How Does Cognitive Fatigue and Mental Workload Influence Alarm Detection in Flight Simulator? Classification of Electrophysiological signatures with Explainable IA

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INTRODUCTION

Increased operational capabilities of aircraft had considerably modified the pilots' missions. These changes concern an increase in the time spent onboard and the complexity of technologies or operations, particularly in the military domain. These long periods of intense and sustained cognitive activities induce cognitive fatigue that is one of the major risks of incidents/accidents in aviation (e.g., Dönmez & Uslu, 2018; Marcus & Rosekind, 2017).
Cognitive fatigue has been shown to occur when the costs of cognitive effort to perform the activity are higher than the expected benefits (e.g., Boksem & Tops, 2008; Kurzban et al., 2013). In this case, after performing an effortful task, disengagement from the current task or unwillingness to sustain the effort on a second task is likely (Inzlicht et al., 2014; Müller & Apps, 2019). Previous studies found that cognitive fatigue can impair cognitive performance, leading to impaired ability to suppress irrelevant information (selective attention found by Faber et al., 2012), alter the automatic motor response (online action control found by Salomone et al., 2021), and more generally disrupt attentional processes (Boksem et al., 2005). The influence of cognitive fatigue on electrophysiological activities has been also reported as, for example, an increase of the spectral power of δ, θ, and α frequency bands but a decrease of the spectral power of β band, as well as a decreased amplitude of ERP components such as P300, N100 and N200b (e.g., Boksem et al., 2005; Barwick et al., 2012; Borghini et al., 2012; Zhao et al., 2012; Wascher et al., 2014 ; Sabeti et al., 2017; Schmidt et al., 2009). However, these findings are not always replicated, and some authors do not report any impairment of performance with cognitive fatigue (e.g., Ackerman & Kanfer, 2009; Boksem et al., 2005; Lorist et al., 2005; Möckel et al., 2015; Trejo et al., 2007). Unknown is whether the decreased performance or electrophysiological changes associated with cognitive fatigue are caused by a progressive deterioration of the cognitive resources or by an inadequate recruitment of unaltered cognitive processes, and this is the issue we address here. Moreover, we aimed at developing a passive brain-computer interfaces (pBCI) based on explainable classification and explainable machine learning to infer the influence of cognitive fatigue on inattentional deafness in the context of flying. To achieve these ends and following previous studies (Dehais et al., 2019, 2018), we asked participants to perform an alarm-detection task during repeated landing sessions on flight simulator. To accentuate the presence of cognitive fatigue, we also manipulated the mental workload. Most originally, we tested whether a real flight glider-instruction prior the experiment influence performance in the alarm detection task on flight simulator. We hypothesized that (a) cognitive fatigue impairs alarm detection as a function of the mental workload (b) cognitive fatigue modulates electrophysiological activities and (c) these modulations can be used as a predictor of a loss in pilot's efficiency.

METHODS

Twenty-four pilot-students were recruited for the experiment (*mean age*: 22.6 years old, *SD* = 2.0; flight experience: 75.6 hours, *SD* = 79.6 hours, including 44.7 hours of glider experience, *SD* = 58.9 hours). Half of the participants had normal daily activities without any training flight during the whole day of the experiment (NFBE group), and the other half had an instruction flight just before the experiment (IFBE group).

In a first time, participants were asked to evaluate their level of subjective fatigue (with Visual Analogous Scales of fatigue and sleepiness, VASf, and VASs), sleepiness (Karolinska's Sleepiness Scale), and alertness (Samn-Perelli scale). Then, they performed a Stroop task and an arithmetic task to assess their cognitive control.

In a second time, participants had to perform 6 identical and successive landings in a flight simulator (on a glider) while performing an alarm detection task (i.e., auditory Oddball). In this task, they had to detect rare sounds (i.e., target) and press a key on the joystick as fast and accurate as possible. The landing was composed of 2 phases: a low cognitive load phase (i.e., corresponding to the downwind leg of the approach: they had to pilot the glider and perform the Oddball task) and a high cognitive load phase (i.e., composed of the base leg, the final and the landing: they had to pilot the glider, perform the Oddball task, and perform a backward counting task). Brain activity was recorded by a Bionic-EEG (32 passive electrodes).

After the experimental task, they had to perform again the cognitive tests and the subjective evaluations.

MAIN FINDINGS

Alarm detection task

Performance was analyzed with mixed-design ANOVAs, 2 (Group: NFBE, IFBE) x 2 (Time on Task: beginning—the first three landings, end—the last three landings) x 2 (Cognitive Load: low, high) with group as a the only between-participants factor.

In the low cognitive load condition, participants were faster and more accurate to detect alarms than in the high cognitive load condition. A lack of attentional resources is thus associated with higher rates of inattentional deafness. Surprisingly, we found better alarm detection in the IFBE group than in the NFBE group. One possible explanation to this finding is that participants of the IFBE group were more trained to detect alarms due to the prior instruction flight, compared to NFBE group participants. No difference of alarm detection rate was observed throughout successive landings.

Electrophysiological signatures

Data were analyzed with mixed-design ANOVAs, 2 (Group: NFBE, IFBE) x 3 (Electrode: Fz, Cz, Pz) x 2 (Sound: target, standard) x 2 (Cognitive Load: low, high) x 2 (Time on Task: beginning, end) with group as the only between-participants factor.

ERPs Analysis.

We found that the amplitude of the P300 component was higher with target sounds (i.e., rare alarms) than with standard sounds (i.e., frequent sounds to ignore) only in the low cognitive load condition. Moreover, for target sounds, we found an increase of the P300 amplitude under high cognitive load condition compared to the low cognitive load condition.

No effect of cognitive fatigue was observed on the amplitude of the P300 component. Possibly, our task was not sufficiently difficult to increase cognitive fatigue and to observe modifications on ERPs.

Frequency Analysis.

Results showed that the spectral power of δ band tended to vary as a function of the temporal window. The spectral power was larger at the beginning compared to the end of the task. The effect of cognitive load was observed on the β spectral power for the NFBE group. β spectral power was larger for high cognitive load condition than for low cognitive load condition. These results are correlated with slower latencies in alarm detection observed under high cognitive load conditions.

Subjective scales and Cognitive Tests

No differences were observed between the beginning and the end of the experimental session for the Visual Analogous Scale of Fatigue, the Samn-Perelli scale and the Karolinska scale.
Performance in the Stroop task was analyzed with mixed-design ANOVAs, 2 (Group: IFBE, NFBE) x 2 (Session: pre, post) x 2 (Congruency: congruent, incongruent), with group as the only between-participants factor. We found a significant congruency effect (i.e., better performance on congruent trials compared to incongruent trials). Most interestingly, the NFBE group performed better than the IFBE group (i.e., 96.3% vs. 94.6%). The interference score increased after the experimental task only in the IFBE group. These results suggest a decrease of cognitive control for participants of the IFBE group compared to the NFBE group. Performing the same activity before and during the experiment could lead participants to be less accurate particularly when they had to inhibit automatic responses. The control of automatic response and more generally the cognitive control seems to depend on the nature of the preceding task.
To summarize, we cannot conclude that cognitive fatigue is responsible for the observed modulations of electrophysiological activities. However, it is possible that the manipulation of cognitive load during sustained activity influences brain activity, as suggested by the modulation of the δ and β frequency bands. These manipulations could have resulted in a significant modulation of the subjective cognitive fatigue in other conditions (i.e., longer runs, more complex weather conditions, more landings...). In the low cognitive load condition, participants benefit from more attentional resources to process target sounds than in in the high cognitive load condition. These differences do not exist for standard sounds that must be ignored. In other words, cognitive fatigue could seem to impair performance as a function of attentional resources available. The frequency analysis can also be explained in term of decrease in attentional resources, but the differences between the beginning and the end of experiment could also reflect a lack of motivation at the end of the experiment.

Single Trial Classification of Alarm Detection or Omission and Decision-Making Trees

To compare electrophysiological signals between alarm detections and alarm omissions, we focused our analyses on the high cognitive load condition. Data were analyzed with 2 (Group: IFBE, NFBE) x 2 (Time on Task: beginning, end) x 3 (Electrode: Fz, Cz, Pz) x 2 (Response: hit, miss) ANOVAs with group as the only between-participants factor.
The spectral power of the δ frequency band and the α frequency band was larger for hit trials compared to miss trials. The differences between hit and miss trials were significant only at the beginning of the session. Moreover, the spectral power of the mid-β frequency band in the NFBE group was larger for hits than for missed alarms at the beginning of the session. We then classified trials with respect to alarm omission or detection and we reached a maximum averaged performance of 76.4% (range: 57.7% — 90.5%) in participant-specific single-trial classification from the spectral power of δ and α frequency bands with Support Vector Machines classifier. Frequency features, and more specifically δ and α bands, implemented in a support vector classifier formed an efficient tool to assess auditory alarm misperception in simulated flight conditions.

A way to improve the experimentation domain consists of putting the classification work above in the loop; to do so, we need explainable classification methods. Such an understandable information (numerical, symbolic, logical) constitutes the support of rich human/machine interactions and justifies the interpretability criterion providing a good level of confidence at the operational level. For instance, a decision tree delivers logical rules characterizing the criteria separating alarm omission and alarm detection. Starting from a normalized form of these rules, we can generate the appropriate code in a static context or in dynamic context. In a static context, once EEG values are available, one can predict attention failure regardless to the software involved as the implementation context; in a dynamic context, one can reengineer completely these rules according to a simulation platform intertwining actuators and sensors. The idea is to detect abnormal behaviors by our apparatus, and, from sense-making information, to apply decision-making, for instance, to enable a sequence of actions to be engaged, whether these actions are automatic or not. As a use-case, one can mention the situation in a cockpit characterized by a loss of attention of the pilot and his/her inability to continue his/her current mission. That is, the operator did not consciously detect the alarm although his brain processed the signal. It is therefore necessary to inform the operator that he has omitted the alarm (by feedback) and to adapt the work environment with the explainable AI to help him in his task so that he comes back in the loop.

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