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► **To cite this version:**

Frédéric Dehais, Imad Rida, Raphaëlle N. Roy, John Iversen, Tim Mullen, et al.. A pBCI to Predict Attentional Error Before it Happens in Real Flight Conditions. IEEE International Conference on Systems, Man, and Cybernetics (SMC 2019), Oct 2019, Bari, Italy. pp.4155-4160. <hal-03125182>

HAL Id: hal-03125182

<https://hal.science/hal-03125182v1>

Submitted on 29 Jan 2021

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Dehais, Frédéric and Rida, Imad and Roy, Raphaëlle N. and Iversen, John and Mullen, Tim and Callan, Daniel E. A pBCI to Predict Attentional Error Before it Happens in Real Flight Conditions. (2019) In: IEEE International Conference on Systems, Man, and Cybernetics - IEEE SMC BMI, 6 October 2019 - 9 October 2019 (Bari, Italy).

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A pBCI to Predict Attentional Error Before it Happens in Real Flight Conditions

Frédéric Dehais¹, Imad Rida¹, Raphaëlle N. Roy¹, John Iversen², Tim Mullen³, and Daniel Callan⁴

Abstract—Accident analyses have revealed that pilots can fail to process auditory stimuli such as alarms, a phenomenon known as inattentional deafness. The motivation of this research is to develop a passive brain computer interface that can predict the occurrence of this critical phenomenon during real flight conditions. Ten volunteers, equipped with a dry-EEG system, had to fly a challenging flight scenario while responding to auditory alarms by button press. The behavioral results disclosed that the pilots missed 36% of the auditory alarms. ERP analyses confirm that this phenomenon affects auditory processing at an early (N100) and late (P300) stages as the consequence of a potential attentional bottleneck mechanism. Inter-subject classification was carried out over frequency features extracted three second epochs before the alarms' onset using sparse representation for classification (SRC), sparse and dense representation (SDR) and more conventional approach such as linear discriminant analysis (LDA), shrinkage LDA and nearest neighbor (1-NN). In the best case, SRC and SDR gave respectively a performance of 66.9% and 65.4% of correct mean classification rate to predict the occurrence of inattentional deafness, outperforming LDA (60.6%), sLDA (60%) and 1-NN (59.6%). These results open promising perspectives for the implementation of neuroadaptive automation with as ultimate goal to enhance alarm stimulation delivery so that it is perceived and acted upon.

I. INTRODUCTION

Operating aircraft is a demanding activity that involves the management of multiple visual (e.g. monitoring the flight parameter) and auditory tasks (e.g. radio communication) in a dynamic and uncertain environment [1], [2], [3]. Distribution of attention is a key issue for piloting and relies on a trade-off between focused attention (eg. performing a check-list) to avoid distraction, and diffused attention to detect unexpected changes (eg. failure). These top-down and bottom-up types of attention are respectively supported by the dorsal and ventral neural networks that are in close interaction [4]. However, when task demand exceeds mental capacity, the homeostasis between these two neural pathways could be disrupted, leading to an impaired processing of unexpected stimuli [5], [6]. Although this shielding mechanism can prevent mental overload, missing critical information can jeopardize flight safety [7]. For instance, accident analyses

[8] and experiments conducted in flight simulators [9], [10], [11] reported that auditory alarms could fail to reach awareness when engaged under demanding cognitive flying tasks. This phenomenon, known as inattentional deafness, has been shown to take place at an early stage of auditory processing [12] through top-down inhibitory mechanisms implemented via the activation of cortical regions associated with an attentional bottleneck [13]. Complementary evidence of this phenomenon was supported by an electrophysiological experiment conducted in real flight conditions which revealed that a reduction in phase resetting in alpha and theta band frequencies was a neural signature of inattentional deafness to auditory alarms [14].

A relevant approach to improve flight safety is to implement passive brain computer interfaces (pBCI) or neuroadaptive technology [15], [16], [17], [18] to continuously monitor pilots' attentional state and to detect the possible occurrence of degraded states. Recently, [12] implemented an offline pBCI to detect inattentional deafness to auditory alarms during a simulated flight. Such an approach opens promising perspectives for pilot-cockpit interaction, however a step further would be to predict rather than detect episodes of inattentional deafness [20]. As a consequence, one could imagine the design of a smart cockpit that would implicitly adapt itself to the pilots' attentional state with a set of counter-measures.

To meet this challenging goal, supervised dictionary learning approach has been shown to be an efficient means to lead state-of-the-art results in many applications including signal classification [21]. Indeed, in recent years there has been a growing interest in the use of techniques such as sparse representation for classification (SRC) or sparse and dense representation (SDR) in order to build discriminative representations by minimizing the intra-class homogeneity, maximizing class separability and promoting sparsity for more generalization ability [22], [23], [24]. This is done by learning a dictionary per class and making them dissimilar by boosting the pairwise orthogonality. When compared to conventional dictionary learning techniques [25] which they solely try to minimize the reconstruction error, supervised dictionary learning has the merit to be a very efficient way to classify EEG signals for BCI purposes [26], [27].

The objective of the present study was to develop a pBCI to predict auditory alarm misperception in the context of flying. Participants were asked to perform a demanding flying scenario along with an auditory alarm detection task in real flight conditions. In line with previous studies, we used dry-electrode EEG that has proven to be suitable for measuring

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Fig. 1. Left: ISAE-SUPAERO DR400 aircraft. Right: EEG dry electrode Enobio system used for the experiment

brain response [14], [28] and to perform single trial classification [29], [30], [31], [32] in actual flight conditions. We proposed to use SRC as well as SDR techniques to predict inattentive deafness with frequency features computed over the EEG signal in a 3-second time-window preceding the onset of each auditory alarm. More conventional approaches including Nearest Neighbor (1-NN), Linear Discriminant Analysis (LDA) and shrinkage Linear Discriminant Analysis (sLDA) were also used as a benchmark.

II. METHODS

A. Experimental protocol

Ten pilots were recruited among the students of the ISAE-SUPAERO engineering school to participate in the study (10 males; 25- 48 years old, with 40-230 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: 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) experimental DR400 light aircraft (see Fig 1). The DR400 light aircraft was powered by a 180HP Lycoming engine and was equipped with classical gauges, radio navigation equipment, and actuators such as rudder, stick, thrust and switches to control the flight. A switch button was attached to the stick to collect the pilots response to auditory alarms.

2) *Scenario:* The experiment lasted approximately one hour in duration and involved navigation tasks, diversions, simulated engine failure exercises, and series of touch-and-go (landings and takeoffs) involving low altitude circuits patterns. Along with the flying task, the participants had to perform an auditory oddball detection task with a total of 1000 auditory stimuli: 25% were alarm stimuli (250 normalized pure tone at 1100 Hz, 90 dB SPL) and 75% were non-alarm stimuli (750 normalized pure tone at 1000 Hz, 90 dB SPL). The inter-trial interval was set to 3000 ms with a 2000-ms jitter. The participants were instructed to

respond quickly by pushing a button attached to the flight control stick after hearing the alarm stimuli. The auditory task started during takeoff and would end before or during landing.

3) *Experimental protocol:* The participants were first trained to perform the auditory task alone for five minutes while seated in a calm room at ISAE-SUPAERO hangar. After completing the auditory task, they were equipped with the 30 dry electrode Enobio EEG cap. The volunteers were then left-seated on the aircraft and had to wear a Clarity Aloft headset that was used to trigger auditory stimuli from a PC via an audio cable. The participants could still communicate with the other crew members and the air traffic controllers when they received auditory alarms. The safety pilot was right seated and had the authority to stopping the experiment and taking over the control of the aircraft for any safety reason. The backseater was the experimenter: his role was to set the sensor, to trigger the experimental scenario and to supervise data collection.

4) *Data recording:* EEG data were recorded at 500 Hz using the 30 dry-electrode Enobio Neuroelectronics system positioned according to the 10-20 system. We used Lab Streaming Layer libraries (LSL, Swartz Center for Computational Neuroscience, UCSD, November 2018) to synchronize the oddball task in Matlab (Ver. 2017.b) and the response button with the Enobio acquisition software (NIC V2.0). The data were processed using EEGLab (Ver. 15).

5) *Event Related Potential (ERP) and Frequency domain analysis with sLoreta:* Similarly to [14], we computed ERP over Cz electrode. Our motivation was to check that we actually picked brain signals and that the N100 and P300 amplitudes were lower for misses than hits as demonstrated by [12]. To do so, the continuous EEG data was filtered between 0.5–30 Hz (windowed-sinc FIR filter with an order of 250). Noisy portions of data (e.g., trials) were cleaned using the Artifact Subspace Reconstruction (ASR) [33]. Independent component analysis (ICA) was then run over the filtered data and IClab Label function was used to keep only brain components. The epochs for auditory misses and

hits were extracted from the continuous data 0.2 s before and 1 s after stimuli onsets. The trials used for the ERP analyses were baseline normalized using data from 200 to 0 ms prior to the stimulus onset. We also ran descriptive frequency domain analyses using sLoreta over three second epochs extracted before the alarms' onset. The objective was to localize and identify potential neural mechanisms that could predict alarm misperception. To do so, we used the same pipeline described previously to the exception that the data were epoched starting 3000 ms before and ending 0 ms before the auditory misses and the auditory hits.

III. CLASSIFICATION

1) EEG processing pipeline for classification purpose:

The signal was first epoched starting 3000 ms before and ending 0 ms before the auditory alarms (see figure 2). Each epoch was then high-passed (0.5 Hz). Noisy portions of epoched data were cleaned using ASR. The ASR filter was calibrated using the first 30 s of EEG recording that were not used for the classification. Frequency based features were computed for each trial in the delta [1 4], theta [4 8] Hz, alpha [8 12] Hz, beta [12 30] Hz and gamma [30 80] Hz bands using a 250-order windowed sinc FIR-filter trial. Eventually, we computed an EEG engagement ratio $\frac{\beta+\gamma}{\alpha+\theta}$ adapted from [36].

A. Sparse representation for classification

Let us consider $\{(\mathbf{x}_j, y_j)\}_{j=1}^n$ where $\mathbf{x}_j \in \mathbb{R}^m$ be signal and $y_j \in \{1, \dots, c\}$ be its class label. We consider a class based dictionary $\{\mathbf{D}_i\}_{i=1}^c \in \mathbb{R}^{m \times n_i}$ the n_i training samples associated to class i . The global dictionary $\mathbf{D} = [\mathbf{D}_1 \dots \mathbf{D}_c] \in \mathbb{R}^{m \times n}$ represents the concatenation of the class based dictionaries $\{\mathbf{D}_i\}_{i=1}^c$. The sparse representation of a test sample \mathbf{p} over the global dictionary \mathbf{D} noted $\boldsymbol{\alpha}^T = [\boldsymbol{\alpha}_1^T \dots \boldsymbol{\alpha}_i^T \dots \boldsymbol{\alpha}_c^T]$ is given by:

$$\min_{\boldsymbol{\alpha}} \frac{1}{2} \|\mathbf{p} - \mathbf{D}\boldsymbol{\alpha}\|_2^2 + \lambda \|\boldsymbol{\alpha}\|_1 \quad (1)$$

where $\|\cdot\|_1$ denotes the ℓ_1 -norm corresponding to the absolute sum of the vector $\boldsymbol{\alpha}$, λ is a parameter controlling the compromise between the reconstruction error and sample-wise sparsity and $\boldsymbol{\alpha}$ represents the sparse representation over the global dictionary \mathbf{D} .

With the assumption that subspaces of distinct classes are independent to each other, the formulation (1) achieves a discriminative representation where significant nonzero coefficients are only associated to the correct subject. Thus the resulting sparse representation in (1) named in the literature Sparse Representation for Classification (SRC) [39] is suitable for classification. The classification is performed by computing residual reconstruction error of the test sample \mathbf{p} using the training samples of each class i serving as a dictionary \mathbf{D}_i and their corresponding sparse coefficients $\boldsymbol{\alpha}_i$ as follows:

$$e_i = \|\mathbf{p} - \mathbf{D}_i \boldsymbol{\alpha}_i\|_2^2 \quad i = 1, \dots, c \quad (2)$$

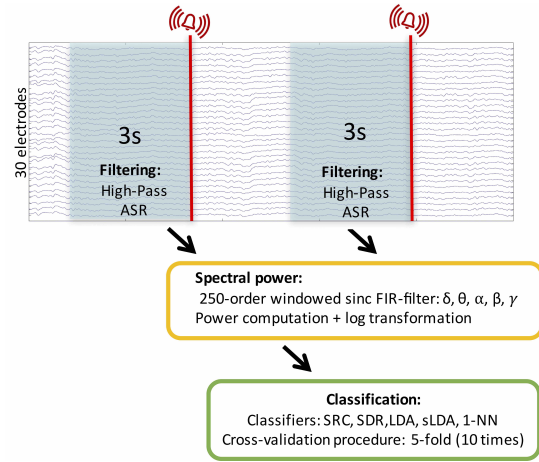


Fig. 2. Classification pipeline

The class label of the given test sample is assigned to class i that minimizes the reconstruction error using \mathbf{D}_i and $\boldsymbol{\alpha}_i$.

B. Sparse and dense hybrid representation

Despite of the impressive results of SRC, a number of works put in doubt its effectiveness for classification [48] [47]. To solve this problem, it has been proposed to separate the class-specific information from others to allow the sparse representation of the query signal to coincide with the correct classification target specified by the class labels of the training data. Therefore, a query EEG signal \mathbf{p} is decomposed into three main components as follows:

$$\mathbf{p} = \mathbf{a} + \mathbf{b} + \mathbf{s} \quad (3)$$

where \mathbf{a} is the class-specific component, \mathbf{b} the non-class-specific variations and \mathbf{s} contains random sparse noise.

Lets \mathbf{A} a dictionary containing only class-specific component, the sparse representation $\boldsymbol{\alpha}$ of the class-specific component of the query signal \mathbf{p} can be computed using SRC as follows:

$$\mathbf{a} = \mathbf{A}\boldsymbol{\alpha} + \mathbf{e}_a \quad (4)$$

the sparse vector $\boldsymbol{\alpha}$ of (4) will directly coincide with the class label of the query signal \mathbf{p} as the both \mathbf{a} and \mathbf{A} only contain the class-specific information.

Unfortunately, separating the class-specific component \mathbf{a} from a single unknown query signal \mathbf{p} is a very challenging problem if not impossible. To address this problem, a non-class-specific representation \mathbf{z} is defined by the dictionary \mathbf{B} containing non-class-specific information as follows:

$$\mathbf{b} = \mathbf{B}\mathbf{z} + \mathbf{e}_b \quad (5)$$

the component \mathbf{b} does not contribute in the classification and hence \mathbf{z} in (5) is defined as dense representation. The summation of (4), (5) and \mathbf{s} yields the hybrid sparse-and-dense representation (SDR) [45] of the query signal as follows:

$$\mathbf{p} = \mathbf{A}\boldsymbol{\alpha} + \mathbf{B}\mathbf{z} + \mathbf{e} \quad (6)$$

where $\mathbf{e} = \mathbf{e}_a + \mathbf{e}_b + \mathbf{s}$ is the combined representation error.

To represent a query signal \mathbf{p} , every training sample only uses its class-specific component to compete against the others collaboratively with the non-class-specific component of all training samples. As $\boldsymbol{\alpha}$ represents the class-specific information and contributes in the classification through a sparse minimization, it is chosen sparse. In the other hand, \mathbf{z} stands for the non-class specific and does not contribute in the classification, as consequence is taken dense. The solution of the SDR, $\boldsymbol{\alpha}$, \mathbf{z} and \mathbf{e} is obtained by solving the following optimization problem [45]:

$$\begin{cases} \min_{\boldsymbol{\alpha}, \mathbf{z}, \mathbf{e}} \|\boldsymbol{\alpha}\|_1 + \beta \|\mathbf{z}\|_2^2 + \gamma \|\mathbf{e}\|_1 \\ \text{s.t. } \mathbf{p} = \mathbf{A}\boldsymbol{\alpha} + \mathbf{B}\mathbf{z} + \mathbf{e} \end{cases} \quad (7)$$

the optimization problem (7) can be solved by the Augmented Lagrange Multiplier (ALM) scheme [46].

The representation of a query signal \mathbf{p} by the class-specific component of class i and the non-class-specific component of all classes collaboratively is given by:

$$\mathbf{p} = \mathbf{A}\mathbf{L}_i\boldsymbol{\alpha} + \mathbf{B}\mathbf{z} + \mathbf{e}_i \quad (8)$$

where $\mathbf{L}_i \in \mathbb{R}^{n \times n}$ is a selection operator given by

$$\begin{cases} \mathbf{L}_i(k, k) = 1 & \text{if } k^{\text{th}} \text{ training} \in \text{class } i \\ 0 & \text{otherwise} \end{cases} \quad (9)$$

The class-wise representation residual is defined by:

$$r_i(\mathbf{p}) = \|\mathbf{e} - \mathbf{e}_i\|_2 = \|\mathbf{A}(\mathbf{I} - \mathbf{L}_i)\boldsymbol{\alpha}\|_2 \quad (10)$$

where \mathbf{I} is an identity matrix. The query signal \mathbf{p} is classified into the class that produces the minimum residual $r_i(\mathbf{p})$.

It is very difficult if not impossible to decompose a single signal \mathbf{p} into a class-specific component \mathbf{a} and a non-class-specific component \mathbf{b} . However, given a labeled training database \mathbf{D} , it is possible to decompose it into a class-specific dictionary \mathbf{A} , a non-class-specific dictionary \mathbf{B} and a random sparse noise \mathbf{E} based on machine learning from the labeled training database. The underlying principle is that the both dictionaries \mathbf{A} and \mathbf{B} must be low rank matrices. We can first initialize \mathbf{A} by a very low rank matrix, for example, a matrix that contains the class means of all classes. Then we can gradually transfer more information from \mathbf{D} to \mathbf{A} so that after training, the class-specific dictionary \mathbf{A} will contain much more class-specific information than just class means. This can be done by the iterative low rank matrix decomposition of \mathbf{A} and \mathbf{B} from \mathbf{D} . It utilizes the low rank matrix recovery to transfer information from the supervised assigned dictionary \mathbf{B} to \mathbf{A} . More details can be found in [45].

C. Classification pipeline

As explained in the section II-A.2, our participants faced 25% of auditory alarms and 75% of non-alarm stimuli. Our behavior results disclosed that our participants missed 36% of the 25% presented alarms stimuli. For classification purpose, we then used 1400 recorded EEG signals (i.e. 3s epoch before the auditory alarms): 700 miss alarms and 700 hit alarms. An equivalent number of misses and hits were selected for each participant. To avoid the dependency of the classification techniques to a specific training / testing set, we evaluate the robustness using different training and testing set, as a consequence we have divided our initial data into $L = 10$ different training and testing set. Supervised Dictionary techniques such as SRC as well as SDR were tested over the different extracted frequency features separately or all together. We then benchmarked their performance with more conventional approaches including Nearest Neighbor (1-NN), Linear Discriminant Analysis (LDA) and shrinkage Linear Discriminant Analysis (sLDA).

IV. RESULTS

A. Electrophysiological results

At the group level (see figure 3 left), statistical analyses disclosed lower N100 and P300 amplitude for the auditory misses than hits over Cz electrode ($p = 0.01$ bootstrap statistics with FDR for multiple comparisons). Descriptive analyses using sLoreta, ran over 3 second epochs preceding the alarms, disclosed that audio misses relative to hits had lower oscillatory activity in the low alpha band in the right inferior frontal gyrus (see figure 3 right) but also in the right middle frontal gyrus and the right insula.

B. Classification results

Inter-subject classification accuracy using different features as well as algorithms is depicted in Table I. It can be seen that the best results were obtained using all aggregated features.

V. DISCUSSION

The objective of this paper was to implement an EEG based pBCI to predict inattentional deafness to auditory alarms in aviation. This goal was challenging as the EEG data were collected in a real flight conditions. The behavioral results revealed that our participants missed 36% of auditory alarms on average, confirming that such a phenomenon could take place in the cockpit [10], [9], [14], [13]. ERPs analyses over Cz electrode disclosed that this phenomenon takes place at a perceptual (N100) and attentional (P300) level as previously demonstrated in flight simulator [12]. Descriptive analyses using sLoreta indicated lower alpha oscillatory activity in brain regions generally involved in attentional bottleneck processing including the inferior frontal gyrus, the insula and the superior medial frontal cortex [42]. As higher alpha oscillation are thought to reflect inhibition mechanisms, lower alpha oscillation preceding misses may suggest, on the contrary, greater activation of the attentional bottleneck to prevent the processing of incoming alarms [14].

TABLE I
INTER-SUBJECT CLASSIFICATION ACCURACY.

Methods	Features						
	Delta	Theta	Alpha	Beta	Gamma	Engagement	Fusion
1-NN	59.08 ± 3.29	57.29 ± 2.85	57.38 ± 4.06	58.21 ± 2.15	59.50 ± 3.01	58.04 ± 1.76	59.60 ± 2.70
LDA	60.20 ± 4.15	59.60 ± 2.79	58.71 ± 2.25	58.67 ± 3.06	58.50 ± 3.60	62.20 ± 2.50	60.60 ± 4.00
sLDA	60.75 ± 3.64	54.38 ± 3.45	53.38 ± 3.13	53.96 ± 3.20	56.25 ± 2.56	59.25 ± 3.33	60.00 ± 3.07
SDR	61.50 ± 3.50	62.60 ± 2.80	60.50 ± 1.80	60.40 ± 1.80	58.90 ± 1.60	62.50 ± 3.07	65.40 ± 2.80
SRC	65.60 ± 4.02	64.58 ± 2.25	63.83 ± 3.37	63.96 ± 3.42	64.08 ± 3.78	63.58 ± 2.94	66.90 ± 3.10

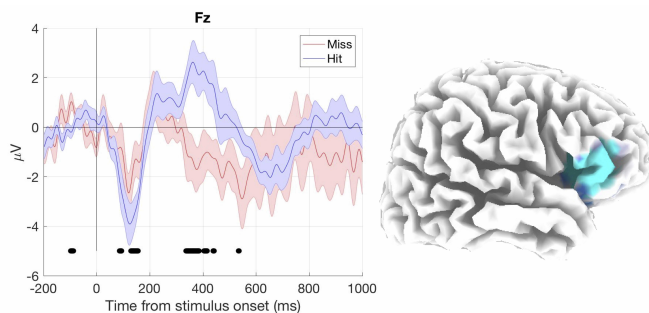


Fig. 3. Left: Grand averaged waveforms of the ERPs for Fz with standard error. The black lines on the x axis specify the time range when the auditory misses and hits related ERPs amplitudes were significantly different ($p = 0.01$, corrected). Right: Frequency domain EEG source analysis using sLoreta. Lower alpha oscillatory activity in the right inferior frontal gyrus during misses than auditory hits.

Our classification results showed that the mean prediction accuracy rate reached almost 67% in the best case with SRC. This performance is close to the 70 % accuracy defined as a sufficient accuracy for BCI [41]. The use of supervised dictionary learning approach seems to outperform more conventional techniques such as 1-NN and LDA/sLDA (60%). These latter results are consistent of our previous study with shrinkage LDA [20] which had 58% mean accuracy to predict the onset of inattentive deafness in simulated conditions. Moreover, this prior study considered intra-subject but not inter-subject classification as was used in the present study. Therefore, these findings show that our approach is a well-suited method for processing EEG signal as previously demonstrated by [26], [27]. Moreover, the performance obtained here with inter-subject classification and a dry-EEG system is altogether quite high in a general manner, but also very promising in its robustness to inter-subject variability and to ecological settings.

Taken together, these findings open good prospects for the implementation of a smart cockpit that would adapt to the user's state. For instance, one could imagine that the modality (e.g. tactile, visual) of the alarm could be optimized to increase the likelihood of reaching pilot's awareness. Another possibility would be to consider adaptive autonomy and to lower the pilots' engagement by giving more authority to the autoflight system to reduce

their workload. Nonetheless, there is a need to improve the accuracy of this pBCI before it could be implemented into real cockpits. Future research should investigate other metrics such as connectivity features that have been shown to efficiently predict long term attentional performance [43]. Another possible approach would be to apply adaptive mixture independent component analysis to identify different brain network associated with auditory misses and hits, as it has previously been shown to identify brain dynamics underlying attention fluctuation in driving [44].

ACKNOWLEDGMENT

This study was supported by the Agence Innovation Defense (AID - DGA), the AXA research fund and the Artificial and Natural Intelligence Toulouse Institute (ANITI). The authors wish to express their gratitude to Fabrice Bazelot, Stephane Juaneda and all the pilots who took part in the experiments.

REFERENCES

- [1] T. Gateau, G. Durantin, F. Lancelot, S. Scannella, and F. Dehais, "Real-time state estimation in a flight simulator using fnirs," *PLoS one*, vol. 10, no. 3, p. e0121279, 2015.
- [2] M. Causse, F. Dehais, M. Arexis, and J. Pastor, "Cognitive aging and flight performances in general aviation pilots," *Aging, Neuropsychology, and Cognition*, vol. 18, no. 5, pp. 544–561, 2011.
- [3] F. Dehais, J. Behrend, V. Peysakhovich, M. Causse, and C. D. Wickens, "Pilot flying and pilot monitoring's aircraft state awareness during go-around execution in aviation: A behavioral and eye tracking study," *The International Journal of Aerospace Psychology*, vol. 27, no. 1-2, pp. 15–28, 2017.
- [4] S. Vossel, J. J. Geng, and G. R. Fink, "Dorsal and ventral attention systems: distinct neural circuits but collaborative roles," *The Neuroscientist*, vol. 20, no. 2, pp. 150–159, 2014.
- [5] K. Molloy, T. D. Griffiths, M. Chait, and N. Lavie, "Inattentive deafness: visual load leads to time-specific suppression of auditory evoked responses," *Journal of Neuroscience*, vol. 35, no. 49, pp. 16046–16054, 2015.
- [6] J. J. Todd, D. Fournie, and R. Marois, "Visual short-term memory load suppresses temporo-parietal junction activity and induces inattentive blindness," *Psychological science*, vol. 16, no. 12, pp. 965–972, 2005.
- [7] F. Dehais, H. M. Hodgetts, M. Causse, J. Behrend, G. Durantin, and S. Tremblay, "Momentary lapse of control: A cognitive continuum approach to understanding and mitigating perseveration in human error," *Neuroscience & Biobehavioral Reviews*, 2019.
- [8] J. P. Bliss, "Investigation of alarm-related accidents and incidents in aviation," *The International Journal of Aviation Psychology*, vol. 13, no. 3, pp. 249–268, 2003.

- [9] F. Dehais, M. Causse, F. Vachon, N. Régis, E. Menant, and S. Tremblay, "Failure to detect critical auditory alerts in the cockpit: evidence for inattentive deafness," *Human factors*, vol. 56, no. 4, pp. 631–644, 2014.
- [10] F. Dehais, M. Causse, N. Régis, E. Menant, P. Labedan, F. Vachon, and S. Tremblay, "Missing critical auditory alarms in aeronautics: evidence for inattentive deafness?" in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 56, no. 1. Sage Publications Sage CA: Los Angeles, CA, 2012, pp. 1639–1643.
- [11] F. Dehais, C. Tessier, L. Christophe, and F. Reuzeau, "The perseveration syndrome in the pilots activity: guidelines and cognitive countermeasures," *Human Error, Safety and Systems Development*, pp. 68–80, 2010.
- [12] F. Dehais, R. N. Roy, and S. Scannella, "Inattentive deafness to auditory alarms: Inter-individual differences, electrophysiological signature and single trial classification," *Behavioural brain research*, vol. 360, pp. 51–59, 2019.
- [13] G. Durantin, F. Dehais, N. Gonthier, C. Terzibas, and D. E. Callan, "Neural signature of inattentive deafness," *Human brain mapping*, vol. 38, no. 11, pp. 5440–5455, 2017.
- [14] D. E. Callan, T. Gateau, G. Durantin, N. Gonthier, and F. Dehais, "Disruption in neural phase synchrony is related to identification of inattentive deafness in real-world setting," *Human brain mapping*, 2018.
- [15] P. Aricò, G. Borghini, G. Di Flumeri, N. Sciaraffa, A. Colosimo, and F. Babiloni, "Passive bci in operational environments: Insights, recent advances, and future trends," *IEEE Transactions on Biomedical Engineering*, vol. 64, no. 7, pp. 1431–1436, 2017.
- [16] T. O. Zander, L. R. Krol, N. P. Birbaumer, and K. Gramann, "Neuroadaptive technology enables implicit cursor control based on medial prefrontal cortex activity," *Proceedings of the National Academy of Sciences*, vol. 113, no. 52, pp. 14 898–14 903, 2016.
- [17] T. O. Zander and C. Kothe, "Towards passive brain–computer interfaces: applying brain–computer interface technology to human–machine systems in general," *Journal of neural engineering*, vol. 8, no. 2, p. 025005, 2011.
- [18] F. Lotte and R. N. Roy, "Brain–computer interface contributions to neuroergonomics," in *Neuroergonomics*. Elsevier, 2019, pp. 43–48.
- [19] R. N. Roy, S. Bonnet, S. Charbonnier, and A. Campagne, "Efficient workload classification based on ignored auditory probes: A proof of concept," *Frontiers in Human Neuroscience*, vol. 10, no. 519, 2016.
- [20] A. Duprès, R. N. Roy, S. Scannella, and F. Dehais, "Pre-stimulus eeg engagement ratio predicts inattentive deafness to auditory alarms in realistic flight simulator," in *3rd International Mobile Brain/Body Imaging Conference (MOBI 2018)*, 2018, pp. pp–1.
- [21] I. Rida, "Temporal signals classification," Theses, Normandie Université, Feb. 2017. [Online]. Available: <https://tel.archives-ouvertes.fr/tel-01515364>
- [22] S. Al Maadeed, X. Jiang, I. Rida, and A. Bouridane, "Palmprint identification using sparse and dense hybrid representation," *Multimedia Tools and Applications*, pp. 1–15, 2018.
- [23] I. Rida, S. Al-Maadeed, A. Mahmood, A. Bouridane, and S. Bakshi, "Palmprint identification using an ensemble of sparse representations," *IEEE Access*, vol. 6, pp. 3241–3248, 2018.
- [24] I. Rida, R. Héroult, and G. Gasso, "An efficient supervised dictionary learning method for audio signal recognition," *arXiv preprint arXiv:1812.04748*, 2018.
- [25] B. Hamner, R. Chavarriaga, and J. d. R. Millán, "Learning dictionaries of spatial and temporal eeg primitives for brain-computer interfaces," in *Workshop on Structured Sparsity: Learning and Inference, ICML 2011*, 2011.
- [26] W. Zhou, Y. Yang, and Z. Yu, "Discriminative dictionary learning for eeg signal classification in brain-computer interface," in *2012 12th International Conference on Control Automation Robotics & Vision (ICARCV)*. IEEE, 2012, pp. 1582–1585.
- [27] D. Wen, P. Jia, Q. Lian, Y. Zhou, and C. Lu, "Review of sparse representation-based classification methods on eeg signal processing for epilepsy detection, brain-computer interface and cognitive impairment," *Frontiers in aging neuroscience*, vol. 8, p. 172, 2016.
- [28] F. Dehais, R. N. Roy, G. Durantin, T. Gateau, and D. Callan, "Eeg-engagement index and auditory alarm misperception: an inattentive deafness study in actual flight condition," in *International Conference on Applied Human Factors and Ergonomics*. Springer, 2017, pp. 227–234.
- [29] F. Dehais, A. Duprès, S. Blum, N. Drougard, S. Scannella, R. N. Roy, and F. Lotte, "Monitoring pilots mental workload using erps and spectral power with a six-dry-electrode eeg system in real flight conditions," *Sensors*, vol. 19, no. 6, p. 1324, 2019.
- [30] T. Gateau, H. Ayaz, and F. Dehais, "Detecting pilot's engagement using fnirs connectivity features in an automated vs manual landing scenario," *Frontiers in human neuroscience*, In revision.
- [31] C. A. Scholl, Y. M. Chi, M. Elconin, W. R. Gray, M. A. Chevillet, and E. A. Pohlmeier, "Classification of pilot-induced oscillations during in-flight piloting exercises using dry eeg sensor recordings," in *Engineering in Medicine and Biology Society (EMBC), 2016 IEEE 38th Annual International Conference of the*. IEEE, 2016, pp. 4467–4470.
- [32] D. E. Callan, G. Durantin, and C. Terzibas, "Classification of single-trial auditory events using dry-wireless eeg during real and motion simulated flight," *Frontiers in systems neuroscience*, vol. 9, p. 11, 2015.
- [33] T. Mullen, C. Kothe, Y. M. Chi, A. Ojeda, T. Kerth, S. Makeig, G. Cauwenberghs, and T.-P. Jung, "Real-time modeling and 3d visualization of source dynamics and connectivity using wearable eeg," in *Engineering in Medicine and Biology Society (EMBC), 2013 35th Annual International Conference of the IEEE*. IEEE, 2013, pp. 2184–2187.
- [34] E. Arad, R. P. Bartsch, J. W. Kantelhardt, and M. Plotnik, "Performance-based approach for movement artifact removal from electroencephalographic data recorded during locomotion," *PLoS one*, vol. 13, no. 5, p. e0197153, 2018.
- [35] T. P. Luu, J. A. Brantley, S. Nakagome, F. Zhu, and J. L. Contreras-Vidal, "Electrocortical correlates of human level-ground, slope, and stair walking," *PLoS one*, vol. 12, no. 11, p. e0188500, 2017.
- [36] L. J. Prinzel, F. G. Freeman, M. W. Scerbo, P. J. Mikulka, and A. T. Pope, "A closed-loop system for examining psychophysiological measures for adaptive task allocation," *The International journal of aviation psychology*, vol. 10, no. 4, pp. 393–410, 2000.
- [37] I. Ramirez, P. Sprechmann, and G. Sapiro, "Classification and clustering via dictionary learning with structured incoherence and shared features," in *2010 IEEE Computer Society Conference on Computer Vision and Pattern Recognition*. IEEE, 2010, pp. 3501–3508.
- [38] I. Rida, N. Al-Maadeed, S. Al-Maadeed, and S. Bakshi, "A comprehensive overview of feature representation for biometric recognition," *Multimedia Tools and Applications*, pp. 1–24, 2018.
- [39] J. Wright, A. Y. Yang, A. Ganesh, S. S. Sastry, and Y. Ma, "Robust face recognition via sparse representation," *IEEE transactions on pattern analysis and machine intelligence*, vol. 31, no. 2, pp. 210–227, 2009.
- [40] T. H. Vu and V. Monga, "Fast low-rank shared dictionary learning for image classification," *IEEE Transactions on Image Processing*, vol. 26, no. 11, pp. 5160–5175, 2017.
- [41] A. Kubler, V. Mushahwar, L. R. Hochberg, and J. P. Donoghue, "Bci meeting 2005-workshop on clinical issues and applications," *IEEE Transactions on neural systems and rehabilitation engineering*, vol. 14, no. 2, pp. 131–134, 2006.
- [42] Tombu, M. N., Asplund, C. L., Dux, P. E., Godwin, D., Martin, J. W., & Marois, R. (2011). A unified attentional bottleneck in the human brain. *Proceedings of the National Academy of Sciences*, 108(33), 13426-13431.
- [43] M. Senoussi, K. J. Verdier, A. Bovo, C. P. C. Chanel, F. Dehais, and R. N. Roy, "Pre-stimulus antero-posterior eeg connectivity predicts performance in a uav monitoring task," in *Systems, Man, and Cybernetics (SMC), 2017 IEEE International Conference on*. IEEE, 2017, pp. 1167–1172.
- [44] S.-H. Hsu, L. Pion-Tonachini, J. Palmer, M. Miyakoshi, S. Makeig, and T.-P. Jung, "Modeling brain dynamic state changes with adaptive mixture independent component analysis," *NeuroImage*, vol. 183, pp. 47–61, 2018.
- [45] Jiang, X., Lai, J.: Sparse and dense hybrid representation via dictionary decomposition for face recognition. *IEEE Transactions on Pattern Analysis and Machine Intelligence* 37(5), 1067–1079 (2015)
- [46] Bertsekas, D.P.: *Constrained optimization and Lagrange multiplier methods*. Academic press (2014)
- [47] Rigamonti, R., Brown, M.A., Lepetit, V.: Are sparse representations really relevant for image classification? In: *Computer Vision and Pattern Recognition (CVPR), 2011 IEEE Conference on*, pp. 1545–1552. IEEE (2011)
- [48] Shi, Q., Eriksson, A., Van Den Hengel, A., Shen, C.: Is face recognition really a compressive sensing problem? In: *Computer Vision and*

Pattern Recognition (CVPR), 2011 IEEE Conference on, pp. 553–560.
IEEE (2011)