Detecting interruption events using EEG

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Abstract— **Contemporary computing devices subject their users to continuous interruptions that can seriously harm productivity and well-being. Understanding how people react to notifications can provide valuable information in managing undesirable interruptions. We test whether a wearable EEG system can detect interruption decision events. Participants in a lab experiment (n=15) received notifications while carrying out a primary task, at the same time their brain activity was recorded with a wearable EEG system. We show that specific EEG features can distinguish between notifications that interrupt the user's activity and notifications that the user can disregard. Our results demonstrate that wearable EEG can serve as a basis for managing interruptions.**

Keywords—EEG, interruption, mental load, workload

I. INTRODUCTION

Interruption is "the suspension of one stream of focused activity prior to completion, with the *intent of returning to,* and completing, the original stream of activity" [1, p. 286]. Interruptions can be harmful to productivity and can be dangerous in some situations, such as driving [2]. The user's attention can be drawn to an interrupting task using notifications delivered by a computing device. At the same time, it's impossible to get rid of notifications altogether because they help users maintain information awareness.

Researchers have tried to improve the interruption experience by delivering interruptions at breakpoints between tasks [3], which correspond to low mental load levels (the subjective effort applied by a person performing the required work). Electroencephalography (EEG) is well established as a tool to measure mental load [4], and indicate opportunities for interruption [5] as well as the effects of interruptions [6]. The Neurosteer EEG system selected for this study includes a novel output channel (called VC9), positively correlated to mental load [7].

Managing interruptions requires identifying and mitigating them. However, the literature still has a gap in documenting physiological measurements of interruption events. Specifically, we did not find physiological markers that are linked to sensing notifications. Once the notification is sensed, whether a physiologically measurable difference exists between being interrupted and ignoring the notification. We believe this understanding is important as it lays the foundation for developing smart systems that can learn the interruption handling preferences of a user [8].

Fig. 1. Neurosteer EEG system. A wearable one-lead medical electrode with a single-use sensor that attaches to the forehead and a relay computer connected to the Neurosteer® Cloud server.

II. EXPERIMENTAL SETTINGS

We developed and performed a user study where an interrupted task is integrated with an EEG system. We asked the question: Can EEG detect notifications and interruption decisions? Specifically, we evaluated whether EEG features exist that are different when notifications are detected (Q1) and which specific EEG features are different between the acts of performing the interruption and ignoring the notification (Q2). The notifications contain a preview that is purposefully different as a way to communicate the appropriate action required from the interruptee; to switch or not switch to the interrupting task.

A. EEG Recording

A wearable EEG sensor from Neurosteer® measured the brain activity. It consists of a 1-lead medical grade electrode connected by Bluetooth to a relay computer that retransmits the data to the Neurosteer Cloud server (Figure 1). In the server, a series of signal processing and machine learning models approximate features that are normally accessible with large EEG electrode arrays to produce 251 features that update every second [9].

B. Experimental task

Fifteen participants (mean age 25, nine males and six females) underwent a custom-developed experiment consisting of a main task and an interruption. The main task, is a mental arithmetic task with the equation broken up. The participant needs to remember the result momentarily and respond whether their answer agreed or disagreed with the computer-generated result [10]. It was selected to produce

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equivalent mental load in repeated short trials without being trivial nor monotonous. The interruption task consisted of clicking with the mouse cursor on a hexagon target on a screen with seven pentagon distractors of the same color [11]. The experiment consisted of 3 interruption conditions. Firstly, a notification comprising a 5Hz flashing indicator that should be responded to (referred to as *high*) and a notification consisting of a 1Hz flashing indicator that participants were told not to respond to (referred to as *low*). Additionally, we included a control condition where no notification was presented (referred to as *none*). Each condition occurred 48 times, resulting in 144 trials. The study was performed within subject, each participant performed all trials presented in random order.

Five participants performed the experiment on one day, and their data were analyzed to identify EEG features-of-interest (training group) before inviting the second group of ten different participants to create the hold-out data (testing group) [12]. Participants received $15 for participating in the study taking approximately one hour.

C. Data analysis

Analysis was performed on one second of EEG data before interruption decision is made. Repeated trials were averaged to generate feature vectors. We performed a 2-way ANOVA p-value to filter features of interest from the training group. Paired T-Tests were evaluated on data from the testing group of participants to evaluate research questions.

III. Experiment and Results

The "training" group of five participants exhibited significant main effects of interruption on twenty of the EEG features. Paired T-Tests indicated that most (fifteen) of the features-of-interest could distinguish between *low* and *high* conditions. The fewest features could distinguish between the *low* and the no-interruption conditions (two features).

The "testing" group of ten participants exhibited significant main effects in the ANOVA analysis within seven features out of the twenty significant in the "training" set (Table 1). Paired T-test results reflected all features were different between the *high* vs. *low* conditions, six were different between the *no interruption* condition and the *high*, and none were different between the *no interruption* condition and the *low* condition.

TABLE I. Seven features with low p-value for the two-way ANOVA on the test data and results for paired T-Test results.

Feature Name	Train	Test			
	AOV p-val	***AOV p-val***	***t-test high vs low***	***t-test none vs high***	***t-test none vs low***
Baf_35	0.005	0.002	0.014	0.009	0.263
VC_9	0.023	0.003	0.013	0.012	0.327
T4	0.002	0.002	0.005	0.019	0.392
T5	0.028	0.008	0.006	0.046	0.520
T6	0.015	0.048	0.035	0.109	0.772
T7	0.041	0.003	0.007	0.008	0.231
L1	0.010	0.004	0.019	0.012	0.446

IV. Conclusions

In this study, we set out to find EEG features that identify whether an interruptee sensed a notification. Secondly, whether a notification resulted in performing the interruption task. The question was partially confirmed as six of the features of interest are different between the no interruption and high importance notifications. In contrast, none of the features are different between the no interruption and the low importance notifications. The second question was confirmed as seven of the features of interest are different between the different interruption decision conditions.

The ability to detect the occurrence of notifications and notification decisions makes an important step towards filtering interruptions [8]. A notification detection marker could enable an indication of "message received" that could prevent accidents in high risk environment [13]. Since the EEG hardware is not tied to the computer it can be applied to different contexts like 911 emergency operators [14].

[1] Y. Miyata and D. A. Norman, "Psychological issues in support of multiple activities," *User centered system design: New perspectives on human-computer interaction*, pp. 265–284, 1986.

[2] S. T. Iqbal and E. Horvitz, "Notifications and awareness: a field study of alert usage and preferences," in *Proceedings of the 2010 ACM conference on Computer supported cooperative work - CSCW '10*, Savannah, Georgia, USA, 2010, p. 27, doi: 10.1145/1718918.1718926.

[3] P. D. Adamczyk and B. P. Bailey, "If Not Now, When?: The Effects of Interruption at Different Moments Within Task Execution," in *Proceedings of the SIGCHI conference on Human factors in computing systems*, 2004, pp. 271–278.

[4] D. Grimes, D. S. Tan, S. E. Hudson, P. Shenoy, and R. P. Rao, "Feasibility and pragmatics of classifying working memory load with an electroencephalograph," in *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 2008, pp. 835–844.

[5] D. Chen and R. Vertegaal, "Using mental load for managing interruptions in physiologically attentive user interfaces," in *CHI'04 extended abstracts on Human factors in computing systems*, 2004, pp. 1513–1516.

[6] I. Rejer and J. Jankowski, "EEG Patterns Analysis in the Process of Recovery from Interruptions," in *Proceedings of the 9th International Conference on Computer Recognition Systems CORES 2015*, vol. 403, R. Burduk, K. Jackowski, M. Kurzyński, M. Woźniak, and A. Żołnierek, Eds. Cham: Springer International Publishing, 2016, pp. 587–596.

[7] N. B. Maimon, L. Molcho, N. Intrator, and D. Lamy, "Single-channel EEG features during n-back task correlate with working memory load," *arXiv preprint arXiv:2008.04987*, p. 23, 2020.

[8] B. O'Conaill and D. Frohlich, "Timespace in the workplace: Dealing with interruptions," in *Conference companion on Human factors in computing systems*, 1995, pp. 262–263.

[9] G. Castellani, N. Intrator, and D. Remondini, "Systems biology and brain activity in neuronal pathways by smart device and advanced signal processing," *Frontiers in Genetics*, vol. 5, Aug. 2014, doi: 10.3389/fgene.2014.00253.

[10] S. Hameed, T. Ferris, S. Jayaraman, and N. Sarter, "Using Informative Peripheral Visual and Tactile Cues to Support Task and Interruption Management," *Hum Factors*, vol. 51, no. 2, pp. 126–135, Apr. 2009, doi: 10.1177/0018720809336434.

[11] J. Peirce and M. MacAskill, *Building experiments in PsychoPy*. Sage, 2018.

[12] M. Stone, "Cross-Validatory Choice and Assessment of Statistical Predictions," *Journal of the Royal Statistical Society: Series B (Methodological)*, vol. 36, no. 2, pp. 111–133, Jan. 1974.

[13] S. Mathan, S. Whitlow, M. Dorneich, P. Ververs, and G. Davis, "Neurophysiological estimation of interruptibility: Demonstrating feasibility in a field context," in *In Proceedings of the 4th International Conference of the Augmented Cognition Society*, 2007, pp. 51–58.

[14] D. McFarlane, "Comparison of four primary methods for coordinating the interruption of people in human-computer interaction," *Human-Computer Interaction*, vol. 17, no. 1, pp. 63–139, 2002.

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