Operator Engagement During Prolonged Simulated UAV Operation

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Abstract: Unmanned aerial vehicle (UAV) operation is demanding in terms of attentional resources' engagement. As systems grow more automated, the operators are placed in long monitoring phases most of the time. Although UAV operators' fatigue state has been extensively assessed at the behavioral and oculomotor levels, to our knowledge there is a lack of literature regarding potential cardiac and cerebral markers. Therefore, this study was designed to investigate which markers of operators' engagement could be used for mental state estimation in the context of UAV operations. Five volunteers performed a UAV monitoring task for two hours without any break. The task included an alarm monitoring task and a target identification task using a joystick. Only ten alarms occured during the session, amongst which only seven required an identification from the operator. The investigated markers were of oculomotor (eye-tracking), cardiac (ECG) and cerebral (EEG) origin. In addidtion to a significant modulation of the alpha power, the blink rate and the number of fixations with time-on-task, the main results are a significant correlation of response times with both the cardiac Low Frequency / High Frequency ratio and the number of ocular fixations.

Keywords: UAV operators; Fatigue; Eye-tracking; ECG; EEG.

1. INTRODUCTION

Unmanned aerial vehicle (UAV) operating is a complex task performed in a dynamic and uncertain environment. During UAV operation, the human operator is often faced with difficult decisions that have to be made within a limited amount of time. However, and as the systems grow more automated (higher decision-making autonomy) the operators are requested to operate at irregular and very interspaced intervals (Cummings et al., 2013). Hence, they can be waiting in a very long and monotonous monitoring phase. Recently, the behavior and the attentional level of operators placed in such a task has been studied (Cummings et al., 2013; Mkrtchyan et al., 2012). These studies have shown that during prolonged missions, operators' performance decreases (e.g. increase in reaction time). These behavioral degradations are due to the occurence of mental states that seem relevant to estimate online in order to implement adaptive systems. Such biocybernetical systems could adapt themselves online to the operator's mental state in order to optimize its performance and increase operation safety in general.

1.1 Mental states and markers

Amongst the mental states that are of particular interest for monitoring monotonous tasks, mental fatigue and attentional resource engagement are crucial. They relate to increases in time-on-task (TOT), modulations of vigilance, and the occurrence of mind wandering. Attentional engagement fluctuates with time and decreases when mental fatigue increases. Mental fatigue is known to occur during and following long tasks that demand sustained attention like driving (Lal and Craig, 2002). It is characterized by a drop in performance. Hence, participants's reaction times increase almost linearly with growing time-on-task (Gale et al., 1977). The oculomotor activity is impacted by engagement and fatigue, with an increase in blink rate and blink duration (Morris and Miller, 1996). And the number of fixations are reported to decrease when the subjects disengage from the task at hand and perform mind wandering (Smilek et al., 2010).

As regards cardiac activity, this attentional disengagement is associated with an heart rate (HR) decrease and an heart rate variability (HRV) increase in the temporal domain. Moreover, the high frequency component of the frequential HRV increases and, depending on authors, the low frequency component decreases or increases (for a short review see Roy et al. (2013)). At the neurophysiological level, a decrease of engagement is characterized by an increase in power in electroencephalographical (EEG) low frequency bands such as the theta and alpha bands (Pope et al., 1995). Mind wandering is also known to elicit a higher power in very low frequency bands (i.e. delta and theta) and a lower power in higher frequency bands (i.e. alpha and beta) (Braboszcz and Delorme, 2011).

1.2 Towards neuro-adaptive systems

The main point in considering human operator's mental state is to perform an online interpretation of it that can be used to implicitely adapt the whole system. When concerned with cerebral markers, this biocybernetic loop (Fairclough, 2009) has recently been named passive brain-computer interface (BCI) by Zander and Kothe (2011). When these systems include additional measures such as cardiac and oculomotor measurements, the appropriate term is hybrid BCI (Pfurtscheller et al., 2010). In the context of UAV operations, the aim is to merge mental state measurements with the system state as well as the level of achievement of the mission, in order to, when a degraded state is measured, adapt the interface to relaunch the interaction (Talamadupula et al., 2014). In other words, a decisional framework, issued from the artificial intelligence literature, can for instance produce a plan (Talamadupula et al., 2014) or policy (Taha et al., 2011; Talamadupula et al., 2014) to handle such an adaptive interface's behavior, and in this sense, close the control loop as suggested by Pope et al. (1995).

As far as we know, research on operator-UAV interaction has mainly been conducted at the behavioral level (Cummings et al., 2013; Tessier and Dehais, 2012). Yet it has been proved possible to accurately estimate an operator's fatigue using multimodal information (i.e. cerebral, cardiac and oculomotor features) in a laboratory setting (Laurent et al., 2013). It remains to be evaluated whether these features are relevant in operational settings.

In this sense, the goal of this study was to evaluate the relevance of different mental fatigue markers extracted from different sensors in order to, in the future, perform an online evaluation of the engagement of operators that perform a UAV operation task during a prolonged period of time. The experimental protocol was carried on by five volunteers that performed an alarm monitoring task and a target identification task using a joystick during two hours without any break. This duration has been proved to be sufficient to reach the operators' maximal distraction state (Cummings et al., 2013). In order to put them in a monotonous setting, only ten alarms occured during the session, amongst which only seven required an identification. The investigated markers were of oculomotor (eye-tracking), cardiac (ECG) and cerebral (EEG) origin. With this experimental protocol, we expected to elicit performance degradations -in particular with increasing time-on-task- that would hopefully be correlated to several cardiac, oculomotor and cerebral markers.

2. METHODS

2.1 Participants

Five volunteers underwent the experiment (2 males; 24.6 years old - sd 2.6). All participants had a normal or corrected-to-normal vision. They were free of any medical treatment at the time of the experiment, and had no history of neurological or psychiatric disorder. Data acquisition was performed at the experimental facility of ISAE-SUPAERO (Toulouse, France).

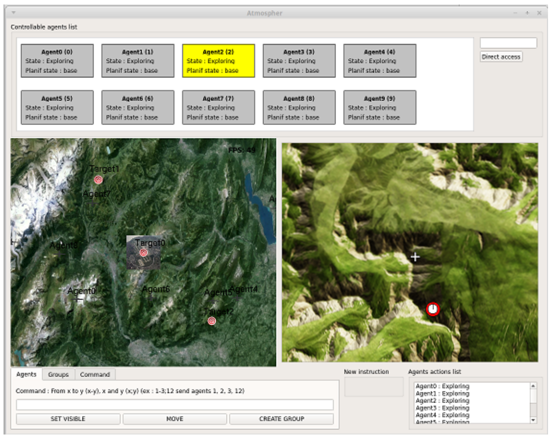

Fig. 1. Screen print of software Atmospher showing the yellow blink that announces the occurrence of a new target in the interface's right part.

2.2 Experimental protocol

The experimental protocol was implemented using Atmospher (Collart et al., 2015), a software simulating drone supervision. In this software, the participant has to monitor one UAV among ten. This UAV can end up in two situations that require an action from its supervisor:

- Identification task: The UAV is next to a target and must identify it. To that end, the participant must use a joystick to bring a reticle on the target's symbol. This situation is announced by the yellow blink of the UAV's button, which lasts for at most 30 seconds, and stops as soon as the participant moves the joystick (figure 1).

- Refuel task: The UAV's fuel level is starting to be low. The participant must then order the UAV to go back to base in order to refuel, or the UAV's default action (going on with the current mission) would risk totally emptying its fuel tank and bringing it to a crash. This situation is announced by the red blink of the UAV's button, which lasts for at most 30 seconds and stops as soon as the participant presses the Enter key on the numpad. At this moment, a decision pop-up appears and the participant must enter her decision using keys 1 (go back to base) or 2 (go on with the mission) of the numpad (figure 2). The participant is strongly encouraged to always choose 1.

During the whole experiment, the UAV's button can also blink in green for 5 seconds, but this signal does not require any response from the participant. The buttons standing for other UAVs may also blink in red or yellow for 30 seconds or in green for 5 seconds and do not require any response from the participant either.

2.3 Data acquisition

The experiment took place on mornings, from 9am to 12pm, in a room with low light. The participants sat on a chair in front of a computer screen, a joystick and a numpad. The screen showed only the window of the software Atmospher, with which they interacted through

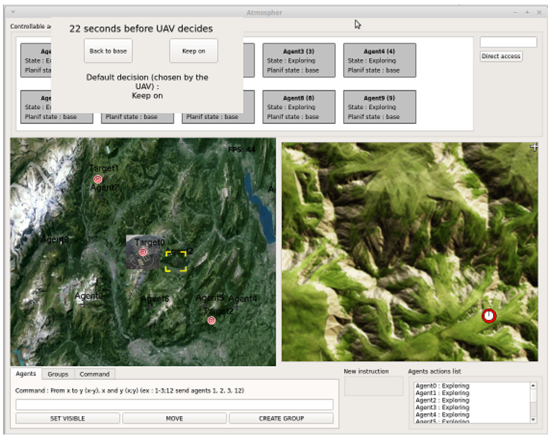

Fig. 2. Screen print of software Atmospher showing the decision to take about low fuel.

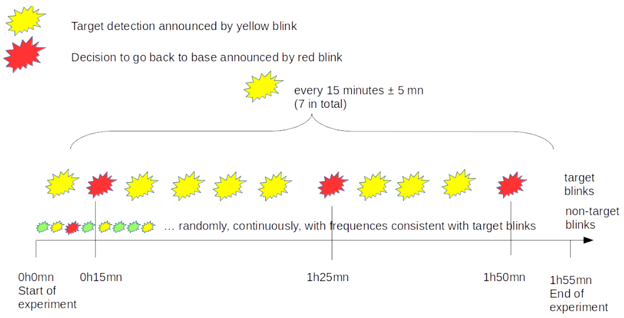

Fig. 3. Experimental protocol.

the joystick and numpad. They performed a 2-min training per task before the main task. They were asked to remove their watch and shut down their phones.

The participants reaction times (RTs) and accuracy to the identification and the refuel tasks were measured. In addition, participants mental fatigue elicited by time-on-task was measured before and after the experiment using the Karolinska Sleepiness Scale (KSS) (Kaida et al., 2006). They were also asked to rate their estimated engagement in both sub-tasks, at the beginning and at the end of the experiment on a 1-to-9 scale, and were asked whether they had had any non task-related thoughts.

Their oculomotor activity was recorded using an eye tracker (SMI RED250) placed under the computer screen. Moreover, their electroencephalographical (EEG) activity was continuously recorded using the BioSemi ActiveTwo system equipped with 32 Ag-AgCl unipolar active electrodes that were positioned according to the 10-20 system. Along with the EEG data, the electrocardiographical (ECG) activity of the participants was recorded using two electrodes positionned respectively on the sternum and at the 5^{th} intercostal space on the left of their body. Impedance was kept below 20 kΩ for all electrodes. The signal was sampled at 512 Hz. It was then band-pass filtered between 1 and 40 Hz using a 4^{th} order Butterworth filter, and re-referenced to the mastoids. Participants were instructed to limit their movements as much as possible. All data were kept for analyses.

2.4 Data analysis

First, repeated-measure analyses of variance (ANOVA) and Tukey post-hoc tests were performed on the behavioral measures (i.e. repsonse times and accuracy), the subjective ratings (i.e. KSS and engagement), but also on markers extracted from the signals that were recorded. Hence, from the eye-tracker were extracted the number and duration of fixations that exceeded 80 ms, as well as the number and duration of blinks, for each of our 6 Areas Of Interest (AOI; AOI1: agent 2; AOI2: other agents; AOI3: UAV flying visualization area; AOI4: reticule area; AOI5: out of preceding AOIs, but still on screen ; AOI6: out of screen).

From the ECG were extracted the heart rate (HR; instantaneous heart rate), the heart rate variability in the temporal domain (HRVT; sdann), both the low frequency (LF) and high frequency (HF) components of the heart rate variability on the frequency domain (i.e. respectively [0.04 0.15] Hz and [0.15 0.4] Hz), as well as their ratio (LF/HF).

Lastly, from the EEG data were extracted the power spectral density in three frequency bands: theta ([4 8] Hz), alpha ([8 12] Hz) and beta ([13 30] Hz) from 9 virtual electrodes computed by averaging the signal from 9 scalp regions (i.e. LF: left frontal; LC: left central; LPO: left parieto-occipital; RF: righ frontal; RC: right central; RPO: right parieto-occipital; MF: median frontal; MC: median central; MPO: median parieto-occipital).

In addition to the analyses of variance that were performed to assess the impact of factors such as time-on-task and area of interest, a matrix of Pearson's correlations was computed between all markers and response times. This analysis was performed to evaluate which markers reflected the best the participants' engagement as revealed by their behavioral performance.

3. RESULTS

3.1 Subjective & Behavioral measurements

All participants were kept for these analyses. Although in average they reported feeling more tired at the end than at the beginning of the experiment, the effect was not significant ($p = 0.13$). However, there was a significant effect of time-on-task on their engagement subjective evaluation ($F(1, 4) = 12.57, p < 0.05$) as they reported having been less engaged in both tasks at the end of the experimental session than at the beginning ($p < 0.05$). Moreover, it has to be noted that they all reported having performed mind wandering during the experiment.

Regarding the behavioral results (response time), there was no significant main effect of TOT on the refuel task ($p = 0.23$) nor on the reticule task ($p = 0.58$). This may be due to the presence of a great variance for the two last blocks. Indeed, two participants out of five had a drop in their response times, leading to say that they

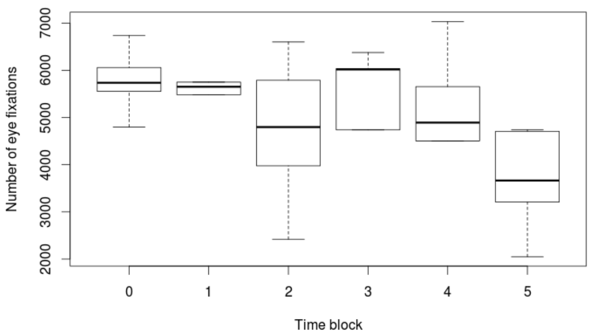

Fig. 4. Box plot of the number of fixations per time block.

might have had an increase in arousal at the end of the experiment. This is why we thought it appropriate to study the modulations of performance across time and performed next a correlation analysis.

3.2 Eye-tracking data

All participants were kept for these analyses. There was a significant main effect of TOT on the number of fixations that exceed 80 ms ($F(5, 20) = 5.47, p < 0.01$). The participants performed significantly more fixations at the beginning than at the end of the experiment (during the first 40 min compared to the last 20 min, $p < 0.01$; figure 4). There was also a significant main effect of the AOI ($F(5, 20) = 48.75, p < 0.001$). The participants performed significantly more fixations outside the screen than on the UAV flying monitoring area and the other areas ($p < 0.001$), and significantly more fixations on the UAV flying monitoring area than on the other areas ($p < 0.001$). Moreover, there was a significant interaction between TOT and the AOI ($F(25, 100) = 2.85, p < 0.001$). Indeed, there was a significant decrease in the number of out-of-screen fixations with TOT ($p < 0.05$). Although not significant, it is interesting to note the reduction in number of fixations on the relevant agent with increasing TOT (figures 5 and 6). This might reflect a habituation to the task or a change in strategy over time.

As regards the duration of fixations, there was only a trend for a main effect of the AOI ($F(5, 20) = 2.43, p = 0.07$). The participants had a tendency to perform longer fixations on the UAV flying monitoring area (AOI 3) than on other AOIs.

Although blink duration was not significantly impacted by TOT ($p = 0.38$), there was a trend for an effect of TOT on the number of blinks, that is to say on blink rate ($F(5, 20) = 2.18, p = 0.09$). The blink rate had a tendency to increase. Moreover, planned comparisons revealed that the quadratic polynomial was significant ($F(1, 4) = 8.95, p < 0.05$) while all others were not (linear $p = 0.12$, cubic $p = 0.30$, quartic $p = 0.78$, quintic $p = 0.61$) revealing an increasing and decreasing pattern consistent with an increase in arousal at the end of the session.

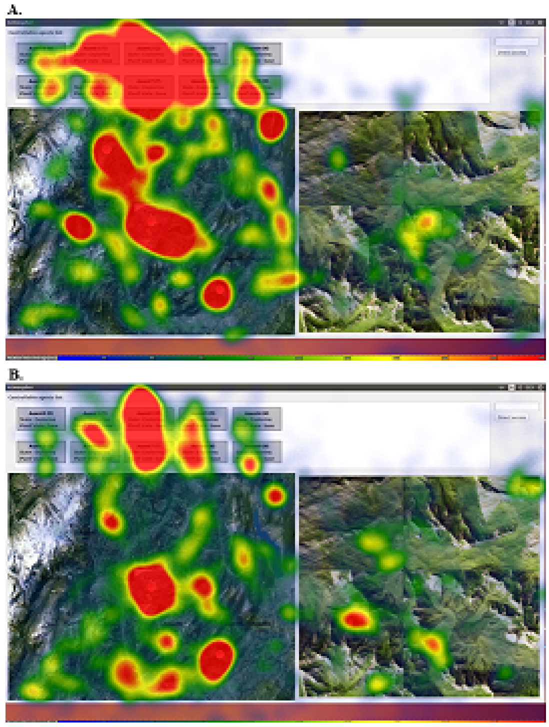

Fig. 5. Heat maps that illustrate the number of on-screen fixations for A. the first 20-min block, and B. the last 20-min block.

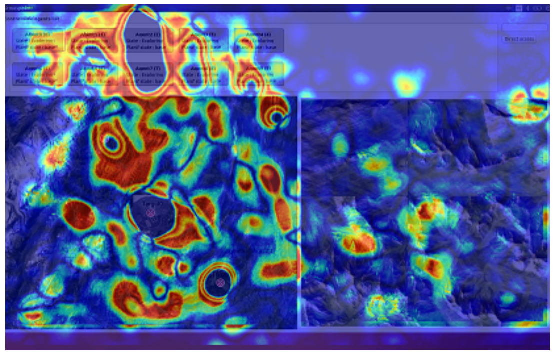

Fig. 6. Difference heat map between the first and last blocks. Dark blue indicates more fixations at the beginning than at the end of the experiment, and dark red the oppposite.

3.3 Physiological data

One participant reported that he sang to maintain himself more alert and was therefore excluded from the physiological data analyses. We also had to remove another participant due to technical problems with the acquisition, therefore only three participants were kept. There was no significant effect of TOT on the heart rate nor on the heart rate variability in both the temporal and frequential domains, and nor on the LF/HF ratio ($p > 0.25$ for all). Planned comparisons performed to study a potential quadratic modulation were non significant either. On the contrary, there were significant modulations of cerebral activity due to TOT. The ANOVA performed on the EEG frequential markers revealed a significant interaction between the virtual electrode and TOT ($F(40, 80) = 2.07, p < 0.01$). The power in all bands decreased at the left frontal site after the

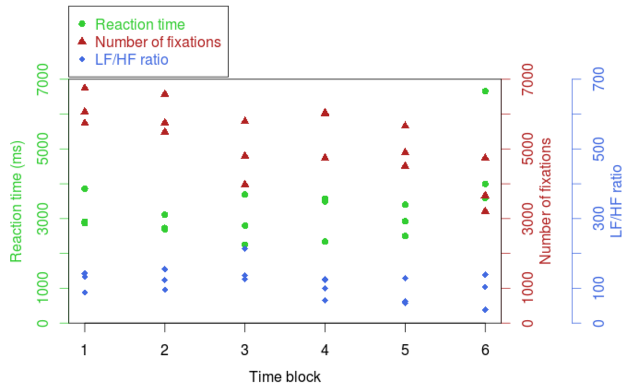

Fig. 7. Response time, number of fixations and cardiac LF/HF ratio across blocks.

first hour. Also, there was a significant interaction between the frequency band and TOT ($F(10, 20) = 3.84, p < 0.01$). After the first 40 minutes, there was a significant increase in alpha power, and then after one hour a significant decrease ($p < 0.05$). There was also a trend for an increase in beta power in the last block ($p = 0.10$). Lastly, there was a significant interaction between the virtual electrode, the frequency band and TOT ($F(80, 160) = 1.46, p < 0.05$). Indeed, the decrease in alpha power occurred mainly at the left sites ($p < 0.05$). After one hour, there was also an increase in alpha power at right central sites, and an increase in beta power for the last block at median central sites, however these modulations were not significant.

3.4 Correlations

A Pearson correlation analysis was performed in order to reveal which markers were the most relevant to assess the operator's performance and engagement (table 1). The response times that are used to perform this analysis are the ones of the identification task, that is to say the response times to the yellow alarms. For legibility purposes, besides response times, oculomotor and cardiac markers, the cerebral markers reported here are only the ones for which there was a significant effect or a trend at the group level in the ANOVA. As listed in the table, the main results are a significant correlation between performance and the number of fixations as well as the LF/HF ratio. These are inversely correlated; when response times increases (i.e. drop in performance) the ratio and the number of fixations decrease (figure 7).

As could be expected from their origin and computation, most markers are significantly correlated to the other markers extracted from the same recording modality. Hence, blink duration is inversely correlated to fixation duration and fixation number. Heart rate is inversely correlated to the LF/HF ratio and the HF marker. Heart rate variability in the temporal domain is correlated to the LF and the HF component of the varibility in the frequential domain. And of course all cerebral markers are correlated.

The most important point shown in this study is the fact that markers from different origins are correlated. Thus, fixation duration is inversely correlated to the HR. And HRV in the temporal domain and its LF component are inversely correlated to the alpha power at left parieto-occipital sites and the beta power at median central sites.

4. DISCUSSION

This study details ongoing work regarding the characterization of physiological markers relevant for UAV operators' engagement assessment. Besides a significant modulation with increasing TOT of the subjective feeling of disengagement, the main results are a significant decrease in the number of fixations and an increase in alpha power after the first 40 minutes, which are both consistent with a decrease in arousal with TOT. However, there was also an increase in blink rate during the first hour and then a decrease towards the session end. This might reflect an increase in arousal at the end of the two hour session. This phenomenon was not expected since they had no way to check the time, but it seems they have had a sense of it.

Yet, we were more interested in engagement than mere time-on-task. Engagement -as reflected by the behavioral performance- fluctuates and is not linear. Therefore, it made sense to analyze which markers were significantly correlated to performance. There was a significant correlation between performance and the number of fixations as well as the cardiac LF/HF ratio. These were inversely correlated; when response times increased the LF/HF ratio and the number of fixations decreased, in line with the literature (Smilek et al., 2010; Roy et al., 2013). What is also interesting is the correlation observed between markers of different recording modalities. Most particularly, there was an inverse correlation between the heart rate variability in the temporal domain and its low frequency component with the alpha power at left parieto-occipital sites and the beta power at median central sites. This phenomenon might reflect a state of mind wandering in which the subject is fully oriented towards her own thoughts, as the power modulations are in accordance with the literature (Smallwood et al., 2008; Braboszcz and Delorme, 2011).

This study will be pursued by the assessment of an online closed-loop neuro-adaptive system. This system would take as an input the mental state of the operator using the engagement markers that were determined as relevant for a prolonged UAV operation, that is to say mainly the number of fixations and the cardiac LF/HF ratio, but also the power in the alpha and beta bands. In order to implement such a system, one should make use of tools originally designed to palliate motor handicaps, called brain-computer interfaces (BCIs). Those tools consist of a processing chain that generally includes a feature classification step. They have recently been used for mental state monitoring purposes in order to implicitely adapt interfaces and were nammed passive BCIs (George and Lécuyer, 2010). Using such systems it could be possible to prevent the operator's performance degradation (Van Erp et al., 2012), and data fusion should improve the estimation of degraded states.

The ultimate goal is of course to use this information to generate useful actions or counter-measures (de Souza et al., 2015). For instance, a certain level of engagement could be required from the operator during a long UAV

Table 1. Correlation analysis between performance, ocular, cardiac and cerebral markers. *Significant correlations in bold ($p < .05$). RT: response time; Fix: Fixation; D: duration; Nb: number; HR: Heart rate; HRV: Heart rate variability; ratio: LF/HF ratio; LF & HF: power of the low or high HRV frequency components; L: Left; R: Right; M: Median; F: Frontal; C: Central; PO: Parieto-Occipital.*

	RT	BlinkD	BlinkNb	HR	HRV	ratio	LF	HF	FixD	FixNb	LFα	LCα	LPOα	RCα	MCβ
RT	1.00	0.07	-0.07	0.43	-0.20	**-0.57**	-0.23	-0.09	-0.25	**-0.57**	-0.22	-0.09	-0.27	-0.19	-0.22
BlinkD	0.07	1.00	-0.27	0.12	0.26	0.26	0.38	0.13	**-0.81**	**-0.51**	-0.13	0.13	-0.16	-0.03	-0.12
BlinkNb	-0.07	-0.27	1.00	-0.07	-0.32	0.11	-0.32	-0.25	0.07	-0.29	0.24	0.23	0.26	0.24	0.36
HR	0.43	0.12	-0.07	1.00	0.35	**-0.54**	0.24	**0.56**	**-0.48**	-0.29	0.02	0.16	0.01	0.08	0.09
HRV	-0.20	0.26	-0.32	0.35	1.00	-0.07	**0.98**	**0.94**	-0.10	-0.19	-0.46	-0.42	-0.48	-0.47	**-0.52**
ratio	**-0.57**	0.26	0.11	**-0.54**	-0.07	1.00	0.08	-0.30	0.08	0.07	0.27	0.27	0.30	0.28	0.32
LF	-0.23	0.38	-0.32	0.24	**0.98**	0.08	1.00	**0.88**	-0.16	-0.25	-0.46	-0.39	**-0.47**	-0.45	**-0.51**
HF	-0.09	0.13	-0.25	**0.56**	**0.94**	-0.30	**0.88**	1.00	-0.13	-0.16	-0.38	-0.34	-0.39	-0.38	-0.42
FixD	-0.25	**-0.81**	0.07	**-0.48**	-0.10	0.08	-0.16	-0.13	1.00	0.46	0.05	-0.24	0.07	-0.08	-0.04
FixNb	**-0.57**	**-0.51**	-0.29	-0.29	-0.19	0.07	-0.25	-0.16	0.46	1.00	0.31	0.09	0.35	0.25	0.27
LFα	-0.22	-0.13	0.24	0.02	-0.46	0.27	-0.46	-0.38	0.05	0.31	1.00	**0.95**	**0.99**	**0.99**	**0.95**
LCα	-0.09	0.13	0.23	0.16	-0.42	0.27	-0.39	-0.34	-0.24	0.09	**0.95**	1.00	**0.94**	**0.98**	**0.93**
LPOα	-0.27	-0.16	0.26	0.01	-0.48	0.30	-0.47	-0.39	0.07	0.35	**0.99**	**0.94**	1.00	**0.99**	**0.96**
RCα	-0.19	-0.03	0.24	0.08	-0.47	0.28	-0.45	-0.38	-0.08	0.25	**0.99**	**0.98**	**0.99**	1.00	**0.96**
MCβ	-0.22	-0.12	0.36	0.09	**-0.52**	0.32	**-0.51**	-0.42	-0.04	0.27	**0.95**	**0.93**	**0.96**	**0.96**	1.00

monitoring task. A "neuro-adaptive" system would therefore be of advantage in order to better manage the time interval between the solicitations made to the operator (Mkrtchyan et al., 2012). An promising way to manage interactions is to use a probabilistic decisional framework which is able to handle partial observations or imprecisions on human state measurements. Recently, a Mixed-Observability Markov Decision Process framework has also been proposed to drive the human-robot interaction, in which the human is seen as a partially observable state variable in a joint action context (de Souza et al., 2015).

5. CONCLUSION

By assessing which physiological markers reflect the operator's engagement in a prolonged simulated UAV operation, this study paves the way towards neuro-adaptive systems and enhanced operator-system interaction. Promising results are found which include the relevance of eye-tracking and cardiac measures. This study will be pursued by an online engagement estimation to dynamically trigger cognitive countermeasures.

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