Binary classification of meditative state from the resting state using EEG

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***Abstract*—Objective classification of the meditative state of the brain from its resting state was attempted using electroencephalogram (EEG). The binary classification was performed both under intra-subject and inter-subject settings. The meditation practice used is Rajayoga meditation, which is probably the only meditation practice where the practitioners meditate with their eyes open. To our knowledge, this is the first attempt at such an EEG-based classification of altered conscious state during Rajayoga meditation. Baseline EEG was recorded both before and after the meditation session, separately with eyes closed and open. Common spatial pattern with Tikhonov regularization (TR-CSP) is used for feature extraction and linear discriminant analysis (LDA) is used as the classifier. We have achieved an accuracy of 97.9% for intra-subject classification and 74.0% for inter-subject classification. The classification accuracy improves with the increase in the number of filter pairs used; however, the improvement plateaus for all the subjects after about eight pairs of filters. Regularization by penalizing higher values of the elements in the filter vector deteriorates the accuracy and in most cases, the best classification occurs with no regularization.**

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

I. INTRODUCTION

Meditation is a process believed to enhance awareness about self and the environment around us, and thus is expected to take the brain to a higher conscious state. In the past three decades, meditation research has been acknowledged majorly due to the state and trait changes observed in the electrophysiological indices of meditation practitioners [1]. Meditation or contemplative practices are part of most of the Eastern civilizations and it is considered that early meditation practices originated from the ancient Indian subcontinent [2]. There are many different and distinct practices which are grouped under the domain of meditation such as mindfulness, Vipasana, Zen, Sahajayoga, and Rajayoga. Practice variables include point of focus, initiation of practice, posture, and the most suitable time to practice [3].

The motivation for the present work is to objectively and automatically identify and classify the meditative state from the resting state using EEG data. Previous studies using power spectrum and entropy have revealed the increase of high frequency component during meditation [4]. However, practice variables make a great difference in the brain states achieved during different meditative practices. One of the challenges in meditation research is to characterize how the meditative practices which involve the cognitive or affective functions of the human brain differ from relaxation practices which focus on somatic structures [5]. Identifying the electrophysiological implications of meditation may help in identifying the brain processes involved as well as mechanism which allows to improve one's well being and proved to be a potential complementary therapy for PTSD [6], schizoaffective disorders [7], chronic depressive disorders [8] and developmental disorders such as ADHD [9] and autism [10].

The contributions of this work are:

1) This is the first study to distinguish between the brain's conscious states during Rajayoga meditation and rest.
2) This is the maiden work to analyze the contributions of different frequencies, regularization parameter and the number of filter pairs of TR-CSP in classifying the meditative from the resting state of the brain using EEG.

II. DATASET DESCRIPTION

A. Details of the Study Subjects

EEG data was collected from fifty four meditators at Brahma Kumaris headquarters, Mount Abu, India. The Rajayoga meditators (age 42 $\pm$ 10.1 years) had practice ranging from 4 to 43 years with mean experience of 18 years. The subjects did not have any history of dysfunction of the nervous,

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cardiac or pulmonary system. Experimental procedure was explained to the subjects and written information consent was obtained before recording. It was confirmed that the subjects did not consume any therapeutics, alcohol or cigarette for a period of six months before the recording. More details about the dataset can be found in [11].

B. Experimental Protocol

EEG data was recorded with 64-channel waveguard cap following the 10-10 international electrode placement system. ANT Neuro amplifier and EEGO software were used for data acquisition. The signals were recorded at a sampling frequency of 500 Hz. EEG signals were later digitally filtered from 0.3-75 Hz. All the channels recorded were referenced to CPz and the impedance of all the channels were maintained at less than 10 $k\Omega$. The subjects chose to meditate sitting on a floor mat and it was ensured that the body of the meditator was not in contact with the ground during the recording session.

Initial baselines were recorded with eyes open (IEO) and eyes closed (IEC) conditions for approximately 3 minutes each, when the subjects were asked to relax without meditating. IEC was followed by the Rajayoga seed state meditation (M) with eyes open condition wherein the subjects claimed to shift their awareness to the peaceful nature of their soul. The meditation duration was 30 minutes. During the meditation, the participants were prompted with an acoustic tone around 4 to 5 times to mentally note the observations. Final baselines were again recorded with eyes open (FEO) and eyes closed (FEC) conditions for 3 minutes each as shown in Fig. 1.

C. EEG data preprocessing and band-pass filtering

Data was preprocessed using Brain Vision analyzer version 2.1.2. Using spline interpolation, data was downsampled to 128 Hz and one minute EEG data was eliminated from the meditation segment after each prompt to exclude the possible non-meditation epochs. Independent component analysis was used to remove artifacts related to eye movements and manual component rejection was adopted to remove other artifacts. EEG time series was band-pass filtered using EEGLAB to obtain the frequency bands listed in Table I. EEG data in each frequency band was segmented into 2-second epochs consisting of 256 samples each. These band-limited epochs were used for the proposed classification task.

TABLE I
FREQUENCY BANDS CONSIDERED FOR CLASSIFICATION.

Sl. No.	Band name	Frequency range
1	Alpha	8 - 13 Hz
2	Beta	13 - 25 Hz
3	Lower Gamma	25 - 45 Hz
4	Higher Gamma	45 - 64 Hz

III. FEATURE EXTRACTION AND CLASSIFICATION

Features were extracted for classification using common spatial pattern with Tikhonov regularization (TR-CSP) [12]. CSP is widely used for classifying motor imagery [13], speech imagery [14] etc. In TR-CSP, the following objective function is extremized:

$$J(\mathbf{w}) = \frac{\mathbf{w}^T X_i X_i^T \mathbf{w}}{\mathbf{w}^T X_j X_j^T \mathbf{w}} = \frac{\mathbf{w}^T C_i \mathbf{w}}{\mathbf{w}^T C_j \mathbf{w} + \alpha \mathbf{w}^T \mathbf{w}} \tag{1}$$

where T denotes matrix transpose, matrix X_j contains the EEG signals of class j, with data samples as columns and channels as rows, $\mathbf{w}$ is the spatial filter vector, C_j is the spatial covariance matrix of class j and r is the regularization parameter.

In this work, we have experimented with different values of the number of pairs of spatial filter vector (each pair has both the vectors minimizing and maximising the objective function in Eq. 1), different values of the regularisation parameter α and four different EEG frequency bands (alpha, beta, lower gamma and higher gamma) defined in Table I. The number of pairs of spatial filter vectors is linearly varied from two to 10 in steps of 1 whereas α is varied in logarithmic scale from 10^{-1} to 10^{-10}. In addition to these, we have also experimented by setting α to zero which leads to the classical formulation of CSP. For extracting the features, the EEG signals are projected onto the selected spatial vectors (determined by the number of pairs of spatial filters chosen) and logarithm of the variance of the projected signal is calculated. The dimension of the feature vector is $2N_b$ where N_b is the number of filter pairs chosen. Linear discriminant analysis (LDA) is used for classification. Since the number of epochs of meditation is more than the number of epochs of IEO (ref. Fig. 1), the number of epochs of meditation chosen is such that the chance accuracy is 50%.

IV. RESULTS OF OUR STUDY

We have tested the efficiency of the proposed method for classifying the baseline epochs from the Rajayoga meditation epochs under two different settings:

1) Intra-subject setting where training and test data are taken from the same subject. The evaluation strategy is 10-fold cross validation.
2) Inter-subject setting where the classifier is trained on the data of $N-1$ subjects and is tested on the left out subject in each of the N steps of cross-validation, where N is the total number of subjects. This is more challenging than intra-subject since the classifier has not seen the data of the test subject during the training phase.

The intra-subject classification results for various values of the number of pairs of spatial filter vectors, regularisation parameter α and EEG frequency bands alpha and higher gamma are given in Tables II and III. The performance of the classifier in the intra-subject setting is evaluated using 10-fold crossvalidation. Table IV compares our results with

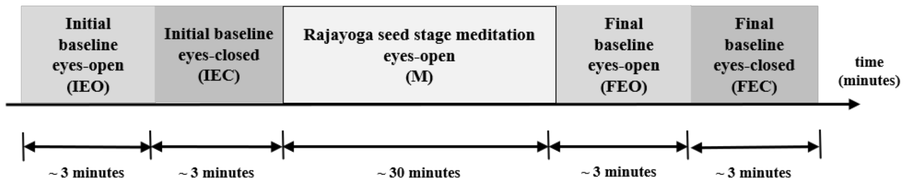

Fig. 1. Experiment protocol: 3 minutes each of initial baseline segments with eyes open (IEO) and closed (IEC) conditions followed by approximately 30 minutes of seed stage meditation (M), 3 minutes each of final baseline segments with eyes open (FEO) and closed (FEC) conditions.

the mean intra-subject accuracies reported for other systems of meditation for the binary classification of meditative state from the resting state using EEG. Lin and Lee [15] have tested their method on different epoch lengths varying from 1s to 60s. Since the epoch length in this work is 2s, the accuracy reported in Table IV for Lin and Lee is for 10s, the smallest epoch length greater than or equal to the epoch length used in this work among the epoch lengths used by Lin and Lee.

The inter-subject classification results for different values of the number of pairs of spatial filter vectors, regularisation parameter α and EEG frequency bands alpha and higher gamma are given in Tables V and VI. The performance of the classifier in the inter-subject setting is evaluated using leave-one-out cross-validation (LOOCV). Comparisons of the performance of the system in intra-subject and inter-subject settings for various EEG frequency bands are given in Fig. 2.

V. Discussion

A. Effect of classification setting

The performance of the proposed system has been tested under two settings: 1) intra-subject setting where the training and test data are from the data of the same subject; 2) inter-subject setting where the data of the test participant is unseen by the classifier during training. Due to the variations in the EEG captured from different subjects even for the same task, it is well-known that there can be differences in the classifier performance where intra-subject classification gives higher accuracies than inter-subject classification [18]. The same trend is seen in our work also. In the case of intra-subject classification using higher gamma band, the accuracy is $97.9 \pm 0.1\%$ whereas for inter-subject classification using the same band, the accuracy drops to $77.3 \pm 0.8\%$. This disparity could be addressed by using subject-to-subject adaptation [13], [19]. Since the data available has only one session per participant, it is not possible to conclude as to whether the reduction in performance is due to subject variability alone or due to both subject and session variabilities.

Meditation is known to produce both temporary (state) [20], [21] and permanent (trait) changes [22] in the practitioners [23], based on the regularity and years of practice. Meditation is known to produce both temporary (state) and permanent (trait) changes in the practitioners [23], based on the regularity and years of practice. Thus, when we are comparing the differences between the resting and meditative states, the levels of trait changes in the EEG characteristics could be significantly different between the different subjects being studied. This is why it is really difficult to obtain very high classification accuracies in the inter-subject experiments. However, it is possible that there are features that we do not yet know, which can clearly classify the transient state changes during the meditative duration, irrespective of the traits acquired by the individuals due to their prior, prolonged practice. To come out with such new, effective features is an important challenge in meditation research. That we are able to obtain a reasonably good inter-subject classification accuracy of 77% using the same features and classification methodology is encouraging. Thus, there is promise that with the right kind of feature-classifier combination, we may be able to solve the problem of identifying transient state changes occurring during the process of meditation in any individual with no or prolonged experience in meditation.

B. Effect of EEG frequency bands

For both intra-subject and inter-subject settings, the performance is higher for high frequency bands than for low frequency bands. This is inline with the studies on classification of mental states during speech imagery [24]–[26]. More focused studies are required to ascertain the reason for this observation.

C. Effect of regularisation

Regularized CSP including TR-CSP has better performance than classical CSP in classifying motor imagery [27]. However, we did not observe an improvement in the accuracy by using regularisation. Tikhonov regularization penalizes higher values for the elements in the spatial vector. This penalty might be the cause for the decrease in performance for higher regularization parameters.

D. Effect of the number of filter pairs used

Consistently, across subjects and frequency bands, we see an improvement in the accuracy for more number of filter pairs. Increased number of filter pairs might be contributing more discriminative information to the classifier but the improvement plateaus for higher values. This is in contrast to the observation by Panachakel et al. in [28] where they have reported a decrease in the performance of a deep neural network trained for classifying imagined speech when the number of filter pairs exceeds nine.

TABLE II

ACCURACIES (IN %) ACROSS ALL PARTICIPANTS IN CLASSIFYING MEDITATION V/S REST STATE USING ALPHA BAND EEG DATA GIVEN AS $mean \pm SD$. THE CLASSIFICATION STRATEGY IS INTRA-SUBJECT USING 10-FOLD CROSS VALIDATION. EACH ROW CORRESPONDS TO A DIFFERENT VALUE OF THE REGULARIZATION PARAMETER OF COMMON SPATIAL PATTERN (CSP) WITH TIKHONOV REGULARIZATION (α). EACH COLUMN CORRESPONDS TO A DIFFERENT VALUE OF THE NUMBER OF CSP FILTER PAIRS USED FOR CLASSIFICATION. THE CLASSIFIER USED IS LDA.

	Number of Filter Pairs								
$\boldsymbol{\alpha}$	2	3	4	5	6	7	8	9	10
10^{-01}	72.5 ± 12.2	74.7 ± 12.7	77.4 ± 13.5	78.3 ± 13.3	78.9 ± 13.2	79.2 ± 12.8	79.6 ± 12.8	80.5 ± 12.5	81.4 ± 12.0
10^{-02}	72.5 ± 13.6	82.2 ± 12.4	83.1 ± 12.5	84.2 ± 11.7	84.0 ± 12.7	84.6 ± 12.0	84.9 ± 12.3	84.8 ± 12.4	84.8 ± 12.1
10^{-03}	72.5 ± 10.8	88.9 ± 9.4	88.8 ± 9.5	89.2 ± 8.6	89.5 ± 8.3	89.8 ± 7.7	90.0 ± 7.5	90.1 ± 7.4	90.1 ± 7.0
10^{-04}	72.5 ± 6.0	92.3 ± 5.9	92.6 ± 5.6	92.8 ± 5.0	92.7 ± 5.1	92.8 ± 5.0	93.0 ± 4.7	92.9 ± 4.7	92.9 ± 4.4
10^{-05}	72.5 ± 4.5	93.3 ± 4.7	93.4 ± 4.3	$\mathbf{93.6 \pm 3.0}$	93.4 ± 3.5	93.4 ± 3.8	93.5 ± 3.5	93.6 ± 3.1	93.6 ± 3.2
10^{-06}	72.5 ± 4.1	93.4 ± 4.3	93.5 ± 3.7	93.5 ± 3.7	93.6 ± 3.6	93.5 ± 3.6	93.5 ± 3.8	93.5 ± 3.5	93.4 ± 3.9
10^{-07}	72.5 ± 4.3	93.3 ± 4.3	93.5 ± 4.2	93.5 ± 4.0	93.5 ± 4.1	93.5 ± 3.9	93.5 ± 3.8	93.5 ± 3.8	93.5 ± 2.8
10^{-08}	72.5 ± 4.0	93.4 ± 4.6	93.3 ± 5.1	93.5 ± 3.6	93.6 ± 3.2	93.5 ± 3.8	93.5 ± 3.9	93.4 ± 3.9	93.5 ± 3.1
10^{-09}	72.5 ± 4.5	93.4 ± 4.2	93.5 ± 4.1	93.5 ± 3.7	93.5 ± 4.0	93.4 ± 3.9	93.5 ± 3.7	93.6 ± 3.4	93.6 ± 3.3
10^{-10}	72.5 ± 4.2	93.4 ± 3.9	93.4 ± 4.1	93.6 ± 3.1	93.5 ± 4.0	93.5 ± 3.6	93.4 ± 4.1	93.6 ± 3.3	93.6 ± 3.2
$10^{-\infty}$	72.5 ± 4.4	93.4 ± 3.9	93.5 ± 3.5	93.5 ± 3.3	93.5 ± 3.8	93.5 ± 4.0	93.4 ± 4.1	93.5 ± 3.7	93.5 ± 3.4

TABLE III

ACCURACIES (IN %) ACROSS ALL PARTICIPANTS IN CLASSIFYING MEDITATION V/S REST STATE USING HIGHER GAMMA BAND OF EEG DATA GIVEN AS $mean \pm SD$. THE CLASSIFICATION STRATEGY IS INTRA-SUBJECT USING 10-FOLD CROSS VALIDATION. EACH ROW CORRESPONDS TO A DIFFERENT VALUE OF THE REGULARIZATION PARAMETER OF COMMON SPATIAL PATTERN (CSP) WITH TIKHONOV REGULARIZATION (α). EACH COLUMN CORRESPONDS TO A DIFFERENT VALUE OF THE NUMBER OF CSP FILTER PAIRS USED FOR CLASSIFICATION. THE CLASSIFIER USED IS LDA.

	Number of Filter Pairs								
$\boldsymbol{\alpha}$	2	3	4	5	6	7	8	9	10
10^{-01}	92.9 ± 8.7	94.0 ± 7.8	94.9 ± 6.0	95.3 ± 5.5	95.5 ± 5.4	95.6 ± 5.8	95.3 ± 6.1	95.6 ± 5.3	95.6 ± 5.0
10^{-02}	96.2 ± 4.0	96.3 ± 4.0	96.6 ± 3.8	96.9 ± 2.9	96.8 ± 3.1	97.0 ± 3.2	97.1 ± 2.3	96.9 ± 2.5	96.8 ± 2.9
10^{-03}	96.7 ± 3.9	97.0 ± 3.1	97.2 ± 2.5	97.3 ± 2.6	97.4 ± 2.1	97.3 ± 2.2	97.4 ± 2.1	97.6 ± 1.5	97.4 ± 1.8
10^{-04}	97.0 ± 3.3	97.4 ± 2.3	97.5 ± 1.6	97.6 ± 1.3	97.6 ± 1.3	97.8 ± 0.8	97.8 ± 1.0	97.8 ± 0.7	97.7 ± 0.9
10^{-05}	97.2 ± 3.0	97.5 ± 1.9	97.6 ± 1.5	97.7 ± 1.3	97.8 ± 1.0	97.7 ± 1.2	97.8 ± 1.2	97.7 ± 1.0	97.8 ± 0.7
10^{-06}	97.1 ± 3.1	97.4 ± 2.3	97.7 ± 1.4	97.7 ± 1.2	97.7 ± 1.3	97.7 ± 1.3	97.8 ± 1.0	97.7 ± 1.1	97.8 ± 0.8
10^{-07}	97.1 ± 3.3	97.4 ± 2.2	97.5 ± 1.5	97.6 ± 1.6	97.7 ± 0.9	97.7 ± 1.4	97.7 ± 1.2	97.8 ± 0.8	97.8 ± 0.9
10^{-08}	97.1 ± 3.2	97.4 ± 2.0	97.5 ± 1.7	97.7 ± 1.3	97.7 ± 1.0	97.8 ± 0.9	$\mathbf{97.9 \pm 0.5}$	97.8 ± 0.8	97.9 ± 0.7
10^{-09}	97.1 ± 3.2	97.3 ± 2.7	97.6 ± 1.7	97.6 ± 1.4	97.7 ± 1.2	97.8 ± 0.9	97.8 ± 0.9	97.8 ± 0.8	97.9 ± 0.6
10^{-10}	97.1 ± 3.1	97.4 ± 2.4	97.6 ± 1.5	97.8 ± 1.2	97.7 ± 1.0	97.7 ± 1.1	97.7 ± 1.2	97.8 ± 1.1	97.8 ± 1.0
$10^{-\infty}$	97.5 ± 6.3	97.7 ± 2.0	97.7 ± 1.6	97.7 ± 2.1	97.7 ± 1.5	97.8 ± 0.9	97.8 ± 0.7	97.8 ± 0.4	97.8 ± 1.0

TABLE IV

COMPARISON OF MEAN INTRA-SUBJECT ACCURACIES REPORTED FOR OTHER SYSTEMS OF MEDITATION FOR THE BINARY CLASSIFICATION OF MEDITATIVE STATE FROM THE RESTING STATE USING EEG. IN THE WORK BY LIN AND LEE [15], THE EPOCH LENGTH IS 10S, FIVE TIMES THAT OF THE EPOCH LENGTH USED IN OUR WORK. SVM: SUPPORT VECTOR MACHINE, LDA: LINEAR DISCRIMINANT ANALYSIS

Sl. No.	**Authors**	**System of Meditation**	**Features**	**Classifier**	**Mean Accuracy**
1	Tee at al. [16]	Theta healing meditation	Discrete wavelet transform	Logistic regression	96.9%
2	Ahani et al. [17]	Mindfulness meditation	Stockwell transform	SVM	78.0%
3	Lin and Lee [15]	Chan meditation	Approximate entropy	Bagged tree	**97.9%**
4	Proposed work	Rajayoga meditation	Common spatial pattern	LDA	**97.9%**

TABLE V

ACCURACIES (IN %) ACROSS ALL PARTICIPANTS IN CLASSIFYING MEDITATION V/S REST STATE USING ALPHA BAND EEG DATA GIVEN AS $mean \pm SD$. THE CLASSIFICATION STRATEGY IS INTER-SUBJECT USING LEAVE-ONE-OUT CROSS-VALIDATION. EACH ROW CORRESPONDS TO A DIFFERENT VALUE OF THE REGULARIZATION PARAMETER OF COMMON SPATIAL PATTERN (CSP) WITH TIKHONOV REGULARIZATION (α). EACH COLUMN CORRESPONDS TO A DIFFERENT VALUE OF THE NUMBER OF CSP FILTER PAIRS USED FOR CLASSIFICATION. THE CLASSIFIER USED IS LDA.

	Number of Filter Pairs								
$\boldsymbol{\alpha}$	2	3	4	5	6	7	8	9	10
10^{-01}	55.6 ± 1.8	56.0 ± 1.7	57.1 ± 2.0	57.9 ± 1.8	58.4 ± 1.7	57.9 ± 1.9	58.1 ± 1.9	58.7 ± 2.0	59.4 ± 1.6
10^{-02}	57.2 ± 1.7	57.8 ± 1.6	59.1 ± 1.6	59.5 ± 2.0	59.6 ± 1.5	59.9 ± 1.8	59.5 ± 1.9	60.0 ± 1.9	60.0 ± 1.9
10^{-03}	60.9 ± 1.6	61.6 ± 1.6	62.1 ± 1.5	62.2 ± 1.7	61.6 ± 1.6	62.0 ± 2.2	62.9 ± 1.9	62.7 ± 1.7	62.9 ± 1.8
10^{-04}	62.7 ± 1.7	63.1 ± 1.6	63.3 ± 1.6	64.2 ± 1.7	64.4 ± 1.9	64.7 ± 2.0	66.1 ± 1.8	66.1 ± 2.0	66.4 ± 1.9
10^{-05}	63.2 ± 1.7	63.3 ± 1.8	64.1 ± 1.9	64.3 ± 1.7	64.9 ± 2.0	65.6 ± 1.6	66.0 ± 2.2	66.6 ± 2.1	67.0 ± 1.3
10^{-06}	62.6 ± 2.1	63.7 ± 1.6	64.3 ± 1.8	64.0 ± 2.2	65.3 ± 1.8	65.1 ± 1.6	66.0 ± 1.8	66.9 ± 2.1	66.9 ± 1.9
10^{-07}	63.0 ± 2.1	63.9 ± 1.8	64.6 ± 1.7	64.1 ± 1.9	65.0 ± 1.8	65.4 ± 1.6	66.5 ± 2.1	66.6 ± 1.8	66.9 ± 2.1
10^{-08}	63.0 ± 2.0	63.8 ± 1.5	64.6 ± 2.0	64.3 ± 2.1	65.2 ± 1.9	65.3 ± 2.2	66.4 ± 2.0	$\mathbf{66.9 \pm 1.8}$	66.7 ± 1.9
10^{-09}	62.8 ± 1.9	64.1 ± 1.7	63.9 ± 1.9	64.1 ± 2.0	65.6 ± 1.9	65.4 ± 1.8	66.3 ± 2.2	66.7 ± 1.9	66.6 ± 1.6
10^{-10}	63.0 ± 1.8	63.4 ± 1.6	64.8 ± 1.6	64.4 ± 2.2	65.4 ± 1.7	65.5 ± 2.1	66.6 ± 2.0	66.6 ± 1.9	66.5 ± 1.8
$10^{-\infty}$	63.0 ± 1.8	63.8 ± 1.7	64.3 ± 1.7	64.2 ± 1.5	64.8 ± 1.7	65.5 ± 1.8	65.9 ± 2.3	66.7 ± 1.9	66.7 ± 1.9

TABLE VI

MEDITATION V/S REST STATE CLASSIFICATION ACCURACIES ($mean \pm SD$ IN %) ACROSS ALL PARTICIPANTS USING HIGHER GAMMA BAND EEG DATA. THE CLASSIFICATION STRATEGY IS INTER-SUBJECT USING LEAVE-ONE-OUT CROSS-VALIDATION. EACH ROW CORRESPONDS TO DIFFERENT VALUES OF THE REGULARIZATION PARAMETER OF COMMON SPATIAL PATTERN WITH TIKHONOV REGULARIZATION (α). EACH COLUMN CORRESPONDS TO DIFFERENT VALUES OF THE NUMBER OF CSP FILTER PAIRS USED FOR CLASSIFICATION. THE CLASSIFIER USED IS LDA.

	Number of Filter Pairs								
$\boldsymbol{\alpha}$	2	3	4	5	6	7	8	9	10
10^{-01}	58.8 ± 1.5	59.5 ± 1.6	60.7 ± 1.7	62.7 ± 1.9	63.5 ± 2.2	63.0 ± 1.7	63.5 ± 1.6	64.2 ± 1.6	64.3 ± 1.6
10^{-02}	65.0 ± 1.8	66.7 ± 1.6	67.9 ± 1.9	68.2 ± 1.7	67.0 ± 2.3	67.6 ± 1.7	68.5 ± 1.5	68.4 ± 1.5	68.6 ± 1.6
10^{-03}	67.1 ± 1.6	70.2 ± 1.9	71.6 ± 2.1	71.3 ± 1.9	71.4 ± 1.8	72.4 ± 1.8	72.2 ± 1.8	72.7 ± 1.8	73.1 ± 1.6
10^{-04}	68.9 ± 1.9	69.7 ± 2.5	70.9 ± 1.9	72.1 ± 2.1	72.2 ± 2.0	73.4 ± 1.9	73.7 ± 1.8	$\mathbf{74.0 \pm 1.8}$	73.9 ± 1.9
10^{-05}	68.5 ± 2.8	70.5 ± 2.1	71.2 ± 2.6	71.6 ± 2.0	72.9 ± 1.8	73.0 ± 2.1	73.4 ± 1.9	73.7 ± 2.1	73.6 ± 2.4
10^{-06}	68.1 ± 2.8	70.3 ± 2.4	71.3 ± 2.2	72.1 ± 2.1	72.5 ± 1.7	72.8 ± 1.9	73.1 ± 1.6	73.8 ± 1.8	73.2 ± 1.7
10^{-07}	68.5 ± 2.8	70.4 ± 2.0	71.3 ± 2.0	71.8 ± 1.8	72.5 ± 2.2	72.9 ± 2.1	73.2 ± 1.9	73.8 ± 1.9	73.8 ± 1.7
10^{-08}	67.2 ± 3.3	70.7 ± 2.3	70.6 ± 2.2	71.8 ± 2.1	72.6 ± 1.7	73.1 ± 2.0	73.5 ± 2.0	73.3 ± 2.3	74.0 ± 2.0
10^{-09}	68.3 ± 2.6	70.7 ± 2.2	71.0 ± 2.3	72.2 ± 2.3	72.6 ± 1.9	73.3 ± 1.9	73.3 ± 1.7	$\mathbf{74.0 \pm 1.8}$	73.3 ± 1.9
10^{-10}	67.9 ± 2.9	70.5 ± 1.9	71.2 ± 2.8	72.8 ± 2.1	72.4 ± 2.3	73.2 ± 1.5	73.3 ± 2.0	73.0 ± 2.0	73.7 ± 1.9
$10^{-\infty}$	68.1 ± 2.4	70.5 ± 1.8	70.9 ± 2.2	72.1 ± 2.0	72.8 ± 2.0	73.2 ± 1.5	73.2 ± 2.0	73.5 ± 2.1	73.5 ± 1.8

VI. CONCLUSION

A CSP-LDA based system for distinguishing meditation state from eyes-open baseline is presented in this paper. The meditation practice chosen is Rajayoga meditation. The proposed method achieves as accuracy of $97.9 \pm 0.5\%$ for intra-subject classification and $74.0 \pm 1.8\%$ for inter-subject classification. This difference in accuracies in the two settings is inline with the differences observed in other tasks such as classification of motor imagery from EEG. Contrary to the results in the literature on classifying motor imagery from EEG, Tikhonov regularization leads to decrease in accuracies. There is an increase in the accuracy when more number of filter pairs are used for classification, similar to the trend observed in speech imagery classification. However, unlike speech imagery classification, the accuracy plateaus in the case of classification of meditation.

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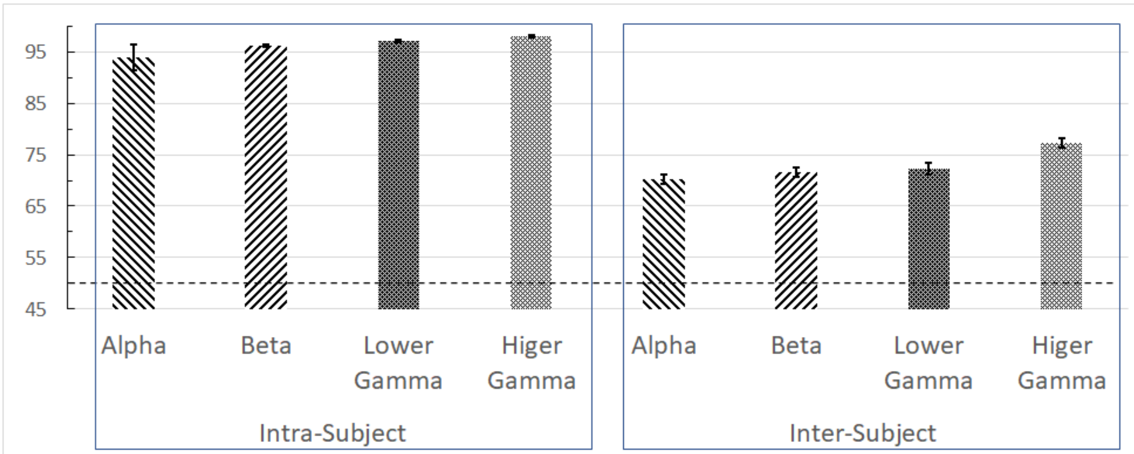

Fig. 2. Comparison of the performance of the proposed system in intra-subject and inter-subject settings. Different EEG frequency bands are given in the x-axis whereas the accuracies in percentage are given in the y-axis. Chance level accuracy is denoted by the dashed line. Error bars indicate standard deviation.

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