EVALUATION OF UAS OPERATOR TRAINING DURING SEARCH AND SURVEILLANCE TASKS

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Unmanned aircraft system (UAS) sensor operators are typically required to execute search and surveillance tasks. Brain-in-the-loop measures during such tasks can help evaluate expertise development and cognitive capacities of the operator, which can be an important asset in designing adaptive and personalized training systems. Emergence of functional near infrared spectroscopy (fNIRS) has enabled monitoring of operators' prefrontal cortex (PFC) area, which is associated with higher level cognitive functioning such as decision-making, problem-solving, working memory and attention in everyday working environments. In a previous sensor operator training study, we investigated and reported preliminary evidence suggesting that fNIRS measures acquired from the left prefrontal cortex were associated with the development of scanning efficiency. Here we extend these findings by exploring skill acquisition in terms of changes in the functional brain activity correlated with the improvement in target search task. During each target search task participants were required to engage in route scanning, and target identification. Neurophysiological measures via fNIRS were found to be positively correlated with behavioral results suggesting that those who were actively engaged in finding targets, had significant changes in both left and right prefrontal cortex.

Unmanned aircraft systems (UAS) afford operational flexibility, including but not limited to effective and efficient surveillance tasks. Although the use of UASs presents a great opportunity, their associated mission success rate is greatly dependent upon human-system interaction and platform capability. In 2004, a comprehensive assessment of UAS accidents in different sectors of the US military, reported that both system and human factors contributed to the likelihood of an incident (Williams, 2004). While technological advances have been able to decrease the contribution of system-related failures, those attributed to human factors still remain at 70%. This issue is somewhat confounded when we consider wider human factors issues to do with the lack of perceptual cues available to the operator, the issues of lag, and the associated issues with operating within the wider national airspace system (NAS) with other air users.

The composition, designated roles and responsibilities of a UAS flight crew is somewhat dependent on the platform and nature of operations (Mccarley & Wickens, 2004). In some instances, several roles within the UAS crew may be shared across several crew members, and alternate between them, or be carried out by the same individual. Regardless of the crew composition, the operator in control of the asset is a focal point for ensuring not only the safe flying of the UAS, but also the operational effectiveness associated with the mission. Specifically, mission effectiveness is very much driven by the payload or sensor operator (SO). In the case of surveillance and search uses, the pilot (or a specific SO crew member) is expected to operate a number of sensors such as a camera during different phases of flight. To accomplish the manipulation of the sensor in relation to the surrounding mission constraints and specialist instructions, it is not surprising to assume that a SO must undergo an effective training program that allows the individual to develop appropriate cognitive skills that best suit the aforementioned SO tasks. The design of an appropriate training methodology must ensure appropriate and effective SO performance related to improved search behaviors, tracking, and classification accuracy to reduce incidents of false identification.

In order for the SO to reach a particular level of operational competence, it is expected that significant cognitive effort and activity will be elicited in specific regions of the brain, particularly the prefrontal cortex (PFC) (Izzetoglu et al., 2014; Menda et al., 2011). Cognitive effort assocaited with regions of the PFC produce a metabolic demand, which in turn causes an increase in blood flow to the specific regions of the human brain taxed by the assigned task and/or specfic target search mission. Recent advances in optical brain imaging techniques, in particular functional near infrared spectroscopy (fNIRS), have allowed portable application of monitoring brain activity of operators within their normal working environments. fNIRS exploits the optical properties of biological tissues and hemoglobin chromophores in assessing changes in brain activity. It does so by deploying wavelengths between 700 to 900nm, where the chromophores of oxygenated and de-oxygenated hemoglobin (HbO_2 and HbR, respectively) are found to be the main absorbers. The changes in HbO_2 and HbR are directly associated with changes in brain activity. Therefore, fNIRS can offer a direct method to assess a SOs' brain activity, via metabolism of oxygen, during task execution.

Methods

Participants

Eleven participants between the ages of 18 to 42 ($\bar{X}$= 22; SD=8) voluntarily consented to participate in the Institutional Review Board (IRB) approved study. Two participants were not included in the analysis due to incomplete sessions. All participants had no prior UAS piloting simulator experience, had normal or corrected to normal vision, were verified as right handed via the Edinburgh Handedness assessment.

Experimental Protocol

A Ground Station simulator, the Simlat's C-STAR (Simlat Inc., Miamisburg, Ohio), was used in this study as it offers a simulator training apparatus that implements SO's tasks and presents a realistic representation of their role (Reddy et al., 2018; Izzetoglu & Richards, 2019). The simulator allows for two trainees and one instructor to operate a generic tactical unmanned system (G-TAC UAS) simultaneously with designated roles. The participants took part in five sessions, of which only the first three training sessions are reported within the scope of this study. The route and scanning area of the map were identical for all the sessions, however location of the target per each sub-area was random. Additionally, to reduce task complexity, task variability, the piloting of the UAS was set to auto-pilot mode following a pre-determined route via pre-designated waypoints.

During each session, the screen display was orientated to show a map (left display) and a sensor payload screen (right display), as per Figure 1. The trainee was provided with real-time field of view (FOV) measures on the map screen in the form of differently sized polygons. On the other hand, the sensor screen displayed the simulated model of the landscape of Mallorca, Spain. It had a crosshair located in the center and zoom level gauge located to the left, which were utilized by the operator to complete their missions.

Figure 1. Trainee's Screen. Left side is showing the map screen with the route that the UAS will be following, while the right is showing the payload screen, with the zoom level indicator placed at the left edge of this screen.

The trainee was expected to move the position of the camera while varying the camera's FOV to search the sub-area (scan task). While an area was being scanned by the UAS camera, participants engaged in a target identification task where they screened the area for a pre-identified target (in this instance a singular *red civilian bus*) located in each sub area. To accomplish this, the participant was instructed to zoom in as close as possible when they located the target. The participant was then instructed to position the camera's crosshair onto the target and lock on. Throughout this task the participant was attached to a 16-Channel fNIRS device that acquired data from the left and right PFC.

Data Analysis

Behavioral data processing. The Performance Analysis & Evaluation module (PANEL) of the C-STAR system outputted sub-area start time, time elapsed since the sub-area started, zoom angle at which the scan was being conducted, scan polygon vertices, region of interest (ROI) polygon vertices, target location within the ROI, and lastly true or false indicating whether a target fell within the camera FOV or not. Target found or NOT found was assessed by extracting all the polygons that happened at a zoom angle less than 20 and had "true" tag in the target in FOV column, an example of this is show in Figure 2.

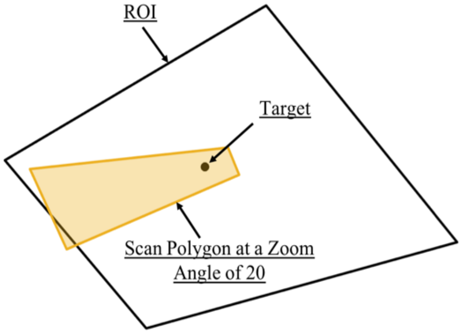

Figure 2. Target was classified as found if there existed a scan polygon (yellow) that happened below a zoom angle of 20 and the target was within the polygon.

fNIRS Signal Processing. fNIRS signal can be corrupted by instrument noise, physiological noise and motion artifacts (M. Izzetoglu et al., 2005). Therefore, to improve the sensitivity and spatial specificity of neuronal activity, a finite impulse response low pass filter, a linear detrending algorithm and a motion correction method (temporal derivative distribution repair) (Fishburn, Ludlum, Vaidya, & Medvedev, 2019) were applied. Then, modified Beer-Lambert Law was used to calculate the oxygenated (HbO_2) and deoxygenated-hemoglobin (HbR) changes at each channel (Villringer & Chance, 1997). Using HbR and HbO_2 measures, oxygenation ($Oxy = HbO_2 - HbR$) and total hemoglobin ($Hb_{total} = HbO_2 + HbR$) were derived. Lastly, samples that were three standard deviations above the expected values were classified as outliers and removed from further analysis.

Statistics. Due to small sample size, non-parametric Independent-Samples Mann-Whitney U Test was used to determine differences between groups.

Results

Each task per sub-area, trial and participant received a Found or Not Found label according to the criteria described previously. There were six targets to be found per trial, making a total of eighteen targets per participant, which sums up to 162 tasks. Investigating total number of targets found per participant, resulted in the identification of two groups. The first group, determined as a high-performance group, consisted of 6 participants who had medium to high counts of total finds, as shown in Figure 3a. Consequently, Figure 3b shows the low-performance group, which comprised of 3 participants who had minimal number of total target finds. On average, as shown in Figure 3c, the total number of finds in the high-performance group was significantly greater than that of the low performance group. Furthermore, significant differences were also observed when average number of finds per trial was assessed, as shown in Figure 3d.

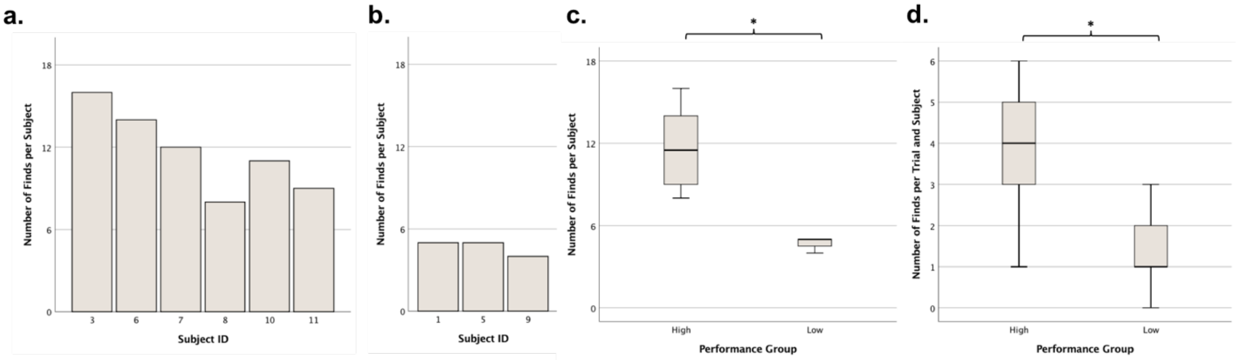

Figure 3. a. Total number of finds per subject in the high-performance group ***b.*** Total number of finds per subject in the low-performance group ***c.*** Average target finds per subject (p = 0.024) ***d.*** Average target finds per trial and subject (p = 0.001)

Our hypothesis for the target task was that oxygenation levels in the prefrontal cortex, especially in left PFC which is part of the working memory network, should be higher in engaged or high performer than that of a low performer (M. Izzetoglu et al., 2005). Comparison of HbO_2 measures from Optodes over middle frontal gyrus between performance groups support our hypothesis that high performers on average have higher activation during target finds than low performers, as indicated in Figure 4a. If a participant is engaged in finding a target, then he/she should also be actively scanning. Therefore, we also expected that the high performer group on average will have more activation in right PFC. fNIRS measures from the right PFC, have been known to be associated with sustained attention (M. Izzetoglu et al., 2005). Results from Figure

4b support this statement, where a significant difference can be seen between HbO_2 measures from high and low performers.

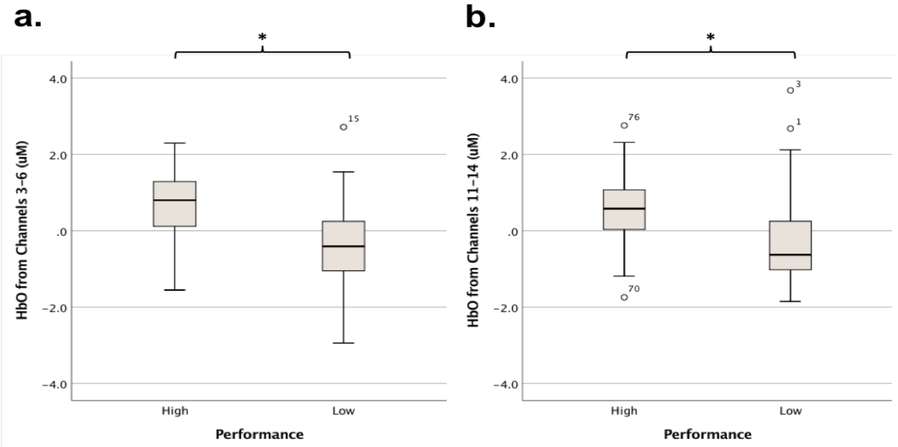

Figure 4. Significant differences were observed in HbO_2 measures between high and low performers in both ***a.*** left PFC ($p < 0.01$) and ***b.*** right PFC ($p < 0.01$) regions

Discussion

The cognitive demands placed on the SO play a crucial role within the context of UAS operation. Understanding the effect of these cognitive demands on the performance of a SO has implications for mission effectiveness, and the associated evaluation of training. Traditionally the assessment of an operator's ability would identify behavioral performance assessment parameters, such as task performance, task load assessment, etc. However, we suggest how direct neurophysiological measures through wearable sensors can provide complementary quantitative assessment methods.

In our previous preliminary studies, we reported separately that as a participant actively scanned or found targets, they had higher oxygenation in attention and working memory PFC regions (Izzetoglu & Richards, 2019; Reddy et al., 2018). In this current study, we sought to further explore the evolving relationship using target search tasks. Our behavioral results from target task demonstrated difference between high and low performers. The fNIRS results were positively correlated with behavioral results suggesting that those who were actively engaged in finding targets, had significant changes in both left and right PFC regions.

Although these behavioral and neuro-physiological measures are in line with previous studies, and provided supporting evidences to the previous findings, a comprehensive analysis on relationship between tasks and their influence on fNIRS measures acquired from all the PFC regions need to be assessed with large sample size. Specifically, we plan to study whether advances in cognitive engagement lead to faster response times in identifying a target and reduce incidents of false positive identification rate as shown in prior studies (Gordon D. Logan, 2011).

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