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Detecting moments of distraction during meditation practice based on changes in the EEG signal

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Abstract*—Electroencephalography (EEG) enables online monitoring brain activity, which can be used for neurofeedback. One of the growing applications of EEG neurofeedback is to facilitate meditation practice. Specifically, EEG neurofeedback can be used to alert participants whenever they get distracted during meditation practice based on changes in their brain activity. In this study, we develop machine learning models to detect moments of distraction (due to mind wandering or drowsiness) during meditation practice using EEG signals. We use EEG data of 24 participants while performing a breath focus meditation with experience sampling and extract twelve linear and non-linear EEG features. Features are fed to ten supervised machine learning models to classify (i) Breath Focus Awake (BFA) vs Breath Focus Sleepy (BFS), and (ii) BFA vs Mind Wandering (MW). We observe that the linear features achieve a maximum accuracy of 86% for classifying awake (BFA) and sleepy (BFS), whereas non-linear features have more predictive ability for classifying between BFA and MW with a maximum accuracy of nearly 78% . In addition, visualization of unsupervised t-SNE lower embeddings supports the evidence of distinct clusters for each condition. Overall our results show that machine learning algorithms can successfully identify periods of distraction during meditation practice in novice meditators based on linear and non-linear features of the EEG signal. Consequently, our results have important implications for the development of mobile EEG neurofeedback protocols aimed at facilitating meditation practice.

I. Introduction

Neurotechnology is the new frontier of neuroscience, enabling complex neuro-sensor technology into consumer wearable products. Electroencephalography (EEG) is a non-invasive technology to record brain signals for clinical and non-clinical purposes. Wearable EEG headset technology is available for consumers for different purposes, one of which is facilitating meditation practice.

Decades of research on meditation have shown significant cognitive and health benefits [1]. A commonly adopted meditation technique consists on focusing on the breath. Novice meditation practitioners often struggle with this kind of meditation as they fail to detect periods of distraction (due to mind wandering or drowsiness) during their practice.

There is a growing interest in the EEG correlates of meditative states, since these could be used to develop EEG neurofeedback protocols aimed at facilitating meditation practice [2], [3] (see Fig. 1 for a depiction of a protocol). In this way, a recent study identified significant EEG changes during meditation practice corresponding to moments of distraction in both expert and novice practitioners [4]. In the same line, another recent study used machine learning to shown that the EEG correlates of moments of distraction during meditation practice can be identified across different meditation traditions. [5].

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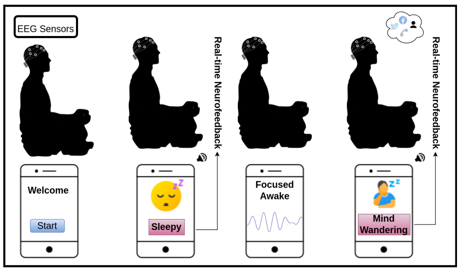

Fig. 1. Exemplary EEG neurofeedback protocol to facilitate meditation practice. A meditation practitioner can be alerted through a sound of moments of distraction during meditation practice based on changes in the EEG signal.

In this study, we aim to develop machine learning models that can distinguish moments of distraction during meditation practice based on EEG features solely. For this purpose, we analyze the EEG data of participants that reported their level of distraction several times during a breath focus meditation.

II. Data Description

The detailed description and availability of the dataset are mentioned in Rodriguez-Larios et al. [6]. EEG of 19 sensors with 512 Hz was used to collect recordings for meditation with probe-caught experience sampling (60 min). Meditation with experience sampling includes epochs classified by participants as breath focus, mind wandering, and other distraction moments (sound, discomfort, or others). A total of 58 participants were included in this study comprising 29 controls (no experience) and 29 meditators (experienced at least three years). The motivation of this article is to develop models for controls (beginner) to get alert on mind wandering in a future EEG neurofeedback protocol. Hence, we extracted the EEG signals of controls only. Participants were asked to close their eyes and follow the breath focus instructions mentioned in Kabat Zinn [7]. Bell sound rang after every brief period within 30 to 90s, and participants were asked to answer the following question: a) focusing on breath, b) distracted by

TABLE I
FEATURES EXTRACTED ON EEG SIGNAL USING LINEAR AND NON-LINEAR METHODS

Type	Feature
Linear	Mean, Variance, Standard Deviation, Skewness, Kurtosis, Root Mean Square
Non-Linear	Katz Fractal Dimension, Higuchi Fractal Dimension, Decorrelation Time, Hjorth Mobility, Hjorth Complexity, Approximate Entropy

thoughts, c) distracted by something else. Any answer leads to further two more questions on a scale of (1 to 7): (a) Level of confidence low (1) to high (7) on the previous answer (b) drowsiness level of fully awake (1) or falling asleep (7). A total of 40 trials were obtained in 60 min. We performed the preprocessing steps followed in the article [6] and code is available in open framework platform [4]. EEG signals were extracted between 2 and 30 Hz, and other frequencies were not included to avoid artifacts from different non-neural sources.

III. METHODOLOGY

Feature Extraction: A wide range of EEG signals has been analyzed from a linear and non-linear dynamics perspective. EEG signals originate from neural activity, which represents a chaotic non-linear dynamical system. Modern research has been putting effort into understanding the underlying mechanisms of the non-stationary change of electrical activity over time. Each technique has a set of limitations regarding its relationship to the data. Therefore, we applied 12 features comprising six linear and six non-linear features. There have been a growing number of research articles using non-linear methods in meditation research [8], [9]. We presented the feature extraction techniques in Table. I.
and code implementation is available at mne-features [10].

Data Segregation: We extracted the 5 seconds (before the bell sound) epochs of breath focus (BF) and mind wandering (MW). In this, we used the score of confidence and drowsiness to segregate the epochs. All epochs of each subject for the complete session was further binarized into awake and sleepy by computing the median of the drowsiness score. Awake and sleepy epochs were segregated for both conditions (BF/MW). After this, we computed the features for each epoch, including all 19 sensors. Features extracted for epochs for a participant were mean weighted by confidence score and thus obtained a mean weighted score of epochs respective to awake and sleepy in both conditions. This approach aims to minimize the influence of epochs where subjects were uncertain about their conditions. Five participants were rejected due to the unavailability of either awake or sleepy in both conditions. Finally, we considered samples of 24 subjects for breath focus in awake (BFA) and sleepy (BFS) and mind wandering of awake state (MW).

Classification and t-SNE Visualization: We used the two analyses to observe the differences between conditions using supervised and unsupervised techniques. First, we built the supervised classification models, and second using the unsupervised technique to reduce the dimension of data to visualize the differences in two dimension. Classification models were built to discriminate neural oscillatory states of (i) Breath Focus Awake (BFA) vs Breath Focus Sleepy (BFS) and (ii) Breath Focus Awake vs Mind Wandering (MW). We trained ten different linear and non-linear machine learning models to classify the EEG feature representation. The models included were AdaBoost, Decision Tree, Random Forest, Gaussian Process, Linear SVM, RBF SVM, Naive Bayes, Nearest Neighbour, Neural Net, and Quadratic Discriminant Analysis. We used the five-fold cross-validation techniques and reported the accuracy, precision, recall, and f1-score. We used t-Distributed Stochastic Neighbour Embedding to reduce the higher dimension of the data into two dimension to visualize the differences between the states.

IV. RESULTS AND DISCUSSION

We present the findings using supervised machine learning models and unsupervised t-SNE visualization. We reported the accuracy obtained using different features and regions.

Region Analysis: We divided the scalp EEG sensors into three regions, including Frontal, Central, and Parietal, as shown in Fig. 2. We obtained the maximum classification accuracy of 85.77% between awake (BFA) and sleepy (BFS) by including FCP (all regions) with precision, recall, f1-score

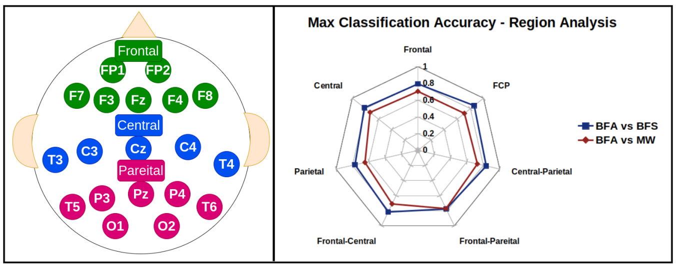

Fig. 2. [Left] Scalp EEG sensors are divided into three regions: Frontal, Central, and Pareital, and combinations of these are used for analysis. Central and Pareital areas include temporal and occipital electrodes, respectively. [Right] Maximum classification accuracy is shown for both conditions, including breath focus awake/sleepy (BFA/BFS) and mind wandering (MW) for the region. FCP includes all 19 sensors covering all regions.

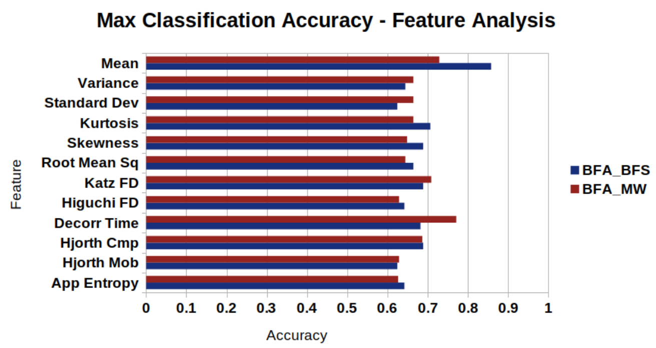

Fig. 3. Max Classification accuracy of each feature is displayed for binary classification.

TABLE II
MAX ACCURACY OF CLASSIFIERS BETWEEN BREATH FOCUS AWAKE (BFA) AND SLEEPY (BFS), AND BFA AND MIND WANDERING (MW)

Awake (BFA)	vs	Sleepy (BFS)					
Classifier	**Frontal**	**Central**	**Parietal**	**Frontal-Central**	**Frontal-Pareital**	**Central-Parietal**	**FCP**
AdaBoost	0.729	0.689	0.744	0.729	0.727	0.731	0.769
Decision Tree	0.729	0.771	0.751	0.711	0.773	0.729	0.767
Gaussian Process	0.753	0.753	0.753	0.773	**0.776**	0.733	0.776
Linear SVM	0.598	0.538	0.598	0.638	0.638	0.578	0.638
Naive Bayes	0.753	0.731	0.669	0.816	0.753	**0.836**	0.753
Nearest Neighbors	0.751	0.689	0.667	0.691	0.669	0.687	0.689
Neural Net	0.582	0.544	0.558	0.564	0.580	0.716	0.656
QDA	0.707	0.691	0.607	0.651	0.602	0.667	0.540
Random Forest	**0.793**	**0.816**	**0.769**	**0.816**	0.729	0.793	**0.858**
RBF SVM	0.773	0.791	0.753	0.796	0.753	0.773	0.753
Awake (BFA)	**vs**	**Mind Wandering (MW)**					
AdaBoost	**0.704**	0.664	0.644	0.707	0.682	0.644	0.707
Decision Tree	0.627	0.667	0.589	0.622	**0.771**	0.664	0.622
Gaussian Process	0.691	0.582	0.620	0.644	0.667	0.711	**0.709**
Linear SVM	0.520	0.558	0.607	0.562	0.567	0.538	0.538
Naive Bayes	0.609	0.687	**0.647**	0.664	0.687	0.622	0.709
Nearest Neighbors	0.602	0.622	0.624	0.624	0.629	0.647	0.607
Neural Net	0.560	0.542	0.542	0.522	0.522	0.524	0.560
QDA	0.627	0.647	0.629	0.662	0.687	0.687	0.598
Random Forest	0.664	0.664	0.642	**0.709**	0.647	**0.727**	0.684
RBF SVM	0.689	**0.729**	0.624	0.669	0.602	0.684	0.649

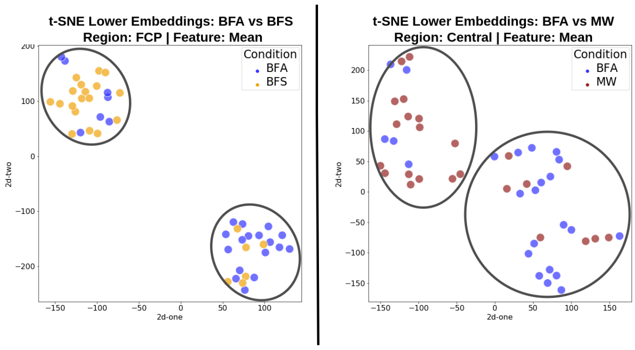

Fig. 4. t-SNE lower dimension visualization of conditions

of 87.85%, 85.5%, 85.16%, respectively. The features included from Central-Parietal showed an accuracy of 83.55%, followed by the Central region. Frontal alone and with the combination of Central showed accuracy around 80% and Central classified with 81.55%. The model returned the minimum accuracy of 77.5% with Frontal-Parietal. Classification between breath focus awake (BFA) and mind wandering (MW) resulted in the maximum accuracy of 77.11% in Frontal-Parietal with precision, recall, f1-score of 80.02%, 77.5%, and 76.47%. We obtained greater than 70% accuracy across all regions except the Parietal. We obtained higher accuracy in classifying the awake and sleepy conditions of breath focus compared to classifying awake and mind wandering. These results showed that the subject-invariant feature representation enables the classification.

Feature Analysis: We achieved maximum accuracy of 85.77% with mean features between BFA(awake) and BFS(sleepy) as shown in Fig. 3. We observed features of kurtosis predicted above 70% accuracy. Classification between BFA and MW showed maximum accuracy of 77.11% with Decorrelation Time. We obtained above 70% accuracy using Katz Fractal Dimension and mean features. We observed a pattern that linear feature mean was more predictive for classifying awake and sleepy conditions of breath focus, whereas non-linear feature Decorrelation Time had the greater predictive ability for awake and mind wandering states.

Machine Learning model evaluation: In Table. II classifiers accuracies are presented. Classification between BFA and BFS resulted in accuracies from chance level to a maximum of around 86%. Random Forest achieved maximum accuracy in five regions, including Frontal, Central, Parietal, Frontal-Central, and FCP. The accuracy of Naive Bayes was maximum at Central-Parietal and followed by the Gaussian process in Frontal-Parietal. The classification between BFA and MW showed the maximum accuracies of 77% using the Decision Tree in Frontal-Parietal. The accuracy above 70% was obtained using Random Forest, RBF SVM, AdaBoost, and Gaussian Process in other regions except for Parietal. The maximum accuracy of around 65% was achieved in Parietal employing Random Forest.

Low Dimensional Visualization: In Fig. 4, we presented the results using the unsupervised t-SNE data visualization technique. The labels were not provided to the model, and the model learned itself the structure present in the higher dimension. t-SNE projected the relationship of data points in two-dimension and showed that BFA and BFS have significant differences in the form of two distinct clusters. Similarly, we reported the differences between BFA and MW. The visualization provided strong evidence that there is a significant difference between conditions.

V. CONCLUSION

This research shows that machine learning algorithms can successfully identify moments of distraction during meditation practice in novice meditators based on linear and non-linear features of the EEG signal. The models developed here could be used in future mobile EEG neurofeedback protocols aimed at facilitating meditation practice.

REFERENCES

[1] T. Brandmeyer, A. Delorme, and H. Wahbeh, "The neuroscience of meditation: classification, phenomenology, correlates, and mechanisms," *Progress in brain research*, vol. 244, pp. 1–29, 2019.

[2] P. Pandey, P. Gupta, and K. P. Miyapuram, "Brain connectivity based classification of meditation expertise," in *International Conference on Brain Informatics*. Springer, 2021, pp. 89–98.

[3] P. Pandey and K. P. Miyapuram, "Brain2depth: Lightweight cnn model for classification of cognitive states from eeg recordings," in *Annual Conference on Medical Image Understanding and Analysis*. Springer, 2021, pp. 394–407.

[4] J. Rodriguez-Larios, "Eeg data-code," Jun 2021. [Online]. Available: https://osf.io/3uszv/?view_only=d41ddd2200e642cf9992a016cb739b90

[5] S. Chaudhary, P. Pandey, K. P. Miyapuram, and D. Lomas, "Classifying eeg signals of mind-wandering across different styles of meditation," in *International Conference on Brain Informatics*. Springer, 2022, pp. 152–163.

[6] J. Rodriguez-Larios, E. A. B. M. de Oca, and K. Alaerts, "The eeg spectral properties of meditation and mind wandering differ between experienced meditators and novices," *Neuroimage*, vol. 245, p. 118669, 2021.

[7] "Kabat-zinn, j. (1990). full catastrophe living: using the wisdom of your body and mind to face stress, pain, and illness." 1990.

[8] Y. Lu and J. Rodriguez-Larios, "Nonlinear eeg signatures of mind wandering during breath focus meditation," *bioRxiv*, 2022.

[9] P. Pandey and K. P. Miyapuram, "Nonlinear eeg analysis of mindfulness training using interpretable machine learning," in *2021 IEEE International Conference on Bioinformatics and Biomedicine (BIBM)*. IEEE, 2021, pp. 3051–3057.

[10] "Features¶." [Online]. Available: https://mne.tools/mne-features/