Collegiate Aviation Review International

Volume 39 | Issue 2 Proceedings of the 2021 UAA Annual Conference, Article #2

12-05-2021

Cognitive State Measurement in Remotely Piloted Aircraft Training

Zachary Waller
University of North Dakota

Thomas Petros
University of North Dakota

The purpose of this study is to determine whether Electroencephalogram (EEG) technology - developed for cognitive state estimation in operational settings - can document cognitive workload and task engagement experienced by Remotely Piloted Aircraft (RPA) pilots during their training.

Recommended Citation:
Waller, Z, & Petros, T. (2021). Cognitive State Measurement in Remotely Piloted Aircraft Training. *Collegiate Aviation Review International*, 39(2), 234-237. Retrieved from http://ojs.library.okstate.edu/osu/index.php/CARI/article/view/8381/7685

Electroencephalograms (EEG) have been shown to reflect workload levels and sustained attention during training and learning. However, a limited number of studies have examined their performance in operational settings (Bernhardt et al., 2019; Mathan & Yeung, 2015; Mills et al., 2017; Yuan et al., 2014).

As measures and methods of cognitive states mature and coalesce into fields such as augmented cognition and adaptive automation, applications have emphasized the value of cognitive state monitoring in the interest of safety, acknowledging "... errors could arise from aberrant mental processes, such as inattention, poor motivation, loss of vigilance, mental overload, and fatigue, that negatively affect the user's performance" (Aricò et al., 2016, p. 296).

The potential of cognitive state monitoring for predicting human error in the interest of safety should be neither diminished nor dismissed. However, the capacity of cognitive state monitoring – to recognize subtle differences in performance that cannot be observed by behavioral outcomes alone – is also a demonstrated interest in educational and training settings (Bernhardt et al., 2019; Borghini et al., 2014; Mathan & Yeung, 2015; Mills et al., 2017; Yuan et al., 2014).

Berka et al. (2007) began the process of establishing and validating the EEG metrics utilized by Advanced Brain Monitoring, Inc. (ABM) and the B-Alert X-24. Thirty EEG features were used by Berka et al. (2007) in calculating a workload metric which was recommended for assessing the effectiveness of training and simulation programs. Bernhardt et al. (2019), a recent effort, execute on this interest and acknowledge cognitive state metrics as a viable tool for enhancing Air Traffic Control (ATC) training. This study continues this interest with preliminary data collected during simulated training events of remote pilots.

Purpose of The Study

The purpose of this study is to determine whether the EEG technology - developed for cognitive state estimation in operational settings - can document cognitive workload and task engagement experienced by Remotely Piloted Aircraft (RPA) pilots during their training.

Findings

EEG data (n = 19) has been collected during simulated training events in the MQ-1 RPA at the University of North Dakota. EEG signals were collected during a simulated training event in the MQ-1 RPA. The lesson calls for approximately 1.2 hours of contact time with the remote pilot, a checklist, and a flight pattern with 12 distinct legs.

Estimates of cognitive metrics for high engagement and workload were averaged for the duration of the checklist as well as each leg of the flight pattern. Results of a one-way repeated measures ANOVAs showed that the cognitive state metric for engagement ($F(11,8704)=4.87$, $p<0.001$) and workload ($F(11,8328)=10.03$, $p<0.001$) varied significantly within the flight pattern. The average probability of high workload is presented in Figure 1 below.

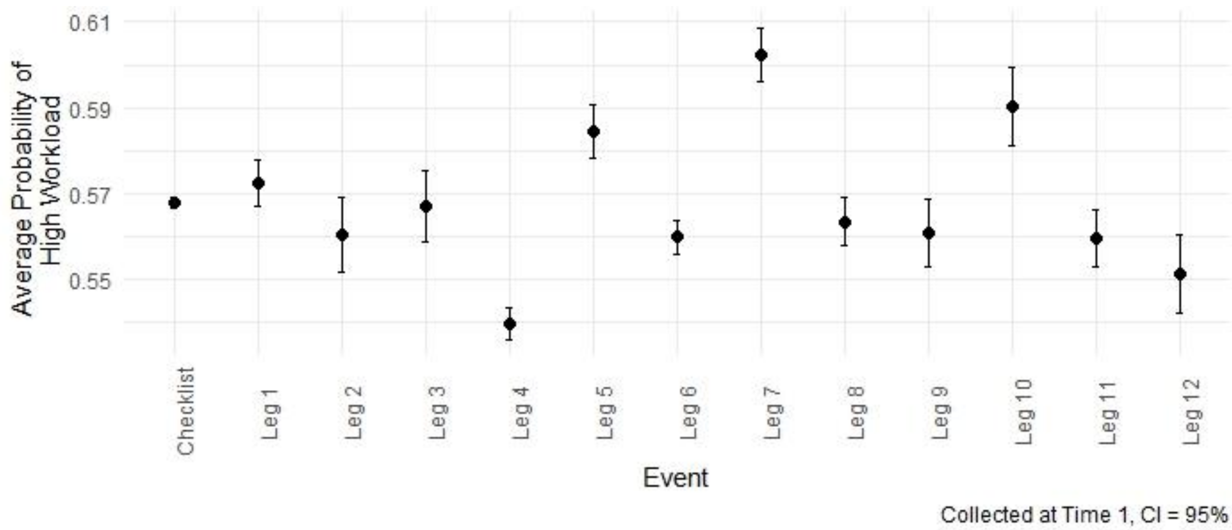

Figure 1. Cognitive State Metric for Workload: ABM's High Workload Metric during Checklist and Flight Pattern Events

Results of a paired sample t-test ($t(8348)=14.21$, $p<.001$) indicated that workload was significantly lower ($M=0.5536$, $SD=0.16$) during legs of the flight pattern assisted by the heading hold function of the autopilot than legs 5 through 10 where remote pilots were unassisted by this automation ($M=0.5718$, $SD=0.16$).

Discussion & Conclusion

As with prior works in operational aviation settings, EEG-based cognitive state metrics demonstrated an ability to detect subtle changes in operator workload (Aricò et al., 2016; Bernhardt et al., 2019). Noted as a limitation in Bernhardt et al. (2019), the NASA TLX was administered following both the checklist and flight pattern tasks in this study to relate the EEG-based workload metric with a subjective measure of workload. Unlike the prominent positive association noted by Aricò et al. (2016), this study noted no significant relationship between the subjective and EEG-based measures of workload.

In this work, EEG-based metrics for measuring cognitive states such as workload and task engagement demonstrate a capacity for distinguishing variation during the training of Remotely Piloted Aircraft (RPA) pilots. These results support the design of a within-subjects methodology using EEG data to assess the effectiveness of RPA training over time.

References

Aricò, P., Borghini, G., Di Flumeri, G., Colosimo, A., Pozzi, S., & Babiloni, F. (2016). A passive brain–computer interface application for the mental workload assessment on professional air traffic controllers during realistic air traffic control tasks. *Progress in Brain Research*, *228*, 295–328.

Bernhardt, K. A., Poltavski, D., Petros, T., Ferraro, F. R., Jorgenson, T., Carlson, C., & Iseminger, C. (2019). The effects of dynamic workload and experience on commercially available EEG cognitive state metrics in a high-fidelity air traffic control environment. *Applied Ergonomics*, *77*, 83–91.

Borghini, G., Aricò, P., Ferri, F., Graziani, I., Pozzi, S., Napoletano, L., Imbert, J. P., Granger, G., Benhacene, R., & Babiloni, F. (2014). A neurophysiological training evaluation metric for air traffic management. *2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 3005–3008. https://doi.org/http://dx.doi.org/10.1109/EMBC.2014.6944255

Mathan, S., & Yeung, N. (2015). *Extending the diagnostic capabilities of artificial intelligence-based instructional systems.* 51–60.

Mills, C., Fridman, I., Soussou, W., Waghray, D., Olney, A. M., & D'Mello, S. K. (2017). Put your thinking cap on: detecting cognitive load using EEG during learning. *Seventh International Learning Analytics & Knowledge Conference*, 80–89.

Yuan, Y., Chang, K. M., Taylor, J. N., & Mostow, J. (2014). Toward unobtrusive measurement of reading comprehension using low-cost EEG. *Fourth International Conference on Learning Analytics and Knowledge*, 54–58.