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Predicting Future Performance based on Current Brain Activity: An fNIRS and EEG Study

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***Abstract*— A familiar construct in everyday life is the use of past performance to predict future performance of individuals such as human operators. Here, we propose that brain activity measured during cognitive task execution can be used for prediction of future performance of the same individual on the same task. We recorded multimodal wearable neuroimaging data (Functional Near Infrared Spectroscopy and Electroencephalogram) from twenty-three volunteers performing a cognitive task on three different days. We have analyzed the relationship of brain activity and behavior for both within and across sessions. Preliminary results across sessions show that, as expected, past performance is related to future performance during other sessions to an extent. However, brain activity captured during the task is a better predictor of the future performance compared to current performance. Moreover, within session results show that medial prefrontal cortex brain activity is correlated with imminent future performance as well. These are the first multimodal neuroimaging results suggesting that brain activity has macro (across days) and micro (across seconds) level links to performance.**

I. Introduction

Our society relies on utilizing past performance track records in order to generate a model for prediction of future performance. Similar to the way in which standardized testing is used to predict college performance and resumes are used to anticipate job aptitude, the triage of operators is often based on task performance only. The efficiency and safety of complex high-precision human-machine systems such as in aerospace and robotic surgery are closely related to the cognitive readiness, ability to manage workload, and situational awareness of their operators [1]. As such, better estimation of future performance could significantly improve training as well as mission-critical operation of such complex systems.

The rapid evolution of personal electronics in the last quarter century has seen remarkable innovation and adoption of wearable sensing technologies. Data that at one time could only be collected in laboratory environments has suddenly become accessible, affordable, and easily integrated into popular electronics and other smart devices. This technological development has moved quickly to meet a growing demand for health analytics, driven by individuals who want to learn more about themselves in order to improve. Currently, consumer usage of these devices is treated primarily as a novelty, but in the near future, continuous biomedical monitoring solutions may play important roles in healthcare as well as in the workplace. While modern activity trackers have introduced physiological measurements such as heart rate to measure physical exertion or correlates of stress, these measures are fundamentally non-specific, thereby leaving a picture that is far from complete. In order to expand on the features currently available and elevate the role of continuous monitoring solutions at work and at home, the application of wearable sensors must be expanded to new areas, and nowhere is there more untapped potential than in the brain [2].

The ability to continuously monitor the brain's function is also distinctly more capable than simply tracking activities, potentially providing direct insight into user intentions, mental states, and more. Yet, despite the central role of the brain in day-to-day tasks and how we interact with the world around us, its capabilities and activities are often overlooked in both research and in practice.

Neuroergonomics is an emerging field that investigates the human brain in relation to behavioral performance in natural environments and everyday settings [3]. Neuroergonomics was coined by Raja Parasuraman at the turn of this century [4-6] and primarily focuses on understanding the brain in natural environments [7]. It was fueled by the emergence and widespread use of portable and wearable neuroimaging systems such as functional near infrared spectroscopy (fNIRS) and electroencephalography (EEG). fNIRS is a noninvasive brain monitoring technology that relies on optical techniques to detect changes of cortical hemodynamic responses to human perceptual, cognitive, and motor functioning [8]. EEG measures the cortical electrophysiological dynamics using electrodes over the scalp [9]. Both techniques matured and evolved into ultra-portable, battery-operated, and wireless hardware, enabling unrestricted measurements for studying natural brain dynamics [10-12].

The finite nature of human cognitive capacity demands an efficient relationship between invested mental effort and task performance. There has long been an implicit understanding that effortful cognition is reflected by changes in brain activity; however, it is only recently with the advent of modern sensing techniques that we have been able to study the relationship between mental workload and its physiological and neurological underpinnings [5, 13-15].

Previous EEG and fNIRS-based research on cognitive workload primarily focused on time-locked physiological changes during task performance. Only a few studies have investigated the potential of neuroimaging-based predictors for cognitive performance estimation. Stikic et al. [16]

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investigated the capability of EEG to assess the impact of fatigue on both present and future cognitive performance using a sustained attention task. They concluded that EEG can be used to predict gross-performance degradations 5–15 min in advance. Campbell et al. [17] utilized EEG for prediction of future performance in a training context for name-object association learning. van der Hiele et al. [18] investigated EEG biomarkers of future cognitive performance in the elderly. They concluded that EEG and cognitive measures combined provided the best prediction of future cognitive performance. Trambaiolli et al. [19] found that EEG amplitude modulation signals during resting state were able to correlate with and predict an fNIRS affective neurofeedback task performance using an LDA model. Also, Ayaz et al. [20] used an n-back verbal working memory task to demonstrate that fNIRS-based biomarkers can provide better estimation of task performance across task conditions compared to task performance.

In this study, we aimed to investigate the relation of brain activity to performance in a multi-day experiment with an inhibitory control task using multi-modal wearable neuroimaging modalities: EEG and fNIRS. We assessed the relation of overall brain activity across sessions (each task condition and iterations from one session to another session's performance), as well as within session (brain activity time series to continuous performance). We hypothesized that mental effort, as measured by brain activity, would provide more relevant correlates than task performance in predicting future performance.

II. METHOD

A. Participants

Twenty-three volunteers between the ages of 18 to 48 (16 female, mean age 23 ± 7 years) participated in the study. All subjects completed pre-session questionnaires stating that they met the eligibility requirements of being right-handed with vision correctable to 20/20, did not have a history of brain injury or psychological disorder, and were not on medication affecting brain activity. In addition, prior to the study all participants signed voluntary consent forms approved by the Institutional Review Board of Drexel University.

B. Experimental procedure

Participants completed three 60-90-minute task sessions over the course of one month, each spaced at least one week apart. Participants completed several different cognitive tasks using a standard mouse and keyboard on a desktop computer presented in pseudorandom balanced order; here we present analysis of the inhibitory control task (see Figure 1 and next section for task details).

All tasks were implemented with PsychoPy [21] in repeated block format and lasted 5-8 minutes each. An instructional slide and short practice period were given before each task for the subjects to familiarize themselves with what to do and allow them to ask questions.

C. Cognitive Task: Inhibitory Control

A variant go-stop task [22] was implemented that incorporated three different types of trials: Go, Ignore, and Inhibit (Figure 1). Each block contained twenty stimuli (trials), each separated by a randomized 750-1250 ms. Every trial began with a stimulus presented as a plus sign contained within a circle. Subjects were instructed to react to every plus sign by pressing the enter key with their right hand. The low workload (easy) condition contained an equal number of Go and Ignore stimuli. In Go trials, the react stimulus (plus sign) was visible for 500 ms. In Ignore trials, the react stimulus was present for 150 ms before turning into a flag symbol, which was to be treated the same as the Go trials. In the high workload (hard) condition, there were an equal number of Go and Inhibit trials. In Inhibit trials, the react stimulus was present for 150 ms before turning into a skull symbol. Subjects were instructed to stop (inhibit) their response and attempt to not press enter. The instructions stated to react as quickly and accurately as possible to all stimuli without "waiting and seeing" what the trial was. Performance measures included accuracy, false positive rate, false negative rate, and response time.

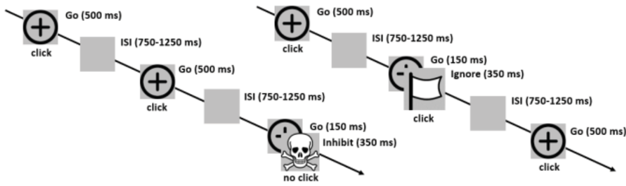

Figure 1. Cognitive task timeline and conditions

D. Data collection and signal processing

Neuroimaging data was recorded simultaneously from all sensors throughout task execution. Prefrontal hemodynamics were measured with an fNIR Devices Model 1200 Imager and flat forehead sensor pad containing 16 optodes using COBI Studio as described in [23]. Electrophysiological activity was measured with a Cognionics HD-72 dry electrode EEG using 32 active electrodes as described in [24] using channels: AFF3, AFF1, AFF2, AFF4, FFC5h, FFC3h, FFCz, FFC4h, FFC6h, FCC5h, FCC3, FCC1h, FCCz, FCC2h, FCC4, FCC6h, CCP5h, CCP1, CCPz, CCP2, CCP6h, CPP3h, CPPz, CPP4h, PO3, PO1, POz, PO2, PO4, O1h, Oz, O2h respectively. Additional physiological signals were recorded by Cognionics extension box: heart activity was measured with three ECG electrodes; eye movements and blinks were recorded with four EOG electrodes; dynamic skin perfusion was recorded with a Photoplethysmography (PPG) ear clip. Eye tracking information including gaze fixation, saccades, and pupillometry was also recorded at 60 Hz using the Smart Eye Aurora system positioned under the computer screen.

Figure 2. Setup of simultaneous fNIRS and EEG headgear

For each participant, raw fNIRS data (16 optodes×2 wavelengths) recorded at 2 Hz were low-pass filtered with a finite impulse response, linear phase filter with order 20 and cut-off frequency of 0.1 Hz to attenuate the high frequency noise, respiration, and cardiac cycle effects [13]. Each participant's data were checked for any potential saturation (when light intensity at the detector was higher than the analog-to-digital converter limit) and motion artifact contamination by means of a coefficient of variation-based assessment [25].

fNIRS data for each task block were extracted using time synchronization markers received via serial port during the experiment, and hemodynamic changes for each of the 16 optodes during each trial block were calculated separately using the Modified Beer Lambert Law. For across session comparisons, the hemodynamic response at each optode was averaged across time for each block to provide a mean hemodynamic response at each optode for each block. The final outputs of each optode were mean block oxygenated hemoglobin (HbO), deoxygenated hemoglobin (HbR), and the difference between HbO-HbR (Oxy) [13].

EEG data were recorded at 500 Hz after checking for impedance and processed using a notch filter at 60 Hz, followed by a bandpass filter between 1-59Hz. Each channel was evaluated for quality using Automatic Subspace Reconstruction (ASR) [26] with default settings implemented in EEGLAB [27]. Continuous band power calculations for each channel were done using Welch's power spectral density of the EEG signal with a moving window of 2 s. Power spectra were divided into delta (1-4 Hz), theta (4-8 Hz), alpha (8-13 Hz), beta (13-30 Hz) and gamma (>30 Hz) bands, as well as certain combinations such as alpha-theta.

E. *Statistical Analysis*

Processing of behavioral data as well as fNIRS and EEG signals were performed using Matlab 2018b (Natick, MA, USA). For the macroscopic level (across session), canonical correlation analysis (CCA) was conducted using NCSS12 (Kaysville, UT, USA) for group comparison of sessions using block averages of each task condition and iterations from all subjects. For the microscopic level (within session: in each task block), assessment of continuous performance prediction was conducted by first generating a measure of continuous performance by convolving the sequence of correct responses during the Inhibit condition with a Gaussian function. Pearson correlation values for the task were averaged on a per-subject basis across trials for each lag value (τ) and biomarker. Correlation values were then compared across subjects by using a one-sided t-test against zero to determine significant group-level positive and negative relationships. Correlations and figures were generated using Python and the SciPy packages.

III. RESULTS

A. *Across sessions*

In this section, CCA linear regression results at the macro level are presented for Session 1 to Session 2 (Table 1), Session 1 to Session 3 (Table 2) and Session 2 to Session 3 (Table 3) with statistical significance and R-squared correlation coefficients. In each table, the first row indicates the behavioral performance accuracy (Acc.) in both predictor and target sessions. The fNIRS biomarker Oxy is the difference between HbO and HbR. Results showed that in all comparisons, optodes 11 and 13 in right medial prefrontal cortex had a higher predictive value than behavioral performance. See supplementary material of [28] where we described the optode locations in Brodmann areas and corresponding anatomical regions.

TABLE I. SESSION 1 TO SESSION 2 COMPARISONS. LINEAR REGRESSION GROUP COMPARISON OF ACCURACY AND FNIRS AND EEG

Predictor	Target	R^2	F	Prob
Acc. S1	**Acc. S2**	**0.0481**	**6.87**	**0.009770**
Oxy11 S1	Acc. S2	0.1928	29.62	0.000000
Oxy13 S1	Acc. S2	0.2058	32.13	0.000000
Alpha AFF3 S1	Acc. S2	0.0738	8.28	0.004863
Alpha AFF1 S1	Acc. S2	0.0807	9.13	0.003160
Alpha AFF2 S1	Acc. S2	0.1189	14.04	0.000294
Theta AFF3 S1	Acc. S2	0.0759	8.54	0.004270
Theta AFF1 S1	Acc. S2	0.0989	11.42	0.001026
Theta AFF2 S1	Acc. S2	0.1165	13.72	0.000342

TABLE II. SESSION 1 TO SESSION 3 COMPARISONS. LINEAR REGRESSION GROUP COMPARISON OF ACCURACY AND FNIRS AND EEG

Predictor	Target	R^2	F	Prob
Acc. S1	**Acc. S3**	**0.0511**	**7.33**	**0.007648**
Oxy11 S1	Acc. S3	0.2937	51.56	0.000000
Oxy13 S1	Acc. S3	0.3793	75.77	0.000000
Alpha AFF3 S1	Acc. S3	0.0569	6.46	0.012461
Alpha AFF1 S1	Acc. S3	0.0640	7.32	0.007931
Alpha AFF2 S1	Acc. S3	0.1065	12.75	0.000534
Theta AFF3 S1	Acc. S3	0.0570	6.47	0.012424
Theta AFF1 S1	Acc. S3	0.0862	10.1	0.001940
Theta AFF2 S1	Acc. S3	0.0996	11.84	0.000827

TABLE III. SESSION 2 TO SESSION 3 COMPARISONS. LINEAR REGRESSION COMPARISON OF ACCURACY AND FNIRS AND EEG

Predictor	Target	R^2	F	Prob
Acc. S2	**Acc. S3**	**0.1886**	**31.62**	**0.000000**
Oxy11 S2	Acc. S3	0.3104	60.33	0.000000
Oxy13 S2	Acc. S3	0.1150	17.15	0.000061
Alpha AFF3 S2	Acc. S3	0.3733	78.03	0.000000
Alpha AFF1 S2	Acc. S3	0.3835	82.11	0.000000
Alpha AFF2 S2	Acc. S3	0.3052	57.09	0.000000
Theta AFF3 S2	Acc. S3	0.2669	47.68	0.000000
Theta AFF1 S2	Acc. S3	0.2809	51.56	0.000000
Theta AFF2 S2	Acc. S3	0.2293	38.67	0.000000

B. *Within session during task*

In order to evaluate the relationship between preceding neurophysiological states and imminent task performance, we performed a time-series cross-correlation of subject results with measures of continuous task performance. Negative values for τ depict temporal segments where brain activity anticipates performance.

fNIRS results showed that optodes in the right prefrontal cortex (PFC) appeared to anticipate continuous behavioral performance on average in all sessions (See Figure 3 and 4). Specifically, optode 12 appeared to have a positive correlation with future continuous performance in the time-range $\tau = -3$ to $-7s$, ($p < 0.001$, t = 4.16-4.38) with peak correlation of 0.19 at $\tau = -4s$.

Significance-masked (thresholded) average correlation with lagged continuous performance for HbO and HbR across all optodes is shown in Figure 3. Colorbar indicates significance levels of the group correlation distribution. Mean group correlations are presented in Figure 4 (Masked at $p < 0.05$).

EEG results suggested that a negative correlation in frontal alpha/theta ratio anticipated improved continuous performance in channel 6 (FFch3, near FC3) with a mean correlation of r = -0.097 at $\tau = -6$ to $-7s$ ($p < 0.017$, t = 2.6). However, parietal alpha/theta engagement measured most prominently in channel 27 (POz) tended to more immediately precede and positively correlate with task performance with a mean correlation of r = 0.093 at $\tau = -1\ to -3s$ ($p < 0.0019$, t = 3.55 to 3.72) (see Fig. 5 and 6).

Together, these results illustrate how cortical dynamics as measured both by fNIRS and EEG may underlie performance. Specifically, increased involvement in the right medial PFC as measured by HbO may precede periods of peak performance, and a similar reduction in frontal alpha/theta ratio with a corresponding increase in the parietal/occipital region may aide in more immediate performance and potentially serve as a status marker for operator engagement.

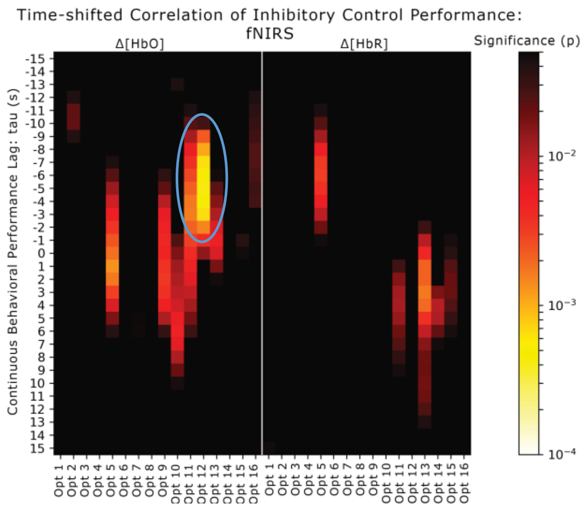

Figure 3. Significance p values of the cross-correlation of fNIRS optodes (Opt.1-16) with continuous performance. Negative lag indicates brain activity precedes accuracy.

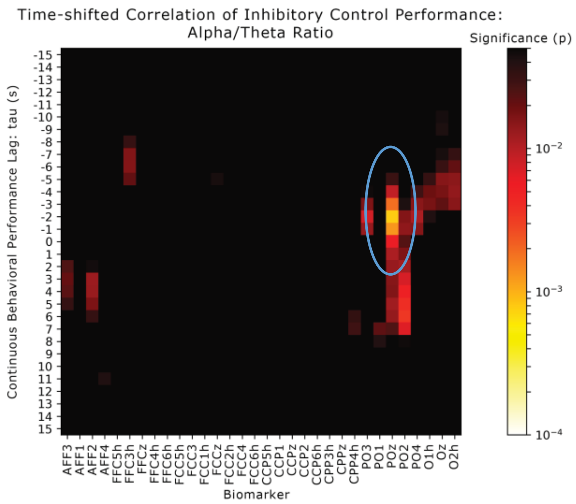

Figure 5. Significance p values of the cross-correlation of EEG alpha/theta ratio with continuous accuracy. Negative lag indicates brain activity precedes accuracy

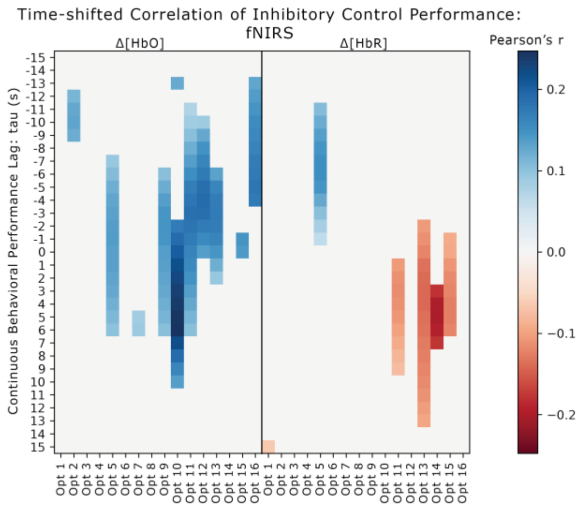

Figure 4. R values of the cross-correlation of fNIRS optodes (Opt.1-16) with continuous accuracy. Negative lag indicates brain activity precedes accuracy

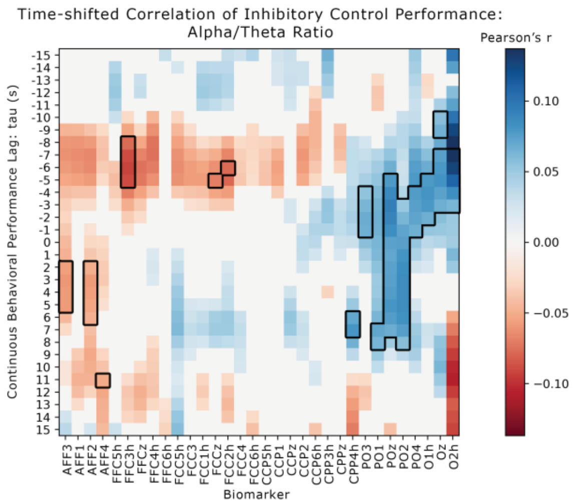

Figure 6. R values of the cross-correlation of EEG alpha/theta ratio with continuous accuracy. Blue border indicates significant correlation distributions.

IV. Discussion

In this study, we aimed to study the relationship of brain activity to both current and future task performance. We investigated this relationship at the macroscopic level (across different sessions over days) as well as on a microscopic level (within session and over seconds). Our preliminary results from the session-level analysis indicated a consistent pattern from EEG (alpha and theta band power from PFC) and fNIRS-based brain activity (from the right medial PFC) possessing a significantly high correlation with future performance (See Table 1-3). Moreover, current PFC activity was a better indicator of a subject's future performance than their currently observed performance. This suggests that a person's behavioral performance on a given day may represent an incomplete picture of their capabilities. However, monitoring brain activity can reveal complimentary information (e.g. mental effort) which may reflect otherwise hidden differences in task strategy, engagement, adaptation and skill acquisition. And, these appear to be a more refined predictor of future performance.

These across-session results are further supported by the within-session analysis that shows significant positive correlations with near-future performance for fNIRS optodes 11 and 12. Participants' utilization of the right medial PFC region may have indicated the use of an optimal task strategy, and participants who successfully activated this region performed at higher functional levels in future sessions.

Similarly, alpha and theta EEG band power showed high predictive value for future task performance according to the across session level analysis. In within-session analysis, a predominant localization of imminent task performance with parietal and occipital alpha/theta ratio suggested that this region may be recruited in successful task performance in a way which was supported by the aforementioned involvement of the right-medial PFC.

These results overall are the first multiscale and multimodal assessment of brain activity's relation to future performance using both hemodynamic and electrophysiological perspectives both at the macroscopic level (across days) as well as on a microscopic level (within session and over seconds). Here we present initial information about the relationship between fNIRS measures of anterior prefrontal cortical hemodynamics, EEG measures of parietal engagement, and the performance of an attentional inhibitory control task. Theories of the regulation of cognition suggest two necessary components: one to execute control and another to monitor performance and identify when adjustments in control are needed [29]. The relationship of dorsolateral prefrontal cortex (fNIRS and EEG results) to future performance here particularly supports the earlier findings in different tasks about this region's role in performance monitoring and particularly response inhibition [30]. Results further contribute and support the idea of a fronto-parietal salience network which is of critical importance to successful operator task performance [31].

However, these preliminary findings are subject to limitations which must be considered here. Primarily, while the use of lagged performance to synchronize brain activity may reveal more coherent patterns underlying cognitive engagement, these patterns may fundamentally vary with the task selected and the method of performance evaluation used.

While these results are preliminary in nature, they reveal the power of joint multiscale and multimodal neuroimaging and performance analysis. Future development of this approach may allow for a more integrated solution for operator assessment during recruitment, training, and in-field evaluations. While we demonstrated that it is possible to use brain activity to anticipate later task performance, it remains to be determined how the relationship between task performance and brain activation may be practically applied to more complex, real-world tasks. Future work should investigate the generalizability of this approach to different cognitive domains.

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