stage biometric recognition method which utilizes the EEG signals generated by mental activities of five subjects. The signals were gathered by Keirn and Aunon. These activities composed of baseline or also known as resting state, mathematical calculation, geometric figure rotation, letter composing and visual counting. For each mental task, ten experiments were conducted in separate sessions for each subject, where each experiment lasted for about ten seconds. The

EEG signal produced by each and every activity was divided into 20 segments of 0.5 second to acquire a greater dataset. Next, AR modeling was used to extract features from the data and the author used Burg's method to determine the AR coefficient. The results of the experiment show that all subjects gave optimum outcome in rejecting imposters which means that the False Acceptance Error (FAE) is zero for each mental activity whereas for the False Rejection Error (FRE), the fifth subject gave 1.5% and 0.75% for baseline and mathematical calculation while the first subject gave 1.0% for letter composing activity. Visual counting and geometric figure rotation were concluded to be the best mental activities because of the fact that the FAE and FRE values for these two activities are zero. However, this method is considered cumbersome and inconvenient for everyone since visual stimulus is a must for this approach.

Brigham and Kumar [5] claimed that a person can be identified from EEG signals that were obtained during imagined speech. The authors used imagined speech EEG data collected from six volunteers at University of California, Irvine (UCI). These volunteers were required to imagine pronouncing one of the two syllables which are /ba/ or /ku/, at varying rhythms covertly while their EEG signals were being computed. The rhythms of the syllables are heard to subjects beforehand through a set of electrostatic earphones. Several assumptions were then made in addition to the applied AR model to the EEG signals. This was done to determine the power spectral density of the signal before SVM classifier was used for the classification of volunteers. The linear SVM classifier gives the most accurate identification result with an average classification rate of 99.41% for the imagined speech dataset. Besides that, the classification process was also done on each rhythm as well as each syllable individually. Although the identification accuracies for rhythms and syllables are slightly smaller than that of imagined speech dataset, these outcomes suggest that the proposed method is suitable for biometric identification. However, these imagined speech characteristics could fluctuate in every experiment which results in uncertainty of information for any kind of classification.

Kostilek and St'astny [6] suggested that the use of movement-related EEG provides better identification results for biometric recognition. The EEG database of nine subjects was collected from two sessions, each spaced one year apart. During each session, subject was requested to perform voluntary movements such as right or left index finger extension or flexion while keeping his eyes closed. For each subject and session, four blocks of EEG were obtained where three blocks comprising of the mentioned movements and the fourth block carries only resting EEG. The first block is expected to have some noise due to the restlessness of subject in the beginning of the session. A total of eight neighbors Laplacian vector is used to filter all EEG signals before Frequency-Zooming Auto-Regression (FZ-AR) were applied to obtain classification features which were the  $\mu$  rhythm parameters. Different combinations of blocks from both sessions were used to test whether the presence of additional noise in one of the EEG database blocks degrades the classification results. The outcome of the Mahalanobis distance classifier shows that the combination of the second and the third block gives the highest classification score of 87.1% whereas the other combinations give almost similar result of approximately 77% in average. Despite the proven state-

ment that the movement-related EEG helps in identifying the subjects, the author believed that the use of  $\beta$  rhythm gives better results for this method.

Thomas and Vinod [7] found that beta band entropy conveys most of the particular information related to subjects during resting state. The authors conducted experiments using EEG signals of 109 healthy subjects which were collected from a publicly available online database called PhysioNet BCI. Two different baseline conditions which are one-minute EC and one-minute EO were used as the dataset. The study used two operating phases: enrolment and identification for the recognition system. During enrolment, sample entropy based features were obtained from five sub-bands of EEG known as delta (1-4 Hz), theta (4-8Hz), alpha (8-12 Hz), beta (12-30 Hz) and gamma (30-50 Hz) to generate template and were stored in the database. Based on Mahalanobis distance based classifier, subject identification was carried out by extracting sample entropy features from multi-band decomposed multi-channel EEG data. The average correct recognition rate (CRR) which is the performance index used for the proposed recognition system shows that, in both EO and EC, beta band gave better identification level than the other four bands where it provides an average CRR of 98.31% in the validation procedure. However, this approach does not give an optimum recognition performance since it uses higher number of EEG channels.

Harshit et al. [8] proposed an online based EEG biometric recognition system that uses both visual and audio stimuli for five subjects. All subjects are right-handed and free from any serious medical conditions. Offline experiment is first conducted to determine the correlation threshold of various stimuli (self, familiar and unfamiliar) for both cases. The visual session is conducted for 10 seconds for each single trial which consist of 10 self-face images, 10 familiar faces images and 10 unfamiliar faces images in random order. For the audio session, subjects were required to hear self, familiar and unfamiliar voices from the same phrase for eight trials in each stimulus. Based on experimental results, it is observed that the amplitude of EEG signal in response to self-face stimuli is higher as compared to familiar and unfamiliar faces for all subjects. On the other hand, the amplitude of EEG signal in response to self-voice is lower than familiar voice and higher than unfamiliar voice. EEG signals are then recorded during online experiment and the feature vectors consist of Power Spectral Density (PSD) values were compared with the template obtained from the offline experiment. The false acceptance rate (FAR) and false rejection rate (FRR) were then computed which gives the average FAR of 13.91% and average FRR of 26.66% while the recognition accuracy was recorded to be 79.73%. Even though the results obtained were quite satisfying, the proposed approach needs to be tested in a greater population over an extended duration. Furthermore, this approach is not applicable for people with disabilities such as blind and deaf.

Bashar et al. [9] have come up with an advanced machine learning technique for EEG based human identification. The EEG signals of nine female adults were acquired using a five channel EEG device known as *Emotiv Insight* in few recording sessions. For each session, subjects were asked to execute two baseline tasks which were EC and EO for one minute with a sampling frequency of 1280 Hz. The signals were first filtered using a FIR bandpass filter to remove the unwanted noise. Then, three methods of feature extraction which are multiscale shape description (MSD),

multiscale wavelet packet statistics (WPS) and multiscale wavelet packet energy statistics (WPES) were applied to the signals. Lastly, the SVM classifier with the applied error-correcting output code multiclass model (ECOC) was used for the classification process. In this study, only the results obtained from EC task were presented and based on the experimentation, the WPS and WPES methods performed better identification as compared to the MSD method. These two methods gave the highest accuracy of 94.44% on channel-3 and channel-5 for WPS and on channel-5 for WPES. Despite the satisfying results produced by WPS and WPES methods, it is believed that there are other potential methods that could give better results which were not analyzed in this study.

### 3 Methodology

The general design of the proposed system starts with EEG signals collection and followed by pre-processing of the signals. Next, alpha and beta sub-bands were extracted using the proposed feature extraction technique and from there, PSD of the two sub-bands were computed. Finally, classification of the signals were performed using correlation and MLPNN models. Figure 2 encapsulates the overall architecture of the proposed system. The next sub-sections will briefly describe about each steps of the proposed system.

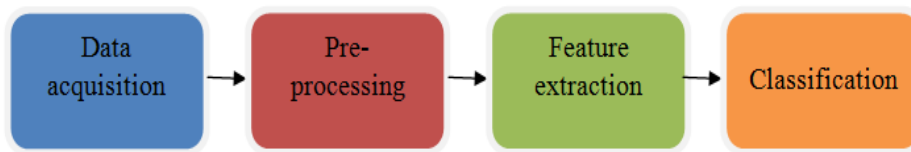


Fig. 2. Overall design of the proposed system

#### 3.1 Data acquisition

In this study, the EEG signals were acquired from an EEG electrode cap which was connected to a BrainMarker EXG system. The EEG system was then connected to a laptop for data recording as shown in Figure 3. Datasets of six subjects that were required to undergo two baseline experiments which are EO and EC were collected. Each experiment was performed for a duration of 60 seconds for each subject. During EO condition, subjects were instructed to minimize eye blinking to reduce noise and artifacts in the signals. The EEG signals of each subject were recorded for one minute at a sampling frequency of 15000 Hz in each condition using a 19-channel electrode cap. The raw signals were then pre-processed using 2<sup>nd</sup> order Butterworth filter with a band pass of 0.01 to remove noise in the signals.



**Fig. 3.** Architecture of devices used for data acquisition [4].

### 3.2 Feature extraction

In order to characterize the EEG signals into five sub-bands as mentioned earlier, db8 wavelet function was applied to the filtered signals. The db8 wavelet decomposes EEG signals into multi-level details with respect to the range of frequencies of each sub-band [10]. Additionally, only signals obtained from electrodes C3, C4 and CZ will be used in this study. This is because, previous works done by neurologists show that, EEG recordings from these three electrodes consist of particularly any brain activities related to imaginary motor movement including movement of the eyes [11]. Besides that, these three electrodes contain two sub-bands which coincide with the brain activity of a normal adult during conscious state that are alpha and beta waves. Thus, EEG signals from the remaining 16 electrodes as well as delta, theta and gamma waves will not be further analyzed in this study because the main focus is to analyzed signals containing alpha and beta waves.

Subsequently, the PSD of alpha and beta waves were computed using Welch's method or also known as periodogram averaging method. Equation 1 depicts the equation of periodogram values to obtain Welch's estimate of the PSD.

$$S_x(v) = \frac{1}{K} \sum_{k=1}^K P_k(v) \quad (1)$$

where the parameter  $S$  refers to the number of points to shift between segments, parameter  $K$  defines the number of segments or batches and parameter  $P$  is the modified periodogram value [12].

### 3.3 Classification

In this final step, two different methods were used to classify EEG signals of six subjects which are correlation model and MLPNN model. These two methods are briefly discussed in the next sub-sections.

### 3.4 Correlation model

Correlation is a method where two signals are required to produce a third signal. If a signal is associated with itself, the third signal is called the autocorrelation, otherwise it is called the cross correlation of the two input signals. Equation 2 shows the cross correlation function used in this classification step

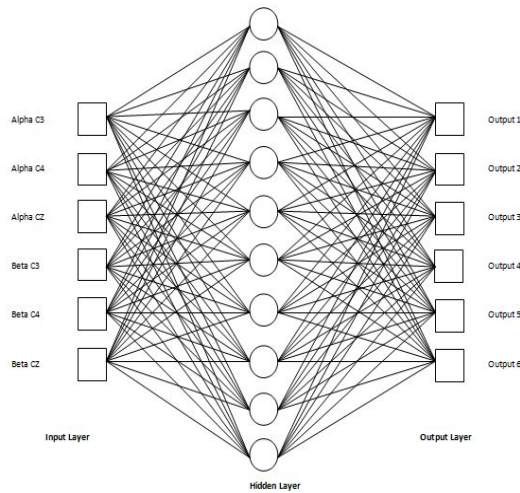
$$C(n, \tau) = \sum_t x(t)y(n, t + \tau) \tag{2}$$

Where  $x(t)$  and  $y(t)$  denote the PSD of the first and second set of EEG signals at time  $t$  and channel  $n$ , respectively. Moreover,  $\tau$  denotes the time lag between the two signals [8].

The association of two variables is stronger as the coefficient value approaching to  $\pm 1$ . On the other hand, a correlation coefficient of 0 signifies that there is no association exists between the measured variables. The correlation coefficients are categorized into three categories for both positive and negative correlations which are low or weak correlation ( $\leq 0.35$ ), moderate correlation (0.36 – 0.67) and high or strong correlation (0.68 – 1.0) [9].

### 3.5 MLPNN model

MLPNN is one of the types of neural networks with error based training mechanism used to classify EEG signals. The multilayer perceptron composes of a system of simple interrelated neurons or nodes. Figure 4 illustrates the architecture of a three-layer MLPNN used for EEG classification. In this study, the multilayer perceptron requires six output nodes where one node is representing one subject. That being said, six binary vectors were assigned as the target output vector where bit 1 indicates the correct classification and bit 0 specifies the incorrect classification.



**Fig. 4.** The architecture of three-layer MLPNN

## 4 Experimentation and Results

In this study, a total of six subjects were required to undergo two baseline conditions which are EO and EC. Subjects were placed in a dim light room and they were asked to be in a calm condition before the recording process started. During EO condition, subjects were instructed to minimize eye blinking to reduce noise and artifacts in the signals. The EEG signals of each subject were recorded for one minute in each condition using a 19-channel electrode cap and the signals obtained were displayed through a laptop as shown in Figure 5.

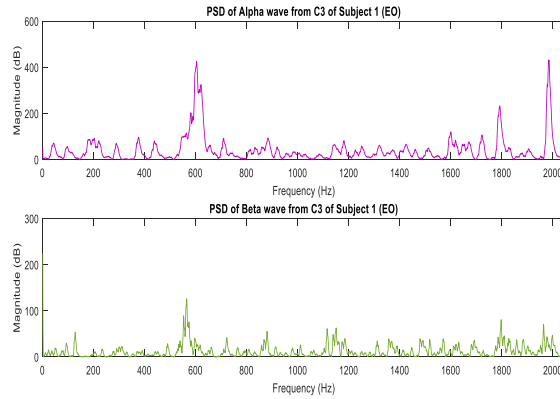


**Fig. 5.** Recorded EEG signals

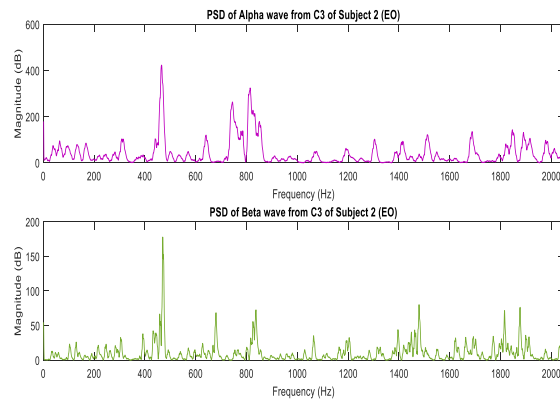
The raw signals were then pre-processed using 2<sup>nd</sup> order Butterworth filter with a band pass of 0.01 to remove noise in the signals. After that, the filtered signals from electrodes C3, C4 and CZ were further analyzed to discriminate alpha and beta waves of each subject where the PSD for these two waves were computed afterwards. For illustration purposes, only the EEG signals from electrode C3 of three subjects are shown which are categorized into EO and EC.

The PSD of alpha and beta waves during EO baseline condition are depicted in Figure 6 for Subject 1, in Figure 7 for Subject 2 and in Figure 8 for Subject 3. As for EC baseline condition, the PSD of alpha and beta waves are demonstrated in Figure 9 for Subject 1, in Figure 10 for Subject 2 and in Figure 11 for Subject 3.

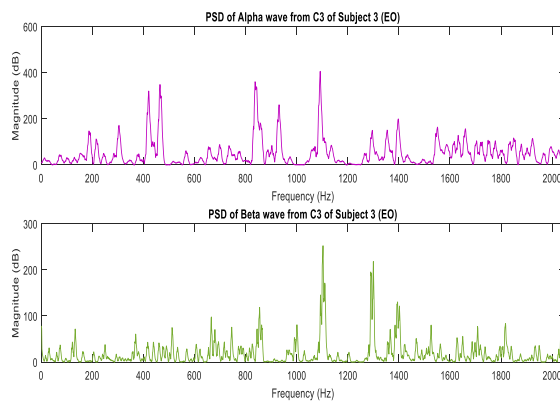




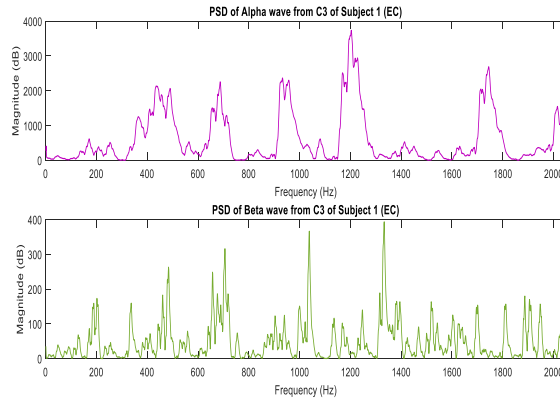
**Fig. 6.** PSD from C3 of Subject 1 (EO)



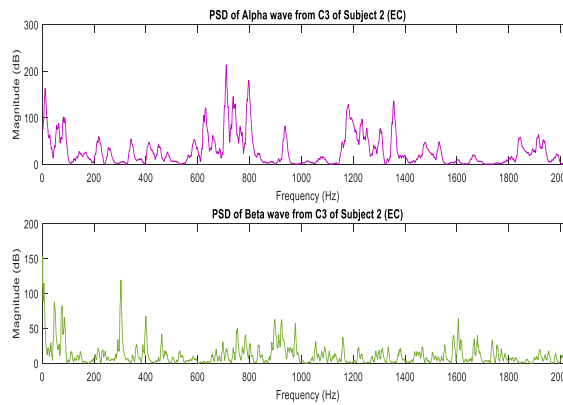
**Fig. 7.** PSD from C3 of Subject 2 (EO)



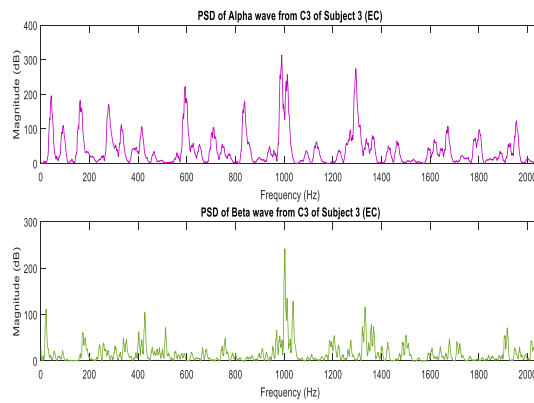
**Fig. 8.** PSD from C3 of Subject 3 (EO)



**Fig. 9.** PSD from C3 of Subject 1 (EC)



**Fig. 10.** PSD from C3 of Subject 2 (EC)



**Fig. 11.** PSD from C3 of Subject 3 (EC)

Finally, correlation model was applied to the extracted features as the first classification method. For documentation purpose, only correlation coefficient values from electrode C3 are depicted which are categorized into EO and EC. The correlation coefficients of PSD values for electrode C3 during EO baseline condition are provided in Table 1 for alpha wave and Table 2 for beta wave. As for EC baseline condition, the correlation coefficients of PSD values for electrode C3 are organized in Table 3 and Table 4.

**Table 1.** Correlation coefficient of PSD of alpha wave from C3 during EO

Alpha EO-C3						
$\theta$	<i>S1</i>	<i>S2</i>	<i>S3</i>	<i>S4</i>	<i>S5</i>	<i>S6</i>
<i>S1</i>	1	-0.07	-0.1486	-0.0499	-0.0864	-0.0225
<i>S2</i>	-0.07	1	0.2784	0.0241	-0.0314	0.0579
<i>S3</i>	-0.1486	0.2784	1	0.0279	-0.1309	0.0978
<i>S4</i>	-0.0499	0.0241	0.0279	1	0.2516	-0.1316
<i>S5</i>	-0.0864	-0.0314	-0.1309	0.2516	1	0.0789
<i>S6</i>	-0.0225	0.0579	0.0978	-0.1316	0.0789	1

**Table 2.** Correlation coefficient of PSD of beta wave from C3 during EO

Beta EO-C3						
	<i>S1</i>	<i>S2</i>	<i>S3</i>	<i>S4</i>	<i>S5</i>	<i>S6</i>
<i>S1</i>	1	-0.0344	-0.0472	0.01	-0.0231	0.1029
<i>S2</i>	-0.0344	1	-0.0376	0.0442	0.1082	0.0106
<i>S3</i>	-0.0472	-0.0376	1	-0.0363	0.0188	-0.0221
<i>S4</i>	0.01	0.0442	-0.0363	1	0.0404	-0.0842
<i>S5</i>	-0.0231	0.1082	0.0188	0.0404	1	-0.0041
<i>S6</i>	0.1029	0.0106	-0.0221	-0.0842	-0.0041	1

**Table 3.** Correlation coefficient of PSD of alpha wave from C3 during EC

Alpha EC-C3						
	<i>S1</i>	<i>S2</i>	<i>S3</i>	<i>S4</i>	<i>S5</i>	<i>S6</i>
<i>S1</i>	1	0.0048	0.1123	0.0198	0.1311	-0.118
<i>S2</i>	0.0048	1	-0.2049	0.1129	-0.0714	-0.1473
<i>S3</i>	0.1123	-0.2049	1	0.0093	-0.0621	0.1403
<i>S4</i>	0.0198	0.1129	0.0093	1	0.0704	-0.0142
<i>S5</i>	0.1311	-0.0714	-0.0621	0.0704	1	0.0069
<i>S6</i>	-0.118	-0.1473	0.1403	-0.0142	0.0069	1

**Table 4.** Correlation coefficient of PSD of beta wave from C3 during EC

Beta EC-C3						
	<i>S1</i>	<i>S2</i>	<i>S3</i>	<i>S4</i>	<i>S5</i>	<i>S6</i>
<i>S1</i>	1	-0.0387	0.0054	0.044	0.018	-0.1134
<i>S2</i>	-0.0387	1	0.1453	-0.0897	-0.1342	0.2838
<i>S3</i>	0.0054	0.1453	1	-0.0814	0.0027	0.0298
<i>S4</i>	0.044	-0.0897	-0.0814	1	-0.0505	-0.0637
<i>S5</i>	0.018	-0.1342	0.0027	-0.0505	1	0.0864
<i>S6</i>	-0.1134	0.2838	0.0298	-0.0637	0.0864	1

As for the MLPNN model, the performance of the system was measured by the total percentage of correct and incorrect classification as shown in Table 5.

**Table 5.** Percentage of correct and incorrect classification of MLPNN system

Baseline condition	Percentage of correct classification	Percentage of incorrect classification
EO	75.8%	24.2%
EC	71.5%	28.5%

Based on the correlation coefficients tabulated in Tables 1 to 4, it is deduced that for signals correlated with their own signals, the coefficient value is 1 for all six subjects. Whereas, for signals that correlated with other subjects' signals, the coefficients obtained are less than 0.35 which falls under the category of weak correlation. These indicate that correlation method is capable of classifying the EEG signals of different subjects with a significant difference between autocorrelation and cross correlation.

Meanwhile, based on the result in Table 4.5, it shows that MLPNN has the ability to match the EEG signals of individuals in this experiment. However, the percentage of incorrect classification for both conditions is probably due to the utilization of EEG electrode cap to record the EEG signals in this experiment. This is because, the position of electrodes on subjects' scalps does not exactly match the 10-20 system international standard of electrode location for EEG signal recording as humans have different sizes of head. Besides that, the algorithm used during feature extraction might be unsuitable and could also contribute to the percentage of incorrect classification.

To summarize, both correlation and MLPNN models have the potential to classify EEG signals of every individuals. However, both methods have several limitations. For the first classification method, even though correlation model yields a very significant difference of coefficient between autocorrelation and cross correlation, it cannot give an exact value of the method's accuracy as this method only measures the degree to which two signals are correlated. As for the MLPNN model, despite its capability to impart the correct and incorrect classification percentage, the percentage for correct classification is not very satisfying.

## 5 Conclusion

To sum up, this study has demonstrated the potentiality of EEG signals to be used for biometric identification. All four steps of the proposed methodology which are data acquisition, preprocessing, feature extraction and classification have been concluded. Based on the experimentation outcomes, correlation model has yielded great significant difference of coefficient between autocorrelation and cross correlation where it gives coefficient value of 1 for autocorrelation and coefficient value of less than 0.35 for cross correlation. Meanwhile, the MLPNN model gives an accuracy of 75.8% and 71.5% for classification during EO and EC baseline condition respectively. Thus, the objectives of this study which are to study the concept of EEG signal and biometric system, to develop an EEG based biometric identification mechanism and to evaluate the performance of the proposed system have been achieved.

## 6 Acknowledgement

I would like to express my deepest gratitude and appreciation towards Management and Science University Malaysia for the financial support.

## 7 References

- [1] M. A. M. Ali and N. M. Tahir, "Cancelable biometrics technique for iris recognition," 2018 IEEE Symposium on Computer Applications & Industrial Electronics (ISCAIE), 2018. <https://doi.org/10.1109/iscaie.2018.8405512>
- [2] Jain, A. K., Ross, A., & Prabhakar, S. "An introduction to biometric recognition", IEEE Transactions on circuits and systems for video technology, 14(1), pp. 4-20, 2004. <https://doi.org/10.1109/tcsvt.2003.818349>
- [3] Teplan, M., "Fundamentals of EEG measurement". Measurement science review, 2(2), pp. 1-11, 2002.
- [4] La Rocca, D., Campisi, P., Vegso, B., Cserti, P., Kozmann, G., Babiloni, F., & Fallani, F. D. V., "Human brain distinctiveness based on EEG spectral coherence connectivity", IEEE Transactions on Biomedical Engineering, 61(9), pp. 2406-2412, 2014. <https://doi.org/10.1109/tbme.2014.2317881>
- [5] Palaniappan, R., "Two-stage biometric authentication method using thought activity brain waves", International Journal of Neural Systems, 18(01), pp. 59-66, 2008. <https://doi.org/10.1142/s0129065708001373>
- [6] Brigham, K., & Kumar, B. V., "Subject identification from electroencephalogram (EEG) signals during imagined speech", In Biometrics: Theory Applications and Systems (BTAS), 2010 Fourth IEEE International Conference on, pp. 1-8, 2010. <https://doi.org/10.1109/btas.2010.5634515>
- [7] Kostílek, M., & Št'astný, J., "EEG biometric identification: repeatability and influence of movement-related EEG", In Applied Electronics (AE), 2012 International Conference on, pp. 147-150, 2012.
- [8] Thomas, K. P., & Vinod, A. P., "Biometric identification of persons using sample entropy features of EEG during rest state", In Systems, Man, and Cybernetics (SMC), 2016 IEEE International Conference on, pp. 003487-003492, 2016. <https://doi.org/10.1109/smc.2016.7844773>
- [9] Harshit, R. S., Thomas, K. P., Smitha, K. G., & Vinod, A. P., "Online Electroencephalogram (EEG) based biometric authentication using visual and audio stimuli", In Biomedical Engineering and Sciences (IECBES), 2016 IEEE EMBS Conference on, pp. 454-459, 2016. <https://doi.org/10.1109/iecbes.2016.7843492>
- [10] Bashar, M. K., Chiaki, I., & Yoshida, H., "Human identification from brain EEG signals using advanced machine learning method EEG-based biometrics", In Biomedical Engineering and Sciences (IECBES), 2016 IEEE EMBS Conference on, pp. 475-479, 2016. <https://doi.org/10.1109/iecbes.2016.7843496>
- [11] Sherwani, F., Shanta, S., Ibrahim, B. S. K. K., & Huq, M. S., "Wavelet based feature extraction for classification of motor imagery signals", In Biomedical Engineering and Sciences (IECBES), 2016 IEEE EMBS Conference on, pp. 360-364, 2016. <https://doi.org/10.1109/iecbes.2016.7843474>
- [12] Sleight, J., Pillai, P., & Mohan, S., "Classification of executed and imagined motor movement EEG signals", Ann Arbor: University of Michigan, pp. 1-10, 2009.

- [13] Solomon Jr, O. M., “PSD computations using Welch's method”, NASA STI/Recon, Technical Report N, p. 92, 1991.
- [14] Smith, S. W., “The scientist and engineer's guide to digital signal processing”, California Technical Publishing, 1999.

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Article submitted 2019-03-27. Resubmitted 2019-05-15. Final acceptance 2019-05-17. Final version published as submitted by the authors.