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Classification of EEG Based Motor Imagery Using Common Basyesian Network

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ABSTRACT

Learning of brain activity patterns represents a big challenge to the brain computer interface(((BCI),It is used for communicating people with devices, but in this project we are using software generated signal. To classify multiclass motor imagerary (MI) for the uncorrelated instantaneous demixing of EEG signals various existing method estimated .The brain regions work with partial or complete collaboration because of this the condition of uncorrelation does not hold true value in practice. The novel method is proposed by the work is termed as Common Bayesian Network (CBN), for discriminate multiclass MI EEG signals. First, For construct a normal Bayesian Network only related channels are selected with constraints of Gaussian mixture model on every channels. Second, In the second stage only common varying edges from various nodes to construct a CB. Third, in third and last stage, to learn about support vector machine for classification various probability on common edges are used To validate the proposed method, we used software generated EEG signal, we perform experiments on it and apply CBN and SVM for MI classification. After getting Experimental results we can easily say that the proposed CBN method has excellent classification performance ,and is highly efficient. Hence, its suitable for the areas where a system is required to respond quickly .

Key Words: EEG Signal, Common Bayesian Network, Gaussian Mixture Network, Motor Imagery, Support Vector Machine.

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I. INTRODUCTION

Brain computer interfaces (BCI) is used in real time application, which enables people to communicate with electronic devices by measuring electric or magnetic signals generated by human brain nervous system through electroencephalography (EEG). EEG signals are changes according to imaging of different types of body movement, such as thinking about left arm, right arm, tongue, and left, right legs etc. For analyzing MI EEG signals, various methods are used for classification of MI classes, e.g. imagery movements of left and right hand. Many useful different methods have been proposed. Common Bayesian Network (BCI) is used for classification MI tasks and also improve the robustness and accuracy of signals. A support vector machine (SVM) is also used to give high quality results of classification. Discrimination algorithm is divided into three categories: The first one is based on Gaussian Mixture Network in which we find various features of signal. The one is based on Common Bayesian Network by using GMM we construct Common Bayesian Network, in CBN we finds common and varying edges and node probabilities and centroid points and plot GMM features CBN model, The Third step is feature extraction in which we used support Vector Machine for MI class classification. We extract all features and classify it using SVM.

II. METHODOLOGY

2.1 Common Bayesian Network (CBN)

After normal BN construction is finished, the next step is to construct CBN. Its major function is to classify multiclass of MI. Thus, the feature extraction from BN should have two properties, One is enough discriminated information for different kinds of MI to guarantee the performance ; The other is a stable position to make the calculation possible.

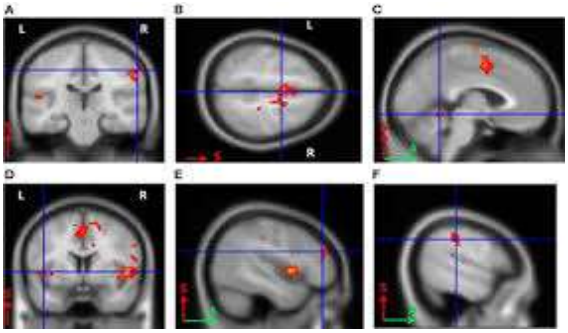

Fig -1: Scanning Brain Signal To Form CBN

In fact, because of extremely low SNR of EEG signal, the structure of learned BN changes from time to time , even for the same MI task. In order to obtain the unique structure and performance robust CBN from various learned BNs, all edges and nodes are evaluated by using the following concepts to help select its appropriate nodes and edges. The CBN here is used for finding the common probabilities at a given node for different MI task. If the common probability is observed for the same MI task at node considered, it helps to identify that MI when the probabilities is observed. Hence the class of MI can be defined by discriminating some other features of same signal.

2.1.1 Edges Common Rate and Common Edge

First, we define the common property of edges. It is known that the feature extracted in most recognition task must show the common property for one MI class. Ideally, different MI classes feature should have totally different common properties. Because of the noise in the EEG signals, the BN structure learned from the same MI task is sometime different. In conclusion, considering that an edge itself in a BN is a structural feature, its common property is very important for MI classification. Such a property also describes the generality of that edge. In this paper, the number of times that edge Ek (i, j) appear in the same MI task is considered in evaluating the edge common character, We define,

$$Ek = \begin{cases} 0, & \text{if } (i,j) \in / Ek \\ 1, & \text{if } (i,j) \in / Ek \end{cases} \quad \text{.....(1)}$$

Inorder to describe the common characteristics, a common rate is defined as

$$Cr(i,j) = \sum_{k=1}^{N} (E_k\ (\cos(i,j) + E_k(i,j))/2N \quad \text{.....(2)}$$

Where N is the total no. of MI runs and E_k is the edge set of the BN G_k.We can see from equation that Cr (i, j) can be viewed as the probability of an edge from i to j. In order to evaluate the stable property of the selected edge, we can define an edge as a common one if Cr(i, j)=1.

2.1.2 Node variation rate and key node

In every MI task, EEG signals are collected through EEG channels from different brain areas. According to BN definition, its node characteristics shows the information of the corresponding brain area. For a BN Gi, in order to calculate node characteristic easily, we first give every node a value. Given the i'th run and j'th node, let

$$Wi = (wi1, wi2, \ldots\ldots, wiN) \quad \text{.....(3)}$$

$$\text{With} \quad wij = \begin{cases} 0, & \text{if no edge on node j is in Gi} \\ 1, & \text{if node j is a parent in Gi} \\ -1, & \text{if node j is a son in Gi} \end{cases}$$

Every node has a value *w*i on the i'th run.

Thus, it is used to evaluate the node distribution across different MI tasks.
Therefore, every node has P interclass distances and P x P interclass distances. We define the node variation rate by using the ratio of α and β as follow:

$$F = \sum_{i=1}^{Ni} \propto_j \sum\!\!\!/ (i = 1)\hat{}Ni \sum_{j=1}^{P} \beta_{ij} \quad \text{.....(4)}$$

The CBN can be constructed in the following four steps :

a) BN is constructed via the classic method

b) ll edges are analyzed in equation (1) and (2) and common edges are extracted via (2).

c) ll nodes are analyzed via (1) – (4) and key nodes are extracted via (4)

d) CBN is constructed based on key nodes and common edges.

CBN is clearly a sub-graph of the original BN based on the discrimination features which are extracted to classify different MI.

III.Feature Extraction

According to the definition of BN (G;P), condition density P is an important feature for CBN. It indicates the statistical relationship among node. Because the working mode of our brain is the same when motor imaging, it is true that all MI tasks share more than one activated brain area and the major difference among them is the activation amplitude.

Therefore, the final feature vector used is P=(*p*1, *p*2, ... , *p*M) with *p*i being conditional probability of common edge in CBN. An SVM method is used to classify MI classes based on P.

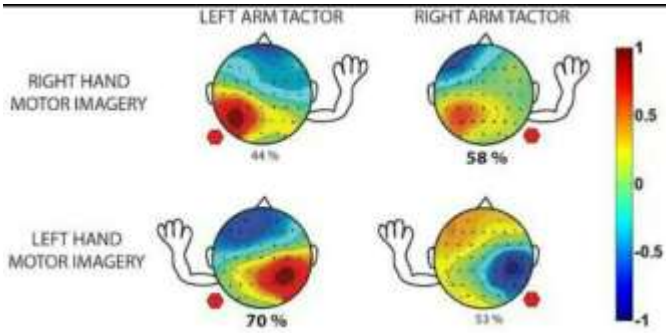

Fig -2: Motor Imagery for Right hand and Left hand

The signal is consisting of various frequencies. In our project implementation, we have considered three frequencies. Different parameters of these frequencies are evaluated here. For evaluating band power and other such parameter, we have to consider the band arround the frequency considered. The frequency band considered here is of 20 Hz. We have done feature extraction by considering different parameters of frequency. In this case we have extracted the features like mean of evaluated signal, median, peak to peak, rms, variance etc.

IV. SUPPORT VECTOR MACHINE (SVM)

4.1 Separating Hyper-Planes:

SVM has successful applications in many complexes, real-world problems such as text and image classification, hand-writing recognition, data mining, bio-informatics, medicine and bio sequence analysis and even stock market! In many of these application SVM is the best choice.

There is the probabilities for Hyper-Planes these are as fallows

4.2 Separating Hyper-Planes

It is depend on which one should we choose but most probably choose the hyper line which is place equal from test and template features.

4.3 Choosing A separating Hyper-Planes

Suppose we have Hyper-Plane that is close to sample. Now suppose we have a new point that should be in class-1 and is choose to. Using our classification function this point is misclassified.

Hyper-Plane should be as for as possible from any sample is point .This way a new data that is close to the old samples will be classified correctly.

4.4 Selection of Hyper-Plane

The SVM idea is to maximize the distance between the Hyper-Plane and the closest same point. In the optical Hyper-Plane. The distance to the closest negative point = The distance to the closest positive point.

SVM goal is to maximize the margin which is twice of the distance ‘d’ between the separating Hyper-plane and the closest sample. It is Robust to outliners as we saw and thus strong generalization ability.

4.5 Properties of SVM

1) Flexibility in choosing a similarity function.
2) Sparseness of solution when dealing with large dataset.
3) Only support vector are used to specify the separating-hyper plane.
4) Complexity does not depend on the dimensions of the feature space.
5) Feature selection.

V. RESULT

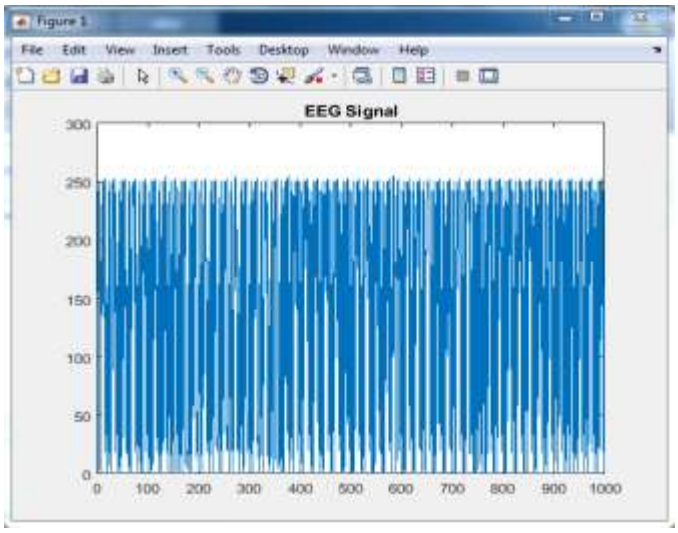

Fig -3: Input signal

In our project we have the input of different EEG signals which are to be classified into the class which it belongs to. Here EEG signal is a software generated signal which is similar in nature as that the signal received from scalp. The EEG signal is first read and displayed at it is. One of the EEG signals from the input database is shown above :

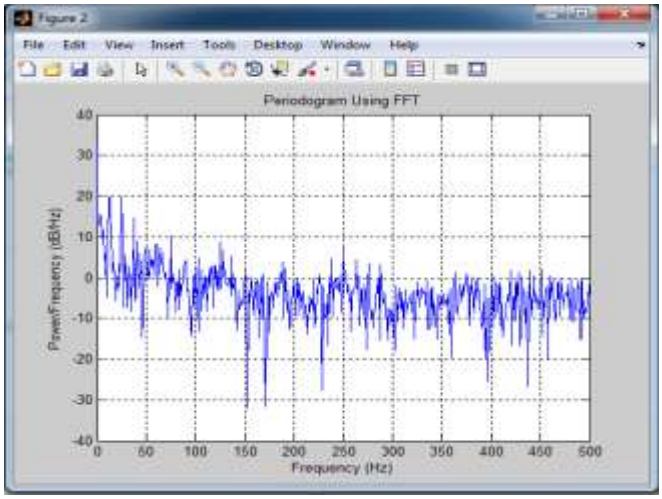

Fig -4: Periodogram

Periodogram is the graphical representation of Power Spectral Density. The power calculated for the frequency components is represented on Y-axis and

frequency on X-axis For obtaining the Periodogram, we have to apply Fast Fourier Transform. The Fast Fourier Transform used here to find out the particular frequencies components. These frequency components along with the power are represented in the Periodogram.

Final Output

After calculation of CBN, we apply conditions to obtain the class of the signal. Different considerations can be made to identify whether it is left motor imagery or right motor imagery. Say if we classifying the signal into ten classes, then first five class can be considered as left motor imagery and remaining five as right Motor Imagery. Here if it is giving output as class one, means it's left MI.

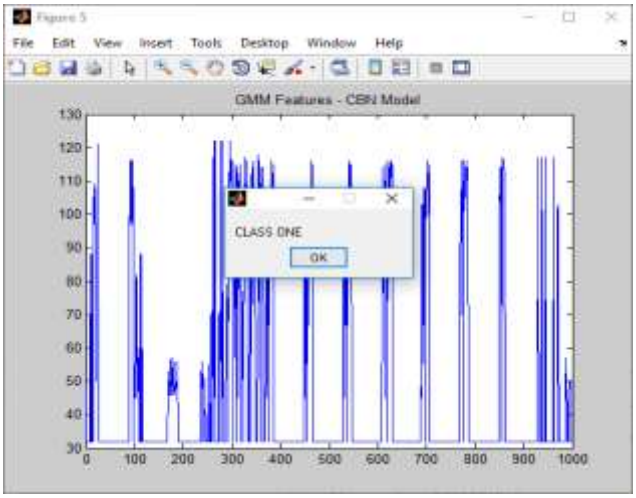

Fig -5: Output class for given EEG input

For multiple inputs, the signal class will be define for each input. In our case, EEG signal is software generated, so its class remains same for multiple iterations. But the output may change in case, if the signal is collected from brain using hardware .It may require trial and error method and filters to be applied as it will be contaminated with too much noise resulting in low SNR.

VI. CONCLUSION

A novel method called CBN is proposed to Analyze multiclass MI BCI EEG data. In order to make, BN more suitable for classifying multiclass BCI tasks, two constraints are used during channel selection and BN structure learning. Furthermore, a two component GMM model is used to calculate the node's probability density that makes it more accurate comp[are to single Gaussian channel. Considering the fact that the constructed BNs have variations because of the noise in EEG signal and the instability of EEG signal, we have proposed the concept of common edges which are extracted after evaluating all nodes and edges from these variants. Because, the proposed CBN, it needs enough data to learn accurate conditional probability during structure learning. Thus, in practical application, it is necessary to spend time to collect training data, which would make subject tired.

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