Development of Smart Security System for Building or Laboratory Entrance Based on Human's Brain (EEG) and Voice Signals

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***Abstract*—The drastic increment in cyber-crimes and violent attacks involving our properties and lives made the world become much vigilant towards ill-intentioned peoples. Thus, it leads to the booming of smart security system industry which relies heavily on biometrics technology. However, due to certain circumstances, some users may find the existing biometrics technologies such as fingerprint, palm, iris and face recognition are unable to detect the necessary data precisely due to the physical injuries of the users. Furthermore, the fact that these biometrics technologies are easily retrieved from the user and be used as counterfeit to access to the security system undetected. Thus, in this research, in order to enhance the existing security system based on the biometric technologies, the combination of the human physiological signals such as brain and voice signals will be employed in order to unlock the magnetic door entrance to the laboratory, building or office. This research has utilized mobile Electroencephalogram (EEG) headset and voice recognizer to capture human's brain and voice signals respectively. The extracted features from the captured signals then are analyzed, classified and translated to determine the device command for the microcontroller to control the door entrance's locking system. The high rate of classification results of the selected features of EEG and voice signals at 96.7% and 99.3% respectively show that selected features can be translated to command parameters to control device.**

***Index Terms*—Brain Signals; Classification; Extracted Features; Voice Signals.**

I. Introduction

Nowadays, biometric technologies become popular and are prominently applied by the companies or firms to enhance their security systems. Biometric systems use human's trait and bio-signals such as face, iris, voice print, fingerprint, palm print, hand geometry, handwriting, gait, heart signal, odour, and brain signals to identify a person [1-4]. Among them, the top biometric technologies are fingerprint, voice print, face and iris. Human biometrics is unique and impossible to duplicate or recreate. This technology has outperformed the common authentication methods using personal identification number (PIN), password, signature, and ID access card. The biometric technologies can be applied in various fields and applications such as access to buildings, rooms, gate control, banking transaction, telephone banking, credit card transaction and surveillance Each biometrics is evaluated based on universality, uniqueness, presence, measurability, performance, acceptability, and circumvention [5-6].

Besides the top biometric technologies, the recent researchers have preferred to implement security system using human's brain signals or EEG signals since those signals can be used for continuous authentication compared to other biometric methods. In addition, brain signals are unique, cannot be duplicated and anti-circumvention [7-15]. Meanwhile, the human voice is unique to the frequency and intensity of the voice. The research on biometric modalities using fingerprint and brain signals were done in 2012. However, the fingerprint cannot provide continuous authentication since its accuracy can be affected by a scar on the finger [16-17]. The main challenges to employ brain and voice signals in security system are the effect of eyes movement to brain signals and the effect of the device or environment noise to human voice [18-20]. Therefore, this project applied the combination of these biometric methods to increase the security performance. Here, the project focuses on the use of brain and voice signals to replace the existing card-based security system which is currently used to enter the laboratory or office at Universiti Malaysia Pahang. These biometric methods are selected since they are able to recognize between real and fake users. Thus, the proposed research will provide a strong and reliable security system in Universiti Malaysia Pahang.

Due to the drawbacks or limitations of the frequency-based and password-based security system which prone to be easily duplicated, the main objective of the research is to provide a reliable access control and authentication system for building or laboratory entrance in Universiti Malaysia Pahang based on the extracted features from human's brain and voice signals. Since the research is still in the development mode, in order to capture human's brain signal, the inexpensive, less complicated and single-channel EEG device is chosen. Nowadays, the single channel EEG devices are widely used to measure the change in brain cognitive state when exercising mental tasks or when experiencing mental stress [21-25]. Meanwhile, the voice recognizer is used to capture human's voice signal.

In the field of Brain Computer Interface (BCI), researchers have come out with various EEG features and feature extraction techniques to be used in the BCI application such as band power spectrum, energy spectral, density, spectral centroid, common spatial pattern, (CSP), wavelet coefficient, autoregressive model, cross-correlation, variant, co-variant, short-time Fourier Transform (STFT), Shannon entropy and z-score [26-29]. In addition, various classifiers were introduced by previous researchers to classify the EEG features such as k-Nearest Neighbor (k-NN), Artificial Neural Network (ANN), Support Vector Machine (SVM), Linear Discriminant Analysis (LDA), Discrete Wavelet

Transform (DWT) and Random Forest [30-31]. The selections of suitable and effective EEG features are crucial in order to implement the application of BCI with high accuracy. Hence, in this research, the spectral centroid is selected to be applied to both EEG and voice signals due to its effectiveness and ability to find the dominant energy or power spectrum of EEG signals from the individual or group members who might experience high cognitive activities or in the stress condition [26-29, 36-37].

In this research, for the classification stage, the k-NN classifier is preferable and used to classify the selected features of the EEG and voice signals. Among the supervised classifiers, the k-NN classifier is chosen due to its ability to perform pattern matching for the non-parametric analysis of the non-stationary signal such as brain or voice signals. Here, the classification is implemented based on the ratio of training and testing data. Then, the k value will be varied to search for the match class between training and testing data. There are various ratio of training and testing data to be used for k-NN classifier such 50:50, 60:40, 70:30 and 80:20. Basically, the highest classification accuracy will be obtained at the small value of k such 1 or 2 and at training and testing ratio is 70:30 [31-35]. In this research, the k-NN classifier is configured with the ratio of training and testing is set to 70:30. However, the k value is varied from 1 until the 70% of the number of selected data in order to see the variation of k toward the classification accuracy. Meanwhile, the classifier configuration on distance and rule is set to the default setting which is "Euclidean" and "Nearest".

In order to achieve the main objective which is to provide features for device control, a single channel EEG amplifier is employed to capture the EEG signals from human's forehead area. Meanwhile, voice recognizer with voice commander is used to record and train human's voice. Next, features extracted from both brain and voice signals are classified and converted to parameters for device control.

II. METHODOLOGY

The project focuses on the analysis of the extracted features obtained from human's brain and voice signals for application of brain-computer interface (BCI). The features are extracted, trained and classified before converting to device command that can be used by the microcontroller to open the magnetic door entrance to the building or laboratory. The project involved several steps as stated as follows.

A. Subject selection

The project begins by selecting 2 males and 1 female subjects which age range from 22 – 45 years old. All subjects are non-smoker and free of drugs or medication.

B. Measurement protocol

In this research, one channel Neurosky Mindwave mobile EEG headset and voice recognizer, EasyVR Shield 3.0 are selected as illustrated in Figure 1 and Figure 2. Here, this EEG amplifier will capture the EEG raw data at a rate of 512 Hz. The electrode of the EEG amplifier (sensor tip) will be placed on the FP1 area of the human brain.

The reference electrode will be attached to the earlobe. The measurement protocol consists of 2 parts. For EEG part, the EEG signals are recorded from each subject at 2 exercises mode using EEG application in a mobile phone as shown in Figure 3. The device pairing between the EEG apps in mobile phone and EEG amplifier must be done first before the amplifier can transfer data to a mobile phone through Bluetooth as shown in Figure 4.

There are two exercise modes are set-up for the experimental procedure; do nothing (relax) and play action computer game to initiate 2 difference brain cognitive states. The relax mode is to activate EEG's Alpha band (relax cognitive state). Meanwhile, the action mode is to activate EEG's Beta band (alert cognitive state). For both modes, the EEG data will be captured for the duration of 3 minutes. The first 1 minutes EEG data will be removed from the data analysis since the data might be corrupted by noises or artifacts during start-up of the measurement. The 2 minutes EEG raw data then will go for the pre-processing or filtering process to remove any remaining noises or artifacts especially from the eye blink or eye movement. Next, the filtered EEG data is converted into power spectrum in MATLAB. Then, the unique features in term of spectral centroids are extracted and classified.

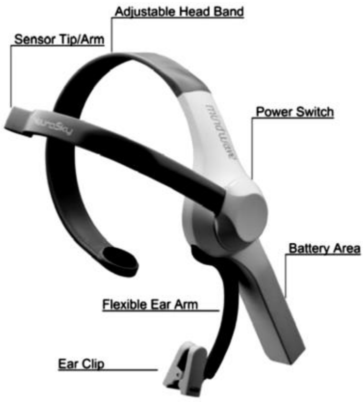

Figure 1: Neurosky EEG Mindwave [16, 23]

Figure 2: EasyVR shield [37, 38]

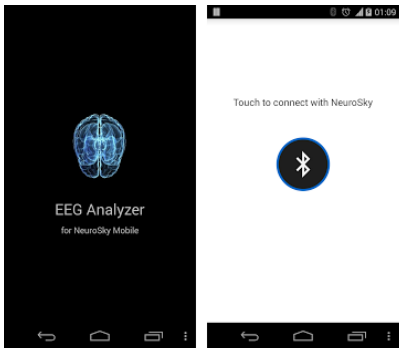

Figure 3: EEG apps in mobile phone [39]

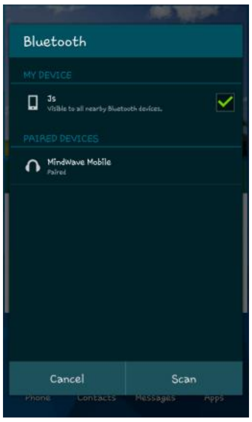

Figure 4: Pairing EEG device using Bluetooth [39]

Meanwhile, for voice measurement mode, voice recognizer, VR Shield is used to capture human voice and then processed with voice recognition software, EasyVR Commander as elucidated by Figure 5.

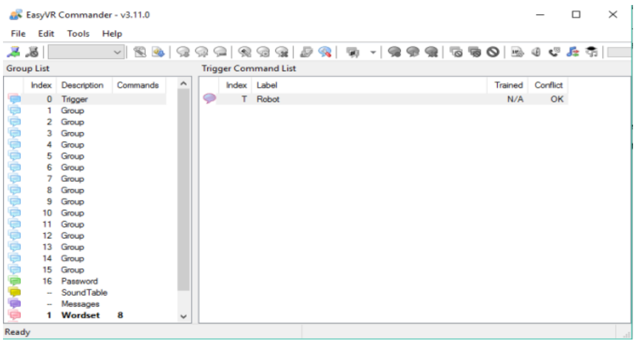

Figure 5: EasyVR Commander

In voice exercise section, the subject is instructed to say the following words; "Open the door" and "Unlock the door" for several seconds. The voice then is recorded and analyzed. Meanwhile, to implement the voice recognition mode, the subjects are asked to say the same words where the words then are trained by the EasyVR software and recognized by EasyVR shield. The step is repeated 3 times. The untrained and trained voice data will be converted to power spectrum before applying spectral centroids on the spectrum data before classifying the data.

The EasyVR Shield is a shield that attaches itself onto the Arduino Uno where it will be used in transmitting and receiving the data onto the computer.

The EasyVR is a multi-purpose speech recognition module designed to easily add versatile, robust, and cost-effective unto my project. The EasyVR can hold up to 32 user-defined commands, divided into 15 speaker dependent groups and can be trained in any language. The device is able to hold up to 21 minutes' worth of pre-recorded sound.

C. Feature extraction and selection

In this research, the spectral centroid of the EEG and voice power spectrum is selected as a feature to be used in the translation algorithm for device command. The equation of the spectral centroid is shown in Equation (1).

$$C_i = \sum_{i=1}^{n} F_i \times |S_i| \Big/ \sum_{i=1}^{n} |S_i| \qquad (1)$$

where: F = Average frequency
S = Power spectrum
i = An index to represent the number of samples in the group

D. Measurement process flow

The overall process flow of the proposed research is elucidated by Figure 6. As illustrated by Figure 6, after obtaining the suitable features by applying spectral centroid to the power spectrum of EEG's Alpha and Beta band and voice data, the database of the brain features and voice features will be created. Next, the translation algorithm will be developed to translate or convert the selected EEG features into device command. Once the features database is ready, the enrollment and verification will be implemented on the system. The testing will be carried out several times until the system runs smoothly.

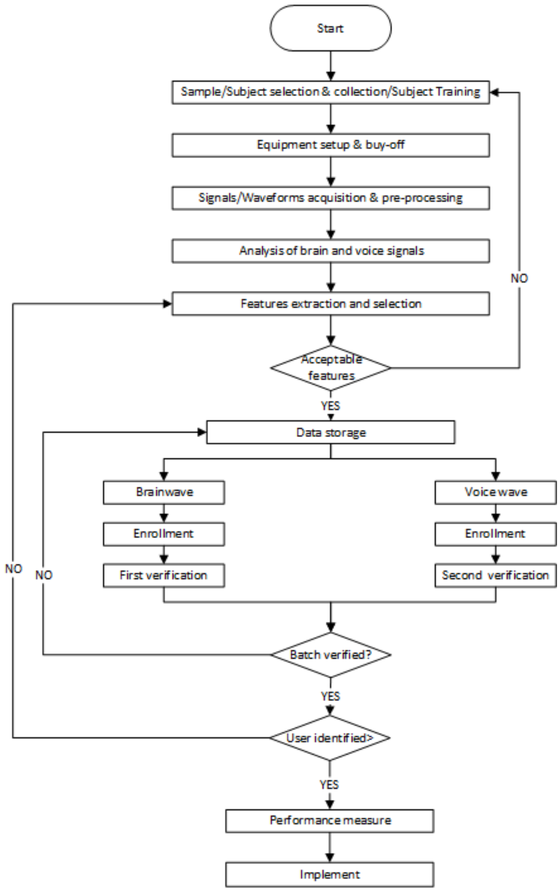

Figure 6: Research process flow

The Beta and Alpha band is selected for the analysis of the EEG signals since the Beta and Alpha band represent brain's cognitive state at alert and relax state respectively. Thus, the change in human's cerebral state can be observed when human in relax state and when doing some mental tasks or doing some physical exercise.

Here, MATLAB R2014a software is used to analyze the raw EEG data and calculate the power spectrum and spectral centroid of both EEG and voice signal. Here, the microcontroller will receive the device parameters from the translation of the classification features as depicted in Figure 7. Hence, the device command for microcontroller will be generated from the classification of the selected EEG and voice features in term of centroid and power spectrum.

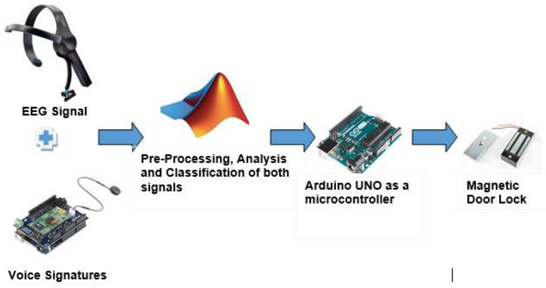

Figure 7: Research block diagram

III. RESULTS AND DISCUSSION

The EEG and voice of the data of 3 subjects were recorded, filtered, and analyzed for 2 difference modes; before and after exercise. Here, the captured EEG signals are undergone several processes such as pre-processing (filtering), conversion of the EEG signals to their power spectrum and centroid, feature extraction, and finally the classification of the features as described below.

A. Power Spectrum of EEG signals

The raw data of the captured EEG signals and after undergoing pre-processing or filtering process is shown in Figure 8 and Figure 9 respectively. Figure 8 illustrates the raw data of EEG signals taken from one of the subjects. Based on Figure 8, the EEG raw data follow the characteristic of the EEG signals which exhibits some noises where the raw data then undergoing filtering process to remove the noises especially the noise that was generated from eyes movement or Electrooculogram (EOG) signals. Meanwhile, Figure 9 depicts the filtered EEG data before and after exercise. The noises then are removed in an offline manner before converting the signals into their power spectrum using Fourier transform technique (FFT) as depicted by Figure 10 and Figure 11. Since the change in cerebral signals or cognitive states cannot be clearly detected from the graph of their overall power spectrum, the power spectrum of the EEG signals then are categorized into its Alpha and Beta band in order to obtain better picture for the changes of the cognitive state when subject in relax and alert state as illustrated by Figure 12 to Figure 15.

Next, the spectral centroid is applied to the selected EEG Alpha and Beta bands in order to identify the changes in the brain's cognitive state.

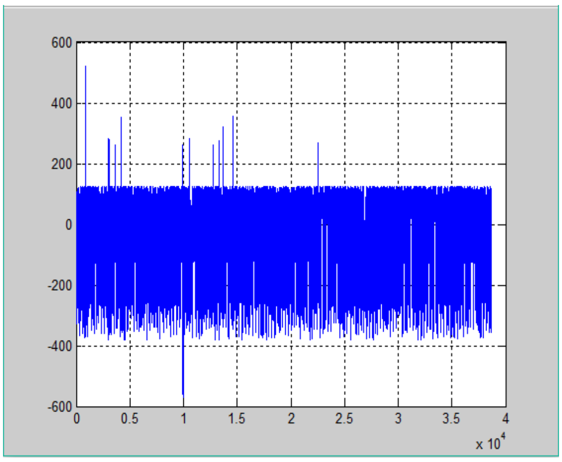

Figure 8: EEG raw data

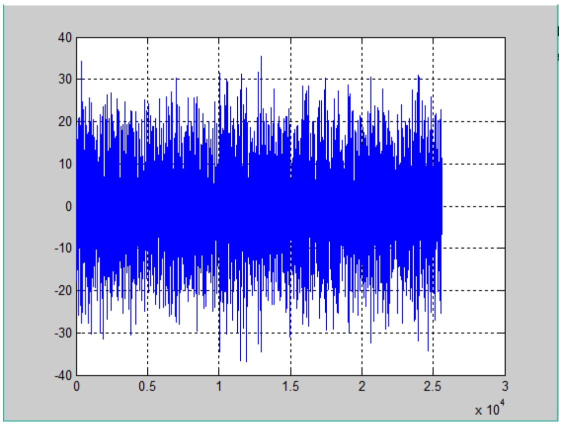

Figure 9 :EEG signal after filtering process

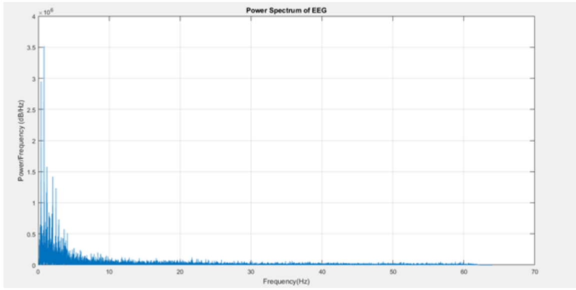

Figure 10: Overall EEG power spectrum before exercise

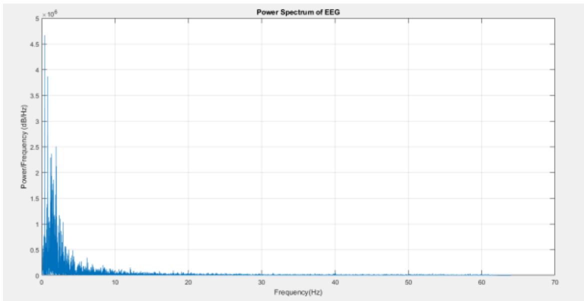

Figure 11: Overall EEG power spectrum after exercise

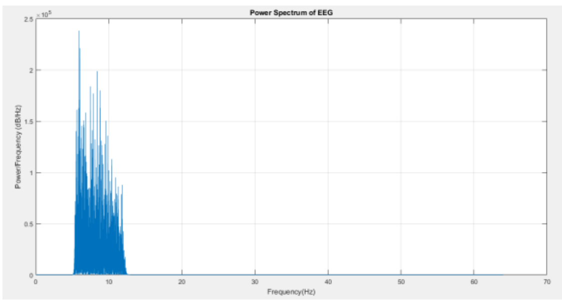

Figure 12: Power spectrum of EEG Alpha band before exercise

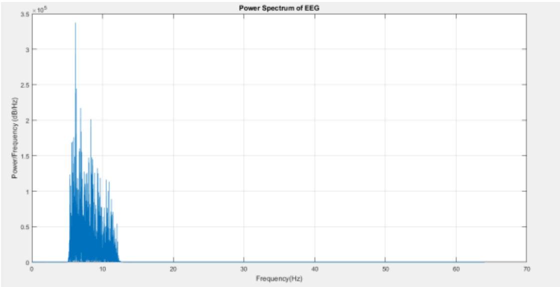

Figure 13: Power spectrum of EEG Alpha band after exercise

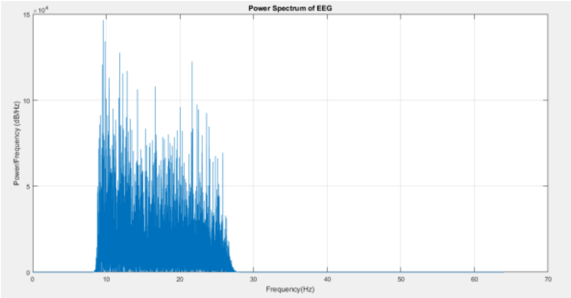

Figure 14: Power spectrum of EEG Beta band before exercise

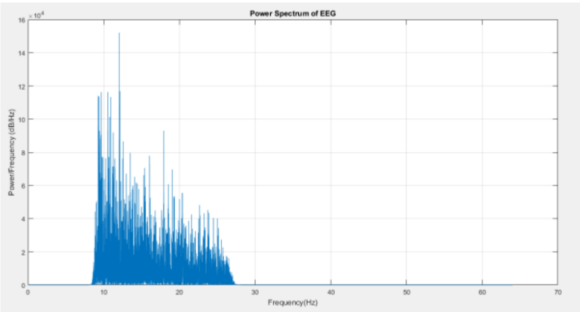

Figure 15: Power spectrum of EEG Beta band after exercise

The frequencies of EEG Alpha and Beta band follow the characteristic of EEG frequency bands as shown in Table 1.

Table 1
Frequency of EEG Sub-bands and Cerebral Activities

EEG Sub-bands	Frequency (Hz)	Cerebral Activities
Alpha	8-13	Relax or eyes-close
Beta	13-30	Alert, working, tension, anxiety

B. Analysis of EEG Spectral Centroid

The average spectral centroid of the EEG signals for each subject is shown in Figure 16 and Figure 17 respectively. Apparently, there is a vital trend in EEG centroid where the centroid value after exercise for all subject is lower than the centroid value before exercise (in relax state) for both EEG Alpha and Beta bands. It indicates that there is a significant change in subject's cognitive state when doing exercise (from relax state to alert state) which indicate that subject experience some alert or tension state when doing some exercise (playing action game). The average centroid value of EEG Beta and Alpha band for the 3 subjects when performing exercise are at 46% and 67% lower than before performing exercise respectively. Thus, an application of spectral centroid value on EEG power spectrum can be employed as classification features for device command.

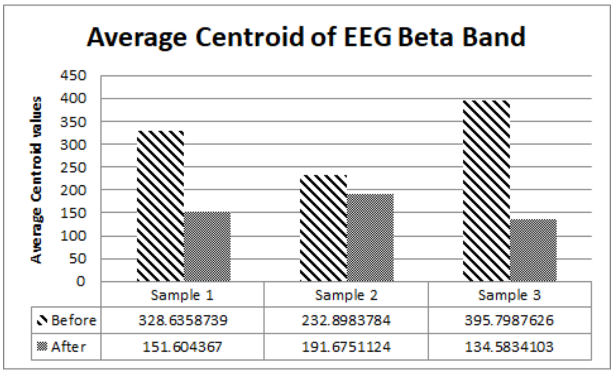

Figure 16: Average spectral centroid of EEG Beta band for each subject

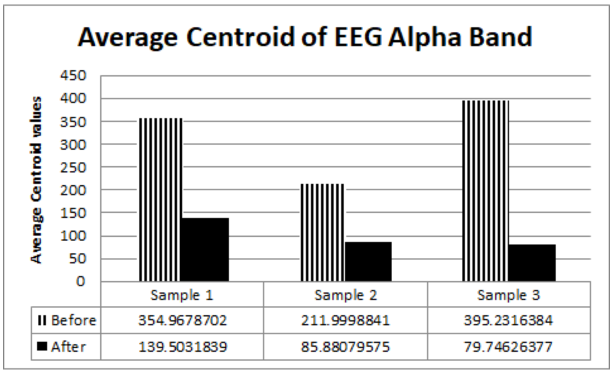

Figure 17: Average spectral centroid of EEG Alpha band for each subject

C. Measurement of Voice Power Spectrum & Centroid

The voice signals taken from one of the subjects and its power spectrum before and after exercise are illustrated by Figure 18 to Figure 21 respectively. The raw data of the voice is recorded before and after exercise (after training the voice with voice recognizer and EasyVR Commander). Next, the voice raw data is converted to its power spectrum using Fourier transform technique (FFT) in MATLAB.

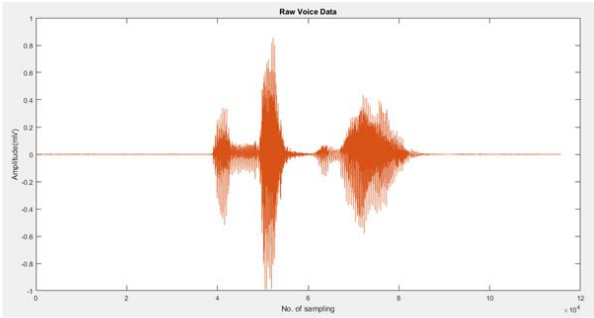

Figure 18: Voice raw data before performing exercise

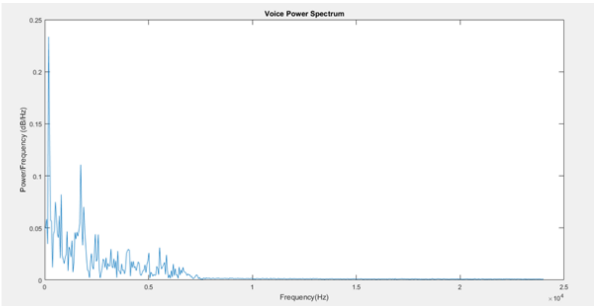

Figure 19: Voice power spectrum before performing exercise

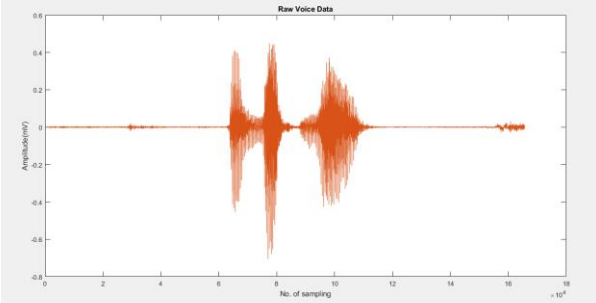

Figure 20: Voice raw data after performing exercise

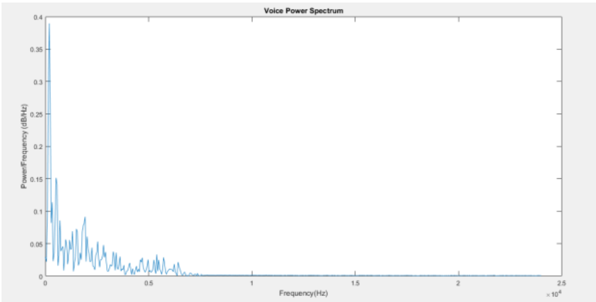

Figure 21: Voice power spectrum after performing exercise

The average spectral centroid of the voice signals for each subject is shown in Figure 22. Unlike EEG signals, the spectral centroid of the voice power spectrum for each subject after undergoing exercise (voice training) is higher than spectral centroid before undergoing exercise (without voice training). It shows that the centroid of the voice power spectrum obtained after the voice training can be classified to determine the voice parameter for device command.

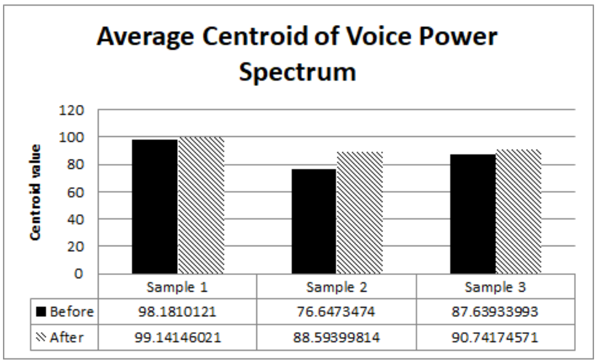

Figure 22: Average centroid of voice power spectrum

D. Classification of EEG & Voice Spectral Centroid

The k-NN classification results for the selected input features of EEG and voice signals are depicted by Figure 23 and Figure 24 respectively. The ratio of training versus testing of the classifier is configured at 70:30 for both input features which indicates 70% of the input features are used for training and the remaining 30% of the input features will be employed for testing. As shown in Figure 23, k value is varied from 1 to 75 data, which represent 70% of the 105 selected EEG features (centroid of EEG power spectrum). The highest classification result of 96.7% is obtained at k=3 and 4.

It indicates that the selected EEG features in term of the spectral centroid from 2 difference brain cognitive states (relax and playing games) can be classified by classifier at high recognition rate. Hence, the classifier can provide the suitable parameters to the microcontroller to control the operation of the door's magnetic lock based on the selected EEG features.

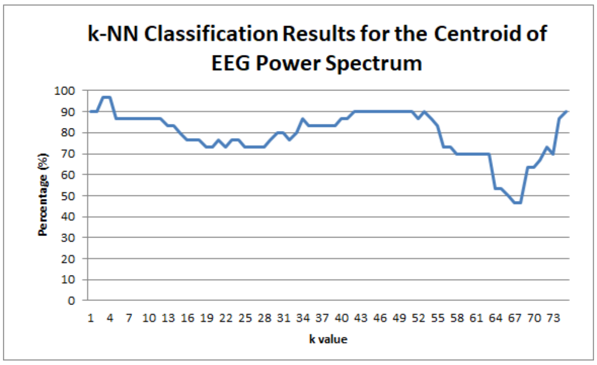

Figure 23: k-NN classification results for EEG centroid

Meanwhile, for the classification of voice power spectrum, k value is varied from 1 to 1077 data, which represent 70% of the 1539 selected voice input features (voice power spectrum). As illustrated by Figure 24, the highest classification result of 99.3% is achieved at k=1 until 8.

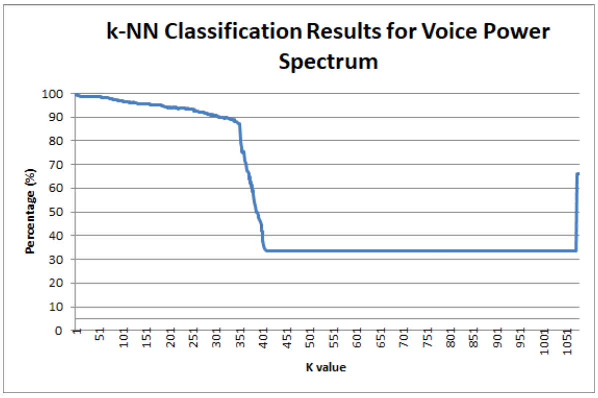

Figure 24: k-NN classification results of voice power spectrum

E. Graphical User Interface of the Proposed System

The graphical user interface (GUI) is created to show the overall process of analyzing EEG and voice signals before and after exercise as illustrated by Figure 25 and 26. The GUI displays the signal processing stage for subject 1 from EEG and voice raw data, conversion of the EEG and voice raw signals to their power spectrum, EEG band allocation to its Alpha and Beta band, and finally, the value of the spectral centroid of the EEG and voice power spectrum. These values are used in the classification process as a classification class to classify the EEG and voice power spectrum.

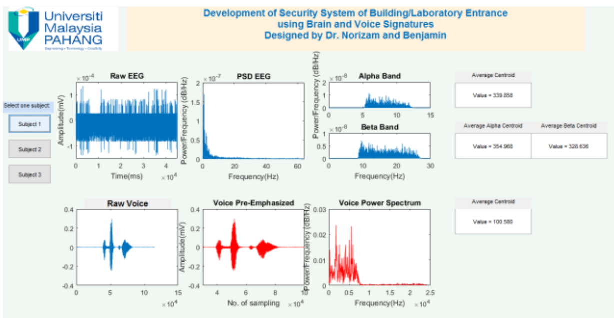

Figure 25: GUI for brain and voice signal processing before exercise

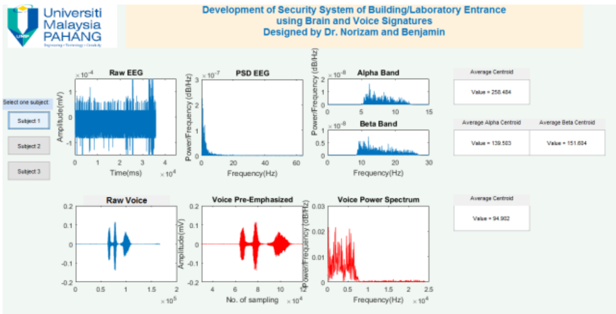

Figure 26: GUI for brain and voice signal processing after exercise

The overall process to obtain the extracted and classified features from human's brain and voice signals which need to be converted to device commands are illustrated by the block diagram shown in Figure 27.

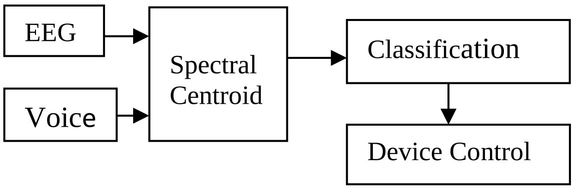

Figure 27: Selected brain and voice features for device control

F. Conversion Parameters of the Proposed System

Based on the selected features and classification results, the proposed parameters for the device controls are shown in Table 2.

Table 2
Conversion Parameters for Device Control

Physiological Signals	Average Centroids After Exercise	Average Centroids Before Exercise	State
EEG Beta	151.6	328.6	Alert
EEG Alpha	139.5	355	Relax
Voice	99.1	98.1	Dominant Frequency

IV. Conclusion

This project highlights the selection process of the brain and voice signals to be used as a signature for accessing the laboratory or building entrance to overcome the limitation of the frequency-based or password-based security system. Based on the experimental results, there is a pattern in spectral centroids that can be used in the translation algorithm to create the device command. The selected EEG and voice features in term of the spectral centroids produce high classification rate at 96.7% and 99.3% respectively. The classification results indicate that the selected features from brain and voice signals can be converted to control parameters which can be employed by the system microcontroller to control the magnetic door lock of the building or laboratory's entrance. The future work includes the real-time implementation of the project based on the selected and classified features of EEG and voice signals.

Acknowledgment

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References

[1] N. Carlson, *Foundations of physiological psychology*, Boston: Mass. London: Allyn and Bacon, 2002
[2] M. Teplan, "Fundamentals of EEG Measurement," *Measurement Science Review*, vol. 2, pp. 1-11, 2002.
[3] E. Niedermeyer and F. L. D. Silva, *Electroencephalography Basic Principles, Clinical Applications and Related Fields*, Philadelphia: Lippincott Williams & Wilkins, 2005.
[4] J. Zhai and A. Barreto, "Stress Detection in Computer Users Band on Digital Signal Processing of Noninvasive Physiological Variables," in *Proc.* 28th *IEEE EMBS Annual International Conference*, 2006, pp. 1355-1358.
[5] C. R. Hema, M. P. Paulraj, and H. Kaur, "Brain Signatures: A Modality for Biometric Authentication," in *Proc. International Conference on Electronic Design Healthline*, 2008, pp. 1-4.
[6] A. M. Intelligence, "The Future of Biometrics Market Research Report," *ACUITY*, Colorado, 2009.
[7] S. Marcel and J. del R. Millan, "Person Authentication using Brainwaves (EEG) and Maximum A Posteriori Model Adaption," *IEEE Transaction on Pattern Analysis and Machine Intelligence Special Issue on Biometric*, Brussels, pp. 1-7, April 2006.
[8] T. Pham, W. Ma, D. Tran, P. Nguyen, and D. Phung, EEG-Based User Authentication in Multilevel Security Systems, Berlin: Advanced Data Mining and Applications, 2013.
[9] J. R. Wolpaw, N. Birbaumer, D. J. McFarland, et al, "Brain-Computer Interface for Communication and Control," *Clinical Neurophysiology*, vol. 113, no. 6, pp. 767-791, 2002.
[10] M. Poulos, M. Rangoussi, V. Chrissikopoulos, and A. Evangelou, "Person identification based on parametric processing of the EEG," Cyprus, Pafos, 1999, pp. 283-286.
[11] A. Rieral, A. Soria-Frisch, M. Caparrini, C.Grau and G. Ruffini1, "Unobtrusive Biometric System Based on Electroencephalogram Analysis," *EURASIP Journal on Advances in Signal Processing*, pp. I-8, 2008.
[12] M. Poulos, M. Rangoussi, V. Chrissikopoulos and A. Evangelou, "Parametric person identification from EEG using computational geometry," in *Proc. 6th International Conference on Electronics Circuits and Systems (ICECS '99)*, vol. 2, pp. 1005-1008, September 1999.
[13] J. Chuang, H. Nguyen, C. Wang and B. Johnson, "I Think, Therefore I Am: Usability and Security of Authentication Using Brainwaves," in *Proc. International Conference on Financial Cryptography and Data Security*, pp. 1-16, 2013.
[14] V. R. Varada, D. Moolchandani, and A. Rohit, "Measuring and Processing the Brain's EEG Signals and Visual Feedback for Human Machine Interface," *International Journal of Scientific & Engineering Research*, vol. 4, No. 1, January 2013.
[15] J. del R. Millan, F. Renkens, J. Maurino, et al., "Noninvasive Brain-Actuated Control of Mobile Robot by Human EEG," *IEEE Transaction on Biomedical Engineering*, vo. 51, no. 6, pp. 1026-1033, 2004.
[16] M. H. Alomari, A. AbuBakar, A. Turani, A. M. Baniyounes, and A. Manasreh, "EEG Mouse: A Machine Learning-Based Brain Computer Interface," *International Journal of Advanced Computer Science and Applications*, Vol. 5, No. 4, 2014.
[17] S.Ito, Y. Mitsukura, K. Sato, S. Fujisawa and M. Fukumi, "Study on Relationship between Personality and Individual Characteristic of EEG for Personalized BCI," in *Proc. IEEE International Conference on Computational Technology in Electrical and Electronics Engineering*, 2010, pp. 106-111.
[18] G. L. Wallstrom, R. E. Kassb, A. Millerc, J. F. Cohnd, and N. A. Foxe, "Automatic Correction of Ocular Artifacts in the EEG: A comparison of regression-based and component-based methods," *International Journal of Psychophysiology*, vol. 53, pp. 105-119, 2004.
[19] K. S. Park, H. Choi, K. J. Lee, J. Y. Lee, K. O. An, and E. J. Kim, "Patterns of Electroencephalography (EEG) change against stress through noise and memorization test," *International Journal of Medicine and Medical Sciences*, vol. 3, no. 14, pp. 381-389, Dec. 2011.

[20] J. L. Kenemans, P. C. Molenaar, M. N. Verbaten and J. L. Slangen, “Removal of the ocular artifact from EEG: A comparison of time and frequency domain methods with simulated and real data,” *Psychophysiology*, vol. 28, pp. 114121, 1991.
[21] C. K. A. Lim and W. C. Chia, “Analysis of Single-Electrode EEG Rhythms Using MATLAB to Elicit Correlation with Cognitive Stress,” *International Journal of Computer Theory and Engineering*, vol. 7, no. 2, Apr. 2015.
[22] I. Homri, S. Yacoub, and N. Ellouze, “Optimal Segments Selection for EEG Classification,” in *Proc. 6th International Conference on Sciences of Electronics Technologies of Information and Telecommunications (SETIT)*, 2012, pp. 817-821.
[23] S. M. U. Saeed, S. M. Anwar, and M. Majid, “Quantification of Human Stress Using Commercially Available Single Channel EEG Headset,” *IEICE Trans. Inf. & Syst.*, vol. E100-D, no. 9, Sept. 2017.
[24] C. Miyamoto, S. Baba and, I. Nakanishi, “Biometric Person Authentication Using New Spectral Features of Electroencephalogram (EEG),” in *Proc. International Symposium on Intelligent Signal Processing and Communication Systems*, 2008, pp. 1-4.
[25] P. Antonenko, F. Paas, R. Grabner, and T. van Gog, “Using Electroencephalography to Measure Cognitive Load,” *International Journal of Education Psychological*, vo. 22, pp. 425-438, 2010.
[26] V. Knott, C. Mahoney, S. Kennedy and K. Evans, “EEG Power, frequency, asymmetry and coherence in male depression”, *Journal of Psychiatry Research: Neuroimaging Section*, vol. 106, pp. 123-140, 2001.
[27] M. Chaouachi, I. Jraidi, and C. Frasson, “Modeling Mental Workload using EEG Features for Intelligent Systems,” in *Proc. International Conference on User Modeling, Adaptation, and Personalization*, 2011, pp. 5061. The cognitive activation theory of stress,” *Psychoneuroendocrinology*, vol. 29, pp. 567-592, 2004.
[28] N. Sulaiman, M. N. Taib, S. Lias, Z. H. Murat, S. A. M. Aris, and N. H. A. Hamid, “Novel Method for Stress Feature Identification using EEG Signals,” *International Journal of Simulation: System, Science and Technology (IJSSST)*, vol. 12, no. 1, pp. 27-33, 2011.
[29] K. Q. Shen, S. J. Ong, X. P. Li, Z. Hui, and E. P. V. Wilder-Smith, “A Feature Selection Method for Multilevel Mental Fatigue EEG Classification,” *IEEE Transaction of Biomedical Engineering*, vol. 54, no. 7, 2007.
[30] T. Y. Chai, S.S. Woo, M. Rizon and CS Tan, “Classification of Human Emotion from EEG signals using Statistical Features and Neural Network,” *International Journal of Integrated Engineering (Issue on Electrical Engineering)*, vol. 1, no. 3, pp. 71-79, 2010.
[31] C. Miyamoto, S. Baba and I. Nakanishi, “Biometric Person Authentication Using New Spectral Features of Electroencephalogram (EEG),” in *Proc. International Symposium on Intelligent Signal Processing and Communication Systems*, 2008, pp. 1-4.
[32] N. Sulaiman, M. N. Taib, S. Lias, Z. H. Murat, S. A. M. Aris, and N. H. A. Hamid, “EEG-based Stress Features Using Spectral Centroids Technique and k-Nearest Neighbor Classifier,” in *Proc. 13th International Conference on Modelling and Simulation (UKSim)*, pp. 69-74, 2011.
[33] N. Sulaiman, M. N. Taib, S. Lias, Z. H. Murat, M. Mustafa, S. A. M. Aris, and N. A. Rashid, “Electroencephalogram-based Stress Index,” *Journal of Medical Imaging and Health Informatics (JMIHI)*, vol. 2, no. 3, pp. 327-335, Sept. 2012.
[34] K. K. Paliwal, “Spectral Subband Centroids Features for Speech Recognition,” in *Proc. International Conference on Acoustics, Speech and Signal Processing*, 1998, pp. 617-620.
[35] M. L. Massar, M. Fickus, E. Bryan, D. T. Petkie and A. J. Terzuoli Jr., Fast Computation of Spectral Centroids, *Journal of Advanced Computing Mathematics*, 2010.
[36] B. Gajic and K. K. Paliwal, “Robust Parameters for Speech Recognition Based on Subband Spectral Centroid Histogram,” in *Proceedings of European Speech*, 2001.
[37] H. Beigi, *Fundamentals of Speaker Recognition*, London: Springer New York Dordrecht Hiedlberg , 2011.
[38] J. P. Campbell, “Speaker Recognition: A Tutorial,” *Proc. IEEE.*, vol. 85, no. 9, pp. 1-10, 1997.
[39] Andrew, "NeuroGadget," 20 December 2012. [Online]. Available: http://neurogadget.net/2012/12/20/neurosky-mindwave-mobile-review/6611. [Accessed 12 April 2017].