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A Passive Electroencephalography Brain-Computer Interface Predicts Mental Workload During Flight Simulation

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A PASSIVE ELECTROENCEPHALOGRAPHY BRAIN-COMPUTER INTERFACE PREDICTS MENTAL WORKLOAD DURING FLIGHT SIMULATION

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The objective of the present research was to investigate an electroencephalography (EEG) brain-computer interface (BCI) for monitoring realistic variations in mental workload during virtual reality (VR) flight simulation. Many aviation accidents are related to pilot cognition and a mismatch between task demands and cognitive resources. Real-time neurophysiological monitoring offers an approach to identifying high-workload mental states by obtaining continuous, objective measurements without adding to the workload of the pilot. Workload was manipulated by varying navigational difficulty and communication tasks during VR flight simulation. EEG data collected during simulated flight was analyzed to evaluate performance of passive BCI for classification of workload level. BCI approaches were guided by EEG workload literature. A classification rate of 75.9% was obtained, with Alpha and Beta frequency bands being most informative. The results indicate that a passive EEG-BCI may be an effective strategy for monitoring workload and enhancing flight safety.

Electroencephalography (EEG) is a relatively non-invasive and temporally precise neuroimaging device and has become a popular instrument for monitoring mental states (Abreu et al., 2018). In recent decades EEG has been applied to indexing mental workload states (e.g., Berka et al., 2007) and more recently has been included in research relating to monitoring mental workload during flight activities (e.g., Dehais et al., 2019; Harja et al., 2020).

The motivation for incorporating EEG in pilot workload monitoring is that EEG provides an opportunity for objective and continuous measurements of workload level. Achieving reliable EEG measurements of workload has the potential to facilitate prevention of frequent workload-related accidents in aviation and contribute to aviation psychology research. The non-physiological standard for workload evaluation is subjective reporting, wherein pilots rank their level of workload (e.g., NASA Task Load Index) *after* performing a flight operation. However, this method has its limitations. For example, perceived workload does not always correlate well with task performance (see Matthews et al., 2020 for a review). Assessing workload through subjective questionnaires also requires stopping the primary task (or directing attention away from it) which restricts use of this method in real-world settings.

Efforts are being made to establish EEG into a passive BCI (pBCI) for the purpose of classifying high-workload mental states during flight. A pBCI system employs a neuroimaging device to acquire a signal that then gets fed to an analysis program for the purpose of classifying neural activity as relating to a certain mental state. pBCI are distinct from conventional ‘active’

BCI which incorporate a response or action such as controlled movement over a robotic limb (e.g., Hochberg et al., 2012). pBCI is now being explored in pilot mental workload research. For example, Dehais et al. (2019) employed an off-line EEG pBCI to classify high- and low-workload periods during flight and obtained 71% accuracy. Although promising, 71% likely illustrates the low-end of potential for pBCI as Dehais et al. employed a 6 dry-electrode system in an actual aircraft which encompasses many engineering and signal acquisition limitations.

The purpose of the present research was to evaluate the efficacy of pBCI as a pilot workload monitoring tool under dynamic flight environments. Workload was manipulated through changes in pilot related tasks. Detecting changes from a 'medium' to high level of workload is most critical for flight safety, therefore participants were continuously loaded with tasks even when not in the high-workload condition. EEG was collected during flight and analyzed off-line to determine the predictive power of EEG-pBCI on workload level. The EEG workload literature guided selection of specific EEG features and scalp locations. Alpha, Beta, and Theta EEG oscillations were hypothesized to reflect workload level, particularly at frontal and parietal electrode sites.

Method

Participants

Fifteen participants with no flying experience were recruited for the present study. All participants were briefed on task requirements, and experiment materials before providing written consent. Ethics were approved by the Carleton University Research Ethics Board (CUREB). Participants were reimbursed for their participation with refreshments and course-credit.

Procedure

Participants 'flew' three practice circuits and four test circuits in a VR flight environment. Half of the test circuits contained a radio-message call-sign memorization task. As shown in Figure 1, participants were instructed to navigate through a series of large rectangular hoops which outlined the oval path of the circuit. Circuits were initiated at altitude of the first hoop at the end of the downwind leg of the circuit. Each circuit took approximately six minutes to complete. Participants were paused by the experimenter when they returned to the starting point of the circuit. After each circuit, participants were presented with questionnaires. Participants were queried about their comfort relating to the VR system and asked to recall the call signs after high-workload circuits.

Mental workload was manipulated between circuits via the presentation of the call sign task, and within circuits by the segment of flight. The high-workload (HWL) condition included all the flight time that occurred during the crosswind and base legs in the circuits that included the call sign tasks. The crosswind segments were relatively challenging for participants as it involved rapid change in heading and altitude. During HWL circuits participants were instructed to listen for and remember the aircraft call signs mentioned in pre-recorded air-to-air communication messages (e.g., "Pendleton Traffic, this is *Delta Echo Foxtrot*, Cessna 150, Five

Miles to the Northeast, Inbound for touch and gos"). The medium-workload (MWL) condition was all flight that occurred during the runway segments in the circuits that did not contain the call sign task. This segment contained straight flight without curves or changes in altitude, heading, or airspeed.

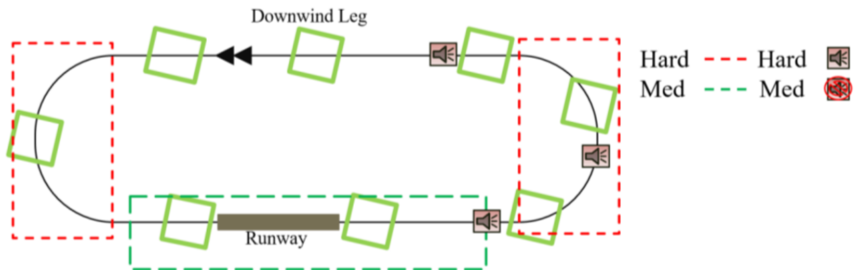

Figure I. Illustration of flight circuit. Participants began each circuit at the location of the double arrows and at altitude of the first hoop (in green). The red dashed line outlines the navigationally challenging portions of the flight path (Base and Crosswind legs) and the green corresponds to the easiest section of flight (runway leg). Each curve took approximately 40 seconds to complete and each straight leg approximately 140 seconds. The speaker symbols represent the locations where pre-recorded messages were played.

Equipment

Flight simulation apparatus*:* An HTC Vive VR headset (2016) was used to graphically display the 3D flight simulation, including a full Cessna 172 model aircraft and all exterior terrain and airspace. The flight simulation was produced by Lockheed Martin's Prepar3d software. The location was geo-specific terrain consisting of coastal and mountainous regions surrounding an aerodrome in Hong Kong. The VR headset provided a 360-degree virtual environment. Flight instruments were made visible in the simulation and corresponded to the physical locations of the yoke, throttle, and flaps in the flight control unit (See Figure 2). The simulation produced aircraft realistic visuals and engine noise. Weather conditions were clear with no experience of turbulence.

Electroencephalography*:* Electrophysiological data was collected using an EMOTIV EPOC+ 14 channel wireless EEG system with electrodes located at AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4. The channel placements follow the international 10-20 system and were referenced online to electrodes P3 and P4. Channels AF3 and AF4 were positioned underneath the top of the VR headset to accommodate the simultaneous use of the two devices (see Figure 2). The EEG recordings were collected at 2048 Hz, and then down-sampled to 256 Hz and were transmitted wirelessly via Bluetooth to an iMac desktop computer.

Figure II. The configuration of the HTC Vive virtual reality headset and EMOTIV EPOC+ EEG headset on the left. The participants' view of the simulation environment is displayed on the top right, and the physical instrument layout is shown on the bottom right.

Measures

Continuous EEG measures were transformed into power spectral densities via Hamming windowed sinc FIR filter using the MATLAB plugin EEGLab. Frequency ranges were defined to correspond to conventional EEG 'frequency bands'. The frequency bands were defined as: Delta (1-4 Hz), Theta (4-8 Hz), Alpha (8-12 Hz), and Beta (12-32 Hz).

Analysis

EEG spectral power densities were used as predictors in a classification scheme using a linear discriminant analysis (LDA) algorithm via BCILab. LDA has been recommended as a favorable machine learning algorithm for EEG-BCI as its relative simplicity is favorable for sampling limitations of most human EEG research paradigms (Lotte at al., 2007). Spectral power densities were computed for each 1-second window in high- and medium-workload conditions. There were 120 data points for each condition for each participant. A k-fold cross-validation scheme was used, where 200 of the total data points were used for training and 40 were used for testing. This classification scheme was applied to various approaches including reducing electrodes and reducing frequency band inclusion with the aim of reducing complexity of the BCI system.

Results

Analysis of power spectral densities and classification scores revealed that classification performance was enhanced by evaluating only the Theta, Beta, and Alpha bands. Figure 3 shows the distributions of classification scores from best performing to worst performing across participants. The model including only the Theta, Beta, and Alpha bands are shown in red.

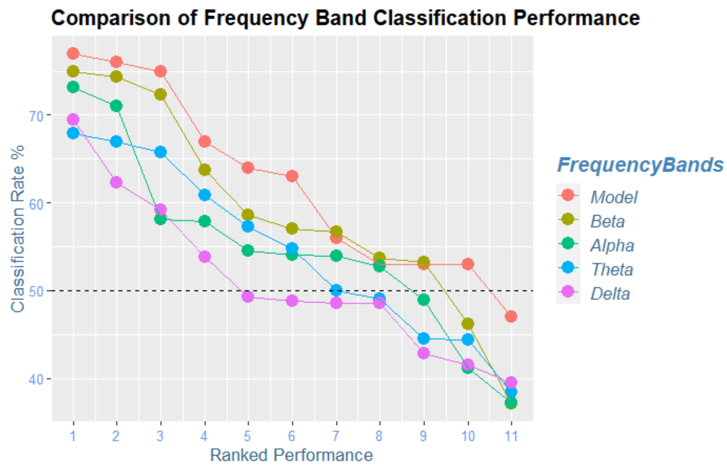

Figure III. Comparison of classification performance for spectral filtering approach. The full model (red) contains oscillatory information between 4 and 32 Hz. Scores from left to right are ordered from better to worse performance separately for each approach (i.e., participant order is varied for each line graph, and y columns do not necessarily correspond to the same participant).

Theta, Beta, and Alpha bands were employed as the spectral filtering model for the following analyses. First all electrodes were included which resulted in a mean classification rate of 56.5% (SD = 13.5%). Classification was improved to a mean of 61.4% (SD = 11.5) with electrode reduction only the primary electrodes that have been related to workload in previous research (AF3, AF4, F3, F4, FC5, FC6, P7, P8, O1, & O2). The third analysis removed the two occipital electrodes due to implications of noise related to eye movements and visual inconsistencies (63%, SD = 11.9). The fourth analysis involved removing four participants with poor BCI performance and may be related to the phenomena of BCI 'illiteracy'. BCI illiteracy occurs in about 20% of subjects where the necessary detection of brain signals is unsuccessful and likely related to neuroanatomical properties (Allison & Neuper, 2010). Lastly, classification approaches were divided into two separate classification approaches for sequential circuits to eliminate temporal effects on EEG signal quality. The classification score for the first two circuits was averaged with the classification score of the last two circuits for each participant and resulted in a classification accuracy of 75.9% (SD = 7.5%).

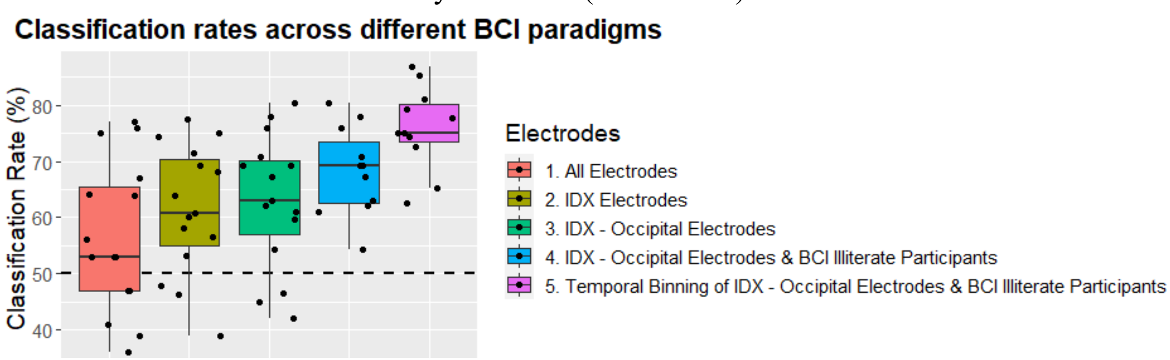

Figure IV. Distributions of participant classification rates as electrode selection was refined. The 'index electrodes' are described in Figure 4. Note: IDX = index electrodes.

Discussion

The present research investigated an EEG-pBCI for monitoring mental workload during VR flight simulation. Workload was manipulated by varying navigational difficulty and performing communication tasks. The workload manipulations were selected for enhancing ecological validity by corresponding with workload variations experienced in regular flight. EEG data was collected and used to classify periods of flight as medium- or high-workload.

Several pBCI approaches were used. Each modification reduced complexity and increased pBCI accuracy, and was grounded in the literature. Similarly, the predictive EEG oscillations and the relevant brain regions matched the hypotheses. Particularly that oscillations within the Theta, Alpha, and Beta range and at parietal and frontal regions were most predictive of workload levels. The final pBCI scheme was successful in classifying medium- versus high-workload conditions 75.9% of the time.

The final classification accuracy is estimated to be a conservative approximation of the potential of pBCI. Longer training phases, individual customization, and training over repeated uses may be feasible strategies to enhance classification. We conclude that, with further development, a passive EEG-BCI may be an effective tool for monitoring pilot workload and enhancing flight safety.

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