Can Mind Wandering Be Measured Using the Unicorn Hybrid Black? A Pilot Study

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Abstract. In brain-computer interface (BCI) research, electroencephalograms (EEGs) such as the Unicorn Hybrid Black (UHB) have entered the market as low-cost alternatives to other EEG devices. This study has two aims: the first is to assess the suitability of the UHB for BCI research, and the second is to assess the feasibility of a meditation BCI designed to provide users with feedback about mind wandering episodes. A BCI was created using the UHB and corresponding Python API to assess various machine learning algorithms' classification accuracy of a meditation paradigm that uses self-caught experience sampling to capture mind wandering. Key findings suggest that while the UHB is sufficient to capture relevant brain signals associated with mind wandering, though more research is required on appropriate intervention techniques.

Keywords: Neuro-adaptive systems · Meditation · Mind wandering · Brain-computer interface (BCI) · Machine learning applications

1 Introduction

Electroencephalography (EEG)-based brain-computer interfaces (BCIs) are information technologies that use brain signals to enable a user to control an interface using their brain alone. Though there has been significant progress towards integrating BCIs into everyday life, the utility and usability of such systems remain an ongoing exploration. Since one of the goals of a BCI is to provide a method to access and interact with information, BCIs can be understood as an information technology artifact and thus a subject of study in Information Systems (IS).

One of the most disruptive developments in the field of BCI is the recent proliferation of lower-cost devices such as the OpenBCI device or Unicorn Hybrid Black (UHB; g.tec medical engineering GmbH, Austria). These developments are an order of magnitude less expensive than many other common BCI systems which promise to make the technology accessible to researchers and consumers on a limited budget. As such, it is valuable to evaluate not only the feasibility and efficacy of such lower cost systems but also new research applications. In this paper, we describe a pilot study to evaluate the suitability of the UHB for IS research related to the real-time detection of mind wandering and associated BCIs. We developed a simple experiment based on a meditation paradigm and sought to extend this to validate the design of a mind wandering feedback system.

Mind wandering was selected as a paradigm of interest due to past discussions in the IS and human-computer interaction communities. Mind wandering is defined as the disengagement from active attention due to spontaneous thought. It is characterized by the absence of strong constraints on both the contents of and transitions between mental states and is often defined by its absence of explicit intent [1, 2, 3, 4]. Though there are two primary types of mind wandering—intentional and unintentional—the present study will focus on the latter concept and hereafter be referred to plainly as mind wandering.

Insofar as neurological markers of mind wandering, research has shown mixed results. Some claim that increased alpha band activity is the strongest indicator of mind wandering [2, 5], whereas conversely, others posit that only theta band activity shows consistently increased power [6]. A meta-analysis on spectral band activity during mind wandering reports that only eight of 13 studies reported increased theta activity [7]. Less importance has been placed on delta, beta, and gamma bands but research shows mixed results [7]. In sum, there is little agreement within past literature on the oscillatory activity associated with mind wandering, though alpha and theta bands seem to be most implicated.

It can be difficult to measure mind wandering without disrupting the user. One approach, known as probe-caught sampling, measures mind wandering using a probe that prompts participants intermittently to collect information on whether they are experiencing mind wandering. While this has been shown to effectively capture mind wandering, it comes at the cost of disrupting the cognitive processes of the participants [8]. Another approach to measuring mind wandering is with self-caught experience sampling in which participants self-report whether they are experiencing mind wandering using a button press, for example [9]. Since this is not as disruptive as a probe, it would be a preferable method in a BCI designed with the purpose of improving attention. Thus, determining whether self-caught experience sampling is a sufficient measure of mind wandering could assist in creating more accurate BCIs in the future.

We selected a meditation task in part because meditation by nature involves the dynamic fluctuation between attention and mind wandering, but also because it is more likely to have minimal muscular artifacts and can be measured using few electrodes [10] which are both possible confounds with the UHB system. Mind wandering is also a useful phenomenon to investigate because it is known to negatively impact the performance of learning and sustained attention tasks [11, 12, 13], so a system that can detect and correct mind wandering may prove to be a helpful device for the design of new information systems. We were further motivated by past approaches by Demazure et al. [14] which applied classifiers created with a controlled paradigm which were then later applied to solve a general cognitive load information technology use problem. Before pursuing the development of a new technology artifact, it is essential to validate the design and feasibility of the tool. The purpose of the present study is thus to investigate the following questions:

1. Can the UHB be used to detect brain signals associated with mind wandering?

2. Is it feasible to create a meditation-based mind wandering BCI using the UHB?

2 Methods

2.1 Participants and Study Procedure

The experimental task consisted of two phases: a self-caught phase and a task disruption phase. The self-caught phase was designed to simulate the training phase of a BCI where user feedback is recorded to train the machine learning algorithm that drives the interface. The task-disruption phase was designed to simulate an interruption which could be used by a BCI to return participants to a state of task awareness. The procedure was approved by the Dalhousie University Research Ethics Board and participants (n = 5) were recruited to participate in the pilot study. The study was inspired by a well-cited investigation into the EEG biomarkers of mind wandering during meditation [14] and followed many of the methods described in that paper, though with some notable differences.

In the self-caught phase, participants were fitted with the UHB and then asked to meditate for 20 minutes while repeatedly counting backwards from 10. A 30-second repeated soundtrack of birdsong was also played from the computer. Mind wandering was measured using self-caught experience sampling using a button press. Participants would press a button when they noticed losing count during the counting task. EEG markers from 10 seconds before and after a button press were compared.

In the task-disruption phase, participants were again asked to meditate for 20 minutes but to not press a button when they detected their mind wandering. Instead, the experimental paradigm was programmed to interrupt the birdsong audio to play traffic noises, a disruptive sound, at the 7-, 12-, and 17-minute marks for a duration of 20, 30, and 10 seconds, respectively. EEG markers from 10 seconds before and after the disruptive auditory onset were compared.

2.2 Data Processing and Analysis

The UHB was used as the primary neural measurement device. It is an eight-channel EEG with electrodes situated at the international 10-20 system electrode positions Fz, C3, Cz, C4, Pz, P7, Oz, and P8 [15]. It is sampled with 24 bits and 250 Hz per channel.

The raw EEG data were processed by applying a bandpass filter, sectioning the data into 10 second epochs, then subjected to rejection criteria. Power spectral density was calculated for each epoch using the multitaper method with the Python MNE library. Using scikit-learn, common machine learning classifiers were prepared for each individual and assessed using 5-fold cross-validation. In total, seven classifiers were investigated, as follows: linear discriminant analysis (LDA), ridge classifier, k-nearest neighbours, support vector machine (SVM), decision tree, multi-layer perceptron, and Naïve Bayes. These classifiers were trained using the processed data collected from the self-caught phase and then were applied to the data collected during the task disruption stage of the task. An accuracy score and a mean *k*-fold cross-validation score (k = 5) were computed for each classifier. Evoked objects were then created for each condition.

3 Results

During the self-caught phase, a total of 105 mind wandering button press events were captured with an average of 21 events per participant (*min* = 10; *max* = 50). During this phase, most power spectral variation was observed in the theta and alpha bands. Though there was considerable individual variation, the grand average of the participants reveals a pattern of elevated general theta when on task (Fig. 1).

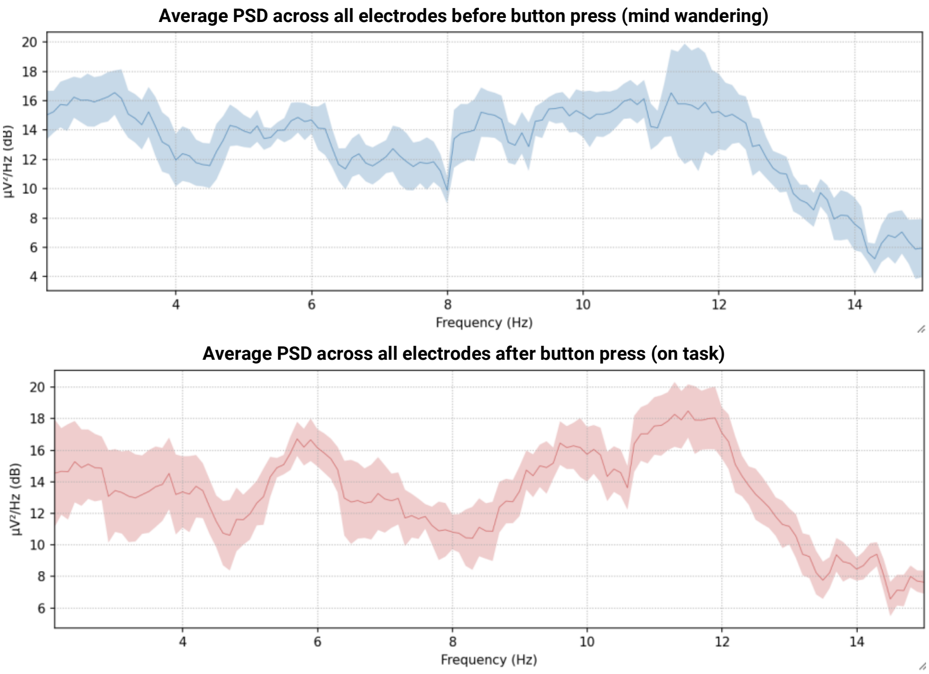

Fig. 1. The average topographic power spectral densities of the mind wandering condition and the on-task condition during the self-caught phase. Data at the theta and alpha bands appear to be elevated at the theta and

On average, the overall classification accuracy for the data generated in the self-caught phase was 52%. In Table 1, we report three select classifiers which are often reported in BCI literature. The ridge classifier consistently performed better than other methods at this classification task which suggests that this method may be capable of reliably detecting the mind-wandering state in this context. However, it should be qualified that, given the limited number of trials, it is still possible that this was due to random chance. Results of the application of the classifiers to the data generated during the task-disruption phase did not reveal any classifier which performed with greater than 50% accuracy at that task.

Table 1. Selected classifier accuracy and results from each participant's self-caught data.

Classifier	P1	P2	P3	P4	P5	Median
LDA	56%	42%	51%	55%	74%	**56%**
Ridge Classifier	69%	73%	43%	58%	68%	**68%**
SVM	49%	47%	51%	53%	68%	**51%**

4 Discussion

These results suggest that it may be possible to detect EEG signals related to mind wandering using the UHB, but that there are major challenges in applying those signals to the development of a useful BCI. The data from the self-caught phase suggests that mind wandering was found to be primarily associated with differentiations in theta activity at frontocentral areas. Our observed theta observations during the self-caught phase are consistent with past research which posits that theta activity in frontocentral areas are markers of mind wandering [16], [7, 8], though there is not enough data to infer whether these results replicate past studies. Importantly, our findings found that theta may have been elevated following button presses, which could be inconsistent with some findings in the mind wandering literature. Further investigations would need to be conducted to determine whether this was indeed a reliable measure of mind wandering or a more general reflection of a different cognitive state, such as task load.

Past literature purports that alpha band activity is often reported to be attenuated during mind wandering and not on-task states, particularly across posterior, frontocentral, and temporal sites [16], [7], [9]. However, we have not observed any alpha power differentiations caused by mind wandering during the self-caught task phase. Furthermore, our task disruption phase data did not show any theta power effects which suggests that mind wandering was perhaps not occurring during the task disruption. Since our BCI administered these disruptions at random time intervals rather than when the interface detected mind wandering, it follows that mind wandering was not guaranteed to occur. Overall, these results suggest that the UHB can successfully detect mind wandering during a self-caught sampling meditation task, though care must be taken to control possible confounds.

While some classifiers performed well at detecting mind wandering using the self-caught data, all the classifiers performed very poorly at differentiating brain activity related to auditory disruption. We expected that the classifiers would have reliably detected instances following the onset of the stimulus as "on task", similar to the episodes following a self-caught probe. This suggests an issue with the assumption of our interface design. The tasks for our two phases were fundamentally different; the training phase relied on self-caught experience sampling whereas the application phase made use of a disparate audio stimulus intended to return participants to attention. We chose self-caught over probe-caught experience sampling because the latter comes at the cost of disrupting the cognitive processes of the participants [8]. However, self-caught experience sampling relies on meta-awareness, defined as the explicit awareness of the contents of consciousness [18, 19, 20]. This is a different context than the prior example demonstrated by Demazure et al. [14], where working memory activation was fundamentally similar between their training paradigm and the application context.

A possible future direction for this work may be found in the distinction between varieties of mind wandering, which has recently been discussed in the context of information technology use [21]. Past research has distinguished between two different states of unintentional mind wandering characterized by the presence or absence of meta-awareness; “tune-outs” are mind wandering with meta-awareness, and “zone outs” are mind wandering without [19, 20]. Using these definitions, we can characterize the present study’s self-caught phase as capturing “zone outs” whereas the task-disruption phase captures “tune outs”, or perhaps even general task disengagement or re-engagement. This could explain why the classifiers did not perform as effectively on the application data as they did on the training data—the tasks may be reflective of different mental processes.

There is little consensus in the literature on what is the best-performing classifier in an EEG-based BCI. One study found that a ridge classifier has superior accuracy after cross-validation in an EGG-based passive BCI [22], whereas others report that an LDA is the most accurate [23]. Though our results suggest that a ridge classifier is the best algorithm to use for our specific paradigm, our limited sample size does not allow us to make definitive conclusions.

Finally, discussions can be raised about the viability of the task for BCI. Like past studies which used the self-caught method to measure the presence of mind wandering, there was considerable variability in user responses to mind wandering episodes [16, 24]. Even with the counting task as a concrete measure of task loss, it is possible that users were not able to reliably detect mind wandering episodes or had a considerable variance in their subjective experience which led to a report. Alternative probe approaches might be able to more reliably identify mind wandering or an entirely task-based approach like Demazure et al. [14] could help further refine the detectable variance in mindfulness during meditation.

As a pilot project, the present study has a very limited scope. A major limitation of this study is the small sample size. Because of this, all results and conclusions drawn in this study are purely speculative in nature and must be further investigated before being reported as true findings. The overarching aim of this paper is twofold; to evaluate one possible approach to designing a mind wandering BCI and to validate the UHB’s potential as a mind-wandering measurement device. The results of this study are thus intended to guide the design of future work that will aim to compare the UHB and a research-grade EEG with a denser electrode array in terms of their performance, usability, and feasibility in a mind wandering BCI. As such, one should view the results of this study through an exploratory lens.

5 Conclusion

Our results suggest that the UHB can be used to detect mind-wandering or related states during a meditation task, though future research should examine effects either resulting from differences in varieties of mind wandering. Similarly, we can cautiously claim that self-caught experience sampling is a promising approach to use in a mind wandering BCI, though perhaps not in conjunction with the selected mind wandering intervention described herein. Alternative approaches to the task design may prove fruitful in the further development of real-time measures of cognitive states using such low-cost systems. Lastly, results suggest that a ridge classifier is the most effective machine learning algorithm in terms of accuracy within the context of this specific paradigm. Future work can refine these results by either refining the probe-caught paradigm or by focusing on a task-based baseline for creating machine learning classifiers that can be applied to the real-time detection of mind wandering states.

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