JAIN RESEARCH LAB

Assessing the Relationship Between Learning Stages and Prefrontal Cortex Activation in a Psychomotor Task

Research Assistant: Jacob Hunter (hunte168@purdue.edu) | Principal Investigator: Dr. Tahira Reid & Dr. Neera Jain (neerajain@purdue.edu)

PURDUE UNIVERSITY®

Ray W. Herrick Laboratories

OVERVIEW

In general, attaining new psychomotor skills with sufficient proficiency can be time consuming and requires substantial practice and repetition. In such circumstances, human learning can be facilitated by automated assessments of learning stages in the psychomotor task. The main objective of this work is to develop tools that can help characterize progression through learning stages in the psychomotor task, by using both performance-based metrics as well as measures of brain activity during the task. An online learning stage classifier, bridging the gap between qualitative and quantitative representation of learning stage (novice, advanced beginner, competent, proficient, and expert) was developed in [1].

The psychomotor task in this work is piloting a quadrotor to safely land repeatedly over 25 trials. A simulator to teach humans this task is described in [2]. By measuring brain activity using functional Near-Infrared Spectroscopy (fNIRS), a neuroimaging tool in which noninvasive optical imaging is used to observe brain activation via the flow of blood [3], we can correlate the cognitive load in the prefrontal cortex to the classified learning stage. By evaluating this relationship between learning stages and brain activation, we contribute an empirical evaluation of fNIRS as a function of learning stage in a difficult psychomotor task.

Figure 1: *Experimental setup for the quadrotor landing task.*

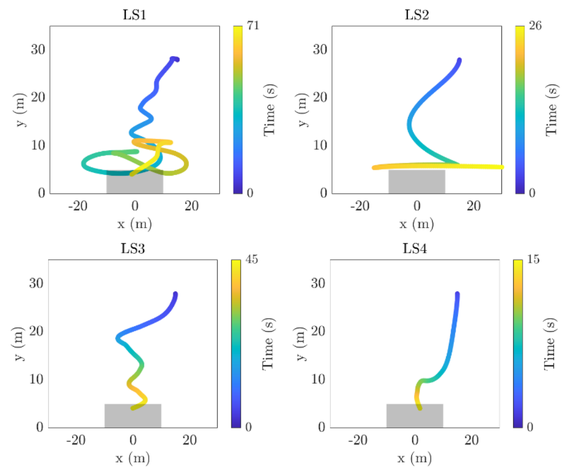
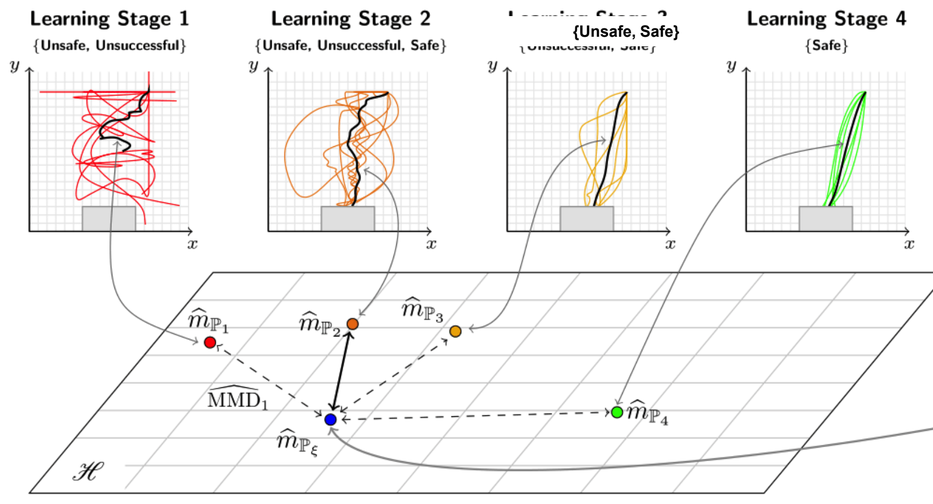


Figure 2: *Example Quadrotor Trajectories for each learning stage.*

Figure 3: *The Obelab NIRSIT fNIRS device is a headset worn on the forehead, covering the prefrontal cortex.*

Experiment Design

- **Participant's Goal:** Learn to manually land quadrotor safely onto landing pad within 25 trials.
- After every trial k, numerical score ($S_k \in [0,1000]$, self-reported self-confidence ($SC_k \in [0,100]$) and mental workload ($W \in [0,100]$), landing type (unsuccessful, unsafe, safe), quadrotor states ($x, y, \phi, \dot{x}, \dot{y}, \dot{\phi}$), classified learning stage ($LS_k \in \{1,2,3,4\}$) are collected.
- The Institutional Review Board at Purdue University approved the study. Participants compensated at $20/hr.
- 31 participants completed the study. 8 participants excluded due to incomplete or corrupted fNIRS data or non-compliant behavior during experiment. This resulted in a total of 23 participants.



A series of processing steps are used to obtain changes in oxygenated hemoglobin (HbO) after collecting the raw fNIRS signal:

1. Light intensity is converted to optical density. Then the signal is corrected for motion artifacts;
2. Bandpass filter to remove noise.
3. Optical density is converted to HbO and Mayer wave noise is filtered with short channel regression.

Trajectory from P11 trial 10 (blue) is classified as LS2. The canonical distribution associated with LS2 has the smallest distance to the observed trajectory in comparison to other feasible learning stages

Table 1: *To classify a trial with one of four learning stages, we compare the distance from the trajectory observed during the trial to a canonical distribution associated with each feasible learning stage [1] and choose the learning stage associated with the canonical distribution that has the smallest distance. The feasibility conditions for each learning stage are indicated in brackets.*

Results

Applying a one-way ANOVA to average HbO and learning stage yields significant differences in HbO across learning stages ($F(2, 45) = 17.04$, $p < .001$). We then use independent *t*-tests to further compare specific learning stages to one another.

- Difference in HbO activation for each participant across the 25 trials is shown in Figure 5. Each participant has unique brain activation and performance trends.
- Table 1 shows independent *t*-test results. Table 2 shows that self-confidence is proportional, and workload is inverse, to LS.
- In Figure 5, the heat map of LS1 and LS2 have considerably higher and more homogeneous HbO activation than those in learning stage 3. This increased heterogeneity could indicate changes in cognitive strategies as proficiency increases.

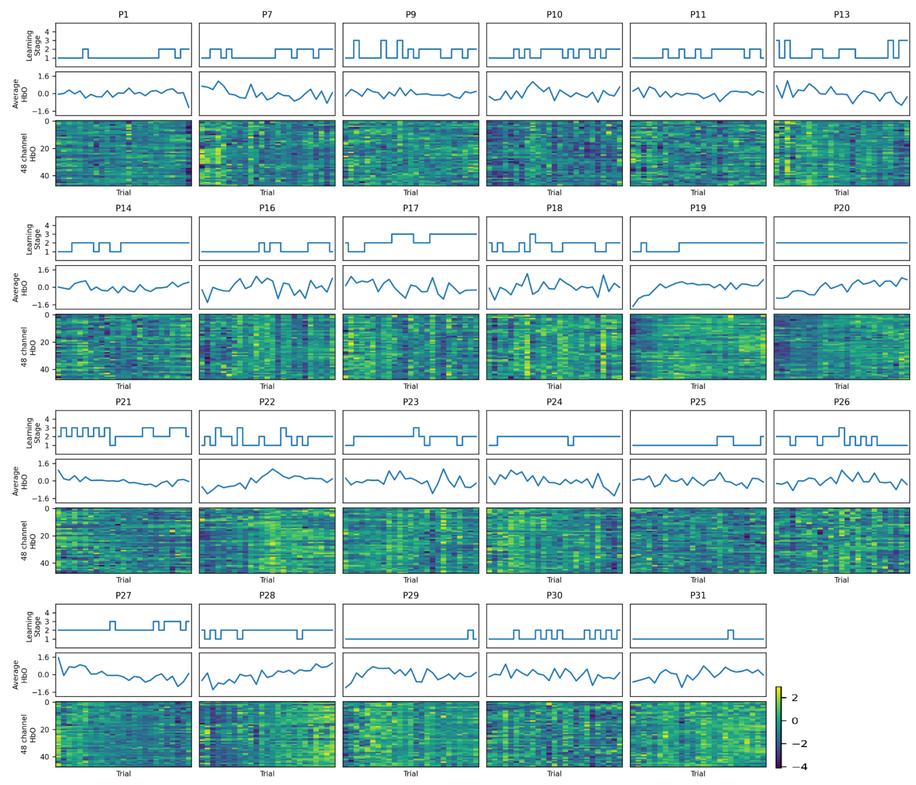


Figure 5*: Learning stage classification, average HbO values, and 48 channel HbO values for all participants across trials*

Table 1*: Independent t-tests on average HbO between pairs of learning*

Learning Stage Comparison	t-value	DOF	p-value
LS1 vs LS2	-3.06	94	$p < .01$
LS1 vs LS3	3.53	94	$p < .001$
LS2 vs LS3	4.79	94	$p < .001$

Table 2*: Self-reported average values of self-confidence and workload.*

Learning Stage	Self-Confidence	Workload
LS1	41.3	54.7
LS2	67.5	49.3
LS3	70.8	40.6

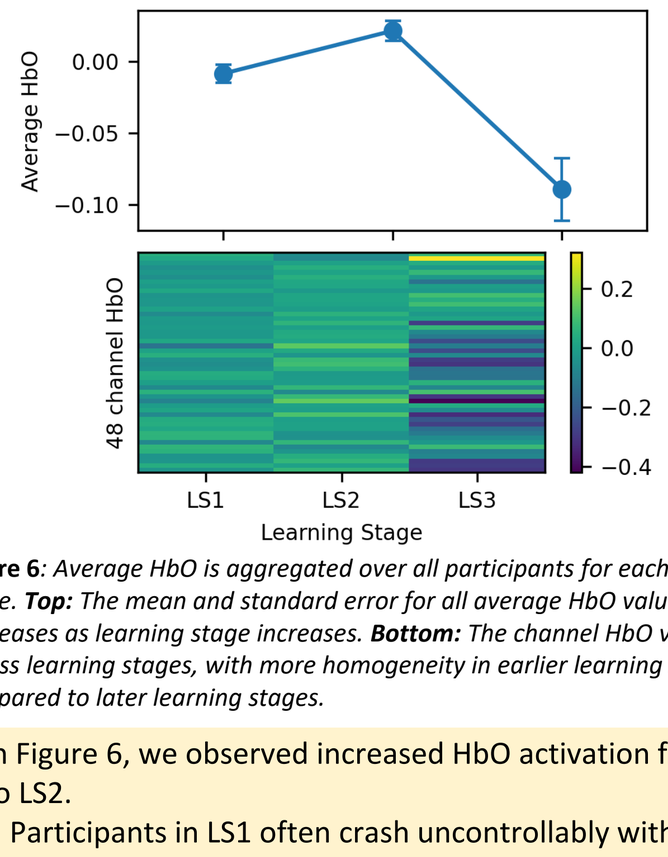


Figure 6*: Average HbO is aggregated over all participants for each learning stage.* ***Top:*** *The mean and standard error for all average HbO values decreases as learning stage increases.* ***Bottom:*** *The channel HbO values vary across learning stages, with more homogeneity in earlier learning stages as compared to later learning stages.*

- In Figure 6, we observed increased HbO activation from LS1 to LS2.
  - Participants in LS1 often crash uncontrollably without the chance to strategize.
  - Participants in LS2 show sustained activation as improve at controlling quadcopter.
- There is a significant decrease in activation in LS3, indicative of a decreased cognitive load.

CONCLUSIONS

- Participant trials classified in learning stage 3 experienced **significant decreases in HbO activation** than those in learning stages 1 and 2, as evidenced by the independent *t*-test results and the average HbO trend in Figure 6.
- Widespread activation in early learning stages could reflect a high cognitive load and exploratory learning processes. As proficiency increases, activation may become more localized, suggesting more efficient neural processing.
- Future work includes determining how to render automated assistance to hasten transitions from one learning stage to the next, using methods to customize feedback to individual participants' learning needs.

ACKNOWLEDGEMENTS

This material is based upon work supported by the National Science Foundation under Award No. 183690. Any opinions, findings, and material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation.

REFERENCES

[1] M. S. Yuh, K. R. Ortiz, K. S. Sommer-Kohrt, M. Oishi and N. Jain, "Classification of Human Learning Stages via Kernel Distribution Embeddings," 2024.

[2] S. Byeon, D. Sun, and I. Hwang, "Skill-level-based hybrid shared control for human-automation systems," in IEEE International Conference on Systems, Man, and Cybernetics (SMC), 2021.

[3] D. Boas, C. Elwell, M. Ferrari, and G. Taga, "Twenty years of functional near-infrared spectroscopy: introduction for the special issue", in Neuroimage, 2014.