Towards Mind Wandering Adaptive Online Learning and Virtual Work Experiences

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Abstract. NeuroIS researchers have become increasingly interested in the design of new types of information systems that leverage neurophysiological data. In this paper we describe the results of machine learning analysis which validates a method for the passive detection of mind wandering. Following the presentation of the results, we describe ways that this technique could be applied to create a neuroadaptive online learning and virtual meeting tool which may improve users' retention of information by providing auditory feedback.

Keywords: Electroencephalography (EEG) · Machine learning applications · Neuro-adaptive systems · Mind wandering

1 Introduction

Since its inception as a field that leverages neurotechnology to give insights into information systems (IS) phenomena, NeuroIS has developed a range of specific interests. Researchers have flagged emotion, attention, and decision making as promising areas of inquiry [1]. These areas promise to contribute to making more human-centered systems, or even designing systems that can adapt to a user's cognitive states [2]. Attention-adaptive systems, in particular, have the potential to contribute to radically new information technology (IT) use experiences, and have begun to gain traction in the community [3].

Mind wandering is an attention-related phenomenon which describes when conscious experience becomes detached from an external environment toward one's internal thoughts or feelings [4]. It is known to have various effects on creativity, attention, and other cognitive processes [5, 6]. Moreover, it has been identified as a topic of interest by IS researchers [7, 8, 9, 10] as well as in learning systems [11, 5]. A system adaptive to mind-wandering episodes could contribute to IT use experiences and might be particularly important for systems related to improved online learning, or remote meeting technologies, as well as other applications.

In this paper, we take the first steps towards such a system by identifying machine learning algorithms which can reliably detect the mind wandering based on its EEG signal correlates. We describe an offline machine learning experiment that leverages previously published data [11]. The techniques used in this experiment apply those used by brain-computer interfaces, with an aim towards improved systems design [12, 13]. The goal of the experiment is to apply classifiers to unlabeled data to demonstrate the technique's feasibility. Following the description of our methods and results, we discuss and provide details about how these findings can be applied to develop an adaptive mind wandering system, which could be applied to create novel online classrooms, personal performance tools or cognitive wellness systems.

2 Methods

2.1 Data acquisition and description

The data analyzed in this experiment were previously disseminated in the literature and we encourage readers to refer to the paper for more details on the methods and justifications for design choices [11]. Participants attended a long lecture as two tones were played in the background, one at 500 Hz played 80% of the time and one at 1000 Hz played 20% of the time. Participants were not given a task to complete related to the tones. They were prompted 10 times at pre-programmed intervals about their degree of experienced mind wandering, based on a Likert scale from 1 ("completely on task") to 5 ("completely mind wandering"). The data of interest comprised 1.2 second epochs extending from 200 ms prior, to 1000 ms after, the onset of each auditory tone. Epochs which occurred in the 10 seconds preceding an experience sample prompt were labelled according to the degree of reported mind wandering. The remaining data represented nearly 73 minutes of the total experiment and were unlabeled. Of the 52 participants who were described in the original study, we included in the present analyses only the 11 who used the full range of the Likert scale (i.e. participants whose minds both wandered and remained on task at various times in the experiment). Each participant's data was divided into two subsets for the machine learning analysis. The classification dataset consisted of the epochs that were labelled with the extremes of the Likert scale; epochs that preceded a response of 1 and those that preceded a response of 5. The unlabeled dataset consisted of the approximately 3500 epochs that were unlabeled throughout the experiment, to which we applied the classifier.

2.2 Data preparation and classification

Data from both datasets were converted to power spectral density using the multitaper method [14]. The tapers generated consisted of frequencies between 1 and 30 Hz over 32 electrodes, which were then normalized and transformed into a two-dimensional array. To ensure a balanced dataset for machine learning, we conducted up-sampling of the minority classes, which generated synthetic data based on the distribution of the data [15]. Each participant's data was analyzed individually. Machine learning classifiers were created for each participant's data from the classification dataset. All classifiers were trained to discriminate between "completely on task" and "completely mind wandering" trials, using Scikit-Learn's linear discriminant analysis classifier with 2/3 of the labelled data. The classifiers were tested for accuracy on 1/3 of the labelled data. The classifiers were then applied to the unlabeled data from each participant.

2.3 Assessment and visualization

Each classifier was assessed individually for accuracy. We created visualizations using the classifications of the unlabeled data were retrieved and averaged and smoothed across 100 second segments to assist with visualization and interpretability. Visualizations were created on the smoothed data and compared to the original Likert scale responses made throughout the experiment [16].

3 Results

The results of the up-sampling and classification tasks are provided in Table 1. The classifiers trained on 6 of the 11 participants performed with over 80% accuracy. All visualizations and analysis are provided as a Jupyter notebook appendix, which is available online.[1]

Table 1. Summary of labels, total support (after up-sampling) and classification accuracy for predicting labelled data

Participant	Likert 1 labels†	Likert 5 labels†	Total support‡	Accuracy
1	56	14	112	0.973
2	13	15	30	1.000
3	13	13	26	0.444
4	9	29	58	0.900
5	29	14	58	0.700
6	26	11	52	0.833
7	28	26	56	0.789
8	22	13	44	0.800
9	14	35	70	0.750
10	36	38	76	0.846
11	13	28	56	0.789

†Denotes actual trials

‡Denotes data investigated with up-sampling; a balanced number for each class.

4 Discussion

The results of the machine learning classifiers suggest that they can accurately classify mind wandering based on the limited data that they were given. The application of the classifiers to the unlabeled data demonstrate that the classifiers might predict mind wandering, though we did not test these relationships statistically. We are nonetheless led to believe that we have some evidence that the classifiers 1) performed classification

[1] https://github.com/cdconrad/2022-towards-adaptive

with a degree of accuracy and that 2) they were applied in a way that demonstrates their use for creating an adaptive mind wandering system. It is not surprising that the linear discriminant analysis technique worked well, as it is commonly used in the development of brain-computer interfaces to achieve a mechanically similar task [10]. Nevertheless, the findings would benefit from future research, ideally on a larger sample. Future researchers can apply our proposed technique and make improvements to it to create adaptive interfaces that can improve users' experience.

A potential limitation of our findings is that there is no way to truly validate the results of the machine learning classifiers on the unlabeled data that we retrieved from the original experiment. However, this is likely true of many applications of a live adaptive system, and the samples that we had labels for suggested that the classifiers, on average, performed similarly to many brain-computer interface paradigms. Future experiments can be conducted to validate their accuracy over time with various labeling methods. A second limitation of our findings is that the data is that we had to rely on synthetic data generated by up-sampling to gather sufficient data for classification. Though up-sampling is leveraged by many machine learning researchers to conduct similar classification tasks, this criticism warrants consideration; it is possible that the classification results were the product of overfitting.

5 Towards a mind wandering adaptive experience

The findings described by the experiment suggest that it is possible to create computer programs that are adaptive to a users' mind wandering state. In this final section, we will outline some of the characteristics of such a system for future work.

5.1 Proposed system design

Like brain-computer interfaces, a useful neuroadaptive system would consist of two phases: a training phase, and a test phase [3, 12]. In the case of a mind wandering system, a training phase should involve the creation of the classifiers. The experiment described in the previous sections outline a feasible design for creating such classifiers by leveraging the experience sampling technique over an extended period of time [5, 13]. A major limitation of this approach is the amount of time that would be required to generate sufficient labels for the task. Furthermore, the Likert scale did not guarantee that any given user would generate sufficient labels for an adaptive system.

An alternative approach is to ask participants to conduct a very boring task that is likely to trigger mind wandering over a period of 20 to 30 minutes. Such an approach could similarly use mind wandering prompts, though ideally adapted from the Likert scale to give a binary classification (i.e., yes/no), or could use a behavioural measure such as missed cues. The labels should be sufficient to conduct machine learning, though the up-sampling technique described in this paper can be used to overcome imbalanced datasets.

Once the classifiers have been created, they can be applied to determine whether a computer should administer a stimulus. Given that applications of adaptive systems to virtual workplaces or classrooms should encourage productivity, it is important that the stimulus is minimally disruptive, and ideally does not require the modification of the workplace software. One approach could be to create an auditory stimulus, such as a beep, that is administered by the neuro-adaptive program. Such stimuli could help remind participants to attend to the task, potentially encouraging them to return to a meta conscious state where they are aware of their surroundings. A study can then be conducted to determine whether the adaptive system helped participants perform better at information retention. Given that we have demonstrated the classifiers can be developed in the Python programming language, such an application could be made using common Python-based interface development tools. Figure 1 summarizes the design of such a system.

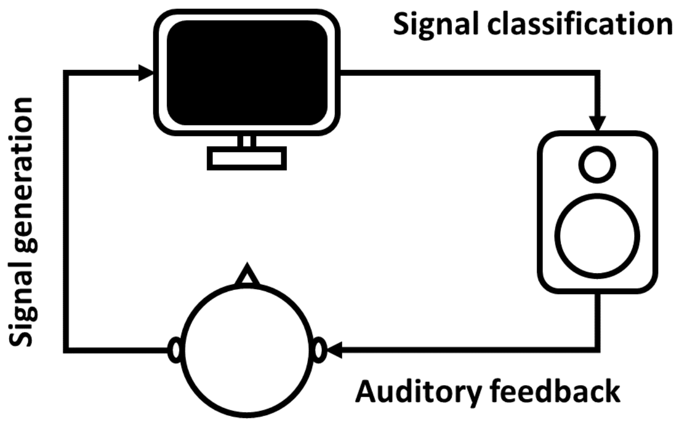

Fig. 1. Overview of a simple auditory feedback mechanism for a virtual meeting.

5.2 Other system applications

If successful, such mind wandering adaptive information systems could have additional applications beyond reminders. For example, wearable technologies are increasingly employing data visualization to encourage desirable behaviour. The system could be similarly applied to provide feedback to participants about their ability to attend to long videos. The system could alternatively be used to passively measure mind wandering as various information system designs are prototyped; it could be that by keeping Zoom videos on, harmful mind wandering is limited.

Regardless of application, the generic system will leverage the training routine, which will continue to limit the system's applicability. Future work on this topic would benefit by identifying techniques for generating labels of mind wandering events in as little time as possible. It would also benefit by identifying labels that can distinguish varieties of mind wandering, some of which may not be harmful to a user's productive experience with a technology.

References

1. Riedl, R., Fischer, T., Léger, P. M., and Davis, F. D.: A decade of NeuroIS research: progress, challenges, and future directions. In: *ACM SIGMIS Database: the DATABASE for Advances in Information Systems*, vol *51, iss.* 3, pp. 13-54 (2020)
2. vom Brocke, J., Hevner, A., Léger, P. M., Walla, P., and Riedl, R.: Advancing a NeuroIS research agenda with four areas of societal contributions. In: European Journal of Information Systems, vol. *29*, iss. 1, pp. 9-24 (2020)
3. Demazure, T., Karran, A., Léger, P. M., Labonté-LeMoyne, É., Sénécal, S., Fredette, M., and Babin, G.: Enhancing Sustained Attention. In: Business & Information Systems Engineering, vol. 63, iss. 6, pp. 653-668 (2021)
4. Fox, K. C., and Christoff, K. (eds.). The Oxford handbook of spontaneous thought: Mind-wandering, creativity, and dreaming. Oxford University Press (2018)
5. Wammes, J. D., Boucher, P. O., Seli, P., Cheyne, J. A., and Smilek, D.: Mind wandering during lectures I: Changes in rates across an entire semester. In: Scholarship of Teaching and Learning in Psychology, vol. 2, iss. 1, pg. 13 (2016)
6. Yanko, M. R., and Spalek, T. M.: Driving with the wandering mind: The effect that mind-wandering has on driving performance. In: Human Factors, vol. 56, iss. 2, pp. 260-269 (2014)
7. Klesel, M., Oschinsky, F. M., Conrad, C., and Niehaves, B.: Does the type of mind wandering matter? Extending the inquiry about the role of mind wandering in the IT use experience. In: Internet Research vol. 31, iss. 3, pp. 1018-1039 (2021)
8. Sullivan, Y., and Davis, F.: Self-regulation, mind wandering, and cognitive absorption during technology use. In: Proceedings of the 53rd Hawaii International Conference on System Sciences (2020)
9. Baumgart, T. L., Klesel, M., Oschinsky, F. M., and Niehaves, B: Creativity loading–please wait! Investigating the relationship between interruption, mind wandering and creativity. In: Proceedings of the 53rd Hawaii International Conference on System Sciences (2020).
10. Weinert, T., Thiel de Gafenco, M., and Börner, N.: Fostering interaction in higher education with deliberate design of interactive learning videos. In: International Conference on Information Systems (2021).
11. Conrad, C., and Newman, A.: Measuring Mind Wandering During Online Lectures Assessed With EEG. In: Frontiers in Human Neuroscience, 455 (2021)
12. Krusienski, D. J., Sellers, E. W., McFarland, D. J., Vaughan, T. M., and Wolpaw, J. R.: Toward enhanced P300 speller performance. Journal of neuroscience methods, vol. 167, iss. 1, pp. 15-21 (2008)
13. Müller-Putz, G. R., Riedl, R., and C Wriessnegger, S.: Electroencephalography (EEG) as a research tool in the information systems discipline: Foundations, measurement, and applications. In: Communications of the Association for Information Systems, vol. 37, iss. 1, pg. 46 (2015)
14. Gramfort, A., Luessi, M., Larson, E., Engemann, D. A., Strohmeier, D., Brodbeck, C., Parkkonen, L. and Hämäläinen, M. S.: MNE software for processing MEG and EEG data. In: Neuroimage, vol. 86, pp. 446-460 (2014)
15. Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., Duchesnay, E.: Scikit-learn: Machine Learning in Python. In: Journal of Machien Learning Research, vol. 12 pp. 2825-2830 (2011)
16. Hunter, J. D.: Matplotlib: A 2D graphics environment. In: Computing in Science & Engineering, vol. 9, iss. 3, 90-95 (2007).