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Brain computer interface based smart keyboard using neurosky mindwave headset

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ABSTRACT

In the last decade, numerous researches in the field of electro-encephalography (EEG) and brain-computer-interface (BCI) have been accomplished. BCI has been developed to aid disabled/partially disabled people to efficiently communicate with the community. This paper presents a control tool using the Neurosky Mindwave headset, which detects brainwaves (voluntary blinks and attention) to form a brain-computer interface (BCI) by receiving the system signals from the frontal lobe. This paper proposed an alternative computer input device for those disabled people (who are physically challenged) rather than the conventional one. The work suggested to use two virtual keyboard designs. The conducted experiment revealed a significant result in developing user printing skills on PCs. Encouraging results (1.55-1.8 word per minute (WPM)) were obtained in this research in comparison to other studies.

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1. INTRODUCTION

The brain is an essential part of the human body, which controls movement, behaviour and regulates the equilibrium of the human body. The brain provides cognition; exudes emotions; stores memories and directs muscular or motor activities [1]. There are over 86 billion neurons in the average human brain, and there are various other cells, which almost equal that number too. The interconnection of neurons is crucial for brain activity, as these neurons form an associative link between brain cells [2]. Figure 1 [3], shows the classification of the human brain, which defines regions within the brain as the forebrain, midbrain, and hindbrain. The Midbrain mostly comprises of a portion of the brainstem, which controls some reflex actions and is a portion of the circuit; concerned with the regulation of eye movements and other voluntary movements. The general definition of the (brain) hemisphere happens into four lobes, namely–the frontal lobe, parietal lobe, temporal lobe and occipital lobe [4]. Perception involves sensing the signals from the external environment and is the major function of the human brain, which is at the core of understanding human senses, feeling and emotion. Furthermore, regulating and controlling the human behaviours; regulating and controlling physical actions; regulating memory functions; the method of thinking and other reasoning processes [5]. Medical professionals use Electroencephalography (EEG) to diagnose abnormalities in human life [6]. EEG is an electrophysiological monitoring technique that logs the electrical signals emanating from the brain. EEG senses the electrical potential difference resulting from neurological ionic currents produced by the brain [7]. EEG provides an automatic real-time recording of the brain's electrical activity using multiple electrodes positioned on the scalp [8]. The past few years have seen a rapid progress of EEG-based BCI; that meteoric rise partly attributes to computer processing and speed improvements; also, that is due to signal analysis technique refinements. That work has produced results with applicable clinical applications [9]. BCI is a revolutionary technology, which reads the user's mind directly from the brain and transforms to the commands of a controllable device, bypassing the peripheral neural system [10]. The motor imagery based BCI system is an essential type of BCI. Traditional motor images produced by BCI acquires data through specific processes, then performs data analysis offline to choose the best channel and parameters [11]. Invasive and Non-Invasive are two essential types of BCI arrangements. Invasive BCI arrangements install a chip inside the brain, which records the brain activity [12]; this is often impractical because this requires brain surgery, while non-invasive types use a headset device and are externally placed on the scalp which measures brain activity [3].

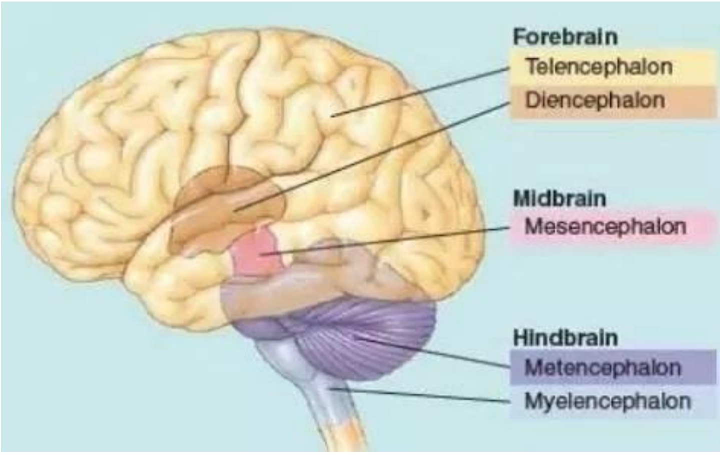

Figure 1. The brain hemisphere

A previous study presented by [13], develops a BCI system using a Mindwave headset. That study senses the activity of the brain and encodes the response in MATLAB, and the decision making, which enables smart home device control uses an Arduino module. The study conducted by [14] employs a P300 BCI system to output digital text. That system displays pulsating characters and a classifier, which determines target characters. Typically, a user must type each symbol within a word at a time. That spelling process is slow, and it can take many minutes to output an entire word. Another research by [15], employs a BCI system to control four-wheel electric vehicles. Emotiv EPOC+ is used to acquire the raw EEG data.Independent Component Analysis (ICA) is used to pre-process the motor imagery EEG; feature extraction involves a Common Spatial Pattern (CSP), which are most related to the ERD/ERS. That research leads to the development of a non-invasive BCI, which realizes the intent of the visual cortex by equating EEG-SSVEP signals to control a wheelchair [16] automatically. That system uses offline data analysis to enable user motive control of the electric wheelchair.

The research conducted by [17] develops a BCI based keyboard with long-term potential for areas such as learning, training, brain stimulation and other clinical purposes. That study presents an average accuracy improvement of all the users from a 40% error rate in the first round to a 10.5% error rate in the fourth round of the trials. This paper describes the use of a low-cost, non-invasive BCI type system, which uses a Neurosky Mindwave headset. This system collects EEG data in real time, to enable people with physical disabilities to communicate with others.

2. RESEARCH METHOD

This work successfully develops a BCI solution which detects and process brain signals in a real-time. Five sub-blocks can represent the system, and the following is a description of the microarchitecture design of each module shown in Figure 2.

2.1. EEG signal acquisition

The primary data acquisition element of the solution is the NeuroSkyMindWave headset. It is an inexpensive, lightweight, portable device with wireless communication. It consists of eight parts, which are a power switch, an ear clip, the ear arm, battery area, adjustable headband, sensor tip, sensor arm, and think gear chip [18]. Two sensors are used to operate this device to obtain and filter EEG signals. The sensor tip locates on the forehead and detects electrical signals emanating from the brain's frontal lobe [19, 20]. The second sensor is an ear clip, which is used as a ground acting as a filter for electrical noise [21]. The NeuroSkyMindwave also has good measurement accuracy, which can result in a broader group of potential users. Figure 3, explains the locations of the electrodes of the MindWave EEG headset in the international 10/20 system [22].

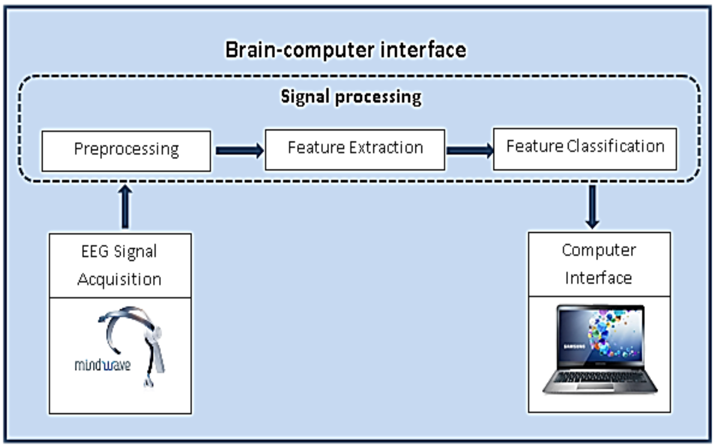

Figure 2. The BCI system

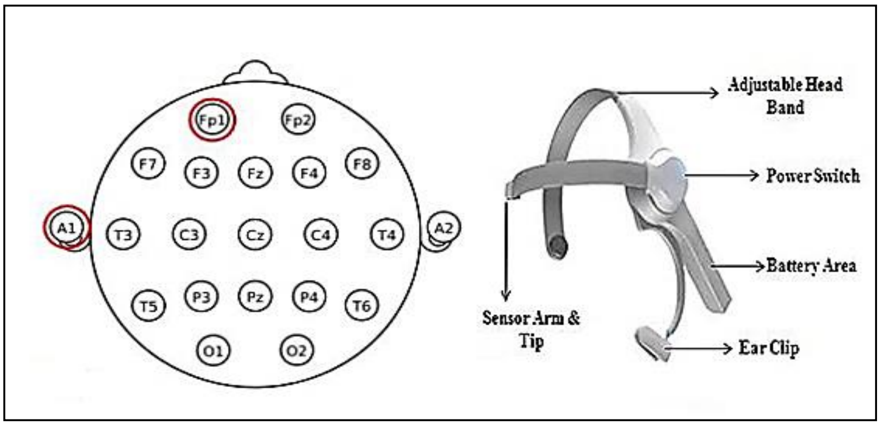

Figure 3. NeuroSkyMindWave system

2.2. Preprocessing

EEG raw signals are very low power signals collected from the user scalp, amplified, digitized and transmitted through a Bluetooth module to the personal computer using the NeuroSkyMindWave device.

2.3. Features of EEG signals

An EEG signal comprises of rhythmic activity and transients. The rhythmic activity is divided into wave bands by frequency while the transient is referring to spontaneous spikes and wave formations that are sharp [23]. There are five types at the most critical frequency ranges: delta (2-4Hz), theta (4-8Hz), alpha (8-12Hz), beta (15-30Hz), and gamma (30-80Hz) [6, 24].

2.4. Classification

The Neurosky uses the ThinkGear Technology to process and classify the EEG output considers quantitative approaches to send signals via Bluetooth to the PC. The EEG processing protocols are closed source software. The output data are Raw EEG signal, eSense Attention and Mediation is an integer value between 0 and 100, Blink Strength is returning an integer value between 0 and 255 [18]. The "eSense Attention" value is used to scan and initialize the virtual keyboard enabling user proper character choice. The Blink Strength value is used to select characters or enables the cursor to move to the next row of the virtual keyboard.

2.5. The virtual keyboard: design and work

The processing development environment (PDE) does process the data. A MindWaveWireless USB Adapter receives the packets of data transmitted from the brain wave sensor. The Neurosky EEG sensor obtains the attention and blink levels. If the attention value exceeds the threshold for a specific time, for example 1 second, then the keyboard scan is 1 second, so the keyboard scan starts. The attention level is received as a series of inputs, at a 1 Hz frequency, while the NeuroSky sensor obtains the unprocessed EEG data at a 512 Hz frequency. The blinking level is used to select characters and enable the pointer to navigate through the keyboard rows to hasten the writing process. The virtual keyboard is designed to contain alphanumeric and control characters. It includes clear, space, screen and delete function characters, as shown in Figure 4. There are thirty cells to provide a virtual keyboard, each alphabetic character and control running a single cell. The cells are organized in a column fashion and arranged in a QWERTY design.

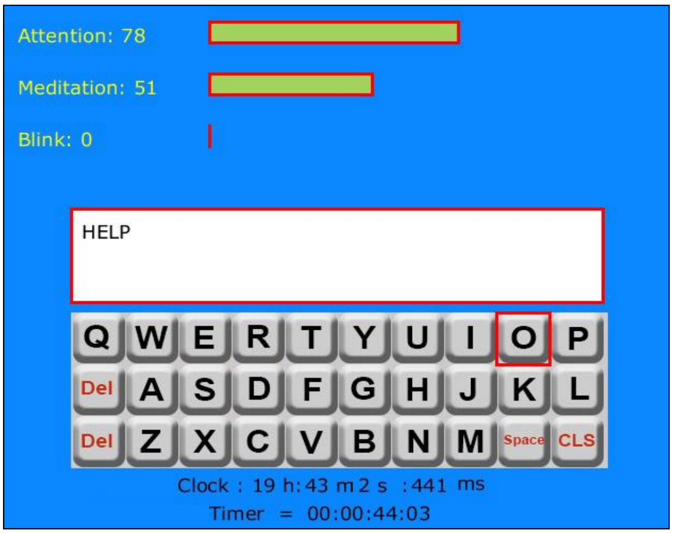

Figure 4. Virtual keyboard design

The red border box represents the cursor that moves on the keyboard so the user can visually recognize the character select. Using a horizontal cursor movement, the user can select the correct character and record within the text box in a second. Figure 5, describes a flow chart of the proposed work. Initially, the NeuroSky headset is turned on, which in order to identify the neuro-signals. The EEG Biosensor capture the signals and send them to the Think-Gear chip for processing. After analysis, the Java environment receives digital signals for attentional extraction and utilizes the Blink Strength signals for further classification. The text process uses eye blink and eye focus levels. The keyboard indicator begins to scan if the signal level of attention exceeds the threshold for a specified period. If the Blink Strength value is between the decimal numbers of 110 and 60, then that action chooses the text box character. If the Blink Strength value exceeds the 110-decimal value, the pointer jumps between keyboard rows. The proposed virtual keyboard uses one blink signal to select any row to increase text writing speed and obtain more text in a fixed time.

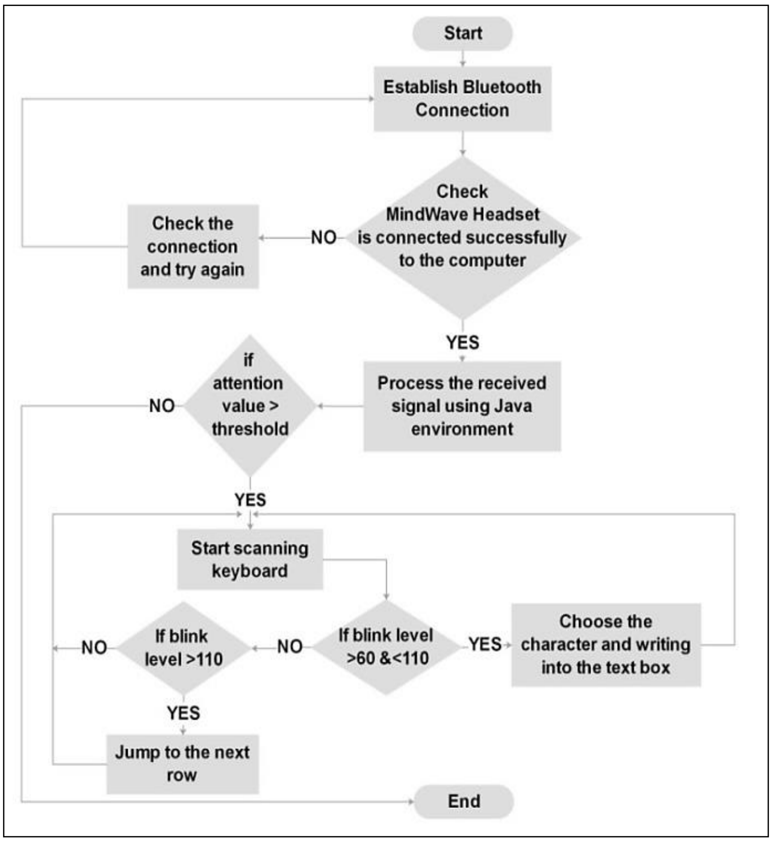

Figure 5. Brain-controlled keyboard flow chart

3. RESULTS AND ANALYSIS

The performance of the system was evaluated by taking five people to the test, ranging in age from 30 to 35 years. During the practical test phase, each participant sits in a comfortable chair in front of the laptop. Each participant performs the following experiments in a certain number of sessions at different times.

3.1. First experiment

Each person was asked to write (Help) word for nine sessions on (QWERTY) virtual keyboard designed as previously mentioned. This study calculates the time required to write the required word and the number of wrong characters; shown in Table 1.

Table 1. Time consumed to write (HELP) word and a character error number

Sessions	Subject 1		Subject 2		Subject 3		Subject 4		Subject 5	
	Time (sec)	Error (ch)	Time (sec)	Error (ch)	Time (sec)	Error (ch)	Time (sec)	Error (ch)	Time (sec)	Error (ch)
1	136.07	5	123.06	5	120.2	4	106.5	5	83.9	4
2	129.16	4	91.95	3	99	2	92	5	70	2
3	76.1	2	80	2	69.81	2	99.11	4	54.3	0
4	58.05	1	116.3	2	69.56	2	82.05	2	72.8	4
5	47.36	0	63	1	65.5	1	77.49	1	71	3
6	50.2	1	53	1	61.2	1	72.04	1	79	3
7	47.64	0	48.2	0	60.5	1	57.5	1	44.04	0
8	46.26	0	49.3	0	55	0	48	0	53.3	1
9	45.29	0	46.2	0	56.4	0	46.9	0	44	0

The words per minute (WPM) variable provides the most frequent empirical metric of text entry performance. It measures the period to produce a certain number of words. WPM is inconsiderate of the number of keystrokes nor gestures types made during the text entry, but only considers text transcription length, which is defined in (1) [25].

WPM= ((T-1)/s)*60*1/5 (1)

Where S is the time in seconds. 60 is a constant. The factor of one-fifth accounts for the average word length in characters, including spaces, numbers, and other printable characters. Table 2, shows the text entry speed and error rate of each subject for nine sessions. Figure 6 Shows the results for every participant, during nine sessions and calculates the average time for all sessions. Figure 7 Shows the average entry speed of text represents as (WPM) with an accuracy of the correct entry text.

Table 2. Word entry speed and error rate

Sessions	Subject 1		Subject 2		Subject 3		Subject 4		Subject 5	
	Accuracy (%)	Entry Speed (wpm)	Accuracy (%)	Entry Speed (wpm)	Accuracy (%)	Entry Speed (wpm)	Accuracy (%)	Entry Speed (wpm)	Accuracy (%)	Entry speed (wpm)
1	44.44	0.26	44.44	0.29	50.00	0.30	44.44	0.34	50	0.43
2	50	0.28	57.14	0.39	66.67	0.36	44.44	0.39	66.67	0.51
3	66.67	0.47	66.67	0.45	66.67	0.52	50	0.36	100	0.66
4	80	0.62	66.67	0.31	66.67	0.52	66.67	0.44	50	0.49
5	100	0.76	80	0.57	80	0.55	80	0.46	57.14	0.51
6	80	0.72	80	0.68	80	0.59	80	0.50	57.14	0.46
7	100	0.76	100	0.75	80	0.60	80	0.63	100	0.82
8	100	0.78	100	0.73	100	0.65	100	0.75	80	0.68
9	100	0.79	100	0.78	100	0.64	100	0.77	100	0.82

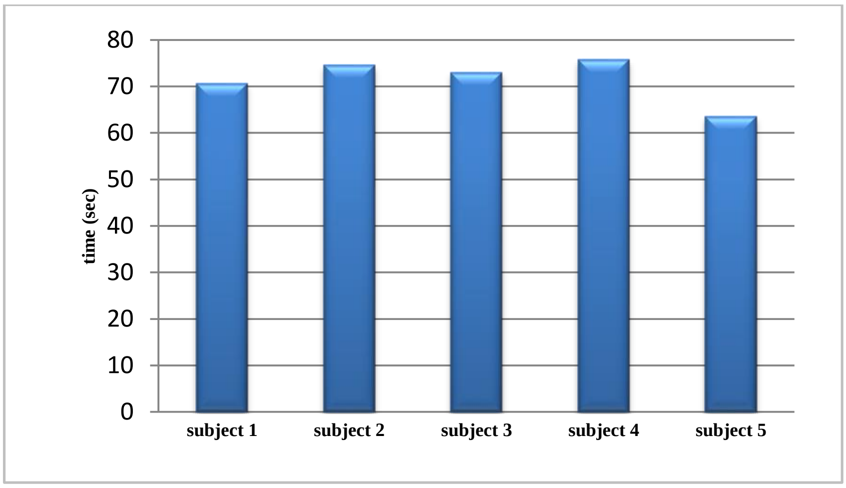

Figure 6. The average time for all sessions

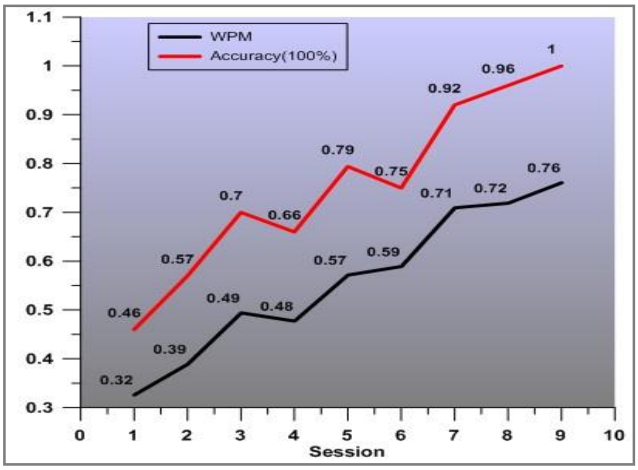

Figure 7. Text entry speed and accuracy

3.2. Second experiment

This experiment uses two types of virtual keyboards, QWERTY type as described previously, ABC type consists of alphabets and two control characters defined as Delete and Space. The keyboard has 30 cells; each alphabet occupies one cell character and two cells for each control button [17]. In this study, two types of keyboard use square pointers. Both keyboards scan with a 600-millisecond delay to allow the user to select a proper character. The persons are required to write a 24-letter sentence, including the white space character within six sessions. The time required to write the chosen word was calculated as shown in Tables 3 and 4. Figures 8 and 9 shows the average text entry speed and error rate of each person for this study. The calculations of the text entry rate of various input methods is straight forward and simple.

In the first study, the users training to write the word HELP, and calculate the time taken, as shown in Table 1. 75.83% accuracy obtained, and the WPM is 0.56, which equivalent to 2.8 letters per minute. In the second study, the user is trained to write a sentence of 24 characters; by reducing the time taken to scan the keyboard and switch between the buttons to be 600 milliseconds, using two types of keyboard design to improved the proposed system. The first keyboard (QWERTY) contains three control buttons in addition to the alphanumeric. The error rate was 5% and WPM = 1.55. The second type of keyboard designed as (ABC), which contains two control buttons in addition to the alphanumeric. The error rate was 5.25% and WPM = 1.8. The results of the proposed system exceed the performance of previous studies that enable the user to write 7.75 to 9 characters per minute. Through the results obtained, it is possible to note the improvement in the performance of the proposed system compared to the previous systems by looking at the time taken to write most characters, taking into account the delay in the movement of the indicator between pressing the buttons.

Table 3. Time and error data of (QWERTY) keyboard

Subjects	Session1		Session2		Session3		Session4		Session5		Session6	
	Time (sec)	Error letter	Time (sec)	Error letter	Time (sec)	Error letter	Time (sec)	Error letter	Time (sec)	Error letter	Time (sec)	Error letter
1	219.0	4	199.2	1	160.2	1	172.8	1	165.6	0	156.0	0
2	208.6	3	190.4	2	175.0	1	177.0	1	160.0	0	149.4	0
3	225.3	5	220.2	4	195.9	2	180.5	1	185.6	0	171.0	1
4	199.6	1	182.8	2	150.0	1	190.5	2	149.4	0	150.2	0
5	195.2	2	202.3	2	181.4	1	185.2	1	155.2	0	157.9	0

Table 4. Time and error data of (ABC) keyboard

Subjects	Session1		Session2		Session3		Session4		Session5		Session6	
	Time (sec)	Error letter	Time (sec)	Error letter	Time (sec)	Error letter	Time (sec)	Error letter	Time (sec)	Error letter	Time (sec)	Error letter
1	176.0	3	156.0	4	149.9	1	213.8	2	146.4	0	142.2	1
2	140.8	1	135.0	2	133.2	2	162.6	1	178.8	0	120.2	0
3	201.0	2	180.5	2	134.4	2	124.7	1	122.4	1	118.8	1
4	185.2	3	180.6	2	151.2	2	155.7	1	149.8	1	130.2	0
5	191.0	2	195.3	2	182.7	1	180.5	1	177.7	0	125.1	0

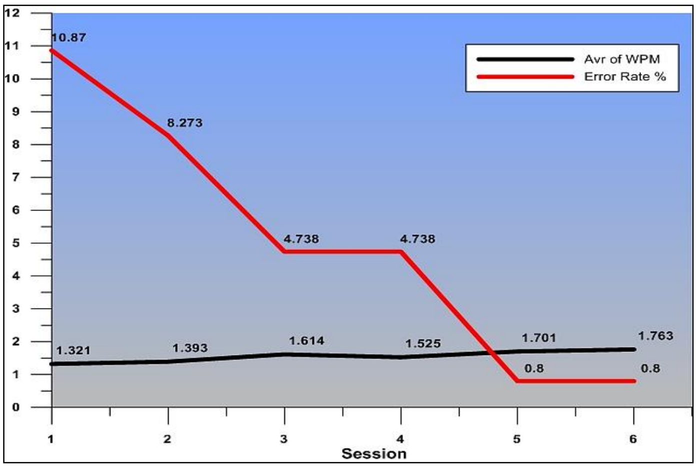

Figure 8. Text entry speed and error rate of (QWERTY) virtual keyboard

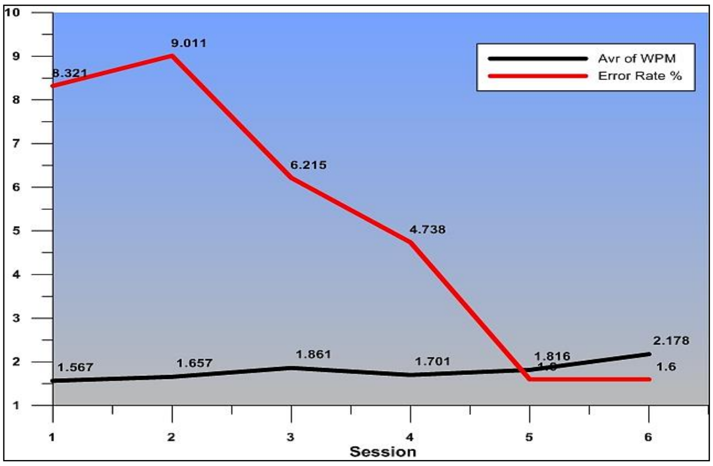

Figure 9. Text entry speed and error rate of (ABC) virtual keyboard

4. CONCLUSION

The proposed virtual keyboard uses EEG signal synchronized with human-eye blinking in term of key selection for printing purposes. The obtained results were encouraging and were about (1.5-1.8 WPM) with an error rate equals to (5-5.25)%. The results of experiments show that the best mode is the one that used the ABC keyboard type. The next challenge focuses on designing a similar keyboard with predicting capabilities with text output interface for native languages.

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