Evidence-Based Training and Adaptive Control: Exploring the Cognitive and Neural Processes and the Interface between the Pilot and Flight Control Systems (Work in Progress)

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ABSTRACT

The safety of an airplane depends highly on the pilot's skills, experience, workload, and mental states. For student pilots, evidence-based training strategies are ideal. The present study recorded Electroencephalography (EEG) of five pilots at various levels of certification as they completed a flight session containing one *takeoff, missed approach and landing* and two circuits each with an *enroute, arrival, and instrument approach* segment. Each pilot completed five sessions in an Advanced Aviation Training Device (AATD). Three segments were chosen from each circuit for initial analysis: *takeoff*, *enroute 1*, and *approach 1*. EEG brainwaves observed across multiple frequency bands were found to have changed over the segments. In particular, we found that the theta band, often an indicator of drowsiness, decreased for the majority of participants. We also computed the engagement index, which was generated as a composite of three EEG channels: alpha, delta, and theta. The engagement index is a measure of workload and mental activity, and it seemed to correlate with the participant's training and flight experience.

INTRODUCTION

Aviation is a high-consequence industry where safety is paramount and error is costly, both in human and economic terms. Additionally, it is a dynamic industry where cockpits and flight control systems are developing rapidly in the digital age. Such factors serve to create a learning environment with increased mental pressure and workload on pilots as they develop their skill and adapt to new technologies and systems. According to Yongchao, Tao, et al., the workload and stress on aspiring pilots may impact learning and lead to other undesirable consequences like pilot errors that could lead to flight accidents [1]. Pilot error contributes to a higher number of crashes than other factors like weather and mechanical failure.

The purpose of this study is to understand the cognitive and neural mechanism of pilots as they complete routine flight activities. It is a preliminary study that is part of a broader collaborative research effort that seeks to enhance the integration of pilots and flight control systems, improve flight education strategies, and facilitate designs of adaptive control for humans and machines. The present study has three objectives: First, to identify the mental and cognitive processes of pilots in each of the segments performed in a flight scenario. Second, to correlate EEG, demographic, and performance data. Finally, to identify any anomalies and look for correspondence across the data.

Pilots were asked to complete five sessions to capture potential variations in performance and attributes from the perspective of their mental mechanisms. Each session contained seven segments including one *takeoff*, *missed approach* and *landing* and two circuits, each containing *enroute*, *arrival* and *instrument approach* segments. The instrument approach was the same for all circuits and sessions. During this initial analysis, we focused on three segments: *takeoff*, *enroute 1* and *approach 1.*

Partcipant	*Pilot Certification*	*Intrument Rating*
A	Commercial Multi-Engine	Yes
B	Commercial Mutli-Engine	Yes
C	Private	Yes
D	Private	Yes
E	Student	No

Figure 1

Electroencephalography (EEG) is a long-developed tool used to understand human brain activity. Previous pilot-related studies mostly used four major brainwaves, namely delta, theta, alpha, and beta [2-4]. The alpha wave appears mostly when the person is relaxed. Regarding the beta wave, it has been long known that the low beta (13−20 Hz) appears together with alpha, whereas the high beta (20−50 Hz) appears when the person is undergoing intensive activation of the central nervous system or under tension [5]. Psychological parameters being studied include mental fatigue, mental workload, cognitive workload, vigilance, situation awareness, anxiety, stress, and emotion in real aircraft and flight simulators [1, 3, 6-16]. A few studies have used pilot performances to correlate and understand the psychological aspects of pilots [7, 10, 17, 18]. The present project seeks to extend this research by using high fidelity experiments to explore neural functions carried out in a realistic training environment and focusing on the physiological evolution related to student pilots' training and education process.

METHODOLOGY

Participants and Procedures

A total of five participants were recruited from a four-year undergraduate professional pilot degree program. Each participant completed five sessions. The EEG of Participant D failed to be recorded in one session. Therefore, a total of 24 sessions were analyzed. Participants A and B each held a commercial certificate with a multi-engine rating. Participants C and D were private pilots while participant E was a student pilot (Figure 1). All the participants except Participant E held an instrument rating. All participants had at least 25 hours experience with an Advanced Aviation Training Device (AATD). Participant E was the only participant with zero actual instrument conditions and less than 25 hours of simulated instrument conditions.

Informed consent was obtained from each pilot before beginning the research while explaining the research objectives and procedures, in accordance with applicable Institutional Review Board (IRB) requirements. All data was maintained on encrypted devices and de-identified with a discreet participant code to maintain confidentiality.

Experimental Design and Materials

Data collection methods included EEG signals, AATD flight data, observations, video recordings, surveys, and unstructured interviews. A pre-survey was given to the participants prior to the flight-simulation sessions. The pre-survey included 21 questions related to flight and training hours, certifications, AATD experience, learning beliefs, etc. Participants were asked to perform the designated circuit twice in each session, with the first terminating with a missed approach (Figure 2). The flight plan developed and used in this effort included: *takeoff*, *enroute*, *arrival*, *approach*, *missed approach*, *enroute-2*, *arrival-2*, *approach-2*, and *landing*. The participants were also provided with charts for the instrument approach.

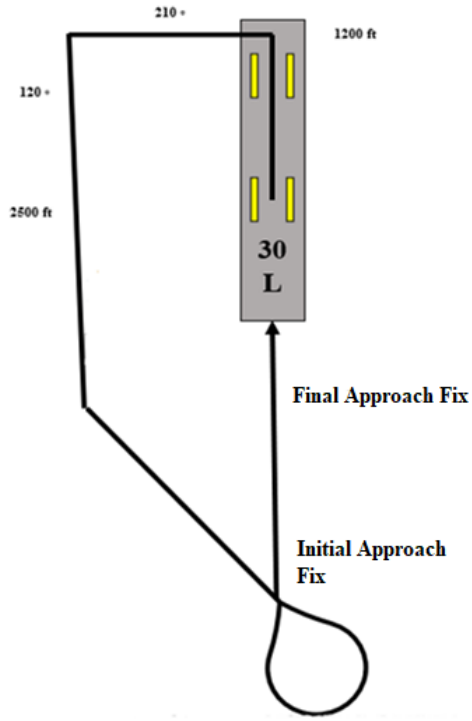

Figure 2. Flight circuit used in each session

EEG data was collected using a 14-channel headset (Emotiv Inc.). Figure 3 shows the electrode positions [19]. The electrodes had sensor pads pre-soaked in saline. The sampling rate of the EEG signals was 128 Hz. The EEG signal was pre-filtered between 0.16−43 Hz. Analysis began with the synchronization of the flight data with the EEG data. The segments corresponding to *takeoff*, *enroute 1*, and *approach 1* were used to develop the brain heatmaps in MATLAB. The topography heatmaps are a representation of the powers of the EEG signal in each of the four frequency bands: delta (0.25−4 Hz), theta (4−8 Hz), alpha (8−13 Hz), and beta II (20−50 Hz). Note that we did not use beta I (13−20 Hz) because it is believed to generally agree with the alpha band [5]. In each frequency band, the power was normalized by the entire-frequency power in 0.1−50 Hz, according to a previous study [20]. Engagement index, EI, was computed as the beta-II power divided by the sum of alpha and theta powers.

Flight data was obtained from the X-Plane flight simulator software on the AATD. The AATD had three high-definition televisions that provided approximately a 120º external environment view. A Diamond DA-20 aircraft model was used for all sessions. The flight parameters collected included: altitude, pitch rate, roll rate, yaw rate, the angle of attack, airspeed, vertical velocity, gravity load, density ratio, elevation, lift to drag ratio, latitude, and longitude. The visibility was set to three miles, winds calm, and a ceiling of 1000ft. MSL. Video recordings were made with a camera attached to the AATD to observe the behavioral elements of pilots, as well as their verbal communication. Participants were randomly asked about their experiences at the end of the sessions.

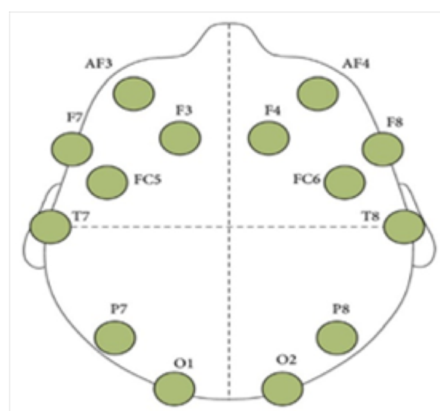

Figure 3. Positions of 14 channels of EEG probes.

This article is limited to the initial analysis of *takeoff*, *enroute 1*, and *approach 1*. In the flight data, *takeoff* was identified by the airplane position in terms of longitude. The second segment, *enroute*, started when the aircraft reached an altitude of 2500 MSL and an appropriate latitude. The *approach* segment was identified when the aircraft reached the Initial Approach

Fix (IAF). The flight and EEG data were synchronized by correlating starting times of the respective data sets and the time stamps of the individual segments.

RESULTS AND DISCUSSION

EEG activity

Figure 4 shows the relative power of all the electrodes in each frequency band obtained in the last (5^{th}) flight session for individual participants. Warm colors represent high powers, and cold colors represent low powers. The first row shows the powers for *takeoff*; the second and third rows show powers for *enroute* and *approach*, respectively.

In general, the delta band did not show consistent or meaningful changes (Fig. 4A) with the flight operation. This is not surprising because delta waves mostly appear during deep sleep. Similarly, a previous driving-simulation study also showed minimal changes with the delta [20].

Figure 4B shows the power of theta wave. Theta is the frequency range most closely associated with drowsiness (i.e., a sign of sleep onset) in adults [20]. The energy in theta decreased over the flight session, indicating that the participant became less drowsy as the flight continued. Such a state of decreased drowsiness is consistent with our expectation, given the nature of the flight segments, where the pilot tends to be less engaged during the *enroute* phase but highly engaged during the *approach*. Most participants had decreased signal power in the *approach* segment. Participants A, C, and D show continuously decreased theta activity over time. Participant B shows a relatively stable and elevated theta over time which may indicate a higher degree of skill or experience, even than participant A. Participant E showed very high theta power in *enroute* indicating a relatively high degree of drowsiness. It might be that, because Participant E did not hold an instrument rating, they were somewhat overwhelmed by the circuit and were more relaxed during the more familiar *enroute* phase. Conversely, during the *approach* phase,

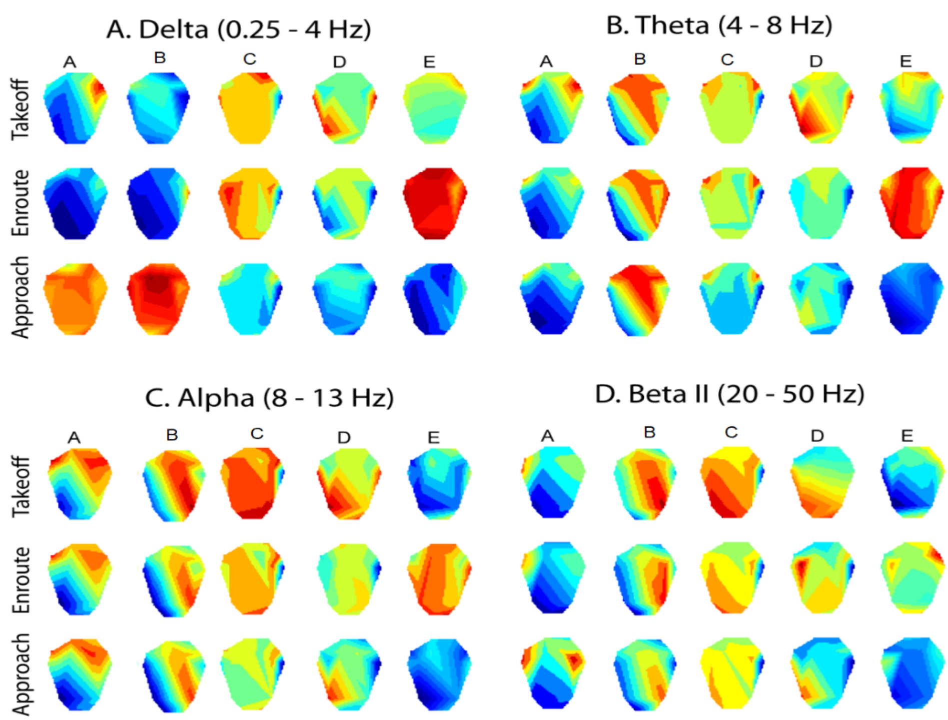

Figure 4. Normalized powers in all EEG frequency bands obtained from one flight session for each participant.

a very low theta power was observed, indicating relatively greater alertness than the other participants. These outcomes merit further investigation.

Regarding the alpha wave, it has been hypothesized that decreased activity indicates more cortical neurons participating in transient task performance [21]. Here, the participants generally showed decreased alpha activity, especially during *approach* (Fig. 4C). Meanwhile, beta II is associated with increased alertness and arousal. Figure 4D shows the change of beta II for each participant in one representative flight session. Certain patterns are similar to the alpha wave, but there are also differences. For example, Participant A showed the highest alpha activity during *takeoff* but highest beta activity during the *approach*.

For participants A, C, and D, the frontal lobe electrodes (AF3, AF4, F3, and F4), showed the highest activity at the beginning of the flight session (*takeoff* and *enroute*). The frontal lobe has been shown to have connections with many important cognitive skills, including motor skills, problem-solving, and memory [22]. The symmetrical activation indicates equal use of the hemispheres. Decreased theta power in the frontal lobe indicates elevated alertness in the *approach*. However, we need to caution that the electrode position does not strictly correspond to brain areas.

Pilot profiles and correlations to EEG

More relevant to the tasks than the individual frequency power may be the engagement index, which has been highlighted in previous studies [23]. The engagement index is computed as $EI = beta\ power/(alpha\ power\ +\ theta\ power)$, which is positively proportional to the beta and negatively proportional to the alpha and theta power. Figure 5 shows the EI's for all participants and sessions over the three segments. Here the EI shown in the bar plot is the maximum across all electrodes for each scale topography. Although some participants and sessions showed unusually high EI's during *approach* and *enroute*, in general, EIs appeared to be more strongly correlated with participants' experience and skill rather than with particular flight segments.

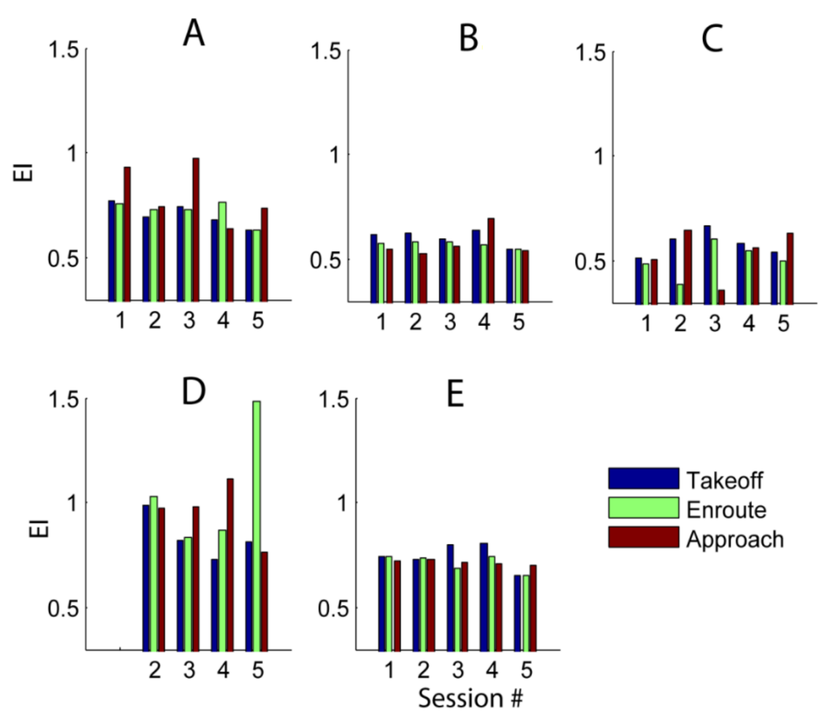

Figure 5. Engagement Index (EI) for all the participants and sessions.

The bar plots show that participant D had the largest EI values, which were significantly higher than the EI values of all other participants (*t*-test, $p < 0.01$). In addition, the EI values varied greatly in some sessions for D, indicating that the participant was struggling at particular moments. For example, the *enroute* of the 5th session was unusually large. This finding agrees with participant D being the least experienced pilot with an instrument rating but does not account for the similarities between participants D and E. A more detailed analysis will be performed to examine the video recording, in search for corresponding flight behavior. Participant E, the student pilot, had EI values significantly higher than B and C; the values were not significantly different from A.

Flight behaviors

In general, participants with a Commercial Multi-Engine rating (A and B) appeared to behave differently in comparison to participants with less advanced ratings. From observational data, pilots A and B exhibited greater discipline and were more systematic in their activities compared to the other pilots. In contrast, participants C, D, and E appeared to become frustrated and confused as the sessions progressed. While it is not possible to draw firm conclusions without additional analysis, the observations suggest correlations between observed behavior and the high engagement index of participant A, the stable theta value of participant B, decrease theta values of participants A, C, and D.

CONCLUSION

The three objectives of the study were to identify the mental and cognitive processes of pilots in each of the segments performed in a given training situation, to correlate the EEG data with pilot's demographic and performance data, and to identify any anomalies and look for correspondence across the data.

The objectives were partially achieved, and analysis will be continued to understand the cognitive and neural aspects of pilots in detail and to support the observations attained across the multiple frequency bands. Given that only three segments were analyzed, further implications are expected to be drawn by examining the remaining segments.

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