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# On Augmenting Working Memory through Neurostimulation

*Abstract*— **This article describes our pilot effort toward building an online predictive framework, and decision support system for augmenting working memory (WM) performance during a *cognitively fatiguing* task through closed loop transcranial direct current stimulation (tDCS). We identify cardiac biomarkers for WM performance during a 60-minute WM task and demonstrate the efficacy of short-duration tDCS (~10 minutes) on the left dorsolateral prefrontal cortex (l-dlPFC) in preserving WM capacity. Importantly, we underscore the need for transparency in the stimulation process, with the goal of building a recommender system that remains accessible to the recipient.**

## I. BACKGROUND

There is now considerable evidence that tDCS can boost brain plasticity processes and cognitive performance in complex tasks, less well known are the accompanying physiological changes. Understanding and measuring these changes could provide opportunities for optimization by customizing the tDCS for individual participants (personalization). This study aims to address the critical question of what it takes to build a truly personalized framework for *closed-loop*, non-invasive neurostimulation – one that remains explicitly informed by physiological, and (or) cognitive biomarkers, unconstrained by the task-specificity that encumbers prior developments in this space. Further, we envision a recommender framework that leaves the decision variable in the hands of the recipient.

## II. METHODS

Thirty participants, 50% males, with a mean age: 24 (± 3.5 years) were recruited from the university community. On informed consent, they were subject to *anodal*, *sham*, and *control* tDCS conditions over three separate days, with the order counterbalanced between them. All procedures were approved by Texas A&M University's institutional review board (IRB2019-1591DCR). During each session participants undertook a fatiguing *two-back* test over 12 blocks, with each block lasting 5 minutes. During block transitions participants responded to three questions on a Likert scale regarding their perceived *effort*, *fatigue*, and *comfort*. For tDCS, the anode was placed over the l-dlPFC, while the cathode was placed over the right-supraorbital region (Fig. 1 (b)). Stimulation was provided across blocks 5, 6 for 10 minutes at 1 mA under the *anodal* condition.

Heart rate and it's variability (HR/V) were derived from time- series electrocardiogram signal during the control experiments from the Actiheart 4 (CamNTech, Inc., UK). The raw data was filtered for ectopics and motion-related artifacts. Further, the HR/V signal was detrended and normalized to account for temporal changes in heart rate. Subsequently, we derived time-, frequency-domain, and non-linear features to construct a feature matrix ($X \in \mathbb{R}^2$) using the time-series inter-beat interval. This workflow employed a sliding window that spanned a duration of five minutes, with an overlap of 50%. Block-wise baseline physiological differences were also included as features within our data set. In our exploratory prototype, we adopted a labeling scheme that relied on differences in task accuracy between the performance baseline (blocks 1, 2) and the block in question, where a positive difference was labeled "good", while a negative difference is labeled "poor". HR/V epochs were assigned a label contingent on their temporal proximity to the labeled performance blocks. The resulting data set had roughly 900 observations with 60 features. The stratified feature set was fed to an exhaustive, ensemble machine learning pipeline, with 10-fold cross validation, and hyper -parameter optimization.

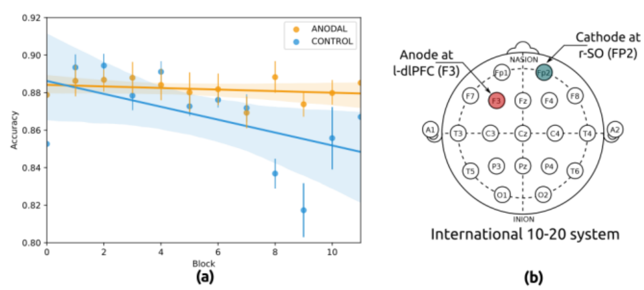


Figure 1. (a) Block-wise performance trends between *anodal* and *control* groups (N = 10). (b) Electrode montage for *anodal* stimulation.

## III. OBSERVATIONS AND FUTURE WORK

Preliminary observations suggest a level of predictive power substantially better than chance with a cross-validated accuracy of 84.72 % when using a *Random Forest* classifier. Notably, *LF_power*, *pNN50*, and *SD1* were among the dominant contributors in the classifier's output. Further, we see statistically significant differences from a *t*-test ($p = 0.0289$) in the performance average between groups that received *anodal* stimulation and those that did not (see Fig. 1 (a)), which is encouraging toward the prospect of non-invasive stimulation in the domain of working memory, and related study outcomes. Although these results signal positively, more robust analyses that represent – **1.** differences between *control*, *sham*, and *anodal* stimulation and the effects of learning; **2.** the predictive power of the features so identified; **3.** algorithmic sensitivity to group or individual differences, latency, and the effects of stimulation; and **4.** discussion around the role of cognitive indices, and their explanatory power will further reinforce our takeaways and subsequent direction.

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