Brain-Computer Interface: Deep Learning Based classification of User Specific movement States from EEG data

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Abstract: A method of developing interaction between brain and computer is provided by the Brain Computer Interface (BCI) device. These BCI devices use various invasive and non-invasive acquisition techniques to record the responses of brain. It is required to use the machine learning and pattern recognition techniques to translate these responses recorded from the brain for the control of any actions. This paper includes a feature extraction and classification techniques applied on data recorded from the brain. As well as we perform a classification based on machine learning technology methods to visualize the features of the arm movement using the 3-dimensional Class Activation Map (CAM). Secondly it reviewed; Autonomous Deep Learning (ADL) is a streaming online learning technique that uses Electroencephalography to distinguish five human fingers. Finally a kernel reinforcement learning based on clustering (RL) algorithm is reviewed that with less computational complexity, achieved a faster intelligence adaptation in brain regulation.

Then experimental results of above discussed methods are evaluated and compared using a BCI lab by considering a set of data samples.

Keywords: Brain-Computer Interface (BCI), Class Activation Map (CAM), autonomous deep learning (ADL), reinforcement learning (RL).

1. Introduction

From the idea of supporting the individuals who were suffering from several neuromuscular disabilities, the motivation towards developing of BCI has been come in providing social recognition to them. As a result, since from the early years this BCI has been attracted many of researches. The brain functionalities and controlling can more briefly understand by a variety of new techniques called neuroscience, cognitive science and artificial intelligence along with

Brain computer interface (BCI). A method for transforming brain responses and

BCI is used to communicate with the outer world by using an interface with computer. The possibility of understanding the neural communication and its function in the brain has made with the new developments in BCI. Studying of the brain has helped researchers not only in the medical field but also in the technology field.

A new technology that arrives to relatively take the advantage of inherent brain computing power is Brain computer interface (BCI). Until the recent days also the development of the BCI was considered science fiction. Acquisition of signals from brain regions has been trying by several scientists since from the Berger's first invention of electroencephalography (EEG). In general four major parts are included in the BCI. They are sensing device, amplifier, filter, and the control system. Electrodes connected to a lid are there in the sensing device that corresponds to International 10-20 standard. One of the most common biological amplifiers used in the market can be taken as amplifier part. Then the main aspects of research in BCI that applied to the brain signal are the filter part and control system. Signal acquisition, signal processing, and output device are the common processes that involved in any control system of BCI which were the mainly focused in this paper. The invasive, semi-invasive and non-invasive are three types of approaches that have been used to carry out the signal acquisition. Signals that acquired in the signal acquisition process are then applied to the amplifiers and converters to process, amplify and convert them into the human recognizable forms.

In this paper, a survey of three papers is provided on the feature visualization and classification on BCI using machine learning techniques for different subject movements. The first paper describes about the deep learning based classification on BCI to visualize the arm movement features in which a class activation map (CAM) is used for the efficient feature extraction [1]. The second paper provides a study on classification of movements in EEG signals of five individual fingers using autonomous deep learning approach which is the one of streaming deep learning method [2]. In third paper a fast learning approach applied to the controlling tasks of brain for adapting the neural responses in BCI is studied. This used a new clustering based kernel reinforcement learning algorithm (KRL). Then the resulting accuracy of these three approaches described in survey are evaluated and compared in the results [3].

2. Signal Acquisition

One of the most important challenges faced by the BCI is the signal acquisition. Signal acquisition is the process of acquiring the signals from the brain using some techniques and methods [4]. This process involves three types of acquisition techniques such as invasive, semi invasive and non-invasive approaches. In an Invasive technique, brain signals are acquired through the micro electrodes penetrating into the brain's diameter. Signals are acquired in the semi-invasive approach by the placing the electrodes under the scalp instead of placing in the gray mater. While in the non-invasive approach signals are acquired by placing the electrodes on the scalp without surgical procedure. Among those three types of signal acquisition approaches non-invasive approach has been used extensively for the researches. Thus some of the most commonly used techniques of non-invasive approach are discussed below.

2.1Functional-Magnetic-Resonance Imaging (FMRI)

FMRI is one of the most suitable methods of neurological activity detection for the research purpose. The Magnetic Resonance Imaging (MRI) machine is used in this process with which the rate of change of hemodynamic response or blood flow of subject laying under it is observed. Basically this rate of flow of blood will occur in brain regions due to the higher neurological activeness and this is required to get higher hemodynamic response. These responses produced from the active neurological processes are called as Blood Oxygen Level Dependency (BOLD).

2.2 Near-Infrared Spectroscopy (NIRS)

The Cerebral Blood Flow (regional) responses similar to that of BOLD responses are monitored in this NIRS method using the light nearer to the infrared spectrum. In order to get most accurate detection LED's have been used in this NIRS method to scan a wide-ranging area of the brain for the activity. Channels have been formed for the signals using illuminators and detectors pairs. The brain signals are received by the detectors in this NIRS method by passing the Near-infrared rays through the skull and brain tissues that are emitted from the every illuminator.

2.3 Magnetoencephalography (MEG)

Large amount of spatial information due to the more number of sensors in contrast to the conventional EEG has been provided in this MEG. A subject is positioned on a chair in a room shielded by a magnetic material with a series of magnometers such as superconducting quantum interference devices (SQUIDs) around their head in order to take MEG recordings. This approach dependence on a room shielded by a magnetic material and requires a huge machine for sensing the brain waves, which were the main limitations of this approach. Despite of these limitations, it was shown from the research that MEG is still a feasible and reliable enough method for further research [8].

2.4 Electrocorticography (ECoG)

One of the invasive methods is this ECoG unlike the previous methods. The brain signals acquisition from the cerebral cortex in this ECoG required surgical operation of directly implanting the electrodes on surface of the brain. Obviously a high spatial resolution, wide bandwidth, high amplitude and lower susceptibility to EMG are cleared as advantage. This ECoG can also often used as an identifier to localize the epilepsy foci points. A part of brain required to remove through the resection surgery is identified by implanting the collection of 64 electrode pads in a part of the epileptic focus of brain. These electrodes with epilepsy were implanted in a study on patients. The BCI can be generated by the researches during the one-to two-week period in which seizure area is localized thorough the data recording using electrodes. The feasible method required to develop a BCI system along with the epileptic can be identified by the accomplishment of this study while removing the electrodes in this case because of epileptic nature of the patients [9].

2.5 EEG

EEG is a technique in which electrodes are placed around an individual's scalp to detect the electric field. These electrodes can be placed in a standardized way using a technique called 10/20 placement [10]. A person of the test is responsible for vigorously clean the hair before a night of measuring recordings. Using a conductive medium such as conductive gel, electrodes are placed against the patient's scalp to facilitate signal acquisition and then measurements are made in accordance with the International Manual 10/20.

3. Feature Extraction And Classification Techniques

3.1 Deep Learning Classification Feature Visualization

It has been illustrating that the types of arm movements were well classified using the deep learning model. Using a 3D CAM, it also able to analyze the information of the cerebral signal in three-dimensional such as channel, time and frequency which features has been used for the classification. The deep learning model that is well trained influenced by which features can be analyzed when certain classes are classified with the three-dimensional input data through the development of a visualization method to verify the classification features. In this study, arm movement characteristics especially in spatial and spectral view point had confirmed in addition to the major difference between the features of right, left as well as movements of both arms with the displayed 3D-CAM image. From this study it can be determined that, in a deep leaning method the feature mostly influenced while they classified in to certain classes can compared directly with the results of neurophysiological research based on EEG, EKG, etc.

The "Densenet" is a so called deep learning framework modified from the one of Convolutional Neural Networks (CNN) which is used in the classification of arm movement.

The class activation map is a well-trained deep learning model that impacted the features of heat map image when the related Event-Related Spectral Perturbation input data are categorized into certain classes. It should be equal to the CAM to obtain a finite CAM value when weight of last convolutional layer is multiplied with their data in a deep learning frame work that is well- trained. Determining the position of the major feature over the in-class classification has provided by the advantages of CAM which because of the acquired heat map image.

The CAM in existed became a 3D CAM by adding it with a one axis to form a three-dimensional volume heat map. Compared with the normal CAM process the process of calculation should be the same in order to obtain this map but for considering of adding an axis, it is different. The localization of affected features of arm movement during the classification is analyzed using this image volume. The “Topo map” called as topographic map has created in order to keep the spatial and spectral information from 3D CAM. Topo map has an advantage of being able to intuitively analyze the spectral and spatial characteristics at any instance of time. Spectral-spatial image was converted from the results of 3D CAM in the topographic map since every time that the point in time was changed.

3.2 Autonomous Deep Learning (ADL)

An ADL neural network is a supervised, flexible, deep-learning neural-network in which the hidden-layers, as well as the structure of the hidden units, can be built by themselves into a long-lasting learning mechanism (ADL). Multi Layer Perceptron (MLP) is the basis for ADL which is made up of a single first layer and a multiple intermediate layers. Depth and width of the network adaptation are the two adaptations that an ADL consists. A new unit(hidden) is created and unpredictable unit(hidden) is deleted using a first adaption method of Network Significance (NS). Then the hidden layers are created and deleted using a second adaption method of Drift Detection Scenario (DDS).

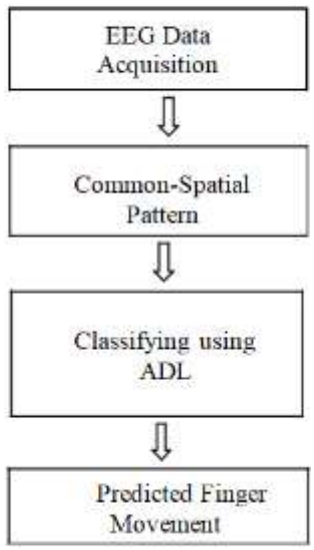

Fig. 1: COMPUTER-BRAIN INTERFACE FOR FINGER MOVEMENT PREDICTION USING ADL

A new method of Autonomous Deep Learning (ADL) based BCI is introduced in this paper to conquer degradation performance in subject-independent classification. The capability of constructing its own structure and adopting of changes in input behavior are the main advantages of ADL. ADL and Common Spatial Pattern (CSP) features are there in this studied BCI. Classification of EEG signals regarding to five individual fingers is the main objective of this paper. As shown in Figure (1), this frame work has performed accordingly. It used a data set from [8] for the BCI which consists of EEG motor images. Five types of mental images such as movements in five fingers are selected as the parts of the recording session in order to distinguish finer motion images. All the pictures of the motor are taken from a one hand. From the overall study on this work, it has been illustrated that the ADL was outperformed both in subject dependent and subject-independent classification by achieving stable accuracies for both training and testing and it has not shown any deterioration in performance.

3.3 Kernel Reinforcement Learning based on clustering

BCI offers a method of controlling artificial devices by using brain signals exclusively. Helping the patients with motor disabilities is a promising approach. If the intention of user is over dominated by the correction, the difference between the desired outcome and the outcome of decoder is recalibrate or refurbishment with the decoders based on supervised learning. Conversely, users can actively regulate their brain signals exclusive of actual limb movement by trial and error with the help of reinforcement learning-based decoders. The dynamic mapping for neural actions is created by this decoder and reinforcement the successful trails of subject trying to control the brain. New brain patterns appeared and increasing the scope of the state that the algorithm can quickly explore in the brain control process. A computational challenge in prior to the subject gets irritated, impatient or even resolved is required to quickly recognize new sequences and therefore adapting the mapping action of the state of neural. The mapping of optimal non-linear neural action is examined in Recreating Kernel-Hilbert-Space (RKHS) by the recently designed Kernel Reinforcement Learning method (quantized and attention gated). All previous data yet in RKHS are taken into account for the decoding which leads to a strong level of computational difficulty and a low degree of adaptation for the newly design brain model.

Figure (2) shows the foremost structure of the proposed algorithm which works on online method. For a BCI, a cluster-based kernel reinforcement learning algorithm is introduced in this paper. In the RKHS only the closest cluster of a neural model is activated when it was generated. The complexity of computation is reduced significantly by the local-support in a subspace. The formation of distinctive robust neural patterns and traces on the little changes are allowed by this present neural model which update the cluster along with its centroid.

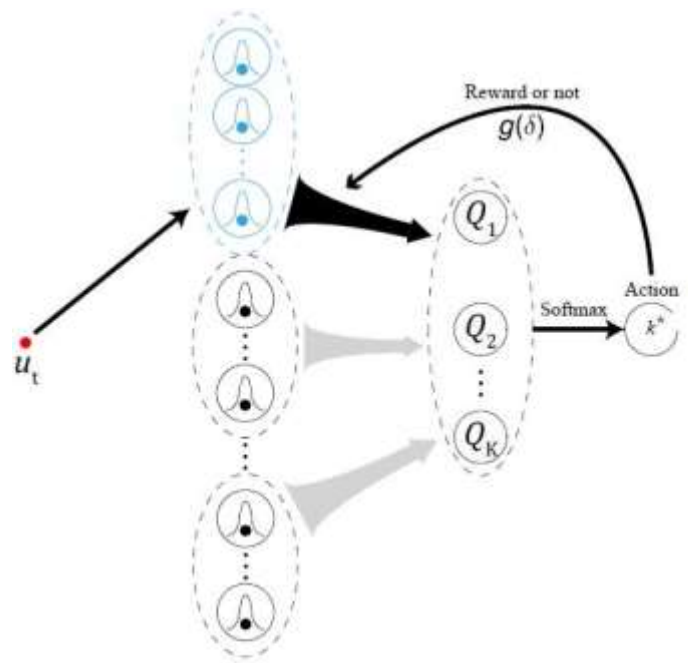

Fig. 2: STRUCTURE OF KERNEL RL((BY USING SUBSPACE IN RKHS SPANNED BY THE ACTIVATED CLUSTER)

The compact kernel achieves clustering-like learning curves by effectively binding data within a local space in the experiments. Because the value of kernel lower neural's number input in the next cluster relative to the entire record is required to compute which saves computing time, the clustering-technique is appropriate to the framework for decoding in a online manner. Reinforcement Learning. Moreover this algorithm is made highly sensitive to newly emerging pattern of brain by the dynamic clustering technique. Robustness of the clustering technique is determined by the number of clusters has a low standard deviation in various data transformations. Furthermore, as an alternative to Euclidean distance Jaccard distance is suggested to use as a threshold measure. This is a normalized 1 standard which takes into account the structure of the neural data. Statistical performance is compared in these two cases under data segments. A small drift is detected using cluster-based RL algorithm in models in brain and is capable of recognizing new brain signals.

4. Results

The performance comparison of different feature extraction and classification algorithms on EEG data of BCI are discussed in this section. The signals acquired from brain cerebrum using EEG method are considered for the comparison of different methods. Thus, a dataset consists of EEG signals regarding to the movements of arm, five different fingers and hand is taken to compare the three different approaches studied in this survey paper. Each of these signals had recorded ERP responses. This data is first band pass filtered then the feature extraction and classification methods that are described are evaluated.

Table 1: COMPARISON OF TRAINING AND TESTING ACCURACIES FOR DIFFERENT CLASSIFICATION METHODS

Classification methods	**Accuracy**	
	Training	**Testing**
CNN	78	75.5
Deep learning	88.3	83.5
ADL	92.8	90.6
Clustering based Kernel Reinforcement Learning Algorithm	98.3	95.6

The results are tabulated in Table (1). From the figure (3), it can be inferred that the accuracy of CNN, deep learning model, ADL and Kernel Reinforcement Learning based on clustering (KRL) acquired almost 77%, 88%, 93% and 98% accuracy respectively. The ADL outperforms than CNN in a Subject-dependent classification when it comes to achieving stable accuracies in both training and testing while good quality of ADL is more marked under an independent subject classification than that of CNN. No performance degradation is reported in ADL while approximately 50% of performance degradation is reported in CNN.

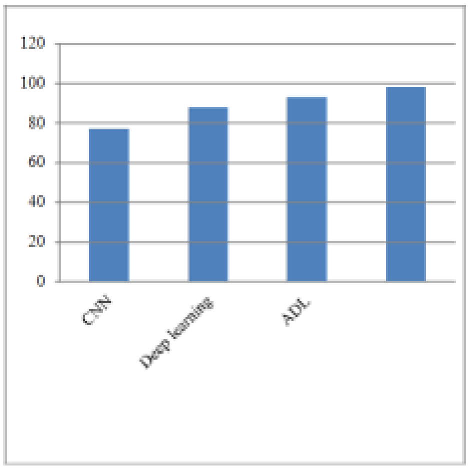

Fig. 3: OVERALL ACCURACY PERFORMANCE COMPARISION

RL algorithm based on clustering can capture the little changes in patterns of brain and is capable of detecting new brain pattern. In addition a less computational complexity for a better performance and faster knowledge adaption are achieved by the KRL algorithm. The total number of kernals in KRL is much larger than the average number of kernals per cluster. The computational complexity is much less including searching for the closest cluster. It The lesser clusters lower the computational complexity (on average 77% less) significantly, but also the reduces the archetypal neural patterns numbers occurring in the control of the brain.

5. Conclusion

A survey on the signal acquisition and classification methods in BCI is provided in this paper. The three approaches of brain recorded data that require to be analyzed are studied in this paper which uses a deep learning model, ADL and clustering based KRL methods for the classification of movements in arm and five different fingers. Then the major comparative analysis of these studied methods is discussed in the results with popular existing BCI techniques. Though the researchers are now more focused on deep learning methods such as deep belief networks, CNN, and a mixture of different classification algorithms, this survey can be useful to implement the best for the BCI and providing a better way of communication between brain and computer is the major focus of this BCI research yet the methods applied to achieve this objective can differ.

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