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A P300-Based BCI Classification Algorithm Using Least Square Support Vector Machine

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Abstract

In this paper, we propose a classification algorithm for P300-based Brain Computer Interface (BCI). Brain Computer Interface (BCI) with P300 speller helps Amyotrophic Lateral Sclerosis (ALS) patients to spell words with the help of their brain signal activities. Amyotrophic Lateral Sclerosis (ALS) also known as Lou Gehrig's disease in which certain nerve cells in brain and spinal cord also called as motor neurons, slowly die. The main goal of the proposed research is to develop classification algorithms for P300-based Brian Computer Interface (BCI). The proposed model can be used to restore basic communicating ability for Amyotrophic Lateral Sclerosis (ALS) patients in a reliable and fast way.

1. Introduction

Amyotrophic lateral sclerosis (ALS) is a progressive neurodegenerative disorder. ALS affected individuals may eventually lose the ability to initiate and control all voluntary movement; bladder and bowel sphincters and the muscles responsible for eye movement are usually, but not always, spared [1]. This condition is also referred as locked in syndrome where patients become completely paralyzed.

Brain Computer Interface (BCI) system is a direct communication pathway between human brain and the external device such as computer or other electronic device used for communication. The main purpose of this system is to interpret brain signals into useful information. Brain Computer Interface (BCI) research is a multidisciplinary field where researchers from neuroscience, psychology, physiology, engineering, computer science, rehabilitation, and other technical and health-care disciplines participate.

There are many kinds of BCIs; our focus for this research is only on non-invasive BCIs that are based on the electroencephalography (EEG), which measures the electrical activity of the brain along the scalp using EEG electrode cap. One problem with the non-invasive EEG recording using electrodes placed superficially on the scalp is that it yields poor signal quality with very low SNR as the skull diminishes the signal amplitudes. The signal that is of interest in EEG is P300, an Event Related Potential (ERP) generated by the brain when it receives a stimulus. P300 is a very weak ERP since it is masked by signals from ongoing brain processes.

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It can still be detected but difficult to find the part of brain that created it. When recorded by EEG, P300 signal appears as a positive deflection in voltage with latency, i.e., delay between stimulus and response is around 300 ms (roughly between 250 to 500 ms). This P300 component is present in every human. There are many studies over four

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decades regarding the features of P300. So detecting P300 is a difficult problem in BCI research.

There are large varieties of BCI systems that are being developed and reported in the literature but many interesting and challenging questions still not yet successfully addressed. Many of the P300-based BCI systems have been successfully implemented using signal-processing techniques such as simple signal averaging, Step Wise Linear Discriminant Analysis (SWLDA), Linear Discriminant Analysis (LDA), Fisher's discriminant analysis (FDA), Independent Component Analysis (ICA), Wavelets, and Support Vector Machine (SVM). However, the speed and classification accuracy still has to be improved for single trial based BCI system.

We chose machine-learning approaches as the neurophysiology of the mental states that are used in BCIs are well known. It seems possible to extract simple features that can very well distinguish between the mental states. As mentioned earlier an event-related potential (ERP) evoked by a specific sensory, cognitive, or motor event can be reliably measured using EEG. The EEG reflects many simultaneously ongoing brain processes and so the brain response to a single stimulus or event of interest is not easily detectable in the EEG recording of a single trial. So, most of the ERP research relies on averaging the responses over many trials to see the evoked event-related response to the stimulus. Larger the number of trials, higher the detection accuracy and longer the response time. Our focus is in this trade-off, i.e., to improve the EEG classification accuracy and the processing speed with fewer number of trials and perhaps even with only a single trial using machine learning algorithms. In this paper, we compare different types of machine learning approaches and the reason for choosing Least Square Support Vector Machine (LS-SVM) as our approach.

2. Method

A. Machine Learning Algorithms

Machine learning is a branch of artificial intelligence and it is all about the study of system and building the system that can learn from the data. Based on desired outcome of the algorithm machine learning algorithms can be classified as supervised learning, unsupervised learning, semi-supervised learning, reinforcement learning, transduction, learning to learn. More details regarding this can be found in [2].

There are many machine learning algorithms used to build P300 BCI systems. Fisher's Linear Discriminant Analysis (FLDA) is a simple and efficient method of supervised learning approach [3-5]. It is related to Linear Discriminant Analysis (LDA). FLDA is very simple and ease of use but major drawback is it becomes impossible to use when we have to classify large number of features.

Another well-known machine learning approach used for classification of P300 in BCI is Support Vector Machine (SVM) [6-9]. SVM is also related to supervised learning model, which is used to analyze data and recognize the patterns used for classification and regression. When you are given a set of training examples, each marked as belonging to one of two categories, an SVM training algorithm builds a model that predicts whether a new example falls into one category or the other [2]. Support Vector Machine algorithms can be further classified as linear SVM and non-linear SVM. Non-Linear SVM can be implemented by using different kernels depending on the classification. The major advantage of SVM is good classification accuracy. The major drawback is training SVMs, which is computationally complex because regularization constants and kernel parameters are typically estimated with a cross-validation procedure. A second issue is that the loss function used in the SVM is designed for problems in which only binary yes/no outputs are needed [10].

The problem with binary yes/no outputs is that no information is given about the confidence the system has in those outputs. Besides FLDA and SVM, other machine learning algorithms have been tested in the context of BCI systems. An overview of these algorithms can be found in [11]. Our main goal would be to learn and work with the algorithms such as non-linear SVM, Bayesian, semi-supervised learning and Clustering (non-supervised learning) and propose an algorithm, which delivers better classification accuracy and data transfer rate for locked-in patients.

In some cases, due to inter- and intra-subject variations in EEG signal, intermittent training/calibration is needed, besides the initial training of classifier. An alternative way to solve these problems is semi-supervised learning that uses both labeled and unlabeled data in the training of the classifier. Such algorithms include expectation maximization (EM), co-training, self-training, transductive support vector machine, entropy minimization, graph-based methods, etc. Comprehensive survey of semi-supervised learning methods can be found in [12] and [13]. For example, to minimize the initial training, a co-training method has been introduced into a P300 BCI speller and constructed high-performance classifier by using unlabeled data [14]. Inspired by the idea of self-training EM algorithm with a naive Bayes classifier [15], a self-training support vector machine (SVM) was proposed and successfully applied in a BCI speller system with small number of labeled data [16]. A self-training method has also been used to calibrate an offline subject-independent model with unlabeled data from a new user so that a reliable unsupervised BCI speller was achieved for the new user in a short course of adaptation [17].

B. Least Square Support Vector Machine

Another machine learning method known as Least squares Support Vector Machine (LS-SVM) was proposed by Suykens and Vandewalle [18]. This is the least squares versions of support vector machines (SVM), which analyze data and recognize patterns, and is used for classification and regression analysis. Here, one can find the solution by solving a set of linear equations instead of a convex Quadratic Programming (QP) problem for classical SVMs.

In this paper, we present an offline P300 BCI speller system. An overview of the proposed P300 BCI system is shown in Figure 1. An offline analysis is done on BCI Competition III Dataset II, which is based on 64-channel electrode cap on scalp. More information about the dataset can be found in http://www.bbci.de/competition/iii/. Here, the experiment was done using a row-column P300 speller paradigm where the user was presented with a 6 x 6 matrix of characters as shown in Figure 2. Each of the 6 rows and 6 columns was randomly intensified for the spelling of one character, and these were termed as a sequence of intensifications. Then, the subject was asked to focus on the character, which he would spell to elicit P300 potential in the EEG when the row or column containing the character-of-interest was intensified. This sequence of intensifications was repeated 15 times for the input of one character so that data processing methods (*e.g.*, averaging) could be applied for reliable spelling [20]. The dataset was collected from two subjects A and B and each consists of one training (85 characters) and one test (100 characters).

From the studies, we know that the evoked potentials appear around 300 ms after the stimulus, so we propose that if we make our window large, we can capture all required time features for an efficient classification, *i.e.*, to extract all data samples between 0 to 667 ms posterior to the beginning of intensification for each channel. After extracting samples from each channel, these samples were filtered using an 8th order Chebyshev Type I band pass filter with cut-off frequencies 0.1 and 10 Hz [21].

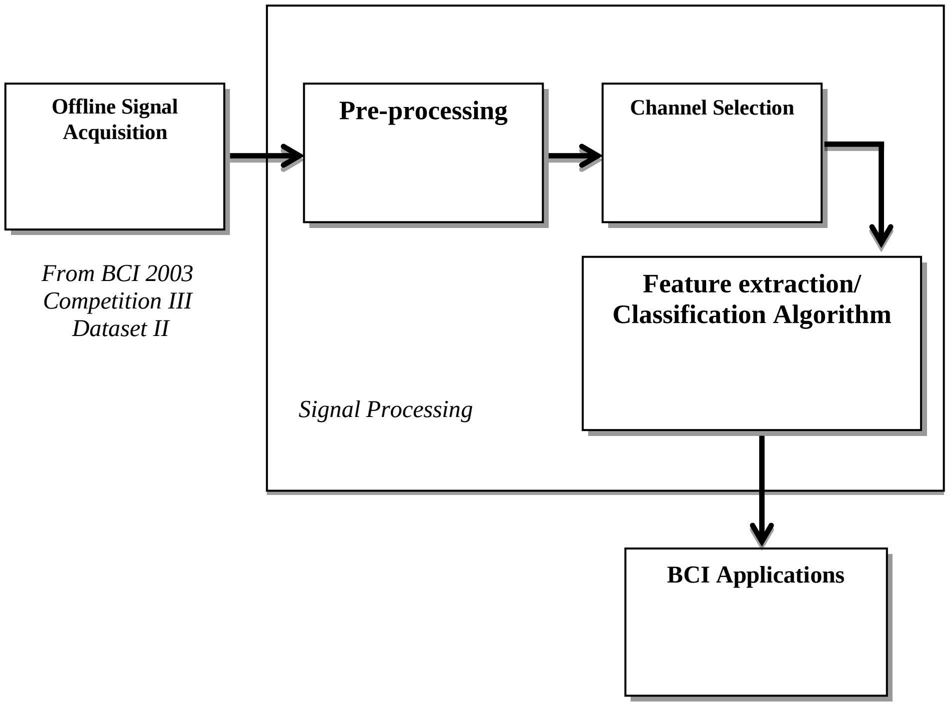

Figure 1. Overview of the Proposed P300 BCI System

Out of the 64 channels of data, only few channels are used in many P300-based BCI systems. For example, only 3 predefined channels were used in [22] and ten of them were used in [23] to build their BCI systems. So, if we want to reduce the number of channels used, the channels should be selected according to the subjects and the mental tasks to be performed. The channel selection algorithms can help us finding the most efficient channels with P300 features among 64 channels. Thus, channel selection helps us to reduce the number of electrodes and also increasing the recognition performance by removing the unwanted channels.

After channel selection we get top ranked 12 channels, then our proposed machine learning algorithm was applied. The algorithm of the system is designed based on LS-SVM and its sequential update to meet the requirement of both performance and complexity. The SVM maps data into a higher dimensional input space and constructs an optimal separating hyperplane in this space. This basically involves solving a quadratic programming problem which is time consuming. The least squares version of SVMs considers equality constraints in least squares sense, resulting in the solution from solving a set of linear equations instead of quadratic programming [18].

A	B	C	D	E	F
G	H	I	J	K	L
M	N	O	P	Q	R
S	T	U	V	W	X
Y	Z	1	2	3	4
5	6	7	8	9	_

Figure 2. A 6 by 6 Speller Matrix

3. Experimental Results

When channel selection algorithm was applied, we observed that there were 4 channels, *i.e.*, Pz, PO7, PO8 and POz that were consistently top ranked for subject A and there were 5 channels, i.e., CPz, PO7, PO8, PO3 and Pz, which were top ranked consistently for subject B. The electrode designations and channel numbers used for this experiment is shown in Figure 3. The proposed LS-SVM algorithm achieves equivalent performance as other nonlinear SVM classifiers, but with lower computational complexity [19]. The algorithm was evaluated using BCI Competition III test dataset and after 5 trials, we achieved a character recognition accuracy of 70% for Subject A and 71% for Subject B.

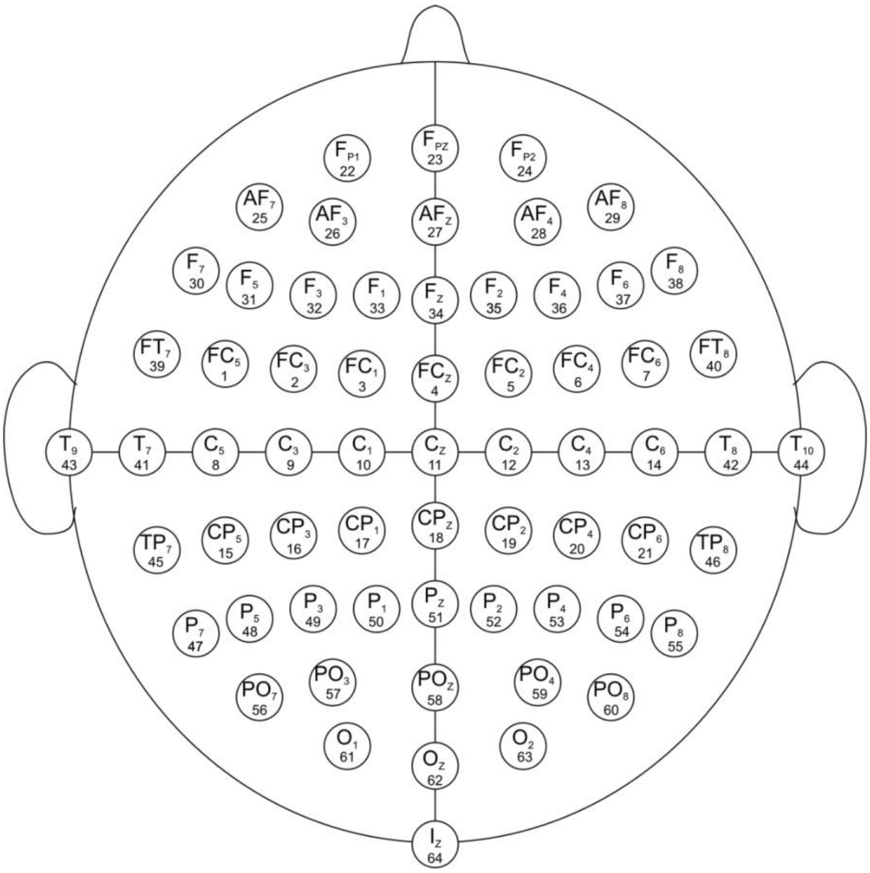

Figure 3. This Figure Shows the Electrode Designations and Channel Assignment Numbers used in the Experiment Provided by BCI Competition III [24]

4. Conclusion

In this paper, we provide an introduction to goals of BCI research and methods, *i.e.*, signal processing and machine learning algorithms. Then, we present our LS-SVM classification algorithm for an offline P300-based BCI. The proposed method has the benefits of low computational complexity and reduced training time. The results show that LS-SVM can provide equivalent performance to that of nonlinear versions of SVM [18] but with a reduced computational cost.

In our experiment, we observed improvements in the character recognition performance as the number of trials increased. This indicates that deep learning in SVM can be achieved with more number of trials. Currently we are planning on extending our research to develop a single trial online P300 response classification method based on Least Square Support vector machine. The ultimate goal is to design a BCI system that is more suitable for real-world applications and clinical use.

5. Helpful Hints

Abbreviations and Acronyms

Here are the list of abbreviations used in this paper are as follows Brain Computer Interface (BCI), Amyotrophic lateral sclerosis (ALS), Electroencephalography (EEG), Event Related Potential (ERP), Step Wise Linear Discriminant Analysis (SWLDA), Linear Discriminant Analysis (LDA), Fisher's discriminant analysis (FDA), Independent Component Analysis (ICA), Support Vector Machine (SVM), Fisher's Linear Discriminant Analysis (FLDA), Linear Discriminant Analysis (LDA), Least squares support vector machines (LS-SVM), and Quadratic Programming (QP).

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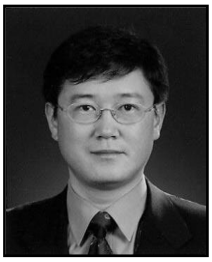

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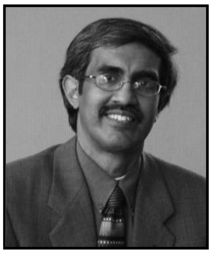

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