A flexible analytic wavelet transform and ensemble bagged tree model for electroencephalogram-based meditative mind-wandering detection

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Abstract

Mind-wandering (MW) is when an individual's concentration drifts away from the task or activity. Researchers found a greater variability in electroencephalogram (EEG) signals due to MW. Collecting more nuanced information from raw EEG data to examine the harmful effects of MW is time-consuming. This study proposes a multi-resolution assessment of EEG signals using the flexible analytic wavelet transform (FAWT). The FAWT algorithm decomposes raw EEG data into more representative sub-bands (SBs). Several statistical characteristics are derived from the obtained SBs, and the effects of MW during meditation on the EEG signals are investigated. A set of significant characteristics is chosen and fed into the machine learning modules using a 10-fold validation approach to detect MW subjects automatically. The proposed framework can be used to design a suitable brain-computer interface (BCI) system to reduce MW and increase meditation depth for holistic and long-term health in society.

Introduction

Mind Wandering also known as spontaneous thought or day dreaming, is the phenomenon in which an individual's mind strays away from the work at hand or the immediate environment and becomes immersed in unrelated, frequently self generated thoughts, dreams, or recollections [1]. People who wander their minds may find themselves thinking about past events, planning for the future, or simply letting their thoughts flow without a defined aim [2]. MW is a common occurrence during meditation, particularly for novices.

Consequently, developing a machine learning framework for automated screening of MW during meditation is the need of the hour. If brain functioning analyses could be successfully connected with MW episodes, it might be able to provide signs of MW as well as information regarding its neurological underpinnings. By motivating these facts, this study presents the multiresolution analysis of occipital EEG sensor data to analyze the impact of meditation on MW and to automatically detect the MW subjects using machine learning model.

Objective

The main contributions of this study are given below:

- The multi-resolution analysis of EEG data during meditation and classifies expert (non-MW) and novice (MW) EEG signals using a machine learning system.
- The FAWT approach is used for the first time in this study to decompose the meditative EEG signals into more representative SBs. Various statistical characteristics are explored for in-depth MW analysis on EEG signals.
- The Kruskal–Wallis (K–W) test is used to determine the significance of evaluated features; selected features are sent into machine learning modules to recognize MW subjects during meditation.

Proposed Method

2.1. Proposed method

Fig.1 depicts the layered architecture of the proposed methodology.

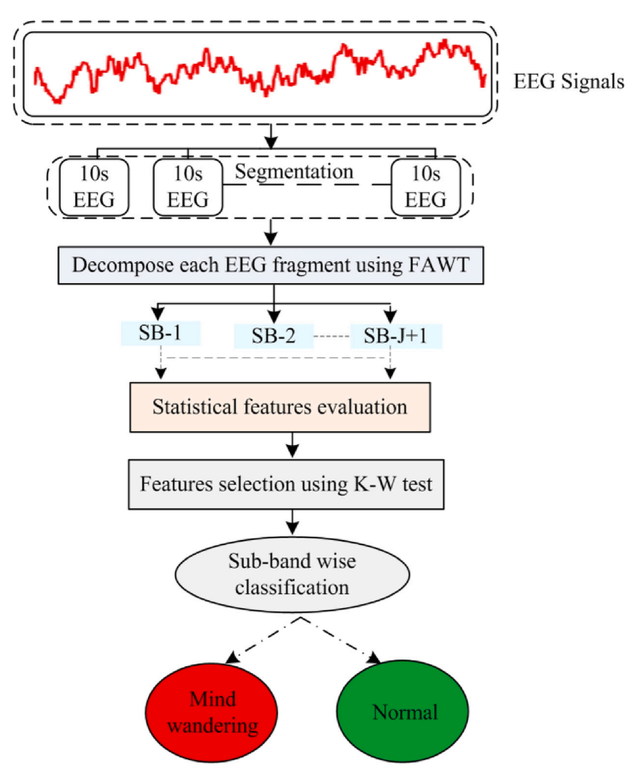

Fig. 1. Schematic diagram of the presented framework.

2.2. Dataset

In this study, publicly accessible data [3] is used to examine the impact of meditation and validate the proposed classification strategy. In this work, only EEG sequences are used and segmented into 10-s fragments and marked as either non-MW or MW as shown in Fig. 2.

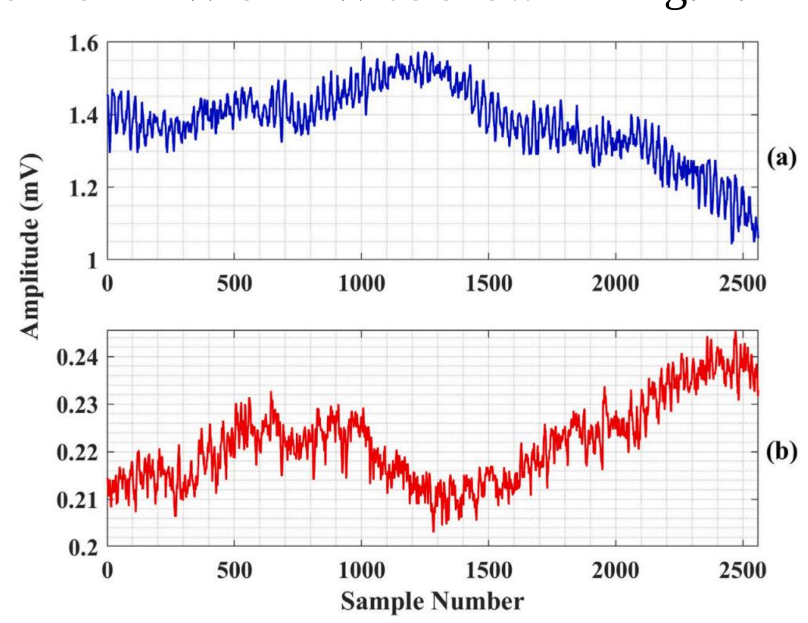

Fig. 2. Typical 10-s EEG fragments of expert and novice class.

2.3. Flexible Analytic Wavelet Transform (FAWT)

FAWT is a versatile signal processing algorithm and an advanced variant of DWT known for its versatility in time-frequency analysis and feature extraction. Unlike standard wavelet transforms that use predefined basis functions (e.g., Morlet wavelets), FAWT enhances the capabilities of standard wavelet transforms by enabling the selection of basis functions to be flexible to better match the features of the signal under study. The FAWT can be formulated mathematically as follows:

$$\mathrm{FAWT}(x)(t,\omega)=\int_{-\infty}^{\infty} x(\tau)\Psi^{*}(\tau,t,\omega)d\tau$$

To decompose input EEG signals into several SBs three tuning parameters are required: quality factor (Q), redundancy rate (r), and number of decomposition stages (J).

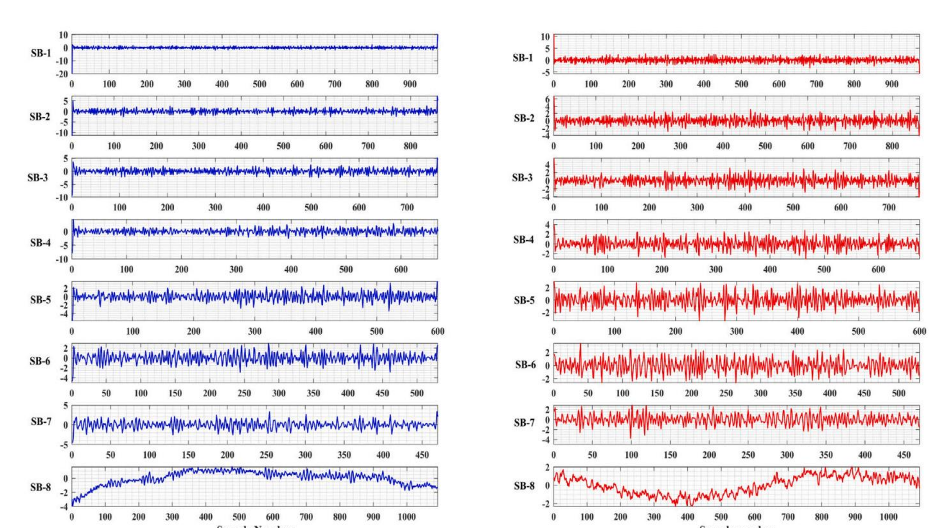

Fig. 3. EEG SBs of the expert and novice class extracted using FAWT.

2.4. Feature Evaluation

The process of finding a subset of relevant qualities that are most helpful in predicting the target variable using a machine learning model is known as feature evaluation. Fourteen statistical features are evaluated from the each SB.

2.5. Machine Learning Classifier

To identify the MW and non-MW, decision tree classifiers with Fine Tree (FT), Medium Tree (MT), Coarse Tree (CT), Ensemble Boosted Tree (EBoTC), and Ensemble Bagged Tree kernel (EBgTC) functions are used in this investigation.

Results

Table 1 shows the SB-wise power obtained for both occipital channels. Table 2 represents the SB-wise PSD computed for both occipital channels.

Table 1
SB-wise power for novice and expert practitioners.

SB	Expert O1-Oz	Novice O1-Oz	Expert O2-Oz	Novice O2-Oz
SB-1	139.02	267.38	137.63	133.25
SB-2	143.36	448.88	76.37	321.57
SB-3	137.57	342.23	119.61	123.48
SB-4	321.21	615.94	617.79	240.98
SB-5	397.09	667.92	199.41	656.09
SB-6	198.36	513.76	255.58	568.42
SB-7	309.91	908.22	824.33	988.32
SB-8	178.73×10^{7}	1.30×10^{7}	89.96×10^{7}	19.11×10^{7}

Table 2
SB-wise PSD computed for both occipital channels.

SB	Expert O1-Oz	Novice O1-Oz	Expert O2-Oz	Novice O2-Oz
SB-1	13.91	21.06	17.734	18.18
SB-2	16.27	21.72	20.94	18.46
SB-3	31.05	38.42	37.63	28.44
SB-4	41.46	72.88	51.34	44.27
SB-5	63.28	98.41	65.71	81.32
SB-6	81.27	125.84	80.12	109.40
SB-7	99.53	200.57	137.71	131.57
SB-8	18.54×10^{8}	50.49×10^{9}	25.52×10^{8}	1.33×10^{11}

A collection of 14 statistical features is computed from each SB to automatically identify MW EEG data from non-MW EEG signals. To determine the statistical significance of features, the Kruskal–Wallis (K–W) technique is used. Tables 5 and 6 represent the SB-wise obtained classification accuracy using different classifiers with O1-Oz and O2-Oz channels, respectively.

Table 5
SB-wise obtained classification accuracy (%) using different classifiers with O1-Oz channel.

SB	Decision FT	Decision MT	Decision CT	EBoTC	EBgTC
SB-1	86.9	87.8	83.8	88.4	85.6
SB-2	84.1	83.9	82.2	85.4	84.6
SB-3	84.1	84.2	81.9	85.1	83.9
SB-4	83.1	84.2	82.5	84.9	83.6
SB-5	83.6	82.8	81.4	84.3	83.7
SB-6	83.0	82.5	79.5	83.5	83.0
SB-7	80.4	80.2	87.9	81.6	89.6
SB-8	85.2	80.9	86.4	89.9	**92.41**

Table 6
SB-wise obtained classification accuracy (%) using different classifiers with O2-Oz channel.

SB	Decision FT	Decision MT	Decision CT	EBoTC	EBgTC
SB-1	81.18	81.04	87.56	82.01	82.98
SB-2	83.2	80.7	87.6	83.4	83.2
SB-3	85.5	84.5	82.2	86.2	84.5
SB-4	84.7	83.6	79.9	84.8	83.6
SB-5	84.1	82.1	78.6	85.2	83.4
SB-6	83.1	79.1	79	83.7	83.0
SB-7	81.9	81.8	88.4	84.2	81.9
SB-8	88.2	84.5	88.9	89.3	**90.85**

Conclusion

The non-stationary and non-linear properties of EEG data include considerable problems when attempting to extract complex information directly from the raw signal. Multi-resolution assessment of the raw EEG signal is required to obtain more representative information from the input data. The following are the study's findings:

- This study provides a novel approach that utilizes the FAWT method to accurately decompose EEG data into multi-resolution SBs. The power and power spectral density of each sub-band are examined and concluded that SB-8 has the highest for both occipital channels.
- The statistical characteristics extracted from the SBs are evaluated and fed into several machine learning modules for accurate detection of MW individuals. The highest MW-detection accuracy of 92.41% and AUC values of 0.95 were yielded using SB-8 and an EBgTC with an O1-Oz channel.

The given work will be used in the future to investigate the impact of different emotional stages on EEG signals and to design an appropriate brain–computer interfacing system to increase the depth of meditation.

Reference

[1] N. Bosch, S.K. D'Mello, Automatic detection of mind wandering from video in the lab and in the classroom, IEEE Trans. Affect. Comput. 12 (4) (2021) 974–988, http://dx.doi.org/10.1109/TAFFC.2019.2908837.

[2] P.A. Facione, et al., Critical thinking: What it is and why it counts, Insight Assess. 1 (1) (2011) 1–23.

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