International Journal of Science and Research (IJSR)
ISSN: 2319-7064
ResearchGate Impact Factor (2018): 0.28 | SJIF (2019): 7.583

Analysis and Extraction of Electroencephalogram (EEG) wave for Brain-Computer Interfacing

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Abstract: ***The present work demonstrates the mining of brain data using non-invasive methods by simply interfacing the brain and computing devices. This work attempts to analyze and collect the Electroencephalogram (EEG) signal by two different sensors for Brain-Computer-Interfacing (BCI) system. A detailed performance analysis is carried out between these two sensors. Then various signal processing techniques and algorithms are used to extract two useful features of the brain, attention and meditation. Finally, for the later portion of the paper, Brain's attention (EEG Beta wave) and meditation (EEG Theta wave) values are conditioned successfully to make them available for a practical application.***

Keywords: Brain-Computer-Interfacing (BCI), Electroencephalogram (EEG), Non-invasive Signal Extraction, Attention, Meditation

1. Introduction

1.1. Motivation

Motor neuron disease is one of the brain dysfunctions in which the affected people cannot move their muscles. So their normal movement is hampered. In this condition, there is no way for the affected person to communicate with the outside world. Statistics show that about 50,000 people are being affected by Motor neuron disease each year [1]. But if a successful signal extraction procedure of the brain signal is developed, we can find a way for the people affected by motor neuron disease to communicate and control an external locomotive devices like an electrical wheelchair.

The study of brain is also of enormous importance because of the brain related diseases. Proper diagnosis and treatment of the disease depend on the proper understanding of the current condition of the brain. For example, Epilepsy is a disease in which brain's electrical signal can be used to analyze the neuron data. Epilepsy can be diagnosed successfully by detecting the patterns typical of Epilepsy extracted from the electrical signal of the brain [2].

Electrical brain signal can also detect abnormal brain waves after a head injury, stroke, or brain tumor. Other conditions such as dizziness, headache, dementia, and sleeping problems may show abnormal brain patterns. So, finding a cheaper and reliable way of collecting brain data and extracting useful features from them lead to this research work.

1.2. Problem Specification

Dependable registration of brain activities requires invasive methods, which is costly, unavailable in rural areas, and can be dangerous to patients [3]. To rectify these problems, an alternative method, non-invasive method is vastly investigated. Electroencephalogram (EEG) [4], Magnetoencephalography (MEG) [5], Functional magnetic resonance imaging (FMRI) [6], Photon migration tomography [7], and, Transcranial magnetic stimulation [8] are the few of the most studied non-invasive methods. Among these methods, EEG has the most decent potential to be used as medical grade diagnostic method [9]. So useful brain signal extraction and making them suitable for practical applications are the areas that need to be further investigated. So, the Main objectives of this work was to analyze and collect Electroencephalogram (EEG) and process them and extract useful features from them, so that The findings of this research would lead to develop a more robust system that will help the physically disabled people to control electrically operated objects with their brain.

Electroencephalography (EEG) signal apprises about the electrical conditions of the brain. The electrical activities are measured as voltage at different parts of scalp and act as the basis of EEG [10]. Human brain consists of 5 different types of brain waves; Delta, Theta, Alpha, Beta and Gamma [11]. These typical primary brain waves are shown in Figure 1.

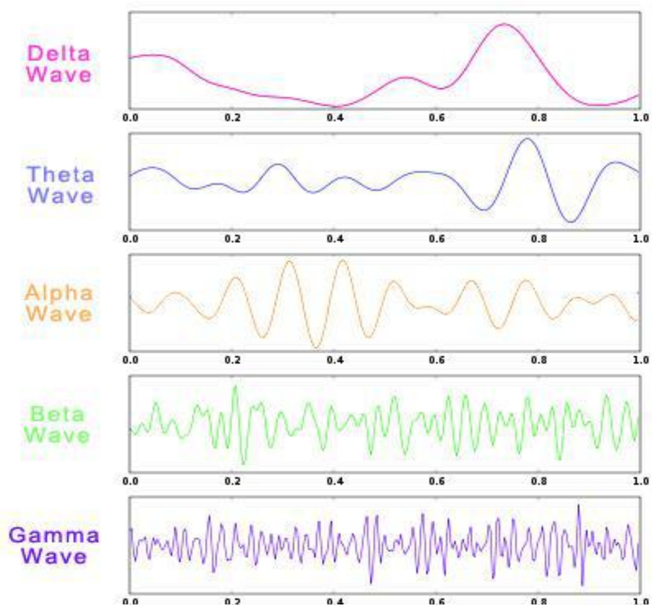

Figure 1: Different types of primary brain signal.

In a perfect healthy brain all the brain waves fall within

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these normal ranges, as shown in Figure 1, and we have the correct strong dominant brainwave depending on our state of mind. Every aspects of our daily lives—stress, poor diet, lack of exercise, trauma, pollution, the environment, and more—causes our brain waves to become unbalanced. Each of these waves has a normal frequency range in which they operate, as listed in the Table 1.

Table 1: List of different primary brain waves with their corresponding frequency and their primary functions

Name	Frequency range	Primary indicating functions
Gamma waves	> 40 Hz	Higher mental activity, including perception, problem solving, and consciousness
Beta waves	13–39 Hz	Active, busy thinking, active processing , active concentration, arousal, and cognition
Alpha waves	7–13 Hz	Calm relaxed yet alert state
Theta waves	4–7 Hz	Deep meditation /relaxation, REM sleep
Delta waves	< 4 Hz	Deep dreamless sleep, loss of body awareness

Each type of brainwave gearshifts a variety of states of consciousness ranging from active thinking to sleep. While all brain waves work simultaneously, one brainwave can be more predominant and active than the others [12]. So it can be said that the dominant brainwave would determine our current state of mind. So if we are awake and relaxed we would be considered to be in an "alpha state of mind" because our Alpha brain waves would be the strongest with the highest amplitude.

EEG signal entails fast, relatively cheap and safe way of checking the functioning of different areas of brain and high precision time measurements are possible, in fact, today's EEG technology can accurately detect brain activity at a resolution of a single millisecond [13]. EEG equipment is also relatively inexpensive compared with other devices and is simple to operate. As a direct result of these benefits, EEG is mainly used in studying the properties of cerebral and neural networks in neurosciences to monitor the neurodevelopment and sleep patterns and enable the physicians to use this information to enhance daily medical care [14]. Many disorders as chronic anxiety, depression etc. can be found out using as EEG pattern [15]. Though EEG sensors can be deployed into a wide variety of environments, the standardized location of scalp electrodes for a classical EEG recording has become common since the adoption of the 10/20 system [16]. The core of this system is the distance in percentages of the 10/20 range between Nasion-Inion and fixed points, as shown in Figure 2.

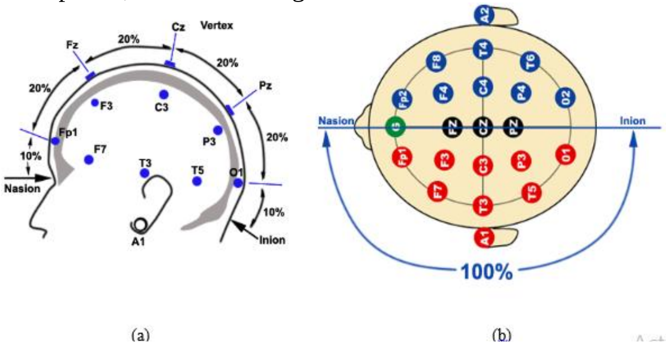

Figure 2: Standard placement of scalp electrodes for a classical EEG recording, (a) Side view, (b) Top View. Points are marked as the Frontal pole (Fp), Central (C), Parietal (P), Occipital (O), and Temporal (T). The midline electrodes are marked with a subscript z, which stands for zero. The odd numbers are used as subscript for points over the left hemisphere, and even numbers over the right.

These signals have time-varying and non-stationary characteristics [17]. As they are decidedly random in nature, it is very difficult to get useful information from these signals directly in the time domain just by observing them. Hence, important features only can be extracted for the diagnosis of different diseases using advanced signal processing techniques [18].

As the EEG recording has very poor spatial resolution, extracted signals are further conditioned using various signal processing techniques. The brain activity signals collected by a sensor can processed by computational devices and an interface can be developed. A Brain-Computer Interface (BCI) system allows a subject to send instructions to an electronic device by brain activities. Brain–computer interfaces (BCI) or brain–machine interfaces (BMI) is of core importance in fields like bio robotics. These technologies can be of great use for directly decoding the user's brain signal and using them to control the bio robotic equipment such as exoskeletons or wheelchairs, and prosthetics [19]. Bio-sensing technologies play a vital role in this system. Raw EEG data is collected by a sensor, analog to digital conversion is done in a microprocessor, digital bit stream is further processed in a digital signal processor, and sent to the PC, as shown in Figure 3.

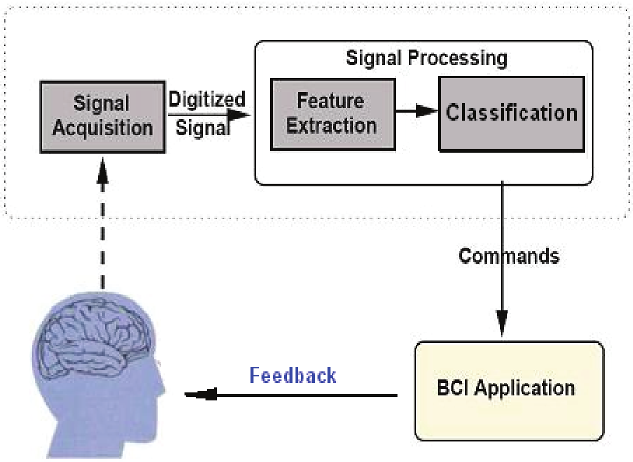

Figure 3: Block diagram of the proposed BCI system.

1.3. Contribution

The most challenging part to work with EEG signal is to properly collect the signal with a suitable sensor. As the collected signal is in the microvolt range, it has a very low spatial resolution. So if the sensor is not an enough fit, then no useful feature can be extracted. So a comprehensive experiment was implemented for EEG sensor. First, a commercially available sensor was set up as a part of the BCI system. After noise reduction, targeted signal was detected with this system, In this case, the target signals were eye blinking, attention (Beta wave), and meditations (Theta wave) as these will create significant pulsating

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behavior and different frequencies in the signal.

These classified signal features were used for a practical application, in this case, controlling LED lights. The eye blinking was used to turn on/off the LEDs. The attention and meditation features were used for controlling the intensity of the LEDs.

For the later part of the work, a sensor was developed from scratch using electrodes, filters, and amplifiers. The collected signal was analyzed and compared with the previous results. The extracted signal was conditioned in the same way to classify the expected feature.

1.4. Paper Organization

The remainder of the paper is organized as follows. Section 2 summarizes the related works in the associated areas of EEG signal collection and application, and brain-computer interfacing. Section 3 broadly discusses the experimental setup of a BCI system with commercially available EEG sensor, noise elimination, and signal processing methods. It also demonstrates how the extracted and processed signal can be used to control LED lights. Section 4 describes the developing of a new sensor for EEG signal extraction and corresponding result analysis. Section 5 concludes the paper.

2. Literature Survey

Electroencephalography (EEG), as in the form of electrical neural activities of the human brain were recorded by Hans Berger using a simple galvanometer in 1924 [20]. By putting only one electrode on a human scalp, one wave was identified, known as alpha wave [21]. Standard medical grade EEG collection that requires 21 electrodes to identify 5 fundamental waves, has a price range of thousands of dollars [22], [23]. In recent years, inexpensive mobile EEG devices have been developed by Avatar EEG Solutions, Neurosky, OCZ Technology, InteraXon, PLX Devices, Emotiv Systems, and so on which are not yet permitted for clinical use, but are in the suitable price range for brain study [24]-[27]. A direct communication pathway between the brain and an external device were needed to use the EEG signal for practical application.

The idea of brain computer interfacing was first proposed in 1973 by Jacques Vidal [28].Since then significant development has been achieved and brain signal is used to translate to useful command [29]. Different potentials are used for detecting the EEG signal such as P300 potential [30]. Steady-state evoked potentials [31], and Error-related potentials [32]. Event-related de-synchronization/ synchronization (ERD/ERS) represent a decrease/increase in the amplitude of the EEG signal at a definite frequency as a response to a certain mental command [33]. The signal processing usually involves the use of spectral and spatial filtering to maximize the signal to noise ratio, as well as procedures to deal with contamination of EEG data such as artifacts [34]. Fernández et.al. showed that a BCI for a natural function can be used by people who, due to an injury or disease, have lost that function [35].

3. Developing BCI system with a conventional EEG sensor

3.1. Experimental Setup

EEG signal, the electrical activities in the brain was detected by electrodes attached to our scalp. In the experiment, Neurosky sensor [36] from Sparkfun was used to develop the first BCI system. The target signal was for this sensor was attention, meditation, and eye blinks. The device consisted of a headset, an ear-clip, and a sensor arm, as shown in Figure 4. The headset's reference and ground electrodes were on the ear clip and the EEG electrode was on the sensor arm, resting on the forehead above the eye (FP1 position). HC-06 Bluetooth module was used for wireless communication between the sensor and a microprocessor. As the microprocessor Arduino development board was used, where Analog-to-Digital conversion (ADC) was performed. The digital signal was then sent to a signal processing module. The artifacts and noise in the system were removed by performing FFT analysis.The Attention and blinking signal levels are differentiated by using the Level analyzertechniques. For serial communication between the sensor and Bluetooth BAUD rate of 9600 was used.

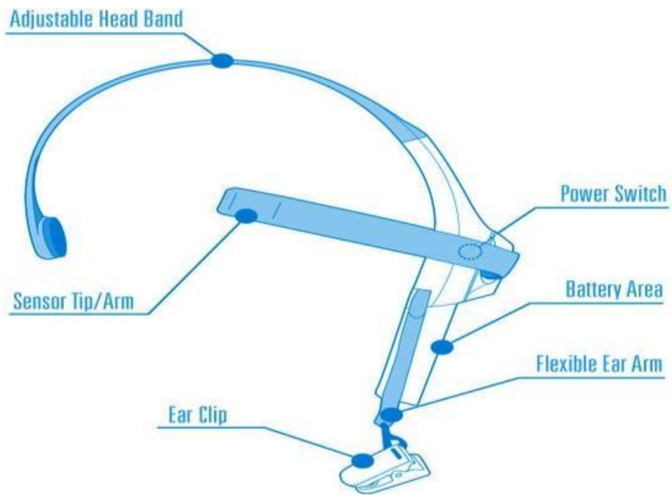

Figure 4: Neurosky sensor for EEG data collection.

3.2. Result Analysis

Without applying any kinds of signal processing, raw EEG data was extracted, as shown in Figure 5, for both active and resting state of the brain. From the figure it was clear that though EEG has high temporal resolution, it has very low spatial resolution. So no useful can be extracted until the noise and artifact are properly removed.

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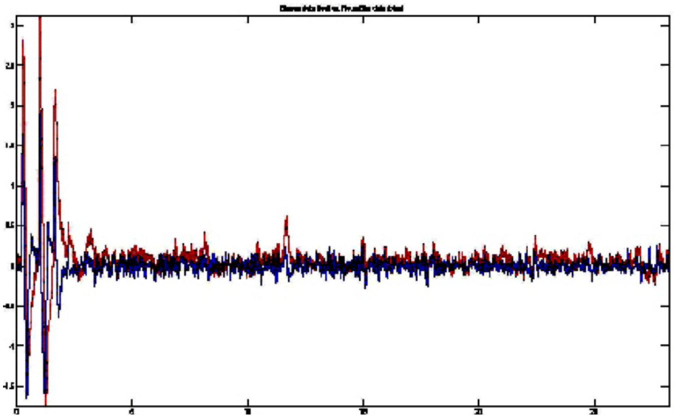
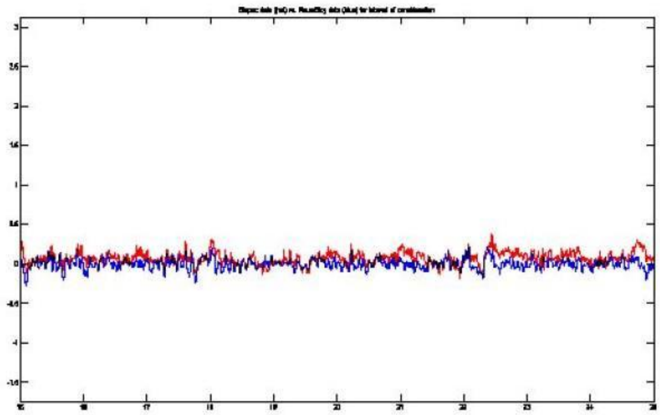


(a)



(b)

Figure 5: Raw EEG data collected from sensor for (a) active state and (b) Resting state of the brain.

The FFTs of the raw EEG were taken over a second for each system. Then, correlation coefficients for the resulting power density values were computed for frequency bands of 1 to 30 Hz. After applying FFTs and using filters to reduce noise, a comparatively better output was found in time domain, as shown in Figure 6.

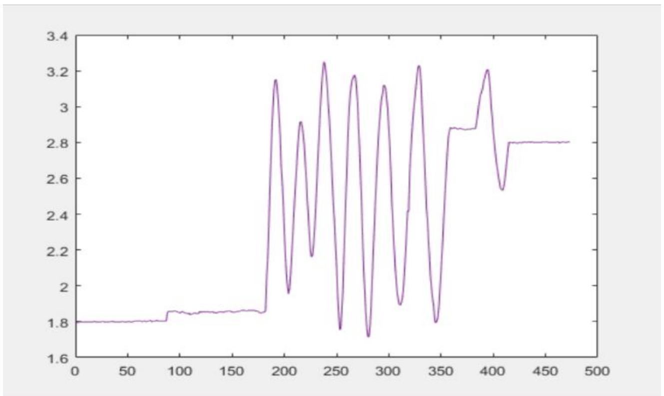


Figure 6: EEG signal after noise reduction.

Eye blink was clearly detected after the amplification, filtering and noise reduction. In Figure 7, it can be seen that the onset and offset of a blink are clearly understood.

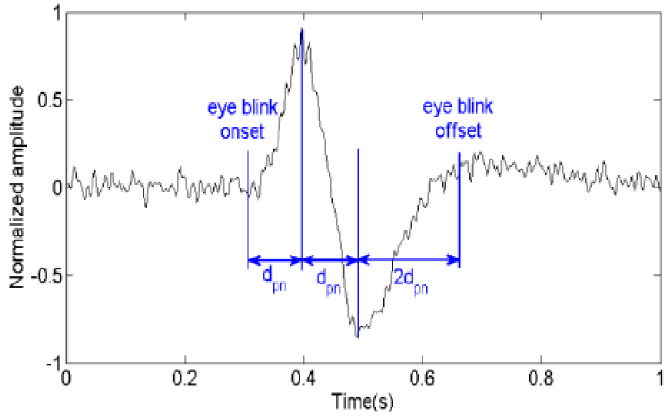


Figure 7: The onset and offset of an eye blink.

3.3. A practical application: Controlling LEDs

One of the most exhilarating areas of BCI research is the development of devices that can be controlled by thoughts. Signals of the brain have been extracted using non-invasive methods. Useful features such as eye blinks, attention levels, and meditation levels, were extracted in the previous subsection. These features were used to control some LEDs. The circuit diagram for interfacing with the sensor and microprocessor is shown in Figure 8.

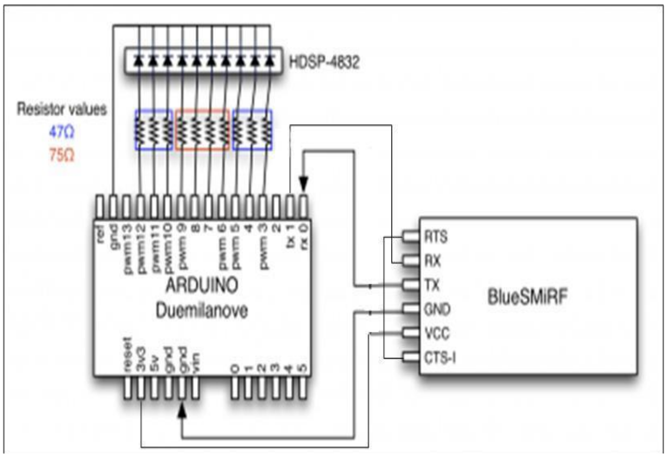


Figure 8: Circuit diagram for interfacing the sensor and microprocessor.

Figure 9 clearly explains the result of the experiment. At first LEDs were turned on by eye blinking. Different color LEDs were used to indicate the strength of the attention level. When the attention level was low, only the green LEDs were on, when the attention level was medium, the yellow LEDs were on, and for high attention level, red LEDs were on. That means this EEG-BCI system had the capability of both digital application (LED ON/OFF operation), and analog application (by turning ON/OFF certain number of LEDs depending on intensity).

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Paper ID: SR201204170853 DOI: 10.21275/SR201204170853

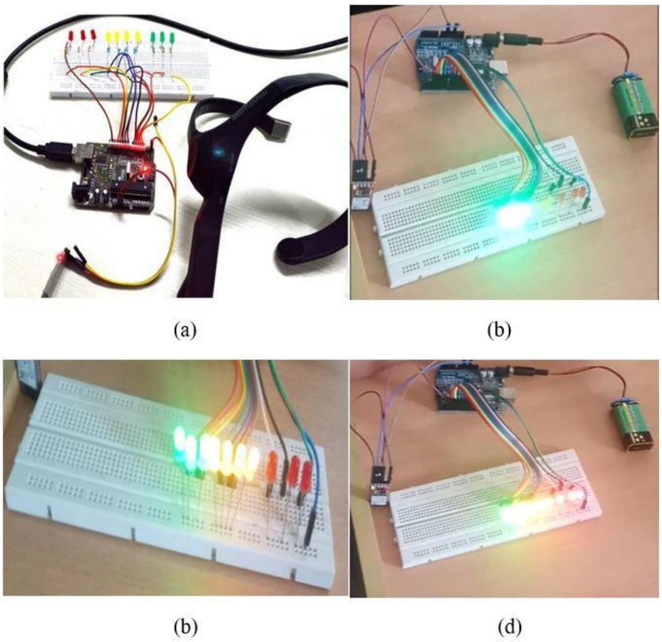


Figure 9: LED control application with feature extracted EEG signal. (a) LEDs are off, (b) LEDs are turned on with an eye blink, and as the attention level was low, the green LEDs were on, (c) the increment in attention level turned on the yellow LEDs, (d) high attention level turned on all the LEDs.

4. Developing a EEG sensor for BCI application

4.1. Experimental setup

The EEG sensor is an analog sensor that is able to collectelectrical activities of the neurons. Electrodes pick up the signal. Signal amplitude is very low and it needs to be amplified. Noise and artifacts need to be reduced. Main sources of the interference are 50 Hz power line and high frequency electromagnetic discharge. Gaussian White Noise also plays an important factor as the amplitude of the target signal is in the same order as the noise. So a 50 Hz notch filter, low pass filter and high pass filter was needed. Operational amplifiers were used to amplify the signal. Figure 10 depicts the final circuit diagram.

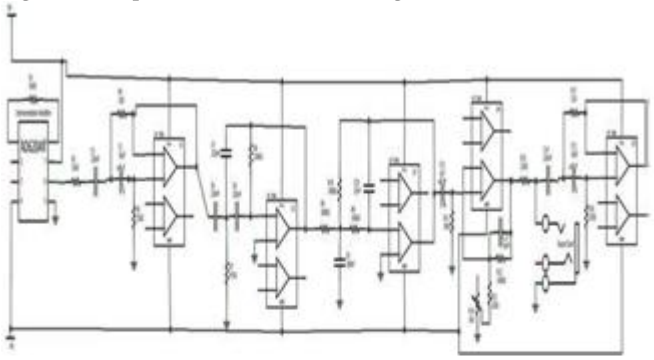
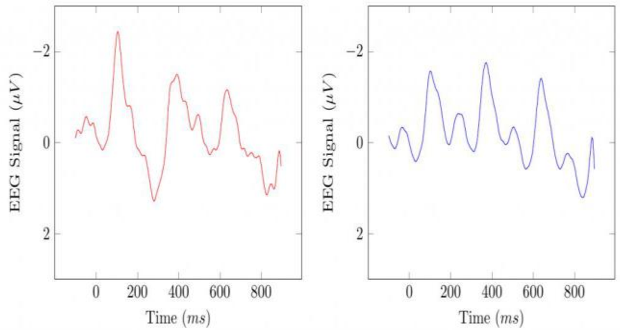


Figure 10: Final circuit diagram for EEG sensor with 50 Hz notch filter, high pass filter, low pass filter and amplifiers.

4.2. Result analysis

Data were collected by attaching the electrodes to the scalp of a test subject. After filtering, amplifying, and ADC conversion, the amplified signal, shown in Figure 11(a), was found. Figure 11(b) shows the signal, collected by the commercial sensor from previous section. As it can be seen clearly from the figures, these two different system resulted in almost same quality for same test subject. Resolution of signal from the handmade sensor may seem slightly better by careful observation.



(a) (b)

Figure 11: EEG signal (a) collected from handmade sensor, (b) Collected from the commercial sensor.

5. Conclusion

A clear representation of constructing the Brain-Computer-Interfacing (BCI) with EEG wave were presented in this paper. Starting with a readymade sensor, the standards of signal extraction was fixed. Then a signal capturing sensor was developed and the findings were compared with the standard set by the previous step. The multidimensional uses by these systems were also shown by a simple application which can easily be scaled and extended for more sophisticated real time application. Though the signal quality is not medical grade yet, this work explored all the phases of EEG—BCI signal processing, such as signal acquisition, signal enhancement, feature extraction, and signal classification.

6. Future Scope

The work can be extended to advanced research. The methods proposed here can be modified for better performance. Some of the scopes for future work are mentioned below-

- Multi electrode headsets can be utilized for EEG acquisition in order improve the accuracy of the output. Furthermore, mediation, eye blink cognitive features can be used to control more aspects.
- To achieve higher mobility and lower cost, instead of a laptop, a powerful single-board computer like Raspberry Pi can be used to implement and train the network.
- Computers can be operated with a mouse and keyboard controlled by EEG signal.
- Speech synthesizers can be developed so that people without the speaking faculty can communicate by using brain signal to ‘talk’ through a speech synthesizers.
- EEG controlled motorized wheelchair can be developed for physically handicapped people.

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References

[1] John Douglas Mitchell, Pauline Callagher, Joyce Gardham, Catriona Mitchell, Mandy Dixon, Robert Addison-Jones, Wendy Bennett, & Mary R. O'Brien, “Timelines in the diagnostic evaluation of people with suspected amyotrophic lateral sclerosis (ALS)/motor neuron disease (MND) – a 20-year review: Can we do better?” Amyotrophic Lateral Sclerosis, vol. 11, no. 6, pp. 537-541, 2010.
[2] U. Rajendra Acharya, Shu Lih Oh, Yuki Hagiwara, Jen Hong Tan, & Hojjat Adeli, “Deep convolutional neural network for the automated detection and diagnosis of seizure using EEG signals” Computers in Biology and Medicine, vol. 100, pp. 270-278, 2019.
[3] Ryan R. Reeves, Lawrence Ang, John Bahadorani, Jesse Naghi, Arturo Dominguez, Vachaspathi Palakodeti, Sotirios Tsimikas, Mitul P. Patel, and Ehtisham Mahmud, “Invasive Cardiologists Are Exposed to Greater Left Sided Cranial Radiation: The BRAIN Study (Brain Radiation Exposure and Attenuation During Invasive Cardiology Procedures)”, JACC Journals, vol. 8 no. 9, pp. 1197–1206, 2015.
[4] Corey Ashby, Amit Bhatia, Francesco Tenore, Jacob Vogelstein, “Low-cost electroencephalogram (EEG) based authentication” IEEE Xplore, 2011 5th International IEEE/EMBS Conference on Neural Engineering, Cancun, Mexico.
[5] Kyousuke Kamada, Yutaka Sawamura, Fumiya Takeuchi, Shinya Kuriki, Kensuke Kawai, Akio Morita, Tomoki Todo, “Expressive and receptive language areas determined by a non-invasive reliable method using functional magnetic resonance imaging and magnetoencephalography” Neurosurgery, vol. 60, no. 2, pp. 296-306, 2007.
[6] Edgar A.DeYoe, Peter Bandettini, JayNeitz, David Miller, Paula Winans, “Functional magnetic resonance imaging (FMRI) of the human brain” Journal of Neuroscience Methods, vol. 54, no. 2, pp. 171-187, 1994.
[7] Andreas H. Hielscher, “Model-based iterative image reconstruction for photon migration tomography” SPIE. Digital Library, vol. 60, 1997.
[8] Masahito Kobayashi, Dr Alvaro Pascual-Leone, “Transcranial magnetic stimulation in neurology”, The Lancet Neurology, vol. 2, no. 3, pp. 145-156, 2003.
[9] J C Quero, I J Hartmann, J Meulstee, W C Hop, S W Schalm, “The diagnosis of subclinical hepatic encephalopathy in patients with cirrhosis using neuropsychological tests and automated electroencephalogram analysis”, Hepatology, vol. 24, no. 3, pp. 556-560, 1996.
[10] Alice F. Jackson, Donald J. Bolger, “The neurophysiological bases of EEG and EEG measurement: A review for the rest of us” Psychophysiology, vol. 51, no. 11, pp. 1061-1071, 2014.
[11] Paul L. Nunez, Ramesh Srinivasan, “A theoretical basis for standing and traveling brain waves measured with human EEG with implications for an integrated consciousness”, Clinical Neurophysiology, vol. 117, no. 11, pp. 2424-2435, 2006,
[12] Michal Teplan, “Fundamentals of EEG measurement”, Measurement science review, vol. 2, no. 2, 2002.
[13] E. Niedermeyer, F. H. Lopes da Silva. “Electroencephalography: Basic principles, clinical applications and related fields”, Lippincott, vol. 3, 1993.
[14] Williams, R. L., Agnew, H. W., & Webb, W. B., “Sleep patterns in young adults: An EEG study”, Electroencephalography & Clinical Neurophysiology, vol. 17, no. 4, pp. 376-381, 1964.
[15] Stefan Schmidt, José Raúl Naranjo, Christina Brenneisen, Julian Gundlach, Claudia Schultz, Holger Kaube, Thilo Hinterberger, Daniel Jeanmonod, “Pain Ratings, Psychological Functioning and Quantitative EEG in a Controlled Study of Chronic Back Pain Patients”, PLoS ONE, vol. 7, no. 3, 2012
[16] Dezhong Yao, “A method to standardize a reference of scalp EEG recordings to a point at infinity”, Physiological Measurement, vol. 22, no. 4, 2001
[17] Shiliang Sun, Jin Zhou, “A review of adaptive feature extraction and classification methods for EEG-based brain-computer interfaces”, IEEE, 2014 International Joint Conference on Neural Networks (IJCNN), Beijing, China.
[18] Tao Zhang, Wanzhong Chen, Mingyang Li, “AR based quadratic feature extraction in the VMD domain for the automated seizure detection of EEG using random forest classifier”, Biomedical Signal Processing and Control, vol. 31, pp. 550-559, 2017.
[19] Maged S. AL-Quraishi, Irraivan Elamvazuthi, Siti Asmah Daud, S. Parasuraman and Alberto Borboni, “EEG-Based Control for Upper and Lower Limb Exoskeletons and Prostheses: A Systematic Review”, Sensors, vol. 18, no. 10, pp. 3342, 2018.
[20] Pierre Gloor, “Hans Berger on Electroencephalography”, American Journal of EEG Technology, vol. 9, no. 1, pp. 1-8, 2015.
[21] R J Harvey, M Skelton-Robinson, M N Rossor , “The prevalence and causes of dementia in people under the age of 65 years”, Journal of Neurology, Neurosurgery & Psychiatry, vol. 74, no. 1, pp. 1206-1209 , 2003.
[22] Valer Jurcak 1, Daisuke Tsuzuki, Ippeita Dan, “10/20, 10/10, and 10/5 systems revisited: their validity as relative head-surface-based positioning systems”, NeuroImage, vol. 34, no. 4, pp. 1600-1611, 2007 .
[23] Mousa K. Wali, Murugappan M, R. Badlishah Ahmad, “Classification of driver drowsiness level using wireless EEG”, Przeglad Elektrotechniczny, vol. 89, no. 6, pp. 113-117, 2013.
[24] Cornelia Kranczioch 1, Catharina Zich 2, Irina Schierholz 2, Annette Sterr, “Mobile EEG and its potential to promote the theory and application of imagery-based motor rehabilitation”, Int J Psychophysiol, vol. 91, no. 1, pp. 10-15,` 2014.
[25] Alan V. Oppenheim, Ronald W. Schafer, “Discrete-Time Signal Processing” Prentice-hall Signal Processing Series, 1989.
[26] Marcin KOŁODZIEJ, Andrzej MAJKOWSKI, Remigiusz J. RAK. “Linear discriminant analysis as a feature reduction technique of EEG signal for braincomputer interfaces”, International Journal of Psychophysiology, pp. 1-6, 2013.

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[27] Rejer I., "EEG feature selection for BCI based on motor imaginary task", Foundations of Computing and Decision Sciences, vol. 37, no. 4, pp. 285-294, 2012.
[28] JJ Vidal, "Toward direct brain-computer communication", Annual review of Biophysics and Bioengineering, 1973.
[29] J Wolpaw, EW Wolpaw, "Brain-computer interfaces: principles and practice", Oxford University Press, 2012.
[30] Reza Fazel-Rezai1, Brendan Z. Allison, Christoph Guger, Eric W. Sellers, Sonja C. Kleih, and Andrea Kübler, "P300 brain computer interface: current challenges and emerging trends", Frontiers in Neuroengineering, 2012.
[31] R Lindenberg, LL Zhu, T Rüber, "Predicting functional motor potential in chronic stroke patients using diffusion tensor imaging", Wiley Online Library , 2012.
[32] R Chavarriaga, A Sobolewski, JR Millán, "Errare machinale est: the use of error-related potentials in brain-machine interfaces", Frontiers in neuroscience, 2014.
[33] G Pfurtscheller, FHL Da Silva - Clinical neurophysiology, "Event-related EEG/MEG synchronization and desynchronization: basic principles", Clinical Neurophysiology, vol. 110, no. 11, pp. 1842-1857, 1999.
[34] F Lotte, L Bougrain, A Cichocki, M Clerc, M Congedo, A Rakotomamonjy and F Yger, "A review of classification algorithms for EEG-based brain–computer interfaces: a 10 year update", Journal of Neural Engineering, 2018.
[35] HF Rodríguez, MEG Graus, "The didactics of Geometry in function of the technological development of contemporary Pedagogy", 2016.
[36] MindWave Mobile 2 EEG headsets using EEG biosensor technology. Available at: https://store.neurosky.com/pages/mindwave.

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