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Investigation of Channel Reduction Based on Brain Lobes in EEG-based Authentication System

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Abstract.   Biometric authentication is recently used for verification someone's identity according to their physiological and behavioural characteristics. The most popular biometric techniques are fingerprints, facial and voices recognition. However, these techniques have the disadvantage in which they can easily be imitated and mimicked by hackers to access a device or a system. Therefore, this study proposed electroencephalogram (EEG) as a biometric technique to encounter this problem. The wavelet packet decomposition is explored in this study for the feature extraction method. The wavelet packet decomposition feature is represented, root mean squared (RMS) wavelet features to extract a piece of meaningful information from the original EEG signal. These features were applied to classify between 15 subjects by using Support Vector Machine (SVM). The channel reduction was conducted to investigate the brain lobe effectiveness during the paradigms of familiar and unfamiliar EEG signals which the channel reduction is based on the brain lobes (temporal, occipital, parietal, and frontal). As a result, the above 14 channels obtained the best performance of the system which is 97.44% of correct recognition rate (CRR). The analysis of the paradigms among familiar only, unfamiliar only, and both familiar and unfamiliar was conducted to evaluate the contribution of the paradigms. The results show that 14 channels obtained the best familiar paradigms while the other contributed by unfamiliar. The result is promising because the CRR computed above 90%, however further analysis of channel reduction has to be work to obtain specific channel to develop the small number of channel for comfort and convenience biometric sensor which is suitable for future authentication.

1. Introduction
Recently, a biometric authentication system is implemented in the security of smartphones to recognize the user according to physiological and behavioral characteristics [1]. The physiological and behavioral characteristics are known as biometric traits such as fingerprints, voices, palms, iris, electroencephalograph (EEG) [2]. It has a unique ability to differentiate between individuals. The application of biometric authentication has been popular compared to the traditional authentication system such as Personal Identification Number and text-based password in which it tends to be forgotten and stolen [3][4]. This research implemented EEG in authentication systems due to EEG signals hold specific and unique natural characteristics. Thus, it has a low possibility to be imitated

and mimicked by the imposter. Recent studies revealed EEG signals satisfy the basic biometric trait requirement in terms of collectability, permanence, universality, and distinctiveness [5]. The biometric authentication system develops using advanced techniques by data acquisition, signal pre-processing and classification techniques by applying artificial intelligence. This research investigated the channel reduction based on brain lobes in which the channel re reduced by 2-channels, 4-channels, 6-channels, and 8-channels, then compared each performance with 14-channels. Channel reduction analysis aims to evaluate the performance of EEG-based authentication using Support Machine Vector (SVM).

EEG is a brain signal which captured an electrical activity produced by a trillion of neurons in a non-invasive way. Early on, the purpose of the EEG signal was focused on the diagnostic purposed to detect an abnormality such as epilepsy and schizophrenia, and EEG was introduced in 1980 as a biometric trait as user recognition [6][7]. The brain signal produces five main frequencies which describe the brain activity: delta, theta, alpha, beta, and gamma. Delta ($1 - 4$ Hz) and theta ($4 - 8$ Hz) frequency are usually present in human sleep conditions whereas alpha ($8 - 13$ Hz), beta ($13 - 30$ Hz), and gamma ($30 - 100$ Hz) are dominant in the human wakeful state.

The data acquisition process is the process to obtain the EEG signal by designing the experimental protocol. It is equipped with a specific EEG device to acquire EEG signals. It is crucial to select the specific task to obtain an effective EEG signal. Mustafa et al. [8] utilized all channels of EMOTIV EPOC+ to perform the stimuli of geometric and obtained 80% of accuracy. Nakanishi et al [9] also utilized the same device for 10 subjects by conducting ultrasound stimuli and classified them using SVM. The error rate is 22% and revealed that O1 and O2 obtained a smaller error rate than other channels. Kumar et al. [10] performed live signature on the mobile phone as the 58 subjects remain calms. The system is classified using a Neural network and achieved 73.36 % CRR for the best single channels. Cauthen et al. [11] conducted reading with or without music for 40 seconds, then classified it using KNN by achieving 92.3%.

This paper is structured as follows: Section 1 introduced the aim of this research, Section 2 reviewed the previous research, Section 3 describes the proposed methodology which includes the experimental protocol and signal processing, Section 4 shows the experimental result analysis and Section 5 concludes the finding of this research.
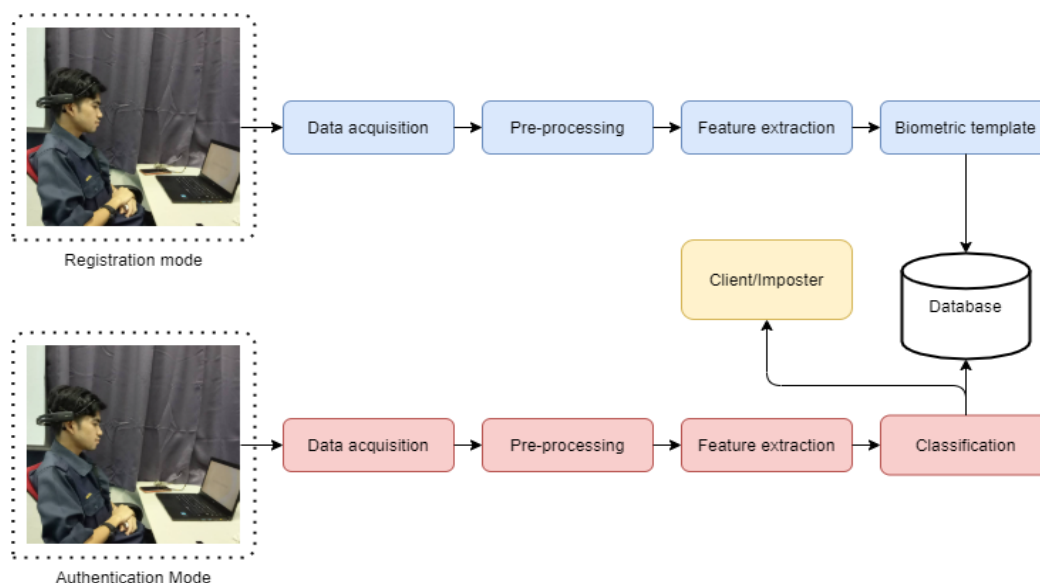
2. Proposed Methodology

Figure 1. Basic schematic of the propose EEG-based authentication system

The proposed authentication system is shown in Figure 1 EEG-based authentication system. It consists of 2 basic operational modes: registration mode and authentication mode [12]. Data acquisition and signal processing methods were applied in the earlier stage of registration mode and authentication mode, followed by feature extraction using root means square (RMS) in alpha, low beta, high beta, and gamma band. In the registration mode, EEG biometric templates were generated and stored in the database of each subject. On the other side, the authentication mode utilized the classification technique using SVM to classify the 15 subjects and evaluated using correct recognition rate (CRR) and error rate. The protocol of EEG signal was designed based on visual evoked potentials (VEPs) from familiar and unfamiliar images.

2.1. EEG Data and Subjects

EEG signals were collected by designing the experimental protocol based on the visual evoked potentials (VEPs) from 15 Malaysian healthy subjects. During the experiment, the subjects were exposed to 7 minutes of familiar images and 7 minutes of unfamiliar images as the visual stimulation to evoke an electric brain potential which was recorded by using 14 channels EMOTIV EPOC+ (AF3, AF4, F3, F4, F7, F8, FC5, FC6, O1, O2, P7, P8, T7, and T8) as follows the international 10/20 electrode location system and the devise was set at 128Hz of sampling rate. Then, for further analysis, the channels were divided into 5 groups: 2-channels (T7 & T8), 4-channels (T7, T8, O1 & O2), 6-channels (T7, T8, O1, O2, P7 & P8), 8-channels (T7, T8, O1, O2, P7, P8, FC5 & FC6) and all 14-channels. The selected channels have been chosen for further analysis. The selection channels are considered based on the function of each brain lobe. Before the experiments, all subjects were requested to fill in the Informed Consent Form and a form to gather the familiar and unfamiliar information of the subjects.

2.2. Signal Processing Techniques

2.2.1. Signal Pre-processing.
Initially, the EEG signals were composed of 107 520 data for 14 minutes (7 minutes of familiar image response and 7 minutes of unfamiliar image response) of the EEG signal recording. After the data acquisition, the multi-channel EEG signals were pre-processed by performing common average reference (CAR) and baseline removal and independent component analysis (ICA) to remove the unwanted signals, artifacts, and noise captured during the experiment session. The pre-processing techniques were applied to extract the meaningful EEG signals and removed the unwanted signals as the EEG signals are contaminated by biological noise such as eye movement, eyeblink, tongue movement, and surrounding artifacts. After acquired the clean EEG signals, the multi-channel EEG signals were band-pass filtered in the range of alpha band (8 - 13 Hz), a low beta band (13 – 20 Hz), a high beta band (20 – 30 Hz), and gamma (30 – 45 Hz). A finite impulse response (FIR) band-pass filter has been applied for the chosen band. Next, the multi-channel EEG signals were segmented to 1 second per epoch in which 1 second recorded 128 EEG data (sampling rate at 128 Hz). Therefore, there were 840 epochs per subject and the overall dataset for 15 subjects were 12 600 epochs (6 300 epochs of 15 subjects for familiar EEG signals and 6 300 epochs of 15 subjects for unfamiliar EEG signal). The flow of methodology is shown in Figure 2.
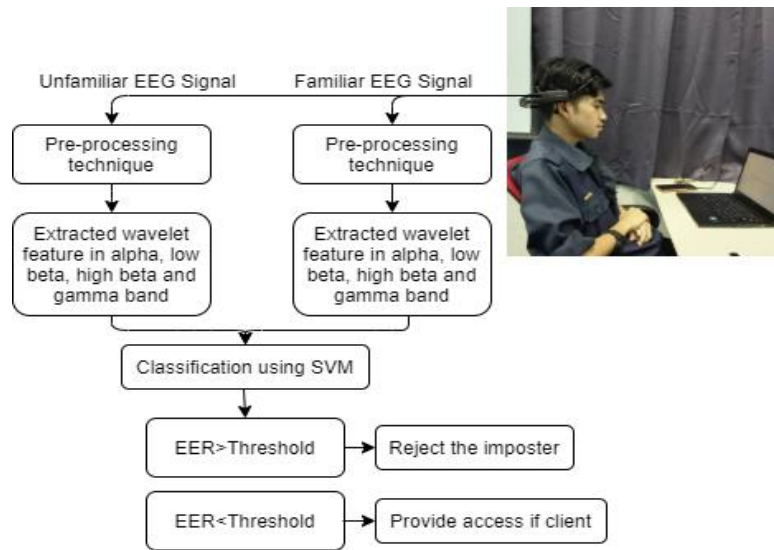
Figure 2. The flow of the proposed methodology

2.2.2. Feature Extraction. In the registration and authentication mode, the feature extraction method is required to minimize the data to be a manageable group of datasets and describing the original data accurately. The wavelet packet-based feature was applied in this research which theoretically functions as signal decomposition which is the generalization of wavelet bases. Moreover, it takes a linear combination of wavelet functions [12]. The signal is decomposed into 2 sub-spaces for each level which at the end it will decompose into coefficients as shown in equation (1). This research converted the signal into Wavelet Packet Decomposition (WPD) signals with 3 levels of decomposition and calculated Root Means Squared (RMS) as the feature representation in equation (2). Ting et al. [13] were proposed the WPD as feature extraction for Brain-Computer Interface (BCI) and revealed that it provides more information and improves the classification performance.

$$\text{The decomposition coefficients,} \; d_j^n(k) = 2^{\frac{j}{2}} \, d^n(2^j - k) \tag{1}$$

where j is the level of decomposition, n is the frequency factor and k is the shift factors.

$$The \; RMS \; wavelet \; = \sqrt{\frac{\sum_k d_j^n(k)^2}{N}} \tag{2}$$

2.2.3. Classification. The classification is a pattern recognition algorithm that can classify and predict the targets by referring to modelling problems using machine learning and deep learning. The dataset consists of two parameters which the first set is the input, X indicates the feature set, and the second set is the output, T as indicates the targets. Classification can be either a supervised learning and unsupervised learning method, as this research applied supervised learning because it requires the output to train the model and provides answers to evaluate the performance of the model. Therefore, this research implemented supervised learning which is SVM with RBF kernel function to classify between 15 subjects.

2.2.4. Performance Metric. To evaluate the system, a k-fold cross validation at k=10 is adopted in this paper. Thus, this research evaluated the classification between the subjects by Correct Recognition Rate (CRR) and error rate in percentages.

$$Accuracy = \frac{True\ positive\ +\ True\ negative}{True\ positive\ +\ True\ negative\ +\ False\ Positive\ +\ False\ Negative} \times 100 \quad (3)$$

3. Experimental Result

In this section, the CRR values is the main performance indices of the proposed authentication system are discussed. The results are evaluated in distinct bands of EEG namely alpha band, low beta band, high beta band, and gamma band. Figure 3 displays the CRR for the selected channels namely 14-channels, 8-channels, 6-channels, 4-channels, and 2-channels. It is visible from the graph that all 14 channels offer the best CRR followed by 8-channels, 6-channels, 4-channels, and the least is 2-channels. In addition, the highest CRR is achieved by the high beta with 14 channels. It can be observed that in every configuration, the high beta band performs better than other bands, giving the CRR values of 96.49 using 14-channels setups. It can be concluded that as the number of channels is reduced, the performance of SVM also becomes poor. A study [14] purposely used SVM and the data sampling rate adjusted at 128Hz which the performance achieved 50% of the overall accuracy at the EEG signal 8 Hz to 30 Hz. Another study [15] of EEG-based biometric implemented SVM with ECOC techniques with 22 channels at 0.5Hz to 100Hz which attained 64.93% of classification accuracy.
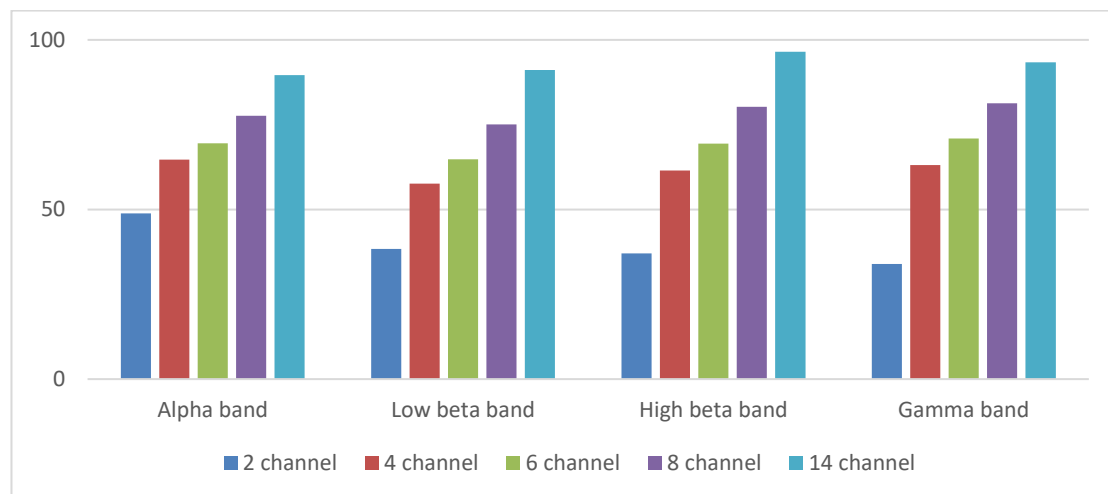

Figure 3. The accuracy for alpha, low beta, high beta and gamma bands for both familiar and unfamiliar using the selected channels configuration.

For further examine, the individual contribution of familiar and unfamiliar in biometric authentication performance is discussed. The computation of CRR values is obtained while the system employed familiar only, unfamiliar only, and both familiar and unfamiliar. The subject authentication is classified by SVM and evaluated the performance with 2-channels. 4-channels, 6-channels, 8-channels, and 14-channels. The experimental result shows that for an alpha, low beta, high beta, and gamma band, the CRR is favored by an unfamiliar paradigm compared to the familiar with 2-channels, 6-channels, and 8-channels whereas it is favored by a familiar paradigm with 14-channels. The combination of familiar and unfamiliar paradigms shows the lowest CRR among all channels and bands.

The error rate values are the intersection point for FRR and FAR values are plotted in Figure 4. EER values achieved is achieved by 10 runs of cross-validation and it can be found that the high beta band obtained below 0.035 EER for 14-channels.
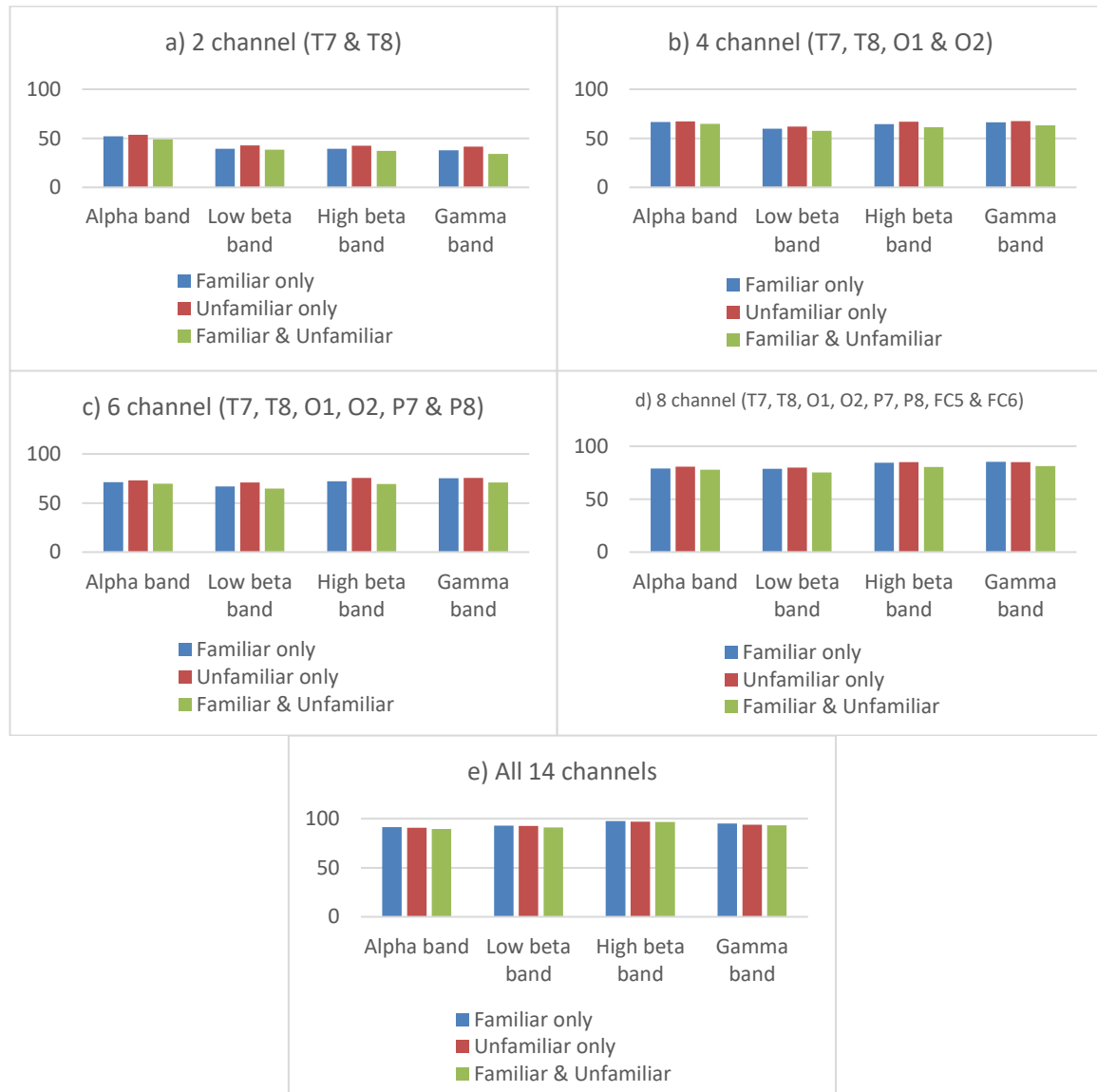

Figure 4. The average of accuracy for familiar only, unfamiliar only and both familiar and unfamiliar configuration for a) 2-channels, b) 4-channels, c) 6-channels, d) 8-channels and e) 14-channels setup
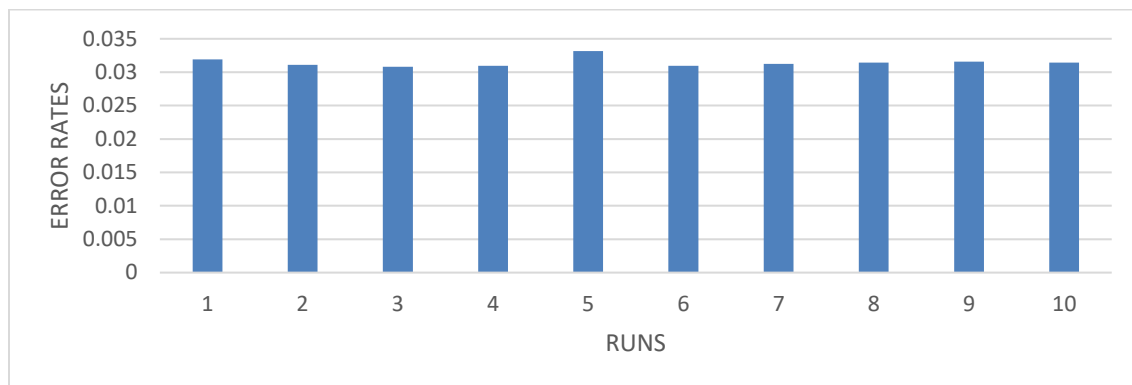
Figure 5. The error rate values in 10 runs of the proposed authentication system for high beta band with 14-channels setup

The comparison of the proposed system performance was explored with the state-of-the-art with the recent research in the authentication system field. The comparison is in terms of the accuracy of the system in Table 1. Studies [7] [8] and [10] employs EMOTIVE EPOC+ with 14 channels with difference paradigm such as visual stimuli and auditory stimuli. It can be noted that the proposed of VEPs using familiar and unfamiliar images to evoke the electricity in the brain to produce specific signals with 14 channels could offer the best CRR or accuracy.

Table 1. Comparison between recent studies

Study	Paradigm	Channel	Results
Mustafa et al. [7]	Visual stimuli	14	Accuracy: 80%
Nakanishi et al. [8]	Ultrasound stimuli	14	EER: 22.0%
Cauthen et. al. [10]	Reading with music	14	Accuracy: 86.4%
This research	VEPs		CRR
	Familiar only	14	97.44%
	Unfamiliar only	14	96.86%
	Familiar &Unfamiliar	14	96.49%
	Familiar	8	85.21%
	Unfamiliar	8	84.87%
	Familiar &Unfamiliar	8	81.29%
	Familiar	6	71.15%
	Unfamiliar	6	75.57%
	Familiar &Unfamiliar	6	70.91%

4. Conclusion

A new biometric trait-like EEG signal has become popular recently due to its universality and robustness. This research proposed an EEG-based authentication system using a high beta band in the range 20 – 30 Hz in wavelet packet decomposition form in which acquired familiar and unfamiliar EEG signals. The proposed system technology is based on the classification using SVM and obtained the error rate and CRR to evaluate the performance of the system. Given that the error rate of the high beta band was achieved below 0.035 over 15 subjects, which is higher compared to the state-of-the-art method employed by other recent researchers. Hence, the result is promising, and future analysis will be planned to improve the robustness of the system. Hence, the basic requirement of biometric has to be considered.

In future work, this research plan to increase the number of subjects to develop a larger database of EEG for the authentication system. Moreover, the feature fusion will be explored and implemented in this research towards the development of a robust EEG-based authentication system incorporates with a larger database to improve the performance of the system. Hence, the analysis of channel reduction

is crucial to develop a comfortable and user-friendly biometric sensor which more suitable applications for users.

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