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A STUDY OF DIFFERENT TYPES OF BRAINWAVES AND THEIR USE IN CONTROLLING REMOTE OBJECTS

AHMED M. D. E. HASSANEIN[1,*],
SHROUK T. M. IBRAHEM[2], NAYERA H. A. HASSAN[2]

[1]Systems and Information Department, Engineering and Renewable Energy Research Institute, National Research Centre (NRC), Dokki, Giza, Egypt. Postal Code: 12622.
[2]Electrical Communication and Electronic Systems Dept, School of Engineering, October University for Modern Sciences and Arts (MSA), Al Wahat Road, Giza, Egypt.
*Corresponding Author: ahmed.diaa.hassanein@gmail.com

Abstract

In this paper, we discussed the use of brainwaves to make an object move in one of two directions namely right or left. Our aim was to find the type of brain waves that was most suitable to interpret the intention of a volunteer when using his/her vision, hearing and pure thinking. We proposed a methodology in which the brain was excited using six stimulants which were Vision Right, Vision Left, Voice Right, Voice Left, Thinking Right and Thinking Left. Recordings of four volunteers were obtained using a Neurosky headset. Each recording contained 60 readings for one of eight types of brainwaves and a class representing the direction of motion intended by the volunteer. The average of the recordings for the right class was higher than that for the left one. Moreover, the standard deviation of the recordings for the left class was higher than that for the right. The average and standard deviation parameters meant that the identification of the recordings for the left class was higher than that for the right class. Moreover, the K-nearest neighbour was used to classify each recording to either right or left class. The Alpha family of brain waves showed values of relative standard deviation in the range of 80 to 120% for 5 stimulants out of the 6 stimulants tested. This meant that recordings from the Alpha family contained enough information to classify them correctly and identify the type of direction intended by the volunteer. In addition, they were not highly contaminated with noise. The Alpha2 brain wave type showed the highest accuracy in our classification problem. 82% was the percentage achieved for the Precision, Recall and F-measure parameters used to describe the accuracy of success in classification.

Keywords: BCI, Brainwaves, Classification, EEG, K-Nearest Neighbor, Neurosky headset.

1. Introduction

Brain-computer interface (BCI) was studied as an approach to use natural human thinking to facilitate interactions with computers. Electroencephalography (EEG)-based BCIs had gained a lot of interest in research recently [1]. Saha et al. [2] reviewed the obstacles facing research and advancements in the field of brain to computer interface. Several issues were discussed among them the use of brain wave readers as a tool for data input between a user and the computer. The efforts done on the international level to create shared platforms that can unite the efforts of developers were clarified. The effects of the psychological and physiological variations on the stability of the emitted brain waves so that the waves were reliable enough for applications to be built for them were explained [2].

Mosslah et al. [3] researched the emitted brain waves (EEG) as a new Biometric in BCI. The factors causing the changes in the EEG signals inside the brain were discussed in [4]. The synaptic connections between the neurons were shown to be one of the factors that affect the emission of EEG signals and the variations in their amplitude over time [4].

To familiarize the audience with the importance of BCI applications, Gu et al. [5] had surveyed the published work which focused on EEG signal sensing technologies and artificial intelligence methods in BCI applications throughout the years 2015 to 2019. Rashid et al. [6] discussed the advancement of the use of feature extraction methods such as principal component analysis (PCA), band power spectrum (BP), fast Fourier transform (FFT) and others. They reported trying several classifiers in BCI applications such as Artificial Neural Network (ANN), k-Nearest Neighbor (k-NN) and others.

In one path, Browarska et al. [7] discussed a case study to investigate the emitted waves from the brain when a person was exposed to a game that contains horrifying scenes. The methodology used was to initiate stress feelings in persons by exposing them to games which contain fearful scenes. The brain computer interface (BCI) was used to analyse the results which showed a correlation between changes in emitted brain waves and playing games which contained fearful scenes [7].

In a different path, Ahmed et al. [8] discussed the suitability of using EEG signals to be used as an indicator of the movement of the human brain when a person closed and opened his/her eyes. EEGLAB was used to compare different EEG data from different persons and also different sources of data such as neuro-scans and other tools [8].

To facilitate research efforts, Kounte et al. [9] analysed Brain waves to find out the information which could be extracted from them. They also discussed the interface of computers with human brain using brain sensor and the precautions which should be taken into consideration when designing a similar system [9]. Hamza-Lup et al. [10] discussed the accuracy of using brain waves in detecting the type of activity a person was performing. Neural Networks were used to train the computer on a training data and then a testing dataset was used to measure of the degree of accuracy [10].

The proposed method was successful in defining the type of activity for a person. Monori et al. [11] had concentrated on extracting features from the EEG signals produced from a Neurosky headset and applied neural networks on them. The presented work succeeded in detecting blinking patterns but not any complex

information [11]. Salih and Abdal [12] presented a control tool using the Neurosky mind wave headset, which detected brainwaves (voluntary blinks and attention) to form a brain-computer interface (BCI) by receiving the system signals from the frontal lobe. The conducted experiment revealed a significant result in developing user printing skills on PCs [12].

Kumar et al. [13] discussed the possibility of using brain waves to predict accurately the class of motor imagery signals. The aim was to classify tasks which were done using right and left hand tasks. The system proved to be more accurate than other proposed systems in real time applications. However, several processing techniques had to be applied to reach satisfying results [13].

Al-Turabi et al. [14] reported 79.2% accuracy in defining the intention of motion of a person. The directions studied were forward, backward, left and right. Three algorithms were used which are artificial neural network, KNN algorithm and support vector machine. The system was non-invasive and proved to be accurate enough to work in health related applications [14].

Koudelková et al. [15] used a BCI method to take recordings of waves emitted from the human brain and classified the state of the body. Two states were put under investigation; the first was logical and analytical reasoning and the second was listening to music. Listening to relaxing music activated theta waves while applying logical and analytical reasoning produced beta waves [15]. A state of a mind could be predicted by monitoring the waves emitted from human brain. A brain wave sensor was used to measure the emitted waves and then processed to predict the intention of the user [16].

The different areas of applications of BCI could be but were not limited to computer-aided design (CAD), entertainment and health areas [5]. BCIs had a role in advancing neuro-computing for pattern recognition and machine learning on brain signals, and the analysis of computational expert knowledge.

Wójcik [17] discussed a rarely investigated application of using brain to computer interface systems. Applications and systems that would benefit from BCI research in advancing Library information systems were very limitedly investigated. The authors showed a theoretical investigation into the possibilities of using BCI systems inside libraries and how this would revolutionize library science [17].

For entertainment, brainwave's headsets became widely available in the market to be used as game controllers. Though their accuracy was not as precise as other BCI devices used in medical areas, they were still practical for game developers and were successfully commercialized [5]. For the healthcare field, brainwave's headset had been utilized to facilitate severely disabled people to effectively control a robot by subtle movements such as neck moving and blinking [5].

Kang et al. [18] discussed the privacy and security concerns of using BCI technology. They reported a gap in researching the two concerns in recent research and the importance of highlighting them in future research papers as BCI applications become more widely used [18].

Sharma [19] proposed a BCI method to detect the state of the mind of the mariners. The study aimed to detect any psychological and /or mental disorders which could affect mariners due to the job hazards to which they were exposed. Also, the

COVID-19 crisis had exacerbated the mental and psychological problems which could be affecting the state of the mind of people who worked up the sea [19].

Emitted Brainwaves changed with what we do and think. Each type of wave was characterized by its frequency band and was emitted at a different state of the mind such as sleepy, thinking, focused, etc. [20]. Brainwaves could be categorized into eight different types namely: Delta, Theta, Alpha, Beta and Gamma [21] where each of the Alpha, Beta and Gamma was divided into two subdivisions as explained later.

The rest of this paper was organized into six sections. The methodology and methods used in this work were detailed in the second section. We described the tools used to obtain the results presented in this paper in the third section. Then, the stimulants which were used to excite the emission of brainwaves were introduced. A study of the effect of the different stimulants on the emitted types of brain waves was given in the fourth section. A classification of the intention of the volunteers through emitting brainwaves to move in a certain direction was discussed in the fifth section. A comparison of the results with the work of other researchers was shown in the last section.

2. Methodology and Methods

Here, we address the problem of classifying the received recordings of brain waves from four volunteers to identify their intention to turn to the right or left direction. In subsection 2.1, the methodology applied in this work was discussed and clarified. In subsection 2.2, the methods used to apply the methodology were given.

2.1. Methodology

This paper proposed a methodology for the suitability of interpreting brain waves as a representation of the willingness of the user to turn right or left. Brain waves are composed of 8 types. We aimed to define which type is most suitable to indicate the direction of motion of the user. Three effects were used to stimulate the emission of the brain waves which are namely visual effect, sound effect and pure thinking effect.

We also aimed to define which stimulant is best in producing high levels of brain waves indicating the direction of motion of the participant. In the theoretical part, we drew black 2D signs on white paper to show a turning left direction arrow and a turning right direction arrow. Also, we selected the two words "left" and "right" as the two words to be pronounced by the user to indicate the intention of his/her direction of motion. Several factors affected our classification problem.

One factor was the type of brain wave that was suitable to be used with the three effects mentioned above which stimulated the brain to produce waves containing valuable information about the intended direction of a person. At the same time, these brain waves should contain the least amount of noise which would negatively affect the accuracy of our results.

Another factor was the type of brainwave which was suitable for this kind of classification and that would enable our proposed system to produce highly accurate classification results. The novelty here was the combined study of identifying the best type of brain waves which can be used to classify intended direction and the most suitable effect to best stimulate this kind of brain wave.

Previous work had used similar methodologies such as the next two examples. Hosťovecký and Babušiak [22] discussed a proposed game which can be used to select players who satisfied certain criteria defined by the game developer. Brain wave activity was used as a method to tell the degree of concentration of a player while playing. Received Beta waves was used as a measure of brain activity towards concentration while playing two dimensional and three dimensional games developed for this purpose [22].

Singh and Gumaste [23] investigated using brain waves to measure imagined speech signals. The proposed method classified imagined speech with accuracy 85% when classifying long versus short words. In addition the method proved successful in determining the resting state of the mind versus the imagined speech state with accuracy 94% [23].

In this paper, two steps were applied. In the first step, we investigated to know which type of brain waves which would produce lowest amount of noise when used with our six stimulants. The average, standard deviation and relative standard deviation were used to evaluate the results for the 6 proposed stimulants and predict the type of brain wave that was most suitable. In the second step, we used the eight types of brain waves to solve our classification problem. Results should verify that the prediction done in the first step was the same type which would produce the highest accuracy in the classification problem.

2.2. Methods

In this subsection, we started by detailing the classification method used to solve our classification problem. Then, the evaluation methods used to evaluate the results were given.

2.2.1. Classification method:

One of the well-known supervised learning methods, the K-Nearest Neighbour was used here [24]. For this algorithm, we prepared a group of instances each had a group of features. Each instance represented a recording of one of the types of emitted brainwaves. Each recording was normalized in order to give all recordings the same weight when compared with each other. The recorded power in 60 seconds (around one reading per second) represented the features of each instance. Each instance belonged to one of two classes namely turning left or turning right. The classification problem addressed here was to assign a class to a new instance. In this paper, we used the Euclidean distance to calculate to which class the new instance belonged to. The K-instances which had the closest distances, a majority vote was done to select the best class for the new instance [24]. Next, we described the hardware which was used in our experimental work.

2.2.2. Evaluation method:

Two kinds of results were evaluated in this work. First, the amount of information in the power received from each type of brain wave when using the proposed stimulants was evaluated using three parameters. We used the average, standard deviation and relative standard deviation parameters to evaluate our results.

The average (Avg) was defined as [25]:

$$Avg = \frac{1}{N-1}\sum_{i=1}^{N}\frac{1}{M-1}\sum_{j=1}^{M}x_{i,j} \tag{1}$$

where M was number of readings in each recording, N was number of volunteers performing the recordings, and x was the power received from each brainwave type.

The standard deviation (Std) was defined as [25]:

$$Std = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}\frac{1}{M-1}\sum_{j=1}^{M}\left(x_{i,j}-Avg\right)^2} \tag{2}$$

The relative standard deviation (RSD) was defined as [25]:

$$RSD = \frac{Std}{Avg}\times 100 \tag{3}$$

We agreed to consider the values of the RSD from 80 to 120% to be in the fit range. Fit range indicated that the readings contained enough information to show the type of direction wanted by the volunteer and they were not highly contaminated by noise. For the values of RSD above 120%, we agreed to consider them to be in the over-fit range. Over-fit range indicated that the readings contained less than enough amount of information to show the type of direction wanted by the volunteer and that they were relatively highly contaminated by noise. For the values of RSD below 80%, we agreed to consider them to be in the under-fit range. Under-fit range indicated that the readings contained enough amount of information but the variations in the readings were not enough to show the type of direction wanted by the volunteer.

Second, the performance of the different types of brain waves to classify the received signals was evaluated. The aim was finding the type of brain wave which would give the highest accuracy in identifying the intention of each volunteer about the direction of motion which he/she would like to take. The accuracy of the result of the classification problem addressed could be defined as the ratio between the number of correctly classified recordings of brain waves and the total number of recorded brain waves. Three terms were used to measure the accuracy namely precision (Prec) , Recall (Rec) and F-measure (FM).

The precision (Prec) could be defined as follows [24]:

$$\Pr ec = \frac{TP}{\left(TP+FP\right)} \tag{4}$$

where TP was number of recordings which were correctly assigned to each class, FN was number of recordings which were falsely not assigned to each class, FP was number of recordings which were falsely assigned to each class, and TN was number of recordings which were correctly not assigned to each class

The Recall (Rec) could be defined as follows [24]:

$$\mathrm{Re}c = \frac{TP}{(TP+FN)} \tag{5}$$

The F-measure (FM) could be defined as follows [24]:

$$FM = \frac{2 * (precision * recall)}{(precision + recall)} \tag{6}$$

The Weka software package [26] had given those parameters as tools to test the reliability of the classification methods included in the package. Al-Turabiet al. [14] had given the accuracy in defining the success of the classification problem presented. Accuracy in [14] had been defined as percentage of true classifications with respect to total number of instance tested.

3. Experimental Tools and Data set Collection

In this section, we introduced the software which was used in our calculations. Then, we presented the hardware used to obtain our data. Next, we discussed the method by which we obtained our dataset. Finally, we showed a sample of our raw dataset and explained the properties of the different types of brain waves.

3.1. Software tools

In this research work, Microsoft Excel and Weka software packages were used for the calculations. Microsoft Excel was used to perform visualization operations on the dataset. For example, it was used to present the results in graph format. The WEKA software package, a free online tool [26], was used to apply classification algorithms on our dataset. A tenfold option was selected to make sure that our results were applicable to all parts of the data. Next, we discussed the classification method which was used to classify our data.

3.2. Hardware tools

The Neurosky headset was used to record the different types of brainwaves for each volunteer. The manuals of the Neurosky headset stated that the signals which were produced from the brain passed through a series of very complicated transformations in order to get a clear signal [27]. Therefore it was stated that the received power cannot be expressed in terms of volts as known but it was referred as "ASCI EEG power units" [20]. In our graphs, we simply referenced this new power unit as "EEG power". Several wave signals produced by the brain contaminated the signals from our experiments. Contamination could be divided into internal and external artefacts [20]. The Neurosky headset was designed to eliminate the contaminations due to all types of artefacts mentioned above which made it suitable for our application. The contamination due to the blinking of the eye specifically through the small frequencies produced was minimized by the headset but the brain wave due to the blinking action itself remained to be a source of contamination. Next, we described how the dataset was prepared.

3.3. Data set collection

The aim of our proposed set of experiments was to collect recordings of the emitted brain waves due to using the vision stimulant, voice/hearing stimulant and the intention to move through thinking stimulant. The idea of our stimulants was encouraged by the research about the method of motor imagery (MI) in which a person imagined that he/she was moving his/her body and the resulting EEG signals were processed to know the intended movement [1].

Six different stimulants were used in our experimental work. The Vision Right (Vi_R) stimulant was initiated when a volunteer looked to a turning right sign and focused his/her thinking on the willingness to take the action of turning right. The Vision Left (Vi_L) stimulant was initiated when a volunteer looked to a turning left sign and focused his/her thinking on the willingness to take the action of turning left. The Voice Right (Vo_R) stimulant was initiated when a volunteer pronounced the word right and focused his/her thinking on the willingness to take the action of turning right.

The Voice Left (Vo_L) stimulant was initiated when a volunteer pronounced the word left and focused his/her thinking on the willingness to take the action of turning left. The Thinking Right (T_R) stimulant was initiated when a volunteer focused his/her thinking on the willingness to take the action of turning right. The Thinking Left (T_L) stimulant was initiated when a volunteer focused his/her thinking on the willingness to take the action of turning left.

The participants who participated were university students from electronics engineering (1 male and 3 females) with the mean age of 20 years (range: 19 – 21 years). The research sample consisted of 4 university students from inside Egypt. Students participated in the research on a voluntary basis, i.e. they decided for themselves whether they would prefer to take part or not. Volunteers were addressed by the project team, who received an accompanying brief about the project clarifying the research and its purpose. As mentioned, four volunteers in their early twenties came forward to try those experiments using a Neurosky headset. The experiments were divided into three stages through which each volunteer had to pass through.

The first stage contained two experiments. Each volunteer applied the Vision Right stimulant in the first and the Vision Left in the second. The second stage contained another two experiments. Each volunteer applied the Voice Right stimulant in the first and the Voice Left stimulant in the second. The third stage contained the last two experiments. Each volunteer applied the Thinking Right stimulant in the first and the Thinking Left stimulant in the second. Each experiment took 60 seconds. Brainwaves were recorded using the Neurosky headset in all experiments and the volunteers were given a break of 60 seconds after each experiment. In our experiments, we had asked our volunteers to close their eyes whenever vision is not required.

Previous research papers such as in [10, 14] discussed the accuracy of using brain waves in detecting the type of activity a person performed. Neural Networks were used to train the computer on a training data. Neural networks were a much more complex classification method than the K-nearest neighbour discussed here as it needed higher computational power and more processing time. A testing datasets in [10, 14] were used to measure the degree of accuracy of neural networks. The dataset addressed a larger number of participants than the group addressed here. However, here in this paper another factor not taken in papers [10, 14] was taken into consideration. The different effects of vision, hearing and pure thinking were taken into consideration when collecting our dataset which made each of our instances reflect different view of the brain wave than just pure thinking. Our dataset was large enough to address the problem presented here as two classes only were targeted; a larger dataset could be addressed in future work to cover larger number of classes.

3.4. Brain wave sample

The Neurosky headset helped us to collect the eight types of brainwaves mentioned in Section 1.

As shown in Fig. 1, a sample of a single recording from one of our volunteers could be seen. Each type of recorded brain wave contained variations with time. The larger the variations were, the higher the content of the recordings which could be either valuable information about the intention of the volunteers or noise.

The first type of brain waves was the Delta one which ranged from 1Hz to 4Hz [11]. It was produced when a person was in deep sleep and unconscious [20].

The second type of brain waves was the Theta type which ranged from 4Hz to 8Hz [11]. Day dreaming and sleeping were the sources of emitting this frequency range. High levels of Theta waves made people susceptible to depression and might make them creative based on whether they were in a deeply relaxed or fantasy state [20].

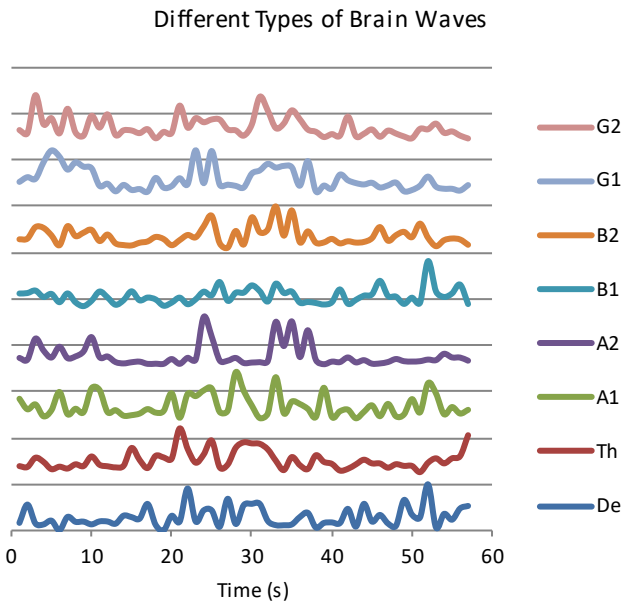

Fig. 1. Sample of pre-processed EEG recording showing all kinds of brain waves namely: Delta (De), Theta (Th), Alpha1 (A1), Alpha2 (A2), Beta1 (B1), Beta2 (B2), Gamma1 (G1) and Gamma2 (G2).

The third type of brain waves was the Alpha type which ranged from 8 to 12Hz [11]. Emitting Alpha waves helped when one wanted to calm down and promote the feelings of deep relaxation [20]. The Alpha range was divided into two sub-ranges namely Alpha1 and Alpha2. Alpha1 had a range between 8Hz and 10Hz while Alpha2 had a range between 10Hz and 12Hz approximately [11].

The fourth type of brain waves was the Beta type which ranged from 12Hz to 30Hz [11]. During conscious thinking, logical thinking and the tendency of the body to stimulate both actions, the brain produced Beta waves [20]. In some cases,

high emissions of Beta waves would suggest that a person was thinking, and his/her eyes were open. The Beta range was divided into two sub-ranges namely Beta1 and Beta2. Beta1 had a range between 12Hz and 18Hz while Beta2 had a range between 18Hz and 30Hz approximately [11].

The fifth type of brain waves was the Gamma type which ranged from 30Hz to 50Hz [11]. Emission of Gamma waves was a symbol of learning, memory and information processing [20]. The Gamma range was divided into two sub-ranges namely Gamma1 and Gamma2. Gamma1 had a range between 30Hz and 40Hz while Gamma2 had a range between 40Hz and 50Hz approximately [11].

Next, we studied the effect of the different stimulants on the power received for each type of brain wave.

4. Studying Wave Type - Stimulant Type Relation:

In this section, we discussed how the Avg and Std changed with the change in the stimulant for each of the eight types of brain waves. According to RSD values, brain wave recordings were categorized into under-fit, fit and over-fit ranges when using the proposed stimulants.

4.1. Effect of Different stimuli per wave type on power

In this sub-section, we studied the effect of changing the stimulant which the volunteers perform to initiate the emission of brain waves on the EEG power received from each type of brainwaves. The figures in this section were plotted with the six different types of stimulants on the x-axis. While on the y-axis, we could find the Avg, and Std of the EEG power received for the specific band of frequency under consideration. Next, the Delta and Theta Types of brain waves were studied as shown in Figs. 2(a) and (b) respectively.

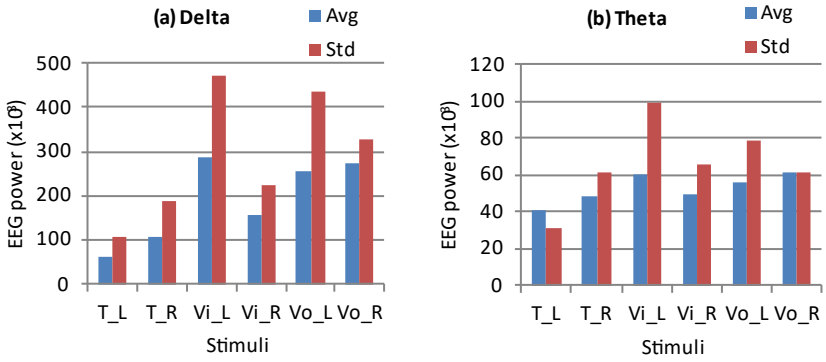

Fig. 2. EEG plotted when six stimulants used. (a) Delta (b) Theta.

As shown for Delta in Fig. 2(a), the RSD for the stimulants: Thinking Left, Thinking Right, Vision Left, Vision Right, Voice Left and Voice Right were 175, 170, 163, 142, 171 and 120% respectively. They were all clearly in the over-fit range.

As shown for Theta in Fig. 2(b), the RSD for the stimulants: Thinking Right, Vision Left, Vision Right and Voice Left were 128, 163, 132 and 140% respectively. They were all in the over-fit range. The Voice Right stimulant had an

RSD in the fit range equal to 98% but the Thinking Left stimulant had an RSD in the under-fit range equal to 75%. Next, the Alpha1 type and Alpha2 type of brain waves were studied as shown in Figs. 3(a) and (b) respectively.

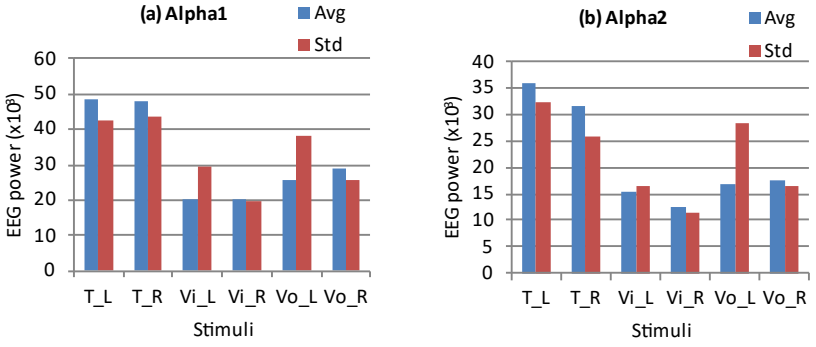

Fig. 3. EEG plotted when six stimulants used. (a) Alpha1 (b) Alpha2.

As shown for Alpha1 in Fig. 3(a), the Vision Left and Voice Left stimulants had an RSD in the over-fit range equal to 147 and 148 respectively. The RSD for the stimulants: Thinking Left, Thinking Right, Vision Right and Voice Right were 87, 91, 97 and 89% respectively. They were all in the fit range.

As shown for Alpha2 in Fig. 3(b), the Voice Left stimulant had an RSD in the over-fit range equal to 167%. The RSD for the stimulants: Thinking Left, Thinking Right, Vision Left, Vision Right and Voice Right were 89, 81, 108, 90 and 95% respectively. They were all in the fit range. Next, the Beta1 and Beta2 types of brain waves were discussed as shown in Figs. 4(a) and (b) respectively.

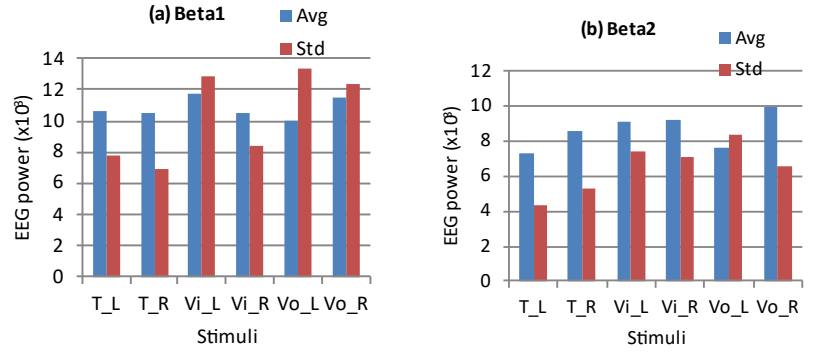

Fig. 4. EEG plotted when six stimulants used. (a) Beta1 (b) Beta2.

As shown for Beta1 in Fig. 4(a), the Voice Left stimulant had an RSD in the over-fit range equal to 133%. The Vision Left, Vision Right and Voice Right stimulants had RSD in the fit range equal to 110, 80 and 107% respectively. The Thinking Left and Thinking Right stimulants had an RSD in the under-fit range equal to 72 and 65% respectively.

As shown for Beta2 in Fig. 4(b), the Vision Left and Voice Left stimulants had an RSD in the fit range equal to 80 and 110% respectively. The RSD for the stimulants: Thinking Left, Thinking Right, Vision Right and Voice Right were 59, 61, 77 and 66% respectively. They were all in the under-fit range. Next, the Gamma1 and Gamma2 types of brain waves were studied as shown in Figs. 5(a) and (b) respectively.

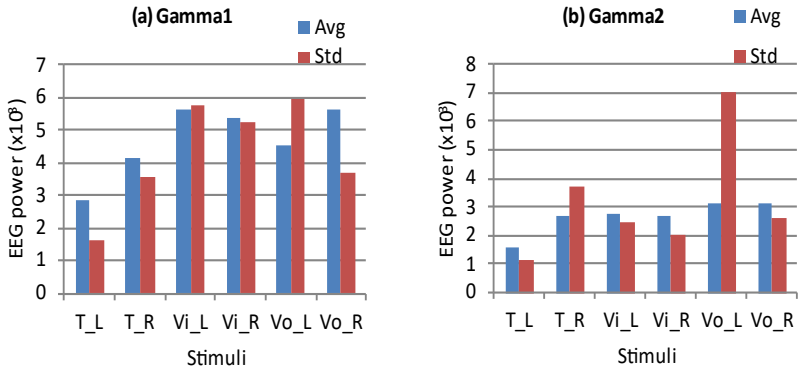

Fig. 5. EEG plotted when six stimulants used. (a) Gamma1 (b) Gamma2.

As shown for Gamma1 in Fig. 5(a), the Voice Left stimulant had an RSD in the over-fit range equal to 132%. The Thinking Right, Vision Left and Vision Right stimulants had an RSD in the fit range equal to 84, 102 and 96% respectively. The Thinking Left and Voice Right stimulants had an RSD in the under-fit range equal to 57 and 65% respectively.

As shown for Gamma2 in Fig. 5(b), the Thinking Right and Voice Left stimulant had an RSD in the over-fit range equal to 138 and 222% respectively. The Vision Left and Voice Right had an RSD in the fit range equal to 90 and 84% respectively. The Thinking Left and Vision Right stimulants had an RSD in the under-fit range equal to 69 and 75% respectively.

For the EEG power received from the Delta waves, all six stimulants had RSD percent in the over-fit range which made us predict that they would be a source of large error when used for classifying our data. As for EEG power received from the Theta, Beta1, Gamma1 and Gamma2 waves, the six stimulants had RSD percentages distributed between over-fit, fit and under-fit range. Moreover for the EEG power of Beta2, the RSD percentages had a majority (4 stimulants) in the under-fit range and only two stimulants in the fit range. We deduced that the Theta, Beta1, Beta2, Gamma1 and Gamma2 might produce confusing results when used in the classification problem.

The RSD percentage for the EEG power of Alpha1 had a majority (4 stimulants) in the fit range and only two stimulants in the over-fit range. The RSD percentages for the EEG power of Alpha2 had a majority (5 stimulants) in the fit range and only one stimulant in the over-fit range. We expected that the Alpha family of brain waves would have the highest precision in our classifying problem since they had majority RSDs in the fit range.

4.2. 4Discussion of the results:

In this subsection, we attempted to rationalize the results discussed above with other published papers especially in the medical field. Two conclusions could be drawn from the results presented in subsection 3.1.

Towards this aim, the number of brain waves per each range of RSD percentages was plotted against the stimulants type as shown in Fig. 6.

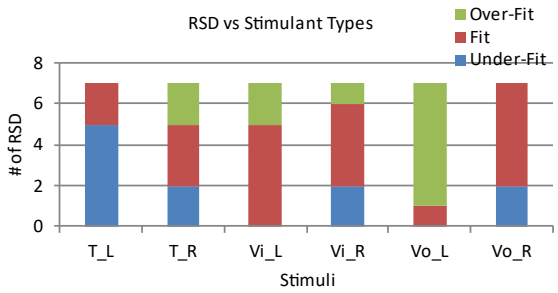

Fig. 6. Number of Over-fit, Fit and Under-fit values of RSD for all types of brain waves.

First conclusion was that the total number of brainwave types which produced RSD percent in the over-fit range was 11 for the left direction and 6 for the right as shown in Fig. 6. The total number of brainwave types which produced RSD percent in the fit range was 8 for the left direction and 12 for the right. The total number of brainwave types which produced RSD percent in the under-fit range was 5 for the left direction and 6 for the right. The number of RSD percentages in the over fit range for the left direction was higher than that for the right which meant that the variations in the readings were higher in the left than the right. The number of RSD percentages in the fit and under fit ranges for the left direction was less than that for the right direction which confirmed that the variations were lower in the right than the left. We found that previous research papers support this result. For example authors in paper [28] had shown that N30 was facilitated during non-dominant hand movement in both right and left hand dominant individuals.

There was no effect for dominant hand movement on the excitation of N30. N30 was defined as a case where phase changes occurred to the excited brainwaves [29] which could alter the Std values more than the Avg ones. Dominant hand movements were defined as moving of the right hand in right handed persons or the left hand in left handed persons. Non Dominant hand movements were defined as moving of the right hand in left handed persons or the left hand in right handed persons [30]. Power with different phase could lead to a decrease or increase in the individual summed power of each volunteer. This increased the proportion of RSD in the over fit range taking into consideration that all volunteers were right handed which agreed with our results here.

Second conclusion was that the Avg for the Thinking Right and Voice Right were higher than that for the Thinking Left and Voice Left for all types of brain waves except for two types. The two types were Alpha2 and Gamma1 waves. The reason could be found in reference [31] which stated that the movement of the

dominant hand produced larger activity in the excitation of brainwaves than the movement of the non-dominant hand.

All volunteers were right handed which explained the high values of the Avg. However the Avg for the Vision Left was higher than that for the Vision Right for all types of brain waves. One of the reasons could be that the recordings for the Vision family were done with opened eyes which had affected the recordings. Another reason could be that eye blinking had contaminated the readings.

In the Voice and Thinking families of stimulants, eye blinking didn't contaminate the readings since recordings were done with closed eyes. However when thoroughly thought; the blinking action was a random one and so its contamination would not affect our results severely since it did not happen at a certain point in time and so it was highly improbable that it could have contaminated the recordings of all types of brain waves for the vision family of stimulants. The effect of vision had larger impact on the recordings than the blinking action. Next, we studied how the different types of brain waves performed when used to train and test for recognition of direction.

5. Effect of Wave Type on Classification

In this section, we used the recordings taken from the four volunteers when the six stimulants were applied to train the Weka software and test the dataset. Next, we discussed the results of the classification problem.

5.1. Classification of the problem results

The success percentages of the classification were discussed using the Delta (De) and Theta (Th) types of brain waves as shown in Table 1(a) and (b) respectively.

Table 1. Precision, Recall and F-measure for classes: Left (L) and Right (R) were shown. (a) Delta (b) Theta

(a)				(b)			
De	**Prec**	**Rec**	**F-M**	**Th**	**Prec**	**Rec**	**F-M**
R	43%	55%	48%	**R**	56%	46%	50%
L	38%	27%	32%	**L**	54%	64%	58%
Avg	40%	41%	40%	**Avg**	55%	55%	54%

In Table 1(a), the percentages of the Precision, Recall and F-measure for the Right class using Delta were higher than that for the Left class by at least 5%. It was shown that the lowest recall came from classifying the brain waves under the Left class.

In Table 1(b), the percentages of the Recall and F-measure for the Left class using Theta were higher than that for the Right class by at least 8%. But the percentage of the Precision for the Right class was higher than that for the Left class by 2%. It was shown that the lowest recall came from classifying the brain waves under the Right class. Next, the same classification problem was discussed using the Alpha1 (A1) and Alpha2 (A2) types of brain waves as shown in Table 2(a) and (b) respectively.

Table 2. Precision, Recall and F-measure for classes: Left (L) and Right (R) were shown. (a) Alpha1 (b) Alpha2.

(a)				(b)			
De	**Prec**	**Rec**	**F-M**	**Th**	**Prec**	**Rec**	**F-M**
R	60%	55%	57%	**R**	82%	82%	82%
L	58%	64%	61%	**L**	82%	82%	82%
Avg	59%	59%	59%	**Avg**	82%	82%	82%

In Table 2(a), the percentages of the Recall and F-measure for the Left class using Alpha1 were higher than that for the Right class by at least 4%. But the percentage of the Precision for the Right class was higher than that for the Left class by 2%. We could deduce that the lowest recall came from classifying the brain waves under the Right category.

In Table 2(b), the percentages of the Precision, Recall and F-measure for the Left class using Alpha2 were equal to that for the Right class. Using Alpha2 type of brain waves had given us the best classification results. Next, the same classification problem was discussed using the Beta1 (B1) and Beta2 (B2) types of brain waves as shown in Table 3(a) and (b) respectively.

Table 3. Precision, Recall and F-measure for classes: Left (L) and Right (R) were shown. (a) Beta1 (b) Beta2.

(a)				**(b)**			
De	**Prec**	**Rec**	**F-M**	**Th**	**Prec**	**Rec**	**F-M**
R	43%	27%	33%	**R**	53%	73%	62%
L	47%	64%	54%	**L**	57%	36%	44%
Avg	45%	46%	44%	**Avg**	55%	55%	53%

In Table 3(a), the percentages of the Precision, Recall and F-measure for the Left class using Beta1 were higher than that for the Right class by at least 4%. It was shown that the lowest recall came from classifying the brain waves under the Right class.

In Table 3(b), the percentage of the Precision for the Left class using Beta2 was higher than that for the Right class by 4%. But the percentages of the Recall and F-measure for the Right class were higher than that for the Left class by at least 18%. It was shown that the lowest recall came from classifying the brain waves under the Left class. Next, the same classification problem was discussed using the Gamma1 (G1) and Gamma2 (G2) types of brain waves as shown in Table 4(a) and (b) respectively.

Table 4. Precision, Recall and F-measure for classes: Left (L) and Right (R) were shown. (a) Gamma1 (b) Gamma2.

(a)				**(b)**			
De	**Prec**	**Rec**	**F-M**	**Th**	**Prec**	**Rec**	**F-M**
R	50%	46%	48%	**R**	40%	36%	38%
L	50%	55%	52%	**L**	42%	46%	44%
Avg	50%	50%	50%	**Avg**	41%	41%	41%

In Table 4(a), the percentages of the Precision, Recall and F-measure for the Left class using Gamma1 were equal to or higher than that for the Right class by at least 4%. It was shown that the lowest recall came from classifying the brain waves under the Right class.

In Table 4(b), the percentages of the Precision, Recall and F-measure for the Left class using Gamma2 were higher than that for the Right class by at least 2%. It was shown that the lowest recall came from classifying the brain waves under the Right class. The Alpha family had the highest Precision, Recall and F-measure in the classification results. As discussed in section1, the Alpha waves were excited when the body was in relaxation and tried to calm down. In our experiments, we encouraged the volunteers to relax and free their mind from all thoughts except thinking about the direction of motions required. All reasons of emitting the other different types of brain waves didn't match the case of the volunteers except the case of the Alpha family. Next, a discussion of the results was shown.

5.2. Discussion of the results

In this subsection, we compared the Precision, Recall and F-measure of the 8 types of brain waves discussed in Subsection 5.1 as shown in Fig. 7.

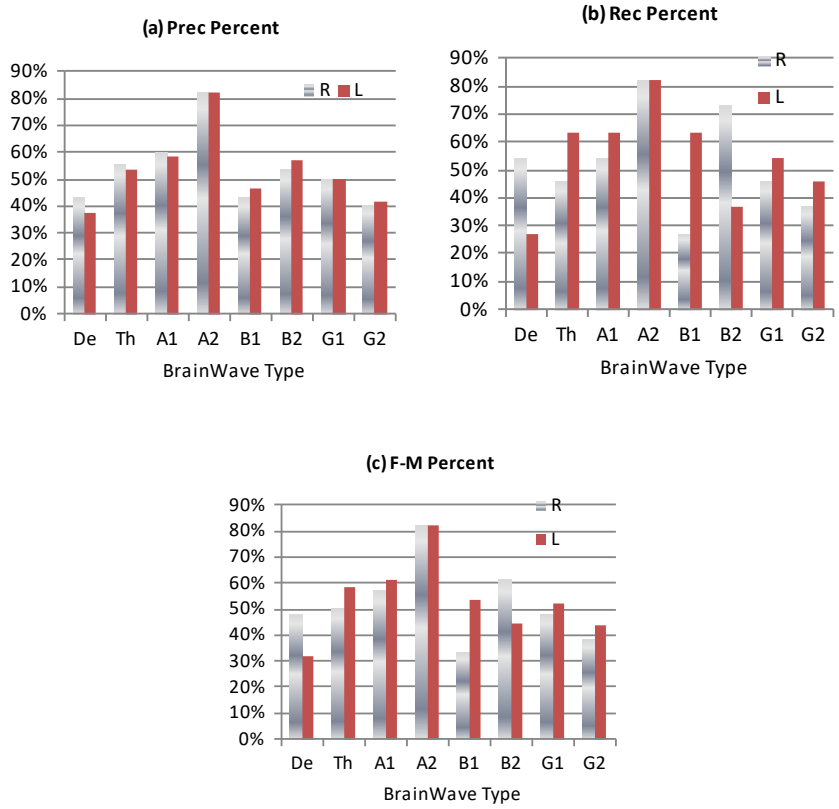

Fig. 7. Accuracy percentages for classifying recordings of 8 types of brain waves to two categories Right (R) and Left (L). (a) Precision (b) Recall (c) F-measure.

As shown in Fig. 7(a), four out of eight types of brain waves had precision percentages for the detection of the Right class higher than that for the detection of the Left class. The four were Delta, Theta, Alpha1 and Gamma1 types. As shown in Fig. 7(b), two out of eight types of brain waves had recall percentages for the detection of the Right class higher than that for the detection of the Left class. The two were Delta and Beta2 types. As shown in Fig. 7(c), two out of eight types of brain waves had F-measure percentages for the detection of the Right class higher than that for the detection of the Left class. The two were Delta and Beta2 types.

This result could be supported by the recent research in biomedical science [30] which had suggested that three dominant-hand movements were correctly classified from the EEG signals with average accuracy 65-75%. Same research reported that the same three movements were repeated in non-dominant hand movements and were correctly classified from the EEG signals with average accuracy 67-85% [30]. In this paper, percentage of correct classification of the left class was higher than that for the right class as concluded from above.

6. Comparing Achieved Results with other Work and Conclusion

In this section, we compared the results presented in this work with one of the published work of other authors as shown in Fig. 8.

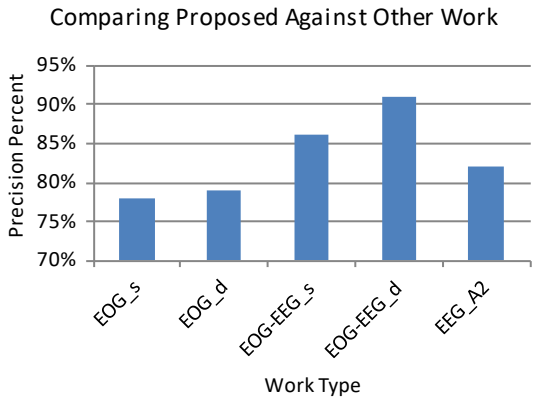

Fig. 8. Comparing the highest precision percentage for the Alpha2 brain wave in predicting the Right or Left class in this paper with other peoples' work.

Postelnicu et al. [32] experimented the use of Electro-oculography (EOG) and EEG signals to help disabled persons with their daily needs. For single blink events from EOG-based experiments, the results (EOG_s) showed in Fig. 8 revealed that the average accuracy for direction detection was 78.60% [32]. For double blink events, the results (EOG_d) revealed an average accuracy of 79.05% [32].

For the EOG-EEG-based experiments, the average accuracy was 86.50% for the results (EOG_EEG_s) obtained when using single blinking [32]. The average accuracy was 90.9% [32] for the results (EOG_EEG_d) obtained when using double blinking. For our EEG based system, the average accuracy for the selection of commands (EEG_A2) was 82%. This accuracy was achieved using the Alpha2 type of brain waves only. Blinking was not used to improve our results. The precision for

the work presented here was higher than the one achieved in other people work except when both EEG and EOG were used together to reinforce each other.

The error within the accuracy of the results presented in our work could be because of several reasons. Volunteers were not trained on using the Neurosky headset so some loss of signal could have happened [20]. The processing of the raw data by the headset could have decreased the reliability of the data. The manual work required by each volunteer to make a recording such as using the mouse and the software accompanying the headset had placed some mental demands on the volunteers which altered the dataset [27].

Volunteers were given 1min break between the recordings of the readings which might have affected the results. It was possible that giving volunteers longer breaks my affect the results. The headset was placed on the forehead which had higher electrical resistance when compared to the head scalp due to being thicker. This could have led to achieve less than clean signals.

In conclusion, the Alpha family of brain waves showed values of relative standard deviation in the range of 80 to 120% for 5 stimulants out of the 6 stimulants tested. This meant that recordings from the Alpha family contained enough information to classify them correctly and identify the type of direction intended by the volunteer. In addition, they were not highly contaminated with noise.

Generally, the number of RSD percentages in the over fit range for the left direction was higher than that for the right which meant that the variations in the readings were higher in the left than the right. The number of RSD percentages in the fit and under fit ranges for the left direction was less than that for the right direction which confirmed that the variations were lower in the right than the left.

The Alpha2 brain wave type showed the highest accuracy in our classification problem. 82% was the percentage achieved for the Precision, Recall and F-measure parameters used to describe the accuracy of success in classification using Alpha2 waves. As for the Alpha2, Beta1, Beta2 and Gamma1 waves, the precision percentage for detection of the left class was higher than that for the right class. AS for the Theta, Alpha1, Alpha2, Beta1 and Gamma1, the Recall and F-measure percentages for detection of the left class was higher than that for the right class. Future work could concentrate on trying using multiple types of brain waves to increase accuracy.

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