STUDY ON THE EEG-BASED MACHINE LEARNING: THEORY AND APPLICATIONS

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Abstract: Electroencephalography is a widely used clinical and research method to record and monitor the brain's electrical activity – the electroencephalogram (EEG). Machine learning algorithms have been developed to extract information from the EEG to help in the diagnosis of several disorders (e.g., epilepsy, Alzheimer's disease, and schizophrenia) and to identify various brain states. Despite the elegant and generally easy-to-use nature of machine learning algorithms in neuroscience, they can produce inaccurate and even false results when implemented incorrectly. In this chapter, we outline the general methodology for EEG-based machine learning, pattern recognition, and classification. First, a description of feature extraction from various domains is presented. This is followed by an overview of supervised and unsupervised feature-reduction methods. We then focus on classification algorithms, performance evaluation, and methods to prevent overfitting. Finally, we discuss two applications of EEG-based machine learning: brain-computer interface (BCI) and detection and prediction of microsleeps. 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: Machine learning is a set of algorithms that enable us to automatically identify patterns in the data and make predictions on newly observed measurements [14,15,16]. This is often the case in neural engineering and neuroscience experiments to (1) contrast between conditions [17,18], (2) diagnose a disease [19,20], or (3) identify electrophysiological changes associated with behavior [21, 22]. Despite different applications, the machine learning procedure remains similar in most cases, as shown in Fig. 1. In general, 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. It is important 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

Emotions are the changes in people's psychological and physiological states when they face external stimuli such as sounds, images, smells, temperature, and so on. And it plays a vital role in mental and physical health, decision-making, and social communication. To realize emotion recognition, Ekman regarded emotions as six discrete and measurable states related to physiological information, namely happy, sad, anger, fear, surprise, and disgust (Ekman, 1999; Gilda et al., 2018). Subsequent studies on emotion recognition mostly followed this emotion classification basis, but some researchers had added new emotional states, including neutral, arousal, relaxed (Bong et al., 2012; Selvaraj et al., 2013; Walter et al., 2014; Goshvarpour et al., 2017; Minhad et al., 2017; Wei et al., 2018). Some people had also provided a new classification standard for emotions, including relaxation, mental stress, physical load, mental stress combined with physical load (Mikuckas et al., 2014). The setting that emotions are discretized states makes the emotion recognition can be perfectly realized by classification in machine learning. The overall process of machine learning for emotion recognition is as follows: the subjects' facial expressions, speech sounds, body movements (Kessous et al., 2010), electromyography (EMG), respiration (RSP) (Wei, 2013), galvanic skin response (GSR) (Tarnowski et al., 2018), blood volume pulsation (BVP), skin temperature (SKT) (Gouizi et al., 2011), photoplethysmographic (PPG) (Lee et al., 2019), electrocardiogram (ECG) (Hsu et al., 2020), heart rate (HR) (Wen et al., 2014) and electroencephalography (EEG) will appear corresponding changes when stimulated by external audio, visual, audio-visual and other stimuli. In addition to the above external factors that will affect the changes in emotions, autonomic nervous system (ANS) activity is viewed as a major component of the emotion response (Kreibig, 2010). Ekman (1992) analyzed six basic emotions by recording six ANS parameters. And Levenson (2014) discussed emotions activate different patterns of ANS response for different emotions. 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.

Acquisition of Electroencephalography Signals for Emotion Recognition

There are generally two ways to acquire EEG signals related to emotions. One way is to stimulate the subject to produce emotional changes by playing audio, video, or other materials and obtain the EEG signal through the EEG device worn by the subject. Yuvaraj et al. (2014) obtained EEG data using the Emotive EPOC 14-channel EEG wireless recording headset (Emotive Systems, Inc., San Francisco, CA) with 128 Hz sampling frequency per channel from 20 PD patients and 20 healthy by inducing the six basic emotions of happiness, sadness, fear, anger, surprise, and disgust using multimodal (audio and visual) stimuli. Bhatti et al. (2016) used music tracks as stimuli to evoke different emotions and created a new dataset of EEG signals in response to audio music tracks using the single-channel EEG headset (Neurosky) with a sampling rate 512 Hz. Chai et al. (2016) recorded EEG signals related to audio-visual stimuli using a Biosemi Active Two system. And EEG signals were digitized by a 24-bit analog-digital converter with a 512 Hz sampling rate. Chen et al. (2018) used a 16-lead Emotiv brainwave instrument (14 of which were EEG acquisition channels and 2 of which were reference electrodes) at a frequency of 128 Hz. Later, Seo et al. (2019) used a video stimulus to evoke boredom and non-boredom and collected EEG data using the Muse EEG headband from 28 Korean adult participants. And Li et al. (2019) conducted an experiment based on emotional face stimuli and recorded 28 subjects' EEG data from 128-channel HydroCel Geodesic Sensor Net by Net Station software. In Hou et al. (2020), the Cerebus system (Blackrock Microsystems, United States) was used to collect EEG data at a 1 kHz sampling rate using a 32-channel EEG cap. In the same year, Maeng et al. (2020) introduced a new multimodal dataset via Biopac's M150 equipment called MERTI-Apps based on Asian physiological signals. And Gupta et al. (2020) used an HTC Vive VR display to enable participants to interact with immersive 360° videos in VR and collected EEG signals using a 16-channel OpenBCI EEG Cap with a 125 Hz sampling frequency. Later, Keelawat et al. (2021) acquired EEG data based on a Waveguard EEG cap with a 250 Hz sampling rate from 12 students from Osaka University, to whom song samples were presented. What's more, to effectively collect EEG signals, the attachment position of electrodes for EEG equipment in many studies follows the international 10–20 system (Chai et al., 2016; Seo et al., 2019; Hou et al., 2020; Huang, 2021). Another way is to use the existing, well-known database in the field of emotion recognition based on EEG, including DEAP (Izquierdo-Reyes et al., 2018), MAHNOB-HCI (Izquierdo-Reyes et al., 2018), GAMEEMO (Özerdem and Polat, 2017), SEED (Lu et al., 2020), LUMED (Cimtay and Ekmekcioglu, 2020), AMIGOS (Galvão et al., 2021), and DREAMER (Galvão et al., 2021). After obtaining the original EEG signal related to emotion states, the following operation is to preprocess the EEG signal to improve the quality of the EEG data.

Conclusion

Time-domain features are extracted from EEG signals without any transformation. Zero crossing is a time-domain feature that indicates the number of times the signal has crossed zero. This measure and the zero-crossing interval have been used for epilepsy detection [23], emotion recognition [24], and sleep staging [25]. Hjorth parameters are a set of three time-domain features describing a single channel of EEG [26]. These features are activity, mobility, and complexity. Hjorth activity (HA) is the variance of an EEG signal (i.e., signal power) and represents the width of the signal. Hjorth mobility (HM) estimates the mean frequency of the signal. Hjorth complexity (HC) estimates the bandwidth of the EEG signal by computing the mobility of the first derivative of EEG relative to the mobility of the EEG itself. Mathematically, the Hjorth parameters are calculated as [26, 27] 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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