Applications Of the EEG-Based Machine Learning

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Abstract

machine learning has two phases: training and testing. In the training phase, a set of examples (i.e., data with their corresponding labels) are available. With a given machine learning algorithm, the example data are used to train a model (i.e., tune its parameters) so that it can identify the relationship between input data and the labels. In the testing phase, input data without labels go through the same methodology as the training phase for preprocessing, feature extraction, and feature reduction, and a trained model, which was estimated during training phase, predicts the output (i.e., labels). The main objective during the training phase is to estimate a model that has maximal predictive performance at the time of testing.

Keywords: EEG-BASED MACHINE LEARNING, THEORY, APPLICATIONS

Introduction

Electroencephalography is a noninvasive method to directly measure neural activity from electrodes placed on the scalp [1]. Synchronous activity of a large population of neurons generates an electric field that is strong enough to reach the scalp, which is recorded as the electroencephalogram (EEG) with a high temporal resolution [2]. Directly recording neural activity is one of the advantages of EEG compared to other neuroimaging methods, such as functional magnetic resonance imaging (fMRI) and functional near-infrared spectroscopy (fNIRS), which measure biochemical activity as a proxy for neural activity [3, 4]. Moreover, due to its high temporal resolution, EEG captures a wide range of neural oscillations. These rhythms have been categorized into five standard bands: delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–12 Hz), beta (13–30 Hz), and gamma (>30 Hz) [5]. Studies have shown that brain activity in each frequency band is associated with different cognitive functions [5]. These advantages make EEG a viable and practical option to investigate important questions in not only neural engineering and neuroscience but also clinical applications and disease diagnosis. EEG signals contain a substantial amount of information with respect to spatial, temporal, and spectral aspects. This makes EEG a suitable method to investigate various aspects of brain function and cognition. However, the richness of EEG [5] comes at a cost, where data can be high dimensional and may have a low signalto-noise ratio, which poses a considerable challenge to process EEG and identify patterns of interest. Machine learning has received considerable attention in the field to address the inherent challenges of EEG. EEG is usually contaminated with noise and artifacts, such as eye movement, slow drift, and muscle artifact [6]. To increase the signal-to-noise ratio, a preprocessing step is commonly included to minimize artifacts and reduce unwanted noise. This step can include various procedures such as band-pass filtering [7], artifact subspace reconstruction [8], independent component analysis, spatial filters, minimizing muscle artifact, and artifact rejection [3]. In preprocessing, however, one has to be cautious and visualize data to avoid eliminating any meaningful and informative component of EEG

Applications

An immense amount of research has focused on machine learning in EEG-based systems. There are numerous applications for EEG-based machine learning. An important application is to use machine learning to identify and extract biomarkers from EEG for neurological disorders, such as Alzheimer's disease [5], Parkinson's disease [6], epilepsy and epileptic seizures [4], and dementia [7]. Other applications of machine learning in EEG include brain-computer interface (BCI) [8], sleep staging [5], drowsiness detection [6], estimation of depth of anesthesia [4], and microsleep detection and prediction [2]. Despite different applications, implementation of the machine learning procedure in these EEG systems follows similar steps as described in this chapter. For the rest of this section, we provide further details for two applications of machine learning in EEG. These are brain-computer interface (BCI) and microsleep detection and prediction. **References:**

Brain-Computer Interface

A BCI system enables users to interact with their surrounding using brain activity [6]. BCI systems are of particular importance for people with severe disabilities, where BCI systems empower them to control their prosthetics and/or environment without using any muscles or peripheral nerves [5]. These systems commonly use EEG to record electrical activity of the brain because EEG is lowcost, has high temporal resolution, and has a low associated risk [4, 2]. One class of BCI systems focuses on motor imagery [2]. In this paradigm, a participant mentally simulates performing a series of movements. The aim of the BCI system is then to distinguish different types of movements using brain activity. Several studies have investigated motor imagery BCI and have achieved relatively acceptable performances (e.g., [5]). Using a similar concept, other systems have been developed to control robotic arms and unmanned aerial vehicles [6]. In these systems, a diverse range of feature extraction methods have been employed, including CSP [7], coefficients of wavelet transform [8], spectral features [159], convolutional neural networks [6], and autoencoder [1]. Additionally, a range of classifiers have been used to separate motor imagery tasks, such as LDA [7], SVM [4], kNN [8], ensemble classifier [6], naive Bayes [6], and deep neural networks [6]. P300 speller is another paradigm of BCI [4]. In the P300 speller, participants are presented with a table of characters where the intensity of one row or column is randomly increased. Participants are instructed to focus on the letter of interest, which randomly gets highlighted. This change in intensity produces a reaction in brain activity of the participant which happens approximately 300 ms after the letter is highlighted – i.e., P300. Using the P300 pattern, a BCI system can identify the letter of interest. The P300 speller paradigm has been widely studied in the literature and has achieved relatively good performances (e.g., [6]). Several classifiers have been used to identify the letter of interest in a P300- speller paradigm, such as LDA [8], SVM [9], deep neural networks [5], ensemble classifier [7], and random forest [3]. There are other BCI paradigms such as steady-state visual evoked potential (SSVEP), auditory, visual, and hybrid [2]. These paradigms have also been the subject of many studies (e.g., [8]). There are numerous studies investigating different BCI paradigms, and the number of publications is increasing. The findings of these studies show a promising future to improve quality of life for those who suffer from severe neurological and musculoskeletal disorders.

Microsleep Detection and Prediction in Time

The prediction of imminent microsleeps has also been the subject of several studies [8]. In these studies, selection of the EEG window corresponding to a microsleep state was done in a manner so that the EEG window preceded its corresponding microsleep state by a certain amount of time [5]. In terms of performance, microsleep detection and prediction systems have achieved relatively high AUC-ROC values (e.g., 0.95 [7]). However, the precision of these systems is relatively low (e.g., 0.36 [8] and 0.42 [1] for microsleep prediction 0.25 s ahead). One of the challenges associated with microsleep systems is that microsleep data has an inherently high class imbalance. Additionally, the class-imbalance ratio varies across individuals. This introduces complexity for training the system and evaluating its performance.

Conclusion

An immense amount of research has focused on EEG and its applications in medicine, neuroscience, rehabilitation, and other fields. Integration of the EEG and machine learning fields has provided a framework to develop accurate EEG-based predictive systems. Such advances have resulted in EEG-based BCI systems that can substantially improve the quality of life for those suffering from severe neural and neuromuscular disorders. In this chapter, we have provided an overview of machine learning algorithms for EEG-based systems. We divided the process into EEG data acquisition, preprocessing, feature extraction, feature reduction, classification, and performance evaluation. For each step, a brief summary was provided and potential challenges were discussed. However, the field of machine learning is vast, and therefore this chapter makes no attempt to review all of the existing literature. Instead, we have provided an overview of different steps that can be combined to develop an EEGbased predictive system. We consider that machine learning will play an increasingly important role in EEG-based systems and their applications. In particular, deep neural networks will become an increasingly popular choice to develop EEG-based systems. These methods provide a framework to benefit from both model-based and data-driven approaches, which requires minimal processing for EEG data.

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