



Brain Computer Interface (BCI) Machine Learning Process: A Review

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ABSTRACT

The abstraction of Brain Computer Interface (BCI) is a communication and control system that translated human mind thoughts into real-world interaction without any use of neural pathways and muscles. BCI is used as a tool to help person that suffered from impairment to be able do their daily activities independently. In general, BCI process its signal through several process such as pre-processing, and classification. However, providing information of pre-processing and classification process is barely found. Therefore, in this review paper we present the various pre-processing and classification methods that used in the BCI system application.

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1. INTRODUCTION

The Musculoskeletal system is a system in the body that responsible for to movement such as walking, jogging, and running which required the brain to have complex coordination. However, the ability to do those activities can be lose among people who is suffering from severe injury or trauma. Not only, the survivors also lose their ability in speech [27]. Spinal cord injury survivors is one of the example of people who lose their ability to control some body parts (i.e upper, and lower). Over the years, the researchers had been trying to help the survivors to invent artificial communication channel to restore the function of paralyzed body parts based on the human brain [27].

Brain Computer Interface (BCI) is a communication and control system that translated human mind thoughts into real-world interaction without any use of neural pathways and muscles [51]. BCI has become the innovation among researchers that help impaired person by become the bridge between the brain and the

machine to do their daily activity [50]. These days, the development of BCI techniques is growing rapidly, where it helps people to their daily activities become easier through communication or operating assistive device [52]. BCI system is a communication system that translates the signals produced by brain activity into control signals without the involvement of peripheral nerves and muscles in the form of hardware and software muscles [48][49].

The first research on BCI was held using non-human subjects such as monkeys and rats in the late 1970s, which led them with the finding that cortical neurons can be used to control their neural actions [50][52]. Nevertheless, the research remain slow in the BCI area due to the limited computer capabilities and knowledge about the physiology of the brain [52]. These days the research of BCI area is keep developing due to the technology that growing rapidly [50]. The research is also develop the scope of BCI research to Artificial intelligence (AI) [50]. The technology helped researchers to record the activity of the human brain, emotion recognition, human limb/hand movement detection, and many more [50].

BCI begins the application by recording the human brain signals by using several tools, then the task is execute by transmitting the signals to the machine [50]. There are five main components to process the signals of the brain into the assistive device which are signal acquisition, pre-processing, feature extraction, classification, and the application interface [47]. This paper is going to discuss about the process of the signals that mostly used by researchers.

The popularity of the BCI system among researchers has made their target into three classes [46]. The first target is the patients that suffering from losing their motor function named as Complete Locked-In State (CLIS) patients. CLIS patients are a person that suffer from severe cerebral palsy or are at the terminal stage of Amyotrophic lateral sclerosis (ALS). The second target is the patients who almost completely paralyzed which named as Locked-In State (LIS). People with LIS however are still able to do voluntary movement such as eye movement, eye blinks, or twitches. As the technology keep increasing the target of the application of BCI system is also develop, not only for impaired people but also among healthy people which become the last target. The healthy people in this area of target mean is a person with substantial neuromuscular control, particularly speech and/or hand control. There are several area of BCI system application that are being develop such as gaming, entertainment, neuromarketing, and experimental learning [46][50]. In addition, BCI system is also targeting a person that suffered from neurological diseases such as schizophrenia and depression [46].

BCI system may process its data through several important step the first step is signal acquisition. Signal Acquisition is signals collecting process from numerous sensors modalities. The brain area that widely collected for BCI system purpose are primary motor cortex and prefrontal cortex. Prefrontal cortex is the part of the brain that recorded mental arithmetic, mental imagery, mental counting, music imagery, and landscape imagery. Meanwhile the rest part of the brain recorded motor execution, and motor imagery. To collect the signals from human brain, one of two tools such as invasive and non-invasive is used. Invasive tool is a tool that used to record the signals by implanted the electrodes in the skull through the surgical process. In another hand, non-invasive tool record the signals without surgical process and this tool is widely used by researchers to collect the brain signals. There are several non-invasive tools which mostly used in BCI system application such as functional magnetic resonance imaging (fMRI), magnetoencephalography (MEG), electroencephalogram (EEG), and functional near-infrared spectroscopy (fNIRS).

Among those tools, EEG and fNIRS are the most widely used as the tools for BCI system application [43]. EEG has become the most advantageous tool because of its portability, easy to use with a high temporal resolution, and inexpensive [48]. However, this tool has a poor spatial resolution and inherent sensitivity to motion artifacts [26]. fNIRS in another hand has come as a tool that able to overcome the limitation that EEG. This tool is able to provide a good balance between spatial and temporal resolution [48]. Not only, fNIRS shown to be more effective in capturing brain hemodynamics rather than EEG [44]. Besides balancing the EEG limitation, the application of this tool is suitable due to its insensitivity to noise, low cost, and portability [48]. In addition, combining EEG and fNIRS resulting in higher BCI performances that has been proven by [44].

fNIRS is a powerful tool among others neuroimaging tools because of its ability to carry information of haemodynamics activities [43]. This tool recorded the signals by determining the changes in the concentration of haemodynamic response from the oxygenated hemoglobin (HbO) and deoxygenated hemoglobin (HbR). The measurement of concentration changes is based on the theory of neurovascular coupling and optical spectroscopy [45]. According to the theory, the oxygen consumption is increasing as the

activities of neural network increased in order to fulfill the needs for neural tissue. In conclusion, when oxygen is consumed HbR is increasing and causes HbO decreasing and vice versa [45].

fNIRS works by using pairs of near-infrared light emission of a detectors within amplitude range 650-690 nm at two or more wavelengths. Multiple photon caused by near-infrared scattering by radiating the red light to the scalp and diffusing through the brain tissue. Photon that had been absorb and scatter are detected by optical fiber that returned to the surface. The different absorption spectra in the haemoglobin lead the researchers to use modified Beer-Lambert Law (MBLL) [40]. MBLL converts the optical density changes into concentration changes of HbO and HbR. MBLL is already applied to numerous studies of NIRS such as classification of mental workload on the human brain [25], monitoring of blood in the deep tissues [42].

The second step is pre-processing, this step is used to removed unwanted signals from noises. Noises are the disturbances that carried by the raw or unprocessed of data signals. Noises that carried in the raw data of brain signals may includes from motion artifacts (i.e movement of face, head, and upper body), coupling variations from time to time due to the optode distances changes (i.e sources and detectors) on the scalp, and blood flow changes that are irrelevant to neural network [40]. Movement becomes noise in signals because it causes displacement of the optode on the scalp that may create a sharp high-frequency displacement, slow wave drifts, or baseline shift in the signal. Pre-processing is required in BCI system application because the noises may affected the processed signals.

Feature extraction is the third step of processing signals of BCI system. Feature extraction played a crucial role in the identification of the discriminatory information carried by the biosignals [38] [39]. Feature extraction selection is also crucial in clinical applications, because it may cause dropped in the accuracy result of the signals if the feature extraction used is inappropriate. Following by classification process as fourth step where it is used as recognition of the user's intention that based on feature vector of the brain characterization activity set by the feature map [46]. Classification step played a crucial role in discriminating various tasks that based on the brain signals that has been extracted. Last step is classified signals produced the translated signals into instructions for a device such as a computer or assistive appliance.

2. METHOD (10 PT)

In this paper, the writer will be discussing the data that used by researchers in the BCI research. Pre-processing is one of the important process in the BCI data processing. This process is used as noise removing by researchers. This paper will also discuss different pre-processing method mostly used by different researchers. Classification is one of the process in the BCI system to classified the signals that has been through several process. Various types of classification based on machine learning approach will be discuss for BCI research also discussed here. The information of those will be collected from 31 papers from different sources. The papers that collected are the papers that have matched with the writer's topic. The papers were collected from 2012 to 2023.

3. RESULTS AND DISCUSSIONS (10 PT)

Data that used by researchers are from human brain signal that collected through EEG and fNIRS. EEG and fNIRS are used as a tool to record the human brain because of their low-cost and others abilities. There are different numbers of participants that participate in different studies of BCI system application. The amount of participation can be from 9 to 30 participants from different studies. Most of the participants are young healthy adult that are willing to join the studies as participant. Different signals are collected from different part of the brain from different channels in the EEG. From the papers that has been collected, there are numbers of channels that selected which from 14 channels to 36 channels. Most of the signals that are taken for the studies in BCI are Motor Imagery (MI) and Motor Arithmetic (MA). During the recording of the brain signals, participants were asked to do several tasks. For example a study by Shin et al in 2017 were asked the participants to imagine a hand gripping as for their MI data. In another hand, for MA data Shin et al were asked the participant to solve a simple calculation.

Raw data from the recording process is need to be processed in order to get the signal that wanted by the researchers. The first process that is going to do is signal pre-processing. This process is used to remove the unwanted signals that caught in the recording process. Filtering is the most popular pre-processing method in the BCI system. And in this process, bandpass filter is the widely used filter than others with numbers of 19 papers over 31 papers. On the other hand, different classification have been used in many BCI systems. Classification used to solve classification problem such as accuracy prediction in BCI studies. There are many classification types that used by researchers. However, in this paper the classification methods are narrowed into the most used classification methods based on machine learning approach to process BCI data.

3.1 Pre-processing

Movement or displacement of optodes on the scalp during signal acquisition may caused irrelevant results. To prevent the signals from irrelevant result, pre-processing has become an effective procedure to remove the unwanted signals [37]. Filtering is one of the pre-processing method that popular among BCI system application, this happened because filtering is able to being quick and easy to process [37]. To apply this approaching process, the researcher need to choose suitable type of filter for their study. Next step is to select the filter order, in this process by choosing higher number of filter order my given greater slope at the cut-off frequency. In addition, at last is choosing the suitable cutoff frequencies for the signals. There are numerous types of filtering that used to remove the unwanted signals such as low-pass and high pass filter, bandpass filter, smoothing filter, etc.

3.1.1 Low-pass and High-pass filter

Low-pass filter is a filter that used to remove high-frequency signal. High-frequency noise my affect by such as extraneous light and physiological noises. In another hand, high-pass filter is a filtering step that used to remove low-frequency signal. Several example of low-frequency noise that may faced by researchers are baseline drift from the displacement of optodes on the scalp. In 2015, low-pass filter was used by Henrich et al [24] to his study in BCI system application. And following in 2022, another study that held by Hamid et al [27] also used both of low-pass and high-pass filter to their study. The range of cut-off frequency in studies in low-pass filter is 0.5 to 1 Hz. In another hand, high-pass filter is 1Hz.

3.1.2 Bandpass Filter

Among others filtering, bandpass filter is the most popular filtering tool that used by lots of studies. Bandpass filter is a combination of low-pass and high-pas filter, this filter passing through certain numbers of band and attenuate frequencies outside the band. Bandpass filter has several subtypes such as Butterworth, Chebyshev type I and II, and the Elliptic filters [36] [47]. Chebyshev is a filter which separate one band of frequencies from another. There are several studies that used this approaching filter to remove the unwanted signal. In 2017, Shin et al [35] applied these filter to their BCI data and following in 2020 Li et al [23], and Sattar et al [38] in 2022 also used the filter to process their EEG signals.

Butterworth bandpass filter is a filter that widely used by papers that has been collected by the writer. Butterworth filter is designed to be maximally flat magnitude response filters, the distortion was experienced through both the passband and stopband in that range of frequency [36]. Most of the studies applied 3rd-order, 4th-order, and 6th-order Butterworth filter with the range of cut-off frequency 0.01 to 0.2 Hz.

3.1.3 Smooth Filter

Smooth filter is a filter that also used in the pre-processing technique that has same principle as low-pass. Nevertheless, smooth filter has different method from low-pass filter to remove the noise. Smooth filter has numerous subtypes such as moving average, Gaussian smoothing, and Savitzkky-Golay. Moving average filter is a filter that reduce high-frequency noise through averaging a number of data points together [23]. Gaussian filter is a filter that applied Gaussian weighting function which multiple the values at each point that depends on the data distribution. Last, Savitzky-Golay filter is a filter that estimate the values of fNIRS waveform in the specific time window using a polynomial fitting function [21]. Time domain and spatial domain are two types of the smooth signals that used in this filter to process the data. Time domain smoothing reduces the noise in the data, meanwhile, spatial domain smoothing reduces noise from poor channels which surrounding fNIRS channels.

According to the papers that has been collected, there are not much information and researchers that used smooth filter to remove unwanted signal from their signals. In 2013 and 2019, Nguyen et al and Lopez et al used Savitzky-Golay filter which invented in 1964 to smoothed their data. In another hand, Gaussian smooth filter also applied by Tanveer et al in 2019 [18].

3.1.4 Wavelet Transform

Motion artifacts is one of the noise type that mostly removed by researchers using Wavelet Transform. Wavelet filter begins the process by scaled and translated mother wavelet into daughter wavelets which used later to decomposed the recorded signals. Wavelet coefficient is used to describe the effectiveness of the wavelet transform which represent in the signals. Wavelet transform performing better by using greater number of wavelet coefficients. This filter has two subtypes, which are Discrete Wavelet Transform (DWT), Continuous Wavelet Transform (CWT), and the Minimum Description Length wavelet

(wavelet-MDL). The studies that applied this filter are from Trakoolwilaiwan et al in 2017 [2] and Jahani et al in 2020 [28].

3.2 Classification

Classification is the fourth step of data processing in BCI system application. Not only feature extraction, but also classification is playing a crucial role in the BCI [28]. The main function of classification discriminating various signals based on user's intention based on the data that has been extracted from brain signals. There are several classification based on machine learning branch that used in BCI system that explained in this paper.

3.2.1 Support Vector Machine (SVM)

Support Vector Machine (SVM) is a supervised machine learning branch that widely used to solving classification and regression problem. The application of SVM is popular among medical field. Not only, SVM also popular in BCI system application as classification to the data. In BCI system, SVM is a classification method that successful in processing of synchronous BCI system in large numbers of data. This machine learning branch also has low misclassification error and scale well to high-dimensional data, and has reasonable interpretability [34]. Several study applied this classification such as Jahani et al in 2020 [28], Qureshi et al in 2017 [11], and Gao et al in 2023 [13]. SVM is used as application to diagnosis and prognosis of disease due to its ability efficiency by using smaller samples and implementation of a data-driven algorithm [10]. Not only but SVM is also applied in classification in neuromarketing that have done in Ramirez et al in 2021. SVM used hyperplanes to proceed the data by maximize the margins of the distance between the nearest training samples, and hyperplane [46]. SVM construct the hyperplane to separate the observation of different classes. Even though SVM is a good classifier however, this technique is quite time-consuming and the standard of kernel functions does not guarantee the optimal function.

3.2.2 Random Forest

Random Forest is a classification method that used a combination of multiple decision trees to defined a single result. This tool proceed the data by using random vectors to select random subsets of features in feature space, and trains decision tree classifiers. The process to proceed the data will be repeated by using many random feature sets to produce many decision trees [45]. Decision rules is created by a decision tree which based on the continuous and/or categorical input variables in order to predict the outcome [34]. A graph that form like a tree named Classification and regression trees (CART) is used to represent the result, which classification trees predict categorical outcomes, and regression trees predict continuous outcomes. Not many studies has found by writer process their data in classification using Random Forest in BCI system application. However, the writer found few studies that applied this tool as their classification method such as Bizzego et al in 2022 [8]. Less popularity of Random Forest may caused by their unstable changes in the data, highly sensitive to small perturbations in data, and may lose information by dichotomizing or categorizing variables [34].

3.2.3 Linear Discriminant Analysis (LDA)

Linear Discriminant Analysis (LDA) is a machine learning branch that has same function as PCA, reduced the data output data dimensionally. However, LDA is quite different with PCA, where LDA focused on maximize separability among the groups by finding feature supspace. Meanwhile, PCA represent the maximum data set of maximum variation direction. LDA is a common tool that used in the BCI system application due to its quick response [46], simplicity, and effectiveness [45]. LDA in BCI system application may use by reseachers as feature extraction [7] or classification [35]. LDA maintaining the original data by reduce the data into a smaller subspace dimensionally with excellent class separability [6]. LDA has proven to be success in accuracy in numbers of BCI system application such as synchronous, classification of EEG and fNIRS for gait Disorder [5] [4], and more. LDA classified its pattern into two classes and assume those classes are separate linearly. Then linear discrimination function is assigned to differentiate the classes as in the feature space as hyperplane. Even though this technique is quite popular, however LDA has limited computational resources as their limitation [46].

3.2.4 Artificial Neural Network (ANN)

Artificial Neural Network (ANN) is a popular machine learning branch nowadays. ANN is machine learning that used by many fields for example computer science, physics, neuroscience, and more. The purposed of ANN is being able to solve numerous problem fast by mimicking the brain activity which cannot be solve by conventional computer. The architecture of ANN is inspired from the signal behavior of neurons in neural networks. It contains of neurons that connected to each other's through complex signal pathways. The data that has been collected is going through a training process in order perform a task. The training of the data is keep looping until it reaches a steady state, with no significant improvements. The trained data is

used to recognize the output which related to the training data patterns. ANN composed of three layers which are input layer, hidden layer, and output layer. This tool is widely used as classification among numerous BCI system application such as Trakoolwilaiwan et al in 2017 [2], Jahani et al in 2020 [28]. Even though ANN is able to variable interactions and nonlinear associations, however this tool is complex, lacks transparency, and requires large data sets.

3.2.5 Convolutional Neural Network (CNN)

Convolutional Neural Network (CNN) is one of the machine learning branch that has human-level performance in image classification [30]. CNN gaining popularity nowadays because this tool is able to give a higher result of classification accuracy without compromising on the number of commands [28]. Not only, CNN able to do automatically feature extraction on the raw signals. This machine learning branch is popular in BCI system application to solve feature extraction and classification problem that using EEG, EMG, and fNIRS signals [28]. CNN consists of three layers to process their data, which is convolutional layer, pooling later, and output later. This method proven successful in solving classification problems of both EEG and fNIRS in BCI applications [3]. However, there are not many studies that do classification for fNIRS signals using CNN [28].

4. CONCLUSION (10 PT)

In conclusion, to process BCI data there five steps that used which is signal acquisition, pre-processing, feature extraction, classification, and application interface. According to the papers that has been collected in the pre-processing step, many study do filtering to their data to remove the unwanted signals one of the famous filtering that have been applied lately is bandpass filter. Lastly in classification numbers of machine learning approach have been applied to solve classification problem which are SVM, LDA, random forest, ANN, and CNN. The information in this review paper may help researchers in current and future to process their data in BCI system

CREDIT AUTHORSHIP CONTRIBUTION STATEMENT

Author1: Conceptualization, Methodology, Software, Project administration. **Author2:** Software, Writing – original draft. **Author3:** Writing – review & editing. **Author4:** Validation.

DECLARATION OF COMPETING INTERESTS

There is no competing financial interests or personal relationships

DATA AVAILABILITY

Data will be made available on request.

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