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Brief Report

The Age of Neuroergonomics: Towards Ubiquitous and Continuous Measurement of Brain Function with fNIRS

ADRIAN CURTIN and HASAN AYAZ* *Drexel University*

Abstract: Neuroergonomics is an emerging field that investigates the human brain in relation to behavioral performance in natural environments and everyday settings. Functional near-infrared spectroscopy (fNIRS), a noninvasive brain-monitoring technology that relies on optical techniques to detect changes of cortical hemodynamic responses to human perceptual, cognitive, and motor functioning, is an ideal candidate tool. Ultraportable wearable and wireless fNIRS sensors are already breaking the limitations of traditional neuroimaging approaches that have imposed limitations on experimental protocols, data-collection settings, and task conditions at the expense of ecological validity. This review summarizes emerging trends for fNIRS applications, from aerospace to medicine, with diverse populations and towards clinical solutions. We will review recent studies, such as mental workload assessment of specialized operators performing standardized and complex cognitive tasks and development of expertise during practice of complex cognitive and visuomotor tasks (ranging from aircraft piloting and robot control). Various recent synergistic fNIRS applications for human–human and human–machine interaction, including synthetic speech perception, interpersonal neural synchronization, and brain computer interfaces, highlight the potential use and are ushering the dawn of a new age in applied neuroscience and neuroengineering.

Key words: functional near-infrared spectroscopy (fNIRS), neuroadaptive systems, human–machine interaction, mobile brain/body imaging (MoBI), brain–computer interface (BCI).

The ability to continuously monitor the brain's function carries an enormous potential to provide direct insight into user intentions, mental states, and more. Yet, despite the central role of the brain in day-to-day tasks and how we interact with the world around us, its capabilities and activities are often overlooked in both research and in practice. Human factors and ergonomics research devoted to enhancement of work environments and technology has often been conducted "mindlessly," that is, without consideration of the brain's state. However, rapid development of neuroscience in both technique and finding has led to the emergence of an interdisciplinary field known as *neuroergonomics* (Parasuraman & Rizzo, 2006). Neuroergonomics is founded on the central tenant that the merger of translational neuroscience and human factors research builds not only a more complete perspective, but also a necessary one. This field of research has led to an exponential growth of practical neuroimaging tools, modeling capabilities, and algorithmic methods that have rapidly begun to shift our understanding of brain and behavior.

*Correspondence concerning this article should be sent to: Hasan Ayaz, School of Biomedical Engineering, Science and Health Systems, Drexel University, 3508 Market Street, Monell Suite 101, Philadelphia, PA 19104, USA. (E-mail: hasan.ayaz@drexel.edu)

For decades, noninvasive neuroimaging techniques have been constrained to laboratory settings. Powerful imaging techniques, such as functional magnetic resonance imaging (fMRI) and positron emission tomography, have provided insight into the structure and dynamic mechanisms of the brain; however, the large size and expense of these operations cripple the technologies' application to real-world settings. Studies using these techniques for everyday activities typically employ high-quality simulators but remain hampered by unnatural restrictions on participant movement and position. Even electroencephalography (EEG) previously required substantial pre-recording preparation and was once hampered by wiring and immobile recording equipment. Fortunately, the same trends in electronic miniaturization that have revolutionized consumer electronics have freed neuroimaging from the lab, and with the introduction of wireless and portable systems, it is now possible to capture brain dynamics in untethered and natural environments. In parallel with the rapid development of consumer EEG devices, great strides have been made in the field of optical brain imaging. In this paper, we will explore the operational principles and an overview of select applications of optical brain imaging via functional near-infrared spectroscopy (fNIRS) that we have investigated with collaborators in order to contribute to neuroergonomic solutions that engage in the continuous and comprehensive monitoring of the mind.

fNIRS Technology

The initial impulse that set in motion the field of functional optical brain imaging was an observation that the relative transparency of biological tissue in the near-infrared spectrum (600–900 nm) allowed the continuous measurement of functional changes in chromophores, specifically, deoxygenated hemoglobin (deoxy-Hb) and oxygenated hemoglobin (oxy-Hb; Jobsis, 1977). Because the metabolic demands of neural activity result in localized changes in blood flow and oxygenation (Cauli, 2010), the discovery that cortical hemoglobin concentrations could be monitored noninvasively meant that changes associated with neural activity could be too. However, it was not until the early 1990s that the photonic behavior and optical properties of cortical chromophores were characterized (Delpy et al., 1988) and the technique was first applied to human cognition (Chance, Zhuang, UnAh, Alter, & Lipton, 1993). Modern fNIRS systems employ arrays of light sources (LEDs or lasers) and light detectors to measure relative changes in near-infrared light absorption associated with changes in oxy-Hb and deoxy-Hb via the modified Beer–Lambert law. The technical simplicity of fNIRS's operational principle affords the technique many advantages, including the ability to obtain high sampling frequencies, quiet operation, and increasingly portable implementations (Ayaz et al., 2013).

Although fNIRS measurements are lower in spatial resolution and restricted to only a few centimeters in depth (depending on system setup), the technique can be favorably compared to fMRI as the measurements in hemoglobin changes are highly correlated to the blood-oxygen-level dependent signal (Cui, Bray, Bryant, Glover, & Reiss, 2011), making fNIRS an important tool for translating novel fMRI biomarkers into practical utility. In this process, areas with significant functional activity in an fMRI scan (or other techniques) are related to specific cortical regions of interest that can then be specifically targeted and measured inexpensively by fNIRS. Although fNIRS does not provide any structural information itself, optode positions can be co-registered with MRI images of individual participants using commercially available systems, or through probabilistic registration using 3D digitizers (Tsuzuki et al., 2012) or 10–20 system positions (Okamoto et al., 2004). Registration to anatomical landmarks and normalized atlases, such as the Montreal Neurological Institute (Cutini, Scatturin, & Zorzi, 2011; Evans et al., 1993; Singh, Okamoto, Dan, Jurcak, & Dan, 2005; Tsuzuki et al., 2007) or Talairach (Collins, Neelin, Peters, & Evans, 2000) spaces improves not only the inter-participant reliability of fNIRS measures but allows experimenters to adequately compare differing works and build more informed hypotheses. For a detailed review of structural and probabilistic registration techniques, the reader is referred to Tsuzuki and Dan (2014).

When compared to the other major scalable neuroimaging methodology, EEG, fNIRS offers a higher spatial resolution, but lower temporal resolution due to the slower timescale of the hemodynamic response. However, direct comparisons of EEG and fNIRS typically overlook the fact that the two, by nature of an orthogonal information source, offer distinct perspectives on neural activity that can be combined with no mutual interference to provide a richer picture (Y. Liu, Ayaz, & Shewokis, 2017b). Whether used in a hybrid context or independently, fNIRS systems function as a powerful tool for unobtrusively monitoring cortical activities in laboratory settings and also in everyday work and field conditions (Figure 1).

Here, we will explore the relationship between fNIRS and cognitive workload, beginning with controlled laboratory tasks, and follow its continuing evolution in diverse applications as an experimental tool to assess individual cognition, evaluate expertise, and refine systems and training environments. Finally, we will discuss ongoing research into online cognition monitoring using fNIRS where states determined by passive online monitoring can be used to dynamically shape the systems we interact with.

Assessing Cognitive Workload with fNIRS

Cognitive workload refers to the collective multidimensional demands placed on an individual as they engage with various tasks (Paas, Tuovinen, Tabbers, & Van Gerven, 2003). Effectively, this workload can be viewed as a measure of the effort associated with the task and is a major consideration in design due to the central role of human cognition in virtually every system. Approaching tasks with an optimized workload level is crucial to successful system operation. Situations in which

Figure 1 Wearable and miniaturized fNIRS sensors allow for the monitoring of brain activity in increasingly realistic and natural environments from minimally restricted office settings (left) to unrestricted outdoor settings (right).

operators are “underloaded” or distracted can be equally as dangerous as situations in which they are “overloaded” or overwhelmed. Despite being a critical factor in operator performance across a range of applications, mental workload itself can be difficult to observe. Key indicators, such as primary or secondary task performance, lack significant insight into an individual’s mental state, and subjective rating methods, while sensitive, are either after-the-fact or obtrusive. In the absence of a clear and objective method for continuously measuring mental workload, significant neuroergonomic research has focused on the development of reliable neural biomarkers of workload. The deployment of continuous workload-monitoring systems to real-world environments would be most critical in occupations where the risks associated with workload failures are relatively high. The need for a careful balance of workload is readily present in air traffic control (ATC), where both performance and safety are of importance.

Increased air traffic density in recent years has necessitated the development of new technologies and procedures to manage the additional traffic while maintaining safety. Both the safety and performance in these integrated systems are reliant on managing the demands imposed on human operators and therefore the development of systems capable of accurately assessing controller workload may allow prevention of operator error arising from performance declines associated with operator fatigue, inattention, or overload (Byrne & Parasuraman, 1996). To this end, we investigated the utility of fNIRS to operate as an assessment technique for mental workload within the complex work environment of ATC (Ayaz, Shewokis, et al., 2012). In a collaborative research project with the US Federal Aviation Administration’s William J. Hughes Technical Center Human Factors Laboratory, we explored fNIRS workload measures in the context of controlled working memory (WM) tasks as well as during realistic ATC scenarios under normal operation and emergency situations (Ayaz, Shewokis, et al., 2012). The objective was to derive neurophysiological measures of workload from controlled tasks and evaluate the cognitive impact of newly developed ATC interfaces.

One of the key restrictions on human cognitive ability is the amount of WM available to process incoming information. Due to this cognitive bottleneck, overall cognitive workload is often well proxied by WM demands. Therefore, in order to establish fNIRS-based correlates of workload, we first restricted our task to the *N*-back WM task, a parametric task that has been widely applied in neuroscience research as a tool to investigate the mechanisms of WM. In the *N*-back, the participant is serially presented with stimuli and asked to respond by keypress when the present stimulus matches the stimuli 1, 2, or 3 presentations ago (1, 2, and 3-back, respectively), as well as a baseline condition (0-back) where only a single predefined target is shown. Coupled with decreased behavioral performance with higher WM demand, participants showed average increases in oxygenation with increased task difficulty in the left prefrontal cortex (PFC) near AF7 of the International 10–10 System (Ayaz, Shewokis, et al., 2012). These results validated a host of studies observing similar workload–activation relationships. The *N*-back has been shown to reliably activate the dorsolateral PFC (dlPFC) and the ventrolateral PFC (vlPFC) in both positron emission tomography (Smith, Jonides, & Koeppe, 1996) and fMRI (Owen, McMillan, Laird, & Bullmore, 2005), and our previous research demonstrated monotonic activation in the left PFC in different populations (Ayaz, Izzetoglu, Bunce, Heiman-Patterson, & Onaral, 2007). First explored by Hoshi et al. (2003), the use of fNIRS to investigate the *N*-back task has exploded, in part due to the ease of implementation, and due to the integral role of WM in cognitive operations, as well as the potential to translate these results beyond controlled tasks (Baddeley, 2003). Researchers have extended *N*-back findings to show increased frontal parietal connectivity (Fishburn, Norr, Medvedev, & Vaidya, 2014), reductions in deoxy-Hb (Peck, Yuksel, Ottley, Jacob, & Chang, 2013), and to explore clinical applications (Kuruvilla, Green, Ayaz, & Murman, 2013; Merzagora, 2010; Stojanovic-Radic, Wylie, Voelbel, Chiaravalloti, & DeLuca, 2014) as well as hybridized systems to more accurately determine WM load

(Herff et al., 2014; Y. Liu, Ayaz, & Shewokis, 2017a; Putze et al., 2014).

Our findings from the *N*-back task not only served as further validation of the utility of fNIRS as a technique to measure mental workload, but also provided an important comparison point for the more complex task of managing air traffic (Ayaz, Shewokis, et al., 2012). We hypothesized that the same methodology could predict changes associated with varying the workload in a realistic simulation of ATC operation. Imposed workload was adjusted by changing the number of aircraft that the controller was responsible for managing (six, 12, 18); in addition, the type of interface was pseudo-randomly altered between the legacy interface (VoiceComm) and the candidate replacement (DataComm). Increased air traffic was associated with higher oxygenation near Fp1 of the 10–20 system with a small to moderate effect size ($d = 0.28$) for communication type. These results corroborated subjective workload measurements (NASA-Task Load Index) and implied that the new DataComm system required less cognitive resources in otherwise identical task conditions than the legacy system (Ayaz, Shewokis, et al., 2012). Together, behavioral, subjectively assessed, and fNIRS-based measures from controlled WM tasks and complex ecologically valid human–machine interaction were collectively harmonized for the neuroergonomic assessment of a new ATC interface. This template for neuroergonomics work features how basic neuroscience research can be integrated to inform high-level decisions on system integration and design.

Capturing Cognitive Capacity with fNIRS

An important utility of workload measurement in complex environments is the ability to identify optimal parameters to ensure continued engagement at sufficient performance levels. An ideal system would use these conditions to maximize operator efficiency and minimize human error; however, these estimations cannot be based on performance alone as maintained performance may conceal the effects of extended effort and fatigue (Izzetoglu, Bunce, Onaral, Pourrezaei, & Chance, 2004). Within the limits of WM capacity, increased WM demand coincided with monotonic increases in dlPFC activity. However, as capacity limits are approached, it is no longer possible to further increase brain activity to maintain performance, creating an "inverted U" response typical of a capacity-constrained response (Callicott et al., 1999). From a neuroergonomics perspective, the characterization of this response allows the use of fNIRS and behavioral performance to determine cognitive capacity, where the trade-off between concerted effort and performance breaks down.

To explore this phenomenon, we examined the mental efficiency of ATC operators as they progressed through the *N*-back task, during which the ability of both performance and neural measures to predict performance at greater difficulty levels were assessed. Changes in task performance showed substantial decreases as *N*-back difficulty increased, but more importantly neural measures proved a more sensitive predictor of behavioral performance. Results showed that neural activation during the 2-back condition was a better predictor of behavioral performance during the 3-back condition than performance on the 2-back condition itself (Ayaz, Bunce, et al., 2012). These neural measures may therefore be indicative of the cognitive reserve available to the participant, which is the difference between the applied cognitive resources and the total available cognitive capacity.

Through quantification of cognitive capacity, the maximum practical performance can be estimated through neural and behavioral measures such that sufficient cognitive reserve is available to perform effectively under unexpected increases in situational demand. In a separate study, fNIRS correlates of workload were measured in ATC operators using a next-generation conflict resolution advisory system as workload was varied according to the monitor alert parameter (MAP), a measure of the number of aircraft that can be safely accommodated in an airspace (Harrison et al., 2014). Participants were monitored as air traffic increased from low levels (33% MAP, ~six aircraft) to unsafe levels (150% MAP, >24 aircraft) while subjective workload was intermittently assessed using a workload assessment keypad. The fNIRS measures showed increases in oxygenation of the left dlPFC corresponding with increased workload consistent with previous results; however, as air traffic began to exceed safe levels (>100% MAP), fNIRS measures plateaued, revealing a critical turning point in safe operation not apparent in self-reported measures.

Tracking Training with fNIRS

The performance of complex cognitive tasks requires extensive use of capacity-limited executive processes, especially WM and attention. While increases in executive network activity in areas such as the PFC co-occur with increased task demand, the extent of neural demands resulting from task performance is driven not only from the actual task parameters, but also the expertise of the individual performing the task. With additional experience, individuals will progressively become more capable at cognitive tasks by adapting less taxing strategies and employing a process of cognitive automation (Y. Liu & Wickens, 1994). Throughout this learning and adaptation process, areas of the PFC associated with attentional control and problem-solving may be relieved as more inefficient strategies are refined, diverting activity to more optimized functional circuits and freeing up valuable attentional resources, effectively expanding task capacity (Garavan, Kelley, Rosen, Rao, & Stein, 2000). Expertise in one task domain therefore results in decreased cognitive demands in the face of the preserved task difficulty, with experts showing reduced or more specific brain activity relative to novices (Milton, Solodkin, Hluštík, & Small, 2007). Functional imaging techniques therefore offer the ability to track changes in brain activity associated with expertise development which can be used both for assessment of learning and training methodologies.

Using fNIRS, we investigated the changing relationship of neural demands while individuals with no prior experience participated in a 9-day training program for simulated unmanned aerial vehicle piloting. As participants progressed from naive to more experienced operators, fNIRS measures in terms of evoked total-Hb, gradually decreased, mirroring increases in behavioral performance (Ayaz, Shewokis, et al., 2012). Visualizing fNIRS and performance changes in terms of neural efficiency revealed distinct phases of learning where initially, increased performance (measured by reduced deviation from optimal flight path) appeared to correspond primarily with increased effort as measured by fNIRS. However, in later stages, improvements in performance were associated with increases in efficient cognition marked by reduced cognitive demand, proposing cognitive efficiency as an effective index of expertise development.

In an effort to improve training and educational practices, the measurement of cognitive load has the potential to differentiate learning strategies in order to develop more efficient instructional methods (Paas et al., 2003). In a pilot study of spatial navigation, we used fNIRS to track the cognitive demands associated with learning under randomized (high contextual interference) and block-order schedules (low contextual interference), demonstrating the efficiency advantage for randomized learning during retention and transfer to new environments (Ayaz et al., 2011). In another study, we examined the introduction of gamification to help further mathematics education. Elementary school students were monitored before and after training with MathDash and increases in computational fluency were associated with decreases in oxy-Hb in the left dlPFC consistent with results from earlier training studies (Çakır, Çakır, Ayaz, & Lee, 2016).

WM training is motivated by the importance of WM capacity as a defining component of individual cognitive capability. Individuals featuring high WM capacity perform better on reasoning skills favored by intelligence testing (Kyllonen & Christal, 1990), along with improved attention and decision-making (McCabe, Roediger, McDaniel, Balota, & Hambrick, 2010). For this reason, methods to improve capacity are viewed as tools for neurocognitive enhancement or rehabilitation in cases of cognitive decline. Although the ability of WM training to translate into other domains of cognition (i.e., far transfer) remains controversial, growing public interest in cognitive health has prompted the development of adaptive protocols capable of individualizing training to a participant in order to optimize the potential benefits of the training (Gibson et al., 2013).

Exploring the design of cognitive interventions to improve WM capacity, we compared the effectiveness of adaptive dual-task WM training with an incongruent training that featured demands yoked to performance of the adaptive group (McKendrick, Ayaz, Olmstead, & Parasuraman, 2014). WM training through the 5-day protocol increased verbal and spatial spans under both adaptive and yoked conditions. However, in the later half of the training protocol, verbal span in the adaptive protocol continued to increase, whereas the non-adaptive protocol showed no additional benefit. Differences between these two training methods could be explained by changes in fNIRS measures of cortical demand, as in the latter half of the intervention; adaptive training resulted in increased total-Hb and yoked training in decreased total-Hb in the right PFC near AF8. These changes that occurred are thought to be involved in the monitoring of stimuli during multitasking (Burgess, Dumontheil, & Gilbert, 2007), suggesting that initially the yoked group required additional effort towards the processing of dual-task representations and that later the adaptive group could improve its performance further by applying additional cognitive effort, whereas the yoked group could not. Alternatively, the lack of performance increase by the yoked group in the second half of training may have been due to fatigue associated with the extended level of effort required in the first 3 days. Additional nonlinear changes in hemodynamic activity were noted in the left dlPFC and the right vlPFC as a result of training, which were sensitive to training, but not task condition. Following training, activity in the bilateral vlPFC was found to be negatively correlated with verbal span performance, implying increased processing efficiency (Neubauer & Fink, 2009), possibly due to improved response selection.

The recent resurgence in noninvasive brain stimulation techniques, such as transcranial direct current stimulation (tDCS) and transcranial alternating current stimulation (tACS), has become another motivating factor in neuroergonomic research of training and is increasingly investigated as a technique for the neurocognitive augmentation of healthy individuals. While mechanistic studies show the ability of techniques like tDCS to engage in excitatory and inhibitory behavior in manners resembling the basic mechanisms of neural plasticity (Hunter, Coffman, Trumbo, & Clark, 2013) and there exists evidence that tCDS can be used to accelerate performance and skill acquisition in complex environments (Clark & Parasuraman, 2014), little is known about the relationship of stimulation to higher-order behavioral effects and the neural circuits responsible for effecting these changes. Therefore, the combination of neuromodulatory stimulation with neuroimaging methods is necessary in order to further understand the impact and efficacy of stimulation, as well as help identify optimal stimulation parameters.

Due to its impartiality to interference from electrical stimulation, fNIRS is in a unique position to offer neuroergonomic insights into the neural mechanisms (Merzagora et al., 2010). We explored in a pilot study the ability to use high-definition tDCS to enhance spatial WM using the same dual-task paradigm previously mentioned and targeting the right vlPFC (AF8), which had demonstrated functional activity associated with task performance (McKendrick, Parasuraman, & Ayaz, 2015). The tDCS stimulation was associated with increased task performance from baseline, offsetting performance decrements attributable to fatigue and increased bilateral activity in the dlPFC. Although the results are promising, the complexity between tDCS stimulation and task parameters is still large, with specific stimulator models, tDCS montages, and stimulation parameters producing unknown interactions.

Towards Real-Time Monitoring of Individuals and Interaction

Neuroergonomic methods introduce valuable perspectives into the operation and design of human–system interaction; however, with current implementations this insight is largely a work of post hoc analysis. As sensing techniques and methodologies increase in their reliability, the ability and reliability of neural-assessed cognitive states will improve such that they are available for immediate use as a control signal for implicit brain–computer interfaces (BCIs). While extensive work has been done with EEG-based BCI systems (Daly & Wolpaw, 2008), the development of fNIRS-based BCIs has become a recent area of interest due to its increased localization, low susceptibility to electrical noise, and maintained performance in the face of degraded muscle control (Naseer & Hong, 2015). Unlike explicit BCIs where the user is expected to consciously engage with the interface in order to effect an operational command, implicit BCIs instead passively monitor ongoing cognitive activities and inform the system of user state, providing operational context in real time. In the absence of explicit interaction from the user, implicit BCIs envision semi-autonomous systems that adapt to changing user states and expectations without interrupting or requiring conscious effort on the part of the user (Solovey, Afergan, Peck, Hincks, & Jacob, 2015). Implicit BCIs naturally extend neuroergonomic workload monitoring during training and systems operation, allowing the parameters of training scenarios and task execution to be dynamically adjusted or, in situations where continued operation may be unsafe, automate or delegate some aspects of the operator's duties.

Automotive driving demands a litany of problem-solving, attentional, and motor functions in order for safe operation. Unfortunately, traffic fatalities remain a rather common occurrence in both developed and undeveloped countries. Research into neuroergonomic applications of fNIRS to monitor cognitive demands of driving have tried to identify activity related to the demands of driving to inform design of both cars themselves and transportation infrastructure. Several studies have examined the use of fNIRS during the operation of automobiles showing that various regions of the PFC are involved in complex driving maneuvers (Yoshino, Oka, Yamamoto, Takahashi, & Kato, 2013). With the recent trend towards semi-autonomous vehicles, a particular challenge is to determine opportune times to adjust the level of automation due to user preference, critical events, or failures of automation. In a pilot study, we observed that autonomous driving conditions reduced fNIRS workload conditions relative to manual driving while a variety of secondary tasks imposed additional demands even in the autonomous state (Sibi, Ayaz, Kuhns, Sirkin, & Ju, 2016), similarly to reductions observed in cruise control (Tsunashima & Yanagisawa, 2009). Assessment of cognitive workload may help autonomous vehicles detect distraction and identify safe ways to restore manual control. Alternatively, a BCI may try to detect when users are engaged in distracted multitasking to increase automation and proactively diminish the risks associated with distracted driving. Implicit BCIs targeting multitasking classification have been previously reported outside of automotive contexts (Solovey et al., 2012). Recently, hybridized fNIRS+EEG has been reported as a technique for the detection of the transition to drowsiness, another important factor in automotive accidents (Nguyen, Ahn, Jang, Jun, & Kim, 2017).

In the contexts of aviation, workload monitoring may allow adaptive systems to adjust or prioritize information in a manner that improves safety. We explored the capability for fNIRS to perform single-trial workload estimation using licensed pilots during simulated and actual flight (Gateau, Ayaz, & Dehais, 2018). Workload level was manipulated in a realistic manner by asking pilots to retain and then repeat information delivered over radio by the ATC operator while pilots were asked to maintain a straight and stable flight path with only marginal avoidance maneuvers allowed. Results showed that the high-workload condition increased oxygenation bilaterally within the PFC in both simulated and flight conditions, although high-workload conditions during actual flight evoked higher oxy-Hb levels, along with more recall errors than in simulated flight. Using single-trial support vector machine classification, the fNIRS state could classify workload conditions with an average accuracy of 77.5%. Current monitoring solutions may provide pilots perspective on their own cognitive state, or stream neurophysiological state information to the flight recorder for retrospective accident analysis. However, when workload estimation can be improved to the point where fNIRS measures can reliably and asynchronously predict state, these measures may offer more powerful operational strategies for enhancing flight safety.

A complete implicit BCI might engage both in the continuous monitoring of cognitive state as well as the detection of transitions that alter these states or the context in which they occur (Zander & Jatzev, 2012). In this sense, one role of such passive BCIs may be to inform active BCIs that they are prepared to be engaged with, rather than continuously (and inaccurately) attempting to interpret a disengaged user. It has been proposed that one such way to determine user engagement may be to determine the modality with which the user is actively processing information. In a hybridized fNIRS +EEG study, it was reported that discrimination of auditory and visual processes could be classified with up to 95% accuracy (Putze et al., 2014). Speech-evoked activity as measured by fNIRS has been found to be highly reliable at group level in the temporal lobe (Wiggins, Anderson, Kitterick, & Hartley, 2016), and our own research has suggested that degradations in audio quality during comprehension can increase cognitive load in the PFC (Curtin & Ayaz, 2017). However, determining the mode of information or its imposed demand alone may be insufficient to determine engagement.

The detection of speech perception may eventually be able to expand to determine the source of audio information or its comprehension. Building on findings from fMRI (Stephens, Silbert, & Hasson, 2010), we examined the relationship between brain activities during the production of speech as well as the comprehension of that speech in different participants (Y. Liu, Piazza, et al., 2017). Participants listened to pre-recorded stories recorded by other participants and fNIRS from speakers and listeners were recorded in the prefrontal and bilateral parietal areas. We observed that participants' brain activities were tightly coupled to the activity of the speaker only when listeners could understand the speaker. Correlations were primarily observed between the dlPFC in the speaker and the parietal areas of the listener, suggesting a coupling of informational, but divergent functional roles in story telling and comprehension. Furthermore, we compared individuals listening to the real-life stories under fMRI, with those individuals previously recorded using fNIRS and found that a number of cortical voxels within the regions measured by fNIRS were significantly correlated with regional changes in oxy-Hb, serving as further validation of inter-listener reliability as well as fNIRS–fMRI correspondence.

These findings are a small part of a burgeoning trend towards the use of fNIRS in social cognition work as well as in hyperscanning contexts. Researchers have begun to use fNIRS in a host of contexts, including cooperative games (Cui, Bryant, & Reiss, 2012), puzzles (N. Liu et al., 2016), conversation (Nozawa, Sasaki, Sakaki, Yokoyama, & Kawashima, 2016), motor imitation (Holper, Scholkmann, & Wolf, 2012), as well as competition (Balconi & Vanutelli, 2017). Although it is common practice in laboratory research, it is often difficult to divorce individual activity from the social context that occurs in natural environments. Within the context of implicit BCI research, metrics of interpersonal synchrony and group cognitive state may be instrumental in characterizing the context and changes in adaptive systems. Potential applications include assessment of group dynamics to optimize roles in response to different situations, or even judging information transfer in the classroom between teacher and students. Although the addition of multiple individuals adds substantial variability to an already complex human–computer relation, this research already promises to revolutionize our understanding of cognition and the way in which we interact with each other.

Future Directions: Where Do We Go From Here?

There exists a vast potential offered by continuous neural measures to reshape not only our understanding of the mind but the way in which we engage with the world. These neuroergonomic uses for fNIRS technology may eventually be an integral part of the way we learn, the way we work, and the way we play. In the meantime, ongoing hardware and processing improvements are only making fNIRS systems more portable, more reliable, and more affordable.

Ultraportable wearable fNIRS sensors are positioned to break the limitations of traditional neuroimaging approaches that impose limitations for experimental protocols, data-collection settings, and task conditions at the expense of ecological validity. These newer systems can allow the combination of optical imaging with EEG measures for faster time-resolution or tDCS/tACS for online neurostimulation and working together with new adaptive computer interfaces from the cockpit to virtual reality. Improvements in artificial intelligence/machine-learning aim to recognize and label behavioral patterns to provide much-needed task context to cerebrally derived signals. Together with interpersonal neural measures, this may soon give birth to new means of cooperation, education, competition, and reconciliation. Collectively, these developments may lead us into an age of neuroergonomics where the behavior of the mind is envisioned as a central figure in design, development, and routine use of technology, rather than just a means to an end.

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