Cognitive fatigue assessment in operational settings: a review and UAS implications ⋆

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Abstract: Recent technological improvements allow UAS (Unmanned Aircraft System) operators to carry out increasingly long missions. Shift work was introduced during long-endurance missions to reduce the risk of fatigue. However, despite these short work periods and the creation of a fatigue risk management system (FRMS), the occurrence of intense and monotonous phases remains a factor of cognitive fatigue. This fatigue can have an impact on vigilance, attention, and operator performance, leading to reduce mission safety. This paper aims at presenting different ways to characterize the cognitive fatigue of UAS operators. The use of machine learning to estimate cognitive fatigue based on physiological measures is also presented as a promising venue to mitigate these issues.

Keywords: UAS operator, cognitive fatigue, passive BCI

1. UAS OPERATOR TASKS

Unmanned Aircraft Systems (UAS) are being increasingly used in both military and civilian applications. The European Drones Outlook Study (SESAR, 2016) forecast that more than 400,000 drones will be providing services in the airspace by 2050. In the military field, different categories of UAS are used to cover a wide range of needs, from mini drones to support patrols of soldiers to combat or surveillance drones that can operate for more than twenty-four hours anywhere in the world. Civilian applications nowadays cover a wide range of fields, from surveillance for firefighting, agriculture, weather, to power line and border inspections.

As the civilian UAS operation market continues to grow, the European Commission mandated in 2017 the Single European Sky ATM Research Joint Undertaking (SESAR JU) to coordinate all research and development activities related to drone integration in the commercial air space. Major efforts are now being made by private companies and public institutes to develop the freight transport sector for UAS. In the future, Unmanned Cargo Aircraft (UCA) could be a small drone used to deliver parcels at home or large and long-range aircraft capable of transporting heavy loads between continents.

1.1 UAS operations and fatigue

Unfortunately, the evolution of UAV operations previously described seems particularly favourable to the emergence of problems related to operator fatigue. First, these UCA could be operated 24 hours a day, which can lead to performance degradation due to night work (Basner et al., 2008), among other things. Second, to reduce operating costs and inactivity during the cruise phases of these UCA, a remote pilot could also have to manage several aircraft at the same time. Both time-on-task and increased workload are known to increase operator fatigue (D'huyvetter, 1988). If the UCA remote pilot, as opposed to a jet pilot, can be relieved at any time, there is still an issue related to fatigue. Particularly, the Federal Aviation Administration (FAA) and the US Air Force reported safety issues linked to fatigue while operating long-endurance drones (above 24 hours), mainly due to shift work (Tvaryanas et al., 2008). Understanding and mitigating these risks is a major safety issue. Therefore, existing regulations for fatigue management in air traffic services and airline operations are relevant for UAS operators. In particular, the work of air traffic controllers, which generally takes place on two-hour shifts at times of the day when their performance may be impaired, seems quite similar to what the work of a UAS pilot might be.

1.2 The current approach of the fatigue issue

The International Civil Aviation Organization (ICAO) defines fatigue as "a physiological state of reduced mental or physical performance capability resulting from sleep loss or extended wakefulness, circadian phase, or workload (mental and/or physical activity) that can impair a crew member's [in our case, the crew members refer to the crew that manages the UAV(s)] alertness and ability to safely operate an aircraft or perform safety-related duties" (ICAO, 2016). To improve the safety of

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air traffic operations, several regulations have been published about this topic by ICAO for general aviation, airlines, and air traffic services operators. ICAO fatigue policy proposes two approaches, the first one is normative and defines rules to be followed (Standards And Recommended Practices or SARP; ICAO 2016), the second one is performance-based (Fatigue Risk Management Systems or FRMS; ICAO 2016). ICAO defines an FRMS as: "A data-driven means of continuously monitoring and managing fatigue-related safety risks, based upon scientific principles and knowledge as well as operational experience that aims to ensure relevant personnel are performing at adequate levels of alertness" (ICAO, 2016). FRMS purpose for air traffic operators is to achieve a better balance between safety, productivity, and costs by constantly monitoring fatigue-related safety risks. As the risk associated with mental fatigue is clearly explained, the performance-based FRMS usually relies on biomathematical fatigue models (Van Dongen, 2004) based on shift work schedule, time-on-task, and circadian cycles. Those models provide a fatigue prediction value (Powell et al., 2010; Gander et al., 2014) for work period usually expressed using a subjective scale like the Karolinska Sleepiness Scale (Hoddes et al., 1972) or the Samn Perelli fatigue scale (Samn and Perelli, 1982). The System for Aircrew Fatigue Evaluation (SAFE; Authority 2007) model has been specifically developed for aircrew and is being used by major airlines and several regulators agencies worldwide. Therefore, this predictive approach which is only based on pilots' or air traffic controllers' rosters cannot take into account the fatigue induced by abnormal situations during the task (hazardous weather, traffic density, etc.) or during the rest time.

1.3 The need to take cognitive fatigue into account

A critical question that remains unanswered at this time is the impact of emergency situations or certain phases of flight characterized by high workload on the ability of the human operator to effectively operate systems during and after such events. These episodes are likely to generate a particular state of fatigue (Dehais et al., 2018a), known as cognitive fatigue, which is currently given relatively little consideration in fatigue risk management systems. Both long-haul routes pilots and remote pilots' activity are prone to phases of hypo- and hyper-vigilance (Smith, 1979), which will possibly lead to safety issues linked to mental fatigue during high workload phases. Personalized fatigue monitoring could strengthen the FRMS of a UCA company by taking into account this cognitive fatigue induced by those situations.

2. COGNITIVE FATIGUE

Cognitive fatigue can be defined as difficulty in initiating or in sustaining voluntary activities (Chaudhuri and Behan, 2004). In the absence of pathology, the onset of cognitive fatigue can be explained by having performed complex mental activity over a period of time. This fatigue is therefore different from physical fatigue and drowsiness, the latter being associated with a lower level of alertness, and is characterized by intense cognitive activity for a longer or shorter period of time. Today, the causes of this cognitive fatigue are still widely debated. While some authors suggest a decrease in metabolic resources (e.g. glucose; Christie and Schrater 2015) as a possible cause of this cognitive fatigue, others highlight the role of effort and argue that cognitive fatigue should arise when the costs of the cognitive effort required to perform the activity are higher than the benefits it brings (Boksem and Tops, 2008). Crucially and regardless of its origin, this cognitive state appears to negatively impact human performance.

2.1 Impact of cognitive fatigue on performance

Cognitive fatigue has been found to impair performance in a variety of cognitive tasks (Lorist et al., 2000). From a purely behavioural perspective, cognitive fatigue is classically associated with decreased performance (see van Erp et al. 2010). Notably, cognitive fatigue leads to an increased propensity to make errors (Boksem et al., 2005) and slowing reaction time (Paus et al., 1997).

Cognitive fatigue and adaptive capabilities In most cases, tired participants remain capable of performing automated and highly overlearned tasks. On the contrary, cognitive fatigue seems particularly detrimental when it comes to reacting to unexpected situations. In particular, cognitive fatigue has been shown to impaired executive functioning, whether it be the capacity to inhibit irrelevant information (Faber et al., 2012), the ability to adaptively change strategies in the face of negative outcomes (i.e, flexibility; Lorist et al. 2000; van der Linden et al. 2003), or the ability to update information in memory (Shigihara et al., 2013). In addition, action monitoring and response preparation (Boksem et al., 2006) as well as post-error performance adjustment (Lorist et al., 2005) seem also impaired with increasing fatigue. Considering these findings, it would seem coherent that cognitive fatigue leads to an increase of perseveration (the person is no longer able to evaluate the situation and persists in irrational actions; Dehais et al. 2019) and prolonged planning time (van der Linden et al., 2003). Taken together, these different works indicate that cognitive fatigue corresponds to a suboptimal neurocognitive state in which the ability to adapt to unexpected situations could be severely impaired. The human operators performance, such as when the situation requires a rapid reaction to deal with a change (in concrete terms, critical functions during abnormal situations and recovery phase) could be massively impacted by this deterioration.

Cognitive fatigue and vigilance decrement In parallel with the evolution of adaptive capabilities, cognitive fatigue is also regularly associated with changes in alertness, and in particular with the vigilance decrement phenomenon. The vigilance decrement has been described as a slowdown in reaction times or an increase in error rates as an effect of time-on-task during tedious monitoring tasks (Pattyn et al., 2008). The question of the processes underlying this phenomenon of vigilance decrement remains a matter of debate. Whereas some studies suggested that the vigilance decrement reflects a reallocation of processing resources away from the task at hand during a less demanding situation (Manly et al., 1999; Pattyn et al., 2008), others assume that the vigilance decrement results from a depletion of attentional resources as time-on-task and task demands increase (Helton and Warm, 2008; Neigel et al., 2020). Recently, some authors have promoted a proposal that synthesizes both views (Langner et al., 2010). These authors argued that maintaining vigilance over time will depend on both subjective costs (i.e. effort exertion) and benefits (i.e. intrinsic rewards) of such sustained attention. Accordingly, the vigilance decrement would occur when an unbalance between cost and benefit appears. Interestingly, levels of fatigue could play an essential role in this management of resources that can lead to strategic changes in the investment of effort during sustained cognitive performance. Indeed, effortful behaviors may impact the brain process that weighs up the costs and benefits of exerting an effort. As fatigue increases, the benefit of providing effort in a task decreases, resulting in reduced performance. In other words, the result is a reduced willingness to make efforts over time (see Müller and Apps 2019 for more details).

More generally, motivation plays an important role in the onset of cognitive fatigue. High motivation, usually associated to a high reward or an important flow for the activity (Engeser and Rheinberg, 2008), can delay cognitive fatigue (Boksem and Tops, 2008), and decreases in performance can be explained by reduced motivation or loss of interest in the task (Ackerman, 2011). The opposite is also true, motivation can increase performance (Boksem et al., 2006). In this context, it seems obvious that cognitive fatigue could be associated with difficulties in sustaining attention during monitoring tasks and come with task disengagement. A particular question concerns the impact of cognitive fatigue when performing a monotonous task (for example, a monitoring task following an intense emergency situation). Supervisory tasks are also prone to boredom and its effect can be confused with cognitive fatigue (Pattyn et al., 2008). Boredom is characterized by a low level of stimulation, regular repetition of identical stimuli, or little physical and mental demand from the operator causing feelings of weariness, drowsiness, decreased alertness, and lack of interest in the task (Grandjean, 1979). Particularly, boredom situations could affect motivation and increase the impact of cognitive fatigue.

2.2 Exploring the impact of cognitive fatigue

Because of this impact of fatigue on cognitive functioning, it has been widely studied and different methods have been proposed to induce it in laboratory conditions. These methods can be categorized according to two criteria:

The first concerns the origin of this fatigue. Because cognitive fatigue has been considered as the direct result of working for a prolonged period of time, the most commonly used experimental means of inducing fatigue are to increase task duration, also called time-on-task (Ackerman and Kanfer, 2009). However, fatigue may also be experienced after working for a relatively short period of time, while working long hours does not always lead to fatigue (Park et al., 2001). In this sense, task demand has been used to induce cognitive fatigue too (Shigihara et al., 2013).

The second refers to the direct or indirect nature of the fatigue induction (Ackerman, 2011). The direct method consists of evaluating the impact of cognitive fatigue by performing one task for an extended period of time, whereas the indirect method requires the use of two tasks. The first task is used to induce cognitive fatigue, and the second task, performed immediately afterward, is used to assess the impact of fatigue on the individual. While the direct method is easier to implement and therefore often used, the indirect method has revealed interesting results concerning the transfer of the effects of fatigue. An important feature related to these fatigue induction protocols is the time required to induce fatigue. Most studies involve long tasks, sometimes lasting several hours (Blain et al., 2016). The effects usually observed could, therefore, be explained by learning factors, motivational factors, or factors related to the individual's level of alertness. On the other hand, recent studies have shown that cognitive fatigue can be induced in a few minutes of intense activity (Borragán et al., 2016).

For example, a recently developed method combines two classic laboratory tasks (parity task and N-Back type memory task) performed simultaneously to induce cognitive fatigue in a relatively short time (about 20 minutes; Borragán et al. 2016). This induction is then used to explore the impact of cognitive fatigue on performance in the next task. Such a method has the potential to abstract from the biases associated with the methodologies usually used to study cognitive fatigue. Also, this method is relevant to the operational context being studied. Indeed, it is not uncommon for the human operator to be confronted with situations that require intense cognitive activity, whether it is a particular phase of the flight or an emergency situation. These situations are often preceded but also followed by less intense periods but for which the operator must maintain a level of performance necessary for the safety and efficiency of his/her mission. Today, we know relatively little about the impact of these phases of intense activity on the performance of operators during the period following this activity. This method could be informative on this issue.

3. COGNITIVE FATIGUE ASSESSMENT

As cognitive fatigue seems to be multifactorial, it requires a multidimensional approach to be tackled (Bartley and Chute, 1947). Despite a large number of studies on the subject, there is no consensus on how it should be assessed (Christodoulou, 2005). Three approaches can be used and combined to define and measure fatigue: report-based (i.e. subjective measures), performance-based, and physiology-based measures. The most used metrics and tools for these three approaches are detailed in the following subsections.

3.1 Subjective measures

A large number of questionnaires have been developed to measure self-reported fatigue. In their book on sleep assessment tests, Shahid et al. (2012b) listed multiple of them on non-pathological fatigue. The Stanford and Karolinska Sleepiness Scale (SSS; Hoddes et al. 1972 and KSS; Shahid et al. 2012a; 7 and 9-point scale respectively) are widely used to measure sleepiness at a given time (Kaida et al., 2006). The Samn-Perelli 7-point fatigue scale (SPF; Samn and Perelli 1982) subjectively measures the level of fatigue from 1 "fully alert, wide awake" to 7 "completely exhausted, unable to function effectively". Both KSS and SPF are also being used as output for predictive biomathematical fatigue models used in the aviation industry like the Boeing Alertness Model (BAM) and the SAFE. Also, the Visual Analogue Scale to Evaluate Fatigue Severity (VAS-F, 18 scale-items; Lee et al. 1991) can be used to assess fatigue, more in the sense of energy. The latter can be used in parallel with the Visual Analogue Scale of Sleepiness (VAS-S, see Tanaka et al. 2013) to control for potential differences in the subjective notions of cognitive fatigue and sleepiness (Borragán et al., 2017). The Multidimensional Fatigue Inventory (MFI; Smets et al. 1995) proves to be more versatile since it evaluates five dimensions of fatigue: general fatigue, physical fatigue, reduced motivation, reduced activity, and mental fatigue. The Swedish Occupational Fatigue Inventory (SOFI; Åhsberg et al. 1997) also assesses five dimensions of fatigue: lack of energy, physical exertion, physical discomfort, lack of motivation, and sleepiness. In the context of a long activity such as UAS piloting and given the impact of circadian rhythms on performance (Lamberg, 2000), their study using the Owl/Lark Self-Test (Shahid et al., 2012b) or the Circadian Type Inventory (CTI; Folkard et al. 1979) questionnaires can be useful.

Another theme that can be addressed is the de-motivation and boredom felt during a monotonous task. The Motivation and Energy Inventory (MEI; Fehnel et al. 2004) and the Boredom Proneness (Farmer and Sundberg, 1986) can be used. Since sleep deprivation is one of the most important factors in fatigue, the quality of the previous night's sleep is a measure that should be taken into account when assessing performance on a task. The St. Mary's Hospital Sleep Questionnaire (QSN; Ellis et al. 1981) appears to be an appropriate tool for this purpose.

3.2 Behavioral measures

As previously presented, fatigue causes a decrement in task performance. In monotonous vigilance or monitoring tasks, reaction time (Paus et al., 1997), the accuracy or propensity to make errors (Boksem et al., 2005), false alarm rates (Basner et al., 2008), declines in planning ability, and increases in perseverative errors (van der Linden et al., 2003) are usually used to assess performance. These measurements are appropriate to assess UAS operators in an ecological and operational setting. Also, oculomotor behavior, as measured thanks to eye-tracking, is a useful fatigue detection measure, widely used in pilot research (Peißl et al., 2018), including UAS domain. For example, some authors (Wickens et al., 2005; Mannaru et al., 2016) used eye-tracking to study UAS pilot's attention response to various levels of automation.

3.3 Psychophysiological measures

Psychophysiology-based measurements provide greater objectivity and are a complementary approach allowing a more comprehensive characterization of cognitive fatigue. In an ecological context such as UAS piloting, some of them prove to be more appropriate thanks to their portability and a presentation of them will be made here.

The brain rhythms, visible thanks to electroencephalography (EEG), now become one of the reference tools for the study of sleep and can be considered a promising measure of cognitive fatigue. In the frequency domain, the power spectral density (PSD) can be calculated for different frequency bands. Cognitive fatigue is reflected by a progressively increase with time-on-task in both theta (4-8 Hz) power at frontal-midline sites, and alpha (8-13 Hz) power at parietal sites (Trejo et al., 2015; Balasubramanian et al., 2011). Moreover, Zhang and Yu (2010) showed that a decrease in beta power (13-30 Hz) and the ratio β/α, as well as an increase in the ratio $(\alpha + \theta)/\beta$ before and after the task were associated with an increase in cognitive fatigue. But, as mentioned by the authors, these metrics are also used to assess sleepiness (Kecklund and Åkerstedt, 1993). Indeed, as previously mentioned, most of the literature on mental fatigue addresses arousal-related effects with usual modulations of power for the bands between 1 and 30 Hz (Lal and Craig, 2002; Balasubramanian et al., 2011; Borghini et al., 2014). Additionally, the effects of cognitive fatigue on attention can be highlighted by amplitude modulations of specific time-domain features: the event-related potentials (ERPs). Hence, the decrease in amplitude of the N1 and N2b components across time reveals a time-on-task effect (Boksem et al., 2005). It has also been shown that the amplitude of the P3 can be decreased (Schmidt et al., 2009) with a decrease in vigilance or also delayed (Zhao et al., 2012) with mental fatigue.

Because of the intermingling of cognitive fatigue and sleepiness, another approach could be to study patterns of functional connectivity in the brain. This allows to show that a change in mental fatigue level is associated with a functional coupling of the frontal, central and parietal brain cortical areas (Liu et al., 2010). Also, the hemodynamic changes of the brain can be assessed thanks to functional near-infrared spectroscopy (fNIRS). Changes in the global and functional connectivity in the prefrontal cortex, which plays a major role in executive control processes, and motor cortex are closely related to cerebral fatigue (Xu et al., 2017).

Regarding peripheral measures, electrocardiography (ECG) measurements can also be used as measures of cognitive fatigue. A decrease in heart rate (HR; Lal and Craig 2002), and an increase in the heart rate variability (HRV; Huang et al. 2018) have been shown to be good indicators of an increase in cognitive fatigue (Zhang and Yu, 2010). Lastly, as an additional measure of oculomotor behavior, electrooculography (EOG) can bring complementary information for vigilance estimation (Zheng and Lu, 2017).

It is only recently that the mental state of UAS operators has been studied thanks to EEG. Hence, Roy et al. (2016) focused on the characterization of physiological markers (EEG, ECG) to evaluate UAS operators' engagement, while Senoussi et al. (2017) used EEG connectivity measures to predict an operator's attentional state and performance. As EEG, fNIRS has been used to study UAS operators' mental states. Richards et al. (2017) used fNIRS to study UAS operators' mental workload and vigilance. Others used it to assess cognitive performance through oxygenation changes in the prefrontal cortex (Armstrong et al., 2018; Reddy et al., 2018).

As uncovered by this non-exhaustive literature review, regarding physiology-based assessment, the main challenge

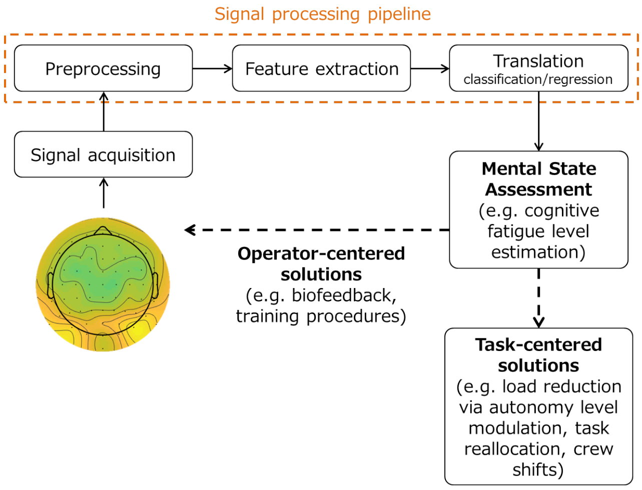

Fig. 1. General structure of a passive BCI pipeline for UAS operator mental state assessment, inspired from Roy and Frey (2016).

remains to ascertain the modulation of the aforementioned markers due to cognitive fatigue. Indeed, most of the literature relates to arousal-related effects and even though the same markers might be reflecting both states (i.e. low vigilance and high cognitive fatigue), it still remains to be clarified. Also, all these recording methods have different strengths, and in order to enable better mental state assessment, their complementary use and redundancy are highly advisable. Hence, the combination of several physiological metrics, including EEG, EOG, ECG, and fNIRS, has been shown to improve the estimation of cognitive fatigue (Ahn et al., 2016).

4. MACHINE LEARNING AS A NEW TOOL FOR COGNITIVE FATIGUE ASSESSMENT

Machine learning is a powerful tool that has been used in the neuroscience field for a few decades to enable extracting information from brain signals in order to enable heavily disabled people to communicate or control a wheelchair, robotic arm, or exoskeleton. These systems are called Brain-Computer Interfaces (BCIs; Wolpaw et al. 2002). Recently, they have been modified in order to enable operator monitoring for an implicit modification of an interface or a given system. In this case, the user is not voluntarily controlling it, hence these systems are called passive BCIs (George and Lécuyer, 2010). Another term that can be found to define systems that enable operator monitoring based on cerebral and/or peripheral measures is physiological computing (Fairclough, 2009). The general structure of a given mental state estimation pipeline is briefly detailed in Fig. 1. It encompasses the signal acquisition step, several processing steps including the classification, and the interpretation step based on the labeled data that enables to alert and/or modify a given interface or system accordingly.

The machine learning-based estimation of arousal, sleepiness, drowsiness, and time-on-task based on physiological markers has been thoroughly studied (Roy et al., 2013, 2014; Charbonnier et al., 2016), notably for driving and piloting applications (Borghini et al., 2014; Dehais et al., 2018b; Charbonnier et al., 2016; Lin et al., 2005). Hence, time-on-task during monotonous tasks can be very easily classified using EEG frequency markers with for instance up to 97% of accuracy using a linear regression classifier (Trejo et al., 2015) and 100% using a linear discriminant analysis classifier with a spatial filtering step (Roy et al., 2013). Moreover, the study of patterns of functional cerebral activity also enables classifying cognitive fatigue levels as demonstrated by Sun et al. (2014) with 81.5% accuracy obtained using a Support Vector Machine classifier.

Regarding UAS operators' fatigue level estimation, the literature is still scarce. ECG and eye-tracking features have been used successfully to assess engagement and workload in human-robot interaction applications (Chanel et al., 2020). But for UAS pilots, to our knowledge, studies on fatigue are only based on subjective and behavioural measures (Caid et al., 2016). Thus, it seems that even though arousal-related states are widely studied and estimated, the actual estimation of operator cognitive fatigue levels in the literature is still lacking. This is even truer regarding UAS operators, although the safety issues in this context are paramount.

5. POTENTIAL SOLUTIONS AND OUTLOOK

This article was intended to briefly present a review of the literature regarding UAS operators' cognitive fatigue and to present a solution that we propose to implement in order to mitigate its impact on both mission safety and performance, namely to perform a cognitive fatigue assessment using machine learning tools. Solutions that can be considered to make use of such an assessment are twofold:

Operator-centered solutions An online cognitive fatigue assessment could allow providing real-time biofeedback (for an example of biofeedback utilisation see Sitaram et al. 2017) to the operators in order to increase their awareness as to their own state, as well as to increase their motivation and consequently to try and mitigate the occurrence of the drop after intense work. Also, another solution could be to use the assessment to enhance training procedures, as well as to add a cognitive fatigue module to the existing FRMS procedures currently in use.

Task-centered solutions Other solutions to mitigate the impact of cognitive fatigue in UAS operation would be to modify the task itself when a high level of cognitive fatigue is detected thanks to a passive BCI system. For instance, the task demand could be diminished so as to reduce the workload of the operator and enable him/her to maintain an adequate performance level. Such a modification could be performed by reducing the number of UAS (Ruff et al., 2002), or the number of parameters to monitor by allocating this load to other members of the crew (Walters and Barnes, 2002), or by increasing the automation levels of the artificial agents (Ruff et al., 2002). This passive BCI approach would be complementary to the approaches already used in the construction of cognitive UAS interfaces (Neville et al., 2012; Lim et al., 2016).

However, to implement a passive brain-computer interface, it is necessary to find physiological markers that are sufficiently specific to cognitive fatigue, since it is often confounded with arousal, sleepiness, or boredom. A solution might be to use a combination of various sensors to better target this precise mental state. Moreover, there is a need for robust algorithm development to cope with the issues generated by the non-stationarity of the cerebral signal arising from the individual, session, and task-related variability. Regarding the solution of implementing adaptive interfaces, the levels of automation should be selected carefully, as they may impact the workload, situation awareness, and trust (Ruff et al., 2002) which can lead to accidents (Glussich and Histon, 2010). Lastly, the issue of acceptability by the operators is of course crucial and needs to be addressed, as for any personal data acquisition device. Yet despite all these issues to deal with, the potential for a better interaction with long-endurance UAS that might lead to safer missions is of growing interest for the research and the engineering communities, and this brief review of the literature and position paper advocates for a new means to achieve this goal.

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