Real-Time Neurophysiological Measure of Individual and Team Operators' Cognitive Performance for Defence Applications

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ABSTRACT

In high responsibility defence contexts, effective evaluation of operators 's cognitive performance and cooperation is crucial for preventing errors due to sudden impairment of their mental capacities. Recently, neuroscience has made a large effort to investigate the psychobiological mechanisms underlying cognitive and emotional states (Human Factors - HFs), which human behaviour and performance depend on. To now, the approaches based on neurophysiological signals like the brain, heart and skin electrical activity, namely the electroencephalogram (EEG), electrocardiogram (ECG) and skin conductance (electrodermal activity - EDA) are application-specific and often related to a single HF. Applying advanced machine-learning (ML) technique and multivariate autoregressive (MVAR) models on operator's neurophysiological data will allow for i) objectively assessing the individual performance in terms of HFs like the mental workload; and ii) quantifying the degree of cooperation analyzing the causal relations between teammates' HFs. At the moment, an objective index to assess team members' cooperation in real-time has not been proposed. The creation of this neurophysiological framework will provide an entirely new set of tools and knowledge for understanding and predicting the cognitive performance of operators and teams. In other words, the integration of data coming from the operators' neurophysiological signals will significantly improve the cognitive training and capability of the operators. The preliminary results reported in this work derives from professional pilots which were asked to perform realistic flight simulations while their brain activity and subjective data were gathered. The collected data were then used to develop the methodology and neurometrics for assessing pilots' mental workload and cooperation while dealing with flight simulations.

1.0 INTRODUCTION

Conventional methods to gather information about individual's psychophysical and operational status, and evaluate their cooperation while dealing with tasks are typically based on expert supervision (e.g. briefing and de-briefing), self-reports, or performance statistics [1]. These measurements are highly operator-dependent (who may be prone to personal experience, cognitive, and emotional biases), require interrupting the execution of tasks (i.e. invasiveness and low temporal resolution), and do not include information related to team members' cognitive demand and emotional profile (i.e. paucity of user's insights). It is therefore clear how these measurements alone cannot be used to accurately and properly assess the members of a team and consequently their teamwork. Neurophysiological measures (Electroencephalogram – EEG, Electrocardiogram – ECG, Electrodermal Activity –EDA, Electrooculogram - EOG) have gained momentum in different research and operative areas, and represent an objective, unobtrusive, and a powerful tool to determine user's affective-cognitive state on the basis of mind-body relations [2]. Coherently with this aspect, Industries and Defence started to be very interested in evaluating cognitive and emotional aspects together with skills acquisition since this kind of insights provide additional values for user's assessment, management, and safety [3]. Additionally, although teamwork (cooperation) is crucial in the operational contexts, objective methodologies, procedures and objective index to evaluate its dynamics and effectiveness are still missing. In this regard, Human Factor (HF) refers to psychological concepts linked to cognitive and emotional processes such as mental workload, attention, stress and so on, characterizing and affecting individual behaviour at work [4]. The computation of synthetic neurophysiological measures, called hereafter *neurometrics*, for the investigation of HFs may radically change the entire field of single-operator's cognitive states and team assessment in multi-domain defence contexts. The need and importance of having a tool able to combine different data and continuously monitor the single-operator's cognitive states and team members' cooperation level has been also highlighted in a recent review [5]. In this perspective, the proposed work aims at employing machine learning (ML), hyperscanning techniques, and multivariate autoregressive (MVAR) models for developing an entirely new way of obtaining real - time insights of each operator's cognitive states and measuring their teamwork (cooperation) based on advanced neurophysiological data processing. In fact, recent works [6], [7], [8] on cooperation evaluation are based on conventional hyperscanning technique which requires perfect raw EEG signals (time series) synchronisation (ideally the data must be recorded by the same device)therefore its employment in real contexts is not possible, especially when the team has many members.

In line with the 2022 theme of the Operations Research and Analysis (OR&A) "New ideas, old realities", the preliminary results presented in this work demonstrate the capability and reliability of the methodology developed for analysing in real-time operators' neurophysiological signals and assessing both single-pilot's mental states and crew cooperation while dealing with realistic tasks. The application of our multimodal approach and methodology is fully transversal and can be employed in any defence domain where the concept of operators' cognitive superiority must be tackled and objectively assessed.

2.0 MATERIALS & METHODS

2.1 Participants and Experimental Protocol

Two flight crews took part at the experimental protocol at the training pilot school "UrbeAero" (Rome, Italy). In particular, a crew of Experienced (EXP, i.e. working for a commercial airline) and a crew of Unexperienced (UNEXP, i.e. just got the integrated ATPL license) pilots were asked to perform the same flight simulations on the Mechtronix Ascent XJ Trainer Boeing 737-800 simulator. The experimental protocol consisted in three main phases. In the first phase each pilot performed an approach and landing under limited visibility condition (*calibration* phase), while in the second and third phase each crew performed flight missions (*operational* scenarios) aimed at, respectively, inducing a high mental workload demand, and requiring high level of teamwork. In particular, the high mental demand was created by a failure on the flaps, while the teamwork condition by injecting a failure on the landing gears during the approach phase. At the end of each flight mission, the pilots provided their subjective assessment of their own mental workload demand, and cooperation level by a Visual Analog Scale (VAS). An instructor supervised all the activity and provided subjective assessments of the pilots' mental workload and teamwork (cooperation) by a rating scale on a tablet (Figure 1). Additionally, the pilots' brain activity (Electroencephalogram – EEG) was acquired during the flight missions. Before the experiment, each participant was informed about the purpose and contents of the study and provided written informed consent.

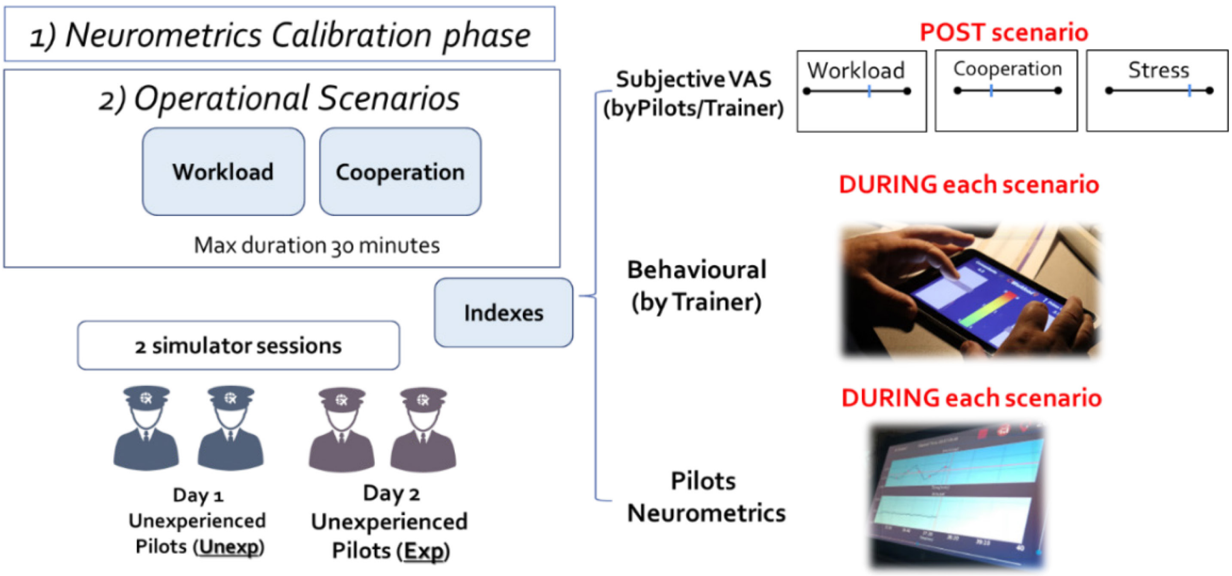

Figure 1: Experimental protocol. The flight crews performed the same flight simulations, and the subjective, behavioural, and neurophysiological data were collected during the missions. An instructor supervised the flight simulations and provided subjective assessment of pilots' mental workload and teamwork (cooperation) level.

2.2 Neurophysiological Data Recording and Analysis

The pilots' EEG signal was acquired by the Mindtooth touch [9] water-based EEG system with a sample rate of 125 (Hz) and from the following brain channels: AFz, AF3, AF4, AF7, AF8, Pz, P3, and P4. The EEG was firstly band-pass filtered with a fifth-order Butterworth filter in the interval 2–30 Hz. The blink artefacts were detected by means of the Reblinca method [10] and corrected by leveraging the ocular component estimated through a multi-channel Wiener Filter (MWF). EEG signals were segmented into epochs of 1 s, and the threshold criterion (±80 μV) was applied for artifacts rejection.

2.3 Mental Workload Index Definition

Measurement of mental workload represents the quantification of mental activity resulting from performing a task. Several empirical investigations have indicated that performance declines at the extremes of the workload demand continuum - that is when the event rate is excessively high (*overload*) or extremely low (*underload*). For these reasons, the mental workload is an important and central construct in ergonomics and human factor research. The brain electrical activities fundamental for the mental workload evaluation are the theta and alpha EEG rhythms, in particular on the *Pre-Frontal Cortex* (PFC) and the *Posterior Parietal Cortex* (PPC) regions. The theta rhythm, especially over the PFC, presents a positive correlation - i.e. increases when the mental workload increases, while the alpha rhythm, especially over the PPC, presents an inverse correlation - i.e. decreases [11]. The workload index was calculated by using the *automatic stop Stepwise Linear Discriminant Analysis* (asSWLDA) machine learning-based algorithm [12].

2.4 Cooperation Index Definition

The pilots' cooperation (teamwork) can be seen as the output of a multivariate system composed by the interaction between behavioural, affective and cognitive mechanisms belonging to the two pilots. The measures we are referring to are the neurophysiological synchronous time-series describing the affective and cognitive state of each pilot. If any sample of the time series thus obtained was missed due to the artefacts rejection phase, the missing value was found from a spline interpolation of the nearest epochs. Finally, each time-series has been normalized. To explain the interactions between the different components of the system the Mutual Information has been computed. The Mutual Information allows for discovering the maximum information shared between two random variables even multivariate [13]. In this case each variable includes the two different time-series describing the affective and cognitive state of pilots cooperating. It has been already proved that there is a statistical relationship between cooperation effectiveness and the exchange of information between variables: higher mutual information values are associated to enhanced cooperation [14]. Therefore, the cooperation (teamwork) index has been obtained computing the Mutual Information between the pilots' brain activity (EEG signals) on time buffers of 90-sec length and one-sec shifted.

2.5 Correlations

Pearson correlation analyses were performed between the mental workload and cooperation indexes (*neurometrics*) with the pilots' and instructor's subjective assessment to assess if there were any relations between the two kinds of assessment.

3.0 PRELIMINARY RESULTS

3.1 Mental Workload Evaluation

The EEG-based mental workload index allowed us to keep monitoring both the EXP and UNEXP's mental workload for the whole flight scenario (Figure 2). The Spearman analyses between the mental workload index and perception of the instructor returned positive (all $R > 0.6$) and significant (all $p < 0.05$) correlations for each pilot (Figure 2). In particular, the subjective assessment of the instructor and the EEG-based mental workload index of both the EXP and UNEXP showed similar trends along the flight simulation. However, the advantage of using the EEG as unintrusive mean to track and assess the pilots' mental workload without interrupting their activity and asking an extra task (i.e. providing mental workload ratings) is clear. Also, neurophysiological-based pilots' cognitive states monitoring could be used to adapt in real-time the scenario and take the pilots (or operators) to extreme conditions and better tailor their cognitive and operational training.

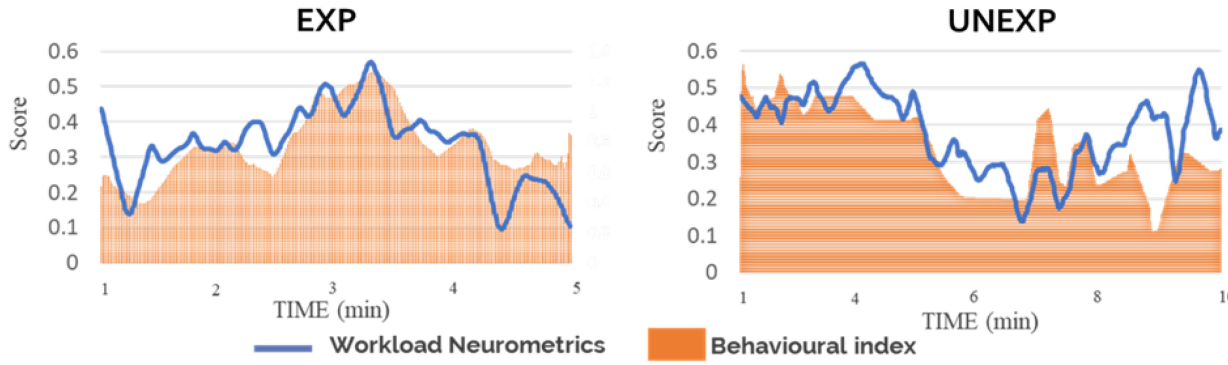

Figure 2: Mental workload index (blue line) and subjective assessment (orange bars) provided by the instructor overtime for the EXP (left panel) and UNEXP (right panel).

3.2 Cooperation Assessment

Figure 3 shows the capability of the proposed method to track and assess the degree of the crews' cooperation (teamwork) while dealing with the flight simulation. In particular, the pilots' cooperation indexes are reported by the green lines, whereas the subjective assessments provided by the instructor by the orange lines for the EXP (left panel) and UNEXP (right panel). When the crew's teamwork was significantly higher than a statistical threshold, estimated separately for each crew based on the *solo* condition, the time portions were highlighted in green colour. It has to be noted the higher number of green areas exhibited by the EXP than the UNEXP.

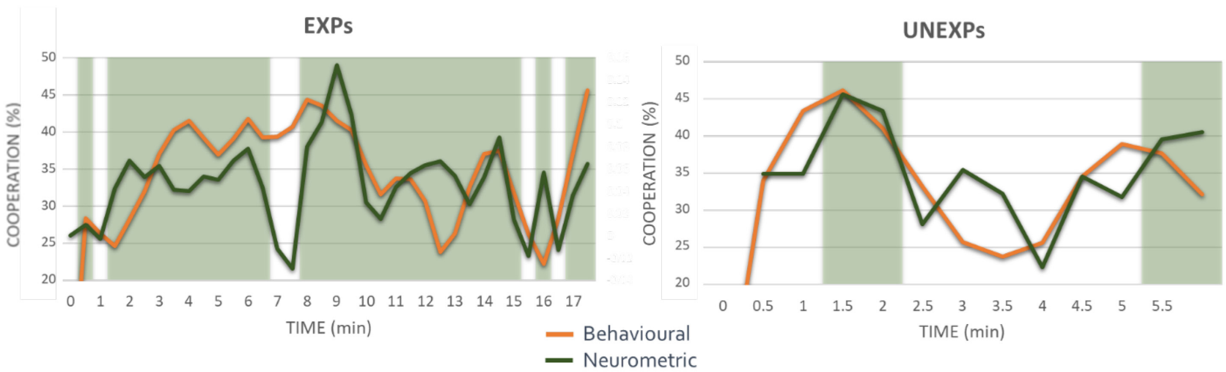

Figure 3: Cooperation index (green line) and subjective assessment (orange lines) provided by the instructor overtime for the EXP (left panel) and UNEXP (right panel). The green areas indicate when there was cooperation.

In particular, the quantification of the percentage of time during which the teamwork (cooperation) index was above the threshold showed how the EXP crew was able to maintain a proper cooperation for most of the scenario (85% of the time) with respect to the UNEXP crew, that was able to properly cooperate just for the

33% of the scenario (Figure 4). This result demonstrates how the teamwork of experienced pilots was significantly higher than unexperienced ones, and this could radically change the outcome, thus safety, of the mission, especially under extreme or emergency conditions. The capability of objectively measure the teamwork could be employed to identify the best crews in terms of cognitive cooperation, and adapt the training programs to optimise cooperation strategies, for example, when dealing with new procedures or under specific situations.

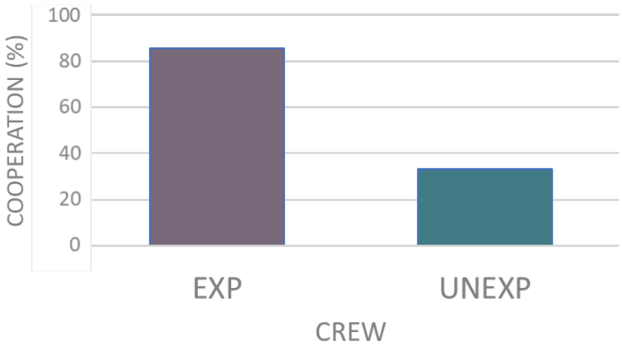

Figure 4: Averaged cooperation index of the EXP (purple bar) and UNEXP (green bar).

4.0 CONCLUSIONS AND DEFENCE APPLICATIONS

Although the preliminary results have been derived from only two pilot crews, they demonstrate the capability and reliability of neurophysiological signals-based methodology to provide real – time objective data on the operators' cognitive states and cooperation while dealing with tasks with respect to conventional methods. In fact, conventional measures for cooperation (teamwork) assessment still rely on subjective measurements derived from external supervision or questionnaire. The advantage in terms of invasiveness (task interruption), quantification (objective data) and time resolution is therefore clear. The correlations between the subjective and neurophysiological assessment further demonstrate the reliability of the method. However, the advantage of having a tool able to keep collecting data without interfering with the execution of the tasks and interrupting the operators is very clear, especially in defence contexts. The employment of neurophysiological signals will completely change the way the operators are trained, and the instructors tailor and manage the training program. In fact, neurophysiological-based data allow for an innovative and more accurate tool for assessing the operators' cognitive and emotional states, and their teamwork. This aspect can therefore be used to better tailor training programs for improving the cognitive capability and skills of single-operators and optimise the teamwork under specific conditions and when learning new procedures for defence applications. The experimental campaign is still ongoing, and the proposed methodology will be validated on a larger pilots sample size to further improve its capability and reliability.

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