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Research Article

Classifying action based on features of higher order statistics from EEG signal in BCI

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Abstract

Within the field of bio-medical, the brain interface is to make and adapt methods of human-computer Interaction. This is Brain– Computer Interfaces (BCI). An assortment of use spaces to think about and approve BCI collaboration, including correspondence, natural control, neural prosthetics and innovative articulation. Electroencephalograph (EEG) signals acts as a communication between men and machines. The BCI-based control framework for robots utilizing the EEG has been recommended for versatile robots and humanoids, and some different machines to control. In this undertaking we do the control interface to decipher. Human goals into proper movement directions for mechanical frameworks. The experimental procedures consist of extraction of EEG signals, optimizing the exact signal and machine control.

Keywords: *Brain–Computer Interfaces (BCI), Electroencephalograph (EEG)*

Introduction

This global estimation is on the rise due to aging population and a rapid spread of chronic diseases. Many of these people suffer from neuromuscular disorders such as amyotrophic lateral sclerosis (ALS), spinal cord injury, brainstem stroke and many other disorders responsible for causing the loss of voluntary muscle control. Such people are often locked in a wheelchair or on a bed unable to move their limbs or go anywhere they would like to go by themselves.

They have to face great barriers in the modern society due to their disabilities and deprivation of common activities like interacting or playing games with other people, activities that are crucial for personal development and have a significant impact on the quality of life. Those with a scarcity of motor skills would benefit enormously from devices which will augment their mobility. Over the last few years, the state of the art technology known as the Brain-Computer Interface (BCI) has become more and more accessible to the wider public and it is our moral responsibility to use such technologies so as to lift these barriers and provides disabled people an opportunity to regain a traditional life.

There has been a lot of work in this direction during the past few years where researchers have tried innovative solutions for developing a user-friendly and easy to use assistive systems for controlling a system. In 2012, Yipeng et al designed a BCI system that was using motor imagery (MI) signals acquired from thinking left, thinking right and thinking push combined with the artifact signals from eye blinking and tooth clenching in order to control an AR system. A different setup was suggested by Byung et al, where a hybrid interface was used.

In their study, the system was controlled by using a low-cost electroencephalogram ic (EEG) headset together with an eye-tracking device. Although the BCI systems presented by previous authors come as affordable solutions for those that want to regulate a system with their minds, an equivalent studies have confirmed that BCI systems supported motor imagery commands are vulnerable to artifacts like inappropriate eye blinking or muscle activity. The novelty of the work presented in this study is in achieving a user-friendly, fully independent multi-class BCI system based on the Steady State Visual Evoked Potential(SSVEP) paradigm that allow users to control a system in 3D physical space only by using their EEG signals. In addition, the system we propose is ready-to-go which means users do not require any previous training or experience in order to actuate the system.

The rest of this paper is organized as follows. Section II summaries the literature survey. Section III introduces the proposed methodology. Design in Section V. Result and discussion in Section IV. Section V focuses on the conclusion.

Literature Survey

In this section, we have discussed different papers referred, based on ECG Signals using various techniques.

In this paper [1] has studied grouping calculations used to configuration Brain-Computer Interfaces (BCI). These calculations were separated into five classifications: direct classifiers, neural systems, nonlinear Bayesian classifiers, closest neighbor classifiers and blends of classifiers. The outcomes they acquired, in a BCI setting, have been broke down and contrasted all together with give the perusers rules to pick or structure a classifier for a BCI framework. More or less, it appears that SVM are especially proficient for synchronous BCI. This presumably is because of their regularization property and their insusceptibility to the scourge of-dimensionality.

S.-A. Chen, C.-H. Chen, J.-W. Lin et al. proposed a wireless EEG and EOG BCI system for detecting eye movements in 9 directions. This system is capable of transmitting EEG and EOG signals wirelessly to a computer, where the signals will be processed and classified. Compared with other eye movement detection methods, no more electrodes are needed in our system to extract EEG signals. For testing the performance of the proposed system, a baseball game was designed. The results demonstrated good classification accuracy with 9 directions. Also, the users can easily play the BCI game and have fun with high accuracy.

[3] Over the past 25 years, and especially in the recent 15 years, many productive BCI research programs have arisen. Because of its relatively low cost, high temporal resolution, and low clinic risk, EEG based BCIs are probably the best choice for a practical BCI. So far, many EEG-based prototypes have been demonstrated in laboratories such as: cursor control, visual keyboards, and mind controlled wheelchairs and prosthetics. These new innovations in neuroscience will be a milestone in human history. While we have only made a baby step into the world of biomechatronics, through this field we can slowly enter a world where there are no longer physically handicapped people other than the most severely brain damaged. At the same time, the possibilities for use for augmentation of our abilities are also endless, as the barrier between our minds and our computers is weakened and finally broken.

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In another work Bell CJ1, Shenoy P, Chalodhorn R *et al.* [5] Controlling a cursor and spelling a word, however it has been viewed as a far-fetched possibility for increasingly complex types of control attributable to its low motion toward clamor proportion. Here they show that by utilizing progresses in apply autonomy, an interface dependent on EEG can be utilized to order an in part self-ruling humanoid robot to perform complex errands, for example, strolling to explicit areas and getting wanted articles. Visual criticism from the robot's cameras permits the client to choose subjective articles in the earth forget and transport to picked areas. Results from an examination including nine clients show that a direction for the robot can be chosen from four potential decisions in 5 s with 95% precision.

In [6] Brain-computer interface combining eye saccade two electrode EEG signals and voice cues to improve the maneuverability of wheelchair. A two electrode EEG system combining eye movement classification and a voice-menu. Eye movements are used to access a voice menu giving voice cues, which is proposed used in a system to control several things such as wheelchairs, TV, smart lights and smart doors. There are in total four classes: Looking straight, looking to the right, looking to the left and blinking. Feature extraction is done with a method called Independent Component Analysis (ICA), while classification is performed with two machine learning algorithms: Support Vector Machine (SVM) and K-Nearest Neighbors (KNN).

In this paper [7] author presents a low-complexity eyeclassification scheme using a self-made algorithm instead of machine learning. The directions classified are rightglancing, left-glancing, up-glancing and down-glancing. The electrode placements used are F7 and F8 for right and left glances, while AF3 and AF4 are used for up and down glances. A low complexity Extended Moving Difference filter is used as edge detection, with Pulse Width Modulation (PWM) and demodulation used to differentiate between the movements and blinks.

Here [8] author presents a way to classify the up, left, right and down by using 19 channels. Normalization is performed to remove the DC offset present in the electrodes, and Fast Fourier Transform (FFT) is used on the normalized signal to exclude frequencies outside the 0 – 42 Hz range. A total of 78 features are presented based on four different properties.

In this[9] author presents a system using an Auto Regression (AR) model with a neural network to distinguish looking straight ahead, blinking, looking to the left and right. Data was recorded through 3 channels (Fp1, F7, F8) and an AR model of second order was used where two coefficients were calculated for each channel resulting in a total of 6 features.

This paper [10] created a GUI solution with a moving ball to instruct the test subjects. Electrode placements are F7 and F8 and the recorded signal is then filtered with a band pass filter from 0.5 to 100 Hz using an 8th order
Butterworth filter and a 4th order notch filter with stop band from 48 to 52 Hz. Feature extraction is performed by wavelet transform and classification is done with a selfdesigned algorithm with six classes. The classes were up, down, left, right, straight, and blink. They achieved an online average accuracy of 85percent.

Proposed Methodology

A] Architecture of Proposed Scheme

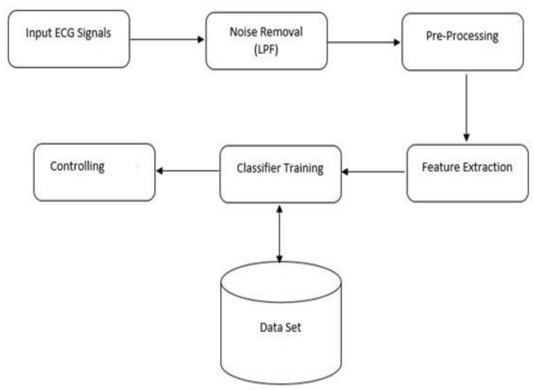

Fig. 3.1 Proposed Scheme

Stage 1: EEG signals contain increasingly significant data about mind issue and various kinds of relics. Signals as dataset are as of now stacked to the apparatus so we will utilize that signs to plot the information and representation of the time-recurrence space plots which can be shown all together.

Stage 2: Basically we will screen the EEG signals as indicated by the arrangement of anodes which is called montages. After that we will watch the EEG signs to perceive and dispense with various illness related antiquities. At that point undesirable sign will be subtracted by differential enhancer.

Stage 3: Finally we will continue for the sign separating dependent on the various sorts of brainwave frequencies to finding and mimic assortment of mind issue by utilizing Python.

B] Algorithm

Step 1:- Plotting the Point in N Dimensional Space
Step 2: - Point Segregation
Step 3:- Hyperplane Possibility
Step 4:- Hyperplane with maximum margin
Step 5:- Multi Dimensional Space in SVM
Step 6:- Prediction

Examples of SVM boundaries
Selecting best hyperplane for our classification. We will show data from 2 classes. The classes represented by triangle and circle.

1. Case 1:
In the case of Fig 2, were the data is from 2 different classes. Now, we wish to seek out the simplest hyperplane which may separate the 2 classes. Please check Fig 1. On the right to find which hyperplane best suit this use case. In
SVM, we attempt to maximize the space between hyperplane & nearest datum . This is known as margin. Since 1st decision boundary is maximizing the space between classes on left and right. So, our maximum margin hyperplane will be “1st “.

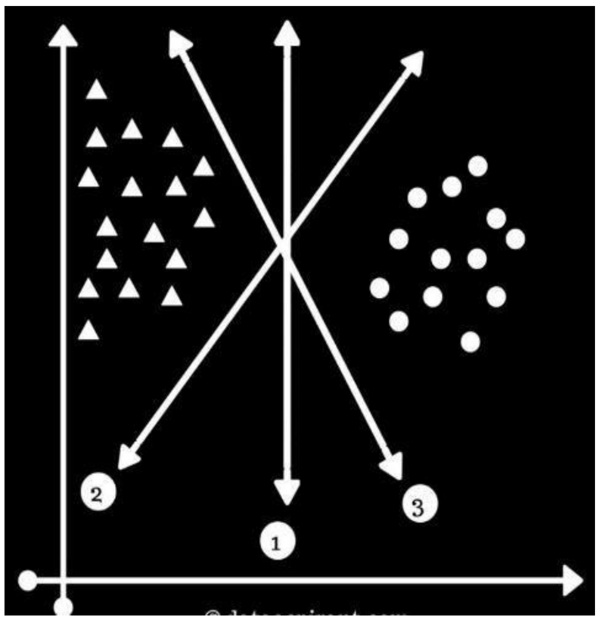

Fig 2: Case 1

Case 2:
Consider the case in Fig 2, with data from 2 different classes. Now, we wish to seek out the simplest hyperplane which may separate the 2 classes.
As data of each class is distributed either on left or right. Our motive is to pick hyperplane which may separate the classes with maximum margin.
In this case, all the decision boundaries are separating classes but only 1st decision boundary is showing

maximummargin between Δ & ○..

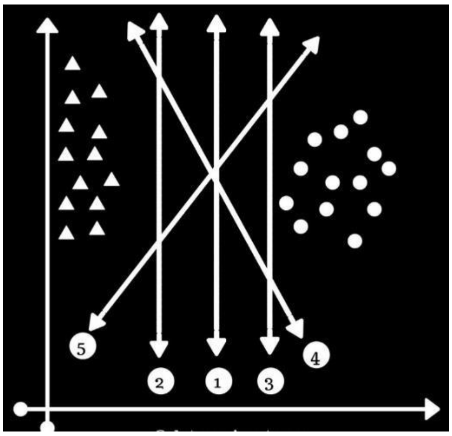

Fig 3: Case 2

Case 3:

In the case of Fig 3, with data from 2 different classes. Now, we wish to seek out the simplest hyperplane which may separate the 2 classes. Data isn't evenly distributed on left and right. Some of the ○ are on right too. You may feel we will ignore the 2 data points above 3rd hyperplane but that might be incorrect. SVM tries to seek out maximum margin hyperplane but gives first priority to correct classification.
1st decision boundary is separating some Δ from ○ but not all. It's not even showing good margin. 2nd decision boundary is separating the data points similar to 1st boundary but here margin between boundary and data points is larger than the previous case.
3rd decision boundary is separating all Δ from all ○ classes.
So, SVM will select 3rd hyperplane.

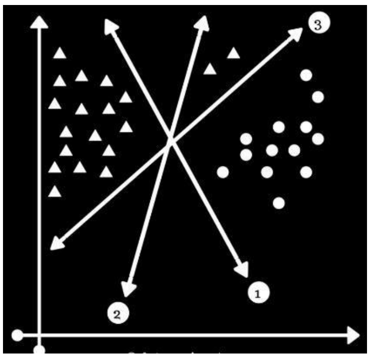

Fig 4: Case 3

Case 4:

Consider the figure 4, we will learn about outliers in SVM. We wish to seek out the simplest hyperplane which may separate the 2 classes. Data isn't evenly distributed on left and right. Some of the are Δ on right too. In the real world, you may find few values that correspond to extreme cases i.e., exceptions. These exceptions are known as Outliers. SVM have the potential to detect and ignore outliers. In the image, 2 Δ 's are in between the group of ○. These Δ 's are outliers. While selecting hyperplane, SVM will automatically ignore these Δ 's and select bestperforming hyperplane.1st & 2nd decision boundaries are separating classes but 1st decision boundary shows maximum margin in between boundary and support vectors.

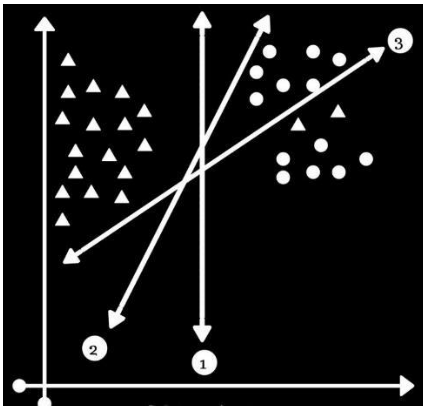

Fig 5: Case 4

Case 5:
We will learn about non-linear classifiers. Please check the figure 5 on right. It's showing that data can't be separated by any line , i.e, data isn't linearly separable. SVM possess the option of using Non-Linear classifier. We can use different types of kernels like Radial Basis Function Kernel, Polynomial kernel etc. We have shown a decision boundary separating both the classes. This decision boundary resembles a parabola.

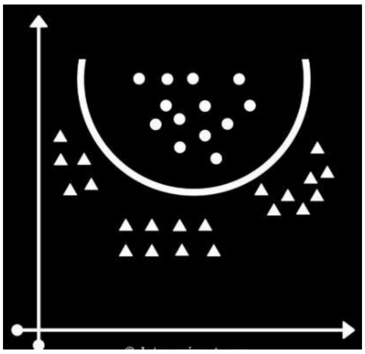

Fig 6: Case 5

Result And Discussions

We had performed first experiment without extracting features. We also tested number of different combination from dataset. In next experiment we performed feature extraction and pre-processing on dataset. The feature were selected from signal x[n] by using proposed technique by SVM algorithm. All features were selected giving total of 25 features were trained and tested.
While comparing both the training and testing it was observed that sometime there are miss-predictions for up, down and blink. Overall performance the accuracy achieved was 94.1%, Precision of 94.16% and recall of 94.33%. Below is the mentioned Confusion Matrix

Blink	0.98	0	0	0	8	10
Down	0	0.91	0	0	0	0
Left	0	0	0.99	0	12	0
Straight	1	0	2	0.95	0	3
Right	0	0	0	0	0.94	3
Up	0	0	0	0	0	0.89
	Blink	Down	Left	Straight	Right	Up

Fig: -Confusion Matrix

An ideal model for this test case would have 32 true positives for Blink, 128 for straight, 34 for Left, 34 for Right and 30 for the Up class.

Table 1:- Classification Report

Class	Precision	Recall	F1score	Support
Blink	0.94	0.98	0.98	32
Down	0.98	0.91	0.89	35
Left	0.94	0.99	0.96	34
Straight	1	0.95	0.98	128
Right	0.96	0.94	0.97	34
Up	0.92	0.89	0.91	30
avg/Total	0.94	0.94	0.94	293

Conclusion

Brain actuated System control system which can serve as a platform to investigate a relationship between complex unmanned robot behaviors and human mental activities. This is the novel idea of controlling robots by mapping asynchronously high-level mental commands into a finite state automaton. This automaton is a key feature for the efficient control of the mobile robot. This type of new research lines are very promising in order to resolve the different open problems which are not satisfactorily solved with current techniques.

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