ITERATIVE OPTIMIZATION TECHNIQUE FOR ROBUST CHANNEL SELECTION

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Abstract

Abstract—Brain Controlled Interface is a hardware and a software device which is used to capture the signals generated from brain and perform analysis on those signals to understand which brain signal is related to which activity performed. It helps in understanding the cerebral activities of a human brain. Using Electroencephalography(EEG) as a Neuroimaging method, we acquire signal and perform preprocessing and feature extraction to study brain activities. Common Spatial Patterns is used to perform feature extraction. In this paper, we have analyzed the performance of different Classification algorithms on IRIS dataset and later have worked on BCI COMPETITION III, IVa dataset to analyze and understand the BCI signals and perform an iterative algorithm for robust channel selection in Motor Imagery.

Index Terms—Brain Computing Interface, Channel Selection, Common Spatial Patterns.

1. Introduction

Brain Controlled Interface(BCI) is a hardware and a software device which is used to capture the signals generated from brain and perform analysis on those signals to understand which brain signal is related to which activity performed. It helps in understanding the cerebral activities of a human brain. BCI is mainly used to help people who are suffering from disease where their muscle movements are not possible. BCI can be used to communicate what the people's intentions are using the brain signals generated. A set of conventional steps such as signal acquisition, preprocessing, feature extraction, classification and control interface is performed to analyze the signals.

- In signal acquisition stage, the signals are captured and also lowering of noise signals is done.
- In preprocessing stage, the signal received from signal acquisition stage is converted into a form such that it can be used in further processing.
- In feature extraction stage, we apply certain algorithms to reduce the dimensions of the dataset present, so that the computation becomes efficient without losing the accuracy of the classification.
- In classification stage, we classify the given dataset along with its features into separate classes. This helps in communicating people's intentions with the help of brain signals alone.

There are two types of signals generated by brain, which can be monitored using BCI.

1. Electrophysiological : It is generated by electro- chemical transmitters exchanging information between the neurons.
2. Hemodynamic : This activity is analyzed with the level of glucose released by neurons.

Types of Neuroimaging Methods used to implement Brain Computing Interface:

:

1. Electroencephalography(EEG)
2. *Electrocorticography (ECoG)*
3. Magnetoencephalography
4. Intracortical Neuron Recording
5. Functional Magnetic Resonance Imaging (fMRI)
6. Near Infrared Spectroscopy (NIRS).

In this paper, we are primarily focusing on channel selection algorithm which is used to select ten best channels given any number of channels as input. The channel selection is basically done by assigning weights to each of the channels and selecting the best channels with maximum weights. Weights calculated is a factor of the distance from the reference weight and the power spectral density of each channels.

2. Implementation:

Iterative Optimization technique for robust Channel Selection Algorithm:

In this section, we have performed an iterative algorithm to optimize the number of channels used to classify the given data. Here, the dataset consists of 2984598x118 number of data, where 2984598 represent the signal value at each time period and 118 represents the number of channels present. Hence, using all the channels to classify will give good accuracy but increases a lot of time for computation which is not feasible for real time application of BCI. Hence, in this algorithm we try to reduce the number of channels used making sure that the accuracy doesn’t reduce. The signals generated for the visual stimulus performed for the dataset given, can all be captured in the sensorimotor cortex region. Hence, we can focus on selecting the channels around this region which can given the same accuracy as by selecting all the channels with much less computation time.At first, we have to select a reference channel, where we know that the signals required are generated. After that, we assign weights to each and every channel depending on the power values it generates. After assigning weights to each channel, we select the 10 best channels depending on its weights. Once, we are done with selecting channels, we apply CSP to select the best features to reduce the number of unrelated features. CSP is applied to 9 different frequency band signals of the input signal. Hence, this gives 18 features, considering 2 features selected from each frequency band signal. After selecting the features, we apply Support vector machine to classify the given data into required classes.

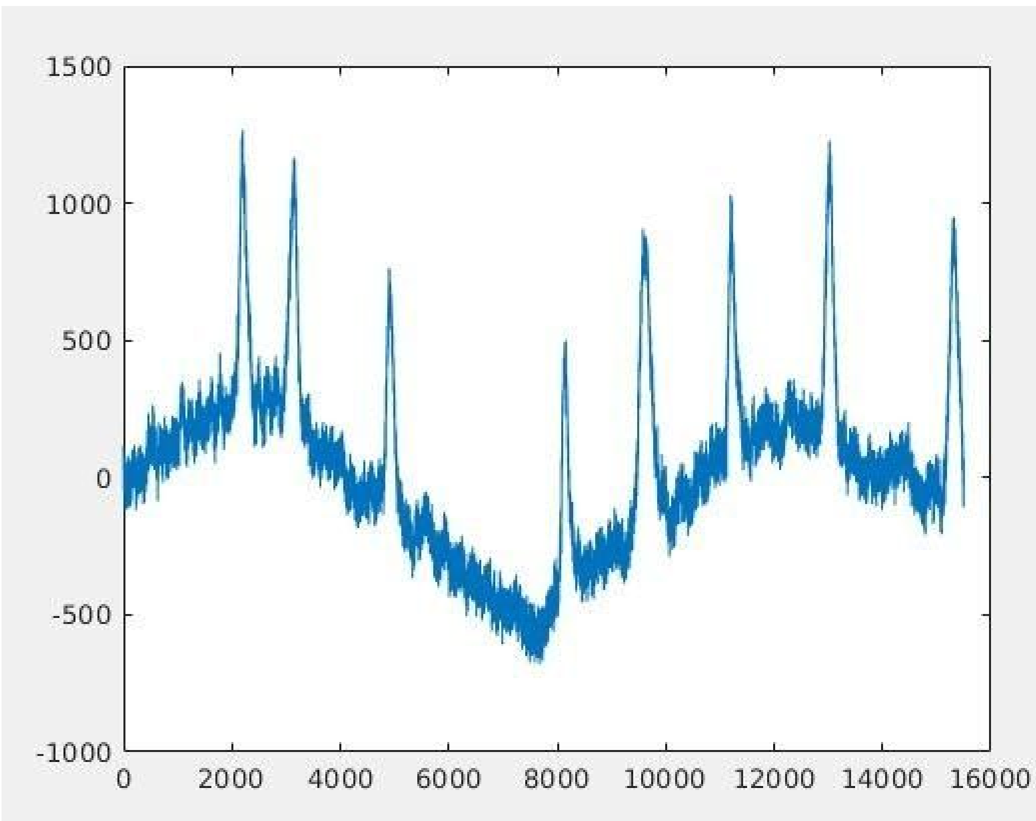

Figure 1

Figure 1 shows the EEG signal value of channel 3 for trial 10. x axis shows the time value in milliseconds and y axis shows the intensity of the signal.

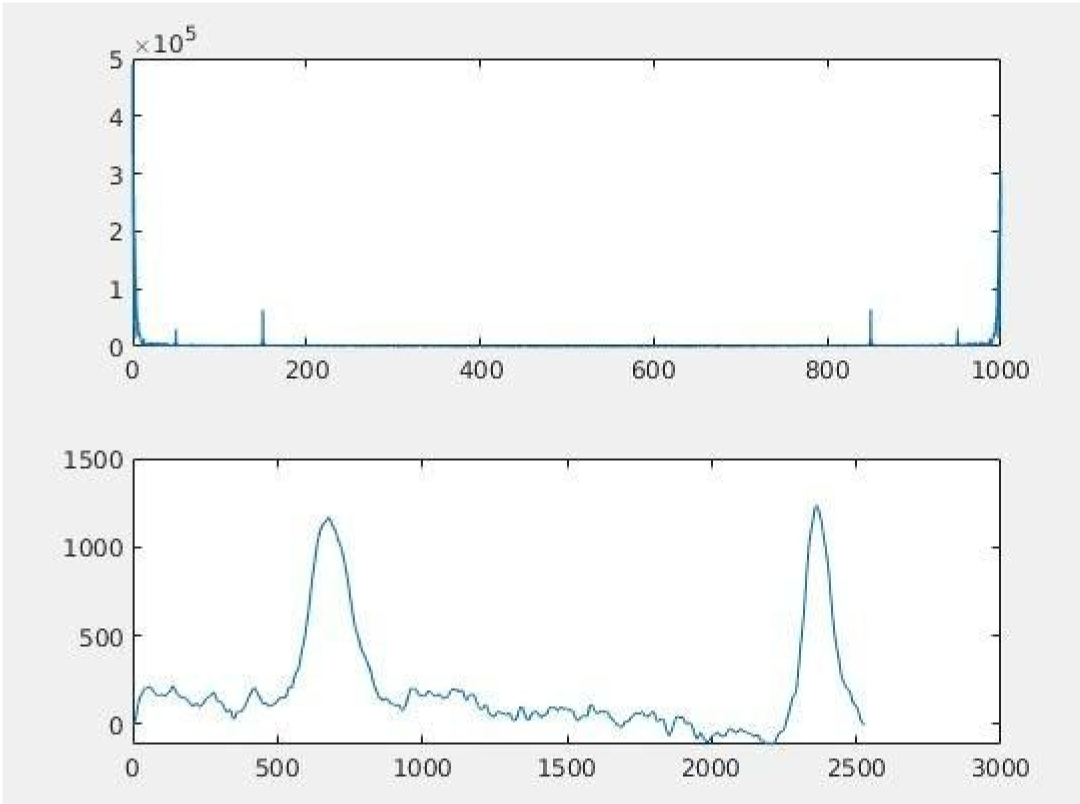

Figure 2

Figure 2 shows the Channel 5's trail 64 signal value. The first subplot shows the frequencies of the signal present in subplot 2. We can clearly see that the subplot 2 signal is made of frequency 50Hz and 150Hz.

The weights of each channels with respect to the reference channel is calculated using the following steps:

- $\phi(r, c) = \phi(r - c)$, where r is the reference channel and c is the set of channels whose weights has to be calculated. We calculate this until φ (| r − c |) < ρ , where ρ is the kernel radius.
- The weight μ_k is proportional to $\frac{1}{\phi(r,c)}$ for each channel c_k.
- For every round i, iteratively update μ_k by $\mu_{i+1}^{(k)} = \mu_i^{(k)} + \phi_i^{(k)}$.

$$\phi_i^{(k)} = \frac{\mu_i^{(k)}\beta_i^{(k)} - argmin(\mu_i)_{forall\ K} \cdot argmin(\beta_i)}{argmax(\mu_i)\ .\ argmax(\beta_i)}$$

$\beta_i^{(k)} = \frac{(P_{0.5-2s} - P_{2-2.5s})}{P_{0.5-2.5s}} * 100$

$P_{xx}(e^{jw}) = \frac{1}{N}\left|\Sigma_{n=0}^{N-1} w_R[n]x[n]e^{-j\omega n}\right|^2$, where $w_R[n]$ = 0.54 + 0.46 $cos(\frac{2\Pi n}{N-1})$

- Once all the rounds are over, select the best ten channels in terms of their weights.
- Apply CSP, to select the best features required.

  The CSP is calculated from the following steps:

  - Calculate Normalized spatial Covariance for each trial

    $R_h = \frac{X_H X_H^T}{trace(X_H X_H^T)}$ $\quad$ $R_F = \frac{X_F X_F^T}{trace(X_F X_F^T)}$

    $X_F = Data\ of\ Right\ Foot$

    $X_H = Data\ of\ Right\ Hand$

- Average of R_h and R_f is calculated over all the trials, given by $\overline{R_h}\ and\ \overline{R_f}$.
- R = $\overline{R_h} + \overline{R_f}$ = $U_o \Sigma U_o^T$,

  $U_o = Eigen\ vector\ matrix\ and\ \Sigma = Diagonal\ matrix\ of\ eigenvalues.$

- Calculate the whitening transform given by P.

  P = $\Sigma^{-\frac{1}{2}} U^T$

- Average covariance matrix can be written as

  $S_H = P\overline{R_h}P^T$ and $S_F = P\overline{R_f}P^T$

  $S_H = U\Sigma_H U^T$ and $S_F = U\Sigma_F U^T$, $\Sigma_H + \Sigma_F = I$

- The projection matrix can be written as W = $U^T P$.
- Using projection matrix, we can obtain the original EEG data by the equation Z = WX.
- The columns of W^{-1} gives the spatial patterns which can be used to select the relevant features which gives maximum variance between two classes and minimum variance within a single class.

3. Results

The implementation of the above algorithm gave an ordinary result with highest accuracy of 63.39 with 53rd channel as the reference channel.

```
Algorithm for Reference Channel 50 is running
Accuracy given by reference channel 50 is 46.428571
Algorithm for Reference Channel 51 is running
Accuracy given by reference channel 51 is 41.964286
Algorithm for Reference Channel 52 is running
Accuracy given by reference channel 52 is 51.785714
Algorithm for Reference Channel 53 is running
Accuracy given by reference channel 53 is 63.392857
Algorithm for Reference Channel 54 is running
Accuracy given by reference channel 54 is 50.000000
Algorithm for Reference Channel 55 is running
Accuracy given by reference channel 55 is 46.428571
Algorithm for Reference Channel 56 is running
Accuracy given by reference channel 56 is 46.428571
Algorithm for Reference Channel 57 is running
Accuracy given by reference channel 57 is 46.428571
Algorithm for Reference Channel 58 is running
Accuracy given by reference channel 58 is 47.321429
Algorithm for Reference Channel 59 is running
Accuracy given by reference channel 59 is 46.428571
Algorithm for Reference Channel 60 is running
Accuracy given by reference channel 60 is 46.428571
```

Figure 3

Below is the table showing the results obtained for different algorithms.

Proposed Method	Implementation of Proposed Method	SCSP1	SCSP2	FBCSP
90.68	63.39	93.97	80.71	71.42

By taking all the channels and applying CSP for 9 different frequency bands and then applying the classification algorithm, we get an accuracy of 46.42%.

3. Future Work

The above mentioned algorithm is mainly for the selection of best channels. For further works on channel selection algorithm, we can apply genetic algorithm to obtain the best possible channels. The other method which can be applied to select the best possible channels can be particle swarm optimization method, which can be used to randomly select the channels and figure out the best possible channels.

4. Conclusion

Brain Computing Interface in one of the emerging techniques used to make the life of the people who has a problem of muscle movements, easier by interpreting their brain signals and making them communicate with their surroundings. Hence, receiving brain signals, analyzing and performing classification has to be more efficient so that it can be used in real time applications. Hence, channel selection algorithm is very much necessary in reducing the time complexity without the decrease of accuracy.

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