Classification of Brain States Using Principal Components Analysis of Cortical EEG Synchronization and HMM

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Abstract— **The state of brain and its rapid transition from one state to the other is responsible for various activities and cognitive functions. These brain states are the result of balanced coordination between integrating and segregating activities of different lobes through rhythmic oscillations. Such coordination has been studied in recent times through synchronization of EEG signals generated from different lobes. In this paper, the authors have considered Synchronization Likelihood (SL) to measure the synchronization or integration between the lobes. The synchronization information is stored in SL matrix and the principal components of an SL matrix have been used to represent the state of brain at any instant. Finally, the time series of weight vectors corresponding to the principal components of SL matrices at each time point has been used to classify different states of brain at different stages of a sleep deprived experiment.**

***Keywords-* EEG, Brain State classification, Synchronization Likelihood, HMM, PCA**

I. Introduction

EEG oscillations are basic means of communication between various cortical areas. The nature of oscillations in different frequency bands is related to various tasks and performances. For example, the alpha rhythm is related to memory performance [1]. Moreover, different types of synchronization between two or more areas of brain have been observed during different types of activities [2]. For example, a significant higher level of de-synchronization is reported during complex and difficult task than less complex and easy task [1]. During mental activities different neuronal networks start to oscillate at different frequencies, whereas synchronous oscillations of large cell assemblies has been observed during resting state or functional inhibition. It is true for both motor and cognitive types of tasks [1]. From the above facts it is envisaged that a detail study of synchronization of EEG signals from various locations might give an insight into various brain states responsible for different cognitive functions.

Each brain state is a function of corresponding frequency contents of the generated signals. Hence, the nature of synchronization may be different at different frequency bands. It is reported in the literature that the alpha band is more sensitive to the variation of consciousness or alertness of human subjects [1], [3]. For this reason, the authors have considered alpha band for classification of level of fatigue and sleepiness in this work. The alpha band signal has been extracted from the original signal using discrete wavelet transform (DWT) [4].

Various techniques have been suggested in the literature to find the interaction between signals from different electrodes such as correlation [5], phase synchronization [6], synchronization likelihood [7, 8] etc. The functional relationship between two sections of human brain has been established to be non-linear by nature. Therefore, linear measures like correlation or coherence may not be adequate for characterizing the interdependency between different areas of human brain. Phase synchronization considers only the distribution of the phase difference between two time series. But it does not consider the amplitude information and is suitable only for oscillatory systems [8]. In this work, the interaction between the different electrodes has been quantified using a nonlinear measure known as Synchronization Likelihood (SL) which has been effectively used in past to study non-stationary signals like EEG [9].

The proposed method (termed as PCSLM) computes the SL between signals from different lobes, finds the principal components of these SL matrices, computes the weight vectors by projecting the SL matrices along each principal component, and classifies the brain states using HMM [10] and the time series of weight vectors as observation sequence. Also, the accuracy in classification of the proposed method has been compared with other observation sequences (actual time series, time series of Autoregressive (AR) parameters, time series of principal components of segmented EEG signals).

The proposed method has been applied for the classification of brain states at various stages of a sleep deprived experiment. It can also be applied for task classification or detection of diseases such as Alzheimer's, Seizure etc.

The paper has been organized as follows:

Section II describes the experimental method and data collection. In section III, the methodology of analysis has been described. Section IV describes the results and discussions.

II. EXPERIMENT

The proposed method has been applied to classify different stages of a sleep deprived experiment. The experiment was conducted on 12 healthy male subjects and continued for 36 hours with sleep deprivation. During the experiment, fatigue has been induced in the subjects through various tasks. The fatigue and sleepiness were increased gradually though it was affected by circadian rhythm at various stages.

A. *Experiment and data collection*

Subjects

Twelve healthy male subjects in the age group of 20-35 years were chosen for the experiment. All the subjects were reported to have no sleep related disorders. Their fitness and health were checked thoroughly by a medical practitioner before the selection as well as during the experiment. The selected subjects were advised to maintain a prescribed routine during 48 hours prior to the experiment. They were restricted against consuming any type of medicine or stimulus like alcohol, tea or coffee during the experiment. The experiment was performed in compliance with the relevant laws and institutional guidelines. The subjects also provided written consent prior to the experiment.

Procedure

The experiment was conducted in four temperature controlled laboratories in two sessions with 6 subjects in each session. The entire experiment was divided into a number of identical stages. Each stage started with condition monitoring of the subjects by a medical practitioner. After the subject was declared fit, he was asked to perform some predefined tasks. These are: physical exercise on a tread mill for 2-5 minutes to generate physical fatigue; simulated driving for about 30 minutes to generate physical, visual, and mental fatigue; auditory and visual tasks for 15 minutes to generate mental and visual fatigue; finally the computerized game related to driving for about 20 minutes. A single stage of experiment lasted for about 3 hours. Between two stages they were allowed to read books or newspapers in order to keep them awake. The subjects were monitored by CCTV camera during the experiment. The stages were continued for 36 hours (12-stages) when most subjects complained of extreme fatigue.

EEG Recording

EEG data were recorded at the beginning of the experiment and at the final phase of each stage. Three sets of EEG were recorded in each stage, i.e. 3 minutes record during the computer game, 2 minutes data after the game with open eyes and no activity condition, and then 2 minutes data with closed eyes and no activity condition. Total nineteen scalp electrodes (Ag/AgCl, RMS, India) were used in addition to reference and ground to collect the signals from locations Fp1, Fp2, F3, F4, F7, F8, Fz, T3, T4, T5, T6, C3, C4, Cz, P3, P4, Pz, O1, and O2 following the international 10–20 system. All these EEG activity were recorded with respect to the forehead as reference. In this study, the 3 minute EEG recording during computer game have been chosen for the proposed analysis.

III. METHODOLOGY

The process involves extraction of alpha band from recorded signal using DWT, computation of SL from alpha band signal, and the classification of the experiment stages using principal components of SL matrices and HMM. The detailed methodology is explained in the following sections.

A. *Signal preprocessing and decomposition using Discrete Wavelet Transform*

The raw EEG was filtered by a band pass FIR filter with cutoff frequencies of 0.5Hz and 30Hz followed by extraction of alpha band using Discrete Wavelet Transform (DWT). The advantage of using DWT is that the non-stationary nature inherent in the signal is preserved [4]. The detail component at level-2 of DWT represents the alpha band (8-15Hz).

B. *Computation of Synchronization Likelihood (SL)*

Step1: Let, $x_{k,i}$ where $k = 1, 2, \ldots\ldots, M_T$ and $i = 1, 2, \ldots., N_T$, represent M_T simultaneously recorded EEG time series of length N_T. From each time series we form a state vector $\mathbf{x}_{k,i}$ which is represented as

$$\mathbf{x}_{k,i} = (x_{k,i}, x_{k,i+l}, x_{k,i+2l}, \ldots\ldots, x_{k,i+(m-1)l}), \quad i = 1, 2, \ldots. N_T - (m-1)l \tag{1}$$

where, l is the lag and m is known as embedding dimension [7], [11]. These vectors form an *m*-dimensional phase space known as lagged phase space. Thus, each vector $\mathbf{x}_{k,i}$ acts as a point in the lagged phase space.

In other words from each EEG record we construct a matrix whose rows span the lagged phase space as:

$$\mathbf{X}_k = \begin{bmatrix} x_{k,1} & x_{k,1+l} & \cdots & x_{k,1+(m-1)l} \\ x_{k,2} & x_{k,2+l} & \cdots & x_{k,2+(m-1)l} \\ \vdots & \vdots & \vdots & \vdots \\ x_{k,N_T-(m-1)l} & x_{k,N_T-(m-1)l+l} & \cdots & x_{k,N_T} \end{bmatrix} \tag{2}$$

Step2: In each time series we define two windows w_1 and w_2 such that $w_1 << w_2 << N_T$. For each time series k and each time instant i, we compute the Euclidean distance between points $\mathbf{x}_{k,i}$ and $\mathbf{x}_{k,j}$, $\frac{w_1}{2} < |i-j| < \frac{w_2}{2}$, in the lagged phase space and the probability $P_{k,i}^{\varepsilon}$ that the distance is less than ε. Now for each k and i we find the critical distance $\varepsilon_{k,i}$ such that the probability $P_{k,i}^{\varepsilon}$ is equal to a pre-specified value p_{ref}.

Step3: For each time series k and each time instant i, we define a vector $\mathbf{Y}_{k,i}$ that contains all the points whose distance from point $\mathbf{x}_{k,i}$ is less than the distance $\varepsilon_{k,i}$ in lagged phase space. Now the Synchronization likelihood between two time series $x_{k1,i}$ and $x_{k2,i}$, ($i = 1, 2, ..., N_T$) at instant i is defined as the ratio of number of common neighbors of two time series at instant i to the total number of points within the specified distance in each time series, i.e.

$$SL_i^{k1,k2} = \frac{\left|(\mathbf{Y}_{k1,i} \cap \mathbf{Y}_{k2,i})\right|}{\left|(\mathbf{Y}_{k1,i})\right|} \tag{3}$$

In this work, the signal was recorded simultaneously from 19 different electrodes ($M_T = 19$). The Synchronization Likelihood at instant i between all the electrodes has been stored in a 19 × 19 symmetric matrix called SL matrix (SLM).

A time series of SLMs has been obtain by shifting the analysis window to form a new state vector $\mathbf{x}_{k,i+s}$ at a distance s . A very small value of s is computationally difficult, and a large value of s may ignore some valuable information. Literature suggests that a window shift (s) less than w_1 may be a good choice [8].

C. *Computation of Principal components of Synchronization Likelihood Matrices*

The principal components of the SLMs are constructed using the Principal Component Analysis (PCA) [12]. The detail methodology of computing principal components is explained here.

Training data and computation of principal eigenvectors

A training dataset is formed by including 50 SLMs from each subject at each stage. Let the training set of SLMs be $\mathbf{\Phi}_i, i = 1, 2, 3, ..., M_S$ each of dimension $M_T \times M_T$ ($M_T = 19$). First, the upper triangular elements of each SLM is converted into a vector $\mathbf{a}_i, i = 1, 2, 3, ..., M_S$ of dimension $L \times 1$ where $L = M_T (M_T - 1)/2$. Thus each SLM can now be considered as a point in L dimensional space. This set of vectors is then subjected to PCA which seeks a set of L orthonormal vectors $\mathbf{u}_i, i = 1, 2, 3, ..., L$ and their associated eigen values $\lambda_i, i = 1, 2, 3, ..., L$ which best describe the distribution of the data. The vectors $\mathbf{u}_i$ and the scalars λ_i are the eigen vectors and eigen values of the covariance matrix $\mathbf{C} = E\left(\mathbf{a}\mathbf{a}^T\right)$. From these eigenvectors, k principal eigenvectors have been selected. This completes the Training part of the algorithm. These principal eigenvectors form a new space known as SL space.

Computation of weights

The input SLM $\mathbf{\Phi}_t$ is then converted into vector $\mathbf{a}_t$ of dimension $L \times 1$ and is projected on to the SL space to find the weights $w_i = \mathbf{u}_i^T \mathbf{a}_t,\ i = 1 : k$. The weights form a weight vector $\boldsymbol{\omega} = [w_1\ w_2\ ....\ w_k]$ which describes the component of input SLM along each principal direction.

The time series of weight vectors obtained from the time series of SLMs has been used for classification of fatigue and sleepiness stages using HMM.

D. *Classification using Hidden Markov Model (HMM)*

HMM is a probabilistic method for modeling time series data [10]. It is successfully used earlier in classifying EEG time series in various applications [13]. It assumes a number of discrete hidden states, discrete or continuous (real) valued observation and the probability of transition from one state to other. In this work continuous HMMs has been applied because the signals and the features are real valued observations. For continuous or real valued observation an HMM can be defined by the following elements [10]:

i. Number of hidden states in the model (N_H) denoted as $S = \{S_1, S_2, ..., S_{N_H}\}$

ii. State transition probability distribution
$$A = \{a_{ij}\}\ where\ a_{ij} = P[q_{t+1} = S_j \big| q_t = S_i],\quad 1 \le i, j \le N_H$$

iii. Emission probability distribution function $f_Y(y_t \big| q_t)$

iv. Initial state distribution
$$\pi = \{\pi_i\}\ where\ \pi_i = P[q_1 = S_i],\quad 1 \le i \le N_H$$

The parameters of HMM were learnt using Baum-Welch algorithm. The emission distribution function is considered as the mixture of two Gaussians for each hidden state. The classification using HMM typically has following steps.

i. Initialization of state transition probability A and initial state distribution π .
ii. Training of HMM for each class
iii. Computation of log-likelihood that each model gives to the test signal
iv. Selection of the most likely model

IV. RESULTS AND DISCUSSIONS

The analysis has been carried out on 3 minute EEG records (during the computer game) of 12 subjects at 11 stages. The synchronization of alpha band signal from different cortical areas has been computed via SL. The mean synchronization between alpha bands of 19 electrodes at various stages of the experiment is shown by SLMs in Fig.1.

Fifty randomly selected SLMs from each stage and from each subject (i.e. a total of 6600 matrices) have been used as training set for PCA. The principal components of SLMs are obtained as explained in section IIIC. Twelve principal components ($k = 12$) were selected (as shown in Fig. 2) based on a minimum of 90% information content.

For further processing, the SL matrices of all stages are projected on to the above principal components to find the weight vectors indicating the contribution of each principal component. Thus, the synchronization between different lobes at any instant is now represented as a weight vector. The time series of these weight vectors at different time points has been used as observation sequence for classification of different stages of fatigue using HMM.

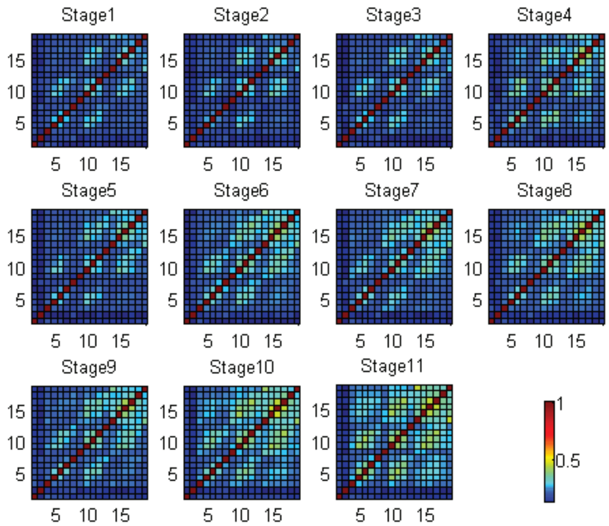

Fig.1: Mean synchronization likelihood matrices of 12 subjects at 11 stages in alpha band

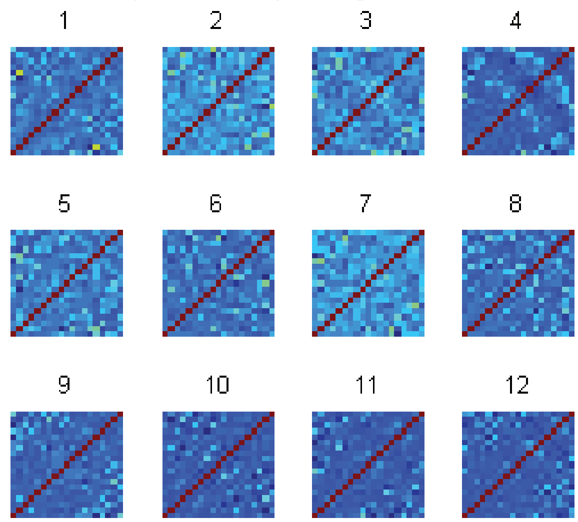

Fig.2: Twelve principal components of SL matrices

The method of classification of SLMs using HMM has already been discussed in section IIID. The method has been applied to classify 2 & 3 stages of sleep deprived experiment. The classification accuracy (percentage of true classification) of the proposed method has been compared with three other methods. All the methods use HMM for classification, but use different features as observation sequence. These are

i. Actual time series
ii. Time series of AR parameters
iii. Time series of principal components of segmented EEG (PCEEG)
iv. Proposed: Time series of weights along principal components of SL matrices (PCSLM)

The accuracy in classifying various numbers of stages is given in Table 1. It can be seen that the accuracy is maximum when actual time series is considered as observation sequence. The reason may be the large number of data which helps in better training of the HMM. But it is not always possible to work with the time series as it takes longer computation time. Among the feature based classification methods the proposed method gives maximum accuracy in classifying 2 and 3 stages of fatigue and sleepiness during the experiment.

Table 1. Accuracy in classifying different stages based on different observation sequences.

Stages	Accuracy (%)			
	Time Series	AR	PCEEG	PCSLM (Proposed)
2 (3, 9)	87.50	68.75	65.00	70.41
3 (3, 6, 9)	74.44	49.16	56.25	56.80

V. Conclusions

In this experimental study the variation of synchronization has been measured using SL due to its superiority in analyzing non-stationary signals. The SL matrix at any instant captures the interaction of different lobes. At different time points it shows the variation of such interaction. This gives more insight of change in brain states. Moreover, the principal components of these SL matrices help in reducing the complexity of computation.

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