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Monitoring pilot's cognitive fatigue with engagement features in simulated and actual flight conditions using an hybrid fNIRS-EEG passive BCI

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***Abstract*—There is growing interest for implementing tools to monitor cognitive performance in naturalistic environments. Recent technological progress has allowed the development of new generations of brain imaging systems such as dry electrodes electroencephalography (EEG) and functional near infrared spectroscopy (fNIRS) to investigate cortical activity in a variety of human tasks out of the laboratory. These highly portable brain imaging devices offer interesting prospects to implement passive brain computer interfaces (pBCI) and neuroadaptive technology. We developed a fNIRS-EEG based pBCI to monitor cognitive fatigue using engagement related features (EEG engagement ratio and wavelet coherence fNIRS based metrics). This mental state is known to impair cognitive performance and can jeopardize flight safety. In this preliminary study, four participants were asked to perform four identical traffic patterns along with a secondary auditory task in a flight simulator and in an actual light aircraft. The two first traffic patterns were considered as the low cognitive fatigue class, whereas the two last traffic patterns were considered as the high cognitive fatigue class. As expected, the pilots missed more auditory targets in the second part than in the first part of the experiment. Classification accuracy reached 87.2% in the flight simulator condition and 87.6% in the actual flight conditions when combining the two modalities. This study demonstrates that fNIRS and EEG-based pBCIs can monitor mental states in operational and noisy environments.**

***Index Terms*—Cognitive fatigue, Hybrid fNIRS-EEG BCI, Real flight conditions, Neuroergonomics**

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I. Introduction

Operating aircrafts is a complex activity that takes place in a dynamic, complex and uncertain environment. Flying requires high working memory capacity as well as divided and focused attentional abilities to control the flight, monitor the flight parameters, interact with air traffic control and adapt to external contingencies [1]–[3]. There is now a large body of evidence that long periods of intense and sustained cognitive activity induce active cognitive fatigue [4], [5] also referred as mental fatigue [6] or time on task (TOT) [7]. In return, this cognitive fatigue has been shown to promote task disengagement, thus leaving human operators ill-equipped to respond to unexpected events [5], [8], [9]. Interestingly enough, such "cognitive fatigue induced-disengagement" is literally mirrored by a disengagement of the prefrontal and the parietal cortices as measured by changes in hemodynamic response [7], [8], [10]. Other techniques such as electroencephalography have been considered to study this degraded mental state. For instance spectral analyses over the EEG signal revealed that shifts in alpha, theta and beta power are a neural signature of cognitive fatigue that can be efficiently used for he estimation of this mental state [11]–[17] (see also [18] for a review).

A relevant approach to improve flight safety is to implement passive brain computer interfaces (pBCI) or neuro-adaptive technology [19]–[21] to continuously monitor pilots' brainwaves and hemodynamic responses to derive cognitive fatigue. Recent technological progress has allowed the development of new generations of highly portable brain imaging systems for BCIs such as wireless dry electrodes EEG and functional near infrared spectroscopy (fNIRS) to investigate cognition under ecological settings. EEG is by far the most popular technique [18] but fNIRS has recently gained momentum for online state estimation in real life situations such as in aviation [1], [22] and was succesfully used to classify cognitive fatigue [23], [24], [53]. The combination of these two techniques offer complementary prospects for the BCI community [25] as it takes advantage of the high temporal resolution of the EEG and superior spatial accuracy of the fNIRS. Moreover, several BCI studies have revealed that their hybridation provides better accuracy than when used separately [26], [27].

The objective of the present study is to develop a fNIRS-EEG based pBCI to infer cognitive fatigue in the context of flying. Participants were asked to perform four identical traffic patterns at Lasbordes airfield (Toulouse, France) along with a secondary auditory task in simulated and real flight conditions. The secondary task is used as an indirect index of cognitive fatigue since its performance is expected to decrease over time if fatigue is increasing. We thus implement a fNIRS-EEG based classifier to discriminate the first part of the experiment (i.e. the two first traffic patterns) versus the second part of the experiment (the two last traffic patterns). An originality of this work is to compute the EEG engagement ratio defined by [28] as an index of cognitive fatigue. This index presents the advantage of aggregating the main frequency band associated with cognitive fatigue (α, β and θ) [16] but it also reflects fluctuations of task engagement [12], [28], [29] as a consequence of TOT. A complementary approach to account for the dynamics of such a mental state is to use connectivity measures computed over the fNIRS signal [9]. Indeed, cognition cannot be reduced to the activation of specialized brain areas but should rather be seen as the cooperation among large scale distributed neural networks [23], [30]–[34]. We propose to compute a connectivity feature known as wavelet coherence which has gained some momentum in fNIRS signal analysis [35]–[38] and that has been shown to be efficient to predict levels of pilot's engagement in a flight simulator [39].

II. METHODS

A. Experimental protocol

Four pilots were recruited among the students of the ISAE-SUPAERO engineering school to participate in the study (4 males; 25-30 years old, with 50-150 flight hours experience). All had normal or corrected-to-normal vision and no history of neurological or psychiatric disorders. The study was approved by the European Aviation Safety Agency (EASA60049235) and all participants gave their informed written consent.

1) Experimental environment: ISAE-SUPAERO flight simulator and DR400 aircraft: The study was conducted using the ISAE-SUPAERO (Institut Supérieur de l'Aéronautique et de l'Espace - French Aeronautical University in Toulouse, France) flight simulator and experimental light aircraft (see Fig 1). The flight simulator was composed of a Primary Flight Display, a Navigation Display, and an Electronic Central Aircraft Monitoring Display, a rudder, thrust, and stick. The DR400 light aircraft was powered by a 180HP Lycoming engine and was equipped with classical gauges, radio and radio navigation equipment, and actuators such as rudder, stick, thrust and switches to control the flight.

2) Scenario: The scenario in the simulated and in the real flight conditions was identical. It consisted of four identical and consecutive traffic patterns at Lasbordes airfield. Each traffic pattern, according to the standards of visual flight rules (VFR), is divided into five flight phases—the upwind take-off leg, the crosswind leg, the downwind leg, the base leg and the final landing. The experiment lasted around 50 minutes. The participants were asked to perform a secondary classical oddball paradigm with a total of 600 auditory stimuli: 25% were targets (120 normalized pure tone at 1100 Hz, 90 dB SPL) and 75% were non-targets (480 normalized pure tone at 1000 Hz, 90 dB SPL). Inter-trial interval was set to 2000 ms with a 2000-ms jitter. The volunteers had to ignore the frequent non-targets and report the number of auditory targets during the first part of the experiment - defined as the two first traffic patterns - and the second part of the experiment - defined as the two last traffic patterns. The number of reported auditory targets was used as an indirect index of cognitive fatigue. It was expected that pilots would commit more errors during the second part than the first part of the experiment as a consequence of TOT. The order of the conditions (real flight vs simulated flight) was counterbalanced across participants. A flight instructor was present in the simulated and real flight conditions and was left-seated. The experimenter was the backseater and his role was to place and calibrate the sensors, trigger the odd-ball task and write the number of auditory targets reported by the volunteer.

3) EEG and fNIRS recording and preprocessing: EEG data were recorded at 500Hz using the 32 dry-electrode Enobio Neuroelectrics system positioned according to the 10-20 system. Only 23 channels out of 32 were recorded (P7, P4, Cz, Pz, P3, P8, O1, O2, F8, C4, F2, Fz, C3, FPz, F7, Oz, AF4, CP6, CP2, CP1, CP5, FC1 and AF3). Remaining channels were removed in order to put the fNIRS sensors on the same cap and to allow sufficient comfort for the participants. fNIRS data were recorded at 8.93Hz using the NIRSport NIRX system using 7 sources (F3, FP1, AFz, FP2, F4, T7, T8) and 8 detectors (AF7, AF3, AF8, AF4, TP7, FT7,TP8, FT8) which resulted in 12 channels.

EEG and fNIRS data were synchronized using Lab Stream-

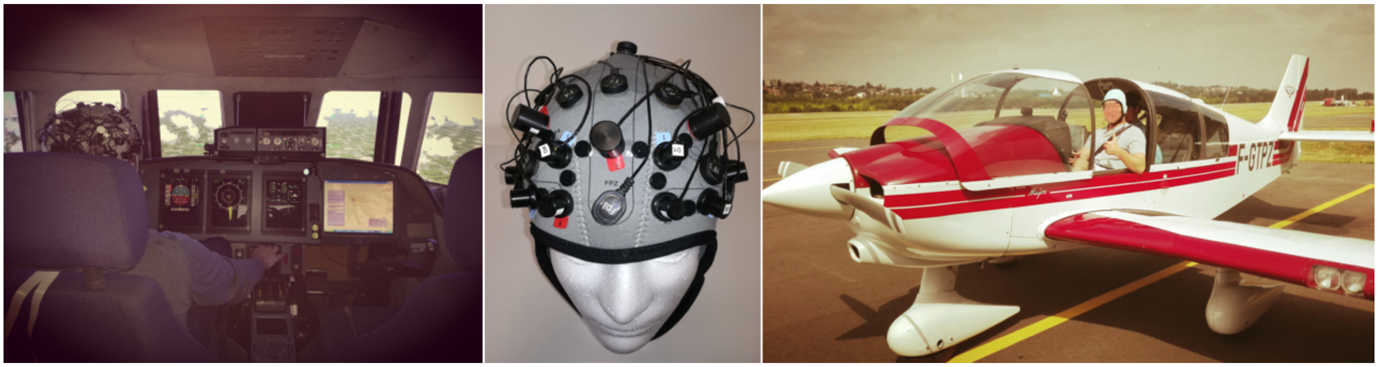

Fig. 1. Experimental environment: flight simulator (left), EEG-fNIRS cap (middle) and DR400 light aircraft (right).

ing Layer, they were analyzed using Matlab R2015b using EEGLab and several functions from the Homer2 software package [41].

EEG and fNIRS data were firstly epoched into successive and non-overlapping 1 minute time windows. Epochs were then analysed independently in order to extend our method to online classification (see section II-B).

Regarding EEG, Automatic Subspace Reconstruction (ASR) [42] (default settings) was used to remove non-stationary high-variance signals from the EEG by means of an interpolation of components that exceeded a threshold relative to the covariance of the calibration set of relatively clean data segments. The calibration set has been extracted from EEG signals recorded prior to the first traffic pattern, and therefore was independent from EEG epochs used for classification.

Regarding fNIRS, they were converted into optical density. Artifacts were identified by detecting high variance parts of the signal, a spline interpolation was then used to remove those parts. The artifact-free optical density signal was then band-pass filtered using 2 butterworth filter (low-pass: 0.5 Hz order: 3 and high-pass: 0.01 Hz order: 5). Optical density were converted to chromophore concentrations ([HbO] and [HbR]) using the Modified Beer-Lambert Law (MBLL).

a) EEG feature - engagement ratio: We used the following EEG engagement ratio $\frac{\beta}{\alpha+\theta}$ defined according to [28]. The power of each frequency band (α, β, and θ) was computed by estimating the one-sided Welch's power spectral density of the EEG signal. The engagement ratio was computed independently for each channel, resulting in as many features as EEG channels.

b) fNIRS feature - wavelet coherence: A coherence measure based on the wavelet transform was used : the wavelet coherence [42]. The wavelet coherence power $R_n^2(s)$ can be defined as:

$$R_n^2(s) = \frac{|S(s^{-1}W_n^{xy}(s)|^2}{S\Big(s^{-1}|W_n^x(s)|^2\Big)S\Big(s^{-1}|W_n^y(s)|^2\Big)} \quad (1)$$

Where $W_n^x(s)$ and $W_n^y(s)$ represent respectively the wavelet transform of x and y at the n time point for a wavelet scale s.$W_n^{xy}(s)$ is the cross wavelet transform of x and y (being the wavelet transform of the cross correlation function). S is a smoothing operator (for more detail see [42]).

This measure can be seen as a localized correlation coefficient in time frequency space [43]. Coherence values range from 0 to 1, 1 meaning there are perfectly phased-locked oscillations at a given frequency for the 2 analyzed signals.

The wavelet coherence was computed only on the [HbO] signals for each couple of channels namely $C\binom{n}{k} = 66$ couples ($k = 2$, $n = 12$).

The resulting coherence was averaged for frequency band ranging from 0.0781 Hz to 0.3125 Hz corresponding to 1/12.8 sec to 1/3.2 sec according to the litterature [35]. This 66 averaged coherence measures were then used as features by the classifier for the pBCI implementation.

B. Passive BCI implementation

A shrinkage linear discriminant analysis (sLDA) was performed, providing better results in a high dimensional feature space [44]. This method has already been applied with success to efficiently classify auditory event-related potentials [45]. EEG and fNIRS features were computed based on data recorded during the same trials. For each class (first part versus second part), trials correspond to successive and non-overlapping 1 minute time windows. The number of trials differed from each subject, depending of the time spent to realize the traffic patterns. Finally, balanced classification accuracy was assessed, for each subject, by using a random 5-fold cross-validation procedure with an equal number of trials per class.

III. Results

The behavioral results on the secondary auditory task disclosed that participants exhibited lower performance to report the exact number of auditory targets in the second part than in the first part of the experiment (first part: mean error= 6.6; second part: mean error =18, *Cohen's d*=0.72 - equivalent to a moderate size effect) whatever the flight condition was. More specifically, the errors were higher in the real flight condition (first part: mean error =10; second part: mean error=26.5) than in the simulator condition (first part: mean error =3.25; second part: mean error =9.5).

As regards the estimation of the cognitive fatigue using a pBCI pipeline, the mean accuracy in the simulator condition was 86.7% when using the EEG features only, 81.5% when using the fNIRS features and reached 87.2% when combining the EEG and fNIRS features (see Fig. 3). The mean classification accuracy in the real flight condition was 86.4% when using the EEG features only, 83.2% when using the fNIRS features and reached 87.6 % when combining both EEG and fNIRS features (see Fig. 3).

IV. Discussion

The objective of this paper was to implement an hybrid fNIRS-EEG based pBCI to monitor cognitive fatigue in aviation. The pilots had to perform four traffic patterns along with a secondary oddball task. This latter task was used as a probe to infer cognitive fatigue between the first part (i.e. the two first traffic patterns) and the last part of the experiment (i.e. the two last traffic patterns). This goal was challenging as this study was the first to report the combination of these two brain imaging techniques under realistic settings such as real flight conditions. As expected, the pilots committed more errors when reporting the number of auditory probes during the second part of the experiment than during the first part as a consequence of TOT. This finding indicates that cognitive fatigue can impair auditory attention to an extent that auditory sounds can be missed. This phenomenon known as inattentional deafness is a critical safety issue that has been generally attributed to flying task difficulty [46], [47], over-engagement [49] and stress [48]–[50]. To our knowledge this is the first study to bring to light the involvement of cognitive fatigue in the occurrence of this phenomenon.

Moreover, the classification results disclosed that the fNIRS and EEG engagement-related metrics allowed to classify the variation of cognitive fatigue between the beginning and the end of the experiment with a high level of accuracy (i.e. above 87%). Although our small sample size (*N*=4) did not allow us to statistically test the classification accuracies between the used features (i.e. EEG only, fNIRS only or EEG-fNIRS concatenation), or the flight setting (i.e. simulator or real aircraft), nevertheless the average results reveal that the combination of the two recording modalities provided better accuracy that when used separately. Also, they reveal that for this aeronautical application, increasing the level of ecology in the setting, that is to say going from the simulator into the real world, did not negatively impact mental state estimation as one could have expected. Indeed, there was no decrement in classification performance since cognitive fatigue estimation reached 87.2% in the simulator and was still at 87.6% in the real light airplane. Therefore, the results of this preliminary study show that these highly portable devices can be effectively used in the noisy environment of a flight simulator and more importantly, even in the noisy environment of an airplane by using various signal processing techniques. This finding confirms and complements previous studies that dry-electrode EEG could be used in real flight to monitor cognitive performance such as spatial disorientation [51] and auditory processing [52]. To the authors' best knowledge, only one study implemented a fNIRS-based BCI to infer working memory load in actual flight context [53]. Taken together these results open promising perspectives to monitor mental states such as cognitive fatigue, bringing us closer to the realization of neuroergonomics based technology in the cockpit to promote performance and safety of the pilots, crew, and passengers.

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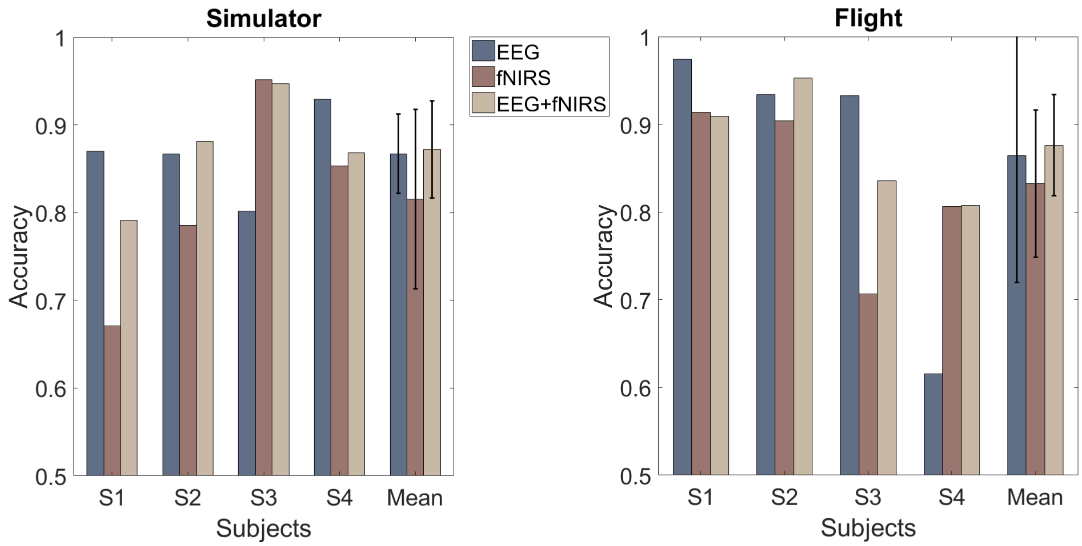

Fig. 2. Classification accuracy for all subjects and mean classification accuracy (vertical black bars represent standard deviation). Left: in the simulator condition. Right: in the real flight condition.

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