BRAIN COMPUTER INTERFACE SYSTEM USING DEEP CONVOLUTIONAL MACHINE LEARNING METHOD

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Abstract

Brain-computer interface (BCI) decoding connects the human nervous world to the external world. People's brain signals to commands that computer devices can detect. In-depth study the performance of brain-computer interface systems has recently increased. In this article, we will systematically Investigate brain signal types for BCI and explore relevant in-depth study concepts for brain signal analysis. In this study, we have a comparison of different traditional classification algorithms new methods of in-depth study. We explore two different types Deep learning methods, i.e., traditional neural networks Architecture with Long Short term Memory and Repetitive Neural Networks. We check the classification Accuracy of Recent 5-Class Study-State Visual Evoked Opportunities dataset. The results demonstrate in-depth expertise learning methods compared to traditional taxonomy Algorithms.

Keywords: Deep Learning, Brain Computer Interface, Neural Network, Taxonomy Algorithm, Classification

1. Introduction

Brain-Computer Interface (BCI) Systems: The human brain understands names as messages or Commands to communicate with the outside world. BCI emphasizes many new applications, this is especially important in the daily lives of people, especially those with mental / physical delusions or disabilities [1]. For example, allowing high duplicate-resistant user identities-quotations based on brain waves for the general public to enjoy good entertainment and security; BCI allows people with disabilities, Adults, wheelchairs, appliances and other people with limited consciousness to control

Robots. The main challenge for BCI is to detect brain signals with a trivial signal-to-noise ratio (SNR), which is accurately given by the human utility [2].

Poor generalization efficiency and low taxonomic citation performance limit the wide real-world application of BCI. Over the past few years, in-depth study or deep neural networks have been applied for brain information processing to overcome the above challenges. As a growing subset of machine learning, deep the study shows excellent representational learning ability which has an impact Natural language processing, functional recognition, computer vision and more Logic. Breaking away from traditional machine learning algorithms is an in-depth study authority to study differentiated high-level representation for raw brain signals without manual Feature selection. It achieves high accuracy and standards along with training set size. Although traditional BCI systems have made great strides BCI research still faces signal will not be challenged [3].

First, the brain signals various biological agents (e.g., eye blinks, Muscle cramps, fatigue, concentration level) Environmental cramps (e.g. sounds). In the past, collecting informational data from damaged brain signals was crucial. Powerful system that works under strong conditions. Second, BCI is characterized by low SNR of non-electrophysiological brain signals. Low SNR is not traditionally easily fixed the time complexity of that method due to pre-processing or feature engineering methods Risk of data loss [4].

First, feature engineering depends on the skill of the human being dedicated domain. For example, basic biological knowledge is required to investigate sleep State by electroencephalogram (EEG) signals. Human experience can help in some respects but in more common cases, the incense drops. Automatic feature extraction method Most desirable in addition, current machine learning research focuses on static data [5].

Therefore, rapidly changing brain signals cannot be accurately classified. For example, the state-of-the-art classification accuracy of the motor imaging EEG is only 60% to 80%. This requires a novel learning methods for managing dynamic data streams in BCI systems. So far, in-depth study in BCI applications has been widely applied and has shown success solves the above challenges. In-depth study has two advantages. First, it works directly among raw brain signals, avoiding time-consuming pre-processing and feature engineering. Second, deep neural networks can copy high-quality features and hidden ones. In this paper has following sections, section 2 describes related works, section 3 gives various brain computer interface methods and section 4 explains comparative studies.

2. Related work

We are conducting this survey for three reasons. First, there is a systematic and comprehensive error Introduction to BCI Signals. Our best Knowledge and current limited surveys focus only partially EEG signals. For example, Lossie et al and Wang et al, focus on the EEG without analyzing EEG signal types; Sekosi et al, focus on event-related opportunities (ERP); Hazir et al, Functional Proximity Focus on Infrared Spectroscopy (FNRS); Mason et al, Summary of Neurological Event-Related Disynchronization (ERD), P300, SSVEP and Visually Induced Probability. Abdul Qadir and others [5].

Introduces brain topology, but makes no mention of autoimmune EEG and acceleration Serial Visual Presentation (RSVP); Lossie et al, ERD and RSVP were not considered; Roy et al, list some in-depth study-based EEG studies, but Lile provides analysis. Second, some studies have examined the relationship between in-depth study of BCI. To the best of our knowledge, this paper is comprehensive Survey of recent developments in BCI based on in-depth study. We pointed out boundaries and promises sleeping EEG. Sleep EEG is mainly used to diagnose and diagnose sleep disorders Sleep disorders or developing a healthy habit [3][7].

(i) Non-discriminatory models - CNN regularly uses single-channel sleep stage classy quotations EEG. For example, Vyamala et al, time-frequency frequency characteristics were collected manually. In addition, the classy quotation accuracy is 86%. Others rely on RNN and LSTM . Different properties from the frequency domain, correlation and graph theoretical properties [9].

(ii) Representative models - Tan et al, the DBN-RBM algorithm was used to detect sleep based on PSD features collected from dormant EEG signals, 92.78% F1 was obtained. Local dataset Zhang et al, DBN-RBM integrated with three RBMs for sleeping feature Extraction. (iii) Hybrid models. Manzano et al, introduced a multi-view algorithm for estimation Sleep stage connecting CNN and MLP. CNN was used to receive the raw time-domain EEG oscillations when singles receive MLP of short-term processed spectrum switching between 0.5-32 Hz (STFT). Supratak et al, a model with a multi-view combination is suggested CNN and LSTM for automatic sleep stage scoring for time-dependent dependence, the laser (two-way LSTM) is tentatively accepted symptoms of sleep [7].

Dong et al, A hybrid in-depth study model has been proposed for this purpose. The temporal sleep phase is used by the MLP to classify and find hierarchical features With LSTM for continuous data study. MI EEG deep learning models work best in the classic citation of motor imagery (MI) EEG and real-motor EEG [8].

(iii) Non-discriminatory models - CNN uses such models extensively to identify the MI EEG. Some Based on manually collected features. For example, Lee et al and Zhang et al, CNN and 2-D CNN were used for classification, respectively; Manikandan et al, study Best information from EEG Signals based on Modi Ed LSTM Control Smart Home Appliances. Others have used CNN for feature engineering. For example, Runge et al, used CNN then applied weak classifiers to capture hidden connections from MI-EEG signals Select the main features for Class Knoll classion; Hartman et al, How CNN investigated MI refers to spectral features within the range of EEG samples. And MLP MI has been applied for EEG recognition, which is highly sensitive to EEG phase characteristics. Previous stages and high sensitivity of the EEG [10].

3. Brain Computer Interface

The Brain-Computer Interface (BCI) is also a growing field of research Applications. BCI Live Communication Channel Control external devices or applications that contain brain signals. That's all Allows users to communicate freely with the environment Peripheral nerves and muscles with large neuralgia Signalling systems in the brain. BCI finds applications in a variety of fields, including medicine and neuro economics. Good atmosphere without games, education, self-control Entertainment [1], Security and Authentication [2]. In recent years, extensive work has been done in this regard BCI's Application in Biomedical Systems: and Detection Tumors, Neurological Disorders [3], Neuro Rehabilitation [4], and Daily Life Activities (ADL), In the design of neuroprosthetics.

The BCI system consists of the following components: signal acquisition, signal pre-processing, feature extraction and classification [5]. In signal acquisition, electrical activity is generated The brain records by doing the proposed manual Task. There are generally two methods for signal acquisition Policies: Aggressive and non-aggressive. Aggressive signal Acquisition involves surgical intervention and electrodes Placed on the surface of the brain. In non-aggressive acquisitions, the signal is collected without surgical intervention. The first gives good signal quality, but the second Priority due to ease of implementation. Functional Magnetic resonance imaging (FMRI), operated near the infrared Spectroscopy (FNIRS), magnetoencephalography (MEG), and Electroencephalogram (EEG) is widely used Non-invasive signal acquisition methods [9].

EEG is commonly used for BCI problems because it is non-invasive, financial security, ease of use, portability. EEG the amount of electrical signals the brain produces By placing electrodes on th e skull. Proposed Opportunity (EP) BCII is the most widely studied category of electrical signals. E.P. These are electrical signals that the brain produces in response to stimulate. Based on the EP can be divided into three categories about the type of stimulus: visual (VEP), auditory (AEP) and Somatosensory (SEP). In this paper, we will do VEP analysis Dataset. When the stimulus frequency decreases (less than 4) Hz), the signals are called transient VEPs and when the excitation frequency is higher (greater than 6 Hz),. The signals are called fixed-state VEP (SSVEP).

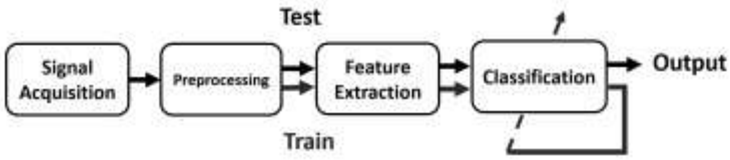

Figure 1: The basic BCI Model

This happens if there is a similar visual range Stimuli are exhibited at high frequency and enter the brain Produces neuronal signals to a steady state Without (or modules), is like the frequency of the frequency Any transient phase. Here we apply SSVEP dataset Analyzed in a study designed by Oikonom et al, retrieved from the Physionet database. And then the signal Acquisition, data pre-processed. Many features can be done Extract from pre-processed signals, including wavelet Modules, energy spectral density and amplitude parameters. The collected feature vector is then applied to train the classification. Classifier aims to identify the functionality intended for the user One of the pre-defined classes based on feature values. There are various challenges facing BCI studies. The Experimental design, data acquisition and training require high organization and time. Expanding a large database is very labour intensive and expensive. Variability the brain signals that arise throughout the subjects are also perfect High. A system trained in a specific subject does not work effectively on another topic. Quality the data obtained is another concern.

4. BCI System and Methods

Figure 1, shows a typical model of the BCI system that receives and converts brain signals. They go to control commands for computers. The system consists of several important parts: the brain Signal collection, signal preprocessing, feature engineering, classification and smart devices. First, the system collects and processes brain signals from humans. Preprocessing Less SNR codes are required to depreciate and expand. For example, the EEG collects signals a set of electrodes must be placed in the human skull to record the electricity in the brain Information. The ionic current explodes inside the brain, but the skull measures the size of the brain this greatly reduces the SNR.

The pre-processing component consists of multiple steps such as signal Cleaning, signal normalization, signal enhancement, signal reduction. The system feature distinguishes features from engineering-processed signals. Extracts traditional attributes from the time domain (e.g. variations, mean value, Kurtosis), frequency domain (e.g. fast forwarder conversion) or time-frequency domain (e.g. difference) Wavelet exchange). Features Features Improve specific information about user intent.

Much depends on the knowledge of the feature engineering domain. For example, it is required biomedical technology to learn informational features from brain signals to diagnose epilepsy capture.

The manual feature is abstract and time consuming and challenging. Recently, deeper this study provides beer selection to automatically collect unique features. Finally, it recognizes and converts classic signals based on the collected properties. External device commands. The in-depth learning algorithm looks more robust in most cases than traditional machine learning methods. Discreet in-depth study models that classify input data into known categories by studying discriminatory traits in an appropriate manner. Non-discriminatory algorithms are studied separately Characteristics by non-linear transformation and classification based on probability assessment. Discretionary algorithm can be used for feature engineering and classification quotation.

Mainly multi-layer perceptron (MLP) and recurrent nerve Networks (RNN) (including long-term memory (LSTM) and gated repeating units (GRU)), transitional neural networks (CNN) and their variants. In-depth representative in-depth study models. Such models study pure representative properties From input data. Such algorithms provide services instead of feature engineering Classic Asian citation. The most commonly used algorithms in this category are Autocode (AE), Regulated Boltzman Machine (RBM), Deep Belief Networks (DBN) and their variants. Deep Generative Deep Learning Models. Such models study the joint probability distribution Input data with target label. Generative algorithms are mostly used Rebuild or create a set of brain signal patterns to improve set training BCI. Commonly used models in this category include Variable Autocoder (VAE) 3 Generative Advertising Networks (GANs). Hybrid in-depth study models,such models combine more than two in-depth study models. Two common hybrid in-depth learning models are: 1) the well-known LSTM and CNN combination in the extraction of spatial-temporal features; 2) Integration Representative algorithm (for feature extraction) and non-discriminatory algorithm (Classic Asian Quotation)

Parameters	Values
Convolution Layer	5
Pool Layers	5
Fully Connected Layer	10
Hidden Layers	25
Drop Rate	0.5
Activation function	100
Dimensions	500

Table 1: Optimized Table for set of non-discriminatory values

Classifier	Parameter	Values
AdaBoost	Kernels	0.75
DeepQ	Hidden Layers	15
SVM	Drop Rate	0.01
PVSM	Dimensions	10
MLP	Kernel	0.75
K-Means	Association	0.01

Table 2: Classifier with Parameters

As we move forward training for more complex features with layers from the total output from the previous layers. We assess two types of in-depth learning methods: CNN and RNN With LSTM architecture. CNN is a multi-layered feed-forward neural network. The weight of the system is updated by the process Error back propagation. It is a combination the following types of layers: input layer, convection layer, Corrected Linear Units (ReLU) layer, pooling layer, completely connected layer. The recurrent neural network (RNN) is a type of nerve A network that dictates connections between units Loop. This creates an internal state of the network that allows This is the purpose of exhibiting dynamic temporal behaviour What RNs can do through neural networks Use their internal memory to process arbitrary scenes Inputs. The following figure 2 shows that LSTM structure with parameters.

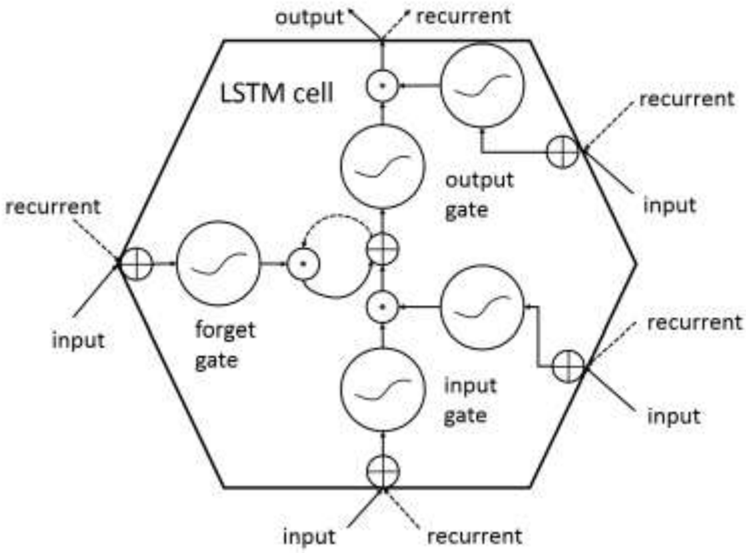

Figure 2: LSTM Structure of BCI Model

Parameters	Values
Type	Omni Direction (Hexagonal)
Layers	10
Learning Input date	0.50
Units	1000
Count Index	100
Connected Components	25/1

Table 3: Optimized Parameter and Values of LSTM of BCI Model

We will apply this 257 point feature as vector input Classification algorithms. Feature selection is widely applied Technology that enhances the performance of classifiers. We are here comparing the results of traditional class fires with character Selection based on correlation. Most of the time we work with data that has so many features, there is only a fraction they are important to solve our problem. Probably Unnecessary attributes provide information similar to other information Features. Our goal is to select and apply only what is “interesting” Properties or in other words, select a subset of such attributes this gives as much classification accuracy as possible. Feature selection this process has improved the performance of traditional classifiers Except MLP. In-depth learning techniques even with inclusion, traditional class fires have been overcome Feature selection process. In-depth learning techniques Feature extraction can be done with or without minimization the network automatically learns the required features. The Deep learning methods are adapted to practice the required features are unknown.

5. Conclusion

In this paper, we will systematically examine recent advances in in-depth learning models for the brain-computer interface. Compared to traditional methods, in-depth study does not only make learning depending not only on high-level features, but also on manual-crad features automatically from BCI signals. In-depth study methods of CNN and LSTM shows better accuracy compared to other traditional classification algorithms. SVM also performed well Accuracy for certain elements when applied with a feature Selected. The main reason for this is that it mainly depends on the performance of shallow classifiers the quality of the feature selection process. Domain knowledge summarized BCI signals and dominant in-depth study models by discussing the newest in-depth learning methods for BCI and identifying the appropriate depth learning algorithms for each BCI signal type. Finally, we review the in-depth study-based BCI Suggest applications, open challenges and future directions.

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