Towards Bidirectional Brain-computer Interfaces that Use fNIRS and tDCS

Samuel W. Hincks[1], Maya DeBellis[1], Eun Youb Lee[1], Ronna ten Brink[1], Birger Moëll[2] and Robert J. K. Jacob[1]

[1] *Tufts University, Medford, MA 02155, U.S.A.*

[2] *Stockholm University, 11418 Stockholm, Sweden*

Keywords: BCI, Implicit Brain-computer Interface, fNIRS, Near-infrared Spectroscopy, tDCS, Transcranial Direct Current Stimulation, Cognitive Workload, Bidirectional Brain-computer Interface, Entropic Brain-computer Interface, N-back, ADHD, Attention.

Abstract: We envision a future user interface that measures its user's mental state and responds not only through a display but also by sending output directly to the brain, leading to a primitive bidirectional brain-computer interface. Previous interactive systems have measured brain state with functional near-infrared spectroscopy (fNIRS) for communication from user to computer; we now explore transcranial direct-current stimulation (tDCS) as a channel in the opposite direction. Our goal is to integrate this with brain measurements from fNIRS, so that the stimulation parameters governing tDCS may be set dynamically to enhance user cognition based on current mental state and task demands. To do this, the first step is to determine how long it takes for tDCS to register cognitive effects and how long these effects last. We present an experiment that investigates the temporal dimension of tDCS for this purpose. The findings suggest a long lag-time between the onset of stimulation and any measurable cognitive effect, which may prohibit the effectiveness of tDCS in a brain-adaptive application.

1 INTRODUCTION

Computers support several methods for communicating with the user, but currently these output methods are constrained by users' sensory channels. Non-invasive brain stimulation techniques, such as transcranial direct-current stimulation (tDCS), might transcend this limitation. Evidence in the psychology literature suggests that tDCS can temporarily enhance or emphasize aspects of user cognition (Brunoni and Vanderhasselt, 2014) without imposing a health risk (Bikson et al., 2016). tDCS delivers a weak (1 to 2 milliamp) electrical current to the exterior of the subject's scalp through an electrode, taking the path to the nearest cathode, which has been carefully placed so that the current will enter and alter particular regions of the subject's brain. tDCS has been used to treat depression (Nitsche et al., 2009), as well as enhance language learning (Flöel et al., 2008), working memory (Fregni et al., 2005) and attention (Gladwin et al., 2012). With the introduction of tDCS to the standard output arsenal of HCI, an interactive system may be able to judiciously enhance these abilities depending on the circumstance and user state.

Our study is aimed at a future user interface that uses brain measurement as input and responds not only with the usual screen output but also by sending output directly to the brain, suggesting a primitive bidirectional brain-computer interface. Previous systems have measured brain state with fNIRS for communication from user to computer (Afergan et al., 2014a; Afergan et al., 2015; Solovey et al., 2012); we now explore tDCS for the opposite direction in a bidirectional brain-computer interface, with fNIRS or another brain monitor as input, and tDCS as output. For example, consider a brain-adaptive UAV system (Afergan et al., 2014a). In this experiment, we trained machine learning algorithms operating on data from an fNIRS brain monitor to predict the user's cognitive workload as he or she was controlling the flight paths of several simulated unmanned aerial vehicles (UAV). The system added extra UAVs to the user's task when brain activity indicated that she was in a state of low cognitive workload; and it removed some in order to simplify the user's task when workload increased. The bidirectional version we propose would

Hincks, S., DeBellis, M., Lee, E., ten Brink, R., Moëll, B. and Jacob, R.
Towards Bidirectional Brain-computer Interfaces that Use fNIRS and tDCS.
DOI: 10.5220/0006380500570064
In *Proceedings of the 4th International Conference on Physiological Computing Systems (PhyCS 2017)*, pages 57-64
ISBN: 978-989-758-268-4

apply tDCS stimulation briefly, precisely when the measured workload increases and only for the duration of the workload spike. For such a bidirectional brain-computer interface to work in practice, the lag time between stimulation and its result should be short. However, much previous tDCS research, especially experiments aimed at treating depression (Shiozawa et al., 2014), have emphasized longer term effects and longer stimulation periods, because interactivity was not the goal.

To proceed with an interactive system, the key question is to determine how long it takes for tDCS stimulation to register cognitive effects and how long these effects last. We investigate that in this paper with two experiments. At present, there are many unknowns regarding the relationship between settings of the device and its associated cognitive effects, making it difficult to gauge whether the device warrants study and inclusion in next generation user interfaces. An alarming percentage of experiments (Horvath et al., 2015) fail to elicit significant improvements to user performance. The consensus is that results vary across person, possibly because each individual has a different brain and unique rules for how to conduct brain stimulation. However, deciding to abandon tDCS for that reason is premature, because the device has not yet been studied interactively. The missing ingredient for effective tDCS may in fact be a two-way digital ecosystem in which settings can be dynamically adjusted based on their judged, subject-to-subject effectiveness.

In this paper, we evaluate the feasibility of a bidirectional brain-computer Interface. We present two experiments aimed at estimating temporal properties of tDCS by estimating performance changes in a visuospatial n-back task over a 15 minute time-course. In the first experiment, we compare 5 minutes of tDCS stimulation to a placebo condition; and in the second experiment, we compare 10 minutes of stimulation to a placebo condition. We evaluate changes in reaction time and accuracy for each minute of the experiment.

2 BACKGROUND

2.1 Transcranial Direct Current Stimulation

While introducing tDCS brain stimulation into HCI raises safety and ethical questions, research to date has shown that when stimulation does not exceed 2 milliamps and lasts shorter than 40 minutes, there have been no cases of irreversible injury caused by tDCS in a sample of 33,200 sessions (Bikson et al., 2016). Compared to other brain stimulation techniques, tDCS is easy to use and potentially inexpensive; it already supports a do-it-yourself community (Fitz and Reiner, 2013). Although experiments typically use a more advanced setup, the basic device consists of just two electrodes and a battery to energize them. Direct current is then administered through a saline-soaked sponge or rubber electrode with conductive gel on the subject's scalp. In a typical setup (and the one used in this experiment), one electrode is placed over the target of stimulation, initiating a path for the current to take to a second electrode placed somewhere nearby. The current is presumed to alter the cortical excitability of the neurons it interacts with, either depolarizing their membranes and making the neurons more likely to fire in the case of anodal stimulation, or hyperpolarizing the membranes, making the neurons less likely to fire in the case of cathodal stimulation (Medeiros et al., 2012).

Given that working memory, compulsivity, and attention are often impaired in individuals with Attention-deficit/hyperactivity disorder (ADHD) (Moëll et al., 2015), tDCS has been explored as treatment for individuals with this condition (Cachoeira et al., 2017). Experiments aimed to enhance working memory typically administer anodal stimulation to the left dorsolateral prefrontal cortex (dlPFC) at the site F3 (in the International 10-20 system (Nitsche et al., 2008)) and allow current to flow through a reference electrode at a symmetrical location on the brain's right hemisphere at site F4 (Zaehle et al., 2011) (see Figure 1). Many experiments have used this montage to enhance performance at an n-back test (Brunoni and Vanderhasselt, 2014). The present experiment makes use of the same montage and n-back paradigm, except we investigate shorter stimulation periods and track performance on a minute-by-minute basis in order to evaluate the usage of tDCS in an interactive system.

2.2 Functional Near Infrared Spectroscopy

fNIRS is a non-invasive neuroimaging technique, which can be implemented cheaply since it consists merely of light sources and detectors (Piper et al., 2014). fNIRS depicts brain activation by shining near-infrared light into the scalp and detecting the amount that returns to the sensor, which changes based on the relative concentration of oxygenated and deoxygenated hemoglobin, the basic energy supply for neurons. These measurements have been found to fluctuate in response to the user's cognitive workload (Herff et al., 2014).

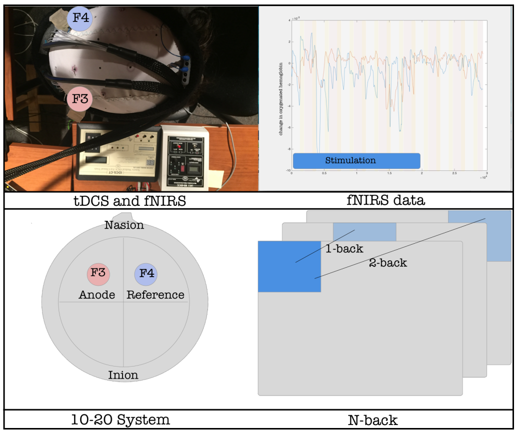

Figure 1: The n-back task, pictures of the device, and one subject's fNIRS activity.

2.3 N-Back

Cognitive workload is a basic index of the cerebral strain a task poses on a user (Herff et al., 2014). We focus on the workload in the prefrontal cortex, which generally correlates with short-term memory workload. In experiments, this type of workload is typically induced using an n-back task. In the visuospatial variety of this task (see Figure 1), the user tracks a 3-by-3 grid where one box is colored. The colored box changes every couple seconds, and the user's job is to indicate whether or not the colored box is in the same location as it was n iterations ago. Higher values of n induce higher degrees of short term memory workload. tDCS has been reported to improve n-back performance (Brunoni and Vanderhasselt, 2014) and fNIRS has been reported to differentiate brain signals pertaining to trials with higher or lower associated cognitive workload (Herff et al., 2014; Hincks et al., 2016).

2.4 Implicit Brain-computer Interfaces

Implicit Brain-Computer Interfaces (Zander et al., 2014; Treacy Solovey et al., 2015) listen to running classifications of the user's state as measured by portable brain sensors (such as EEG and fNIRS), and update implicit system settings to the user's current needs. Using fNIRS, predictions of the user's cognitive workload have been applied to control cursor selection expansion (Afergan et al., 2014b), musical scores (Yuksel et al., 2016), robot automation (Solovey et al., 2012), and task difficulty (Afergan et al., 2014a). Likewise, this measure could drive the administration of tDCS.

3 EXPERIMENTS

3.1 Equipment

For measuring brain activity, we used the *multichannel frequency domain Imagent fNIRS* device from ISS Inc. (Champaign, IL) to acquire brain data. It uses two probes, each with four light sources emitting light at 830 and 690 nanometers, and detectors located between 0.5 and 3.5 centimeters away from these sources. Sampling frequency was set to 11.79hz.

For altering brain activity, we used *Soterix 4x1 HD-tDCS multi-channel stimulation interface* (*model 4X1-C2*) to pass electrical currents and the *Soterix tDCS-CT* (*model 1507-LTE*) to control stimulation and placebo according to a double-blind protocol.

3.2 Experiment 1

Nine undergraduate college students (5 female) participated in the first experiment. They were monetarily compensated and gave consent at the beginning of the experiment. A university Institutional Review Board approved the experiment. The experimenter explained the visual n-back task (Figure 1) on a whiteboard, and let the user practice two trials of the 1-back and two trials of the 2-back. For the 1-back, the user hit the left arrow key if the visual arrangement matched the previous one and the right arrow key otherwise, and for the 2-back they indicated whether or not it matched what they saw 2 iterations ago. These keys were marked with 'YES' and 'NO' with tape on the keyboard. This task was implemented with custom software for the purpose of recording reaction time and dynamically labeling fNIRS data. After these practice trials, the experimenter fit the user with tDCS and fNIRS. This entailed first measuring the size of the subject's head and selecting between four cap sizes, and then placing one gel-covered anodal electrode at site F3 and the other reference electrode at site F4 (Nitsche et al., 2008), and then connecting the electrodes to the *Soterix* device (see Figure 1). Next, we placed the two fNIRS probes as near as possible to those sites. (We do not report on any fNIRS data in this paper for experiment one or two because we were unable to discover stimulation dependent patterns).

The subsequent experiment proceeded in two phases. In the first phase, subjects alternated between 30 seconds of the 1-back and 30 seconds of the 2-back, performing each task 7 times. This served as practice as well as the opportunity to group participants by the separability of their fNIRS data. In the second phase, the subject alternated between 40 sec-

Table 1: Differences in N-Back Accuracy and Reaction Time for each Minute of Experiment 1.

	Percent Accuracy					Reaction Time (milliseconds)				
	Sham		Real			Sham		Real		
min	**mean**	**std dev**	**mean**	**std dev**	**p-value**	**mean**	**std dev**	**mean**	**std dev**	**p-value**
1	74	24	77	22	0.82909	930	247	808	209	0.4575
2	82	34	93	10	0.58809	701	216	852	250	0.36142
3	80	39	90	14	0.65056	770	261	880	41	0.43568
4	81	28	98	5	0.27549	808	310	811	40	0.98716
5	84	29	88	10	0.84721	651	189	832	166	0.17768
6	82	34	93	15	0.60227	744	201	728	167	0.90031
7	78	32	100	0	0.2236	681	224	691	96	0.9418
8	83	28	93	10	0.52828	669	198	718	149	0.69088
9	80	33	87	13	0.70177	631	218	699	146	0.61433
10	82	29	98	5	0.33798	655	230	651	73	0.97642
11	84	35	95	10	0.57964	637	182	723	109	0.43732
12	80	39	89	16	0.67354	658	159	763	93	0.28151
13	81	28	90	8	0.54059	666	273	620	81	0.75824
14	84	35	90	8	0.76657	590	168	704	149	0.32322
15	78	26	92	5	0.34072	624	201	715	187	0.50996
m	81	31	91	4	0.53000	694	209	746	52	0.65

onds of the 2-back and 20 seconds of rest, repeating this 15 times for a total of fifteen minutes. In the n-back task (for experiment 1 and 2), a new stimulus appeared every 3 seconds, and accuracy and reaction time for the 40 second task was therefore based on the average of 13 responses.

We used a between subject design. Prior to the experiment, the participant had been placed in two groups: four in the real tDCS group and five in the sham group, and neither experimenter nor subject knew the groups. The real group received 2 milliamps of anodal stimulation at site F3 for 5 minutes. The sham group received 2 milliamps of stimulation only for 30 seconds, a standard placebo, since subjects tend to sense when the device turns on but forget about it when it has been on for a while (Brunoni and Vanderhasselt, 2014). Participants began the experiment in parallel to onset stimulation. Afterwards, the experimenters removed the equipment from the user and debriefed them.

Results: We have summarized the results of the first experiment in Table 1, and there were no significant effects for the 5 minute stimulation, although stimulated user's trended towards better accuracy and the control group trended towards faster speed, hinting more at a speed-accuracy trade-off than cognitive enhancement. Table 1 shows the mean and standard deviation of the participants' mean accuracy and reaction time for each of the fifteen trials under both sham and real conditions, as well as the probability that these averages differed between sham and real conditions in an independent t-test. Without a clear indication that 5 minutes of stimulation exerted significant improvements to user performance, we modified our design and conducted a second experiment.

3.3 Experiment 2

Fourteen college students (4 female) participated in the second experiment. Based on the lack of significant results in the first experiment, we increased stimulation time from 5 to 10 minutes, and used a within subject design so that all participants received both real and sham stimulations. Participants alternated whether or not they received real stimulation first, and both experimenter and subject were blind to this information. To allow time for both conditions, we removed the initial fifteen minute practice period, and participants alternated between 1-backs and 2-backs, starting with the 1-back. For both real and sham stimulation, participants thus completed 8 sets of 40-second 1-back and 8 sets of 2-backs with a 20 second rest in between. In total, each condition lasted sixteen minutes, separated by a five minute break. Because interference from hair prevented fNIRS measurement in the first experiment, we placed the two fNIRS probes on the user's forehead. Apart from these changes, the second experiment proceeded identically to the first.

Results: We have summarized the results of the second experiment in Table 2, which is arranged identically to Table 1, and illustrate changes in accuracy in Figure 2 and changes in reaction time in Figure 3. Overall, tDCS did not significantly improve either n-back accuracy or reaction time after 10 minutes of stimulation. However, there was a significant im-

Table 2: Differences in N-Back Accuracy and Reaction Time for each Minute of Experiment 2.

	Percent Accuracy					Reaction Time (milliseconds)				
	Sham		Real			Sham		Real		
min	**mean**	**std dev**	**mean**	**std dev**	**p-value**	**mean**	**std dev**	**mean**	**std dev**	**p-value**
1	93	7	95	6	0.3028	716	167	719	219	0.9216
2	95	7	95	5	0.7184	851	260	799	203	0.2297
3	94	11	92	9	0.7229	799	193	706	222	0.0629
4	95	8	94	7	0.7001	770	260	783	341	0.8458
5	93	12	94	11	0.5162	731	208	669	205	0.1777
6	91	10	88	15	0.4098	793	249	843	355	0.7569
7	93	10	95	8	0.4657	684	157	684	154	0.7898
8	90	13	95	7	0.1775	751	278	709	217	0.2580
9	88	9	97	6	0.0034**	741	204	639	185	0.0323*
10	94	9	91	10	0.2456	749	230	771	313	0.9678
11	90	9	95	8	0.0631	720	177	628	234	0.0975
12	99	5	95	8	0.2519	762	299	707	277	0.2690
13	93	7	91	12	0.7966	649	157	626	193	0.5743
14	96	7	89	20	0.1930	701	211	715	270	0.9637
15	88	12	89	9	0.7260	624	144	595	155	0.2914
16	94	11	98	4	0.1944	640	198	710	314	0.4852
m	93	7	93	5	0.5049	746	185	706	223	0.3618

provement to n-back accuracy during the last minute of stimulation. For minute 9-10, the mean accuracy of the 1-back in the sham condition was 88% (std = 9) and the mean accuracy in the 10 minute stimulation condition was 97% (s = 6) (N =13, p = 0.0034 in a *paired sample t-test*). At minute 9-10, improved accuracy in the 1-back did not come at the expense of speed. In fact, reaction times in the 10 minute stimulation condition (m = 639 ms, s = 185 ms) were significantly faster than reaction times in the sham condition (m = 741 ms, std = 204 ms) (N =13, p = 0.0323 in a *paired sample t-test*).

Note that since 1 out of 20 tests should be significant with a threshold set to 0.05, it is hard to verify whether variation has occurred due to chance or not. If significance thresholds are modified according to a Bonferroni correction, then the new threshold is 0.05 / 16 = 0.003125 since there are 16 tests, and neither accuracy nor reaction time are significantly better in the stimulation condition than in the sham condition, although accuracy at minute 9 misses Bonferonni corrected significance by less than 0.0003. There are two reasons why the results between minute nine and ten could be regarded as more valid. First, significance occurs at the very last minute of stimulation and not in a more random minute during the ten stimulation minutes or five non-stimulation minutes. Second, the two dependent variables exhibiting a statistically significant effect according to non-conservative statistical thresholds refer to the same minute, which is improbable unless there was a true effect driving enhancement at this minute, especially given the expectation of a speed accuracy trade-off.

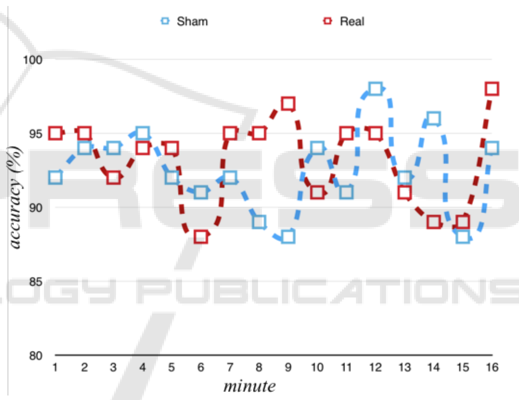

Figure 2: Changes in percent accuracy over time, recorded at the end of each minute.

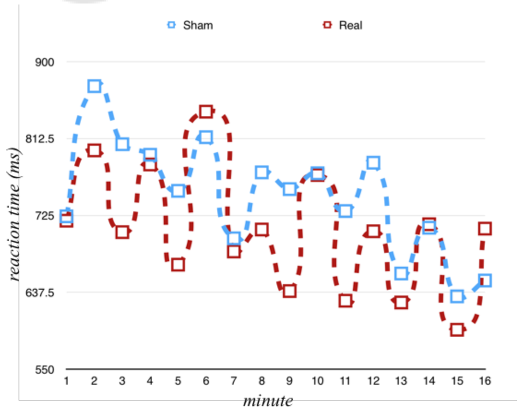

Figure 3: Changes in reaction time measured in milliseconds, recorded at the end of each minute.

4 DISCUSSION

According to these results, tDCS requires at least 9 minutes of stimulation in order to register an effect. Whether or not effects escalate beyond 10 minutes is an interesting investigation for future work. For present purposes, the delayed response between stimulation and effect implies that fNIRS-adaptive stimulation using tDCS may not work effectively. In the interactive application that motivated the design of this experiment, a subject would perform a computer task under the interrogation of fNIRS measurement, and tDCS would apply stimulation to the user when brain activation measures indicated that cognitive workload had increased. The results indicate that the user would need to wait at least 9 minutes before enjoying a boost to cognition, and a brain-adaptive deployment of the technology would therefore be applicable to tasks with a time span in this range. This is feasible in practice, but less amenable to study in an experimental setting.

It is not clear why it takes 9 minutes of stimulation for behavioral effects to register nor whether this limitation disappears given better settings to the device. Individual differences in skin texture, bone density, and brain structure may imply that standardized stimulation protocols fail to appropriately customize to any given subject. If that is the case, better settings to device parameters such as intensity, polarity, duration, and probe location could be discovered and change based on simultaneous brain measurements (McKendrick et al., 2015).

We envision a design in which fNIRS could monitor the relative activation of the user's task-positive and task-negative networks, which oscillate in inverse correlation to each other depending on whether or not the user is sensorily immersed or in an introspective mode of cognition (Raichle et al., 2001). The back-and-forth activity of these networks could be monitored; a bidirectional brain-computer interface might discover how to stimulate the user's brain in order to maximize task-positive immersion and minimize task-negative introspection when warranted. A first step in this direction would be to evaluate whether or not fNIRS detects short term neurobiological reactions to stimulation. We attempted such an investigation in this experiment, but in the first experiment hair prevented our device from appropriately measuring the targeted F3 and F3 nodes. We note that other fNIRS devices (such as *Hitachi ETG 4000*) can solve this problem. In the second experiment, when probes were placed approximately 3 inches from the site of stimulation, we did not observe any obvious fNIRS patterns separating the stimulation and real conditions. However, we found no severe limitations preventing the two devices from being used in concert. Our target is an interactive system in which real-time fNIRS measurements are used to modify the tDCS stimulation parameters for better effectiveness. Our experimental configurations and results present a first step in support of such a bidirectional brain-computer interface.

5 FUTURE WORK: ENTROPIC BRAIN-COMPUTER INTERFACING

Because of the lag-time between the onset of stimulation and any measurable cognitive effect, research into bidirectional brain-computer interfacing might instead focus on stimulation modalities with a more immediate impact on the user's mental state. Research suggests that listening to music with lyrics is detrimental to performance on tasks that require concentration (Shih et al., 2012), but the conclusion is unclear for music without lyrics, which may or may not enhance cognition depending on task, user, and song. As with tDCS, there likely exists some cognitively enhancing stimulation procedure for a given user although the exact procedure may vary person-to-person and the necessary information to determine which stimulation procedure to administer is encoded as a physical constellation in the user's brain.

The problems of cognitive enhancement via music and electrical stimulation may have similar computational solutions, and should thus be studied in concert. In both cases, variables controlling procedures that output physical events to the brain (as current or sound) need to be configured such that stimulation is both safe and beneficial to the recipient. For tDCS, these variables describe the location of electrical probes applying current of a given intensity and polarity for a duration of time. For music, the variables of interest govern a procedure for generating an array of decibel amplitudes in the frequency domain.

The collective work of music theory describes rules for producing harmonious sound, restricting the large space of sound possibilities. For example, a given sequence of sounds should be organized around some tonic note (or frequency series) known as the key of the song, and harmonious sounds are mathematically related to this fundamental frequency according to some scale of intervals (e.g., the major or minor scales). Engineers have encoded these rules into digital audio workstations, enabling an opportunity for auditory bidirectional brain-computer interfacing if the song is augmented with an interface that allows it to branch between different versions depending on implicit input from sensors measuring the user's physiology. For this research, we recommend music production via the Web Audio API (Rogers, 2012) and open source javascript software that extends it (Choi and Berger, 2013; Mann, 2015) since adaptive songs written using web tools can be played in a browser and distributed online for use by anyone with access to the Internet.

In (Hincks et al., 2017), we refer to information-based bidirectional brain-computer interfacing as *entropic brain-computer interfacing* to emphasize a useful model of consciousness that relates subjective measures of rich experience to fMRI-based measures of system entropy (quantified as the difficulty to predict future states of the brain from previous states) (Carhart-Harris et al., 2014). This model and the larger enterprise of Bayesian cognitive neuroscience suggests that a major goal of the brain is to optimally compress and learn from sensory data. The brain uses existing models to predict the content of sensory signals, and propagates information which violates expectation up cognitive hierarchies where existing models are modified (Friston, 2010). Music - or sound which obeys mathematical patterns - may exist as a happy coincidence of the brain's proclivity to direct computation (and associated conscious experience) towards stimuli which engages its predictive machinery (Huron, 2006). By this reasoning, the state of the brain and attention can be modulated by manipulating the user-relative predictability of sound.

Several components of a system which adapts sound to physiological measures of the brain could be recycled to perform bidirectional brain-computer interfacing in other modalities (e.g. electrical stimulation). This generic brain optimization algorithm hinges on non-invasive methods for detecting some aspect of user cognition worth optimizing in all cases. In (Hincks et al., 2017), we argue for two user dimensions describing the direction (internal vs. external origin) and intensity (high vs. low entropy) of attention and attempt to measure these states using fNIRS and EEG. If these states are measured in real-time and allowed jurisdiction over variables governing concurrent stimulation, a machine learning algorithm could infer a relationship between state transitions and the variables governing stimulation, so that the system over time learned how to coerce desirable states.

ACKNOWLEDGEMENTS

We thank Tad Brunye, Erika Hussey, Leanne Hirshfield, Tomoki Shibata, Daniel Afergan, Beste Yuksel, Remco Chang, Evan Peck, Angelo Sassaroli, and Sergio Fantini who are students, alumnni, and professors at Tufts University.

Research was sponsored by the U.S. Army Natick Soldier Research, Development and Engineering Center,and was accomplished under Cooperative Agreement Number W911QY-15-2-0001. The views and conclusions contained in this document are those of the authors and should not be interpreted as representing the official policies, either expressed or implied, of the U.S. Army Natick Soldier Research, Development and Engineering Center, or the U.S. Government. The U.S. Government is authorized to reproduce and distribute reprints for Government purposes notwithstanding any copyright notation hereon.

REFERENCES

Afergan, D., Hincks, S. W., Shibata, T., and Jacob, R. J. (2015). Phylter: a system for modulating notifications in wearables using physiological sensing. In *International Conference on Augmented Cognition*, pages 167–177. Springer.

Afergan, D., Peck, E. M., Solovey, E. T., Jenkins, A., Hincks, S. W., Brown, E. T., Chang, R., and Jacob, R. J. (2014a). Dynamic difficulty using brain metrics of workload. In *Proceedings of the 32nd annual ACM conference on Human factors in computing systems*, pages 3797–3806. ACM.

Afergan, D., Shibata, T., Hincks, S. W., Peck, E. M., Yuksel, B. F., Chang, R., and Jacob, R. J. (2014b). Brain-based target expansion. In *Proceedings of the 27th annual ACM symposium on User interface software and technology*, pages 583–593. ACM.

Bikson, M., Grossman, P., Thomas, C., Zannou, A. L., Jiang, J., Adnan, T., Mourdoukoutas, A. P., Kronberg, G., Truong, D., Boggio, P., et al. (2016). Safety of transcranial direct current stimulation: evidence based update 2016. *Brain Stimulation*, 9(5):641–661.

Brunoni, A. R. and Vanderhasselt, M.-A. (2014). Working memory improvement with non-invasive brain stimulation of the dorsolateral prefrontal cortex: a systematic review and meta-analysis. *Brain and cognition*, 86:1–9.

Cachoeira, C. T., Leffa, D. T., Mittelstadt, S. D., Mendes, L. S. T., Brunoni, A. R., Pinto, J. V., Blazius, V., Machado, V., Bau, C. H. D., Rohde, L. A., et al. (2017). Positive effects of transcranial direct current stimulation in adult patients with attention-deficit/hyperactivity disorder–a pilot randomized controlled study. *Psychiatry Research*, 247:28–32.

Carhart-Harris, R. L., Leech, R., Hellyer, P. J., Shanahan, M., Feilding, A., Tagliazucchi, E., Chialvo, D. R., and

Nutt, D. (2014). The entropic brain: a theory of conscious states informed by neuroimaging research with psychedelic drugs.

Choi, H. and Berger, J. (2013). Waax: Web audio api extension. In *NIME*, page 499–502.

Fitz, N. S. and Reiner, P. B. (2013). The challenge of crafting policy for do-it-yourself brain stimulation. *Journal of medical ethics*, pages medethics–2013.

Flöel, A., Rösser, N., Michka, O., Knecht, S., and Breitenstein, C. (2008). Noninvasive brain stimulation improves language learning. *Journal of Cognitive Neuroscience*, 20(8):1415–1422.

Fregni, F., Boggio, P. S., Nitsche, M., Bermpohl, F., Antal, A., Feredoes, E., Marcolin, M. A., Rigonatti, S. P., Silva, M. T., Paulus, W., et al. (2005). Anodal transcranial direct current stimulation of prefrontal cortex enhances working memory. *Experimental brain research*, 166(1):23–30.

Friston, K. (2010). The free-energy principle: a unified brain theory? *Nature Reviews Neuroscience*, 11(2):127–138.

Gladwin, T. E., den Uyl, T. E., Fregni, F. F., and Wiers, R. W. (2012). Enhancement of selective attention by tdcs: interaction with interference in a sternberg task. *Neuroscience letters*, 512(1):33–37.

Herff, C., Heger, D., Fortmann, O., Hennrich, J., Putze, F., and Schultz, T. (2014). Mental workload during n-back task—quantified in the prefrontal cortex using fnirs. *Frontiers in human neuroscience*, 7:935.

Hincks, S. W., Afergan, D., and Jacob, R. J. (2016). Using fnirs for real-time cognitive workload assessment. In *International Conference on Augmented Cognition*, pages 198–208. Springer.

Hincks, S. W., Bratt, S., Poudel, S., Phoha, V., Dennett, D. C., Jacob, R. J. K., and Hirshfield, L. M. (2017). Entropic brain-computer interfacing: Using fnirs and eeg to measure attentional states in a bayesian framework. In *PhyCS*.

Horvath, J. C., Forte, J. D., and Carter, O. (2015). Evidence that transcranial direct current stimulation (tdcs) generates little-to-no reliable neurophysiologic effect beyond mep amplitude modulation in healthy human subjects: a systematic review. *Neuropsychologia*, 66:213–236.

Huron, D. B. (2006). *Sweet anticipation: Music and the psychology of expectation*. MIT press.

Mann, Y. (2015). Interactive music with tone.js. In *Proceedings of the 1st annual Web Audio Conference*. Citeseer.

McKendrick, R., Parasuraman, R., and Ayaz, H. (2015). Wearable functional near infrared spectroscopy (fnirs) and transcranial direct current stimulation (tdcs): expanding vistas for neurocognitive augmentation. *Frontiers in systems neuroscience*, 9:27.

Medeiros, L. F., de Souza, I. C. C., Vidor, L. P., de Souza, A., Deitos, A., Volz, M. S., Fregni, F., Caumo, W., and Torres, I. L. (2012). Neurobiological effects of transcranial direct current stimulation: a review.

Moëll, B., Kollberg, L., Nasri, B., Lindefors, N., and Kaldo, V. (2015). Living smart—a randomized controlled trial of a guided online course teaching adults with adhd or sub-clinical adhd to use smartphones to structure their everyday life. *Internet Interventions*, 2(1):24–31.

Nitsche, M. A., Boggio, P. S., Fregni, F., and Pascual-Leone, A. (2009). Treatment of depression with transcranial direct current stimulation (tdcs): a review. *Experimental neurology*, 219(1):14–19.

Nitsche, M. A., Cohen, L. G., Wassermann, E. M., Priori, A., Lang, N., Antal, A., Paulus, W., Hummel, F., Boggio, P. S., Fregni, F., et al. (2008). Transcranial direct current stimulation: state of the art 2008. *Brain stimulation*, 1(3):206–223.

Piper, S. K., Krueger, A., Koch, S. P., Mehnert, J., Habermehl, C., Steinbrink, J., Obrig, H., and Schmitz, C. H. (2014). A wearable multi-channel fnirs system for brain imaging in freely moving subjects. *Neuroimage*, 85:64–71.

Raichle, M. E., MacLeod, A. M., Snyder, A. Z., Powers, W. J., Gusnard, D. A., and Shulman, G. L. (2001). A default mode of brain function. *Proceedings of the National Academy of Sciences*, 98(2):676–682.

Rogers, C. (2012). Web audio api. *s Draft [online specification], Version*, 1.

Shih, Y.-N., Huang, R.-H., and Chiang, H.-Y. (2012). Background music: Effects on attention performance. *Work*, 42(4):573–578.

Shiozawa, P., Fregni, F., Benseñor, I. M., Lotufo, P. A., Berlim, M. T., Daskalakis, J. Z., Cordeiro, Q., and Brunoni, A. R. (2014). Transcranial direct current stimulation for major depression: an updated systematic review and meta-analysis. *International Journal of Neuropsychopharmacology*, 17(9):1443–1452.

Solovey, E., Schermerhorn, P., Scheutz, M., Sassaroli, A., Fantini, S., and Jacob, R. (2012). Brainput: enhancing interactive systems with streaming fnirs brain input. In *Proceedings of the SIGCHI conference on Human Factors in Computing Systems*, pages 2193–2202. ACM.

Treacy Solovey, E., Afergan, D., Peck, E. M., Hincks, S. W., and Jacob, R. J. (2015). Designing implicit interfaces for physiological computing: guidelines and lessons learned using fnirs. *ACM Transactions on Computer-Human Interaction (TOCHI)*, 21(6):35.

Yuksel, B. F., Oleson, K. B., Harrison, L., Peck, E. M., Afergan, D., Chang, R., and Jacob, R. J. (2016). Learn piano with bach: An adaptive learning interface that adjusts task difficulty based on brain state. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*, pages 5372–5384. ACM.

Zaehle, T., Sandmann, P., Thorne, J. D., Jäncke, L., and Herrmann, C. S. (2011). Transcranial direct current stimulation of the prefrontal cortex modulates working memory performance: combined behavioural and electrophysiological evidence. *BMC neuroscience*, 12(1):1.

Zander, T. O., Brönstrup, J., Lorenz, R., and Krol, L. R. (2014). Towards bci-based implicit control in human–computer interaction. In *Advances in Physiological Computing*, pages 67–90. Springer.