A Neuroergonomics Approach to Measure Pilot's Cognitive Incapacitation in the Real World with EEG.

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Abstract. Mental overload and mental fatigue are two degraded cognitive states that are known to promote cognitive incapacitation. We adopted a neuroergonomics approach to investigate these states that remain difficult to induce under laboratory settings thus impeding their measurement. Two experiments were conducted under real flight conditions to respectively measure the electrophysiological correlates of mental fatigue and mental overload with a 32 channel-dry EEG system. Our findings revealed that the occurrence of mental fatigue was related to higher theta and alpha band power. Mental overload was associated with higher beta band power over frontal sites. We performed single trial classification to detect mental fatigue and over-load states. Classification accuracy reached 76.9% and 89.1%, respectively, in discriminating mental fatigue vs. no fatigue and mental overload vs. low-high load. These preliminary results provide evidence for the feasibility of detecting neural correlates of cognitive fatigue and load during real flight conditions and provide promising perspectives on the implementation of neuroadaptive technology especially in the context of single pilot-operation.

Keywords: Mental Overload · Mental Fatigue · EEG · Neuroergonomics

1 Introduction

Operating aircrafts is a complex activity that takes place in a dynamic, complex and uncertain environment. Flying requires high cognitive abilities to control the flightpath, monitor the flightdeck, interact with air traffic control, adapt to unexpected events [1], [2] and monitor complex automated systems [3]. At the neurofunctional level, such abilities are supported by the so-called executive network [4] or task positive network [5] for which the dorsolateral prefrontal cortex (DLPFC) exerts a crucial role. There is now a large body of evidence

that mental overload and cognitive fatigue can disrupt the activity of this DLPFC that in return induces task disengagement and promotes cognitive incapacitation [6]. On one hand, mental overload can be the consequence of an excessive task demand that has to be performed under time pressure. On another hand, cognitive fatigue, also known as time-on-task generally results from a sustained attentional activity over a prolonged period of time. There is a need to better understand these phenomena and to implement neuroadpative technology [7] to assist the pilot when facing such incapacitation. This is particularly crucial as the next generation of transportation airplanes will most likely be operated by a single pilot [8]. Several researchers have identified electrophysiological correlates of cognitive fatigue that can be efficiently used for the estimation of this mental state [9], see [10] for a review. Few experiments addressed the neural correlates of mental overload but opened promising perspective to detect it [11]–[13]. Despite these relevant findings, mental fatigue and mental overload states remain difficult to induce under laboratory settings thus impeding its measurement. We therefore adopted a neuroergonomics approach which promotes the use of brain imaging techniques to monitor cerebral activity in the field [14]. Two experiments were conducted under real flight settings to investigate these two degraded mental states separately. Participants were equipped with a dry EEG system as several studies succeeded in measuring cognitive activity [15],[16] and implementing a brain-computer interface to predict performance [17]–[20] under real flight settings.

2 Material and Method

2.1 Experiment 1: Mental Fatigue

Three ISAE-SUPAERO pilots participated in the study (3 males; 22-44 years old, with 60-120 flight hours experience) and were supervised by a safety pilot. The study was approved by the European Aviation Safety Agency (EASA60049235) and all participants gave their informed written consent. The experiment lasted around 40 minutes and was conducted using the ISAE-SUPAERO DR400 light aircraft. The

scenario consisted of four consecutive traffic patterns at Lasbordes airfield (Toulouse France). Along with the flying task, the participants were asked to perform a secondary classical oddball paradigm with a total of 600 auditory stimuli: 25% were targets (chirp sound from 4 to 2 kHZ, 90 dB SPL) and 75% were non-targets (chirp sound from 2 to 4 kHZ, 90 dB SPL). The inter-trial interval was set to 1000 ms with a 2000-ms jitter. The volunteers had to report the number of rare auditory targets after each traffic pattern, just after touch down. After the flight, participants also had to report their level of cognitive fatigue using an analog scale from 1 (no cognitive fatigue) to 10 (high level of cognitive fatigue) for each traffic pattern.

2.2 Experiment 1: Mental Overload

Five ISAE-SUPAERO pilots, who did not take part to the first experiment, participated in this second study (5 males; 25-44 years old, with 120-3000 flight hours experience) and were supervised by a safety pilot. The experiment lasted around 40 minutes and was conducted using the ISAE-SUPAERO P68 twin-engine light aircraft. The scenario consisted of a navigation task as well as several maneuvering tasks including take-off and landing at Lasbordes airfield (Toulouse France). The flight instructor was in charge of modulating the participant's mental demand from low load to high load to overload. The flight instructor manually indicated changes in participant's mental demand to the experimenter sitting in the back seat, who recorded the demand level (1= normal, 2=high and 3=overload) synchronized with the EEG data. The study was approved by the European Aviation Safety Agency (EASA60049235).

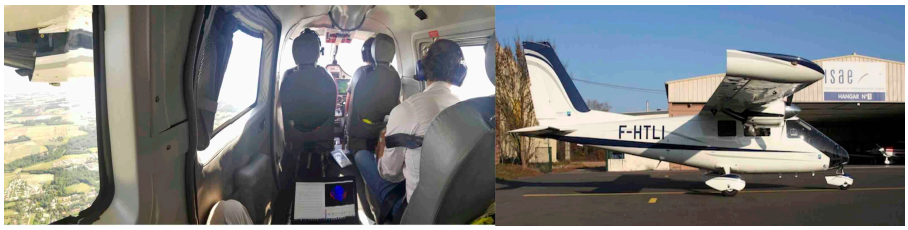

Fig. 1.: P68 ISAE-SUPAERO Experimental plane: the participant was left-seated, the flight instructor was right-seated and the back-seater was in charge of collecting the data.

2.3 EEG Recording and Pre-processing

Participants were equipped with the 32 channel dry-electrode Enobio Neuroelectrics (500Hz) system positioned according to the 10-20 system. CMS and DRL clip electrodes were placed on each of the participant's ears. EEGLab 15.1 and Matlab2017b were used to process the electrophysiological data. The continuous EEG data was filtered between 0.5-30Hz and cleaned using Artifact Subspace Reconstruction (ASR, default settings) [21]. Independent component analysis (ICA) was then applied to only keep brain components with the IClabel toolbox. We then computed the power spectral density in the alpha (8 – 12 Hz), beta (13 – 30 Hz), theta (4 – 8 Hz) and delta (1 – 4 Hz) bands for each experimental condition and analyzed with bootstrap statistics (10,000 iterations) for subsequent statistical analyses.

2.4 EEG Pre-processing for Single Trial Classification

We implemented a classification pipeline, described thereafter, to discriminate the no-mental fatigue condition vs the mental fatigue condition. The same pipeline was applied to the data collected in the second experiment to discriminate the mental overload condition against the low and high mental load conditions (i.e. low and high mental load were merged into a single dataset and compared with the targeted mental overload dataset). Epochs were extracted over each experimental condition from successive and non-overlapping epochs of 2 s. An ASR filter on EEG signals was applied on each epoch. We then computed for each epoch the frequency power in the delta [1 4] Hz, theta [4 8] Hz, low and [8-10] Hz and high alpha [10 12] Hz, low [13 20] Hz and high beta [20 30] Hz bands. Then, for each band, EEG signals were spatially filtered using two pairs of Common Spatial Patterns (CSP) filters. We used a regularized CSP with automatic covariance matrix shrinkage as recommended by [22]. The resulting spectrally and spatially filtered signals were then squared, averaged over the epoch duration, and log-transformed. A shrinkage Linear Discriminant Analysis (sLDA) classifier with a five-fold cross-validation procedure was used to compute the balanced classification accuracy for each pilot.

2.5 Mental Fatigue: Results

The pilots reported higher mean mental fatigue during the last traffic pattern (mean=8) than during the first one (mean=4.66). The percent of the absolute difference between actual and reported audio targets was greater for the pilots during the last traffic pattern (mean=59.9%) than during the first traffic pattern (mean=46.9%). The results of spectral analysis across the 32 electrodes revealed statistically significant differences in alpha and theta frequency bands in predominantly frontal, parietal and occipital electrode sites (See Figure 2).

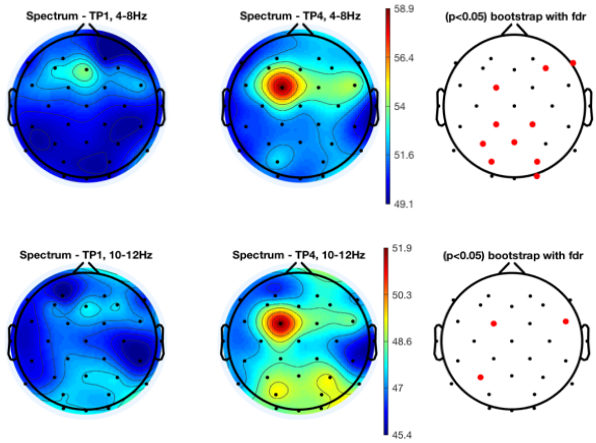

Fig. 2.: 2-D topographical views. Left: first traffic pattern (TP1); middle: fourth and last traffic pattern (TP4); right, statistical differences in the theta band (up) and in the upper alpha band (down).

An equal number of 957 epochs was extracted for each class (no fatigue vs. fatigue) for each participant. The mean balanced classification accuracy reached 76.9% (SD=5.8%). Subject 1: 73.0 %, SD=7.8%; Subject 2: 74.4%, SD=3.2%; Subject 3: 83.1%, SD=6.4%.

2.6 Mental Overload: Results

The results of spectral analysis revealed statistically significant differences in the beta frequency band in predominantly frontal electrode sites (See Figure 3).

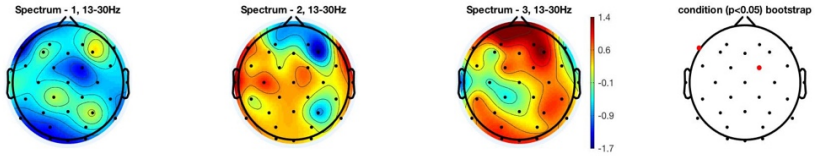

Fig. 3.: 2-D topographical views. From left to right: normal load, high load, overload and statistical differences in the Beta band (red dots: p<0.05, uncorrected

An equal number of 356 epochs was extracted for each class (no mental overload vs mental overload) for each participant. The mean balanced classification accuracy reached 89,1% (SD=4.5) to discriminate the overload condition against the other load conditions (Subject 1: 96.7 %, SD=0.88%; Subject 2: 95.3%, SD=6.1%; Subject 3: 99.5%, SD=0.41%; Subject 4: 65%, SD=10.6%). We were not able to perform classification for Subject 5 as this latter experienced very few episodes of mental overload

3 Discussion

The objective of this study was to adopt a neuroergonomic approach to identify and monitor electrophysiological correlates of cognitive incapacitation in real flight conditions. We first ran an experiment involving mental fatigue that we induced using a traffic patterns paradigm along with an active auditory oddball task. Subjective and behavioral results both supported that the two flight patterns flown at the end was subject to higher fatigue than the first ones flown. Interestingly enough, our participants exhibited lower performance to perform the secondary auditory task during the two last traffic patterns. Similarly to [19], these findings confirmed that mental fatigue can promote task disengagement and impair auditory processing. Such an issue might be critical for the processing of auditory alarms [15],[18]. The EEG findings show differences in theta and high alpha band activity between first and last traffic pattern that may be a neural signature of fatigue. We then conducted a second experiment in which the flight instructor attempted to induce inducing three different levels of mental load: low, high and overload. The participants confirmed that they

experienced episodes during which they were not able to control the airplane and needed to be assisted by the flight instructor. Our electrophysiological findings disclosed differences in the beta band with high power during the overload episodes during which the participants confirmed that they were unable to properly operate the airplane. Increased beta band activity is generally associated with high arousal states [10],[23]. Taken together, these preliminary results confirm that mental fatigue and mental overload can induce cognitive incapacitation (i.e. inability to respond to the auditory task and/or to control the plane) and are in line with previous electrophysiological laboratory studies [10], and demonstrate the feasibility of collecting meaningful EEG data in noisy and complex flight environments. We recognize, however, that despite artifact removal, some of the observed activity could be due to muscle and other physiological artifacts, which will be further examined in future analyses. Finally, we performed single trial classification to detect no-fatigue vs. mental fatigue states, and mental overload vs. low-high load states. Our results revealed that we could successfully detect episodes of mental fatigue with 76.9% mean balanced accuracy (SD=5.7) and mental overload with 89.1% mean balanced accuracy (SD= 4.5). These findings open promising perspectives to implement neuroadaptive technology and adaptive cockpits to improve flight safety [24].

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References

1. Gateau, T., Ayaz, H. & Dehais, F. In silico versus over the clouds: On-the-fly mental state estimation of aircraft pilots, using a functional near infrared spectroscopy based passive-BCI. *Front. Hum. Neurosci.* 12, 187 (2018).
2. Wickens, C. D. & Dehais, F. Expertise in Aviation. (2019).
3. Somon, B., Campagne, A., Delorme, A. & Berberian, B. Performance monitoring applied to system supervision. *Front. Hum. Neurosci.* 11, 360 (2017).
4. Baddeley, A. D. & Hitch, G. *Working memory*. vol. 8 (G. A. Bower (ed), Recent advances in learning and motivation, 1974).
5. Harrivel, A. R., Weissman, D. H., Noll, D. C. & Peltier, S. J. Monitoring attentional state with fNIRS. *Front. Hum. Neurosci.* 7, 861 (2013).

6. Dehais, F. *et al.* Momentary lapse of control: A cognitive continuum approach to understanding and mitigating perseveration in human error. *Neurosci. Biobehav. Rev.* (2019).
7. Hettinger, L. J., Branco, P., Encarnacao, L. M. & Bonato, P. Neuroadaptive technologies: applying neuroergonomics to the design of advanced interfaces. *Theor. Issues Ergon. Sci.* 4, 220–237 (2003).
8. Liu, J., Gardi, A., Ramasamy, S., Lim, Y. & Sabatini, R. Cognitive pilot-aircraft interface for single-pilot operations. *Knowl.-Based Syst.* 112, 37–53 (2016).
9. Roy, R. N., Bonnet, S., Charbonnier, S. & Campagne, A. Mental fatigue and working memory load estimation: interaction and implications for EEG-based passive BCI. in *Engineering in Medicine and Biology Society (EMBC), 2013 35th Annual International Conference of the IEEE* 6607–6610 (IEEE, 2013).
10. Borghini, G., Astolfi, L., Vecchiato, G., Mattia, D. & Babiloni, F. Measuring neurophysiological signals in aircraft pilots and car drivers for the assessment of mental workload, fatigue and drowsiness. *Neurosci. Biobehav. Rev.* 44, 58–75 (2014).
11. Durantin, G., Gagnon, J.-F., Tremblay, S. & Dehais, F. Using near infrared spectroscopy and heart rate variability to detect mental overload. *Behav. Brain Res.* 259, 16–23 (2014).
12. Ewing, K. C., Fairclough, S. H. & Gilleade, K. Evaluation of an adaptive game that uses EEG measures validated during the design process as inputs to a biocybernetic loop. *Front. Hum. Neurosci.* 10, 223 (2016).
13. Fairclough, S. H., Burns, C. & Kreplin, U. FNIRS activity in the prefrontal cortex and motivational intensity: impact of working memory load, financial reward, and correlation-based signal improvement. *Neurophotonics* 5, 035001 (2018).
14. Ayaz, H. & Dehais, F. *Neuroergonomics: the brain at work and in everyday life*. (Academic Press, 2018).
15. Callan, D. E., Gateau, T., Durantin, G., Gonthier, N. & Dehais, F. Disruption in neural phase synchrony is related to identification of inattentional deafness in real-world setting. *Hum. Brain Mapp.* (2018).
16. Dehais, F., Roy, R. N., Durantin, G., Gateau, T. & Callan, D. EEG-engagement index and auditory alarm misperception: an inattentional deafness study in actual flight condition. in (2017).
17. Callan, D., Durantin, G. & Terzibas, C. Classification of Single-Trial Auditory Events Using Dry-Wireless EEG During Real and Motion Simulated Flight. *Front. Syst. Neurosci.* 9, 11 (2015).
18. Dehais, F. *et al.* A pBCI to Predict Attentional Error Before it Happens in Real Flight Conditions. in *2019 IEEE International Conference on Systems, Man and Cybernetics (SMC)* 4155–4160 (IEEE, 2019).
19. Dehais, F. *et al.* Monitoring pilot's cognitive fatigue with engagement features in simulated and actual flight conditions using an hybrid fNIRS-EEG passive BCI. in *2018 IEEE International Conference on Systems, Man, and Cybernetics (SMC)* 544–549 (IEEE, 2018).
20. Dehais, F. *et al.* Monitoring pilot's mental workload using ERPs and spectral power with a six-dry-electrode EEG System in real flight conditions. *Sensors* 19, 1324 (2019).
21. Mullen, T. *et al.* Real-time modeling and 3D visualization of source dynamics and connectivity using wearable EEG. in *2013 35th annual international conference of the IEEE engineering in medicine and biology society (EMBC)* 2184–2187 (IEEE, 2013).
22. Lotte, F. Signal processing approaches to minimize or suppress calibration time in oscillatory activity-based brain–computer interfaces. *Proc. IEEE* 103, 871–890 (2015).
23. Okogbaa, O. G., Shell, R. L. & Filipusic, D. On the investigation of the neurophysiological correlates of knowledge worker mental fatigue using the EEG signal. *Appl. Ergon.* 25, 355–365 (1994).

24. Dehais, F., & Callan, D. E. (2019). A Neuroergonomics Approach to Human Performance in Aviation. Improving Aviation Performance through Applying Engineering Psychology: Advances in Aviation Psychology, 3, 123.