Fundamental of Electroencephalogram (EEG) Review for Brain-Computer Interface (BCI) System

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Abstract - *Nowadays, medical monitoring systems have become more advanced as it becomes a hot topic to be researched on. One of the medical monitoring systems that we have seen much development is Brain Computer Interface (BCI) system which is based on Electroencephalogram (EEG). BCI system provides the communication channel without utilizing muscle or nerve. Hence, for the purpose of research in the future, an overall understanding about EEG and BCI system is needed. This paper is written to review the EEG based BCI system. It is divided into three main parts which are basic concept of EEG, wearable EEG devices and BCI system. The basic concepts of EEG are reviewed in term of basic brainwaves and EEG definition. The second part is reviewing the EEG devices that are used to extract EEG data and being commercialized. The last part is a review on the BCI system which made up mainly based on Signal Acquisition and Signal Processing. From this review paper, it will help for the understanding on each EEG based BCI system component for the purpose of BCI research.*

Key Words: Brain-Computer Interface, brain signals, EEG, classifier, pre-processing, BCI frameworks

1. INTRODUCTION

Nowadays, EEG technology has been developed for multiple areas of studies such as in medical, computer interfaces and even in robotic field. EEG is one of the electrobiological measurements that applies in modern medical imaging technique [1]. Basically, EEG is a method to extract the human brainwaves information and apply it in any field of studies. EEG is a measuring brainwaves technique where electrodes are positioned on user scalp. The signals are able to be detected as the result of synchronized neuronal action within the brain [2]. As mentioned before, EEG is also used in robotic field as it is still necessary to have and develop interfaces, as autonomous systems can cause awkward feeling to the user. The wearable EEG device has been developed and being applied for the research purpose. In term of robotic field, the most popular research is on EEG controlled mobile robot and applicable to a wheelchair that help people who lost their muscle control to be in charge of their motion as much as possible [2]. In this case, a brain-computer interfaces need to be achieved and it can be done by having an EEG technology. An EEG technology can be divided into two which are invasive and non-invasive. Recently, non-invasive technique is growing in term of research. It is because the invasive technique involving planted an electrode in the brain but non-invasive only measure from the head surface. Through the brainwaves, user can control or communicate with computer system. The integration of brain and the computer is called Brain-Computer Interface (BCI).

BCI in robotics field is a challenge as we need to create a system that has a direct communication and control between human brain and physical device. Based on Kachenoura et al. [3], BCI is a relatively new field of research that has been growing rapidly over the past 15 years. As in 2017, it should be 24 years of BCI research growing rapidly [4][5][6]. For BCI, we focus on the EEG as EEG specify for brain. According to Niedemeyer and da Silva [7] cited by Shamla et al. [8], to have an EEG biofeedback system is it comes from the fact that brain is a very special biological structure in human that its functioning and processes are not available for everyone to acknowledge. It is because researchers are encouraged by new understanding about how the brain functioning as nowadays the technology of powerful low-cost computer equipment help in BCI studies. Besides that, by growing recognition of the need of disable people, the BCI studies concentrate on new communication and control technology, especially for those with severe neuromuscular disorders, such as amyotrophic lateral sclerosis, brainstem stroke and spinal cord injury [6].

As for the purpose of brain controlled robot, the understanding of EEG concept is needed and from there the proper BCI system can be developed so that its implementation to the robot can be achieved. In this paper, the concept of EEG will be reviewed and summarized from previous research papers in term of brainwaves classification and the type of EEG method. Then, this paper provides an overview about the commercialized EEG devices used for research purpose in term of their effectiveness for BCI system. Last but not least, this paper is also providing a review for the BCI systems which will be discussed in term of brain activity analysis that include pre-processing, feature extraction and feature translation. The last part of this paper concludes the idea of EEG usage for the purpose of controlling robot.

2. Electroencephalogram (EEG)

There are a lot of research papers that discussed about the fundamental of EEG. First of all, the range of brainwaves signals need to be known based on the previous research result. Hence, it can be a reference for us to know the typical signals detected by the EEG on the head scalp. For medical purpose called electroencephalography, it is a medical imaging technique to read scalp electrical activity generated by brain structures. According to Niedermeyer [7], EEG is defined as electrical activity of an alternating type which is picked up by metal electrodes and conductive media for recording from the scalp surface. Based on Binnie et al. [9], typical signals detected on the scalp are in the range of 20-150μV over a 0.5-60 Hz bandwith. As the signals vary, both temporally and spatially, multiple channels are used with electrode positions based on the international 10-20 standard. International Federation in Electroencephalography and Clinical Neurophysiology, in 1958, has adopted standardization for electrode placement called 10-20 electrode placement system. Electrode positions are determined using internationally standardized 10-20 systems due to recording spontaneous EEG [10]. This 10-20 systems of EEG electrodes are positioned as shown in Figure 1.

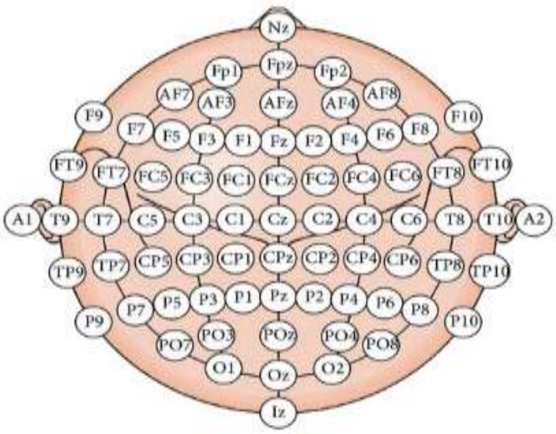

Fig -1: 10-20 electrode placement system [11]

According to a survey paper by Mantri [8], brain patterns form wave shapes that are commonly sinusoidal, measure from peak to peak and normally range from 0.5 to 100 μV in amplitude. The EEG signal has been classified into several bands which are Alpha, Beta, Delta, Theta and Gamma. Each of the signal being differentiated based on the frequency spectrum range. Malmivuo and Plonsey [12], Sornmo and Laguna [13], have classified EEG brainwaves. It is summarized as in the table shown in Table 1.

Table -1: Sample Table format

Differences of brainwaves from the EEG signal				
Alpha Waves	Frequency 8-13 Hz	Measured from occipital region	Awake person with closed eyes	Disappears with attention
Beta Waves	Frequency 13-30 Hz	Detect over the parietal and frontal lobes	Regard as normal and dominant for people who anxious and have their eyes open	
Delta Waves	Frequency 0.5-4 Hz	Detectable in infants and sleeping adults	Indicative of cerebral damage or brain diseases	
Theta Waves	Frequency 4-8 Hz	Detectable from children and sleeping adults	Occurs during drowsiness and in certain stages of sleep	Abnormal in awake adults but normal in children up to 13 years and in sleep
Gamma Waves	Frequency >30 Hz	Related to state of active information processing of the cortex		

The measured activity by the electrode on the scalp is coming from the summation of the activity of hundreds of neurons on the surrounding of the electrode. As the electrical is measured, the signal is called electroencephalogram or EEG [14]. These signals are seen as brainwaves and being categorized in different frequency as a group of neurons fire more synchronously in the measured signals. As it becomes stronger it become more synchronous to the firing frequency.

3. Wearable EEG for Brain Computer Interfaces

Lately, an increasing number of products and product concepts on the market focusing on EEG can be seen. The commercialized EEG products target on EEG acquisition in a more convenient way for non-invasive EEG method mainly using dry electrodes. Non-invasive EEG technology has a great potential until this technology being commercialized as mentioned before. EEG is the only one that uses sensors and mounting capabilities as it can be worn during locomotion. Theoretically, brainwaves cause an electrical changes that can be detected and uses for computer interfaces when responding to any stimulation. According to Casson et al. [10], a lot of EEG methods for computer interfaces purpose are still at research stage but the success of the signal processing is depends on the physical unit of the EEG itself. For wearable EEG development, two research topics that being overviewed are electrodes and power consumption. The commercialized EEG nowadays using dry electrodes which does not need for a specific preparation of the subject such as injection of conductive jelly [10]. Based on Popescu et al. [15] cited by Gargiulo et al. [16], the usage of conductive gel, as it loses it adhesion, will not increase the contact of impedance between electrodes and scalp that causing a large reduction in signal-to-noise ratio. Besides that, shorts also might occur as sweats smearing the conductive gel to the neighboring electrode. Depending on the application, the design of the EEG device may vary. Current EEG device which being use for medical purpose requires time for preparation and may lead to unpleasant experience. It is because the device involves gel-electrode application and a numbered of wired sensors that connects electrodes to computer or main acquisition unit. However, based on research done by Saab et al. [17] which comparing dry and wet electrodes, the classification accuracies for dry electrodes is 60.83% and classification accuracies for wet electrode is 63.88% . The value of dry electrode is comparable to wet electrode but the fact is wet electrode classification accuracy is higher than dry electrode classification accuracy. It is less comfortable to user but it brings the researcher to developing an EEG technology that convenient, wireless and wearable. According to Mihajlovic et al. [18], issues of current EEG device lead to a progress on developing a convenient to wear and wireless EEG device that can be utilized and encourage different brain related research areas. Several researches have led to commercialize EEG device which are: Neurosky's MindWave, Emotiv Epoc headset, g.tec gSahara, and Quasar DSI 10/20. If we look at the Neurosky's product, it has one-channel measurement platform with dry electrodes. The electrode platform for Neurosky positioned at the forehead which allows for frontal recordings. The dry electrode on the forehead is made of a stainless alloy. The data obtain from this product will be transmitted using Bluetooth. This product market is targeting the low-end consumer market as the price is the lowest of all commercialized EEG devices [19]. The Emotiv Epoc is among one of EEG device that is used widely. The Emotiv Epoc headset has 14 channels around the head and it is at the affordable cost. It is a versatile and flexible for research platform. Instead of Bluetooth, the data extracted is transmitted through a proprietary radio link. The system allows for 12-hour continuous transmission. To get access to the raw EEG data, more expensive license is needed to use Epoc as research purpose [20]. For Quasar DSI 10/20 headset, it comes with 21 channels. The data is transmitted wirelessly through the system which uses USB dongle. This device can continuously transmitted data for 24 hour. This device focusing on achieving the highest quality but the price for this device is high [21]. Next is g.tec's g.Nautilus platform. This is a recently developed EEG device that allow for measuring data based on the 10-20 electrode placement system. The data for this device is transmitted through radio link and this device can continuously operates for 8 hours without being charged [22]. To be precised, the commercialized EEG devices are summarized and compared as in Table 2.

Table -2: Commercialized EEG Devices

	Neurosky's Mindwave	Emotiv Epoc	Quasar DSI 10/20	g.tec's g.Nautilus
Bandwidth	3-100 Hz	0.2-45 Hz	0.02-120 Hz	0.1-40 Hz
Channel Number	1	14	12	32
Bit Number		16	16	24
Coupling		AC	AC	DC
Type of electrodes	Dry	Wet	Dry	Dry
Transmission Medium	Wireless (Bluetooth)	Wireless (Proprietary device)	Wireless (Proprietary device)	Wireless (Proprietary device)

4. Brain Computer Interface (BCI)

As mentioned before, Brain Computer Interface (BCI) is a new field of research that growing rapidly over past 15 years [3]. BCI is an important research that is related to brain science, neural engineering, sleep studies and rehabilitation. BCI is to give user the control and communication with the computer. This system idea come out with the hope to give opportunity to people with disabilities able to use technologies by having BCI. BCI involves the usage of EEG, which recorded from the scalp or within the brain for communication and control. EEG was introduced first by Hans Berger in 1929 [23]. As the EEG being introduced, it gives researchers a hope that it might be able to be used for control and communication without using nerves or muscle. Basically, BCI systems can be divided into signal acquisition, pre-processing, feature extraction and classification. The schematic diagram can be seen as in Figure 2.

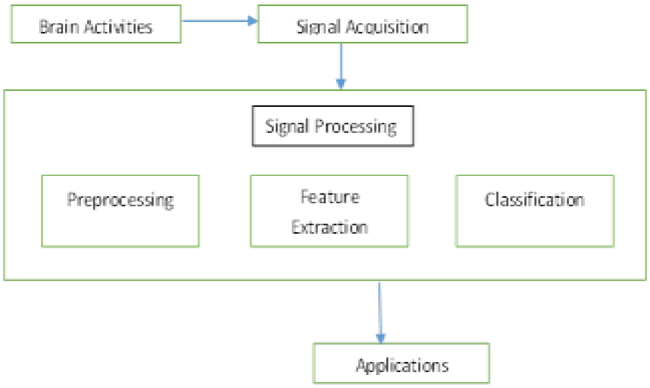

Fig -2: Basic BCI system

For the BCI system, there are several classifications that can be made. The classification made based on Transmission Medium, Target Users, Sensor Placement, Number of Channels, Training Time, Target Activity and Neurological Phenomena. The stated classification to characterize the systems is based on the comprehensive survey by Mason et al. [5]. Transmission Medium is the transmission method used for transmitting the EEG data to the system. The transmitting method can be wireless and wired transmission. The target user means the user that is expected to use the technology. Some studies even using animal as the target user. The target user also considering the patient or disable people who have no voluntary muscle control. Sensor placement is divided into invasive and non-invasive. Generally, invasive EEG signals have a lower signal-to-noise ratio which indicates more noise than the signal transmitted [24]. However, it is still preferable to be used by human. Number of channels characterize the system is number of electrode channels to be used for certain applications. For the BCI system, training may be required to fully control their brain activities. But, there are studies which indicate that training time might be less or eliminated as done by Cheng et al. [25]. For target activities, it indicates the activities that people wish to do by having this BCI technologies. Neurological phenomena refer to the brain activities which being produced and featured for BCI system. Review on several articles are being summarized according to the BCI classification, as shown in Table 3.

Table -3: BCI Systems Classification

Classification	Characteristics	Reviewed Research Paper
Transmission Medium	Wired	[26][27][28][29][30]
	Wireless	[25][31][32][33][34]
Target Users	Normal people	[25][35][36][32][37][34]
	Patient	[26][30][36]
	Animal	[27][28][31]
Number of Channels	1, 2, or 3 Channel	[25][26][27][29][30][35][39][36]
	More than 3 Channel	[31][32][33][38][34]

Training Time	Required	[26][28][30][35][33][38][34]
	Not Required	[25][27][29]
Target Activity	Controlling	
	Devices (TV, Mobile Phones, Computer)	[25][29][35][33]
	Virtual Reality Purpose	[34]
	Wheel Chair for Personal Mobility	[36]
Neurological Phenomena	Cell Firing Rate - Imagined Movement - Cognitive Task	[39][28]
	Frequency Rhythm brainwaves	[30][36][32][34]
	ERD or ERS	[26]
	P300 response	[40]
	SSVEP response to visual stimulus	[25][29]

Based on the research papers reviewed for BCI Classification, the system used by the researchers' mostly featuring wearable and wireless EEG system for physiological signal monitoring. Cited by Lin et al. [41], an online BCI that detected and classified Steady-state visual Evoked Potential (SSVEP) had been developed which using 2 active electrodes. It is based on wireless transmitter and the average transfer rate was 27.15 bits/min [25]. Besides that, WLAN was used by Obeid et al. [31] for transmitted data analysis system and data acquisition circuit to the host computer. A wireless multi-channel system for EEG measurement in operational settings was developed by Matthews et al. [32]. The system is more towards wireless EEG system instead of a complete BCI system. Furthermore, Cincotti et al. [33] has developed several softwares and hardware to control EEG based signal by using vibrotactile feedback and the system is wireless by utilizing Bluetooth.

Basically, the idea of BCI is involving signal acquisition, preprocessing, feature extraction and classification as mentioned before. However, we need to understand about the suitable Brain Signals that are used to develop BCI system. The brain signals used for BCI system development is P300, Steady-state Visual Evoked Potential (SSVEP), and Event-related desynchronyzation (ERD)/Event-related synchronization (ERS). P300 is a positive deflection that occurs randomly by a desired target stimulus from non-target stimuli. The stimuli can be touch, visual and auditory [42][43]. The P300-based BCI frameworks utilize the event that induce the P300 brain signals in EEG. Such frameworks mostly are being utilized as spelling devices, as various characters to be chosen and can improve the communication speed of the BCI [44]. Besides that, SSVEP occurs as an increase in EEG activity at the stimulus frequency which is evoked by a stimulus modulated at a fixed frequency [45][29]. The SSVEP is based on numbers of frequency components and often recorded by noninvasive EEG [46]. ERD/ERS is induced by having a mental task for example mental arithmetic and motor imagery [47]. One of the characteristic of ERD/ERS in term of it measurement is that it is within a predefined frequency relative to the power of the same EEG derivations [48]. Basically, P300 and SSVEP are BCI signals that depend on external stimulation while ERD/ERS is independent towards the external stimulation. The dependency towards external stimulation can be called as exogenous or synchronous BCI while the independency towards external stimulation can be called as endogenous or asynchronous BCI. As from the research papers reviewed, we can differentiate and compare between the brain signals which are P300, SSVEP and ERD/ERS. As asynchronous BCI signal does not required external stimulation, the user only need to focus their attention solely to BCI system purpose. However, synchronous BCI signals performance is vary between users and training is needed for this signal. Besides that, asynchronous BCI signal accuracy is lower than synchronous BCI signal. Furthermore, synchronous BCI signal is more stable and not require training or require minimal training. As from the reviewed research papers the comparison between three signals can be summarized as in Table 4.

Table -4: Comparison between Brain Signals

Comparison between Brain Signals			
Brain Signals	P300	SSVEP	ERD/ERS
Stimulation	Required	Required	Not Required
Accuracy	High	High	Low
Training Requirement	Not Required	Not Required	Need training
Reviewed Paper	[42][49]	[45][29][50]	[51]

As the suitable brain signal has been determined, in order to develop a BCI system, it is necessary to have an EEG signal acquisition as mentioned before. For signal processing, it involves preprocessing, feature extraction and classification. As for signal acquisition, it is related to Electrode-Tissue Interface (ETI) which is between dry electrodes and wet electrodes. In clinical applications, the EEG electrode used which is silver/silver-chloride (Ag/AgCl), is in contact with the head scalp through electrolyte gel. The electrolyte gel, is the bridges for the ionic current flow and the electron flow in the electrode. The electrolyte gel also increase the adhesion between the electrode and the scalp [52]. Nowadays, the commercialized EEG devices mostly used dry electrodes. Without the electrolyte gel as dry electrodes is being used, the transition of ionic currents from tissue to electrode electron become more complex. It requires more stabilization time and it is more towards noise and disturbances [53]. From the signal acquisition, the acquired signal need to be pre-processed as we need to eliminate the noise or other unnecessary artifacts such as electromyogram (EMG), electrooculogram (EOG) and electrocardiogram (ECG). Then, the signal extraction will take place and the classifier will translates those extracted features into desired output.

Preprocessing of the EEG signals involving referencing of the recorded signals, band-pass filtering the signals, resampling the signals, signal epoching or segmentation and selection of the clean EEG segments [18]. The simplest way for removing the artifacts during preprocessing is the band-pass filtering which is suitable to eliminate line noise and other frequency-specific noise such as body movement. Referencing method is required due to the difficulty to find the 'Neutral' EEG position and all electrodes are located over regions on the head to record the brain activity. For this scenario, potential difference need to be measured between two random electrodes hence referencing method is needed. For band-pass filtering, the filter characteristic will be different based on the frequency range and the signal analysis. For example, it can be as the use of high-pass filtering for event-related potential (ERP) studies or it also can be specific frequency band filtering used in spectral analysis which can be 8-13 Hz filtering for alpha waves activity. However, by filtering method, the useful data of EEG signals might be the same as artifacts so it might be removed from the EEG data [54]. The way for the data to be processed cannot be determined based on the frequency range of filters only. Hence, it is necessary to choose the filter implementation properly. The feature extraction is needed as BCI system significantly need to differentiate the classes for the feature that is extracted. According to the survey paper by Bashashati et al. [55], extracting EEG features and EEG feature interpretation involves algorithm that involving different techniques and tools and it is based on the Neuromechanism. Toolboxes that exist for feature extraction will be used for developing application implementations. The most use toolbox for feature extraction are EGGLAB [56] and OpenVibe [57]. The algorithms are based on spatio-temporal linear or nonlinear signal processing methods, the usage of averaging methods and supervised or non-supervised classification algorithms. Besides that, graph theory algorithm also being introduced for the purpose of brain network study [59]. Based on Luzheng et al. [2], EEG feature extraction for robotic purpose (mobile robot) can be divided into two main categories which are features in time domain and features in frequency domain. Features in time domain is amplitudes of event-evoked potentials, and features in frequency domain is frequency power spectra of EEG signals. Those features are estimated using Welch's periodogram algorithm which is for estimating signal at different frequencies, and this is an approach to spectral density estimation or other estimation algorithms [60]. Classifier will be used to translate the feature extracted into output command. The basic classifiers used for translating feature extracted are nearest neighbour, linear discriminant analysis (LDA), neural network (NN) and support vector machine (SVM). LDA and SVM can be categorized as linear classifier that use linear function to differentiate the classes. The classifiers called Nearest Neighbour involved assigning a feature vector to a class according to its nearest neigbours. Neural Networks (NN) is one of the most used classifiers for BCI research. It is for producing artificial neuron for producing a nonlinear decision boundaries. The purpose of LDA is to differentiate the classes of the data based on the hyperplanes. For data generated from each class, LDA algorithm will creates models of the probability density functions, then a new data point is classified by determining the probability density function whose value is larger than others. This classifier will assume that each of the class probability density functions can be modeled as a normal density, and that the normal density functions for all classes have the same covariance. The resulting LDA decision boundaries between classes is linear. According to Fukunaga, cited by Lotte Fabien et al. [61], LDA will use the hyperplanes to diffrentiate the data into different classes. The advantage of using this technique is that this technique is low computational requirement, easier to be used and basically able to come out with good results. The disadvantage of using LDA is it gives a poor result on complex nonlinear EEG data. It is according to Garcia et al. [62] that Fourier analysis for SVM gives a better result when the classes are assumed to be linearly separable because each feature component is considered independently in the LDA based classifier. One of the successful BCI research that apply LDA classifier is P300 classifier [63]. Just like LDA, SVM too uses hyperplane to identify classes but it maximizes the margins to increase the generalization capabilities by maximizing performance and minimizing the complexity. SVM also have no concern to the curse-of-dimensionality [64]. As SVM still produces linear decision functions, it is linear to feature space than input space. According to Cover's Theorem, the linear decision function is expected to perform well because of the high dimensionality of feature space [65]. According to Garret et al. [66], SVM is a very useful classifier as SVM has solid algorithm foundation and able to find optimal decision fumction for a set of training data. Nearest Neighbor classifiers is a classifier that its algorithm assign a feature vector to a class based on to its nearest neigbor. Two types of Nearest Neigbor classifier are K Nearest Neighbors and Mahalanobis distance. K Nearest Neighbors for BCI system is usually obtained by using metric distance. It can estimates any function which produce nonlinear decision boundaries, for example the reseach done by Blankertz [67]. K Nearest Neighbor is known for their high sensitivity to the curse-of-dimensionality [68]. Mahalanobis distance is an algorithm by assuming a Gaussian distributing for each class prototype. Mahalanobis distance is suitable for multilclass or asynchronous BCI systems [69]. NN is often used to develop nonlinear classification boundaries. It is the BCI classifier that often used in most BCI researches. It is because, based on Garret [66], NN is robust for choosing parameter values and its similarity to other nonlinear regression methods. For NN classifier, Multilayer Perceptron (MLP) is the most widely used NN for BCI system. MLP is based on multiple layers of neurons which are input layer, possible several hidden layer and an output layer. MLP can estimate any continous function when MLP is composed with enough layer. It is very flexible to adopt variety of problems because it can classify any number of classes. Instead of its flexibility, based on Balakrishnan and Puthusserypady [70] this classifier is sensitive with noise and non-stationary data as EEG. However, MLP mostly used NN classifier for BCI system such as synchronous, asynchronous, multiclass or binary BCI system. If the BCI is being implemented for the robotics purpose, the mostly used classifier is LDA, SVM and NN. Main advantages of LDA is that it is less computational complexity hence it is easier to be applied. This advantage lead to the numerous developments of brain-controlled robot by using LDA as classifier. NN has the advantage to minimize error in classifying training data but need a lot of configurations and parameter set up. Meanwhile, SVM does need many configurations and parameter set up and it is good for small training data gained and as mentioned before, it maximizes generalization capabilities. The problem of the brain signals is that it is not constant over time. Hence the robustness of all BCI system is not statisfying. To improve the robustness, Millan et al. [71] proposed a research direction which is the online adaptation of classifier during its utilization of brain signals. Summarization of reviewed classifier based on multiple research papers is summarized in Table 5.

Table -5: Classifier Used in BCI

Classifier Used in BCI			
Classifier	Description	Characteristics	Reviewed Paper
Linear Discriminant Analysis (LDA)	Use hyperplanes to separate the data representing the different classes	- Low computational requirement - Easier to be used - Give a poor result on complex nonlinear EEG data	[62] [63] [72]
Support Vector Machines (SVM)	Finds a decision hyperplanes by maximizing the margin between the different classes.	- Good generalization - No concern to the curse-of-dimensionality	[64] [65] [73]
Neural Network (NN)	Developing nonlinear decision boundary	- Nonlinear classifier - Sensitive with noise and non-stationary data - Need many parameters	[66] [74]
Nearest Neighbour	Algorithm assigning a feature vector to a class based on to its nearest neigbor	- Estimate function that produce nonlinear decision boundaries - Sensitive to the curse-of-dimensionality	[67][69]

Based on the reviewed research papers, we can obtain information which will help as a guide to determine the two important aspects for good BCI system which are the brain signal to utilize and the data classifier. The framework of Figure 3 shows basic BCI system that can be developed based on our reviewed information.

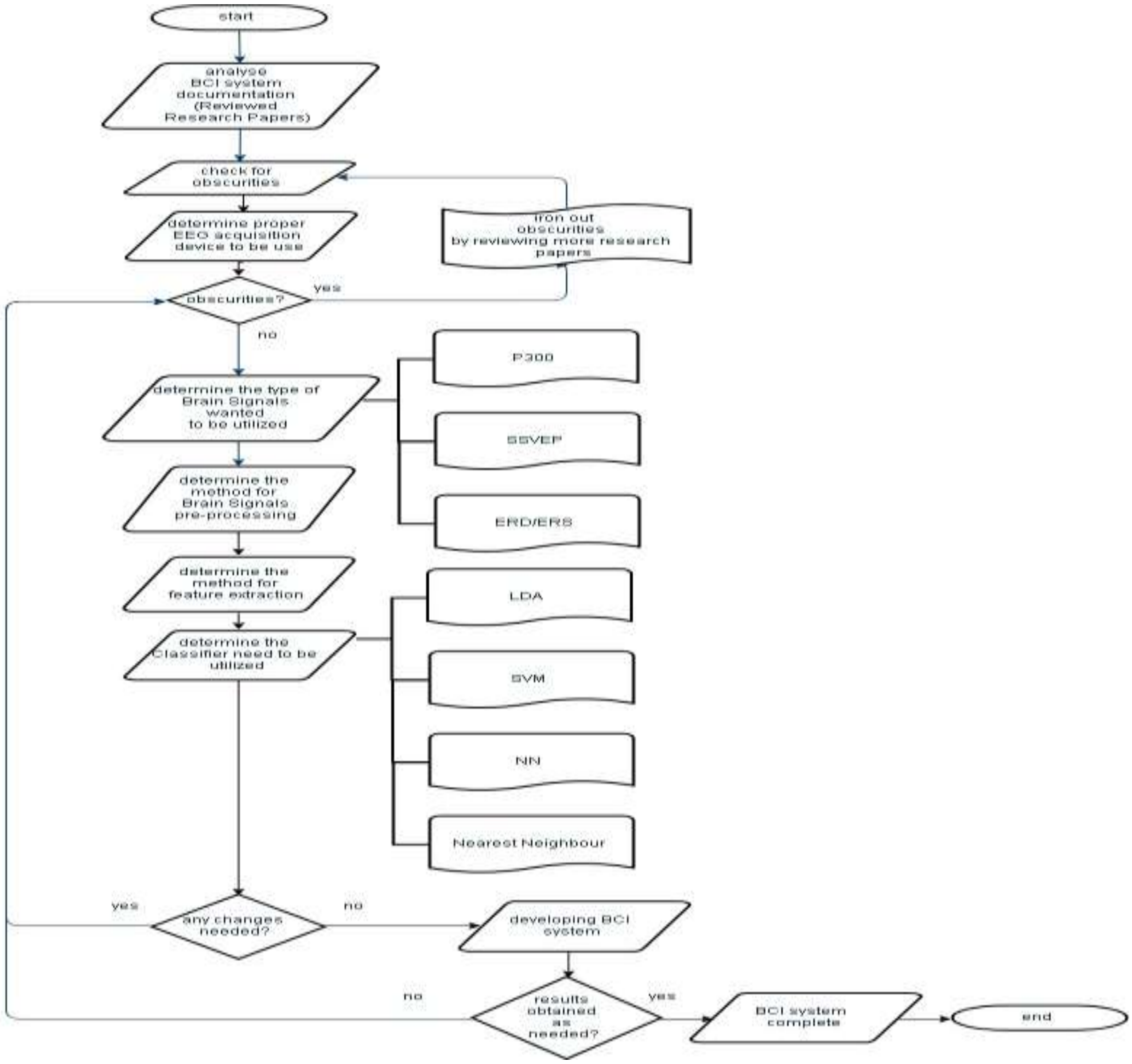

Fig -3: Framework for developing basic BCI system

5. CONCLUSION

This paper has reviewed about the EEG technology in term of its concept, its design for commercialization and its application for BCI system. Nowadays, EEG mostly used for BCI system and BCI system also used by researchers for the purpose of controlling robot. BCI is a communication and control channel that does not based on brain's normal output. Besides that, there are several brainwaves that can be differentiated based on frequency which are Alpha, Beta, Delta, Gamma and Theta. As research on EEG grows, commercialized EEG device has been developed. Wearable EEG devices face a lot of difficulties in research as it need to be user friendly and able to implement for BCI purpose. EEG is mostly used for BCI system and basically the BCI system involved Signal Acquisition, Signal Processing (Preprocessing, Feature Extraction and Classification) and Application. Signal Acquisition involve understanding of signals which are P300, ERD/ERS and SSVEP. Before analysis of EEG, the data undergo preprocessing. Then, the data will undergo Feature Extraction to differentiate the feature based on class and it will be transformed into output command during Classification. EEG devices nowadays can be improved and extended beyond its current practice use. In future, it is expected that with EEG devices technologies, BCI system will gives further understanding for the complexity of the brain activity.

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