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Augmented cognition is a form of human-systems interaction in which physiological sensing of a user's cognitive state is used to precisely invoke system automations when needed. The present study monitored the in-flight physiological state of the pilot to determine the optimal combination of EEG indices to predict variations in workload, or opportunities for augmented cognition.The participants were 10 collegiate aviation students with FAA commercial pilot certificates and current medical certificates. Each participant performed a uniform flight scenario that included procedures that varied in workload demands. All maneuvers were performed while simultaneously acquiring EEG data in flight. The EEG data were divided into periods of high and low workload. Power spectral density values were computed and subjected to several machine learning methods to distinguish high and low workload periods. The results indicate excellent classification accuracy for distinguishing low and high workload. The present results further demonstrate the potential of augmented cognition.

A growing body of research focusing pilot, driver or operator physiological and cognitive state monitoring during operations of air or ground vehicles facilitates our understandings of the role of human and machine operations (Dussault et al., 2004; Wilson et al., 2019; Guragain et al., 2019; Wang et al., 2019). Within this domain of research, we can apply observed changes in physiological and cognitive state to invoke augmented cognition, or system adaptation based on the condition of the operator. One promising avenue of research in augmented cognition involves developing the capability to continuously monitor an individual's level of fatigue, stress, attention, task engagement, and mental workload in operational environments using physiological parameters (Berka et al., 2007). These physio-cognitive monitoring systems have a wide range of potential applications that could significantly enhance performance, productivity, and safety in military, industrial, and educational settings, including evaluating alternative interface designs, enhancing skill acquisition, and optimizing the ways humans interact with technology (Berka et al., 2007).

Monitoring of the operator functional state can determine if or when the operator is task-saturated, stressed or disengaged and allow the introduction of adaptive aiding by implementation of some form of automation. Attempts to implement adaptive aiding have utilized physiological triggering of adaptive aiding (Wilson & Russell, 2007). One of the challenges for those engaged in operator state monitoring is to utilize the most sensitive set of sensors that are the least intrusive and most practical for the operator.

Blanco et al. (2018) examined the utility of dry electrode EEG measures for distinguishing workload during simulated flight. All participants had previously experienced basic flight training and tested under three different flight scenarios of differential levels of difficulty (easy, medium difficulty, difficult). Each participant flew each scenario once for 10 minutes in counterbalanced order. Scalp EEG dry electrode signals were recorded from Fz, FCz, Cz and Pz using the International 10-20 system. The authors reported that a strong negative correlation between behavioral performance and EEG workload measures. However, a subset of subjects demonstrated increased cognitive workload without any decrement in flight performance. Perhaps physiologically based workload measures can be used to assess learning proficiency during pilot training to identify pilots who are cognitively saturated and at a higher risk to perform poorly as new cognitive challenges emerge.

The present study collected physiological data from pilots while they executed flight patterns that varied in their workload. The purpose of this research was to demonstrate the validity of EEG measures for distinguishing workload in flight. Some of the higher workload flight maneuvers are executing a missed approach at minimums and performing consecutive steep turns. Whereas maneuvers that were classified as low workload included flying straight and level and taxiing at an un-towered airport. To cross-validate perceived workload differentiation between maneuvers, elements of the flight profile were individually ranked by experienced faculty and/or flight instructors at the University of North Dakota's John D. Odegard School of Aerospace Sciences.

Methods

Participants

Ten undergraduate aviation students participated in this study. Study participants held a Federal Aviation Administration (FAA) commercial pilot certificate and either a FAA Class I or Class II medical certificate. The average self-reported flight hours of each participant were 323.6 at the time of the study, with a range of 170 to 840. Each participant was current in the aircraft type flown and all had experience with the Garmin G1000 avionics system. Study participants were informed and provided consent through the approved Institutional Review Board (IRB) protocol. Participants were provided a monetary incentive for their participation.

Experimental Procedure

Informed consent was first obtained from each participant in advance of the meeting time at the airport. Upon arrival at the airport, the participant completed a demographic, recent sleep, and recent stimulant (e.g. caffeine) intake questionnaire and was subsequently connected to the ABM-B-Alert X24 data collection system (Advanced Brain Monitoring, Inc). A baseline recording was collected while the participant was in a quiet, closed office space. Once the baseline recording was completed, the participant boarded a common four-seat single engine trainer aircraft equipped with Garmin G1000 avionics. The participant then performed a pre-determined flight sequence while at the control of the aircraft at the direction of a safety-pilot (the PI) with support of a research assistant sitting in the back seat of the aircraft. During the collection of physiological data, the safety pilot and research assistant noted times of maneuvers. Later the aircraft flight data was downloaded from the avionics to cross-reference against the performed maneuvers. To add a second cross-reference of workload, the PI collected survey data from "experts" aviation faculty or airport leadership to classify maneuvers included in the data collection flight profile as "high" "medium" or "low" workload. This information was used to determine time periods where changes in workload are anticipated to occur.

Image 1

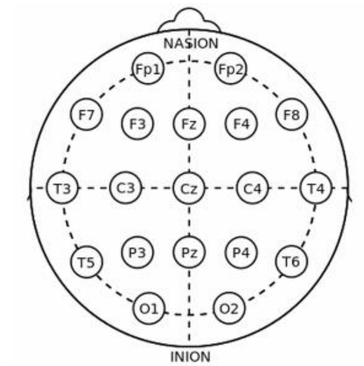
ABM B-Alert

Image 2

Data Collection

Figure 1

EEG 10/20 Placement



Note. Image 1 showing the ABM B-Alert X24 system. Image 2 showing the data collection flight environment. Figure 1 showing the international 10/20 electrode placement.

EEG recording was accomplished using the Advanced Brain Monitoring (ABM) X-24 system (ABM, 2020). The ABM system includes 20 electrodes placed in the standard international 10-20 system (Fp1, Fp2, F7, F3, Fz, F4, F8, T3, C3, Cz, C4, T4, T5, P3, Pz, P4, T6, O1, POz, and O2) with a sampling rate of 256 Hz. Data is transferred via Bluetooth signal to a laptop with corresponding ABM EEG recording software.

EEG Pre-processing

The recorded EEG data were pre-processed using EEGLAB, an open-source interactive MATLAB toolbox (Delorme & Makeig, 2004) (http://sccn.ucsd.edu/eeglab). The data was filtered using a high-pass filter (1 Hz) followed by a low-pass filter (45 Hz) to remove low-frequency drifts and high-frequency artifacts. Subsequently, the filtered data were visually inspected, and noisy channels, dead channels (channel data indicated no activity over longer periods), muscle activity, mechanical artifacts in the time domain were removed manually, and using EEGLAB "clean_rawdata" plugin. On average, 19.5 EEG channels remained for further analyses (range: 18–20; SD = 0.67). Then, all missing channels were interpolated by spherical algorithm to minimize the potential bias toward a hemisphere. In the next step, Independent Component Analysis (ICA) was computed using the EEGLAB runica function in order to extract independent components (ICs) from signals in scalp level that represent maximum statistical independent sources (Gramann, Ferris, Gwin, & Makeig, 2014; Gramann et al., 2011). Using the ICLabel toolbox (Pion-Tonachini, Kreutz-Delgado, & Makeig, 2019), which is an automatic independent component (IC) classification algorithm, source descriptions including brain, non-brain, eye, muscle, heart, and other sources were automatically assigned to each IC. Consequently, the artifactual ICs with an assigned probability of higher than 0.8 were selected and eliminated from the data, and cleaned EEG signals were used for further processing.

Feature Extraction and Selection

The feature extraction step was performed using power spectral analysis. Fast Fourier Transform (FFT) using one-second hamming windows with 50% overlap was used to transform the EEG into power spectral density (PSD). Each EEG channel based on its frequency was divided into four sub-bands, namely Delta (1-4Hz), Theta (4-8Hz), Alpha (8-13Hz), and Beta (13-30Hz). Since each EEG sub-band has a different frequency range, the average power spectrum for each channel and sub-band was calculated and used for further analysis. Moreover, we calculated the ratios of average spectral powers for theta of each electrode in the frontal area divided by the alpha of the electrodes in the parietal and occipital region; theta divided by beta for each EEG electrode, and beta divided by alpha plus theta for each EEG channel resulting in 148 features. Lasso cross-validation (LassoCV) algorithm was employed to select the most important features.

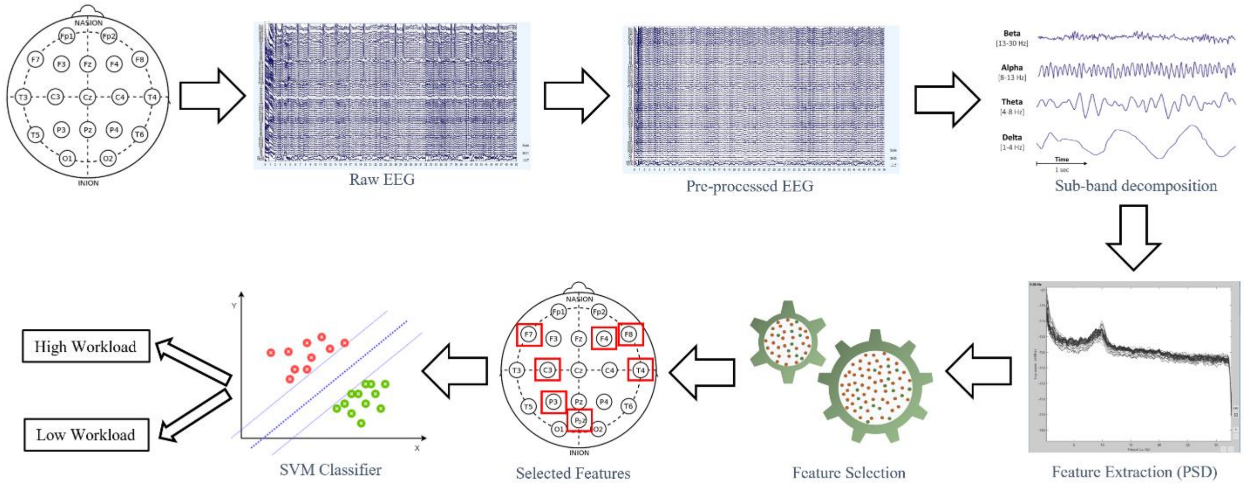
Classification

Classification refers to a supervised method in which algorithms aim to learn from one portion of already labeled data called training data and uses the learned pattern and information to classify the new unseen portion of data into a proper class. The main goal of this study is to determine the level of the cognitive load of pilots in two classes of high workload and low workload, and this task is defined under the binary classification category. We used the support vector machine (SVM) algorithm as the binary classifier because it is considered one of the most widely used technique in the field of brain signal analysis due to the robust approach for recognition of the complex pattern, good generalization performance, and its efficient computational cost (Wei et al., 2018). To achieve a more accurate estimate of the SVM performance on unseen data and prevent our model from overfitting, we used k-fold cross-validation (k=5), in which all the data were split into 5 subsets. The k-fold cross-validation is an iterative process (k times), and each time the model is evaluated by one of the k subsets while the k-1 subsets used for training and the final results will be the average of all k time evaluations. Moreover, we used accuracy, precision, recall and F score to evaluate the performance of the proposed model to differentiate between high and low workloads.

Result

The top ten features out of 148 features were selected using the LassoCV based on the highest absolute coefficient value as follows: frontal (F4) theta/parietal, occipital (Poz) alpha, frontal (F8) theta/parietal, occipital (Poz) alpha, frontal (F7) theta/parietal (P3) alpha, frontal (F4) theta/parietal (P3) alpha, temporal (T4) theta, temporal (T3) delta, central (C3) theta, temporal (T6) beta/T6 alpha + T6 theta, temporal (T3) beta/T3 alpha + T3 theta, and central (C3) beta/C3 alpha + C3 theta. At the next step, to classify the high and low workloads using the features mentioned above, we trained and tested our SVM classifier with 5-fold cross-validation, and 95.00 ± 0.30 percent was the highest accuracy achieved. Moreover, the SVM classifier resulted in 100% precision, 90.00 ± 0.20 recall, and 93.33 ± 0.13 F-score. The results show that the selected feature can successfully be used as an indicator for the level of the pilots' cognitive workloads.

Figure 2
EEG Data Collection and Analysis Process



Note. Process above shows collection of EEG data from participant through pre-processing, decomposition to EEG sub-bands, feature extraction and selection through SVM classifier. Ultimately, periods of high and low cognitive workload are determined.

Limitations and Future Directions

Results of this study are consistent with Dussault et al. (2004) in showing cognitive workload fluctuations during flight scenarios. These results will enhance our confidence in establishing reliability during active monitoring of pilot cognitive workload during periods of high workload. The results of this study also support technical feasibility of continued development of advanced headset technology designed to improve pilot situational awareness and monitoring physiological measures underway by Wilson and Tavakolian (2019). Earlier EEG research within a flight simulator also showed promise of EEG and other external measures such as eye tracking to detect periods of drowsiness and fatigue with pilots in a collegiate aviation environment (Guragain et al., 2019; Wang et al., 2019).

The nature of the data collection was in a "live" flight environment. As such, there is greater possibility of motion artifact as a result of aircraft vibration or typical pilot activity which could influence data quality on individual electrodes. Additionally, environmental conditions such as temperature, wind or turbulence may influence certain workload or stress indicators from one flight to another, however, the flight sequence was nearly identical from one flight sequence to another, as such, changes in workload were expected between maneuvers, regardless of outside environmental conditions. Also, the dataset used in this analysis included only 10 participants. A larger dataset could improve data validity and generalizability.

This research provides a foundation for understanding changes in pilot cognitive workload during live flight of aircraft. Such research allows us to establish benchmarks where augmentation of a pilot's available tools or increases in automation may serve to improve the safety of flight. Examples of changes in automation could include changes in density of displayed flight information during high workload conditions or increases in the control exerted by autopilot(s) on relevant flight control surfaces to aid in aircraft control and stability. Future opportunity exists to establish a more formal link between human and machine (referred to as human-machine interface), within the aviation and aerospace domain.

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