A Review on Machine Learning Based on EEG and ECoG Signal for Brain Computer Interface

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Abstract. Brain-computer interfaces (BCIs) are devices utilized for the detection and recognition of brain activity. With advancements in machine learning techniques, BCI projects have witnessed an increasing application of these techniques, leading to higher performance. BCI also finds utility in medical applications by providing efficient solutions for individuals with neurological disorders or disabilities. The research focus on convenient and non-invasive electroencephalography (EEG) and high signal-to-noise ratio electrocorticography (ECoG) stems from their respective advantages. This paper presents a comprehensive overview of BCI principles, imaging techniques such as EEG and ECoG along with their advantages and disadvantages, as well as discusses the utilization of various machine learning techniques in EEG and ECoG-based BCI system, including classification and regression models. Furthermore, this paper summarizes the challenges faced by EEG and ECoG-based BCI techniques while also discussing future directions such as artifacting removal technique for EEG-based BCIs and closed-loop feedback technique based on ECoG–BCI.

Keywords: Brain-computer interfaces, machine learning, electroencephalography, electrocorticography.

1. Introduction

The brain helps the body process a wide range of signals, determines how the body feels, and allows the body to move. Some diseases or injuries can prevent the brain from sending signals to the body, such as amyotrophic lateral sclerosis. Brain-computer interfaces (BCI) can help these people establish connections between the brain and the outside world, such as prosthetics. This type of medical treatment has brought brain-computer interfaces a great deal of attention and has led to more research into them. BCI is a system that records the brain activity of a test subject and converts the electrical signals into commands that can be accepted by an external device, thus allowing the test subject to interact with the outside world without relying on muscle nerves, a method that is widely used in healthcare and is designed to help patients with neurological disorders or missing body parts to communicate and interact with the outside world. There are various ways of extracting brain signals, ranging from the more convenient electroencephalography (EEG) to the more precise electrocorticography (ECoG), and analyzing what these signals represent requires the use of machine learning techniques. This article describes the components of BCI, the introduction of EEG and ECoG, and the related machine learning techniques, in addition to analyzing the challenges associated with different BCI and the direction of development.

2. Overview of BCI

A brain-computer interface refers to a means of establishing a link with the central nervous system, enabling the conversion of neural activity into artificially recognizable signals. This facilitates interaction with the external environment.

As depicted in Figure 1, the BCI system comprises of 5 components: brain signal acquisition, signal preprocessing, feature extraction, feature classification, and output devices. The module for acquiring signals from the brain is responsible for recording, amplifying, and digitizing the user's brain signals. Signal preprocessing aims to improve the ratio of useful signal to noise in the recorded brain signals. Feature extraction involves extracting representative features from the brain signals that reflect intention. Feature classification is employed to identify EEG features extracted by the feature extraction module. Output devices are utilized to trigger actions in the real world without relying on peripheral nerves and muscles. By utilizing these modules, BCI systems can interpret a user's brain signal and convert it into computer commands for controlling external devices or neural rehabilitation systems.
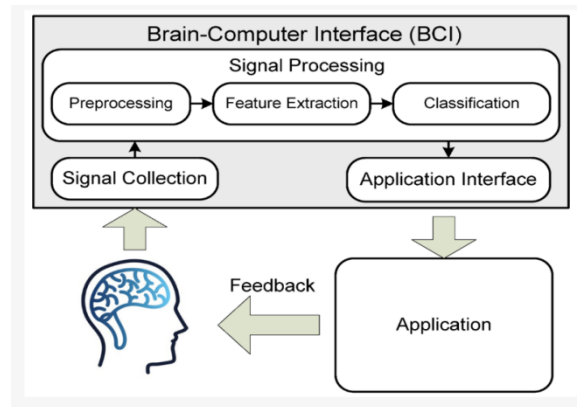

Figure 1. BCI flowchart.

Brain-computer interfaces can be classified into two categories based on the methods used: invasive and non-invasive approaches. Invasive techniques involve the placement of electrodes either inside or on top of the brain, while non-invasive techniques utilize electrodes placed directly on the scalp. Various imaging techniques such as EEG, magnetoencephalography, functional magnetic resonance imaging, positron emission tomography, near-infrared spectroscopy, and ECoG can be employed depending on the specific requirements. This section primarily focuses on providing an overview of EEG and ECoG, which represent examples of non-invasive and invasive techniques respectively.

EEG captures electrical signals from inside the subject's brain by means of electrodes mounted in a capsule. EEG records changes in scalp potentials caused by brain activity. Due to its non-invasive nature, EEG is relatively easy to implement, easy to carry, and very inexpensive, which gives it an advantage in terms of the market [1]. The drawbacks of EEG include its high sensitivity to signal variations, susceptibility to external interference, and limited signal-to-noise ratio and spatial resolution. These limitations arise due to the attenuation of signals during propagation [2]. On the other hand, ECoG is an invasive technique that involves implanting electrodes directly onto the brain's surface. This allows for precise monitoring of electrical signals with exceptional spatial resolution and stability. But accordingly, as an invasive technique, ECoG inevitably carries the risk of infection, and the safety factor is reduced [3].

3. BCI machine learning method

Distinguished by purpose, machine learning can be categorized into regression models and classification models. This part of the article will briefly introduce some machine learning models, their advantages and disadvantages, and their applications in BCI.

3.1. Regression model

Regression is the prediction of continuous variables with quantitative outputs [4]. Currently, the basic regression models include linear regression, polynomial regression, logistic regression, stepwise regression, ridge regression, lasso regression and ElasticNet regression. The principles of some commonly used regression models are described below. Table 1 shows the advantages, disadvantages, and applications of regression models.

Table 1. Comparison of different machine learning models.

Model	Advantages	Disadvantages	Application
Linear Regression	Fast; Tractable; Simple implementation; Simplest model architecture	Low model complexity in performance; Unstable with few samples; Highly dependent on input for performance	predicting individual finger movements from ECoG signals [5]; Training the tremor estimation model [6]
Ridge Regression	Handling multicollinearity; Stable estimates; Preventing overfitting;	Not for feature selection; All features considered; Parameters to be adjusted	Examining Brain Responses to Naturalistic Stimuli [7]
Lasso Regression	Feature selection available; Zeroing coefficients of unimportant features; Multicollinearity problem solved	For high dimensional data, fewer features selected; Regularisation parameters need adjusting	Reconstructing the audio magnitude spectrogram from neural activity [8]
ElasticNet Regression	Combining both regressions' advantages; Coping with multicollinearity&feature selection;	Two regularisation parameters need adjusting	Performing feature selection and classification of EEG signals [9]

Linear regression is a widely used technique in statistics and machine learning for representing linear associations between variables. It is based on the assumption that there exists a linear relationship between the dependent variable (or response variable) and the independent variables. The essence of linear regression lies in capturing the connection between one or more independent input variables (also known as characteristic variables) and the output dependent variable. The linearity of this model stems from expressing the output as a linear combination of the input variables. Moreover, it can be employed to model multivariate linear regression in the following manner:

$$Y = a_1 \times X_1 + a_2 \times X_2 + a_3 \times X_3 + \cdots + a_n \times X_n + b \qquad (1)$$

where a_n is coefficient, X_n is a variable, and b is a bias.

Ridge regression analysis is a statistical technique utilized to handle multicollinearity, which occurs when independent variables are highly correlated. In the presence of multicollinearity, ordinary least squares (OLS) method treats each variable fairly but leads to diverse results that deviate from the true values. Ridge regression introduces a certain level of bias into the regression estimates in order to reduce the standard error. When it comes to regression problems, ridge regression models are essentially similar to linear regression models with slight differences in how the loss function is constructed:

$$J(\theta) = \min\|Xw - y\|^2 + z\|w\|^2 \qquad (2)$$

where X denotes the feature variable, w denotes the weight, and y denotes the true situation. Ridge regression serves as a solution to address the issue of collinearity among predictor variables in a regression model. The presence of collinearity implies that one independent variable can be linearly predicted by other variables in the multiple regression model. To tackle this problem, ridge regression

incorporates a regularization term, which is represented by a small squared deviation factor, into the variable. This inclusion of squared bias factor introduces a slight amount of bias into the model while significantly reducing its variance.

Lasso regression and ridge regression are similar in nature as they both aim to mitigate the impact of collinearity on model variance. However, unlike ridge regression that employs squared bias, Lasso regression utilizes absolute value bias as the regularization term:

$$J(\theta) = \min\|Xw - y\|^2 + z\|w\| \tag{3}$$

Elastic network regression is a combination of ridge regression and lasso regression. It combines the advantages of ridge regression and lasso regression to deal with multicollinearity problems and feature selection:

$$J(\theta) = \min\|Xw - y\|^2 + z\|w\| + z\|w\|^2 \tag{4}$$

A practical benefit of the trade-off between Lasso and ridge regression is that Elastic-Net can acquire some of the stability exhibited by ridge regression when dealing with loops.

3.2. Classification model

Classification is the prediction of discrete variables with qualitative output results [4]. Currently the basic classification model include decision tree, random forest, neural network, support vector machine and light gradient boosting machine. The principles of some commonly used classification models are described below. Table 2 shows the advantages, disadvantages and applications of the classification model.

The Decision Tree (DT) is a popular machine learning model utilized for classification tasks, employing a tree-like structure. It effectively handles both discrete and continuous features in the classification process. Its core idea is to continuously divide the data into different subsets by selecting the optimal features and division points until a certain stopping condition is reached. While Random Forest is an integrated learning algorithm based on decision trees that is capable of handling high dimensional data and non-linear data. Its core idea is to reduce overfitting by constructing multiple decision trees, and finally use voting or averaging etc. to get the classification results.

Neural Network consists of simple processing units (called neurons or nodes) and their connections. The weight of any connection between two units is used to assess the effect of one unit on the other. As shown in Figure 2, The first layer in the network is also called the input layer because in this layer the features are input; the last layer is called the output layer because the neurons in this layer output the final computed result of the hypothesis; and the intermediate layers are called the hidden layers because the data in these layers are not visible in the training set.
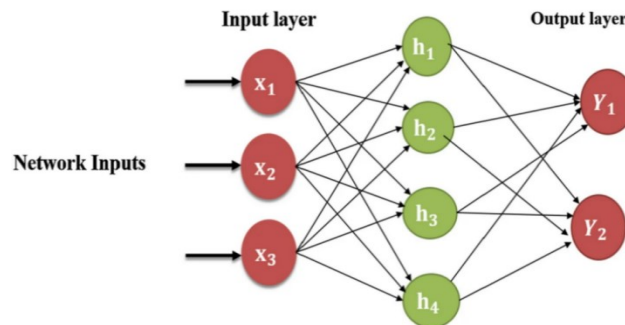

Figure 2. Basic architecture of NN [2].

Last, a support vector machine is a classification model capable of handling both linearly and nonlinearly divisible data. Its core idea is to classify samples into two classes by means of a hyperplane and to maximise the distance from the hyperplane of the sample closest to the hyperplane.

Table 2. Comparison of different classification model.

Model	Advantages	Disadvantages	Application
Decision Tree	Easy to understand; Suitable for various data; handling non-linear relationships	Easily overfitted; Sensitive to noise; Unstable	Classifying signals for studying behavioral patterns under specific tasks [10]
Random Forest	Reducing overfitting; Working well with large data; Robust to noise and missing values	Less interpretable than a single decision tree; Computationally intensive for large datasets	Classifying sensorimotor rhythm patterns in EEG [11]
Neural Network	Modeling complex, non-linear relations; Scalable to large datasets;	Requiring much data and resources; Hard to interpret; Prone to overfitting	Classifying disabled people's facial expressions based on EEG with CNNs [12]
Support Vector Machine	Effective for high dimensional data and small sample datasets	Memory-intensive and slower for large datasets; Sensitive to kernel and hyperparameters	Vehicle pre-crash classification detection based on EEG features to determine emergency braking [13]

4. Challenges

Although the use of machine learning techniques has been able to improve the performance of the BCI system quite well, there are still some difficulties to overcome in order to be more efficient.

The EEG based BCI system requires a lot of training before use to instruct the user on how to control the EEE signal, which is not very user friendly. In terms of signal processing, artifacts are still present in some applications, and it is difficult to find a way to remove the effects of artifacts in a way that meets all the application constraints, so finding out how to remove artifacts for specific applications will be the way forward [1]. In addition, there is a lack of unified evaluation metrics for various EEG machine learning approaches, although most tasks are indexed by accuracy, the criteria for evaluating whether they are accurate or not are almost different, and finding unified metrics is the next goal of the EEG based BCI system [14].

ECoG based BCI systems are currently widely used in the study of diseases such as epilepsy and Parkinson's, but they are mainly used for research purposes and do not play a therapeutic or auxiliary role, and breakthroughs in medical treatment are needed in the future. In addition, most of the ECoG based BCI systems studies are on the upper limbs, and there is a lack of studies on the lower limbs, so further research is needed to decode the nerve signals from the lower limbs [15]. Closed-loop research is the way forward, as most of the feedback users get from ECoG based BCI systems is visual, and somatosensory feedback (e.g., vibration, compression, and temperature) needs to be further investigated to refine user interaction with objects outside the line of sight [15].

5. Conclusion

As computer technology continues to be iteratively updated, machine learning modelling techniques are evolving towards larger and more complex models. This has led to the development of BCI. This article provides a brief introduction to brain-computer interfaces, understanding the five components of a brain-computer interface and their roles, as well as introducing EEG and ECoG separately, analyzing the advantages and disadvantages between them and the differences in model arrangements. Explanations are provided for two kinds of machine learning models, regression model and classification model ranging from simple models (e.g., linear regression) to complex models (e.g., neural networks). In addition to this, the strengths and weaknesses of each of these machine learning models and related applications are presented. The current challenges of EEG based BCI systems and ECoG based BCI

systems and future research directions are summarized. EEG based BCI systems require higher transmission efficiency as well as specialised training methods due to their signal attenuation. In addition, EEG based BCI systems are seeking more generalised de-artifacting methods to mitigate the effects of environmental signals. ECoG based BCI systems require greater input into therapeutic research as well as more realistic feedback. The relevant literature found in this paper is in the Elsevier, IEEE, and pubmed these sites, based on the keyword search of BCI, machine learning, EEG, ECoG, which provided a lot of additional knowledge for this paper.

References

[1]   Pawan and R. Dhiman (2023) "Machine learning techniques for electroencephalogram based brain-computer interface: A systematic literature review, " Measurement: Sensors, 28: 100823.

[2]   E. H. Houssein, A. Hammad, and A. A. Ali (2022) "Human emotion recognition from EEG-based brain–computer interface using machine learning: a comprehensive review, " Neural Computing and Applications, 34(15): 12527-57.

[3]   K. Volkova, M. A. Lebedev, A. Kaplan, and A. Ossadtchi (2019) "Decoding Movement From Electrocorticographic Activity: A Review, " Frontiers in Neuroinformatics, 13.

[4]   T. Merk, V. Peterson, R. Köhler, S. Haufe, R. M. Richardson, and W.-J. Neumann (2022) "Machine learning based brain signal decoding for intelligent adaptive deep brain stimulation, " Experimental Neurology, 351: 113993.

[5]   R. Flamary and A. Rakotomamonjy (2012) "Decoding Finger Movements from ECoG Signals Using Switching Linear Models, " Frontiers in Neuroscience, 6.

[6]   S. Castaño-Candamil et al. (2020) "A Pilot Study on Data-Driven Adaptive Deep Brain Stimulation in Chronically Implanted Essential Tremor Patients, " Frontiers in Human Neuroscience, 14.

[7]   I. Sturm, S. Dähne, B. Blankertz, and G. Curio (2015) "Multi-Variate EEG Analysis as a Novel Tool to Examine Brain Responses to Naturalistic Music Stimuli, " PLOS ONE, 10(10): e0141281.

[8]   C. Herff, G. Johnson, L. Diener, J. Shih, D. Krusienski, and T. Schultz (2016) "Towards direct speech synthesis from ECoG: A pilot study, " in 2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), 16-20: 1540-43.

[9]   V. Peterson, D. Wyser, O. Lambercy, R. Spies, and R. Gassert (2019) "A penalized time-frequency band feature selection and classification procedure for improved motor intention decoding in multichannel EEG, " Journal of Neural Engineering, 16(1): 016019.

[10]   N. S. Bastos, D. F. Adamatti, and C. Z. Billa (2016) "Discovering Patterns in Brain Signals Using Decision Trees, " Computational Intelligence and Neuroscience, 2016(1): 6391807.

[11]   D. Steyrl, R. Scherer, J. Faller, and G. R. Müller-Putz (2016) "Random forests in non-invasive sensorimotor rhythm brain-computer interfaces: a practical and convenient non-linear classifier, " 61(1): 77-86.

[12]   A. Hassouneh, A. M. Mutawa, and M. Murugappan (2020) "Development of a Real-Time Emotion Recognition System Using Facial Expressions and EEG based on machine learning and deep neural network methods, " Informatics in Medicine Unlocked, 20: 100372.

[13]   E. J. C. Nacpil, Z. Wang, M. Guan, K. Nakano, and I. Jeon (2023) "EEG-Based Emergency Braking Prediction Using Data Ablation and SVM Classification, " IEEE Sensors Journal, 23(14): 16013-19.

[14]   S. Aggarwal and N. Chugh (2022) "Review of Machine Learning Techniques for EEG Based Brain Computer Interface, " Archives of Computational Methods in Engineering, 29(5): 3001-20.

[15]   X. Wu, B. Metcalfe, S. He, H. Tan, and D. Zhang (2024) "A Review of Motor Brain-Computer Interfaces Using Intracranial Electroencephalography Based on Surface Electrodes and Depth Electrodes, " IEEE Transactions on Neural Systems and Rehabilitation Engineering, 32: 2408-31.