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Investigation of Alpha and Beta Band for Brainprint Authentication with Auditory Distractor

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***Abstract*: This paper aims to investigate the use of alpha and beta band for brainprint authentication modelling by using Incremental Fuzzy-Rough Nearest Neighbour (IncFRNN) technique. Many electroencephalogram (EEG) research worked well in controlled lab environments with the minimum ambient disturbance. It is because the EEG signals are easily influenced by the ambient noise or other physiological noise. Therefore, in order to enhance the use of brainprint authentication, two rhythms of EEG signals: alpha and beta band were examined in three different level of auditory distraction (i.e. quiet, low and high distraction) to simulate the real-world environment. Only 5 electrodes, which represents the auditory and visual are used for the brainprint authentication modelling. The representative features were extracted from the power spectral density (PSD), coherence and wavelet phase stability (WPS) before perform classification. The experimental results showed that the authentication results of quiet and high distraction conditions are performed significantly better than the low distraction condition in the alpha band. However, the statistical tests do not show significant different for the three conditions in beta band. It might because of the tasks given in this environment do not involved much analysis and decision making. Further investigations will be focused on the combination of alpha and beta band for brainprint authentication modelling.**

***Keywords*:** alpha band, beta band, auditory distraction, brainprint authentication

I. Introduction

Brainprint authentication aims to use brain signals in accepting or rejecting the identity that claimed by a particular individual, which is one-to-one matching. An authentication system is seeking to compare or match the presented individual biometric modality against a biometric template that already exists in the database. There are seven specific characteristics must be available in a biometric authentication system [1]. The seven characteristics are uniqueness, universality, collectability, circumvention, permanence, performance and acceptability. Apart from that, a good authentication system should also have the low intra-subject variability and high inter-subject characteristics.

Electroencephalogram (EEG) signals are proven unique among individuals [2]. Besides, the aliveness of EEG signals is an outstanding benefit as compared to the other biometric modalities. Recently, EEG based biometric authentication is growing over the past few years [1], [3]–[9] due to their portability and low cost as well as higher time resolution [10]. However, many studies on the EEG research are conducted in the quiet controlled laboratory to minimize the disturbance towards our human brain. In real-world situation, ambient noise distraction cannot be avoided, and hence it is definitely affecting our EEG signals. Without consider on this problem, the authentication performance will be degraded.

EEG signals can be categorized into five rhythms Gamma (γ), Beta (β), Alpha (α), Theta (θ) and Delta (δ) [11]. Different rhythms represent different brain activities. Among the five rhythms, only alpha and beta band are more suitable to be used for brainprint authentication. The theta and delta band will be occurred during sleeping while the gamma band is occurred if and only if the brain is disorders [11]. Thus, an experiment is carried to assess the performance of alpha and beta band in different environment settings for the brainprint authentication modelling.

The rest of the paper is organized as follows: Section II provides the literature reviews on the EEG-based biometric authentication by using different bands. Section III outlines the experimentation which includes the data pre-processing steps, feature extraction and feature selection, classification, and the performance measures. Section IV portrays the results and discussions and finally, section V draws the conclusion and the direction of future work.

II. Literature Review

EEG is one of the tools that used for analyzing the brain activities, which are recorded noninvasively by attaching the electrodes on the scalp [12]. EEG measures the voltage fluctuations from the ionic current within the neurons of the brain. The recorded waveforms reflect the cortical electrical activity and measured in microvolts (µV) [13]. The first EEG signals was recorded by Berger [14] in 1929. In the early stage of the EEG research, EEG signals are normally used for clinical. EEG reflects the functional state of brain affiliated to the human mental condition, which can extract the crucial information to further analyze patient's health, diagnosis and identify different brain conditions [15]. EEG signals are categorized into five basic rhythms, which are Gamma (γ), Beta (β), Alpha (α), Theta (θ) and Delta (δ). The bandwidth and description of each rhythms is shown in Table 1 below:

Rhythm	Bandwidth	Description
Gamma (γ)	[30, 40] Hz	Indicate event brain synchronization and be used to monitor some brain disorders.
Beta (β)	[13, 30] Hz	Indicates alert state, with active thinking, attention and decision making.
Alpha (α)	[8,12] Hz	Indicates in a relaxed state, with little or no attention, mainly appear at occipital lobe.
Theta (θ)	[4, 8] Hz	Indicates creative inspiration or deep meditation; can also appear in dreaming sleep (REM stage).
Delta (δ)	[0.5, 4] Hz	Primarily associated with deep sleep or loss of body awareness but can be present in the waking state.

Table 1. EEG Signal Rhythms [11].

As described in the Table 1, the theta and delta band are used to measure the EEG signals for sleeping stage. Thus, it is less suitable to be used for the brainprint authentication modelling. The gamma band involved in attention, perception and memory [16]. It indicates the event of brain synchronization and be used to monitor some brain disorders [11]. However, there is a research using the gamma band during resting state for EEG-based biometric authentication [17]. The authentication technique was based on simple cross-correlation of Power Spectral Density (PSD) features during the eyes closed and eyes open resting state. The equal error rate (EER) achieved up to 0.0196 in the experiment.

Alpha band plays essential role of indicating in relaxed state and cognitive processing [18]. Several studies have proven that the alpha oscillations are proposed to reflect the focus of attention in visual [19]. In addition, alpha activity show increasing when the load in working memory increasing [20]. The inter-subject variability in alpha band shows large degree and it explained by the genetic factors [21]. The twins also able to show the obvious inter-subject variability for about 80% [22]. On the other hand, the intra-subject variability in alpha band reflect in different pattern on different task demand [23]. With these justifications on the alpha band, it is possible to be used in biometric trait for brainprint authentication. Research work in [24] also using alpha band for EEG based biometric authentication. The power spectra are extracted from the alpha band to perform further analysis. The EER achieved 11% from a total of 23 subjects.

Beta band indicates the subject with active thinking and concentration on the given tasks. Ong et al. [25] compared the use of alpha band, beta band and the combination of alpha and beta band for human EEG-based biometric identification. The EEG signals are recorded when the subject responses to the different kind of visual stimuli, such as the blue colour paper, own identity card and other people's identity card to trigger the EEG signals. PSD and K-Nearest Neighbour (KNN) were used to extract the representative information and classification respectively. The average classification accuracy for alpha band, beta band and the combination of alpha and beta band are 80.94%, 86.19% and 85.55% respectively. Mohanchandra et al. [26] extracted the spectral power from the alpha, beta and gamma bands for the EEG-based person authentication. The PSD shows the strong or weak frequencies variation [27]. Meditation and math activities are the tasks to be performed during the EEG signals recording. The research work in [26] classified the subjects based on the Euclidean Distance and obtained 0.78 in False Acceptance Error (FAE) which is considered a good match. However, the data acquisition in the research work [26] need to be improved by doing the EEG recording in a clinical conditions to avoid the external interferences. The brain responses outside of a controlled experiment is expected to be different [28] because human tends to be influenced by the ambient distraction.

III. Experimentation

EEG signals classification is tricky due to the very low signal-to-noise ratio [29]. Thus, selection of feature extraction and classification are playing crucial role to capture the weaknesses facing by the EEG signals. In this paper, incremental approach is selected because the classifier with incremental learning able to update the knowledge granules over the time without retrain. Incremental learning model provides a system with the ability to learn from new information when it is available [30].

A. Data Acquisition and Experimental Setup

EEG signals was collected from a group of 45 healthy subjects, which consists of 25 males and 20 females. The subjects are selected based on 3 different age groups, which are 18-25 years old, 26-35 years old, 36 years old and above. Each age group has 15 subjects respectively. Aging influences the distraction tolerant level in auditory task [31]. Hence, multiple age groups were engaged as the target subjects for experiment. Every subject is in good condition with normal or corrected normal vision. The ethical approval and the experimental design have been granted by the Medical Research and Ethics Committee (MREC) from Ministry of Health Malaysia.

Each subject is required to read the participant information sheet in understanding the experiment procedures and requested to sign the consent form before proceeding to the EEG signals experiment recording session. The subject was sat on a rested armchair to provide the maximum comfort. It is to minimize the possible movements or artifacts during the recording session. The distance between the computer screen and subject's eyes was 1 meter. All the visual stimuli with the resolution of 700 x 525 pixels and displayed on a white background at the center of computer screen.

The Inter-Stimulus Interval (ISI) for each trial was set to 1.5 seconds. The picture was displayed for 1 second and followed by 1.5 seconds of white-blank screen as illustrated in Figure 1 [9]. Each subject was completed with 150 trials. There are 60 trials were the selected password picture and the other 90 trials were the pictures randomly selected from the picture set excluding the password picture selected by the subject. The subject was required to recognize their selected password picture from a random set of pictures shown on screen and click the mouse immediately as the password pictures display on the screen. No further action is required from the subject when the password picture was not displayed. The sampling rate used in this experiment is set to 512 Hz.

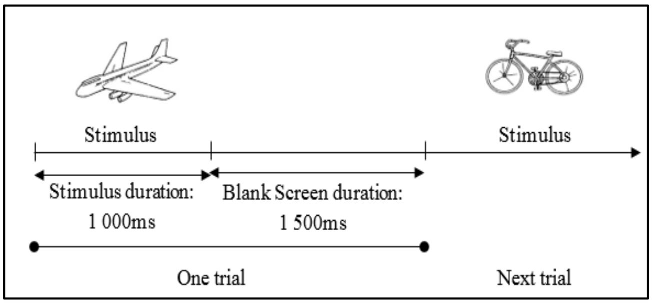

Figure 1. Visual Stimulus Presentation [9]

The experiment paradigm was conducted in three different simulated environments: (1) a quiet condition; (2) a low distraction condition; and (3) a high distraction condition. It is to mimic different level of distraction in the real-world. An audio clip with consistent office noise sound effect was played for the low distraction condition with approximately sound level of 55 decibel (dB). On the other hand, an audio clip with inconsistent office noise sound effects such as working environment with typing keyboard, printer printing, stamping document, etc. were played for the high distraction condition and the sound level is approximately 70 dB.

There are 21 electrodes were used to record the EEG signals by using Twente Medical Systems International (TMSi) Porti system. The electrodes are FP1, FPZ, FP2, F7, F3, FZ, F4, F8, T3, C3, CZ, C4, T4, T5, P3, PZ, P4, T6, O1, OZ and O2. All the scalp electrodes were referred to the right earlobe and grounded on right hand wrist during the experiment setup. However, only 5 electrodes (T5, O1, OZ, O2 and T6) from the visual and auditory area were selected and used in this experiment.

B. Data Pre-processing and Data Preparation

Data pre-processing is a compulsory and crucial step before performing further analysis. Filtration, segmentation and artefact rejection are the pre-processing steps. The EEG data was obtained with a Finite-duration Impulse Response (FIR) filter with the cut off frequency of 8 – 12 Hz for alpha band and 13 – 30 Hz for beta band respectively. Furthermore, the artefact rejection was used to eliminate unwanted EEG signals responses such as the excessive body movements or other types of artefacts with amplitude greater than 100 µV. Thus, the trials with amplitude higher than 100 µV were removed.

Feature extraction is a crucial process to retrieve the representative characteristics from the EEG signals. In this paper, Power Spectral Density (PSD), Wavelet Phase Stability (WPS) and coherence. In addition, feature selection method, Correlation-based Feature Selection (CFS) was used in this paper to reduce the dimension of feature vectors without jeopardized the authentication performance. CFS is a simple and correlated-based filter algorithm that is applicable in discrete and continuous problems [32]. The CFS algorithm evaluates the feature subset according to correlation-based heuristic merit. It judges the usefulness of a feature through the inter-correlation among the features.

C. Classification

In this paper, IncFRNN was used to perform brainprint authentication modelling. It is a binary class problem with the output class yes or no. The significant and selected features were split into train and test set by using 10-folds cross validation (CV). It is to prevent the biased evaluation of the classifiers. The designed 10-folds CV here is divided the data into 10% for train set and 90% for test set due to the incremental learning that able to update training pool from time to time rather than to have a full training data in the early stage of the learning process.

Incremental Fuzzy-Rough Nearest Neighbour (IncFRNN) technique in [9], [33] is an enhanced version of the original FRNN introduced by Jensen and Cornelis [34]. The new algorithm consists of an additional heuristic update method, and the window size threshold parameter to update incrementally the knowledge granules through object insertion and deletion. It allows the object instances in the knowledge base adapt to the changes of the brain states, if it happens. In addition, the incremental module in the proposed model also supports continuous learning from limited training data, towards fully completed knowledge granules through incoming brainwaves data.

The new object is insert selectively into the existing training pool whenever there is availability of new variant test object. By doing this, the knowledge granules able to capture the new characteristics that represent the individual biometric identity for the authentication process. However, insert the new object continuously results to an increasing on the size of training pool. Consequently, the window size threshold is set to control the size of the training pool for the IncFRNN algorithm.

In IncFRNN algorithm, similarity between the two objects is the main concern in order to delete the object from the training pool. It is because the lower and upper approximation are composed by the nearest neighbours as described in the FRNN algorithm. The highest value of similarity is used to quantify the class decision for the test object. Hence, the enhancement of the similarity value can further increase the classification results. An object will be deleted if and only if the number of training objects is greater than the window size threshold and the window size threshold is greater than 0. A frequency counter is introduced to track the number of usages for the objects in the nearest neighbour pool. Hence, the IncFRNN algorithm will only deletes the object with the lowest frequency usage and must be within the same class label. Furthermore, the First-In-First-Out (FIFO) strategy is implemented in the IncFRNN algorithm if and only if the counters of the frequency usage for the training objects are same.

In summary, the IncFRNN algorithm preserves all the representative objects and removes the insignificant objects in the training pool. From the perspective of brainprint authentication, the new individual characteristics of EEG signals will be added into the knowledge granules by inserting the object. At the same time, the old and rarely used of the individual EEG signals characteristics will be removed by deleting the object. It is because the characteristics are less meaningful to be used as the identity for the particular individual. In summary, this heuristic update method is vital to obtain better classification results for the performance of brainprint authentication modelling.

D. Performance Measurement

Several types of performance measures can be used to evaluate the authentication results. Since brainprint authentication is a binary classification, therefore we can evaluate the authentication performance by using the confusion matrix. Basically, the binary class result takes four possible outcomes (as shown in Table 2), which are true positives (TP), true negatives (TN), false positives (FP) and false negatives (FN).

		Actual Class	
		Yes	***No***
Predicted Class	***Yes***	TP	FP
	No	FN	TN

Table 2. Different Outcomes for Binary Class Prediction.

1) Area Under ROC Curve (AUC)

Area under Receiver Operating Characteristics (ROC) curve (AUC) is one of the commonly used measures for binary classification, which relies to specificity and sensitivity. AUC encapsulates a single point on the reception operating characteristic curve. It shows how accurate of the predicted positive examples that vary with the number of inaccurately predicted negative examples. As compare to accuracy measure, the AUC is proven to provide more discriminating value and statistically reliable. The AUC performs well and is frequently employed as a general metric of detection performance. ROC analysis had become a standard evaluation for signal processing and medical area. The range of the AUC measure is between 0 and 1. The higher the AUC, the better the classification performance. The AUC measure is interpreted as in Table 3.

AUC Measure	**Performance**
0.90 – 1.00	Excellent
0.80 – 0.90	Good
0.70 – 0.80	Fair
0.60 – 0.70	Poor
0.50 – 0.60	Fail
0.00	Incorrectly Classify

Table 3. Interpretation of AUC Measure.

2) Recall

In a binary classification task, the recall denotes the number of accurately predicted positive examples divided by the total number of positive examples in the dataset. The recall is also known as true positive rate (TPR). The higher the value of recall, the better the classification performance. The recall is calculated as:

$$Recall = \frac{TP}{TP+FN} \quad (1)$$

3) Precision

In a binary classification task, the precision denotes the number of examples accurately predicted as belonging to the positive class divided by the total number of examples that predicted as the belonging to the positive class, which is the summation of TP and FP. Therefore, the precision is calculated as:

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

4) Accuracy

Accuracy is widely used to evaluate the performance of classifiers. It is used to measure how good is a binary classification that correctly classified test objects. It is also a measure of the agreement with the correct value of the parameter under certain conditions. However, the accuracy can be misleading when the portions of the class distribution are huge different [35]. The range of accuracy is between 0 and 1; the higher the accuracy value indicates the perfection of the classification results. The accuracy is calculated as:

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \quad (3)$$

IV. Results and Discussion

In this stage, the authentication results were evaluated based on the AUC, recall, precision and accuracy [36]. A statistical test was performed to test the significant different between the environment conditions with 95% confidence level. The authentication results are analyzed in two different perspectives, such as analysis in alpha band and analysis in beta band. Finally, the discussion on the alpha and beta band will be described in sub-section C.

A. Auditory Distraction Analysis using Alpha Band

Table 4 shows the authentication results in AUC and accuracy measure while Table 5 shows the authentication results in recall and precision measure for the alpha band. The results are compared between the quiet, low and high distraction conditions.

Auditory Distraction Level	AUC	p-value	Statistical Test	Accuracy	p-value	Statistical Test
Quiet	**0.9387**	0.004	Different	**97.96**	0.004	Different
Low	0.9205			97.55		
Quiet	0.9387	0.491	**Equal**	97.96	0.937	**Equal**
High	0.9422			97.97		
Low	0.9205	0.002	Different	97.55	0.001	Different
High	**0.9422**			**97.97**		

Table 4. Authentication Results in AUC and Accuracy Measure for Alpha Band.

Among the three environment conditions, the best authentication performance is recorded in the high distraction condition with 0.9422 in AUC measure, and then followed by the quiet condition, which is recorded at 0.9387 in AUC measure. The statistical test does not show significant different between the authentication performance in high distraction and quiet condition. The AUC measure in low distraction condition is 0.9205. From the statistical test, we can conclude that the authentication performance in high distraction and quiet conditions are performed significantly better than the performance in the low distraction condition.

From the perspective of accuracy measure, the authentication performance in quiet, low and high distraction conditions achieved 97.96%, 97.55% and 97.97% respectively. The difference of accuracy measure in high distraction and quiet condition is 0.01% only. Thus, the statistical test does not show significant different between the two conditions as mentioned above. This has proven that the authentication performance of brainwaves signals under high distraction is equivalent to its benchmark, the quiet condition. However, both the accuracy in high distraction and quiet conditions are performed significantly better than the accuracy in low distraction condition.

Auditory Distraction Level	Recall	p-value	Statistical Test	Precision	p-value	Statistical Test
Quiet	**0.6965**	0.002	Different	**0.5500**	0.005	Different
Low	0.6369			0.4812		
Quiet	0.6965	0.722	**Equal**	0.5500	0.774	**Equal**
High	0.7024			0.5562		
Low	0.6369	0.001	Different	0.4812	0.001	Different
High	**0.7024**			**0.5562**		

Table 5. Authentication Results in Recall and Precision Measure for Alpha Band.

Apart from the AUC and accuracy measures, the recall and precision also play important roles in evaluating the authentication performance. The highest value of recall and precision are 0.7024 and 0.0.5562 respectively in high distraction condition. In addition, the recall and precision in quiet condition are 0.6965 and 0.5500 respectively, which is 0.0059 and 0.0062 lower than in high distraction condition. Hence, there are not significantly different between the recall and precision for high distraction and quiet conditions. On the other hand, the worst authentication performance was recorded in the low distraction condition with 0.6369 in recall measure and 0.5500 in precision measure.

Based on the authentication results, the recall and precision measure in quiet condition are performed significantly better than in low distraction condition. In the comparison between the low and high distraction condition, the authentication performance in high distraction are significantly better than in low distraction for all the performance measures. However, the authentication results do not show significant different between the quiet and high distraction condition.

B. Auditory Distraction Analysis using Beta Band

In contrast, the authentication results in AUC and accuracy measures for beta band is shown in Table 6 and Table 7 indicates the authentication results in recall and precision measures for beta band. The authentication results in high distraction condition showed the highest results in all performance measures among the three conditions. The authentication results of high distraction condition achieved 0.9306 and 97.81% in AUC and accuracy measures respectively. Meanwhile, the low distraction condition gained 0.9215 in AUC and 97.67% in accuracy measures. In the quiet condition, the AUC and accuracy are slightly higher than in lower distraction condition. The AUC and accuracy are 0.9272 and 97.74% for the quiet condition. Nevertheless, the statistical tests show not significantly different for all the comparisons, such as the comparison between quiet and low distraction condition; the comparison between quiet and high distraction condition; and the comparison between low and high distraction conditions.

Auditory Distraction Level	AUC	p-value	Statistical Test	Accuracy	p-value	Statistical Test
Quiet	0.9272	0.436	Equal	97.74	0.604	Equal
Low	0.9215			97.67		
Quiet	0.9272	0.627	Equal	97.74	0.661	Equal
High	0.9306			97.81		
Low	0.9215	0.229	Equal	97.67	0.372	Equal
High	0.9306			97.81		

Table 6. Authentication Results in AUC and Accuracy Measure for Beta Band.

Auditory Distraction Level	Recall	p-value	Statistical Test	Precision	p-value	Statistical Test
Quiet	0.6613	0.522	Equal	0.5201	0.569	Equal
Low	0.6481			0.5057		
Quiet	0.6613	0.796	Equal	0.5201	0.753	Equal
High	0.6664			0.5287		
Low	0.6481	0.398	Equal	0.5201	0.395	Equal
High	0.6664			0.5287		

Table 7. Authentication Results in Recall and Precision Measure for Beta Band.

Based on the authentication results in Table 7, the recall of quiet, low distraction and high distraction conditions achieved 0.6613, 0.6481 and 0.6664 respectively. Meanwhile, the quiet, low distraction and high distraction conditions obtained 0.5201, 0.5057 and 0.5287 respectively for the precision measure. According to the statistical tests, it does not show significant different between the three conditions.

C. Discussion

In summary, the authentication results in high distraction condition is performed significantly better than the results in low distraction condition but performed as good as in quiet condition in alpha band. It might because of the subjects showed their individual characteristics in the EEG signals when response to the audio distraction.

On the other hand, the authentication results and statistical tests in beta band are not significant different among the three conditions. It might because of our primary task, visual and the secondary task, audio do not involve much thinking or decision making. Therefore, it does not show significant in the three environment conditions. As mentioned in [11], beta band involves active thinking, attention and decision making.

Thus, Figure 2a and Figure 2b show the graphs for alpha band and beta band in the Oz channel respectively for the best authentication results. Besides, Figure 3a and Figure 3b show the graphs for alpha and beta band in the Oz channel for the worst authentication results. The main purpose of showing the alpha and beta band in graphical is to compare and analyze the performance of different band in different environment conditions

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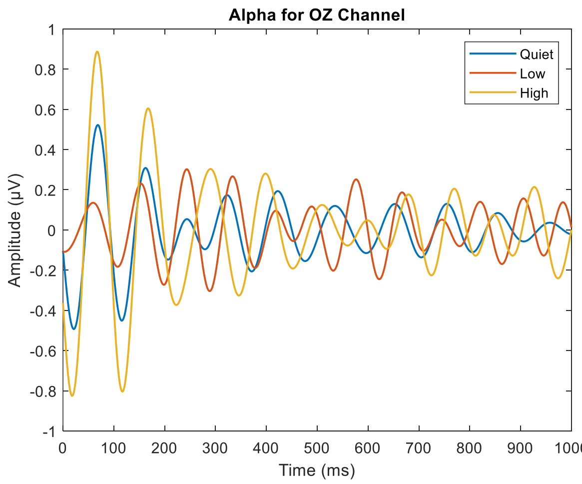

Figure 2a. Alpha Band for the Best Authentication Result

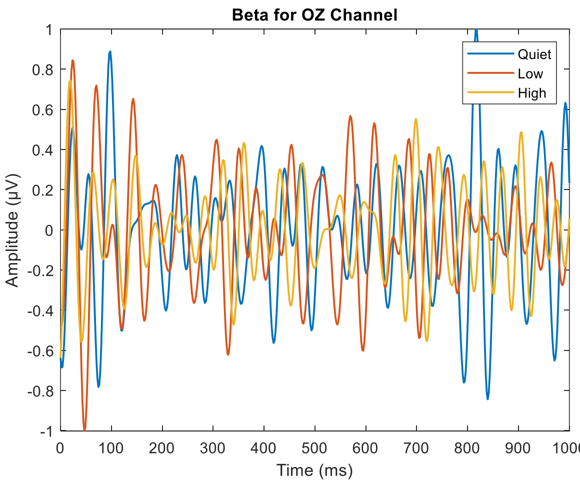

Figure 2b. Beta Band for the Best Authentication Result

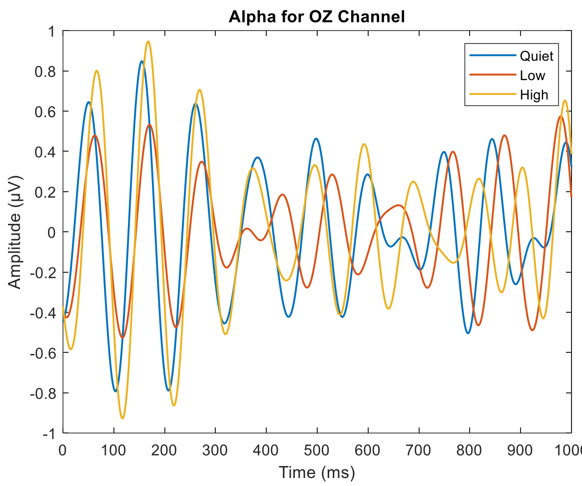

Figure 3a. Alpha Band for the Worst Authentication Result

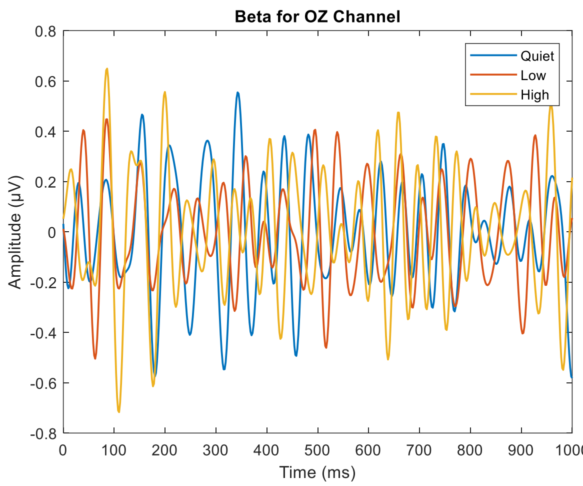

Figure 3b. Beta Band for the Worst Authentication Result

In Figure 2a, we can observe that the alpha band is similar between the quiet and high distraction conditions. However, the alpha band in low distraction condition shows huge different as compared to the quiet and the high distraction conditions. Besides that, we also can clearly observe that the larger peak occurred within the first 300 ms in the alpha band, which involves the processing in the occipital lobe. However, the beta band in Figure 2b does not show obvious different between the three environment conditions. Therefore, the statistical tests on the authentication results are not significant different among the three environment conditions.

On the other hand, the alpha band in Figure 3a unable to show clear different among the three environment conditions. It might because of this subject is not get distracted easily. In addition, Figure 3b shows the worst authentication result in beta band and it also does not show the obvious different between the three environment conditions, which is similar to the beta band in Figure 2b.

V. Conclusion

In this paper, we have investigated the authentication performance by using alpha and beta band. The experimental results have proved that alpha band is more suitable to be use as the biometric modality for the brainprint authentication. The main reason in using alpha band because the task given in this experiment is very simple. Therefore, the beta band is less suitable. Further works should be done to improve the performance of brainprint authentication especially in term of recall and precision measure. It is because the recall and precision measure are very important in order to evaluate the authentication model.

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