Nonlinear EEG signatures of mind wandering during breath focus meditation

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Abstract

In meditation practices that involve focused attention to a specific object, novice practitioners often experience moments of distraction (i.e., mind wandering). Previous studies have investigated the neural correlates of mind wandering during meditation practice through Electroencephalography (EEG) using linear metrics (e.g., oscillatory power). However, their results are not fully consistent. Since the brain is known to be a chaotic/nonlinear system, it is possible that linear metrics cannot fully capture complex dynamics present in the EEG signal. In this study, we assess whether nonlinear EEG signatures can be used to characterize mind wandering during breath focus meditation in novice practitioners. For that purpose, we adopted an experience sampling paradigm in which 25 participants were iteratively interrupted during meditation practice to report whether they were focusing on the breath or thinking about something else. We compared the complexity of EEG signals during mind wandering and breath focus states using three different algorithms: Higuchi's fractal dimension (HFD), Lempel-Ziv complexity (LZC), and Sample entropy (SampEn). Our results showed that EEG complexity was generally reduced during mind wandering relative to breath focus states. We conclude that EEG complexity metrics are appropriate to disentangle mind wandering from breath focus states in novice meditation practitioners, and therefore, they could be used in future EEG neurofeedback and/or neurostimulation protocols to facilitate meditation practice.

Keywords: EEG; Mind wandering; Meditation; Complexity; Nonlinear analysis

Introduction

In the last years, several studies have shown that different meditation practices can promote mental and physical health (Okoro et al., 2013; Tang et al., 2015; Khoury et al., 2017; Deolindo et al., 2020). In an important part of these meditation practices, practitioners focus their attention on a specific object of meditation (such as the sensation of breathing) and try to disengage from distractions (Lutz et al., 2015; Anālayo, 2019). These moments of distraction are usually categorized as 'mind wandering' and they entail self-generated thoughts about the past, present, and future (Smallwood and Schooler, 2006, 2015; Delorme and Brandmeyer, 2019). Mind wandering during meditation is more prominent in novice practitioners, who normally experience more difficulties to detect mind wandering episodes and to re-focus their attention to the object of meditation (Mrazek et al., 2013; Brandmeyer and Delorme, 2018; Linares Gutiérrez et al., 2019; Rodriguez-Larios et al., 2021).

There is a growing interest in the identification of the neural correlates of mind wandering during meditation through Electroencephalography (EEG). This is partly due to its potential to develop EEG-assisted meditation protocols (Brandmeyer and Delorme, 2013; Ros et al., 2013; Brandmeyer and Delorme, 2020). Several studies have adopted experience sampling paradigms to study the EEG correlates of mind wandering in the context of breath focus meditation (Braboszcz and Delorme, 2011; Brandmeyer and Delorme, 2018; van Son et al., 2019; Rodriguez-Larios and Alaerts, 2021; Rodriguez-Larios et al., 2021). In this type of paradigm, subjects are interrupted several times during meditation so they can report whether they were focusing on the object of meditation or thinking about something else. The majority of these studies showed changes in the alpha (8-14 Hz) and theta (4-8 Hz) bands associated with mind wandering, although the direction of the effects is not fully consistent (Braboszcz and Delorme, 2011; Brandmeyer and Delorme, 2018; van Son et al., 2019; Rodriguez-Larios and Alaerts, 2021; Rodriguez-Larios et al., 2021).

Although the neural correlates of different cognitive states are normally studied through linear metrics (e.g., oscillatory power), the brain is known to be a chaotic system that presents nonlinear dynamics (Zhang et al., 2001; Rodriguez-Bermudez and Garcia-Laencina, 2015). Therefore, nonlinear EEG metrics are appropriate to provide complementary information of neural dynamics and their underlying

mechanisms beyond conventional spectral analysis (Pereda et al., 2005; Rodriguez-Bermudez and Garcia-Laencina, 2015; Ma et al., 2018). The application of nonlinear methods to EEG analysis has generated considerable interest in recent years given their ability to characterize both healthy and pathological brain activity (Gomez et al., 2009; Ibanez-Molina and Iglesias-Parro, 2014; Hou et al., 2021). Nonlinear methods can be used to estimate the complexity of a given signal, which can be interpreted as the degree of randomness of a system. In the case of EEG, this can be related to various factors such as the number of EEG signal generators and the level of oscillatory synchronization (Ibanez-Molina et al., 2018).

EEG complexity metrics have been used to characterize mind wandering and meditative states in a few studies (Martinez Vivot et al., 2020; Young et al., 2021). However, these studies were carried out in experienced meditators only. Given the rare occurrence of mind wandering during meditation in experienced practitioners, these studies instructed participants to mind wander (e.g., to remember autobiographical events) instead of performing experience sampling during meditation practice. To our knowledge, no previous study has investigated the relationship between EEG complexity and mind wandering during meditation practice in novices using experience sampling. Nonetheless, a comprehensive understanding of the EEG correlates of (naturally occurring) mind wandering in novices is crucial from a translational perspective because EEG-aided meditation is normally aimed at participants without previous meditation experience (Brandmeyer and Delorme, 2013, 2020).

In this study, we used an experience sampling paradigm to investigate nonlinear EEG features of mind wandering during breath focus meditation in participants without previous meditation experience. Participants (N = 25) were asked to focus on the sensation of breathing and to report whether they were focusing on their breath or thinking about something else after they heard a bell sound. We compared EEG complexity between mind wandering (MW) and breath focus (BF) states. In order to increase the reliability of our measurement and the comparability with previous literature, we adopted three commonly used algorithms to calculate the complexity: Higuchi's fractal dimension (HFD), Lempel-Ziv complexity (LZC), and Sample entropy (SampEn). In the light of previous results showing the effect of drowsiness in the EEG correlates of mind wandering (Rodriguez-Larios and Alaerts, 2021; Rodriguez-Larios et al., 2021), we also assessed how changes in complexity are associated with inter-individual

differences in drowsiness levels.

Methods

Dataset

The dataset for this manuscript was also used for other analyses in our recent study (Rodriguez-Larios and Alaerts, 2021), which includes detailed descriptions of the task during EEG recording, data acquisition, and pre-processing. Here we only include a brief description of these aspects.

Participants

Twenty-eight participants (age 23.46 y, range 20-29 y, 11 males) took part in the study. Twenty-five participants were included for further analysis since three participants were rejected due to technical problems in the experiment. All participants gave written informed consent before the experiment, which was approved by the Social and Societal Ethics Committee (SMEC) of the University of Leuven and was conducted in accordance with the Declaration of Helsinki. Participants did not have previous experience with meditation techniques and they were paid 8 euros per hour.

Task

All participants performed a breath focus meditation (with eyes closed) while EEG was recorded. The meditation was randomly interrupted with a bell sound (after varying intervals of 20 to 60 seconds). Participants were then required to open their eyes and report whether they were mind wandering (MW) or focusing on their breath (breath focus; BF). Two additional questions allowed participants to report their confidence in their answer about their current state and arousal level in each trial. Each participant performed a total of forty trials. Questions were displayed on a computer screen and answers were given by key pressing (using E-prime 2.0 software). Debriefings for the level of drowsiness, arousal, and emotional valence were filled after the task (available for 22 out of 25 participants).

EEG acquisition and pre-processing

The EEG was recorded using a Nexus-32 system (Mind Media) (21 EEG electrodes including two mastoids). EEG data were sampled at 512 Hz. Pre-processing was performed using custom scripts and the EEGLAB toolbox (Delorme and Makeig, 2004) in MATLAB. The data was bandpass filtered between 1 Hz and 40 Hz. Artifact rejection was conducted with the Artifact Subspace Reconstruction method (Chang et al., 2020) and independent component analysis (ICA) (Delorme and Makeig, 2004). Data were average-referenced and epochs (i.e., BF or MW) of 5 seconds before bell sound probes were selected for further analysis. Epochs with absolute amplitudes exceeding 100 μV were rejected.

Estimation of EEG complexity

Higuchi's fractal dimension (HFD). Several algorithms of fractal dimension have been developed. In comparison with other algorithms, HFD (Higuchi, 1988) is a prominent method that is suitable for analyzing EEG signals, which could be deterministic, stochastic, non-stationary, and noisy (Klonowski, 2009). This is due to the following advantages: relatively higher accuracy, faster computation, and applicability with relatively shorter time series of EEG (Accardo et al., 1997; Esteller et al., 2001; Gomez et al., 2009; Ibanez-Molina and Iglesias-Parro, 2014).

The original time series X with N points can be used to construct k time series as follows:

$$X_k^m: \quad X(m), X(m+k), X(m+2k), \ldots, X(m+[(N-m)/k]k) \tag{1}$$

where m denotes the initial time (m = 1, 2, 3, …, k) and k denotes delay between the points. The length $L_m(k)$ is defined by

$$L_m(k) = \frac{N-1}{[(N-m)/k]k^2} \sum_{i=1}^{[(N-m)/k]} |X(m+ik) - X(m+(i-1)k)| \tag{2}$$

The average length $L_m(k)$ for m ranging from 1 to k is then obtained

$$L(k) = \frac{1}{k} \sum_{m=1}^{k} L_m(k) \tag{3}$$

The $L(k)$ is proportional to k^{-D},

$$L(k) \propto k^{-D} \tag{4}$$

where D is the slope of the least squares linear fit through the curve of $\log L(k)$ versus $\log(1/k)$. The D is defined as the Higuchi fractal dimension HFD.

Note that $m = 1, 2, 3, \ldots, k$, thus the k value must be determined, which is used in the analysis is defined as k_{max}. To determine the k_{max}, a range of k_{max} was applied to calculate the HFD, then a saturated HFD plotting indicated an appropriate k_{max}. In the present study, we chose the k_{max} value of 80.

Lempel-Ziv complexity (LZC). LZC was proposed by Lempel and Ziv (1976). LZC does not take into account whether the signal is from deterministic chaos or stochastic processes, i.e., model-independence, therefore it is appropriate for EEG signals (Zhang et al., 2001) and especially for the present study in which we do not aim to test for a model form of deterministic chaos or stochastic processes for our data, but rather interested in the distinct EEG complexity patterns of a specific experimental condition. Furthermore, the core part of the LZC algorithm just comprises sequence comparison and number accumulation. This can remarkably lower the requirement for computation cost, and eventually facilitates the application of this method, especially for real-time neurofeedback usage.

LZC algorithm depends on the process of coarse-graining by using which a data series is converted into a finite symbol sequence before calculating the complexity. We used binary conversion ("0–1") in this study. The LZC can be estimated using the following steps: First, a time series with a length of n is binarised. The threshold can be the mean value or median value of the time series. Here we used the median value: *md*. The values of time series greater than *md* were assigned ones, lower than *md* were assigned zeros. Second, the binary sequence was scanned from left to right for different subsequences of consecutive characters which compose a vocabulary to summarise the series. The amount of different subsequences in the vocabulary is defined as the complexity counter $c(n)$. Imagine a regular and simple signal that be binarised to a sequence of 010101010101, which can also be shown as 0*1*0*1*0*1*0*1*0*1*0*1 (subsequences separated with asterisks). Different subsequences are "0" and "1", thus the complexity of this signal is $c(n) = 2$. Consider another example: an irregular signal be binarised to a more complex sequence such as 110100010110, which can be shown as 1*10*100*0101*10 (subsequences separated with asterisks). This signal has a higher number of different

subsequences: “1”, “10”, “100”, and “0101”, reflecting that the complexity is relatively higher: $c(n) = 4$. Therefore, the basic idea of this algorithm just includes character comparison and number accumulation (Zhang et al., 2001).

To eliminate the effects of signal length, $c(n)$ can be normalized by using the upper bound of complexity:

$$b(n) \equiv \frac{n}{\log_{\alpha}(n)} \tag{5}$$

$$C(n) = \frac{c(n)}{b(n)} \tag{6}$$

For binary conversion, $\alpha = 2$. Here, $C(n)$ is the LZC measure used in the present study.

Sample Entropy (SampEn). Entropy is a concept from information theory, can measure the uncertainty of information/signal, can quantify the complexity of a system. Many algorithms have been developed and/or improved to estimate the entropy of a system. For biological time series data, approximate entropy (ApEn) (Pincus, 1991) and sample entropy (Richman and Moorman, 2000) are the two of the most commonly used measures (Yentes et al., 2013). There are several advantages of SampEn as compared to ApEn including better relative consistency for results, less sensitivity to the length of time series, remarkably faster computation, and without a bias towards regularity (Pincus, 1995; Richman and Moorman, 2000; Ramdani et al., 2009; Zhang et al., 2009; Yentes et al., 2013; Delgado-Bonal and Marshak, 2019).

The algorithm of SampEn is independent of the series length and can be described as follows. For a time series with N points u, a template vector of length m is defined:

$$x_m(i) = \{u(i), u(i+1), u(i+2), \dots, u(i+m-1)\} \tag{7}$$

in which $i = 1, 2, N\text{-}m\text{+}1$. Then, we define:

$$B_i^m(r) = \frac{1}{N-m-1} \sum_{j=1, j\neq i}^{N-m} Count(\|x_m(j) - x_m(i)\| < r) \tag{8}$$

The sum is the number of vectors $x_m(j)$ within a distance r of $x_m(i)$. Here we used the Chebyshev distance. In order to exclude self-matches, set $j \neq i$. The parameter r is the tolerance value for accepting matches,

normally set as a portion of standard deviation (σ) of data. We next define the function $B^m(r)$:

$$B^m(r) = \frac{1}{N-m}\sum_{i=1}^{N-m} B_i^m(r) \tag{9}$$

$B^m(r)$ is the probability that two vectors match for m points. Similarly, we applied the definitions for m + 1 points:

$$A_i^m(r) = \frac{1}{N-m-1}\sum_{j=1, j\neq i}^{N-m} Count(\|x_{m+1}(j) - x_{m+1}(i)\| < r) \tag{10}$$

$$A^m(r) = \frac{1}{N-m}\sum_{i=1}^{N-m} A_i^m(r) \tag{11}$$

The *SampEn* is then defined as:

$$SampEn(m, r, N) = -\log\left[\frac{A^m(r)}{B^m(r)}\right] \tag{12}$$

In the present study, we used $m = 2$, $r = 0.2\sigma$. The higher value of SampEn, the higher irregularity and complexity of the data series.

Statistical analysis

We analyzed the EEG data in the time window involving the last 5 seconds before the bell sound probes, using custom scripts in MATLAB (R2018a). The values of HFD, LZC and SampEn were analyzed separately. For each participant, we calculated the weighted average values across epochs (weighted by the confidence level of each trial) within the same condition for each electrode. These values were then used to evaluate the differences between MW and BF conditions. Dependent samples *t*-test (two-tailed) were computed to evaluate condition-related differences. In order to resolve the multiple comparisons problem, the cluster-based non-parametric randomization test (Maris and Oostenveld, 2007) implemented in the MATLAB toolbox FieldTrip (Oostenveld et al., 2011) was used. All paired samples were computed and a *p*-value of 0.05 was set as the threshold. The samples with a *p*-value under the threshold were clustered based on spatial-temporal adjacency, then the sum of the clustered *t*-values was obtained. This step was then repeated 1000 times by using samples randomized across MW and BF conditions, generating a new distribution of statistical values. The original samples were evaluated based

on this distribution by using the threshold of 0.05 for significant data cluster(s). Data were plotted using the MATLAB toolboxes FieldTrip (Oostenveld et al., 2011) and custom scripts.

Unequal trial counts in different conditions may introduce bias for analysis. To overcome this potential problem, we also matched trial counts (MTC) between MW and BF conditions for each subject by randomly discarding trials from the condition with a larger trial count and then performed a comparison of complexity measures for the count-matched trials between conditions as well. Six participants were rejected due to insufficient (<10) trial counts in both conditions after MTC. Data from the remaining nineteen participants were used for MTC processed analysis. We called the results without MTC processing "non-MTC" for simplicity.

Correlation analysis

Given the relatively high levels of drowsiness of some participants in the sample (see Rodriguez-Larios and Alaerts (2021)), we assessed whether condition effects in complexity measures were associated with inter-individual differences in self-reported drowsiness. For this purpose, we calculated the averaged difference (MW minus BF) of complexity measures in the identified significant clusters for each subject and performed Kendall correlations between the averaged difference and the level of drowsiness across subjects.

Results

Higuchi's fractal dimension (HFD)

We observed decreased HFD during MW compared to BF. The cluster statistics revealed that the decrease in complexity ($t(24) = -52.442$, $p < 0.001$) was widely distributed across electrodes (see Figure 1). For this cluster, the mean HFD value was 1.677 (std: 0.039, median: 1.675) for MW and 1.695 (std: 0.026, median: 1.693) for BF. The values for each subject are shown in the scatter plot of Figure 1.

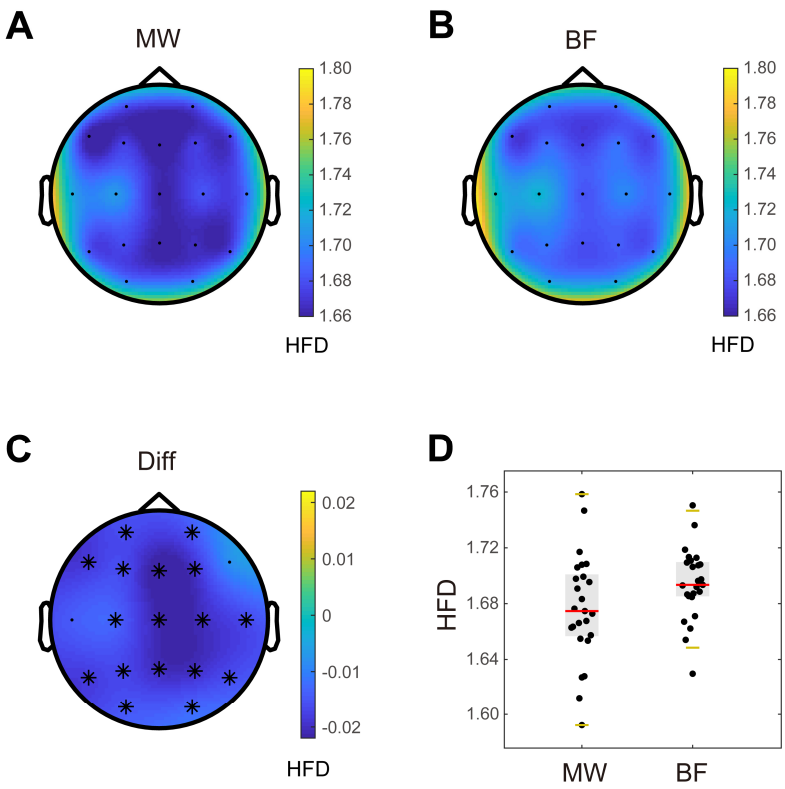

Figure 1. Differences in Higuchi's fractal dimension (HFD) between mind wandering (MW) and breath focus (BF) conditions. (A-B) Topographical plots depicting mean HFD values for MW and BF conditions in each electrode. **(C)** Topographical plot depicting the mean difference (Diff) between MW and BF conditions in each electrode. The black asterisks mark electrodes in which the HFD decrease (MW < BF) was significant ($p < 0.05$). **(D)** Individual HFD values (averaged within the significant cluster) for MW and BF conditions. Each subject is represented by a dot. The gray boxes indicate the 25th and 75th percentiles. Centerlines show the median in each condition. When outliers are present, the whiskers indicate 1.5 times the interquartile range from the 25th and 75th percentiles. When no outliers are present, the whiskers lay on the most extreme data points.

Matched trial count (MTC) analysis revealed a similar pattern of results. Decreased HFD ($t(18) = -45.746$, $p = 0.004$) was also observed during the MW condition relative to the BF condition across electrodes (Figure S1) . The mean HFD value of the cluster was 1.674 for MW (std: 0.034, median: 1.671) and 1.696 (std: 0.018, median: 1.695) for BF. The values for each subject are also shown in Figure S1. This indicates that unequal trial counts did not affect the HFD results.

Lempel-Ziv complexity (LZC)

A significant decrease in LZC was observed during MW relative to BF. Two negative clusters were found (MW < BF) (Figure 2). The first cluster revealed a significant ($t(24) = -9.328$, $p = 0.020$) LZC decrease (MW < BF) in the parietal and right frontocentral area (i.e., F4, Cz, C4, Pz). For this cluster,

the mean LZC value for MW was 0.271 (std: 0.020, median: 0.273) while the mean LZC value for BF was 0.278 (std: 0.016, median: 0.279). The LZC values of this cluster for each subject are shown in the scatter plot of Figure 2. The second cluster (in the left frontal area) did not reach statistical significance ($t(24) = -4.420$, $p = 0.057$) (Fp1, F7).

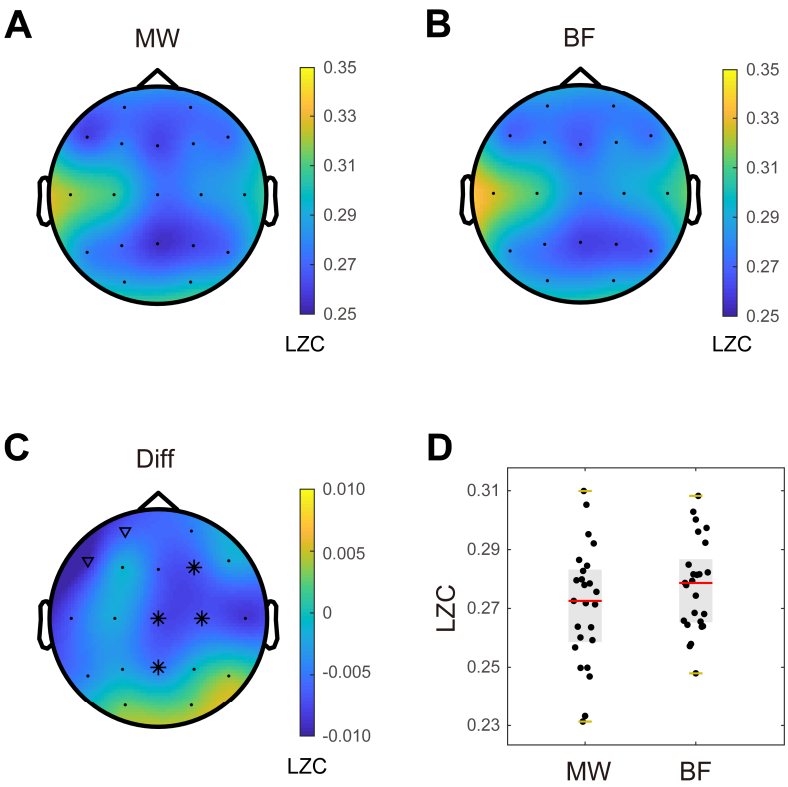

Figure 2. Differences in Lempel-Ziv complexity (LZC) between mind wandering (MW) and breath focus (BF) conditions. (A-B) Topographical plots depicting mean LZC values for MW and BF conditions in each electrode. **(C)** Topographical plot depicting the mean difference (Diff) between MW and BF conditions in each electrode. The black asterisks mark electrodes in which the LZC decrease (MW < BF) was significant ($p < 0.05$). The black triangles represent the second identified cluster which shows a not significant trend ($p = 0.057$) of LZC decrease (MW < BF) in the left frontal area. **(D)** Individual LZC values (averaged within the significant cluster, i.e., represented by black asterisks in Panel C) for MW and BF conditions. Each subject is represented by a dot. The gray boxes indicate the 25th and 75th percentiles. Centerlines show the median in each condition. When outliers are present, the whiskers indicate 1.5 times the interquartile range from the 25th and 75th percentiles. When no outliers are present, the whiskers lay on the most extreme data points.

When adopting the MTC approach, we also obtained two negative clusters (MW < BF) (Figure S2), although they did not reach statistical significance ($p > 0.05$). The first cluster showed a trend-level LZC decrease ($t(18) = -4.248$, $p = 0.058$) (MW<BF) in the parietal and right central area (i.e., C4, Pz). For this cluster, the mean LZC value was 0.267 for MW (std: 0.016, median: 0.267) and 0.273 for BF (std:

0.012, median: 0.272). Figure S2 shows the LZC values of this cluster for each subject. The second cluster showed a non-significant LCZ decrease ($t(18) = -2.314$, $p = 0.154$) (MW < BF) in the left frontal area (Fp1). In summary, although the LZC change became not significant (i.e., statistical trend) after controlling for trial counts, the direction and topography of LZC decreases (MW < BF) were qualitatively similar.

Sample Entropy (SampEn)

A significant decrease in SampEn was observed during MW relative to BF (Figure 3). The cluster statistics revealed that the decrease ($t(24) = -20.041$, $p = 0.007$) occurred in frontal, right temporal, central, and parietal areas (i.e., Fp1, F7, Fz, F4, Cz, C4, T8, P4). The mean SampEn value of this cluster was 0.475 for MW (std: 0.031, median: 0.474) and 0.487 for BF (std: 0.024, median: 0.486) (see Figure 3).

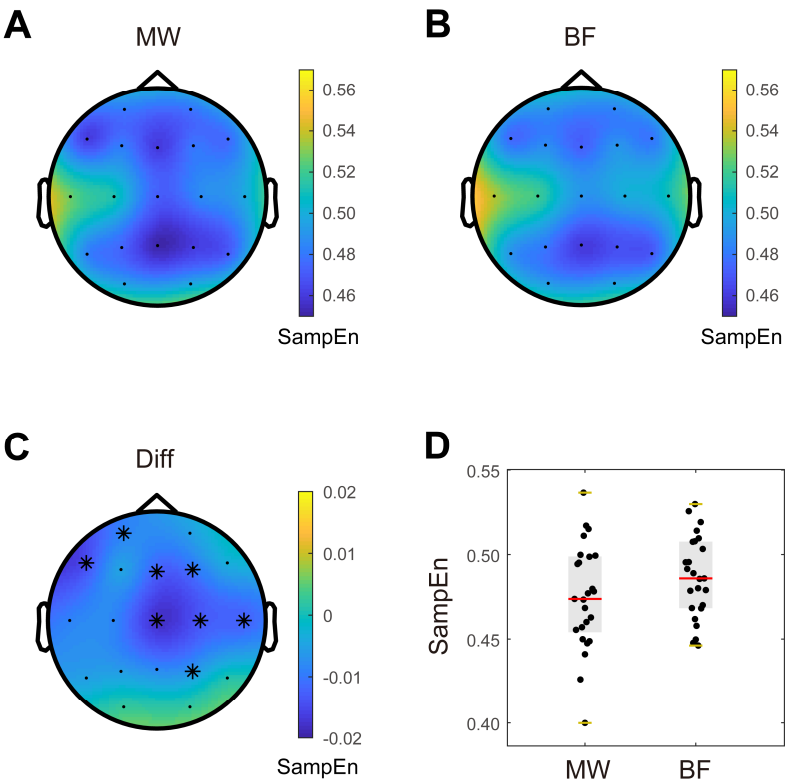

Figure 3. Differences in Sample entropy (SampEn) between mind wandering (MW) and breath focus (BF) conditions. **(A-B)** Topographical plots depicting mean SampEn values for MW and BF conditions in each electrode. **(C)** Topographical plot depicting the mean difference (Diff) between MW and BF conditions in each electrode. The black asterisks mark electrodes in which the SampEn decrease (MW < BF) was significant ($p < 0.05$). **(D)** Individual SampEn values (averaged within the significant cluster) for MW and BF conditions. Each subject is represented by a dot. The gray boxes indicate the 25th and 75th percentiles. Centerlines show the median in each condition. When outliers are present, the whiskers indicate 1.5 times the interquartile range from the 25th and 75th percentiles. When no outliers

are present, the whiskers lay on the most extreme data points.

The MTC analysis revealed a significant decrease in SampEn ($t(18) = -18.171$, $p = 0.009$) during MW relative to BF in midline, right central and left frontal areas (i.e., Fp1, F7, Fz, Cz, C4, Pz) (Figure S3). The mean SampEn value in the cluster was 0.464 for MW (std: 0.028, median: 0.463) and 0.480 for BF (std: 0.020, median: 0.478). SampEn values for each subject are shown in Figure S3. In summary, similar to HFD, controlling for trial counts did not affect SampEn results (i.e., MW < BF).

Relation between changes in complexity and drowsiness

All three complexity measures showed a negative relationship with drowsiness (Figure 4), i.e., a greater decrease in complexity was associated with higher levels of drowsiness. Note that the correlation between complexity and drowsiness reached statistical significance for HFD (Kendall's coefficient $\tau = -0.348$, $p = 0.036$) but not for LZC or SampEn ($\tau = -0.177$, $p = 0.295$ and $\tau = -0.205$, $p = 0.222$ respectively).

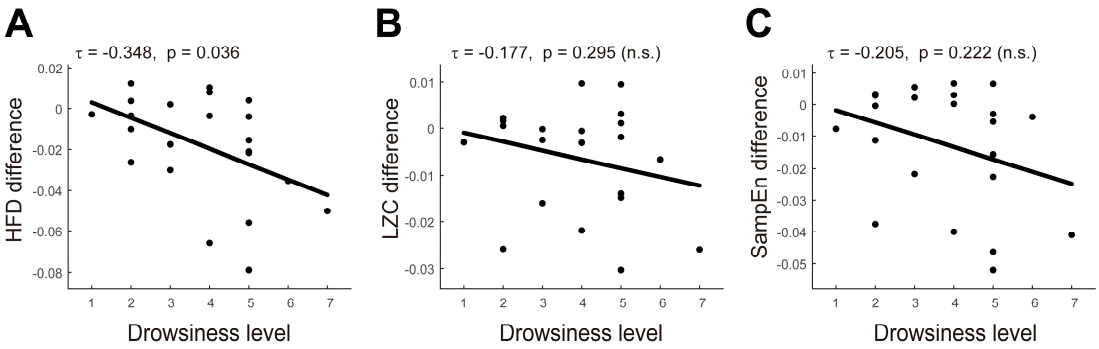

Figure 4. Correlations between condition-related changes in EEG complexity and drowsiness level. In each panel, the difference in complexity (MW – BF) for each metric (HDF, LZC, and SampEn) is plotted as a function of drowsiness level. Each dot represents one subject (average complexity across electrodes showing significant condition effects). Kendall's correlation coefficients and *p*-values are shown for each metric at the top of their corresponding panel. Although a negative correlation was observed for all metrics (i.e., a greater decrease in complexity during MW was associated with greater drowsiness), only HFD reached statistical significance ($p < 0.05$) (n.s.: not significant).

When adopting the MTC approach, we observed that all the complexity measures showed a negative relation to drowsiness, although in this case they did not reach statistical significance (for HFD, LZC and SampEn: $\tau = -0.293$, $p = 0.153$; $\tau = -0.248$, $p = 0.233$ and $\tau = -0.218$, $p = 0.295$, respectively) (Figure S4). Note that, since the LZC metric showed no significant clusters when comparing MW and BF conditions

with the MTC approach, we used the cluster that presented a statistical tendency ($p = 0.058$; see Figure S2) to run the correlation with drowsiness.

Discussion

In this study, we investigated nonlinear EEG features of mind wandering during breath focus meditation in participants without previous meditation experience. For this purpose, we adopted an experience sampling paradigm in which participants were repeatedly probed during a breath focus meditation to report whether they were focusing on their breath (BF) or thinking about something else (MW). Different EEG metrics revealed a significant decrease in complexity during MW relative to BF states. HFD decreased over widely distributed regions; LZC decreased in the parietal, right frontal, and right central regions and SampEn decreased in regions similar to those of LZC. In addition, our results also revealed that participants that reported higher levels of drowsiness tended to show a greater decrease in complexity during MW relative to BF states. However, these latter correlations rendered not significant when controlling for differences in the number of trials between conditions.

The reported changes in the here studied metrics (HFD, LZC and SampEn) indicate that the EEG signal is less complex during mind wandering relative to breath focus states in novice meditation practitioners. Previous analysis of the same data set showed that mind wandering was associated with increased theta power and decreased alpha power relative to breath focus states (Rodriguez-Larios and Alaerts, 2021). In both studies, these significant EEG changes during mind wandering were distributed across electrodes. Based on this, it can be inferred that the decrease in complexity during mind wandering is accompanied by more synchronized neuronal activities in slow frequencies (i.e., theta range). Interestingly, both increases in theta power and decreases in complexity have been reported during states of transition from wakefulness to sleep (Broughton and Hasan, 1995; Cantero et al., 2002; Hou et al., 2021). Hence, it is possible that self-reported mind wandering in participants without meditation practice is associated with drowsiness. Interestingly, we found in our previous study that significant power modulations during mind wandering (i.e., theta power increase and alpha power decrease) were more pronounced in subjects that reported greater levels of drowsiness (Rodriguez-Larios and Alaerts, 2021). In the same line, we here report that subjects with higher drowsiness tended to have a more pronounced reduction in complexity

during mind wandering. However, this latter relationship rendered not significant when controlling for different trial counts between conditions. In this regard, it is important to note that this latter correlational analysis was performed with a relatively small sample (N = 16, for matched trial counts) because drowsiness debriefings were not available in all subjects and therefore, these results have to be interpreted with caution. In the light of these results and previous literature (Brandmeyer and Delorme, 2018; Andrillon et al., 2019; Andrillon et al., 2021), we speculate that the here reported EEG modulations reflect a mixture of mind wandering and drowsiness. Thus, further research is needed to disentangle the EEG correlates of drowsiness and mind wandering. For this purpose, future studies using experience sampling could assess the level of drowsiness (in addition to mind wandering) on a trial by trial basis.

Our results are difficult to compare with previous studies that assessed EEG complexity during meditation (Aftanas and Golocheikine, 2002; Huang and Lo, 2009; Kakumanu et al., 2018; Kumar et al., 2020; Martinez Vivot et al., 2020; Young et al., 2021) due to differences in the meditation tradition, the level of expertise and the adopted complexity metric. If we take into account all these factors, our results are comparable and in line with a recent study (Kakumanu et al., 2018). Kakumanu et al. (2018) reported increased complexity (HFD metric) during vipassana meditation (which entails focused attention to the breath) relative to rest (which entails mind wandering) in novice meditation practitioners. To our knowledge, no other study investigated the exact same metrics in the same population while participants adopted the same meditation technique. Nonetheless, it is important to underline that a previous study showed the opposite pattern of results (decreased complexity during meditation relative to mind wandering) using the LZC metric in experienced meditators (Young et al., 2021). Although this latter study investigated different meditation techniques, their results could indicate that, as pointed by a recent study (Rodriguez-Larios et al., 2021), the EEG correlates of mind wandering and meditative states differ between experienced meditators and novices.

EEG metrics of complexity can be indicative of the number of brain signal generators (Ibanez-Molina et al., 2018). Focused attention meditation is thought to involve the activity of areas associated with attentional control and emotion regulation (e.g., multiple prefrontal regions, the anterior cingulate cortex, the striatum, etc.) (Tang et al., 2015). In contrast, mind wandering is thought to recruit the Default Mode Network (DMN) (Fox et al., 2015; Christoff et al., 2016; Ellamil et al., 2016) which involves areas

compromised in memory and metacognitive elaboration (e.g., medial prefrontal cortex, posterior cingulate cortex, medial temporal lobe, etc.). It can be speculated that brain networks recruited during breath focus states have a greater number of neural generators (and therefore, show higher EEG complexity) than brain networks recruited during mind wandering. Another possibility is that brain activity during breath focus states only appear to have more generators than during mind wandering because part of the regions involved in mind wandering are deeper in the brain and therefore their activity is less likely to be detected through EEG (e.g., hippocampus; see Ellamil et al. (2016)). In this way, future studies using high-density EEG and/or combined EEG-fMRI are needed to assess why the activity of brain networks recruited during breath focus and mind wandering are associated with different levels of EEG complexity.

The identification of the EEG correlates of mind wandering in the context of meditation practice could have an important translational impact. Different meditation techniques are thought to have positive effects on mental health (Desrosiers et al., 2013; Deplus et al., 2016). Nonetheless, some clinical and non-clinical populations show special difficulties to practice meditation due to their inability to control the occurrence of mind wandering (Zylowska et al., 2008; Cachia et al., 2016). Hence, the identification of the neural correlates of mind wandering during meditation could facilitate meditation practice and therefore, promote its health benefits. In this way, neurofeedback and/or neurostimulation protocols can be developed to detect mind wandering online and/or minimize its occurrence (Brandmeyer and Delorme, 2013; Ros et al., 2013; Badran et al., 2017; Brandmeyer and Delorme, 2020). Our results suggest that metrics of complexity could be appropriate for this purpose. In this way, it is important to underline that despite the great number of EEG studies in the field, there is no consensus about which EEG metric differentiates best between mind wandering and meditative states. Given the great number of possible EEG metrics that can be assessed, the only way of achieving a consensus in this field would be to make raw EEG data from different studies publicly available. Hence, future studies could directly compare different EEG metrics in order to find the one with the greatest predictive power, and therefore, more suitable to develop neurofeedback/neurostimulation protocols aimed at facilitating meditation practice.

In conclusion, our results showed a significant decrease in EEG complexity during mind wandering relative to breath focus states in novice meditation practitioners. Based on previous literature, we

speculate that reduced complexity during mind wandering in the context of meditation practice reflects greater low-frequency oscillatory synchronization and a lower number of EEG signal generators. From a translational perspective, our findings suggest that nonlinear EEG features (i.e., HFD, LZC, and SampEn) could be effectively used to facilitate meditation practice through neurofeedback and/or neurostimulation protocols.

Declaration of Competing Interest

The authors declare that they have no conflict of interest.

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Data and code availability statement

Raw EEG data can be found here: https://osf.io/b6rn9/. Codes used for this study are open to access at https://github.com/y-q-l/MW-BF-NL and https://osf.io/b6rn9/.

Author contributions (CRediT)

Yiqing Lu: Conceptualization, Methodology, Investigation, Software, Formal analysis, Visualization, Validation, Writing – Original draft, Writing – Review & Editing. **Julio Rodriguez-Larios:** Conceptualization, Methodology, Software, Data curation, Resources, Writing – Review & Editing.

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