Automated classification of EEG into meditation and non-meditation epochs using common spatial pattern, linear discriminant analysis, and LSTM

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***Abstract*—This study proposes an approach to classify the EEG into meditation and non-meditation segments using a long short-term memory (LSTM) based deep neural network (DNN) framework. Inter-subject classification performance is assessed on EEG recorded from fourteen long-term Rajayoga meditators. Common spatial pattern is used for feature extraction, and linear discriminant analysis is used for dimensionality reduction. The sequence of features thus obtained is fed to a LSTM based DNN, which employs a fully connected layer for classification. We have achieved inter-subject classification accuracies of 79.1%, 86.5%, 91.0%, and 94.1% with the respective use of the alpha, beta, lower-gamma, and higher-gamma bands for classification. To the best of our knowledge, this is the first work to employ deep learning to distinguish between the brain's electrical activity during meditation and at rest.**

***Index Terms*—Rajayoga meditation, LDA, common spatial pattern, meditative state, resting state, LSTM, deep learning**

I. Introduction

Meditation is considered to be an altered state of consciousness involving cognitive components such as attention and alertness. Attention is enhanced with increased mental training and is a prime component of meditation. Various meditation practices focus on breath, a mantra, an object, an image, etc. Applications like the brain-computer interface (BCI) can use this effect of focused attention practice in meditation. The BCI requires subject attention to perform a required task and can enhance the efficiency of the same with the meditation practice [1]. Other meditation methods involve attaining a blissful state, self-reflection, love and compassion, open monitoring, or feeling connected to an entity. Studies on latter concepts have reported the results characterized with inconsistency and non-replicable patterns across subjects [2], [3]. Various physiological and psychological responses are tested to understand the different effects and experiences associated with meditation [4]. A study conducted to assess the responses to emotional stimuli using machine learning was successful in evaluating the meditation experience [5]. It would be a breakthrough if the experience or depth of the meditation can be evaluated using continuous EEG data without any psychophysiological tests. Consequently, it is important to explore the feasibility of using machine learning algorithms to compare the states of meditation with non-meditative states to understand the neural correlations involved in the process of meditation.

As the first step in this direction, this study attempts to classify the meditative states against the non-meditative states using features extracted from the common-spatial patterns (CSP) and long short-term memory (LSTM) classifier. According to the authors' knowledge, although many studies have reported classifying meditative and non-meditative states within a subject, studies on classification with inter-subject data are uncommon due to the inter-subject variability.

II. Dataset Description

A. Details of the Study Subjects

Fifty-four rajayoga meditators with a mean age of 42 ± 10.1 years and with meditation experience ranging from 4 to 43 years with a mean experience of 18 years are part of the study. The subjects did not have any neurological disorders or cardiovascular issues. Written consent has been obtained from subjects after explaining the experimental protocol. Consumption of alcohol or cigarette was verified with the participants, and no participant considered in the study consumed alcohol or cigarette up to six months before the recording date. Data was recorded at Brahma Kumaris headquarters, Mount Abu, India.

B. Protocol used for recording the EEG data utilized

EEG data are recorded with ANT Neuro amplifier and 64-channel waveguard cap following 10-10 international electrode location system. The acquisition and meditation session details have been previously reported [6]. EEGO software is

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TABLE I
EEG FREQUENCY BANDS INDEPENDENTLY CONSIDERED FOR FEATURE EXTRACTION.

Band name	Alpha	Beta	Lower Gamma	Higher Gamma
Frequency range	8 - 13 Hz	13 - 25 Hz	25 - 45 Hz	45 - 64 Hz

used to acquire the data, and all the electrodes are referenced to the CPz electrode with a sampling frequency of 500 Hz. Less than 10 $k\Omega$ impedance is maintained between the scalp and the electrode during the recording sessions. The subjects sat in a comfortable position on a floor mat and we ensured that there was no contact between the participant's body and the ground. EEG data recorded is digitally bandpass filtered from 0.3-75 Hz offline before preprocessing.

Recording sessions include eyes open and eyes closed baseline segments before and after the meditation segment as given in Fig. 1. The duration of baseline segments is approximately 3 minutes, and the meditation segment is around 30 minutes. Participants are instructed to practice rajayoga seed-stage meditation with the eyes-open condition for the study. An acoustic tone prompts the participant every 5 minutes to note their meditative state mentally, which is later recorded from the participants.

C. EEG data preprocessing and band-pass filtering

Brain Vision analyzing software is used to preprocess the EEG data. Data is downsampled to 128 Hz using the spline interpolation method. Data of 1-minute duration immediately occurring after every prompt is removed from the meditation segment to eliminate possible non-meditative state recording. A notch filter is used to eliminate possible line noise, and independent component analysis (ICA) is applied to the data to detect the components related to eye movements. The ICA components are rejected manually, and EEGLAB [7] add-on with MATLAB is used to band-pass filter the data into canonical frequency bands for our experiments. Table I lists the frequency bands used in the study. In this work, the eyes open baseline segments before and after meditation, and approximately 6 minutes of meditation data are only considered to ensure that the classes are appropriately balanced.

III. FEATURE EXTRACTION AND CLASSIFICATION

Unlike our previous work [8] where common spatial pattern (CSP) with Tikhonov regularization was used, we did not apply any regularization in this work. This is because we did not observe any improvement in the accuracy by using regularization. In classical CSP without regularization, the spatial filter $\mathbf{W}$ is obtained by extremizing the following objective function:

$$J(\mathbf{W}) = \frac{tr(\mathbf{W}^T\mathbf{R}_2\mathbf{W})}{tr(\mathbf{W}^T\mathbf{R}_1\mathbf{W})} \tag{1}$$

where $tr(.)$ denotes the trace of a matrix, T denotes matrix transpose, matrix $\mathbf{R_j}$ denotes the normalized spatial covariance of class j. $\mathbf{R_j}$ is obtained by the following relation:

$$\mathbf{R_j} = \frac{\mathbf{X}_j\mathbf{X}_j^T}{tr(\mathbf{X}_j\mathbf{X}_j^T)} \tag{2}$$

where $\mathbf{X}_j \in \mathbb{R}^{D\times S}$ is a $D \times S$ matrix containing the EEG signal of class j having D channels and S time samples.

After computing the spatial filter $\mathbf{W}$ for each set of training data ($\mathbf{X}_j$), the data is spatially filtered as follows to obtain the filtered data ($\mathbf{Z}_j$):

$$\mathbf{Z}_j = \mathbf{W}\mathbf{X}_j \tag{3}$$

In this work, the number of spatial filter pairs used is 10 since in our previous work [8], we have shown that improvement in accuracy with more number of spatial filter pairs plateaus when it is 10 filter pairs. Hence, in this case, the dimension of $\mathbf{W}$ is 20×61, where 61 is the number of EEG channels. Also, the dimension of X_j is 61×64 where 64 is the epoch length in samples. We reduced the epoch length from 256 samples in our previous work to 64 samples in the current work to have enough training samples for the classifier.

The logarithm of variance of each filtered vector is used as a feature resulting in a feature vector of dimension 20. The dimension of these vectors is reduced to one by applying linear discriminant analysis (LDA). These values are fed to an LSTM as sequence data. The number of hidden units in the classifier is 200, and the maximum number of epochs is set at 20 to avoid overfitting. The optimizer used is Adam, with a learning rate of 0.001. Although the architecture of the classifier used in this work is similar to the OPTICAL predictor used in [9], there are differences such as:

1) We use LSTM as a classifier, whereas in [9] LSTM was used in a regression setting, and a support vector machine (SVM) was used as the classifier.
2) We do not apply sliding window during feature extraction.

IV. RESULTS OF OUR STUDY

Figure 3 compares the performance of the proposed work with our previous results [8]. Unlike most of the other works in the literature, where the method is tested on an intra-subject setting, we tested the proposed method on an inter-subject setting where we do not include any test participant data in the training data. Use of higher-gamma and alpha bands results in the highest and lowest accuracy, respectively. This same trend was observed in our previous work. The results are also in line with the observation in classifying EEG recorded during speech imagery, where the alpha and gamma bands give rise to the least and most discriminatory features [10], [11].

V. CONCLUSION

A CSP-LDA-LSTM based system for distinguishing meditation state from eyes-open baseline is presented in this paper. Rajayoga meditation data has been used for this study. We have achieved accuracy values of $79.1 \pm 26.8\%$, $86.5{\pm}8.9\%$, $91.0{\pm}13.1\%$, and $94.1{\pm}8.9\%$ using alpha, beta,

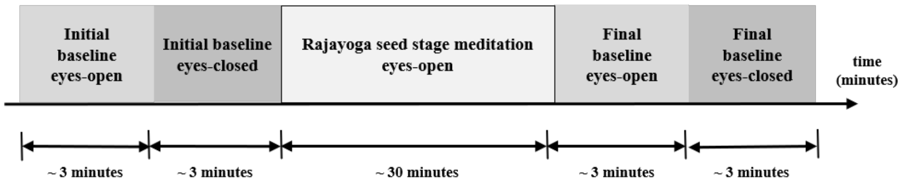

Fig. 1. Recording protocol for the EEG used in this study: 3 minutes each of initial baseline segments with eyes open (IEO) and closed (IEC) conditions followed by 30 minutes of seed stage meditation (M), and 3 minutes each of final baseline segments with eyes open (FEO) and closed (FEC) conditions.

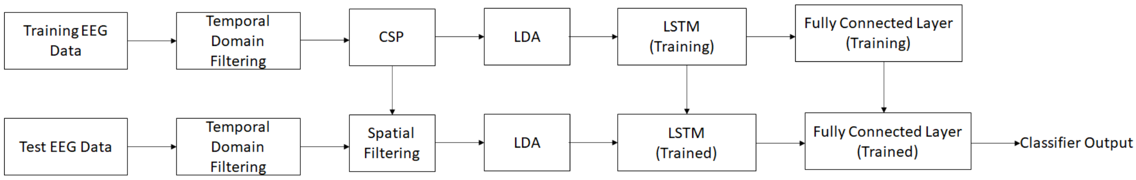

Fig. 2. Architecture of the proposed method. An inter-subject testing strategy is employed, where the classifier is trained on the EEG data of $N-1$ subjects and tested on the left out subject in each of the N steps of cross-validation, where N is the total number of subjects. CSP: common spatial pattern, LDA: linear discriminant analysis, LSTM: long short-term memory.

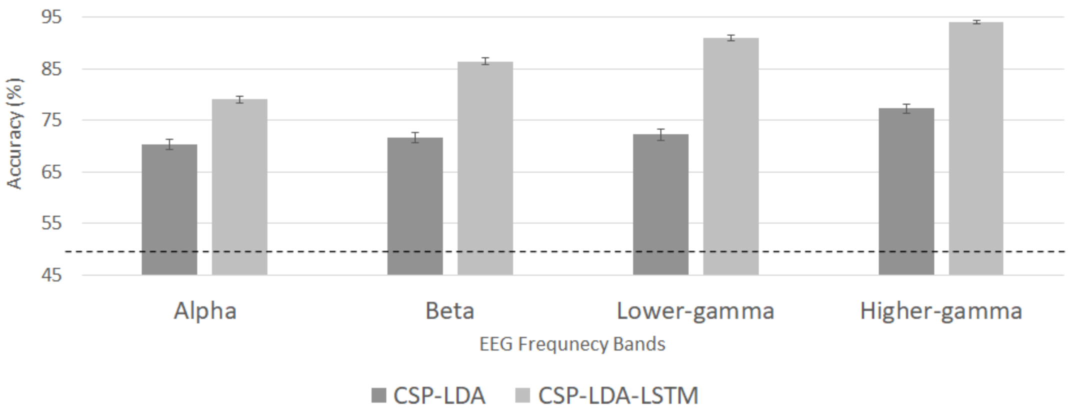

Fig. 3. Comparison of the performance of the proposed system with our previous work. Different EEG frequency bands are given in the x-axis, whereas the percentage accuracies are given in the y-axis. Use of the higher gamma band results in the best performance of 94.1% The dashed line denotes chance level accuracy. Error bars indicate standard deviation.

TABLE II

COMPARISON OF MEAN ACCURACIES REPORTED FOR OTHER SYSTEMS OF MEDITATION IN CLASSIFYING MEDITATIVE FROM THE RESTING STATE USING EEG. IN A WORK BY LIN AND LEE [12], THE EPOCH LENGTH IS 10S, FIVE TIMES THAT OF THE EPOCH LENGTH USED IN OUR WORK. SVM: SUPPORT VECTOR MACHINE, LDA: LINEAR DISCRIMINANT ANALYSIS, LSTM: LONG SHORT-TERM MEMORY

Sl. No.	Authors	System of Meditation	Classification Setting	Features	Classifier	Mean Accuracy
1	Tee at al. [13]	Theta healing meditation	Intra-subject	Discrete wavelet transform	Logistic regression	96.9%
2	Ahani et al. [14]	Mindfulness meditation	Intra-subject	Stockwell transform	SVM	78.0%
3	Lin and Lee [12]	Chan meditation	Intra-subject	Approximate entropy	Bagged tree	97.9%
4	Panachakel et al. [8]	Rajayoga meditation	Intra-subject	Common spatial pattern	LDA	98.0%
5	Panachakel et al. [8]	Rajayoga meditation	Inter-subject	Common spatial pattern	LDA	77.3%
6	Proposed work	Rajayoga meditation	Inter-subject	Common spatial pattern	LSTM	94.1%

lower-gamma, and higher-gamma bands, respectively, for classification. To the best of our knowledge, this is the first work to employ deep learning to classify the meditative state from the resting state. The proposed method has achieved an absolute improvement of more than 15% in accuracy over the earlier result [8] on the same dataset.

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