Towards Multi-UAV and Human Interaction Driving System Exploiting Human Mental State Estimation

Gaganpreet Singh, Raphaëlle N. Roy and Caroline P. Carvalho Chanel
ISAE-SUPAERO, Université de Toulouse, France

Keywords: Unmanned Aerial Vehicles(UAV), Multi-UAVs and Human Interaction, Manned-Unmanned Teaming (MUM-T), Mental Workload, Engagement, Physiological Computing.

Abstract: This paper addresses the growing human-multi-UAV interaction issue. Current active approaches towards a reliable multi-UAV system are reviewed. This brings us to the conclusion that the multiple Unmanned Aerial Vehicles (UAVs) control paradigm is segmented into two main scopes: i) autonomous control and coordination within the group of UAVs, and ii) a human centered approach with helping agents and overt behavior monitoring. Therefore, to move further with the future of human-multi-UAV interaction problem, a new perspective is put forth. In the following sections, a brief understanding of the system is provided, followed by the current state of multi-UAV research and how taking the human pilot's physiology into account could improve the interaction. This idea is developed first by detailing what physiological computing is, including mental states of interest and their associated physiological markers. Second, the article concludes with the proposed approach for Human-multi-UAV interaction control and future plans.

1 INTRODUCTION

Recent automation progress in terms of control, navigation, and decision making brings the speculation of autonomous decision-making multi-UAV systems' deployment closer to reality (Schulte et al., 2015). However, keeping the human in the (decisional) loop is still a compulsory point (Valavanis and Vachtsevanos, 2015; Schurr et al., 2009). In particular, unmanned aircraft's engineering for optimal control strategies are still evolving and the idea of having better control of an unmanned aircraft is shifting to the desire of controlling several UAVs at once.

The actual ratio factor between UAV operators (O) and UAV units (N) is O$\geq$N. For example, in the US army, a UAV is managed by several operators: one is in charge of following the flight parameters, other is in charge of payload, and the last one is responsible for the mission supervision. In the next future, this ratio would probably be inverted (O$<$N) (Gangl et al., 2013a).

Indeed, UAVs are getting more and more automated, taking decisions by themselves, which lightens the need for such a number of operators. The idea is that UAVs could explore safety automation to ensure a completely autonomous navigation and even a completely autonomous mission planning. However, the human operator is still vital, and unfortunately, considered as a providential agent (Schurr et al., 2009; Casper and Murphy, 2003), who gets over the autonomous or automatic system when some hazardous event occurs. Yet, it is known that, in UAV operations, Human Factors represent the most important part of accidents (Williams, 2004; Haddal and Gertler, 2010). Nevertheless, in some cases, it is mandatory to handle a mission from close proximity, by keeping human agents in the loop, which are in charge of taking the difficult decisions.

However, to leverage the advantage of being smart and adaptable like humans, and consistent and precise like machines, the idea is to bring them in close contact beforehand, and so, to design a system that provides authority and integrity to both (non unerring) actors - human and machine - while helping a single human to work collaboratively with multiple UAVs. In particular, considering that neither of them is leading, but both of them are helping each other in accomplishing the mission goal(s). This interesting positioning is also known as mixed-initiative for Human-Machine Interaction (HMI) (Jiang and Arkin, 2015), which should consider that each of the agents could seize (e.g. relinquish) the initiative from the other(s). From a human point of view, such a system that takes over us is not always acceptable (or even desirable),

Singh, G., Roy, R. and Chanel, C.
Towards Multi-UAV and Human Interaction Driving System Exploiting Human Mental State Estimation.
DOI: 10.5220/0007575002940301
In *Proceedings of the 12th International Joint Conference on Biomedical Engineering Systems and Technologies (BIOSTEC 2019)*, pages 294-301
ISBN: 978-989-758-353-7

but should at least be welcome when human capabilities (cognitive or physical) are not forthcoming.

Therefore, this paper proposes a multi-UAV interaction driving concept. Where multiple UAVs are interacting with a single human agent from a plane's cockpit while the latter is being part of the mission, and its physiological measurements are exploited to enhance coordination between man and machine. In other words, the human and UAVs can be seen as a Manned-Unmanned Teaming (MUM-T). In missions scenarios, where a MUM-T is suitable, hot events can occur and the human agent, which is in charge of harder decisions, can experience degraded mental states. In this context, the main idea is to explore the use of mental state estimation in real time (Singh et al., 2018) to drive the Human and Multi-UAVs Interaction.

The paper is organized as follows: section 2 presents multi-UAV applications that take (or not) into account the human operator inputs, directly in the supervisory control-loop, or to well-drive human and multi-UAV interaction. In section 3 promising physiological parameters that could be useful to estimate the cognitive state of human operator are reviewed. The proposed approach is presented in section 4, as well as, a brief description of the experiment scenario currently being designed. At the end, conclusions and future works in section 5 closes this paper.

2 MULTI-UAVs IN ACTION

With the emergence of unmanned aircrafts and the evolution of automation, researchers are pushing the limits to attain the capability of controlling multiple UAVs. But there is still a debate between having a fully autonomous group of UAVs performing different sub-tasks to achieve one common goal or having one human controlling several UAVs all together towards the success of a mission. Moreover, both of these ideologies settle in one common urge of having a fully capable multi-UAV system.

Several multi-UAV applications have already been designed and demonstrated. The COMETS project (Ollero et al., 2005) is one of them with several research organizations involved in design and implementation of a new control architecture for multiple heterogeneous UAVs working cooperatively in forest fire missions. Maza and collaborators (Maza et al., 2011) designed a multi-UAV distributed decisional architecture to autonomously cooperate and coordinate with UAVs while accomplishing high level tasks by dividing and assigning low level tasks to each UAV with respect to the capabilities of each one of them. Perez and collaborators (Perez et al., 2013) developed a ground control station for dynamically assigning tasks to several UAVs, and Schere and collaborators (Scherer et al., 2015) created a distributed control system to coordinate multiple UAVs and override autonomy when required. Brisset and collaborators (Brisset and Hattenberger, 2008) have conducted two multi-UAV experiments using Paparazzi (a free autopilot) (Brisset and Drouin, 2004; Brisset et al., 2006). In these experiments, a formation flight using first 3 UAVs, and secondly 2 UAVs at different locations in Germany and France were controlled by the same Ground Control Station in Germany by two operators. Franchi and collaborators (Franchi et al., 2012) also studied the involvement of human in control loop of multi-UAVs with self arranged autonomy. Whereas, Muller and collaborators (Mueller et al., 2017) targeted 2 problems of multi-UAVs operation: first an effective Human System Interface for better understanding, control, and monitoring of overall activity; and second to authorize UAVs to plan, verify, and act when the connection to the human operator is lost.

Such systems are trying to diminish the need of a human operator by making systems capable enough to take decisions and accomplish the mission without any human intervention, or just with little supervisory control, or takeover when required.

On the other hand, recent works are heading towards an integrated system with human involvement in critical situations (Donath et al., 2010; Gangl et al., 2013a; Gangl et al., 2013b; Schulte et al., 2015). The main idea behind these researches is the involvement of a human operator not just in the supervisory, or control loop, but in the mission itself. The human operator is not remotely controlling the UAVs to perform tasks, but one is also involved in the mission plan and performs the required supervision of accompanying UAVs from the cockpit of a plane. The advantages of this kind of system over those that keep the human operator only for supervision from ground control stations are tremendous. For instance, with this setup there is less physical limitation between the UAVs and the control station (Gangl et al., 2013a), there are long range mission possibilities. Moreover, there is a better availability of the human operator for critical decision making considering better situation awareness, along with real time task (re)planning.

Donath and collaborators (Donath et al., 2010) worked on assistant systems to help human pilot in managing multiple UAVs from a manned aircraft, and also evaluated the workload experienced by the pilot. They used human behavior models to represent the workload experienced and to provide possible solutions to balance it. Their work was further evaluated by Gangl and collaborators (Gangl et al., 2013b) with Unmanned Combat Aerial Vehicles (UCAVs). In this particular study, Artificial Cognitive Units (ACUs) were used to control each UCAV separately along with the presence of a human pilot in a manned aircraft's cockpit working hand-in-hand with the UCAVs.

A very critical issue of mental workload experienced by human pilots in a Manned-Unmanned Teaming (MUM-T) scenarios has been raised in these works (Donath et al., 2010; Gangl et al., 2013a; Gangl et al., 2013b; Schulte et al., 2015). However, a promising way, in our point of view, is to use physiological features over subjective or behavioral human measurements or models in order to better estimate mental workload, this could provide a unique advantage. Indeed, estimating humans' mental state using subjective and behavioral measures can only tell what might have occurred but cannot measure and reveal what actually went on. Hence, physiological measures can help extracting pilots' mental states in real time and can provide better estimates of such states than overt measurements which are relatively sparse (Mehta and Parasuraman, 2013).

In this sense, this work's position aims to explore the benefits of using physiological computing to estimate pilots' mental state in order to drive human-multi-UAVs interaction.

3 PHYSIOLOGICAL COMPUTING

Physiological computing provides a revolutionized way towards Human-Machine Interaction (HMI) by directly monitoring, analyzing, and responding to covert physiological features of a user in real time (Fairclough, 2008). A system that explores physiological computing, works through reading and transforming psychophysiological signals as inputs to a control signal without going through any direct communication channel with the human operator (Byrne and Parasuraman, 1996). It brings in an efficient HMI, or rather opens up a communication channel which was left unused before (Hettinger et al., 2003). The use of such physiological features or markers is a great means to provide sixth sense for research and other applications that are willing to peak into the core of human activity and want to get insight of how a person is actually experiencing the world in their cognitive realm without putting the operator in any direct or indirect conversation.

Previous research supports the use of physiological features to better understand human mental state and enhance a task's outcome (Roy et al., 2016b; Senoussi et al., 2017; Drougard et al., 2017a; Drougard et al., 2017b). For aeronautical applications, several mental states are particularly relevant to try and estimate such as: Mental Workload, Engagement, Fatigue, and Drowsiness. The work presented here focuses on Mental Workload and Engagement since these states are great contributors to human performance modulation in risky settings.

3.1 Mental Workload and Engagement

Workload was defined in several different ways, but it could be understood as *ones' information processing capacity or amount of resources required to meet system demand* (Eggemeier et al., 1991) or *the difference in the capacity of an information processing system to satisfy a task's performance and the available capacity at any given time* (Gopher and Donchin, 1986). A closely related concept is therefore the Engagement, or attentional/cognitive resource engagement. The Engagement level of an operator varies depending on several factors such as time-on-task (and therefore vigilance/alertness), task demands, and motivation (Berka et al., 2007; Chaouachi and Frasson, 2012; McMahan et al., 2015). In our understanding, trying and estimating mental workload is akin to estimate engagement if one thinks in terms of mental resources. Hence, these two concepts will be considered as one in the remaining parts of this paper.

3.2 Associated Physiological Markers

Mental workload and mental resource engagement have been widely studied (Mehta and Parasuraman, 2013), which allowed to reveal several physiological parameters that can enable to effectively estimate human engagement state. Both cerebral and peripheral physiological measures can be used to infer the engagement state. Hence, in order to perform engagement estimation, electroencephalographical (EEG) features in the temporal and frequency domain can be used (Pope et al., 1995).

In the temporal domain, an example is the use of Event Related Potentials (ERP) which are the time-locked cerebral responses to specific events (Fu and Parasuraman, 2007). The amplitude of these voltage variations can be extracted at various time points and is known to fluctuate with engagement. For example, after 300 ms post-event (e.g. after an alarm) there is a lower positive deflection at posterior electrode sites if the operator has not engaged enough resources to correctly process this event.

Next, in the frequency domain one can use modulations in the Power Spectral Density (PSD) of different EEG frequency bands (e.g. θ: 4-8 Hz, α: 8-12 Hz and β: 13-30 Hz) (Roy et al., 2016a; Roy et al., 2016c; Heard et al., 2018a). For instance, a widely accepted and evaluated Engagement Index (EI) developed by Pope and collaborators (Pope et al., 1995) can be used to modulate task allocation in a closed-loop system and is computed using band power as follows: $EI = \beta/(\alpha+\theta)$ (Chaouachi and Frasson, 2012; Berka et al., 2007).

As for peripheral measures that can be useful to estimate operator's mental state, markers can be extracted from the electrocardiogram (ECG). Well known ones are the Heart Rate (HR; time domain metric) and the Heart Rate Variability (HRV; can be computed both in the time and the frequency domains). These metrics are sensitive to workload and engagement but not specific to it, indeed they are also modulated by physical activity (Heard et al., 2018a). Another way of recording peripheral activity is to use an eye-tracker device, which records ocular activity. Thanks to this device, one can for instance extract Blink Frequency (BF; i.e. number of blinks per minute), Fixation Duration (FD; i.e. amount of time the eyes fixated a particular area) and Blink Latency (BL; i.e. amount of time between two blinks) which variate with engagement (Heard et al., 2018a; Heard et al., 2018b).

4 THE PROPOSED APPROACH

Machine intelligence still does not have far reaching capabilities to match human intelligence and abilities, in particular to work in unpredictable and continuously changing environments. Since the human brain does have far reaching capabilities, a better integration of its capabilities with machines could bring unmatched results.

As before highlighted, research has already taken place to achieve high levels of autonomy in UAVs and to make their control system (in terms of flying) capable enough to handle flight parameters without much human intervention. Therefore, this work is not directed towards controlling the dynamics and autonomy of the UAVs. It is neither directed towards achieving a super smart interface to enable human operators to supervise several UAVs through that.

Rather, this work focuses on unveiling and estimating human pilot's mental states involved in the mission to enhance Human-UAVs interaction. Secondly, it focuses on developing decisional systems that understand the situation and choose appropriate actions. Here, understanding the situation means how the overall system's coordinator estimates the state of both human and UAV units, being able to predicts its influence on mission achievement. The appropriate actions could be: managing the amount of work the human pilot could (or should) handle; managing the tasks that could done by the UAV; when and how information should be transferred to the human pilot; and how tasks should be shared between human and UAVs. These concepts should bring to a coordinative approach towards mission success.

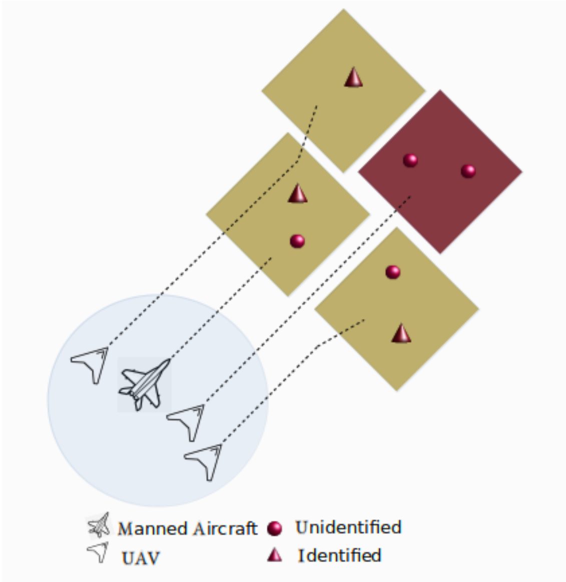

Figure 1: Project layout.

Researchers have been trying to improve mission success, focusing in three main problems associated with Unmanned Aerial Vehicles (UAVs): higher accident rates (Haddal and Gertler, 2010), higher human to machine ratio (Gangl et al., 2013b), and state awareness of human counterpart (Schulte et al., 2015). The approach, here proposed, will try to tackle these issues by increasing state awareness for both human and machine, eventually decreasing human errors and increasing system's performance. The aim is to invert the higher human-to-machine ratio into a higher machine-to-human ratio.

The overall system will contain a human pilot and several UAVs working as a team (MUM-T) on a common mission, see Figure 1. There will be a main system i.e. Mission and Interaction Coordinator (MIC) that has knowledge of overall mission plan and goals, see Figure 2. A search and rescue mission (Souza et al., 2016; Gateau et al., 2016) will be the core of the scenario. In such a mission several actions would be considered: UAV requests to perform identification and confirmation of possible targets; which agent should visit dangerous or accidental zones; communicate the targets position; present or not to present the information to the human pilot; etc. The challenge behind it is to choose when to launch a request to the pilot. The system's coordinator should decide based on the availability of the human pilot i.e. inverse of workload (Gateau et al., 2016), ethical commitment (Souza et al., 2016), or based on degraded mental states like attentional tunneling (de Souza et al., 2015).

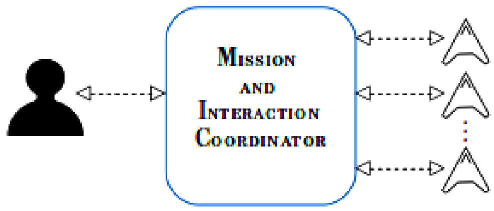

Figure 2: Project architecture.

On the basis of these, the overall mission coordinator has to estimate human pilot's mental state, to assign tasks to UAVs, and to change the level of autonomy to help maintain a human pilot's engagement within a suitable window i.e. neither too high nor too low (Ewing et al., 2016), while maintaining an acceptable system's performance to achieve mission's goal(s).

4.1 Research Milestones

This research will be carried out in three phases: i) data collection, ii) implementation, and iii) closed-loop validation.

In the first phase, the hard-coded experiment should allow behavioral and physiological data collection from the human pilot, equipped with an EEG, an ECG, and an ET. Therefore, for this phase, a controlled environment where a human pilot will handle a simulated flight along with interactions with the UAVs is considered. The experiment is designed to take place considering four experimental conditions: low workload (L), high workload (H), low to high workload transition (LH), and high to low workload transition (HL) (see Fig. 3 for an example). The four conditions will be split in a pseudo-random manner: L-LH-H-HL or H-HL-L-LH, and are expected to bring up engagement-workload variations. The human pilot's workload level will be manipulated by means of:

- choosing from time to time way-points to meet the requirement of staying in a given distance range that allows to maintain communicating with UAVs. These way-points will transform into Air Traffic Control (ATC) instructions for flying the plane and will be given to pilot in the form of audio messages. (Risser et al., 2002) and (Gateau et al., 2018) showed that, depending on their length and complexity, recalling ATC's instruction (e.g. speed, altitude, heading) can create a high cognitive load.
- answering to pop-ups containing UAVs' requests that concern the identification and recognition of detected targets as in (Gateau et al., 2016). Particularly in a search and rescue mission, where lives are at stake (Souza et al., 2016). Errors of identification or recognition may be avoided, which implies an important human involvement;
- and performing checklists related, for instance, to malfunctioning of flight equipment or UAVs embedded systems. Note that, interruptions during checklists can be considered as an issue (Loukopoulos et al., 2001), and can potentially increase the workload while decreasing performance (Loft and Remington, 2010);

Currently we have designed the application shown in Figure 4, that lets the human pilot interact with UAVs during the experiment (e.g. like sending requests for areas to search; answer UAV queries for validation of recognized objects).

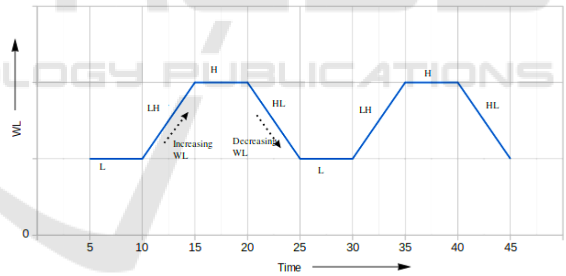

Figure 3: Experiment structure with conditions designed to elicit variations of pilots' engagement.

Following this first experiment (data collection) under the conditions listed, it is expected to design a smart tool (implementation phase) that could estimate mental states of human pilots in real time based on the physiological markers reviewed in Sec. 3. This real time estimation would serve as an input to an overall system's state estimator (i.e. mental state of human and UAVs' states).

Once the overall system's state estimator is designed, a decisional framework, called Mission and Interaction Coordinator (MIC) would reason in a long-term way. In other words, it will predict future states of the whole system (i.e. agents and mission's states) and will have to choose an appropriate action, bringing coordination between all involved

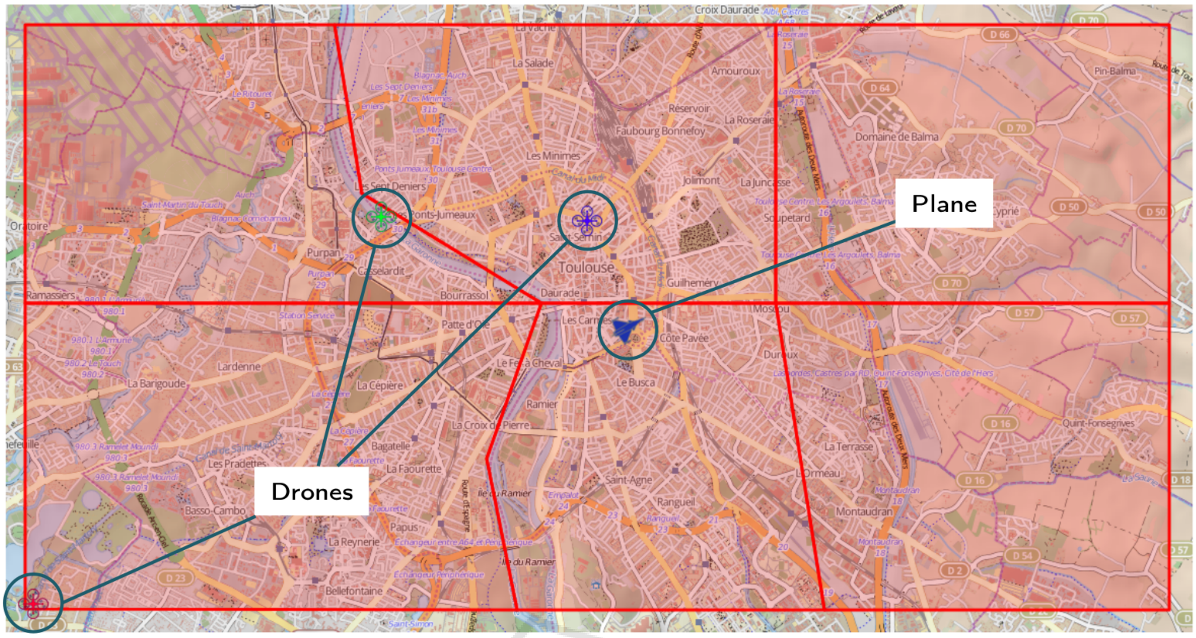

Figure 4: Developed application that enables the human pilot to interact with UAVs (e.g. to choose regions to search, to answer UAVs requests, or to define way-points to meet).

agents (i.e. human and UAVs) while ensuring mission success. This will constitute the closed-loop phase of this research. The evaluation of the closed-loop framework will be handled with an experiment similar to the one described above.

5 CONCLUSION AND FUTURE WORK

This paper presents our current research towards a multi-UAV and human interaction driving system that would exploit human's mental state estimation. The main idea is to integrate the latest advances of physiological computing into a high-level mission coordinator. State-of-the-art approaches were presented as well as promising physiological markers. A mission scenario was also proposed, in which a human pilot should coordinate his actions along with UAVs' requests (MUM-T). In this scenario, four conditions would be evaluated in order to study the variations of engagement of human pilot. In particular, such conditions would constitute labels to the collected data therefore allowing the design of the subsequent smart estimation system.

The next step of this work is to define the experimental protocol of the proposed mission scenario in details, to implement a rigorous experimental setup, hence ensuring the validity of the expected results. Such results will be used in the forthcoming stages of this work, in which an intelligent artificial system will have to reason in a long-term manner. In other words, it should predict future states of agents (i.e. mental state of the human pilot, and UAVs' states) and requirements of overall mission (i.e. needs and possible future actions of the human pilot or of UAVs) in order to take optimal actions to balance the load between human pilot and UAVs while maximizing system's performance.

REFERENCES

Berka, C., Levendowski, D. J., Lumicao, M. N., Yau, A., Davis, G., Zivkovic, V. T., Olmstead, R. E., Tremoulet, P. D., and Craven, P. L. (2007). Eeg correlates of task engagement and mental workload in vigilance, learning, and memory tasks. *Aviation, space, and environmental medicine*, 78(5):B231–B244.

Brisset, P. and Drouin, A. (2004). Paparadziy: do-it-yourself uav. *Journées Micro Drones, Toulouse, France*.

Brisset, P., Drouin, A., Gorraz, M., Huard, P.-S., and Tyler, J. (2006). The paparazzi solution. In *MAV 2006, 2nd US-European competition and workshop on micro air vehicles*.

Brisset, P. and Hattenberger, G. (2008). Multi-uav control with the paparazzi system. In *HUMOUS 2008, conference on humans operating unmanned systems*.

Byrne, E. A. and Parasuraman, R. (1996). Psychophysiology and adaptive automation. *Biological psychology*, 42(3):249–268.

Casper, J. and Murphy, R. R. (2003). Human-robot interactions during the robot-assisted urban search and rescue response at the world trade center. *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, 33(3):367–385.

Chaouachi, M. and Frasson, C. (2012). Mental workload, engagement and emotions: an exploratory study for intelligent tutoring systems. In *International Conference on Intelligent Tutoring Systems*, pages 65–71. Springer.

de Souza, P. E. U., Chanel, C. P. C., and Dehais, F. (2015). Momdp-based target search mission taking into account the human operator's cognitive state. In *Tools with Artificial Intelligence (ICTAI), 2015 IEEE 27th International Conference on*, pages 729–736. IEEE.

Donath, D., Rauschert, A., and Schulte, A. (2010). Cognitive assistant system concept for multi-uav guidance using human operator behaviour models. *HUMOUS'10*.

Drougard, N., Carvalho Chanel, C., Roy, R., and Dehais, F. (2017a). An online scenario for mixed-initiative planning considering human operator state estimation based on physiological sensors. In *IROS Workshop in Synergies Between Learning and Interaction (SBLI)*.

Drougard, N., Ponzoni Carvalho Chanel, C., Roy, R. N., and Dehais, F. (2017b). Mixed-initiative mission planning considering human operator state estimation based on physiological sensors.

Eggemeier, F. T., Wilson, G. F., Kramer, A. F., and Damos, D. L. (1991). Workload assessment in multi-task environments. *Multiple Task Performance*, page 207.

Ewing, K. C., Fairclough, S. H., and Gilleade, K. (2016). Evaluation of an adaptive game that uses eeg measures validated during the design process as inputs to a biocybernetic loop. *Frontiers in human neuroscience*, 10:223.

Fairclough, S. H. (2008). Fundamentals of physiological computing. *Interacting with computers*, 21(1-2):133–145.

Franchi, A., Secchi, C., Ryll, M., Bulthoff, H. H., and Giordano, P. R. (2012). Shared control: Balancing autonomy and human assistance with a group of quadrotor uavs. *IEEE Robotics & Automation Magazine*, 19(3):57–68.

Fu, S. and Parasuraman, R. (2007). Event-related potentials (erps) in neuroergonomics. In *Neuroergonomics the brain at work*, pages 32–50, New York. Oxford University Press.

Gangl, S., Lettl, B., and Schulte, A. (2013a). Management of multiple unmanned combat aerial vehicles from a single-seat fighter cockpit in manned-unmanned fighter missions. In *AIAA Infotech@ Aerospace (I@ A) Conference*, page 4899.

Gangl, S., Lettl, B., and Schulte, A. (2013b). Single-seat cockpit-based management of multiple ucavs using on-board cognitive agents for coordination in manned-unmanned fighter missions. In *International Conference on Engineering Psychology and Cognitive Ergonomics*, pages 115–124. Springer.

Gateau, T., Ayaz, H., and Dehais, F. (2018). In silico versus over the clouds: On-the-fly mental state estimation of aircraft pilots, using a functional near infrared spectroscopy based passive-bci. *Frontiers in human neuroscience*, 12:187.

Gateau, T., Chanel, C. P. C., Le, M.-H., and Dehais, F. (2016). Considering human's non-deterministic behavior and his availability state when designing a collaborative human-robots system. In *Intelligent Robots and Systems (IROS), 2016 IEEE/RSJ International Conference on*, pages 4391–4397. IEEE.

Gopher, D. and Donchin, E. (1986). Workload-an examination of the concept. handbook of perception and human performance, vol ii, cognitive processes and performance.

Haddal, C. C. and Gertler, J. (2010). Homeland security: Unmanned aerial vehicles and border surveillance.

Heard, J., Harriott, C. E., and Adams, J. A. (2018a). A survey of workload assessment algorithms. *IEEE Transactions on Human-Machine Systems*.

Heard, J., Heald, R., Harriott, C. E., and Adams, J. A. (2018b). A diagnostic human workload assessment algorithm for human-robot teams. In *Companion of the 2018 ACM/IEEE International Conference on Human-Robot Interaction*, pages 123–124. ACM.

Hettinger, L. J., Branco, P., Encarnacao, L. M., and Bonato, P. (2003). Neuroadaptive technologies: applying neuroergonomics to the design of advanced interfaces. *Theoretical Issues in Ergonomics Science*, 4(1-2):220–237.

Jiang, S. and Arkin, R. C. (2015). Mixed-initiative human-robot interaction: definition, taxonomy, and survey. In *Systems, Man, and Cybernetics (SMC), 2015 IEEE International Conference on*, pages 954–961. IEEE.

Loft, S. and Remington, R. W. (2010). Prospective memory and task interference in a continuous monitoring dynamic display task. *Journal of Experimental Psychology: Applied*, 16(2):145.

Loukopoulos, L. D., Dismukes, R., and Barshi, I. (2001). Cockpit interruptions and distractions: A line observation study. In *Proceedings of the 11th international symposium on aviation psychology*, pages 1–6. Ohio State University Columbus.

Maza, I., Caballero, F., Capitán, J., Martínez-de Dios, J. R., and Ollero, A. (2011). Experimental results in multi-uav coordination for disaster management and civil security applications. *Journal of intelligent & robotic systems*, 61(1-4):563–585.

McMahan, T., Parberry, I., and Parsons, T. D. (2015). Evaluating player task engagement and arousal using electroencephalography. *Procedia Manufacturing*, 3:2303–2310.

Mehta, R. K. and Parasuraman, R. (2013). Neuroergonomics: a review of applications to physical and cognitive work. *Frontiers in human neuroscience*, 7:889.

Mueller, J. B., Miller, C., Kuter, U., Rye, J., and Hamell, J. (2017). A human-system interface with contingency planning for collaborative operations of unmanned aerial vehicles. In *AIAA Information Systems-AIAA Infotech@ Aerospace*, page 1296.

Ollero, A., Lacroix, S., Merino, L., Gancet, J., Wiklund, J., Remuss, V., Perez, I., Gutierrez, L., Viegas, D., Benitez, M., et al. (2005). Architecture and perception issues in the comets multi-uav project. multiple eyes in the skies. *IEEE Robotics and Automation Magazine*, 12:46–57.

Perez, D., Maza, I., Caballero, F., Scarlatti, D., Casado, E., and Ollero, A. (2013). A ground control station for a multi-uav surveillance system. *Journal of Intelligent & Robotic Systems*, 69(1-4):119–130.

Pope, A. T., Bogart, E. H., and Bartolome, D. S. (1995). Biocybernetic system evaluates indices of operator engagement in automated task. *Biological psychology*, 40(1-2):187–195.

Risser, M. R., McNamara, D. S., Baldwin, C. L., Scerbo, M. W., and Barshi, I. (2002). Interference effects on the recall of words heard and read: Considerations for atc communication. In *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, volume 46, pages 392–396. SAGE Publications Sage CA: Los Angeles, CA.

Roy, R. N., Bonnet, S., Charbonnier, S., and Campagne, A. (2016a). Efficient workload classification based on ignored auditory probes: a proof of concept. *Frontiers in human neuroscience*, 10:519.

Roy, R. N., Bovo, A., Gateau, T., Dehais, F., and Chanel, C. P. C. (2016b). Operator engagement during prolonged simulated uav operation. *IFAC-PapersOnLine*, 49(32):171–176.

Roy, R. N., Charbonnier, S., Campagne, A., and Bonnet, S. (2016c). Efficient mental workload estimation using task-independent eeg features. *Journal of neural engineering*, 13(2):026019.

Scherer, J., Yahyanejad, S., Hayat, S., Yanmaz, E., Andre, T., Khan, A., Vukadinovic, V., Bettstetter, C., Hellwagner, H., and Rinner, B. (2015). An autonomous multi-uav system for search and rescue. In *Proceedings of the First Workshop on Micro Aerial Vehicle Networks, Systems, and Applications for Civilian Use*, pages 33–38. ACM.

Schulte, A., Donath, D., and Honecker, F. (2015). Human-system interaction analysis for military pilot activity and mental workload determination. In *Systems, Man, and Cybernetics (SMC), 2015 IEEE International Conference on*, pages 1375–1380. IEEE.

Schurr, N., Marecki, J., and Tambe, M. (2009). Improving adjustable autonomy strategies for time-critical domains. In *Proceedings of The 8th International Conference on Autonomous Agents and Multiagent Systems-Volume 1*, pages 353–360. International Foundation for Autonomous Agents and Multiagent Systems.

Senoussi, M., Verdiere, K. J., Bovo, A., Ponzoni Carvalho Chanel, C., Dehais, F., and Roy, R. N. (2017). Pre-stimulus antero-posterior eeg connectivity predicts performance in a uav monitoring task.

Singh, G., Bermúdez i Badia, S., Ventura, R., and Silva, J. L. (2018). Physiologically attentive user interface for robot teleoperation: real time emotional state estimation and interface modification using physiology, facial expressions and eye movements. In *11th International Joint Conference on Biomedical Engineering Systems and Technologies*, pages 294–302. SCITEPRESS-Science and Technology Publications.

Souza, P. E., Chanel, C. P. C., Dehais, F., and Givigi, S. (2016). Towards human-robot interaction: A framing effect experiment. In *Systems, Man, and Cybernetics (SMC), 2016 IEEE International Conference on*, pages 001929–001934. IEEE.

Valavanis, K. P. and Vachtsevanos, G. J. (2015). Future of unmanned aviation. In *Handbook of unmanned aerial vehicles*, pages 2993–3009. Springer.

Williams, K. W. (2004). A summary of unmanned aircraft accident/incident data: Human factors implications. Technical report, DTIC Document.