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Human Performance Assessment: Evaluation and Experimental Use of Wearable Sensors for Brain Activity Measures

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The emerging wearable human performance monitoring technologies can help evaluate the cognitive status and capacities of the crew in the cockpit as well as those operating ground control stations. Traditionally the use of behavioral measures and subjective metrics has been used to address cognitive factors associated with pilots or operators of safety critical systems. However, the advance in wearable physiology technologies could provide additional performance metrics directly driven from brain based measures, potentially validating subjective assessments and ultimately bringing us closer towards maintaining safe and effective performance. Furthermore, these techniques may also aid the design and evaluation of new technologies that are being presented as increasing operational capacity, efficiency and safety across the aerospace domain. The measurement of real time brain activity from the operator can help evaluate decision making, and reliably compare workload burden of next generation system versus legacy systems in the air transportation domain. This paper outlines key cognitive areas of interest when attempting to explore the correlation between physiological state changes and psychological constructs. A number of studies are described whereby wearable systems, namely electroencephalography (EEG), and functional near infrared spectroscopy (fNIRS), are used to evaluate human performance. The potential advantages and challenges are discussed in relation to implementing these sensors in real operational settings.

Civilian pilots, air traffic controllers, ground controllers are all increasingly required to utilize larger amounts of data and more complex systems. Hence, we are likely to observe an increase in the information-processing load and decision-making demands on aviation personnel. Many of these issues have been symbiotic with initiatives being developed under initiatives such as Next Generation Air Transportation System (NextGen) and the Single European Sky Air Traffic Management Research (SESAR) programmes. The human element within any future concept still represents a critical point that may either be seen as a point of failure or a means by which these new technologies are optimized. It is therefore important to consider how we not only assess such technologies, but the way in which the human interacts with them and ultimately arrives at making decisions.

The last decade has seen significant advances in physiological monitoring techniques, and in particular their integration into ubiquitous devices. One aspect of this has been the increase in wearable human performance monitoring technologies that can be used to evaluate the cognitive status and capacities of the crew on the flight deck, as well as on the ground (such as the ground control station or air traffic terminals). Non-invasive wearable technologies offer the potential to observe human cognitive performance directly driven from brain-based measures, which would be an important asset in evaluating (and maintaining) safe and effective operational performance. Further, such sensory input from the operator can help evaluate decision making, and reliably compare the cognitive workload burden of future versus legacy systems in the air transportation domain. Currently the most widely used brain activity measures are functional magnetic resonance imaging (fMRI), magnetoencephalography (MEG), electroencephalography (EEG), and functional near infrared spectroscopy (fNIRS).

This paper introduces some key theoretical aspects of cognition that are prevalent within aerospace, with particular attention to cognitive workload and human performance in safety critical environments; with a view to *bridging the gap* between cognition and measurement. Following this, a number of operational views are outlined

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through the description of field use cases: including ATC human-in-the-loop studies and the nature of human performance in weather decision making. Principles of EEG and fNIRS are discussed in relation to application and calibration, before highlighting their potential contribution in providing reliable and objective assessment of pilot' and operator' cognitive performance.

Maintaining the Objective: Assessing Pilot and Operator Cognitive State

The Aerospace Industry is regarded as one of the safest transport domains, with a constantly improving safety record (Harris, 2014). However, when we consider the different roles and responsibilities that we ask of the humans that operate across the national airspace system (NAS) we can appreciate the diversity of tasks and systems that users of those systems have to utilize. When tasks become complex, laborious or dramatically increase, automation is commonly (and effectively) applied. Although we have traditionally seen a rise in the use of automation within aerospace applications, it is fair to say that the human will remain responsible for making critical decisions based on the information they are presented with.

Human Factors (HF) within aviation has provided us with a good understanding of the cognitive processes involved in aviation operations, predominantly focused on manned and unmanned aviation and the critical management task provided by Air Traffic Control Operations (ATCO). It is of little surprise, therefore, that we can identify a number of key cognitive components that play a role in human performance. In order to understand how an individual processes and acts on information it is critical that we define two important aspects that underpin Aviation HF; that of human information processing (HIP), mental workload (MW) and situation awareness (SA).

We must first consider the nature of a number of theoretical constructs that we need to understand when discussing these cognitive constructs. Without descending into an essay on the many different theories and approaches to understanding cognition, it is best to approach this by outlining the way in which humans process information. To start at the beginning we can describe, in general terms, the core aspects of HIP as related to how information travels from the environment to the human, and subsequently how he/she acts on that information. This in turn can be further deconstructed into three key factors: (1) **Encoding** data from the environment, (2) **Processing** the data into meaningful information we can use, and (3) **Executing** actions as a result of the first two steps. Although this sounds like a simple mechanistic approach we must remember that all of this activity must take place rapidly across different dynamic models of memory; namely sensory, short term (often referred to as working memory), and long term memory (Atkinson & Shiffrin, 1968, 1971). These distinct models of memory allow us to understand the processing of information in terms of how we attend to sensory stimuli, before we move on to register and encode aspects of the information, see Figure 1.

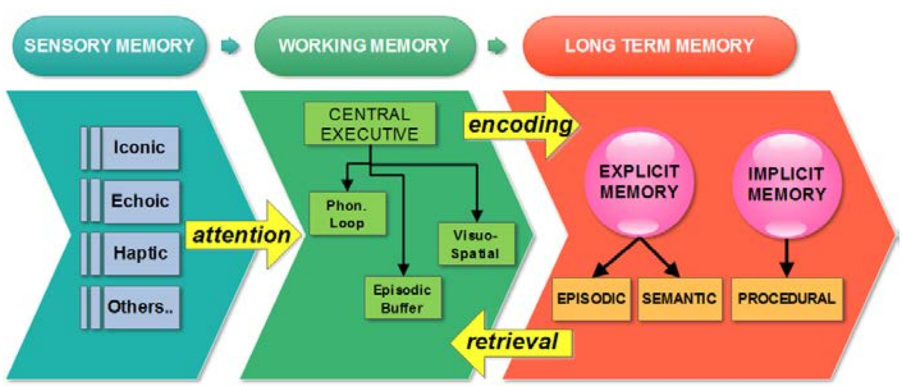

Figure 1 - Three component memory model of Information Processing (adapted from Atkinson & Shiffrin)

Of course the manner by which we process information is somewhat dependent on the characteristics of the information being attended to and the specific requirements of the task. This will further determine how attentional resource is utilized during the context of the task demand and which stimuli are attended to (Baddeley & Hitch, 1974; Baddeley, 2003). Inevitably this represents a constraint in terms of how humans process and store information, more so when confronted with dynamic and complex tasks to perform. Unsurprisingly there are many instances where this constraint of HIP can sometimes lead to *bottlenecks* whereby information will compete for the attention of the individual to process. The human brain adapts to this by selectively attending to certain information (very much dependent on the task context) whilst filtering out less salient information (Moran & Desimone, 1985).

If we focus on the processing of information within working memory, then it has been suggested that this represents our understanding of the external environment - or, to put it another way, our SA (Bell & Lyon, 2000). Endsley (1995) however views SA more as a cognitive product of information processing, and developed perhaps the most influential model of this construct. In essence Endsley (1995, 2000) suggests that SA is an active and ongoing process of achieving a state of knowledge of a given situation. But, in order to achieve this it is necessary to process information sequentially through the stages of (1) **Perceiving** the attributes and state of the elements within the environment, before beginning to (2) **Comprehend** what is being perceived, and then finally understanding this information by (3) **Projecting** ahead what is likely to happen in the future. While there are many different interpretations on the nature of SA as a theoretical construct, what it all boils down to is the nature of what it is we are attempting to measure; trying to make the intangible tangible. Stanton et al (2005) provide an overview of different methods employed to measure SA, which can be categorised into different techniques such as freeze probe recall, real-time probe techniques, post-trial subjective ratings, observer ratings and process indices (Salmon et al., 2006). All of these techniques have both good and bad points and may be used to claim a measure of SA (depending on which technique and definition you ascribe to). Indeed, Endsely (2015) concludes that the very nature of the construct makes it difficult in itself to measure it.

We can all think back to an instant where we have felt overwhelmed by a situation that has affected our ability to act efficiently and in a timely manner. Regardless of whether that experience was within an aviation context or not, it is likely that this increase in MW could also raise the likelihood of inducing human error and ultimately reducing your effectiveness (Moray, 1988). As with many cognitive constructs there is no single agreed definition of MW, but we can broadly agree that it is composed of a number of features that require: an input (or task load), a specified amount of effort required by the human to satisfy the task, and the actual performance of the human in *doing* the task (Jahns, 1973). Clearly the ability to assess an individual's MW during critical tasks can provide important details as to the manner of the task demand, which may then assist in the future design and integration of that system into an operational context.

The key element to consider here is that the assessment of MW requires a tangible value that can be assessed by employing a range of techniques. Primarily we can use observation and measurement to determine whether the task has been successfully completed, which may further be constructed of behavioral markers assigned to primary or secondary tasks. Thus, quantifiable measures (such as holding altitude or maintaining safe separation) may be used to determine whether the individual is operating under a higher or lower amount of MW. Either way we would witness an effect that could be translated as having an impact on the individual completing these tasks. Measuring behavioral response aligned to a particular task does not directly involve direct interaction with the participant, but an observation of the task with which they are engaged. However, it is almost impossible to enforce a completely *sterile* condition whereby we can state that any behavioral effect is solely attributed to MW. A more direct perception of what the participant may report in terms of their perceived effort can be gathered by a large number of available subjective MW measures.

Assessment and Measurement

Both MW and SA are cognitive processes that are theoretical constructs and somewhat illusive to direct measurement. However, all is not lost, as we may use a number of methods to assess human performance. We can see that there are several techniques that can be used, and these broadly fall into three categories: (1) Rating scales, (2) Performance Measures associated with primary and secondary tasks, and (3) Psychophysiological measures. In the past the most widely used of these methods would center on the first two methods of gathering data; due to their ease of use and lack of physiological techniques that can be readily applied and interpreted.

However, when selecting (or developing) an appropriate measurement technique there are a number of factors we must take into account. These factors are outlined in Figure 2, and show that the context within which we conduct human performance assessments plays a pivotal role in how we attempt to measure cognitive processes.

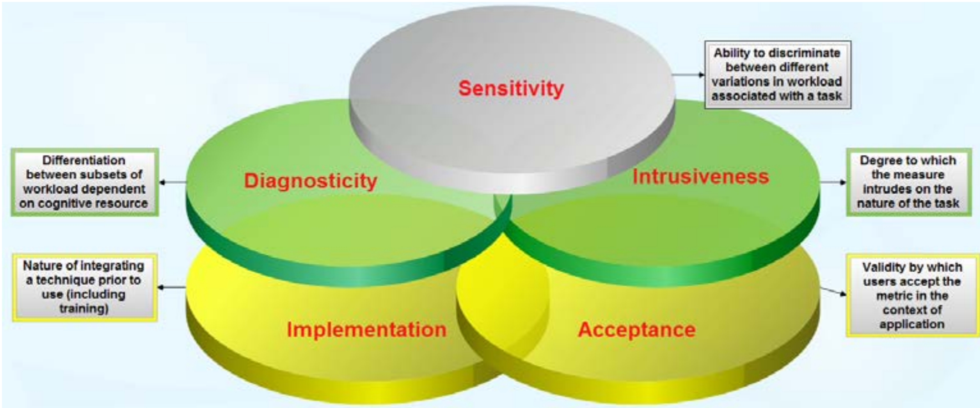

Figure 2 - Factors that should be considered within the selection criteria for metrics

While behavioral measures are largely non-intrusive and possess high participant acceptance, they are poor in terms of their sensitivity and diagnosticity for measuring mental workload. And consequently the validity of such approaches must often be examined.

Operational View of Human Performance Assessment

To assess the impact of changes being adopted under programmes such as NextGen and SESAR, we often run high fidelity Human-In-The-Loop (HITL) simulation experiments. Research efforts commonly examine the the impact of new technologies on human performance, with a particular focus on pilot/operator cognitive processing. Changes to mental state of the operator will directly affect the safety and efficiency of the NAS. One of the challenges with HITL experiments is to use an objective measure that is unobtrusive, real-time, and sensitive enough to detect changes due to human-automation interaction or procedural changes.

We have seen that the cognitive theories discussed in this paper are complex multi-dimensional constructs that are by their very nature difficult to quantify using any one single metric. By adopting a range of metrics, and choosing those that suit the nature of the task being examined, it brings us closer to a clearer picture of what an individual's cognitive response is within a given context. We have used several physiological measures in conjunction with system-derived as well as subjective measures. Here we present our experience across several studies as well as the pitfalls of using subjective measures to assess new technologies. The studies were conducted at the FAA's William J Hughes Technical Center and some reported by Willems (2002), Ayaz., et al., (2011; 2012), and Harrison., et al. (2014. These provide a number of contexts which have shown promising results that appear to benefit from the application of neuropsychological measurement.

Context One: Decision Making and Significant Weather for Air Traffic Controllers and Pilots

About 70% of aviation delays are related to weather. To enhance NAS efficiency and safety, it is important that air traffic controllers and pilots work together to make sound decisions when encountering severe weather. Decision making and communication for air traffic controllers and pilots during severe weather situations could cause excessive MW for both controllers and pilots.

Severe weather creates challenges in decision making and communications for both controller and pilots in the complex sociotechnical system. Air traffic controllers need to make quick assessment about the weather scenarios and understand the current situation as well as future progress of the severe weather phenomenon. Additionally, they need to disseminate relevant weather information to pilots in the most effective way (Ahlstrom, 2005). For the pilots, with challenges created by severe weather, they have to make decisions about whether to divert from their original flight path with the help from air traffic controllers (Chamberlain & Latorella, 2001; Delaura & Evans, 2006). Effective and timely communication between controllers and pilots is critical to ensure safety and efficiency. To maintain a common weather picture and allow for shared SA, which facilitates collaborative decision making between controllers and pilots, communication protocol and channel (via Data Comm, ADS-B weather display enabled by NextGen technologies, voice) should be carefully designed.

As all weather forecasts are probabilistic in nature, controller and pilots also need to be trained to deal with inherent uncertainty in weather. National Severe Storm Laboratory (NSSL) from NOAA is developing Probabilistic Hazard Information (PHI) system, part of the vision of Forecasting a Continuum of Environmental Threats (FACETs; Rothfusz, Karstens, & Hilderbrand, 2014.). This new system provides dynamically updated probabilistic information of areas being impacted by severe weather threats, using graphical design methods to convey the likelihood of threat occurrence (Karstens, Stumpf, Ling et al., 2015). A graphical probabilistic weather display may become a useful tool to enhance decision making and communication for controllers and pilots.

Context Two: To Improve Safety and Evaluation of Training in ATM Using Neuroscience-Based technology

Air traffic management (ATM) is an essential part of air transportation and aviation, connecting cities and people citizens as well as boosting jobs and growth. However, worldwide ATM systems are based on aging technology and procedures and needs updating particularly in light of the expected traffic growth in the near future. The future ATM scenarios describe a system where high levels of automation should be deployed to support humans. However, automation brings a range of new challenges. A series of problems concerning the interaction between human and automation that have been reported are: deficiencies in human operator states, including vigilance decrements, complacency and out-of-the-loop problems, and training deficiencies.

We reviewed the state-of-the-art in assessing human performance and training under the advancement of aviation automation. Such technology capacities have been reflected in documented publications on MW assessment, alertness, training in air transportation management (ATM) with realistic environments and testers. We examined the state-of-the-art portable sensor technologies that are adaptable and inexpensive. This allowed us to identify a number of neurophysiologic conditions that can be associated with the levels of cognitive control (Astolfi et al., 2011; Shou et al., 2012; Borghini et al., 2014b; Kong et al., 2015). Further to this, we obtained information about the level of MW of ATM operators, through a combination of neurometrics and other physiologic measures (Arico et al., 2015; Borghini et al., 2015), in a realistic ATM context (Arico et al., 2014, 2016; Dasari et al., 2015). This allows us to recommend a number of safety measures. Finally, we gathered valuable data on the use of neurometrics that can assess the current learning level of trainees (Borghini et al., 2013, 2014a, 2016; Krishnan et al., 2014).

Context Three: An Investigation of Optical Brain Imaging Sensor in Performance Assessment

The safe and effective performance of aviation personnel depends on their ability to manage and maintain high levels of cognitive performance. A field-deployable optical brain imaging device can provide team member's cognitive state and relative level of expertise for a given level of performance by monitoring cortical areas that are known to be associated with MW, learning and the development of expertise.

Near-infrared spectroscopy (NIRS) has been widely used in brain studies as a noninvasive tool to study changes in the concentration of oxygenated hemoglobin (oxy-Hb) and deoxygenated hemoglobin (deoxy-Hb). Based on the NIRS technique, a functional brain activity assessment (fNIRS: functional Near InfraRed Spectroscopy) system has been deployed as a means to monitor cognitive functions, particularly during attention and working memory tasks as well as for complex tasks such as pilot training and air traffic control scenarios performed by healthy volunteers under operational conditions. The fNIRS is a field-deployable non-invasive optical brain monitoring technology that provides a direct measure of cerebral hemodynamics from the forehead in response to sensory, motor, or cognitive activation. This study also allowed us to progress brain based measures and biometrics across different human roles in aviation.

Our work utilizing fNIRS has allowed us to progress this technique towards deploying this device in the field; whereby operators can be assessed in their normal working condition and have included multiple studies with the Federal Aviation Administration (FAA) as well as with the Department of Defense (DoD). In the first study, we explored the impact of the different Conflict Resolution Advisory (CRA) conditions on air traffic control operator's behavior and MW. The fNIRS sensor was utilized to monitor the MW of the 12 operators using this new CRA system across 3-day human experimentation sessions (Harrison et al., 2014). Further to this, a HITL study was conducted using fNIRS to evaluate MW within a NextGen air traffic system that examined the difference between Data communication (DataCom) and Voice communication (VoiceCom) between pilot and air traffic controllers (Ayaz et al., 2012). Finally, we also adopted fNIRS to assess human performance unmanned aerial vehicle (UAV) operators (Izzetoglu et al., 2015). The results provided within these studies revealed that such fNIRS can be used to monitor true MW changes during aerospace operations. It also proved to be an objective measure of expertise development, i.e., the transition from novice to expert during operator training (Ayaz et al., 2012).

Discussion

Advances in neurophysiology and neuro-monitoring technologies have demonstrated that changes in physiology can explicitly be assessed and correlated with different tasks. These may relate to instances where the human is confronted with high cognitive loading, or events that can be identified as leading to a change in situation awareness. It may also be used to develop adaptive, personalized training regimes and provide indicative markers that are associated with expertise development. It is therefore essential that before we start to decide which metric to use, we must consider the context within which the measurement is to be applied, what we are exactly attempting to measure, and so on. Once we can establish these requirements we can begin to address the robustness of these neurophysiological biometrics in terms of reliability: does it produce the same results in similar situations? and validity: does it actually measure what it says it does?

It is worth noting that the sensitivity of these metrics may only provide one side of the story, in that they are perceived measures and sometimes do not reveal the full picture. Both subjective and objective metrics clearly have a role to play here, but we must exercise caution in not placing all our EEGs in one basket. Indeed, some studies have revealed contrasting results when we compare subjective versus physiological metrics in terms of MW (Richards et al, 2016). There has also been observations that suggest that subjective metrics, such as the NASA-TLX, can be limited by the nature of individual differences in introspection skills (Paulhus & Vazire, 2005). Chen et al (1995) even go so far to suggest that this limitation may even be observed at a cultural level, whereby instructing an individual to report perceived feelings of cognitive state are difficult to articulate.

We have shown that the advances in wearable sensors can be used to measure physiological state changes, and they represent an exciting opportunity to explore the psychology-physiology divide. Brain imaging measures allow us to add to our growing human performance toolkit, and when used with a battery of other metrics (including both behavioral and subjective), it provides us with a more robust understanding of cognitive performance.

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