Using near infrared spectroscopy and heart rate variability to detect mental overload

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Abstract

Mental workload is a key factor influencing the occurrence of human error, especially during piloting and remotely operated vehicle (ROV) operations, where safety depends on the ability of pilots to act appropriately. In particular, excessively high or low mental workload can lead operators to neglect critical information. The objective of the present study is to investigate the potential of functional Near Infrared Spectroscopy (fNIRS) – a non-invasive method of measuring prefrontal cortex activity – in combination with measurements of heart rate variability (HRV), to predict mental workload during a simulated piloting task, with particular regard to task engagement and disengagement. Twelve volunteers performed a computer-based piloting task in which they were asked to follow a dynamic target with their aircraft, a task designed to replicate key cognitive demands associated with real life ROV operating tasks. In order to cover a wide range of mental workload levels, task difficulty was manipulated in terms of processing load and difficulty of control – two critical sources of workload associated with piloting and remotely operating a vehicle. Results show that both fNIRS and HRV are sensitive to different levels of mental workload; notably, lower prefrontal activation as well as a lower LF/HF ratio at the highest level of difficulty, suggest that these measures are suitable for mental overload detection. Moreover, these latter measurements point towards the existence of a quadratic model of mental workload.

Keywords

NIRS, HRV, mental overload, human factors, remotely operated vehicle

1. Introduction

Remotely operated vehicle (ROV) operations are becoming increasingly prevalent in a wide variety of contexts such as border security, intelligence and military operations. Undeniably, the use of ROVs in the military has increased tremendously over the last decade. As noted by Cooke [1], the term “unmanned” that frequently qualifies ROVs can be misleading. Indeed, these systems involve a strong human-in-the-loop component for which the capacity could – and should [2][3] – be improved above and beyond the capacity of fully automated systems. There is a critical need to improve human-machine interaction within ROV systems given that issues relating to human factors are responsible for a large proportion of ROV accidents. For instance, a document prepared for the Office of Aerospace Medicine in the United-States reports that human factors-related deficiencies are responsible for between 21% and 67% of ROV accidents in the US Army, Navy and Air Force [4]; while for accidents in manned flights, this rate rises to 80% [5].

Descriptive models have been proposed to identify latent causes of accidents [6][7], and a large volume of research has highlighted the deleterious effects that high mental demands can have on operator performance [8][9][10]. In such conditions, pilots and ROV operators must perform several tasks simultaneously, each with different priorities. It is well known that humans are cognitively bounded, insofar as human mental resources are fundamentally limited [11][12]. Consequently, allocating more resources to a task will inevitably limit the amount of resources available for other tasks. Moreover, as these environments are highly dynamic, priorities across tasks will be expected to change as the mission develops. It is therefore important for the operator to reallocate mental resources dynamically according to changes in task priorities [13], but dynamic reallocation poses a challenge for the limitations of human cognitive control.

Excessive mental workload can eventually lead to the phenomenon of cognitive tunneling, which can be defined as the inability of the operator to reallocate his/her attention from one task to another [14]. Attentional resource reallocation lies at the heart of the operator functional state framework [15], where sustained performance is assumed to be determined in part by the cognitive potential of the operator in relation to task goals and priorities. According to this framework, operators placed in highly demanding tasks will be able to sustain a good level of performance as long as the task remains predictable, but will fail to perform well in the event of an unexpected change. It is possible that this vulnerability period – when the operator may not be able to adapt to changes in task priorities – could be detected by assessing his/her functional state, or more precisely, the level of mental workload.

Our approach to tackle research issues related to mental workload in a systematic manner is to merge knowledge and methods from cognitive psychology, system engineering and neurosciences. This approach known as Neuroergonomics – initially proposed in 1998 by Parasuraman and progressively developed and refined over the last decade or so [16][17][18] – aims to design systems for safer and more efficient operations through the understanding of human brain functioning in the workplace. Two key neuroergonomics concepts, adaptive automation [19][20][21] and cognitive counter-measures [22], are of particular relevance to our research endeavor. Adaptive automation and cognitive counter-measures are well suited to solving the problem of resource allocation; however, challenges in the implementation of these potential solutions still remain. In particular, a critical aspect of an adaptive support system is to provide help in a timely and accurate manner [23], specifically during periods of high vulnerability. Indeed a key issue is to investigate how mental workload and especially mental overload can be predicted in an operational context.

A possible approach is to use psychophysiological measurements as these techniques offer continuous and objective assessment of the human operator's state that is complementary to classical behavioral performance assessment (e.g., reaction time). The rationale behind the use of psychophysiological measures in assessing mental workload is also related to the well-documented relationships between behavioral performance and the activity of the nervous system. However, the use of behavioral measures alone in automated systems is very constrained due to the rare occurrence of the human operator's overt responses. Moreover, the reallocation of cognitive resources may mean that performance remains constant, thus limiting the sensitivity of such measures to mental overload.

The shift from low to high mental workload may be revealed by changes in activity of the autonomous nervous system (ANS) and can be associated with higher pupil size [24] or heart rate [25]. ANS activity can also be assessed through heart rate variability (HRV) which comprises two components, known as sympathetic and parasympathetic nervous systems. For instance, Kamath et al. [26] associated low frequency (LF) variability of heart rate with blood pressure control, i.e. sympathetic activity; and high frequency (HF) variations with respiratory sinus arrhythmia, i.e. parasympathetic activity. On this basis, the study of LF/HF ratio of heart rate variability provides a reliable indicator of mental workload [27][28][29].

Neuroergonomics also promotes the use of various brain imaging techniques, as they provide a prediction of mental workload by assessing central nervous system activity. It is now well established that mental workload is positively correlated with cerebral activity of dedicated brain areas such as the prefrontal cortex (PFC) [30]. For this purpose, functional near infrared spectroscopy (fNIRS) is an optical brain monitoring method that measures hemodynamic response, based on a modified Beer-Lambert law. It has a good spatial resolution ($1cm^2$) and provides a good correlation with fMRI studies [31]. Moreover it is suited for both laboratory and field experiments as the technique is easy to use in terms of sensor placement, participant mobility, and data collection/analysis. fNIRS has been successfully used to detect changes in oxygenated hemoglobin concentration associated with mental workload variation in operational contexts such as piloting ROVs [32], airplanes [33], or air traffic control tasks [34]. It is already known that fNIRS is sensitive enough to detect a variety of cognitive states such as working memory demands [35], emotional stress [36] or response inhibition [37][38].

Detecting a state of mental overload is a key issue for developing adaptive systems that have been shown to improve human-machine interactions [22][2]. However, these systems should not be based on the assumption that the ANS and central nervous system (CNS) reach a maximum or "saturation level" when workload exceeds mental capacity. Indeed, some authors postulate that mental capacity follows a quadratic law [39] similar to the Yerkes and Dodson inverted U-shaped curve [40], whereby the drop in performance resulting from task overload is associated with a decrease in dorsolateral PFC (DLPFC) activity. Though these results appear promising, there is still debate as to whether this cerebral disengagement could also be explained in terms of motivational issues [41]. However, this important issue has rarely been addressed from Neuroergonomics and Human Factors points of view, as most of the previous studies on mental capacity and disengagement used basic working memory tasks to induce mental overload rather than more complex and ecological tasks.

1.1. Present study

The objective of the present study is to explore CNS and ANS responses when mental capacity is exceeded in a realistic, engaging ROV task. In our attempt to reproduce those conditions that induce mental overload for pilots and ROV operators, we took care to preserve ecological validity whilst using a well-controlled laboratory protocol. We designed a simulation of a ROV operation task that specifically involved psychomotor and working memory (WM) abilities, as several studies have shown these cognitive functions to be highly correlated with complex task performance [34][42][43][44]. Specifically, the volunteers were asked to perform a computer-based task in which they had to follow a dynamic target with their aircraft under different levels of control difficulty and processing load. In all conditions, the participant had to identify the target aircraft amongst five potential distracters by using a Stroop-like cue. In order to increase mental demand further, participants – as would be the case in real operations – had to respond to an auditory warning signal. Mental workload was assessed according to behavioral response (i.e. task accuracy), fNIRS and Electrocardiogram (ECG) measurements, and self-report scales.

2. Materials and methods

Twelve volunteers participated in the study (mean age = 25; SD = 5.25; 10 males). Ten were right-handed. The volunteers were fully informed about the experimental protocol, and informed consent was obtained before participation. They were given financial compensation for their part in the study.

The ECG data of one participant was removed from analyses due to problems with data collection. All volunteers reported normal or corrected vision. They were all native French speakers recruited among students from the ISAE campus in Toulouse, France. Participants performed the computer based ROV operation task, with varying levels of control difficulty and processing load.

2.1. Task

The experimental setting was designed to reproduce at a functional level the requirements associated with piloting. Two factors (control difficulty and processing load) were manipulated to generate different levels of workload. This approach allows the reproduction of key features of the real-world task while keeping a high degree of experimental control [45]. The computerized simulation involved the control of an aircraft with a joystick from a bird's-eye view.

The subjects were instructed to follow a target aircraft with the piloted one, by minimizing the distance between them. Visual stimuli were presented on a DELL 21" monitor placed one meter from the participants. The own aircraft was located at about 24cm from the left of the screen, while potential target aircraft were moving approximately 2cm to 4cm from the left. The target aircraft was indicated to the subject by a visual cue presented on the right-hand side of the screen (approximately 38cm from the left). The cue selection rule was inspired by the Stroop paradigm in order to reproduce high-level cognitive functions such as inhibition and cognitive control, which are deemed critical in piloting operations [46]. A cue consisted of a color name written with red, blue, green or yellow ink. The color name and the ink color were pseudo-randomly chosen so that they could either be congruent or incongruent. Target aircraft had a color name written on their wing, and participants were asked to follow the plane corresponding to the ink color of the given cue. Moreover, 20 percent of the cues contained a word which was not a color name (e.g., "read", "grin"…). In these cases, the participants were asked to follow the unnamed plane (regardless to the color of the ink). A new cue was presented for 1.6 seconds every 8.6 seconds. The interval between two presentations is referred to as an "object tracking phase".

Participants completed four experimental sessions resulting from the manipulation of two levels within two factors: **difficulty of control** and **processing load**. There were two levels of difficulty of control (easy or hard) manipulated by varying the strength of the crosswind (no crosswind in the easy condition, strong crosswind in the hard condition) and the inertia of the plane (low *vs.* high). The processing load was varied in terms of working memory, with an N-Back-like sub-task. It has been shown that processing load can be varied by manipulating the value of N, which is the number of items to be maintained and manipulated in working memory [41]. Subjects had to target the aircraft corresponding to the last cue presented (N; low load condition) or the cue before (N-1; high load condition). The combination of the two factors yielded a 2 × 2 repeated-measures design with four conditions: low load/easy control; low load/hard control; high load/easy control; and high load/hard control.

During the experimental sessions, participants also had to stop a randomly-initiated auditory alarm, by pressing a button on the joystick. Before the start of the experiment, subjects were taught to recognize a 2000ms duration, and were asked to stop the alarm 2000ms after it began. A screen capture of the task is presented in Figure 1.

2.2. Procedure

Participants were first trained in the piloting task. The training session consisted of 10 object tracking phases for each processing load level, and was performed at both the easy and difficult levels of control.

After the training session, participants performed the four experimental sessions consecutively, which were counterbalanced across participants. Each session comprised 40 object-tracking phases and lasted approximately six minutes. During each session, hemodynamics of the PFC (i.e. inferred by variations of the oxygenation level) was recorded at a sample rate of 2Hz using the functional near infrared spectrometer fNIR100 (Biopac®) equipped with 16 optodes, and the acquisition software COBI Studio®. Each optode records hemodynamics of the prefrontal cortex in terms of oxygenation level variations in comparison to a baseline. Optode localization is shown on Figure 2. Heart rate data was recorded at a sample rate of 2048 Hz using the Biopac® electrocardiograph. Participants filled out the NASA-TLX (i.e. subjective workload) after each session, and general information concerning the participants' feelings and strategies used were collected at the end of the experiment.

2.3. Data Analyses

For each optode, fNIRS data (HbO2 concentration relative to a 10-second baseline) was normalized, and mean HbO2 concentrations for each condition were calculated over the session, using MatLab®. Visualization of the data was performed using fnirSoft professional edition®. Using ECG data, mean LF/HF Ratio was estimated over each session using Fast Fourier Transformation (FFT) of the ECGLAB toolbox for MatLab®. Using the distance between the piloted and the target planes, we could determine whether or not the operator followed the correct plane; that is, during any particular object tracking phase, when the mean distance between the piloted plane and the target exceeded 3.1 times the wingspan of the planes, an error would be recorded for that phase. A performance score was then computed for each tracking task over the experimental session.

Repeated-measures ANOVAs with within subjects factors '*processing load*' (low vs. high) and '*control difficulty*' (easy vs. hard) were carried out to test whether the effects of control difficulty and processing load were statistically significant on the different measures (heart rate variability, HbO2 concentration on each optode, object tracking performance, and NASA-TLX for global workload index and for each of the criteria).

3. Results

3.1. Performance on the aircraft tracking task

Performance on the object tracking task (success rate of planes followed correctly) is shown in Figure 3. A repeated measures ANOVA showed a significant decrease in success rate with processing load, $F(1,11) = 50.69$, $p < 0.001$, and with control difficulty, $F(1,11) = 5.55$, $p < 0.05$. This effect corresponded to a lower success rate for high processing load and for hard control difficulty. Moreover, there was a significant interaction $F(1,11) = 4.85$; $p < 0.05$, revealing a decrease in performance with high processing load compared to low, but only within the hard control condition.

3.2. Subjective Load

The ANOVA conducted on the NASA-TLX data revealed significant main effects of processing load, $F(1, 11) = 25.01$, $p < .001$, and difficulty of control, $F(1, 11) = 4.70$, $p = .053$, indicating higher perceived load with high processing load and high control difficulty. However, the two-way interaction was not significant, $F(1, 11) < 1$. Mental demand ($p < 0.001$ with Bonferroni-Holm correction for multiple testing) and Frustration ($p < 0.05$) dimensions were the most affected by the increase in task difficulty. Figure 4 shows how variations of experimental parameters affect perceived mental load.

3.3. Mean oxygenation

A main effect of control difficulty $F(1,11) = 5.82$; $p < 0.05$ was observed on optode 6, showing an increase in the level of HbO2 with an increase in piloting difficulty. A significant two-way interaction was also visible on optode 3 $F(1,11) = 5.11$; $p < .05$, revealing an increase in HbO2 concentration for the higher processing load in the easy control condition, but a decrease for high processing load in the hard control condition. The result is shown in Figure 5 for optode 3, located in the left dorsolateral prefrontal cortex. Although the effect is significant only on optode 3, the same tendency of variation is visible on all optodes in the right and left dorsolateral prefrontal cortex (see Fig. 6 for the data from all optodes).

3.4. Heart rate variability

Average LF/HF ratio for each session was extracted from ECG data. Figure 7 shows average LF/HF ratio under each experimental condition. The ANOVA revealed no main effect of control difficulty or processing load ($F(1,10) < 0.5$ for both factors), but a significant two-way interaction $F(1, 10) = 9.45$, $p < .05$. Within the easy control condition, LF/HF ratio was greater with high than low processing load; however, at the high level of control difficulty, LF/HF ratio was then lower with the high than the low processing load. This result is consistent with the fNIRS results that demonstrated the same pattern; a decrease of average HbO2 concentrations for high processing load in the hard control condition.

3.5. Relation between the oxygenation level and performance

A correlation was computed between the data measured on optode 3 and performance on the aircraft tracking task during the hardest session (high processing load and high control difficulty), in which a dramatic drop in performance was observed. A significant correlation between these measurements ($r^2=0.52$, $p < 0.05$) suggested that subjects with a higher HbO2 ratio performed better on the tracking task. The linear fit is shown in figure 8.

4. Discussion and Conclusion

The objective of this study was to investigate mental workload, especially when mental demand exceeds cognitive resources. From a methodological point of view, fNIRS measurement was compared with subjective self-report and HRV, two well-established measures of mental workload. An experimental laboratory task was designed to artificially reproduce the mental demand of a real ROV operation.

The first issue of this study was to ensure that our laboratory task was sufficiently engaging to elicit different levels of mental demand. Subjective NASA-TLX scores demonstrated that subjective mental workload increased across experimental conditions, thus from the operators' perspective there were real differences in terms of frustration and mental demand across the different task conditions. Processing load and control difficulty both impacted upon aircraft tracking performance. Moreover, results suggest our task successfully involved high-level executive functions as changes in oxygenation level of some areas of the PFC were observed. First, control difficulty modulated oxygenation level in the optode 6 (close to the anterior medial PFC). This result is akin to Ayaz and colleagues' studies [32][34] that showed, with identical fNIRS apparatus, that supervising an aircraft's trajectory in an air traffic control task induces anterior medial PFC activation. Though we did not find a main effect of processing load on PFC activation, our results revealed that interactions exist between subsets of task difficulty as showed by changes in oxygenation levels of optode 3 within the left DLPFC. Again, our findings are similar to previous neuroimaging studies showing that this area is particularly sensitive to mental workload in controlled WM laboratory tasks [47][48][49][32][34] as well as ecologically valid tasks using ROV simulators [50][32].

Indeed, variation of oxygenation level in optode 3, a part of the left DLPFC, tended to follow the inverted U-shaped pattern: HbO2 concentration increased progressively across difficulty levels but then decreased significantly during the most difficult condition. This finding is particularly interesting given that the DLPFC is considered to be a major anatomical correlate of the central executive [51], a region that plays a key role in task supervision and cognitive control [52]. This decline in DLPFC activity corresponded to the poorest performance, and was associated with the highest subjective mental load and the strongest feelings of frustration (during debriefing participants stated that the task in this condition could barely be performed). Taken together, these results suggest that the volunteers were unable to mobilize cognitive resources despite task demand, and may have faced mental overload. The correlation between left DLPFC activity and performance showed that this was particularly true for some of the participants, as those with the lowest levels of activation exhibited the poorest performance during the hardest experimental condition. This pattern of DLPFC lower activation associated with deleterious effects on performance has previously been observed using fMRI or EEG during highly demanding [39], stressing [52] and emotional conditions [53][54][55]. The pattern revealed with fNIRS is similar to previous results obtained with more fundamental cognitive tasks manipulating WM load [56][57].

A possible explanation of the pattern observed on hemodynamics is related to the role played by memory updating in multitasking [58]. Indeed, as stated by Wickens [59] "*the resources on which this updating activity depends seem to be limited in their availability, and, when deployed in the service of one task, their availability to be of service to other tasks is reduced"*. Along these lines, load sensitive brain areas have been shown to elicit either transient or sustained activations over time; a pattern that is often taken to suggest a distinction between areas involved in active maintenance and those involved in time-limited cognitive activities such as memory updating [60][61][62]. Thus, the possible role of the dorsolateral prefrontal cortex in transient activations during multitasking [62] could explain the decline of its activity during the most difficult condition in our experiment. However, the implication of the DLPFC either in the maintenance of information [60][61] or in updating

[62][12] remains uncertain. Further work is required to investigate whether activations observed in the DLPFC were induced sustainably or transiently. The observed inverted U-shaped pattern of DLPFC activity in response to increased mental workload could also be explained by the fact that this study manipulated task difficulty to the extent that it exceeded participants' mental resources. Although it could be argued that this apparent disengagement reflects a lack of motivation leading the participant to somehow abandon the task [41], in our experiment, the volunteers were constantly attempting to adjust the aircraft trajectory even in the most difficult condition. Moreover, it is worth noting that HRV, assessed through the LF/HF ratio, followed a similar pattern with a significant decrease during the hardest condition. This diminished influence of the sympathetic nervous system on the ANS suggests reduced catabolic activity and lower mobilization of mental resources to deal with the situation [63]. As this ratio is known to be a reliable indicator of mental load [27][28], this measure provides supplementary evidence to our fNIRS findings in favor of a deleterious mechanism on resource management induced by mental overload. Such a pattern of physiological response to mental overload has already been observed on other physiological responses such as pupil diameter [64][65], suggesting a change in ANS action to face mental overload. Moreover, it tends to confirm that mental overload could result from a lower level of both cerebral and ANS activities. Interestingly enough, and although no correlation between HRV data and PFC modulation was found here, it is worth noting that such correlations between cardiac metrics and prefrontal neuroimaging data have been found previously [66][67]. Indeed, these results provide a direct observation of the interactions between the PFC and cardiac activity as postulated by previous studies [68][69], although our results do not allow us to determine whether these interactions are mediated by a common factor, or whether there is a causal link between neural and cardiac activity. Thus, this study shows the usability of fNIRS to conduct experiments and the possibility of using complementary behavioral (cognitive) and physiological measurements to derive the operator's functional state.

Ultimately, the fact that high perceived mental load could be associated with a related decline of the central and peripheral nervous systems might represent an issue for adaptive automation perspectives. Indeed, research on adaptive systems [70] aims to infer the human operator's cognitive state from different measurement techniques and then adapt the nature of the interaction to overcome cognitive bottlenecks [71]. In the case of our study, the analysis of the level of cardiac and prefrontal activities does not allow us to formally discriminate the easiest from the hardest condition. One should also consider that the complexity of the link between physiological factors and mental workload, as higher task demands are not necessarily associated with a higher mental workload. Similar findings have also demonstrated that mental workload cannot be estimated precisely with the sole properties of the task because individual factors (e.g., expertise [34]) or environmental factors [28], will impact on the mental effort deployed to perform a given task. Consequently, mental workload should be defined in terms of the interaction between the task and the individual performing the task [72]. This must be taken into account in the development of future adaptive automation by considering other measurements such as behavioral performance (e.g., operator's reaction time and actions on the user interface, eye movement) as well as the state of the global system (e.g., failure).

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APPENDIX : Figures

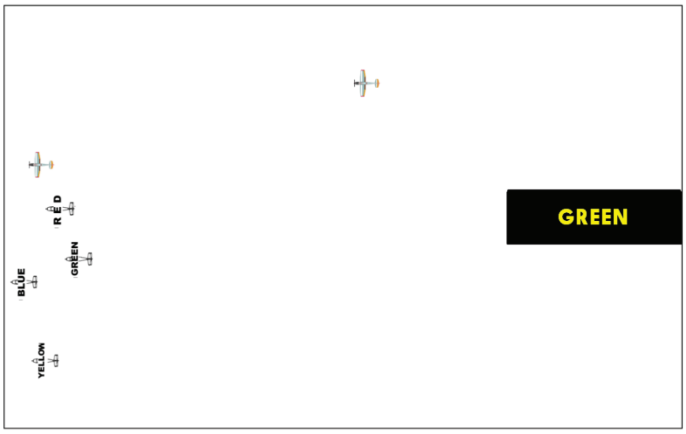

Figure 1. Screen capture of the task. On the top is the controlled plane. On the left side of the screen, the target planes. On the right side of the screen, in the black box, the instruction, consisting of a name written in one of the four colors present (red, blue, yellow, green). If the name written is a color-name, the participant is to follow the plane corresponding to the color of the ink. If the name written is not a color-name, the participant is to follow the fifth plane, on which no color is present.

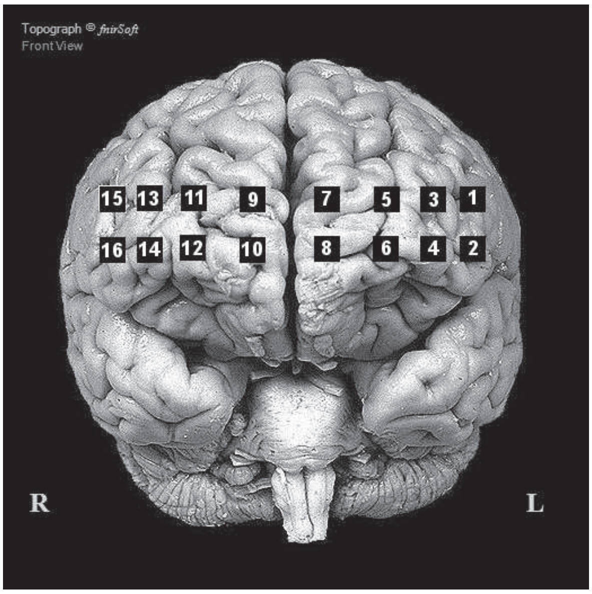

Figure 2. Optode localization of the Biopac® fNIR100 device. Adapted from fnirSoft® software for NIRS data analyses.

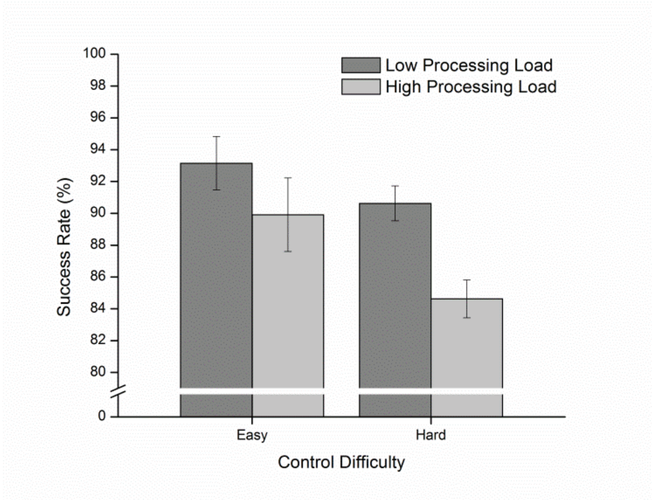

Figure 3. Performance on the aircraft tracking task across the four experimental conditions. The error bars represent the standard error of the mean.

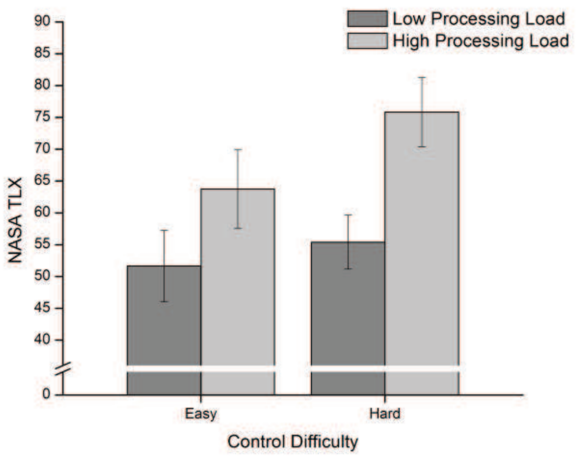

Figure 4. Mean NASA-TLX mental demand scores across the four experimental conditions. The error bars represent the standard error of the mean.

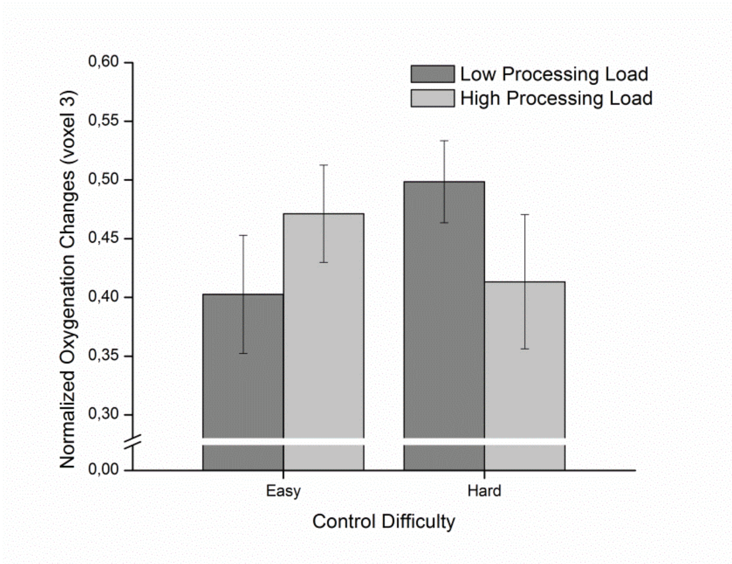

Figure 5. Normalized mean HbO2 changes across the four experimental conditions on optode 3. The error bars represent the standard error of the mean.

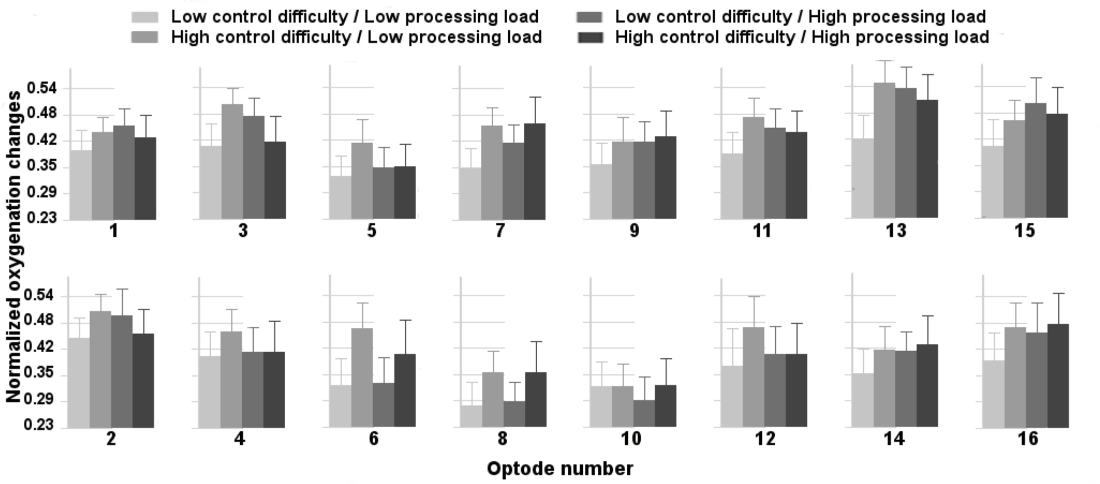

Figure 6. Normalized oxygenation data for each optode over the four sessions. The decrease in oxygenation during the last session, although being significant only at optode 3, is visible on many optodes, especially those in the dorsolateral prefrontal cortex (optodes 1, 3, 13 and 15).

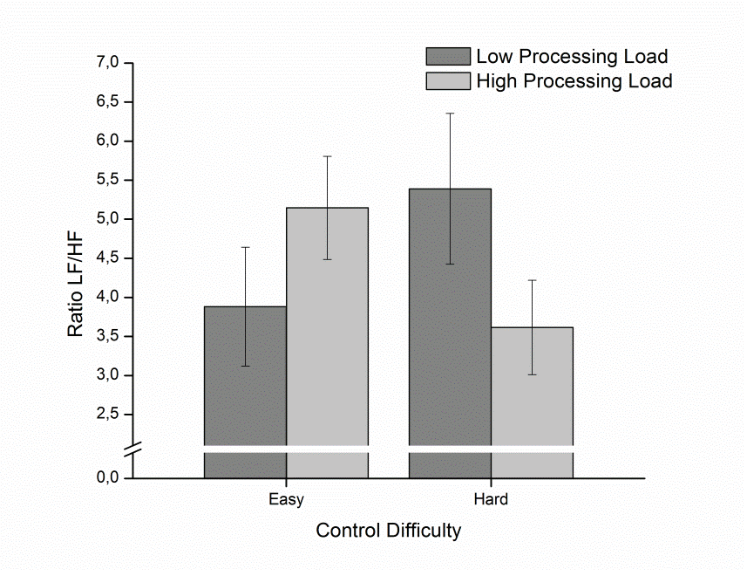

Figure 7. Average LF/HF Ratio across the four experimental conditions. The error bars represent the standard error of the mean.

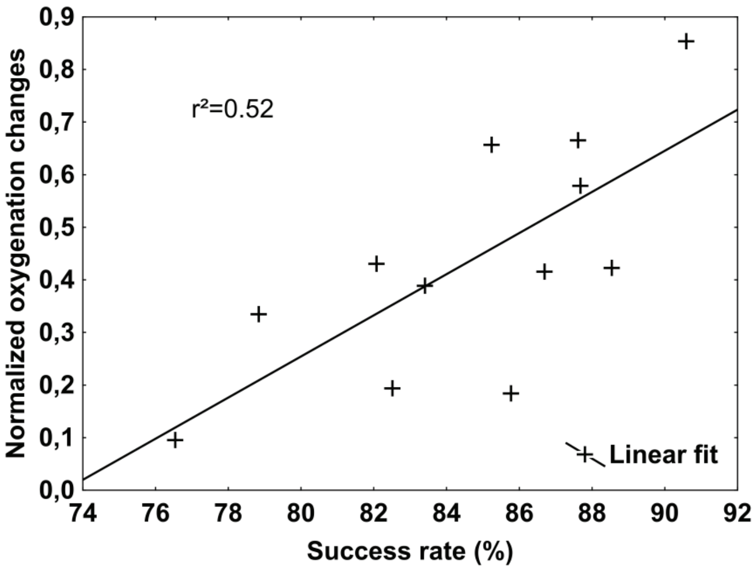

Figure 8. Correlation between task performance and normalized oxygenation changes on optode 3 under high processing load within hard control difficulty.