Assessing Cognitive State with Multiple Physiological Measures: A Modular Approach

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Abstract. The purpose of this effort is to introduce a novel approach which can be used to determine how multiple minimally intrusive physiological sensors can be used together and validly applied to areas such as Augmented Cognition and Neuroergonomics. While researchers in these fields have established the utility of many physiological measures for informing when to adapt systems, the use of such measures together remains limited. Specifically, this effort will provide a contextual explanation of cognitive state, workload, and the measurement of both; provide a brief discussion on several relatively noninvasive physiological measures; explore what a modular cognitive state gauge should consist of; and finally, propose a framework based on the previous items that can be used to determine the interactions of the various measures in relation to the change of cognitive state.

Keywords: Augmented Cognition, Neuroergonomics, Physiological Measures.

1 Introduction

Advances in technologies, research, and interest in Augmented Cognition applications have all but guaranteed a future in which the physiological state of a human operator will impact the interactions with many, if not all, (closed-loop) systems. To the uninitiated, this statement almost assuredly conjures images of cyborgs and bionic beings that seemingly have given up their humanity. While the issue of being “more machine than man” may eventually become an ethical dilemma, current technology has not yet required its serious contemplation. Current technologies do, however, offer the opportunity to create systems in which the user is part of the interface. Through available technology, it is now possible to reexamine the human-centered system design (process) and include measurements of the human’s state as a means to inform and even adapt the system.

Although researchers in fields such as Augmented Cognition (AUGCOG) and Neuroergonomics have begun to establish the utility of physiological measures for informing when to adapt systems, the use of such measures remains limited. While this may be partially explained by the high cost of equipment, it is more likely due to the lack of clear guidance for the use of multiple sensing devices to adapt systems.

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This need was highlighted in 2007 by Reeves, Stanney, Axelsson, Young and Schmorrow [1] in their articulation of the near-, mid- and long-term goals of AUGCOG. The authors specifically noted that there were several impediments to the adoption of such technologies including: (1) the need for valid, reliable, and generalizable cognitive state gauges based on basic neurophysiological sensors; (2) real-time cognitive state classification based on basic cognitive psychology science and applied neuro-cognitive engineering; and (3) proof of effectiveness which demonstrates generalizable application of mitigations (i.e., the ability to control how/when mitigations are applied). Unfortunately, the ability to detect cognitive state through the use of various technologies based on different physiological indices currently poses problems. For example, sampling rates (i.e., resolution) of different measures may cause one technology to indicate a state change while another is reporting the previous state. Additionally, a particular measure may indicate the onset of a state change which may not be reported by other measures, and this dissonance may cause conflict when determining if an intervention is required.

As a tool, a "cognitive state gauge" is a vague concept which has the potential to include a wide range of contributing factors. When considering all of the possibilities, the goal of creating a valid and generalizable cognitive state gauge is a lofty one at best. In fact, the very idea of a cognitive state gauge poses issues of ambiguity similar to those of its conceptual springboard: *mental workload*. This vagueness, perhaps, is why such a measure has yet to be developed and/or proven effective in meeting the goals set by Reeves et al. [1].

Based on the multiple resource theory model [2],[3] and its idea that we draw from multiple distinct pools of cognitive resources, it is therefore proposed that instead of taking on the concept of a holistic cognitive state gauge, it is necessary to first manipulate specific cognitive resources and examine the physiological state as recorded by each of several synchronized measures. By using a modular approach which targets specific cognitive abilities in a controlled environment, it should be possible to build a reliable and generalizable cognitive state gauge based on basic cognitive psychology.

In order to describe a novel approach to assessing cognitive state with multiple physiological measures, this paper will provide a contextual explanation of cognitive state, workload, and the measurement of both. This will include a brief discussion of several relatively noninvasive physiological measures whose use, in concert, are proposed to present a solution to the impediments articulated by Reeves et al. [1]. Inspired by technologies described in the Augmented Cognition Technical Integration Experiment Report [4], the candidate measures that will be discussed include six non-cortical measures: eye blink rate (EBR); pupil dilation (PD); respiration rate (RR); heart rate (HR); heart rate variability (HRV); electrodermal response (EDR), and one cortical measure: electroencephalography (EEG). Specifically, this effort will explore what a modular cognitive state gauge (MCSG) should consist of and will also propose a framework. Additionally, a testbed based on the MCSG and proposed framework will be introduced for the purpose of determining the interactions of the various measures in relation to the change of cognitive state.

2 Measuring Cognitive State

It would be a futile effort to suggest that there is a way to measure cognitive state without first defining what is meant by the term cognitive state. For the purposes of this work, the idea that dynamic changes in human cognitive activity can be identified during task performance [5] allows us to define cognitive state as consisting of those aspects of cognitive ability which are called upon for the completion of a task.

While this may be an acceptable definition of cognitive state, it must be understood that there are numerous factors that contribute to cognitive state. For example, changing levels of fatigue or stress during task performance are responses, not indicators of the capacity of cognitive ability. Simply measuring the physiological response of fatigue and/or stress to a task would be to ignore the mechanisms that explain such responses. The mental capacity that allows for the successful completion of tasks should be the area of interest when investigating cognitive state. Ultimately, it is this capacity that, when taxed, results in performance decrements. The taxing of these mental capacities has been extensively investigated in various environments in order to understand the phenomenon of mental workload. If one intends to work toward the goals set forth by Reeves et al., it is necessary to understand what is meant by the term workload and to identify approaches that can be used for its measurement.

2.1 Workload

At the core, workload can be defined as the amount of demand(s) placed on an operator while attempting to accomplish something. Researchers have gone to great lengths to understand the effect of mental workload on performance. These researchers have proposed various theories and analogous models to explain how the human mind allocates its ability to handle information and task completion from the mundane to the complex. Byrne and Parasuraman [6] state that the general consensus on mental workload is based on theoretical models of resource and capacity for information processing. For this to be the case, it is accepted that humans have a finite amount of available cognitive resources which must be allocated and used to accomplish a task. In essence, mental workload is directly related to the proportion of the mental capacity an operator expends on the performance of a task [7],[8].

As a construct, workload is difficult to examine due to the seemingly limitless attributing variables. In his 2007 report to the Department of Transportation, Reinach [10] suggested that workload can be defined as the interaction between the demands of a task and an operator's ability to meet those demands. When considered in these terms, workload is viewed as being dependent upon an operator's level of training, expertise, experience, fatigue, stress, motivation, and his or her available cognitive abilities and resources for a given task. Of course, *task load* is an integral piece of the workload puzzle. Task load has been defined as the total amount of demands placed on an operator at a given moment in a situation [10]. For a contextual example, Hadley, Guttman, and Stringer [9] describe an air traffic controller's task load to include elements such as the volume and composition of traffic, routing complexity, and weather conditions. Therefore, in the context of this effort, workload is operationally defined as the demands on available cognitive ability and resources placed on an operator by the demands and complexity of a given task.

In 2002, Wickens provided a review of multiple resource theory (MRT) and its application with an updated four-dimensional model [3]. MRT suggests that there is not a single information processing source that can be tapped by an operator. Instead, in order to perform a task or tasks, Wickens [2],[3] proposes that an operator must draw from multiple distinct pools of resources simultaneously. Dependent upon the composition of the task(s), the operator may have to process information serially (if the task(s) require the same resource pool) or in parallel (if the task(s) require differing resource pools).

Central to this effort is the idea that Wickens' theory would view exceeding operator workload (resulting in a performance decrement) as a shortfall of available resources. Further, Wickens suggests that operators have a finite capability for information processing. In short, cognitive resources are limited and conflicts (operator overload) occur when an operator performs two or more tasks that require a single resource

Measuring Workload. Not surprisingly, numerous approaches for assessing workload have been developed, from relatively simple questionnaires to complex brain imaging techniques. Regardless of type, these approaches will generally fall into one of three distinct categories: performance, subjective, and physiological [8],[11],[12]. The following will discuss selected measures which are proposed for measuring cognitive state in this effort.

Performance Measures. As mentioned above, the measure of task performance is a widely used method of inferring the amount of workload experienced during the completion of a task. In general, research has shown that if performance is high (maintaining acceptable performance) then workload can be considered low. Conversely, low performance suggests high workload. However, there are various factors that contribute to the workload construct resulting in a non-linear relationship with performance. As a contributing factor to workload, performance does provide a quantifiable and potentially real-time (provided the parameters are known) method for assessing operator workload. The measurement of performance is generally separated into two main subcategories: primary and secondary task measures.

Primary Task Performance. On the surface, measuring primary task performance is a simple proposition. Unfortunately, this may not always be the case. Several factors can contribute to task difficulty experienced by an operator. For example, an increase in time pressure or the demands on cognitive resources may not always degrade performance [13]. The lack of performance decrement can be attributed to the operator's skill level or motivation to exert more effort to maintain an acceptable level of performance. These contributing factors can result in an incorrect assessment of operator workload due to the fact that acceptable performance is maintained while the operator is approaching the limitations of his or her cognitive capabilities.

Secondary Task Performance. The addition of a concurrently performed task to the primary task can be used to detect the workload of a primary task [14]. The goal of using a secondary task is to additionally tax the cognitive resources being used to complete the primary task. By doing so, an operator who is maintaining an acceptable level of performance is required to divert resources to the additional task and could potentially uncover his or her level of workload through an observable performance decrement in either the primary or secondary task. As suggested by multiple-resource theory [2][3], through the imposition of a secondary task that consumes the same resource(s) as the primary task, it should be possible to measure the excess resource(s) not utilized by the primary task.

Subjective Measures. One of the most commonly used methods for measuring workload is the NASA Task Load Index (TLX). The TLX is a subjective evaluation of workload that is completed by an operator upon completion of a task. The TLX is a multidimensional approach that measures workload by calculating a total workload score from six weighted subscales: mental demand, physical demand, temporal demands, performance, effort, and frustration level. These six subscales are based on extensive research and psychometric analyses from a wide range of contexts [15].

While asking an operator to evaluate his or her own level of workload following completion of a task has utility, most tasks are not static, isolated events and post hoc assessment, by its nature, would fail to offer real-time assistance to the operator. People are expected to perform in complex and dynamic environments which tend to evolve over time with the emergence of information. The complexity and propensity for real world operations to present novel and often hard-to-predict situations makes real time and predictive state assessment extremely intriguing as a way to inform potential mitigations to operator workload. While subjective ratings such as the TLX are useful for eliciting overall task workload assessment, they lack the ability to provide real-time assessment without intrusion.

Physiological Measures. The idea that physiological measures may assess workload is not a new one. For example, in their report for NASA, Scerbo, Parasuraman, Di Nocero, and Prinzell discussed the efficacy of using physiological measures for adaptive automation [16]. Their effort highlighted four promising physiological measures that could be used to assess mental workload: eye blink, respiration, cardiovascular activity, and speech measures. Additionally, EEG was discussed as a cortical measure that may inform the adaptation of automation.

It should come as no surprise that there are numerous methods that use physiological measurement technologies to assess cognitive state. Each of these methods use a unique approach to their measurement and assessment, a detail that must be addressed. The argument that one measure is adequate for operational systems will not suffice in the face of multidimensional tasks which are carried out in dynamic environments. Although, the use of multiple measures, as stated previously, presents confounding factors which must be considered. The responsiveness of one measure to the change of an operator's state may not occur within the same time frame as another measure. One measure may provide a global view of operator state while another may be better suited to detect subtle changes based on discrete events and/or situations. Confusion and even catastrophe can occur if system(s) dependent on these differing physiological measures are based on conflicting indications of operator state change. In order to achieve the goal of assessing cognitive state through the use of multiple physiological measures, it is important to discuss candidate physiological measures. These measures include six non-cortical measures: EBR; PD; RR; HR; HRV; EDR and one cortical measure: EEG. Table 1 provides an overview of each candidate technology.

Table 1. Overview of candidate physiological measures

Type	Description
EBR	Shown to be a useful measure of mental workload [17],[18]. Several laboratory and field studies have shown that blink rate decreases with an increase in task difficulty (e.g., [19],[20],[21],[22])
PD	Shown to decrease or increase depending on autonomic response. Pupil dilation is an important measure of mental workload [7] and has been used numerous times as a global measure of workload. Increased pupil diameter has been observed with an increase in resource taxation [22]
RR	Proposed as a useful physiological indicator of the state of an operator. Increased respiration rate along with a decrease in the depth of inspiration have been associated with increases in stress and cognitive demand
HR	Likely candidate for measuring cognitive workload. Wilson & Eggemeier [23] suggest that heart rate could predict and be an overall indicator of workload. This is supported by a series of workload studies showing that heart rate was the most favorable physiological measure
HRV	Decreases with the increase in heart rate. An increase in workload results in a decrease in heart rate variability [26] when compared to the rest state [8]. Of particular interest for the measurement of mental effort is the varying duration of time between heartbeats, the inter-beat interval [27]
EDR	Measurable change of electrical activity of the skin as a result of sweat gland activity capable of indicating stress-strain, emotion, and arousal [28]. One of the several measures of EDR, Skin Conductance Level (SCL) is measured by the application of a constant voltage to the skin via electrodes in order to measure conductance. Research has shown that there can be a significant increase of SCL across workload conditions [29]
EEG	Provides the total amount of the electrical brain activity of active neurons that can be recorded on the scalp through the use of electrodes [30]. Berka et al. validated use of EEG for measuring task engagement and mental workload. An investigation utilizing their task engagement and mental workload measures had promising results showing that participants' EEG-workload index increased on tasks with increasing difficulty and working memory load. Similarly, EEG-engagement was shown to be related to the processes required for completing vigilance tasks [30]

3 Modular Cognitive State Gauge (MCSG)

As stated in the introduction, the objective of this work is to define a useful approach for using multiple physiological measures to assess one's cognitive state. The paradigm presented here aims to segregate specific contributors to mental workload for measurement. It is proposed that by systematically exploring the manner in which each physiological measure correlates to performance and to each other in targeted areas, a cognitive state gauge that meets the validity, reliability, and generalizability requirements set forth by Reeves et al. [1] can be created.

It is proposed here to use Wicken's MRT model [2],[3] as a practical guide for investigating multiple physiological sensors and their combined ability to predict performance decrements in specific cognitive resource areas. After compiling an understanding of what to expect for particular cognitive resources through empirical research, the MCSG should begin to take shape (Figure 1). Essentially, it is proposed that by parsing out individual cognitive resources (e.g., visual, auditory, spatial, etc.) into modules, they can be empirically investigated and then integrated into a generalizable cognitive state gauge.

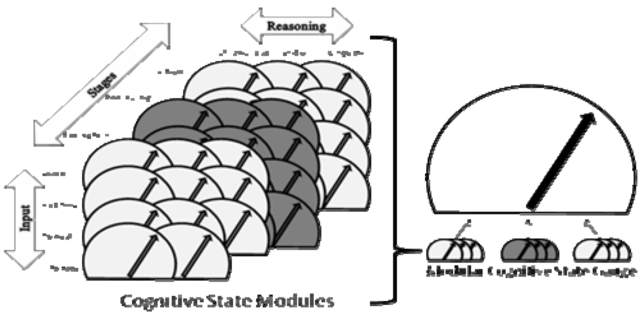

Fig. 1. MRT-based cognitive modules towards a modular cognitive state gauge

By using this modular approach, potential issues with the use of multiple sensors can be identified and addressed as the modules are investigated. For example, HRV and EEG, as discussed previously, have both been shown to be useful for measuring workload. Interestingly, Gohara et al. [31] discovered that HRV becomes less sensitive when measured during a state of fatigue. Discrepancies between measures like these could present serious consequences to the accuracy of any cognitive state gauge if the input were not understood.

While it may seem daunting to examine the multitude of cognitive resources in such a systematic way, the great potential of previous efforts conducted by various academic, private, and government institutions [1],[32] will undoubtedly contribute to the compilation of the proposed MCSG. Of course, once a sufficient amount of modules are understood, the next challenge will be integrating them into a unified gauge. There could be a variety of approaches to accomplishing this task and these will undoubtedly be discussed in subsequent investigations.

4 Proposed Implementation

While the investigation of each module may be unique, the following should provide at least the basic heuristics to determine a course of action. It is proposed here to identify experimental methods from previous foundational studies which focus on the cognitive resource of interest and adopt those efforts for investigation with multiple physiological sensors. Once an effort has been identified, it is suggested that the three types of workload measures described in section 2.1.2 (performance, subjective, and physiological) should be collected for the new investigation. By following this implementation, it is assumed that any new confounds should be limited to the new measure(s).

When determining which physiological measures to use, the most relevant devices should be considered first. For example, eye tracking would be an obvious choice for an investigation exploring visual search and attention but may not provide meaningful data for an effort solely focused on the area of auditory attention.

Once the physiological sensors have been determined it is recommended that all experimental components are synchronized. While it would be inappropriate, and in some cases impossible, to attempt to force physiological measuring devices into having identical sampling rates, they can be synchronized to each other and the experimental environment. At a minimum, a timestamp indicating the beginning and conclusion of an experimental trial common to all data logs should be the included. Additionally, synchronously recording performance in the experimental environment with the selected physiological measures will allow for successful matching of changes in performance for observation. For example, in an effort to use multiple sensors for an adaptive learning system, Vartak et al. [33] proposed a block processing model in order to synchronize and evaluate the volumes of physiological data from multiple measures. Using an approach similar to the one found in Varatak et al.'s model should prove to help streamline the data collection and perhaps even aid in the development of future AUGCOG applications. Finally, perceived levels of workload can only be obtained by asking. Collecting subjective measures, while not dynamic, can be extremely useful in providing consistency across participants.

5 Future Work and Conclusion

Previous research using a dynamic spatial task showed that highly skilled participants outperformed those with lower skills when evaluated on spatial ability tests [34]. Using a similar task and methods, we will investigate the modular approach described here through the implementation outlined in section 4.

This paper proposed an approach that can be used determine under what conditions multiple minimally intrusive physiological sensors can be used together and validly applied to a cognitive state gauge. Through the use of the model and implementation proposed, we are confident that various physiological measures can be used to accurately measure changes in cognitive state while meeting the goals set forth by Reeves et al. [1].

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