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Quantifying the maladaptive neurophysiological correlates leading to lapses of attention during the SART: towards real-time mental state monitoring of mind-wandering*

A. Martel, M. Arvaneh, A. Taylor, P. Dockree & I. H. Robertson

Abstract— **Mind-wandering (MW) constitutes one of the most ubiquitous mental activity humans engage in but it comes at a significant cost. Internal distractions are believed to be a leading cause of performance errors and unhappiness. A brain computer interface (BCI) able to predict the disengagement of attention, e.g. lapses of attention resulting from mind-wandering episodes, harbors numerous useful applications. In this study, the SART was applied to quantify EEG correlates of lapses of attention to assess the viability of a BCI able to monitor attentional states in real-time. Both spatio-temporal classification and filter bank common spatial patterns were applied on a single-trial basis with accuracy reaching 92%. This work represents a potential step towards enhanced human-machine systems and BCI-based treatments of perseverative disorders such as depression.**

I. Introduction

MW dominates the mental landscape, constituting the default mode of our minds, and occupying up to 50% of our conscious cogitations [1]. In a world in which inattention comes at an ever-higher price, the potential costs of MW ranges from the benign, such as zoning out while reading, to the disastrous, e.g. missing a light at an intersection or failing to recognize a medical condition [2]. Distractions, internal chatter and spontaneous ideation all exact our attention rendering monitoring tasks daunting if not impossible [3]. The fickle nature of attention has been firmly established after decades of research and a plethora of experimental paradigms.

In the present work, we were specifically interested in internally driven interferences, further categorized as either being an intrusion, i.e. spontaneously arising MW leading momentary lapses of attention, or an internal interruption, i.e. a deliberate redirection of engaging of cognitive processes to a secondary task. Both kinds of MW typically occur at rest or while performing an undemanding or highly automated task, during which attentional resources are left idle, e.g. driving on a familiar route. MW perpetrated in a deliberate manner qualifies as multitasking because attention is simultaneously being engaged for internal thought processes in addition to the primary task [4]. A large body of research has conclusively demonstrated that humans are inapt at multitasking with attempts invariably resulting in performance deficits (for a review see [5]). The other main cause for performance errors, disregarding external interferences, stems from lapses of attention, when the mind becomes involuntarily distracted by task-unrelated thoughts. Therefore, performance errors either result from a failure to switch from internal cogitations to the task at hand [6] or from an inadequate allocation of attentional resources across multiple tasks. In both cases MW reveals itself as the main culprit behind such errors in both laboratory and real-world tasks (for a review see [7]). The sustained attention to response task (SART; [8]) has been widely used as a laboratory task to assess sustained attention with commission errors serving as a measure of MW related interferences [9].

From a neurophysiological perspective, MW is characterized by a decoupling of attention from the external environment. The same top-down mechanisms which facilitate attendance to an external stimulus are recruited during MW with the difference that external input is suppressed instead of enhanced. During periods of inattention cortical processing of sensory information has been observed to be significantly reduced [10], [11]. Lapses of attention, as operationalized by performance errors, have been shown on multiple occasions to be reliably foreshadowed by reduction in ERP amplitudes [10], [12], [13].

MW and attentional lapses are not only characterized by a reduction of perceptual processing but also by an active suppression of sensory input [14]. Amongst neural oscillations, the alpha band (8 – 14 Hz) has been of interest to MW and sustained attention research. At present, a large body of work explicates alpha activity as an inverse correlate of cortical excitability. In other words, high alpha over visual brain areas is believed to signify a suppression of visual information. Indeed, numerous study conclusively linked increased alpha power over visual areas as reflecting a disengagement from external visual input in favor of a different sensory modality or internal thought processes (for a review see [15]). High parieto-occipital alpha has been identified as a robust predictor of lapses of attention [12], [13]. Moreover, electroencephalographic (EEG) correlates of MW gradually develop over time before leading to a performance error and thus hold predictive power potentially allowing for their detection in real-time with a brain-computer interface (BCI).

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A. Martel is with the Trinity Institute of Neuroscience, Dublin, Ireland (e-mail: amartel@tcd.ie).

M. Arvaneh, was with the Trinity Institute of Neuroscience, Dublin, Ireland. She is now in the department of Automatic Control and Systems Engineering, the University of Sheffield, Sheffield, U.K (corresponding author; e-mail: m.arvaneh@sheffield.ac.uk).

A. Taylor is with the University of Sheffield, Sheffield, U.K (e-mail: ataylor13@sheffield.ac.uk).

P. Dockree & I. Robertson are with the Trinity School of Psychology, Dublin, Ireland (e-mail: dockreep@tcd.ie & iroberts@tcd.ie).

The aforementioned studies employed simple statistics like grand averages to draw their conclusions. To develop more powerful models and to more accurately assess the viability of the recorded signal, more sophisticated methods are required. In recent decades, BCIs have garnered considerable attention due to the attractive promise of covertly monitoring mental states via EEG signals and consequently much effort has been devoted toward the real-time monitoring of mental states such as workload [16], drowsiness [17], fatigue [18] to name a few (for a review see [19]). Failures of attention are a prime cause of traffic fatalities [20], medical misdiagnosis [21], and security screening failings [22] to name but a few. In addition, boredom and the ensuing MW is estimated to be one of the greatest drain on the economy, leading to procrastination and productivity loss [23]. Therefore, a system capable of real-time assessment of attentional levels would not only find use in the training of attention to increase productivity [24] but could also be deployed in safety-critical environment as a redundant control feature to minimize human error. Such systems have become particularly relevant with the advent of ubiquitous automation which have increasingly relegated humans to surveillance roles [25]. Lastly, it could be used in a NFT as a potential treatment for depression as MW has been associated with ruminative thoughts and perseverative disorders [7].

Therefore, the aim of our work was to investigate the theoretical viability of offline EEG data for prospective use in a BCI-based system for the real-time prediction of MW episodes. To this end, we recorded the EEG correlates preceding attentional lapses during a sustained attention task, the SART, and applied BCI methods to determine whether commission errors can be detected on a single-trials basis.

II. Materials & Methods

A. *Experimental paradigm*

Twenty-six healthy subjects (12 female; 23.4 ± 3.2 years) performed the SART, a commonly used GO/NOGO task. Participants performed the fixed SART which presented them with centrally and individually displayed digits from 1 to 9 for 250 ms each. The NOGO target to which the participants were instructed to withhold response was the number 6 (11% of the trials) leaving the numbers 1 to 5 and 7 to 9 as GO stimulus to which they were instructed to respond with a left mouse button press. An inter-stimulus interval of 2.3 s was chosen to maximize the number of MW episodes and of lapses of attention without making the task too challenging. The fixed variant of the SART was picked over the traditional random version to ensure the accurate recording of perceptual decoupling as opposed to motor decoupling. Many have argued that the random version of the SART fosters a speed-accuracy tradeoff (SATO) and that errors during the SART are thus likely to be cause by failures of response inhibition due to speeded responses. To remedy this issue a fixed version was developed [26] in which the numbers are shown in a predictable order giving the participants ample time to prepare their response. Hence, errors due to SATO should be minimized or even eliminated, ensuring that most, if not all, commission errors are the result of perceptual decoupling.

B. *EEG data acquisition, segmentation & analysis*

64-channel EEG data was acquired at 512 Hz using a BioSemi ActiveTwo system (biosemi.com) placed as per the international 10-20 system. To assess eye movements and blinks, 4 electrooculography electrodes (EOGs) were placed above and beneath the left eye, and on the side of the left and right eye near the temples. All data were processed, analyzed and visualized through Matlab (The Mathworks) with the help of custom written scripts.

The data were preprocessed with was high-pass filtered at 0.5 Hz, down-sampled to 250 Hz and finally baseline-corrected to the time interval 200 ms to the onset of the SART stimulus. A period of approximately 10 s prior to a target trial probe was considered to reflect the reported attentional state, in accordance with prior studies [11], [27]. To categorize the SART stimuli according to the subject's attentional state the EEG time-course was segmented into stimulus-locked 2.8 s epochs (-200 to 2400 ms relative to SART stimulus) extending backwards for a maximum of four trials (spanning 9.3 s) from the target.

The SART paradigm instructs participants of to inhibit their response to targets. Epochs preceding a failure of to do were categorized as belonging to the commission error (ERR) condition, i.e. MW. Accordingly, epochs prior to correctly withheld responses (CWR) were associated with focused attention.

C. *Feature selection & classification*

The goal of the analysis was to identify and maximize the temporal and spatial differences between the classes CWR and ERR. Two different approaches were undertaken, a spatio-temporal and spatial filter based classification. The former consists of extracting discriminative intervals and channels in the ERP domain. This was achieved by calculating the signed point-biserial coefficient correlation coefficient (sgn r^2; [28]) iteratively on each channel and moving time window over the epoch. This allowed for the identification of the most discriminative channels (classification rate > 70%) and time intervals for the subsequent classification. The second approach centered around the identification of spatial filters with common spatial patterns (CSP). CSP is a popular and effective BCI method which maximizes the variance of the signal from one class while minimizing it for the second class. It is typically used on oscillatory activity and since alpha is of particular interest, CSP was applied on bandpass filtered data between 8 to 14 Hz. The results were compared with an extension of the algorithm, the multi-band CSP (MBCSP), which applies five bandpass filters (delta: 1 – 3 Hz; theta: 4 – 7 Hz; alpha: 8 – 14 Hz; beta: 15 – 30 Hz & gamma: 30 – 70 Hz). While there is an ongoing debate in the literature whether nonlinear classifier perform better than linear classifiers, the latter has been repeatedly shown to perform just as good as the former at a fraction of the computational costs. Accordingly, regularized linear discriminant analysis (RLDA) with shrinkage was applied on the extracted feature vectors [27].

Lastly, a further extension to the multi-band CSP, filter bank CSP (FBCSP; [29]), was applied on neighboring bands (10 bandpass filters with a width of 4 Hz with lower bounds from 4 to 40 Hz) and overlapping bands (20 bandpass filters with a width of 8 Hz with lower bounds from 4 to 80 Hz), This method uses a mutual information criterion to select an optimal set of spatio-spectral features which is then classified using a naïve-Bayesian Parzen window algorithm. The number of features utilized for the classification ranged from 1 to 10. We only report on the set of features returning the highest classification rate.

Due to the negative impact of muscular artifacts on classification accuracy, the epochs exhibiting max-min differences exceeding 300 µV on EOG channels were automatically rejected as were all epochs with excessive variance.

The reported classification accuracies represent the average rate of 10-fold cross-validations, achieved by randomly dividing the dataset into 10 subsets, training the model on 9 and testing it on 1. This was repeated until testing was conducted on each subset.

III. Results

A. Spatio-temporal classification results

The classification on temporal features after selection of most discriminative channels faired worst of all applied methods, remaining at around chance level (see right column of Table 1). It is worth noting that the channels selected with the highest discriminative power were all over parieto-occipital sites. The classification on temporal features, selected with sgn $r^{2,}$ returned better results with a classification accuracy reaching 63% when including all four trials preceding a target trial.

TABLE I. Spatio-temporal classification accuracies

# of epochs	*Temporal*	*Spatio-temporal*
-1 trial	61 %	49 %
-1 to -2 trials	49 %	51%
-1 to -3 trials	58 %	48 %
-1 to -4 trials	**63 %**	51 %

B. CSP classification results

Spatial filters identified by applying CSP on the alpha band and subsequent classification with RLDA did not contain sufficient information for a competitive classification as can be taken from the maximal accuracy of 61% with all four prior trials considered (see leftmost column of Table 2). Including multiple bands did boost results slightly with a maximum accuracy of 73% when the total number of pre-trials were considered.

The optimal selection of spatio-temporal features by the FBCSP method resulted in a significant increase in performance. Applied on neighboring bands, classification accuracy reached 82% for one and four pre-trials with the most contributive features belonging to the alpha (8 – 12 Hz) and beta band (36 – 40 Hz). The best classification rates were obtained by the FBCSP algorithm with overlapping bands, reaching 92% with only one pre-trial and most contributive features belonging to the high gamma (76 – 84 Hz) and low gamma band (44 – 52 Hz). Selecting the most discriminative bands from overlapping FBCSP had a substantial impact on classification rates (see rightmost column in Table 2).

TABLE II. CSP classification accuracies

	CSP (8-14Hz)	***MBCSP (separate bands)***	***FBCSP (separate bands)***	***FBCSP (overlapping bands)***
-1 trial	59 %	73 %	82 %	**92 %**
-1 to -2 trials	58 %	62 %	76 %	87 %
-1 to -3 trials	53 %	59 %	80 %	86 %
-1 to -4 trials	61 %	71 %	82 %	91 %

IV. Discussion

Amongst the methods tested, the spatio-temporal classification fared worst. This is probably due to the reduced information available to the model after removing less discriminative channels. These results indicate that ERPs are less suited for single-trial classification, at least with the SART paradigm. This is not necessarily a negative outcome since a system able to predict inattention solely based on oscillatory activity is desirable as it obviates the need to probe the individuals' cognition to evoke ERPs. In any case, the spatio-temporal model with one pre-trial did reach the accuracy threshold of 70% required for BCI-usability.

The best classification accuracy, 92%, was achieved by applying FBCSP with 10 overlapping bands and one pre-trial. Interestingly, adding more information in the form of pre-trial numbers did not increase classification performance. Performance worsened with the addition of the second and third pre-trial before stabilizing by the fourth. Although the earlier a system can predict an attentional state the better, it could be a case of overfitting by the model which could result in an increased number of premature false alarms. The lack of a gradual increase in certainty might render the successful implementation in a real-time setting somewhat more challenging. A classification accuracy above 90% for up to 4 trials (approximately 10 s) preceding a NOGO trial is nonetheless very promising for the prospective implementation of a real-time monitoring BCI capable of reliably predicting and informing users of impeding lapses of attention. Our results are of relevance for experimental paradigms employing the SART, as they could potentially form the basis of a continuous index of attention and allow for the accurate assessment and prediction of inadequate levels of attention. Moreover, applications for attentional training can be envisaged to mitigate the negative consequences of MW [30]. Nevertheless, more research is still required to validate our findings on a larger sample size and across experimental paradigms before the practical implementation of a BCI for the real-time assessment of MW can be contemplated.

Further improvements, which are currently being tested, include a larger number of overlapping bands and the development of a subject independent classifier with identification of the highest contributing bands specific to each subject. A subject independent or general classifiers, as opposed to the subject-dependent classifier trained here, severely reduces calibration and subject-training time and are thus preferred for their ease of use and wider application scope [31]. Additionally, subject-independent classifiers are often necessary in clinical applications because building a Neurofeedback application trained on the abnormal brain activity patterns of a patient might potentially reinforce these, thus further deteriorating the patient's condition.

Contingent on these results, future work should focus on the development of a FBCSP-based general classifier and its deployment for the real-time monitoring of attentional states.

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