

Best Practices for the Application of Functional Near Infrared Spectroscopy to Operator State Sensing

Angela R. Harrivel, Alan G. Hylton, and Tristan A. Hearn Glenn Research Center, Cleveland, Ohio

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Executive Summary

This paper identifies approaches for improving the validity and reliability of functional Near Infrared Spectroscopy (fNIRS) data for the purpose of sensing the mental state of commercial aircraft operators. Just as there are many sensors and instruments used to identify the state of an aircraft and its many components and sub-systems, so too are sensors needed to assess the state of the operator. Information obtained via avionic sensors and instruments is used for proper control of the aircraft. Human pilots are complex systems themselves, charged with navigating and communicating as they aviate to maintain safe operations. Thus, operator state assessment is important for improved aviation safety, as intelligent flight decks of the future can be responsive to such state changes to optimally support human performance.

fNIRS is an emerging technique which indirectly measures neuronal activity in the cortex via neurovascular coupling. It is non-invasive, relatively portable, inexpensive, and safe for long-term monitoring and repeated measurements. Operationally useful implementation, however, requires improved instrumentation. The collection of useful signals and appropriate regions to monitor are discussed in this paper in the context of field applications.

Despite the continuing improvement of a variety of research-laboratory-based and commercial instrumentation, headgear currently used to couple optical signals to the scalp for fNIRS behind the hairline is bulky, uncomfortable to painful, susceptible to motion artifact and interference from the hair, not expeditiously self-applicable and not readily integrated with existing environments (for example, cockpits and pilot headsets). Reducing such difficulties, consistently encountered by those in the field in both industry and academia, is a long-term, design-driven aim. The success of efforts to produce "next generation" fNIRS headgear, in combination with optical source and detection hardware miniaturization, would maximize the potential of environmentally valid monitoring with multichannel, whole-head fNIRS. The full benefits of the fNIRS technique have yet to be taken out of the controlled laboratory and into clinical and operational environments.

This paper describes a proposed and exemplary system, including sensor layout as applied to attentional state detection, and headgear design for long duration monitoring. The identification of cognitive performance decrement, such as lapses in operator attention, may be used to predict and avoid error-prone states. We propose that attentional performance can be monitored *in-task* with fNIRS through the quantification of hemodynamic activations in cortical regions which are part of functionally-connected attention and resting state networks. Activations in these regions have been shown to correlate with behavioral performance and task engagement, without the need for cognitive strategy. Specific locations of interest, described in the "Sensor Layout for Attentional State Detection" section below, lie beneath hair-covered head regions beyond the forehead.

Headgear development is key to reliably and robustly accessing locations beyond the hairline to measure functionally-connected networks across the whole head. Data processing employing Support Vector Machines for reliable state classification, based on the fNIRS signals, is discussed. Human subject trials using both fNIRS and functional Magnetic Resonance Imaging (fMRI) will be used to test this system. If accurate classification of attentive state is achieved based on functional activation measurements made with fNIRS, fNIRS will be shown as a useful tool for monitoring attentional performance. Performance decrement, such as an error due to a lapse in attention or reduction in task engagement, can lead to hazardous conditions. These states can result from, for example, workload excesses (over or under), sensory input resource limitations, mind wandering, distraction or fatigue. The ability to predict such decrement could lead to significant increases in aviation safety.

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Best Practices for the Application of Functional Near Infrared Spectroscopy to Operator State Sensing

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Abstract

Functional Near Infrared Spectroscopy (fNIRS) is an emerging neuronal measurement technique with many advantages for application in operational and training contexts. Instrumentation and protocol improvements, however, are required to obtain useful signals and produce expeditiously self-applicable, comfortable and unobtrusive headgear. Approaches for improving the validity and reliability of fNIRS data for the purpose of sensing the mental state of commercial aircraft operators are identified, and an exemplary system design for attentional state monitoring is outlined. Intelligent flight decks of the future can be responsive to state changes to optimally support human performance. Thus, the identification of cognitive performance decrement, such as lapses in operator attention, may be used to predict and avoid error-prone states. We propose that attentional performance may be monitored with fNIRS through the quantification of hemodynamic activations in cortical regions which are part of functionally-connected attention and resting state networks. Activations in these regions have been shown to correlate with behavioral performance and task engagement. These regions lie beneath superficial tissue in head regions beyond the forehead. Headgear development is key to reliably and robustly accessing locations beyond the hairline to measure functionally-connected networks across the whole head. Human subject trials using both fNIRS and functional Magnetic Resonance Imaging (fMRI) will be used to test this system. Data processing employs Support Vector Machines for state classification based on the fNIRS signals. If accurate state classification is achieved based on sensed activation patterns, fNIRS will be shown to be useful for monitoring attentional performance.

Background

This research identifies approaches for improving the validity and reliability of fNIRS data for the purpose of assessing the mental state of commercial aircraft operators. This paper presents an introductory but technically thorough discussion of aspects of an fNIRS system which are important to pilot state sensing. A review of adaptive automation and all factors affecting cognitive state assessment is outside the scope of this paper. First, we present the background for the pursuit of this research.

Operator State Assessment for Improved Aviation Safety

The reduction of accident rates is of great importance in the face of increasing commercial aviation traffic. Even the most expert and conscientious pilots are susceptible to making errors in stressful or boring situations. Intelligent cockpits of the future will interact with operators in ways designed to reduce error-prone states and mitigate dangerous situations at the edges of human performance. One important aspect of this is the development of reliable, sensitive and operationally-relevant metrics for the state of the "human in the loop" by non-invasive, portable, safe and inexpensive means. This work aims to reduce the effects of performance decrement and improve safety by informing intelligent systems of the state of the operator for appropriate interjection of mitigations and operator support. For our initial purposes here, attentional performance monitoring refers to sensing whether the operator is attending or not attending to a task. A state of goal-oriented task engagement, as evidenced by a lack of behavioral errors, will be considered an attending state. Attentional lapses will indicate disengaged states, during which errors are

more likely to be made. Attentional performance can be quantified by measuring the amount of time over which an attentive state is sustained. In other words, monitoring vigilance [1].

This work is focused on the technical issues surrounding the use of fNIRS for operator characterization, and the ultimate development of a useful system for attentional state monitoring. Optical sensing techniques may well evolve into synergistic complements for electroencephalography and other physiological measures used for Augmented Cognition [2, 3], operator performance research [4], and crew cognition research [5].

The fNIRS Technique

For this work in particular, instrumentation and protocol improvements are being investigated for the promising application of the emerging neuroimaging technique called functional Near Infrared Spectroscopy (fNIRS) to operator state characterization. It is non-invasive, relatively portable and inexpensive, and safe for long-term monitoring and repeated measurements [6-9]. Optical absorption is measured as blood oxygenation levels change. Increased blood flow is correlated to local neural activity. This is similar to the correlation of the Blood Oxygen Level Dependent (BOLD) signal measurements in Functional Magnetic Resonance Imaging (fMRI) with neural activity. Both fNIRS and fMRI sense the hemodynamic response, as opposed to Event Related Optical Signal (EROS) and Electroencephalogram (EEG) measurements, which sense the activity of neurons themselves (through cellular changes which affect optical scattering, or through electrical activity, respectively). EROS as a technique is limited for operational applications due to lower signal-to-noise and higher susceptibility to motion artifact.

The general application of fNIRS to functional neuroimaging is being heavily researched.* It is portable, relatively low-cost, non-confining, non-invasive, and safe for long-term monitoring [8-12]. Temporal resolution is sub-second, while spatial resolution is on the order of 1 cm² at best [7, 13, 14]. Measurements have been shown to be consistent with fMRI [11, 12, 15-18] and EEG measurements [19, 20]. The successful development of "next generation" headgear instrumentation through this work will make the benefits of the fNIRS technique available to researchers who wish to perform fNIRS on the whole head in environmentally valid settings where the shortcomings of existing head probes, or the lack of an attending technician to apply the headgear, prohibit its practical and reliable use.

fMRI is a hemodynamic neuroimaging method capable of the indirectly measuring neural activity (via neuro-vascular coupling) in the whole brain by quantifying changes in paramagnetic deoxygenated hemoglobin. In contrast, fNIRS interrogates the outer surface (on the order of mm) of the cortex only, and quantifies changes in oxygenated ([HbO]) and deoxygenated ([HbR]) hemoglobin concentration. Infrared light that has diffused through the capillary bed is detected after being differentially absorbed by both species of hemoglobin.

To make functional activity measurements from the surface of the head, optical delivery and detection is required at 2 to 4 cm apart, straddling each measurement location. Measured optical intensity changes are due to changes in absorption of the light. This change in absorption contains information about the change in hemoglobin concentration ([Hb]) depending on the length of the optical path through the tissue undergoing hemodynamic changes (see [21] for mathematical details). Oxygenated and deoxygenated hemoglobin are the predominant absorbers in biological tissue in the wavelength region used for fNIRS. Relative changes in the concentrations of both these species of hemoglobin over time are calculated using the Modified Beer Lambert Law (MBLL) based on intensity measurements for each of two wavelengths per location, and on path length estimates. These make up the digital fNIRS signals which can be used as inputs to operator state classification algorithms.

Activations are quantified for a region of interest by comparing hemoglobin concentration changes between species. A hemodynamic response is indicated by an increase in [HbO] while [HbR] decreases or

^{*}For example, by Boas, Franceschini, et al. (Massachusetts General Hospital), Chance et al. (University of Pennsylvania), Huppert, et al. (University of Pittsburgh Medical Center), Bunce, Izzetoglu, et al. (Drexel University), and Gratton, et al. (University of Illinois at Urbana-Champaign)

stays relatively constant, then returns to baseline, over time periods on the order of 10 sec (or longer if sustained). Regional or time averages are taken of the activation quantity, and comparisons are made between measurements obtained during different conditions such as work and rest. Care must be taken when comparing activation magnitudes since sensitivity (discussed below in the "Localization" section) is not uniform across probe locations (or even across wavelengths).

Care must also be taken when analyzing the changes in the fNIRS signals over time. A signal component which covaries across all or a subset of channels (locations) is likely due to systemic physiology [22], or due to motion or impact if the optodes are rigidly connected. Variance can masquerade as changes in [Hb] due to an ill-fitting optode or exposure to another source or to ambient light), or can be due to actual changes in [Hb] driven by physiology that is not of interest. Most physiological contributions and artifacts in the signals can be identified by their frequency, but simple temporal filtering can degrade the signal of interest when the frequency band of the confounding noise overlaps that of the hemodynamic response. Regression techniques do not always leave the activations of interest intact [23] and require the use of know stimulus onset times to model the expected hemodynamic response. These onset times are not available in operational contexts. Principal component analysis is commonly used to filter out physiological signals, but the physiology cannot always be separated into consistent and cleanly removable components [22]. To avoid misinterpreting physiology (e.g., Mayer waves [24]) as functionally-connected activity, a close source-detector pair (with shallow sensitivity) will be used to measure physiological signals in the superficial tissue particular to each location along the line between the detector and the main source [25]. The unwanted physiological contributions to the signals of interest might then be removed satisfactorily by subtracting a fraction of that signal. If this close source method is not sufficient for the present work, more sophisticated methods of adaptive filtering may be pursued.

The Utility of fNIRS for Operator State Assessment

In general, fNIRS provides rich potential to supplement behavioral data with objective neurological measures in real-world contexts to further improve operator performance *during* the use of automated systems. The success of fNIRS as a technique to measure hemodynamics associated with neural activity in response to motor and visual stimuli has been shown. fNIRS measurements also are relevant to improve the efficiency of skill acquisition and expertise development [26, 27]. The results of studies involving higher executive function have been varied, although promising [6]. Distinguishing between workload levels and preference, which has been accomplished with fNIRS, is relevant to adaptive automation design models [28]. Features sensitive to which cognitive resources are taxed, extracted from fNIRS measurements made on the forehead, have shown promise for applicability to usability testing of various user-interface designs [29]. Cognitive performance measurement is highly relevant to space flight as well, since adaption to microgravity can cause performance decrement due to motion sickness, lack of sleep, loss of sensorimotor control, increased stress or mood changes [30]. Indeed, an fNIRS system for affective state assessment is under investigation [31]. The detection of particular brain activations could be used to assess the efficacy of countermeasures and predict cognitive performance under stress, such as vigilance decrement due to fatigue [32] or divided attention [33, 34].

In-Task Monitoring

With better motion tolerance than fMRI, and with no claustrophobic and noisy environment, fNIRS enables neuroimaging in ecologically valid environments. For example, gait, pediatric and centrifuge studies can be performed where fMRI studies would be impossible. fNIRS allows real-time monitoring during the actual performance of real tasks, such as for attentional performance, alertness or fatigue monitoring. When combined with near-real-time signal analysis and classification processing, this allows for long-duration monitoring and potential use in brain-computer interfaces (BCI) applications [35, 36] for treatment or rehabilitation. The portability of fNIRS enables its use for biofeedback training in a

physician's office, rehabilitation facility or eventually even in a take-home device. fNIRS has been applied to a train driving simulation task comparing manual and automated modes [37], and to the development of a robot which adapts to the multitasking state of a human operator [38]. We address the detection of cognitive states in which operators are disengaged and more prone to err due to lapses in attention in the "Sensing System Design for Attentional State Monitoring" section below. In general, room for improvement remains regarding the reliability of fNIRS measurements, the specificity of state detection, and the signal processing techniques relevant to operational applications. These challenges are discussed below.

Attentional Performance

The attentional state of the operator drives many important aspects of task (e.g., flight) performance, and may be monitored with fNIRS. A recent review of fNIRS studies on executive function describes monitoring complex goal-directed behavior as effected by the dorsolateral prefrontal cortex and other frontal areas [39]. Executive function is highly relevant in operational contexts. As one of three components of attention, along with orienting and alerting [40], it is employed for conflict resolution and to handle novel situations, such as off-nominal, non-automated piloting scenarios. Workload management and strategic planning also use such high-level executive processes[1, 41]. Examples include disorientation resolution, relinquishment decision making, sensory input resource management, or bad attitude recovery as conflicting or unexpected sensory inputs are resolved.

Activities performed by rote (such as routine monitoring of flight automation) require little vigilant attention and foster disengagement. Activations in right prefrontal and attentional network (ATN) areas are important to maintaining endogenous support for vigilance [42]. Inversely, medial frontal and default mode network (DMN) regions deactivate with goal-oriented task engagement [43, 44]. Errors due to lapses in attention have been predicted under one minute prior to the error by detecting neural activity [45, 46].

Therefore, we propose that attentional state may be monitored through the measurement of neural hemodynamic activity in cortical layers of attentional and default mode network regions of the brain, and that maintaining an engaged, attentive and alert state via automation software can reduce operator error and increase safety.

If functionally-connected network activations as measured by fNIRS are correlated with behavioral measures indicating performance decrement due to lapses in attention, then sustained attention can be monitored with fNIRS to avoid and detect operator states in which errors due to lapses in attention are likely.

fNIRS measures can be made during task performance, when such objective behavioral measures are not available. This allows positive operator support to be provided via flight automation by an intelligent cockpit at the appropriate time to maintain a vigilant state, without giving the pilot yet another task, interruption or alert to which response may be habituated. Such adaptive automation in general has been reviewed [47]. In this way, errors and unannounced off-nominal events are optimally dealt with, or avoided altogether, by the pilot or the responsive automation.

This work explores the use of fNIRS for application to attentional performance monitoring by developing a sensing system to determine attentional state by detecting hemodynamics associated with task engagement. The successful application of this engaged state to the accomplishment of useful work (such as safely piloting an aircraft) is left to the professionally-trained human operator. Technical details of the sensing system and coordinates for the sensor locations are presented in "Sensing System Design for Attentional State Monitoring" section below.

fNIRS also may be useful to detect the recruitment of mental resources in parietal [48] and frontal [49] cortical brain regions characteristic of the enactment of executive control in an effort to maintain performance during either challenging or boring tasks. Activity in certain cortical areas can indicate compensatory mechanisms being used to achieve a certain, even high, performance level [50].

Compensating functional activity patterns could indicate impairment compared to baseline or unimpaired patterns, or simply increased "top down" attentional effort [51, 52]. This points to the need for ongoing performance measures beyond stimuli/response tests (such as reaction time testing) or short duration one-time "readiness" testing, as compensation and extra effort due to motivation may be employed in the short term but may not be maintainable throughout long, safety-critical tasks.

Challenges and Approaches

This paper addresses remaining challenges for this emerging technology with two approaches toward establishing best practices for the use of fNIRS in operational contexts. Approach one addresses development and validation of improved headgear, using novel methods and materials, which will enable a mechanically stable method of applying optical probes to the head, be unobtrusive and comfortable for long-term wear, easy to apply, and compatible with MRI scanning (non-metallic optical components are MRI-safe and do not disrupt the magnetic field and produce artifact). The second approach demonstrates the practical applicability of fNIRS to real-time cognitive monitoring, and identifies appropriate sensor placement, signal processing and state classification for monitoring attentional performance. The proposed fNIRS system will monitor attentional performance continually as opposed to obtaining a single-shot readiness-to-perform measurement. The proposed headgear offers long-term comfort and practical usability for such an application.

Headgear Challenges

Despite the continuing improvement of various research-laboratory-based and commercial instrumentation, hardware currently used to couple optical signals to the scalp for fNIRS behind the hairline is bulky, uncomfortable to painful, susceptible to artifact, not expeditiously self-applicable and not readily integrated with existing environments (for example, cockpits and pilot headsets). Reducing such difficulties, consistently encountered by those in both industry and academia who use fNIRS, is a current design-driven aim. The success of these efforts to produce "next generation" fNIRS headgear would bring the benefits of the fNIRS technique out of the controlled laboratory environment and into both research and unpredictable operational environments where the shortcomings of existing head probes prohibit its practical, routine use.

Many errors are introduced at the optical-tissue interface [53]. Existing methods for fNIRS data acquisition in adults are time-consuming, difficult to use, susceptible to motion artifact, obtrusive and uncomfortable. Many of the disadvantages of existing optode instrumentation result from a normal-to-the-head configuration, which generates a long torque arm and a high-profile. The signal is impaired greatly by motion artifact and shifts in orientation or position, and thus is highly susceptible to mechanical instability.

Currently, optodes are placed according to the International 10-20 system used for electroencephalography [54-57], by trial and error [3], or by shifting the array of optodes a number of times and averaging the detected signals over the general region of interest [58]. If controlled, such methods are useful for laboratory studies but would be completely prohibitive in most types of operational use due to impracticality.

Maximizing the detected signal is one way to attempt to avoid large vascular obstacles, but it decreases the likelihood of accurate measurement of the magnitude of hemoglobin concentration changes (Δ [Hb]) [21]. When properly positioned such that the tissue volume sensed by the optode overlaps with hemodynamic absorbers, optical intensity is reduced during activation as regional blood flow increases to overcompensate for local metabolism. Intensity increases as [HbR] decreases. This is offset by intensity decreases as [HbO] increases.

Probes for practical application in the field should have a low profile (height from the surface of the head) to not interfere with a headset, be comfortable for repeated and extended use, and allow repeatable positioning of light delivery and detection in a quick and easy (yet reliable, stable and repeatable) fashion.

Further, comfortable headgear eliminates significant subject non-compliance and the introduction of distractions or other psychological confounds due to pain and discomfort. FNIRS systems employ optical sensors which project for some length from the head,[†] and require an attendant and much time to position and separate the hair beneath each probe in turn. While existing probes[‡] are successfully used under the controlled conditions of research laboratories, they are not appropriate for application to aerospace challenges which do not enjoy the benefit of available time and attending personnel to place and adjust optodes.

Monitoring: Signal Processing and Classification Challenges

fNIRS as a neuroimaging technology is advantageous in part because the hemodynamic response it measures also underlies the fMRI BOLD response [16]. Localized cortical hemodynamic activations that have been shown to be evoked by known functional tasks using well-established fMRI techniques also should be detectable with fNIRS. However, an optimal method of real-time in-task classification is yet to be determined, and no standard exists in the field [36, 59]. Our proposed method using Support Vector Machines (SVM) is presented in the "State Classification" section below. Ideally, SVM training requirements would be minimized to reduce calibration and set-up time. The fact that information regarding the timing of stimulus events would not be available in operational contexts presents a further challenge to this particular application.

Also, improved headgear is needed to reduce bad channels and loss of signal. This is especially important when the number of sensors is limited and measurements are being made at one location relative to another. These issues are further addressed in the "Selecting Sensor Locations" and "Headgear Design" sections below.

Signals will be temporally filtered to include the hemodynamic response of interest and low frequency functional fluctuations [60] and to reduce cardiac and respiratory signal contributions. However, significant physiological noise sources (especially blood pressure regulation) occur at or near the hemodynamic response function frequency, and so cannot be filtered out, as this is the signal component of interest [36, 59]. Signals from a close, shallow light source can be used to clean physiological signals from the measured signals (by subtracting a portion of this signal) to isolate the functional activations of interest.

Finally, the variability of the cognitive functions themselves, and the physiological state of the operator, are inherent confounding factors [6].

Proposed Approaches to the Challenges

fNIRS is an emerging technique which offers the advantage of direct comparison to hemodynamic activations as measured by the gold-standard of fMRI. The developed operator state sensing system described below will be validated with a parallel fNIRS-fMRI human subject study to demonstrate near-real-time monitoring of attentional performance with fNIRS. Simple behavioral tasks will be used. Classification based on the fMRI data will provide the standard for comparison. This will guarantee within-subject comparison of results between the two techniques for the same activations during the same task performance, controlling for such variables as effort, motivation, practice, anatomy, time of day and physiological state. Many recent fNIRS studies have been restricted to frontal probe placement [29, 31, 38]. The technology developed in this project will overcome this frontal placement restriction, allowing more neural information to be collected, eventually enabling a greater range of tasks to be investigated and more states to be distinguished.

[†]For instance <u>http://robot.ci.ritsumei.ac.jp/bio/nirs.JPG</u>, <u>http://robot.ci.ritsumei.ac.jp/bio/nirs.htm</u> Figure 1. [‡]Such as <u>http://www.nmr.mgh.harvard.edu/PMI/research/probe-kit.htm</u> or http://www.nmr.mgh.harvard.edu/DMI/research/probe-kit.htm

This system will employ customized head probes and software developed in-house for real time functional signal calculations and state classification using Support Vector Machines. We will test whether changes in regional brain activity as measured by fNIRS can be used for binary state classification and propose specifically that periods of sustained attention and rest can be accurately identified without knowledge of external stimulus events during operations (although known states would be required for classifier training purposes). Further, we propose that the temporal covariance of activity in functionally-connected brain regions can be used to qualify proper probe location, and may be used as classifier input features. Correlated time signals will indicate the detection, as intended, of hemodynamic changes in networked brain regions. Functional networks are discussed further in the "Sensor Layout" section below. Standard behavioral performance tests can quantify performance level independent of neuroimaging measurements in the field, but do not lend themselves to in-task real time measurements. Operators cannot break away from safety-critical activities to take such a test. Continuous *in-task* monitoring allows the uninterrupted performance of such activities.

The detection of the default mode network with fNIRS as an indicator of attentional performance is novel. It includes locations other than just the prefrontal areas accessible through the forehead. By monitoring networks instead of single locations of activity, the brain state in a given time period is truly being monitored, as opposed to simply activity over time at one location, which may not be functionally specific for the state of interest [61]. For example, fNIRS measurements made on the forehead only and averaged broadly across each hemisphere may be sensitive to workload while not indicating specific causal states [62]. The application of proper in-flight mitigations may depend on specific state identification. Further, such measurements should be interpreted with care, given the role of the medial frontal gyrus in the DMN. Separately measuring DMN *and* ATN activations may allow state sensing with improved specificity by providing additional information to further differentiate measures that may be sensitive to pilot state but otherwise not predictive of *specific* states.

Best Practices for Performing fNIRS in Operational Contexts

fNIRS is poised to become an important part of a suite of non-invasive, portable human factors tools to assess crew state by monitoring attention and cognitive function during demanding data processing and decisional tasks, or during critical work requiring prolonged vigilance. Development of headgear is one step on the way to enabling in-flight measurements [63]. Recent advances in commercially-available fNIRS systems have improved the availability of the technique to non-engineering research groups. Established sets of standards for fNIRS practice are just beginning to emerge [64-66]. These standards have yet to be widely adopted by the fNIRS community, and often focus on the application of fNIRS to clinical research.

It is the goal of this section to present best practices which are important to the selection, placement and maintenance of probe locations in operational contexts. Depending on the specific application, signal must be measured at appropriate brain regions, known *a priori*, that collectively exhibit some degree of functional specificity for the state or cognitive process of interest. Practical considerations for reliable and sensitive data collection, and regions of interest, are discussed below. Headgear design, and classification, are addressed separately in the "Sensing System" section.

Collecting Useful Signals

There are many challenges and variables associated with performing fNIRS well for cognitive assessment in operational contexts. As it is still an emerging technique, and despite previous good work in this area [3, 37, 62], a prominent opportunity for improvement in the field continues to be the online collection, in the field, of clean, useful data that is mostly free of artifact and confounding or misleading signal contributions. Herein the focus is on useful methods for data collection which balance conflicting optical and ergonomic requirements, and on why this is important.



Figure 1.—Relative hemoglobin concentrations over time showing motion artefact and physiological noise.

Motion Artifact and Physiological Noise in the fNIRS Signals

Many fNIRS systems are commercially available. With sufficient miniaturization of electronic and optical components, most could be suited to operational use. Independent of the type of instrumentation used, the signals obtained will contain motion artifact and physiological noise to some degree. Figure 1 shows signals containing changes due only to motion and systemic physiology which ideally would be filtered out when performing fNIRS. This is intended to demonstrate the ease with which artifact and confounding signal can be interpreted as activation in a fNIRS signal. For these purposes the probe was located over a large vein. These data were calculated and charted using the BOXY software that comes with the Imagent fNIRS instrument made by ISS, Inc. [67]. Relative hemoglobin concentrations over time are presented in milliMolar after calculation using the Modified Beer Lambert Law. Temporal filtering of the Hb signals was set to pass between 0.1 and 2 Hz. Therefore, confounding physiological hemodynamics such as low frequency blood pressure regulation Mayer waves are not seen here. A cardiac signal of about 1 Hz is clearly seen in the upper trace. Five slow voluntarily controlled respirations were begun at 30 sec (these are typically ~0.25 Hz). Since inspiration promotes venous return, total [Hb] and light absorption are both increased, then decreased upon expiration. A drop in signal at about 35 sec is seen during the first of these inspirations due to probe motion. Oxygenated and deoxygenated hemoglobin both increase as blood flows, differentiating such signals from the hemodynamic response (where deoxygenated hemoglobin would decrease). Then six rocking motions about the long axis of the probe holder were followed by two rocking motions along the short axis. The lower trace is a detected channel without an emitting light source. This means signal changes in the lower trace are mainly due to exposure to ambient light. Further examples and details regarding time series analysis for fNIRS signals are available in recent literature [22, 64].

Reliable Measurements Require Consistent Optical-to-Skin Coupling

Regardless of the sources of noise present, the maintenance of good optical signal at all optodes is important to reliable state classification, more so as the number of optodes decreases. Further, regardless of the number of locations used, consistent signal detection depends on good optical-to-skin coupling through direct contact. fNIRS signals are highly susceptible to data loss due to optical-to-skin coupling errors [53]. For example, mechanical instability can introduce air gaps at the contact surface, allow hair and follicles to introduce uncontrolled optical absorption, and can cause probes to slip on the head. Signals collected in highly variable operational environments will be only as reliable as the headgear through which they are obtained. If the signal shows systemic physiological changes, such as respiration and heart rate as described above, these are indications of good coupling. However, these should be removed from the fNIRS signal to analyze whether smooth hemodynamic response function shapes are seen as expected in response to activation [36, 64].

Pressure in the axis that is normal to the scalp at the optode location improves signal. The skin is compressed and optical detection is limited to light that has travelled through tissue. The improvement may be due to a reduction in thickness of the dermis, and possibly structural fiber packing and alignment, as a result of the applied pressure. Such optical clearing of the tissue would reduce attenuation of the light by the skin [68]. Due to the highly scattering nature of the superficial tissue, the technique is relatively tolerant to small changes in angle of source light delivery. However, a longitudinal offset along the normal axis creates complete loss of signal upon loss of contact (air gap), especially for the detection fibers.

Excellent optical-to-skin coupling comes at the expense of some pain to the wearer as fiber-optic probes indent the skin, albeit non-invasively, to avoid such offsets. This reduces wear-time and compliance. The headgear design presented below describes the use of an optically-clear silicone elastomer [Dow Silastic MDX4-4210]. When placed in thin sections between the source and detector fiber optics and the skin, the discomfort is significantly reduced. The skin is compressed while maintaining optical transmission *and* sufficient comfort to extend compliance, opening the door to practical long-duration monitoring.

In a completed human subject study, 12 of 15 healthy adults tolerated wearing helmet-based gear for the full duration of the trial without complaint [69]. This was the first successful employment of the elastomer layer on eight optodes, which were located across all but the back of the head. The trials typically lasted 60 min, including application and adjustment of the probes. One complained of warmth due to the full coverage of the helmet (to be avoided in future designs), one complained of tenderness in the temple region during initial application and adjustment, and one required loosening of the chin strap.

Operationally Useful Implementation Requires Improved Instrumentation

To improve upon motion tolerance, stability, obtrusiveness, weight and sensor footprint, headgear design must move completely away from helmet-based, normal-to-the-head sensor configuration, while addressing key challenges as described here. One key requirement is obtaining good signal from regions beyond the hairline. A comb shape offers a chance for this outside the controlled laboratory environment without a lengthy dressing procedure. A novel headgear design has been proposed [GRC technology disclosure LEW-18280-1] and matured, which is introduced below.

Headgear which is expeditiously self-applicable is easily re-applied or adjusted by the user if it slips out of place. A design employing the bare minimum of parts and components enables very low-profile, light and small-footprint sensor for ease of integration with existing headsets and helmets in operational use. In realistic environments, fNIRS headgear also must avoid overheating the head with thick coverings, generating discomfort due to tight straps and skin-compressing sensors, and be robust to sweat and slipping out of alignment over time during routine movement. Headgear designs which create good optical-to-skin contact without relying on tight straps and pressure will be more comfortable. For example, the Electrical Geodesics, Inc. electroencephalography head net is designed to reduce pressure at each individual sensor [70]. However, an attendant is still recommended for application, and the two techniques share similar requirements, such as the need to avoid hair between the sensor and the scalp.

The curvature of the surface varies considerably both across head and between individuals. A holder for a set of optodes, say in a fixed pattern, which fits one section of the head is likely to not fit well against another section of the head. Air gaps at the detector optical-to-skin interface allow ambient light leakage or channel crosstalk, and produce noisy signals lacking physiological and functional information. As discussed below, losing signal at one optode can impact the entire signal analysis output. Thus, headgear which closely follows the curvature of the head, ideally custom-fit to the individual, will produce reliable signals due to more consistent optical coupling. In lateralized sensor layouts, dummyoptodes may be employed on the opposite side to maintain balance for improved fit and symmetrical placement on the head. Another key requirement of fNIRS headgear for the operational environment is baffling of the detectors such that ambient and cross-channel source light is blocked. Signal changes occurring on a very fast time scale generally are not due to physiology or the hemodynamic response, and instead are likely due to motion affecting the optical-to-skin interface, and brief exposure of detectors to small amounts of light in the environment. Once again, good coupling of the light directly to and from the scalp only is the key.

It is good practice to recognize that a signal with maximum optical intensity is not necessarily a good, informative signal. Maximum intensity at a reasonable detector gain setting could be due to a lack of tissue absorption. Since it is the absorption by hemoglobin, and how this changes over time, which is most informative about functional activations, and since this absorption reduces the intensity, a strong optical signal could be indicating functional changes with *less* sensitivity. In other words, if one moves a probe about the surface of the head looking for a place where optical intensity is large, one will find a spot which likely contains few capillaries of interest. In the other extreme, one may find a vessel that is too large, providing too much absorption and not enough signal intensity. What should be maximized instead is the modulation between baseline (intensity higher, total [Hb] lower) and stimulated activation (intensity lower, total [Hb] higher). Optical intensity at both these extremes should be within the dynamic range of the optical detectors. This is not readily determined in real time without a full, controlled experiment. Also, a large optical signal could be due to static or dynamic ambient light exposure. Thus, baffling, detector sensitivity and sensor placement are very important.

A headgear design concept addressing these issues is discussed in the "Headgear Design for Long Duration Monitoring" section below.

Selecting Sensor Locations

Sensitive Measurements Require Proper Localization

Overlap of the sensitivity profile (the shape of the sensed volume of tissue through which the sourced photons are scattered and absorbed on their way to the detection location) with the active vasculature (the capillaries) of interest is the goal of sensor localization. In other words, the sensitivity of the measurement technique relies on the degree to which the tissue sensed is that which is affected by hemodynamic changes as evoked by experimental stimuli [53, 71, 72]. Systemic physiology which affects the hemodynamic changes within the vasculature sensed (that not due to activation in response to the function of interest) confound the measured signals.

To aid understanding of the many factors affecting the sensitivity of the optical probes, some important optical terms are described here. The distance the sourced photons travel overall through the tissue is termed the *optical path length*. This distance is greater than the chord distance between the source and detector by the *differential path length factor*. Brain activations do not cause changes in all of the tissue through which the light scatters—only a portion of it. The distance the light travels through the parts that do change with activation is the *partial path length*. The light from each probe location encounters different superficial tissue, and the light of each wavelength takes a different path (has a different *differential path length*) through that tissue, even if injected at the same location. The partial path length is not known. Therefore, because the Modified Beer Lambert Law calculation assumes the absorption has occurred along the overall *optical* path length, the absorption, and thus the calculated change in [Hb], is underestimated. In reality, greater absorption has occurred over the shorter *partial* path length [10, 64], contributing to error in the measurements.

The spatial extent of the sensitivity profile determines the spatial resolution. The attempt is made at each probe location to maximize the overlap of the sensed volume with the volume of tissue undergoing the hemodynamic activations of interest. The reduction of the source-detector distance does not necessarily improve spatial resolution, as many factors affect the shape of the sensed volume (which is the path the light takes through the tissue to the detector) and the relative location of the volume of interest. Errors are introduced due to vascular and superficial tissue non-uniformity, both across the head

and between individuals. With few probes, the extent, position and intensity of measured hemoglobin changes strongly depend on probe arrangement [73]. However, if a high spatial density of sources and detectors is used with image reconstruction methods, the measured activation can be a more accurate reproduction of the actual activation in both location and extent, especially for localized activations [21, 73]. Thus, with a greater number of detectors than currently available for this work, sensitivity and accuracy can be improved by using overlapping and neighbouring optodes placed symmetrically about the active region of interest. This further supports arguments to reduce the spatial footprint of the probes, such that more sources and detectors can fit as unobtrusively as possible on the head.

Varying source-detector separation gives rise to depth resolution [74], because greater source-detector separation probes deeper tissue. However, this is far from straightforward, as signal intensity is lowered (signal to noise is reduced) with longer path lengths, and the sensitivity profile itself changes depending on non-uniform superficial tissue through which the photons are scattered. For example, as the thickness of the cerebral spinal fluid layer increases, the lateral extent of the sensitivity profile increases. Greater skull thickness contributes to less fNIRS sensitivity and smaller partial path length. Interestingly, Monte Carlo simulations show an inverse effect for thin layers of cerebral spinal fluid [75]. Unfortunately, individual measurements of these important superficial tissue thicknesses are not readily made *in vivo*. It is possible to measure the overall optical path length with frequency domain fNIRS instruments, but this measurement cannot reveal the individual layer thicknesses [75, 76]. Thus, some adjustments to source-detector separation can be made to account for the depth of the brain region of interest, but it is not feasible to do so with precision.

The change in oxygenated versus deoxygenated hemoglobin concentrations is calculated based on the measured optical intensity, depending greatly on the *optical path length*, which in turn depends on the wavelength, the individual's age [77], and the tissue through which the photons are scattered. However, only the *partial path length*, along which the light has the opportunity to be absorbed by the hemoglobin-containing vasculature of interest, contributes to the hemodynamic information in the signal. An increase in the *partial path length* increases sensitivity and therefore the signal to noise ratio. This increase is limited if the active volume is focal (very small). At the other extreme, optodes placed over vasculature of diameter greater than about 1 mm will see too much absorption to be useful [78, 79].

Errors due to hemoglobin species cross-talk are also affected by localization. Cross talk is due to absorption by one species being attributed to the other due to the nature of the calculations. The *differential* path length is directly used in the MBLL calculations. The *partial* path length is unknown. The determination of the concentration of each Hb species depends on the optical intensity measurements at each of the two wavelengths. Since light of each wavelength takes a different *partial* path, ideally the appropriate calculation for each species would use both these partial path lengths. Since these are unknown, errors are unavoidable [21]. These errors can be avoided with proper wavelength selection and maximized partial path length (keeping the probes within ~1 cm of the active region of interest) [72].

This overlap of the sensitivity profile between each source-detector pair with the active vasculature of interest is most difficult to achieve for very small active regions. This is an important challenge for single-optode-per-location layouts (multiple separate point measurements vs. a regular array of sources and detectors as would be more appropriate for image reconstruction). For the purposes of state sensing, we propose to employ multiple separate point measurements. Imaging or spatial mapping of the activations makes use of multiple-optode-per-location layouts and image reconstruction algorithms to improve spatial resolution [53, 73]. However, the size of the sensed region (spatial resolution) has been quantified as 1 cm across at absolute smallest (best), and so only for the most shallow measurements [72]. The use and improvement of image reconstruction techniques to optimize spatial resolution is interesting and important to the field. However, it is not being pursued for this particular work. Single optodes, if well-placed at their respective locations, will allow detection, but not precise mapping, of relevant activations. We propose that this is sufficient for classification purposes in operational contexts.

Reliable State Sensing Depends on Obtaining Signal From Multiple Locations

It is important to consider some tradeoffs when selecting nominal probe locations. In operational use, due to weight, space, and cost constraints, there may be a limited number of locations at which functional activations can be measured. Each location requires a separate probe on the head and a dedicated channel for data acquisition. Instrumentation size increases with the number of channels. Also, wear-ability and compliance may decrease as probes are added to the head. On the other hand, activations should be shown to be significantly different from those at other locations under varying conditions. There is some minimum number of probe locations with which one may obtain sufficient information for such comparisons and classification accuracy. Therefore, probe locations must be selected carefully.

Once selected, obtaining consistent signal at all locations at all times is important because the quantification of neuronal activation with fNIRS relies on relative measurements. Since the sensitivity changes from probe-to-probe for reasons explained in the "Sensitive Measurements" section above, magnitudes may not be directly comparable. Further, the attribution of regional activations to particular functional tasks are confounded by a lack of functional specificity. It should not be assumed that activation in one region is specific for the stimuli of interest, as one region may be activated (in combination with other regions) by many different kinds of stimuli. Comparisons, between different conditions over time, of the patterns of relative activations are much more telling. Such comparisons over multiple regions allow the measurement of networked activations, improvement of the specificity of brain state assessment, and identification of local versus global hemodynamic changes (such as systemic physiology) and noise (such as motion artifact).

The loss of signal at one optode could reduce the accuracy of the state classifier to unacceptable levels by removing a necessary predictor variable from the classification algorithm inputs. However, if data from a candidate optode location is removed and no significant decrease in classifier accuracy is observed, then the sensor placement design may not need to include this location. Likewise if a location is added and no significant improvement in classification accuracy is obtained. Due to the unpredictable nature of operational use of non-invasive techniques, it may be prudent to retain locations as possible and consider redundant measurement locations. Bilateral measurement locations in sensor placement designs provide one opportunity for redundancy.

Customization May Be Required for Optimal Fit and Localization

Manual probe reapplication can result in about 0.5 cm deviations on the head [57], causing slightly different parts of the cortex to be interrogated. Localization and sensitivity effects are discussed in the "Sensitive Measurements" section above. Custom headgear fitting could begin to improve repeatability of placement between sessions, not unlike repositioning a car seat for specific drivers. Headgear that has been custom-fabricated to fit a particular individual the same and proper way for each application not only would support consistent signal detection, but comfort and long term wear-ability as well. Analogous existing items include boil-and-bite mouth guards, custom-shaped headphones made by fitting to a mold of the head's shape around the ear, and in-ear plugs made to fit a mold of the ear canal. These items make contact and fit such that they function best (by creating a contact seal) with minimal pressure and discomfort. Customized headgear could be connected to the on-board fNIRS instrumentation via standard optical fiber connectors.

For localization, custom sensor placement using functional and structural Magnetic Resonance Imaging (MRI) is ideal. Functional MRI scans measure the BOLD signal to locate volumetric cortical regions of interest to inform fNIRS optode placement on the surface of the head. Concurrent structural scans theoretically can improve estimates of the appropriate source-detector separation length (to sense at the proper depth) based on superficial tissue measurements over the particular volume of interest. This would ideally be on a per-optode basis for each operator. The cost-benefit ratio is likely prohibitively high at this time. Nevertheless, using fMRI and MRI to inform optode placement and improve [HbO] and [HbR] calculations is an interesting research direction in the field of multimodal imaging [16, 80], and future developments should be watched for reconsideration.

Taking advantage of the functional connectivity of known networks in the brain, as will further be discussed in the "Attentional and Resting State Networks" section below, further motivates the need to collect good signal from multiple locations simultaneously by fitting probes across the whole head. Instrumentation and headgear to accomplish this are discussed in the next section.

Sensing System Design for Attentional State Monitoring

A complete sensing system for attentional state monitoring comprises the headgear sensor design, a specific sensor layout, and near-real-time classification methods. These will be described in turn. A parallel fNIRS and fMRI trial is planned to test the full sensing system.

Headgear Design for Long Duration Monitoring

A low-profile, comfortable, easy-to-use apparatus would improve both subject comfort and improve data quality. The development of fMRI-compatible headgear (described in technology disclosure LEW-18280-1) will provide this currently-lacking hardware. This supports the viability of fNIRS as a solution to both civilian research and aerospace challenges in human performance monitoring by enabling the practical use of fNIRS in environments outside the research laboratory and thus facilitating environmentally valid testing situations.

Similar advancements in fNIRS headgear and probe development have been made in many research laboratories, especially in the area of pediatric headgear [65]. However, it is still not possible for non-bald subjects to apply probes alone. Further development is required to reduce the time to apply many sensors, deal with multiple hair types, and remain robust to motion.

Commercially available fibers[§] are folded along the head by bending the fiber itself through 90° in a plastic end piece. This requires either very small core diameter fiber with a small minimum bend radius, or very large robust bundles of fiber. To capture enough light for detection of the weak fNIRS signal, the larger fiber diameter generally precludes a profile (height from the surface of the head) less than 2 cm. This works well in the controlled laboratory, but opportunity for improvement remains.

Compared to reported wearable systems which have been used primarily to interrogate prefrontal areas accessible in front of the hairline [29, 38, 81], the headgear concepts described here will place nothing on the head but the interrogating fiber optics and parts to hold those fibers in place. The parts also will push hair out of the way during application thanks to a comb shape. This saves bulk for applications requiring light weight, low-profile sensors (such as under a helmet), provides for the possibility of increased sensor population due to reduced footprint at each source and detector location, enables selfapplication and allows fMRI compatibility. Izzetoglu, et al., have described their vision of future fNIRS headgear as a "hairbrush" sensor that will part the hair with fibers, including electronic sources and detectors mounted on the hairbrush. No further publications have been made regarding their hairbrush sensor. A different "brush optrode" sensor has been recently introduced which separates the commonlyused single optical bundle into smaller fiber optic strands which can brush through the hair and thus increase signal levels [82]. Both these envisioned hairbrush sensors and the currently proposed headgear will be useful on any part of the head, especially including those beyond the hairline. However, while the handheld hairbrush sensor calls to mind a hand-held instrument that would be useful for momentary scanning of a head [83, 84], the comb-based headgear described here has been designed for unobtrusive, continuous wear and expeditious self-application. The new "brush optrode" sensor seems to be highly compatible with our comb-shaped fiber holder designs. Headgear features and advantages are further discussed below.

[§]For example, NIRS head probes by TechEn, Inc. <u>http://www.nirsoptix.com/assets/custom-headgear-2-small.jpg</u>

Elastomer-Based Headgear Design

The headgear design employs two concepts: the ergonomic *and optical* use of elastomer materials, and a comb shape to part the hair beneath the sensors for expeditious self-application in the field (LEW-18280-1).

In addition to providing comfort and cushioning due to its rubber-like mechanical properties, the elastomer (Dow Silastic MDX4-4210) has multiple relevant advantages. It is lightweight, cleanable, optically transmissive, of biomedical grade, and moldable. There exists the potential of molding optical surfaces into the elastomer to reduce components and allow for a truly low profile, elegant device. Optical transmission through the elastomer was measured to be >95 percent at 2-mm thickness and >75 percent at 3-mm thickness for 690- and 830-nm. It produces no MRI artifact. Further, the index of refraction is ~1.4, which provides some index matching between the optical fibers and the skin [85, 86]. This reduces signal loss due to air gaps and improves consistency of optical coupling [53, 87]. Despite this advantage, recently it has been noted that index matching has not been generally used thus far in fNIRS studies [66]. However, two successful studies have been performed with elastomer between the fiber and the scalp for improved comfort and compliance [69, 88]. Functional signal measurements were made successfully in human subject trials through elastomer disks of 1.0- to 1.5-mm thickness on both the source and detector fibers. Wear time was on the order of an hour for these studies.

Comb-Shaped Headgear Prototypes

The comb shape concept has been matured with multiple prototype fabrication iterations. Smaller comblettes part the hair much more readily than larger shapes, which calls for many individual fibers instead of one solid bundle of fibers. The light from these fibers may be combined and delivered to one detector. Figure 2(a) shows a prototype demonstrating five fiber ends held in place after being inserted into a comb-shaped piece. Each fiber is delivered directly to the scalp in the wake of one of the five comblettes. Dual-material rapid prototyping may be used to combine elastomer-like materials for comfort at the scalp with more rigid materials for the comb and fiber-holding parts. The DOW elastomer can be cured into holes at the fiber ends. Any part which extends to the head must be surrounded by material that is opaque at the wavelengths used to baffle the detector from both the source and any ambient light.

The headgear is self-applicable by sliding rigid headbands on from the hairline as depicted in Figure 2(b). A pigtail of fibers (not shown) would be run to the back to remotely located instrumentation housing sources and detectors. Maintaining contact between the headgear and the scalp will be required as the headgear is slid onto the head through the hairline. The sensor locations are adjustable in two dimensions, and are designed for potential integration with existing headsets. Many of the aspects of this concept are applicable to wireless configurations as well. However, this design is biased to reduce weight and sensor footprint on the head for long-term, comfortable wear.

Optodes will need to cover the head regions relevant to the functional tasks of interest. The shape and hardness of the head-side surface is important to maintaining contact between the scalp and the exposed elastomer at the fiber ends. This will depend on the particular region of the head to be interrogated, as head curvature is highly variable. Therefore headgear must be designed for and dedicated to specific regions of the head, or must be very flexible. In material selection, flexibility and softness often come with a loss of durability. Further resources would be well-spent to identify best materials to meet these conflicting requirements.

The five detecting fiber locations are arranged on the arc of a circle centered at the source location such that they detect at the same source-detector separation distance. As explained above in the "Localization" section, this separation distance determines the depth of the sensed volume. The arc-shaped detection reduces lateral spatial resolution (adding ~0.5 cm on each side on the head surface) but also adds tolerance for overlapping the activation region of interest by increasing the spatial coverage of



Figure 2.—(a) Multistranded fiber with comblettes. (b) Rigid headband design concept.

the sensor. Such tolerance may be required due to variability of placement and probe slippage encountered during operational use. Maturation of these prototypes is ongoing. They have not yet undergone testing with human subjects, their optical signal to noise ratio has not been quantified, and the shape of the larger sensed brain volume has not been modeled. The signal to noise ratio would be expected to decrease for smaller activated regions due to a reduction in the *partial* path length. Whether this is tolerable in the context of the system being described here remains to be seen, and should be explored.

Sensor Layout for Attentional State Detection

Regions of interest for Attentional State Detection, which are shallow enough to be accessible to the fNIRS technique, are shown schematically in Figure 4. Particular locations for attentional performance monitoring are introduced here. The rationale for the use of locations which are part of functionally-connected networks is also given. Notably no cognitive strategy is required, allowing passive monitoring of the brain during task performance. Since the optode layouts are highly configurable, other networks and regions can be interrogated for other operational and clinical applications, if they are known and accessible to fNIRS.

The Pre-Frontal Cortex (PFC) and the right Dorsolateral PFC (rDLPFC) are of interest to monitoring the ATN for task engagement and sustained attention (vigilance) [42, 44, 89]. The Medial Frontal Gyrus and the Angular Gyrus are of interest to monitoring the DMN. The DMN, which is one of many resting state networks of the brain, activates during resting or task-free states at low frequencies (below 0.1 Hz) [60, 90, 91]. These and other parts of the ATN and DMN are also identified as "task positive" and "task negative" in relevant literature [43, 44, 92]. These are the regions which will be used for the system currently under development [93].

Attentional and Resting State Networks

The attentional and resting state networks^{**} of the brain have been selected as sensor locations for this work to exploit the anti-correlation of the ATN and DMN activations. During focused attention and task engagement, relative to during a task-free or rest state, the ATN is expected to activate and the DMN is expected to deactivate, as shown in Figure 3. Whether this anti-correlation originates due to a competition for resources [92] or is a manifestation of intrinsic interactions in the brain [43], it has been shown and quantified. Also, less deactivation of the DMN has been shown to be associated with worse behavioral performance (such as stimulus reaction time) and attentional lapses [44, 92, 94]. Activity differences have been linked to autism [95], attention deficit hyperactivity disorder, and Alzheimer's disease [96].

^{**}Note that it is not the intention of this work to prove the existence of these networks, as they already have been established in the fMRI literature.



Figure 3.—ATN activations are expected to be high while DMN activations are low during task engagement. With no task engagement, the opposite is expected.

Some spatially-separate regions of the brain undergo temporally correlated activation in response to a functional task or stimulus. These regions are said to be functionally connected, and their functional connectivity can be quantified by measuring the temporal covariance of the hemodynamic activations between the regions. The functional connectivity of the networks selected for monitoring is an important aspect of the proposed monitoring system. The brain is regionally organized, but functional specificity of particular regions is not absolute. Particular regions of the brain are specialized for certain functional tasks, but can be active as well for a variety of different functional tasks and respond to a variety of different stimuli. Thus, activity in one region indicated by a single point measurement cannot be assumed to be completely and only due to the functional task of interest. In this way, such measurements can be sensitive to a state or condition, but not specific and thus not predictive. Multiple point measurements per network allow for the detection of a functional network (based on measured temporal correlations) and its level of activation. The detection of the state of activation (or deactivation) of two anti-correlated functional networks provides more confidence that what has been detected actually indicates the functional state that is intended to be measured.

The implementation of a data processing scheme to determine operator state (engaged or not engaged in a task) in near-real-time using fNIRS signals from the ATN and DMN as input variables will be discussed in the "State Classification" section of this report.

Psychological confounds, such as a self-specific or introspective recall during a task, an easy task, or being between tasks, could look like an inattentive state and be labeled as such in error. Such DMN activation while the operator is in an attentive state but not highly engaged (e.g., in a less-demanding situation) might look like rest (False Negative), which would reduce Sensitivity and Negative Predictive Value. A slowly slipping probe, for another example, could look like activity during rest (False Positive), which would reduce Specificity and Positive Predictive Value. Unless behavioral measures or other contextual clues are included, whether a task being worked is actually relevant to the operational task at hand cannot be distinguished.

Location Coordinates

Detailed coordinates of specific surface optode locations are given below and plotted in Figure 4. These coordinates are used to measure the selected volumetric regions of interest. The Brodman Area (BA) is given, along with the depth of the cortex of interest and the Talairach to Ten-Twenty (TT) coordinates. TT coordinates are generated by projecting a line from a volume of cortex in the brain along the normal axis to the scalp surface [97]. Cz is the origin at the center, with Fz at (0,1) and C4 at (1,0).

The two dimensional coordinate system, and relevant volume to surface projections, are also shown in Figure 4. The depth of the tissue is identified by the color bar on the right. The selected regions of interest are bilateral, allowing one detector at one optical gain setting to be used for two bilaterally-paired regions. Symmetrical anatomy and similar levels of absolute absorption should produce signals with similar intensity levels for detection. For laboratory testing, optodes are carefully placed with respect to the International 10-20 locations as marked on a subject's head. In operations, location with respect to anatomical landmarks will be required. One-time customization and fitting may be performed if resources exist to dedicate headgear to each user. In the development stage, this is not practicable because one set of headgear must be used on multiple subjects. In this case, adjustable headgear which can accommodate the regions of interest for each test subject is best.

Based the fMRI literature [43, 44, 92], these task negative resting state network subcomponents should show correlation with decreasing activations with task engagement:

- Medial Frontal (BA 10, TT(±0.2,1.5), depth 18 mm) (marked in Figure 4 bilaterally with blue circles between Fp and Fpz; the center of the forehead)
- Angular Gyrus (BA 39, TT(±1.3,-1.0), depth 15 mm) (marked in Figure 4 bilaterally with blue circles and by projection to the area between P4 and T6)
- Superior Frontal Gyrus (BA 8, TT(1.0,0.6), depth 16 mm) (not shown in Figure 4)



Figure 4.—Tissue projections^{††} with respect to the 10-20 locations are shown. Eight measurement locations (source-detector pair midpoints) are shown schematically with cortex to be interrogated beneath the marked circles. The color scale indicates depth.

^{††}Credit: tissue projection tool available at <u>http://wwwneuro03.uni-muenster.de/ger/t2tconv/conv3d.html</u>

Based on available fMRI literature [43, 44, 92], these task-positive attentional network subcomponents should show correlation with increasing activations with task engagement, and together be anti-correlated with the task-negative network activations:

- DLPFC (BA 46, TT(1.3,1.0), depth 10 to 13 mm) (marked in Figure 4 bilaterally with red circles and by projection to the area between F4 and F8; just into the hairline from the temple)
- Supplementary Motor (BA 6, TT(0.9,0.3), depth 15 mm) (marked in Figure 4 bilaterally with red circles and by projection to the area anterior to the line between Cz and C4)
- Inferior Parietal Lobule (BA 40, TT(1.3,-0.5), depth 19 mm) (not shown in Figure 4)

Methods and State Classification

Simultaneous fNIRS and fMRI testing will be performed to demonstrate attentional performance monitoring with near-real-time state classification. We plan to implement Support Vector Machines (SVMs) for a number of reasons. The number of input features is flexible, they can be optimized for generalizability, they have a clear performance metric given known states, and, once trained, can be implemented with reasonable computational resources for real time prediction. Also, we select SVMs for their potential for high accuracy during sustained activity with minimal training, and for comparison to existing real time fMRI methods [61]. Other classification algorithms have not yet been explored. We will consider the quantification of anti-correlation [92] and functional connectivity [96, 98, 99] over recent time blocks to qualify our measurements, as they rely upon the detection of functionally-connected networks. Kalman estimators hold promise for real-time applications as they provide trial-by-trial adaptability. These recently have been applied to fNIRS state classification with known stimulus event timing [59]. However, this information will not be available in operational contexts.

SVMs will be used to classify the state of the brain based on the hemoglobin concentration changes over time at the various locations for each time period. A prediction is made for each time instance at the fNIRS data rate. We avoid injecting experimenter bias and preserve adaptability by using the fNIRS signals (primarily changes in [Hb] at the selected locations) as input features and not extracting specific features [61]. The classification algorithm outputs a predicted state label for each instance of time depending on the magnitude of a number of input features (the digital fNIRS signals). The classifier must be trained using input data for which true state labels are known. The trained model is then used to classify future test input data. Please refer to the Appendix for a detailed introduction to Support Vector Machines.

Accuracy of classification will be determined by comparison to known state as indicated by behavioral measures, and to fMRI classification [61]. Measurements of more than one location within each network allow the covariance of the activations to be measured. In this way, functional connectivity between each region may be used as additional inputs to the SVM. This may improve the classification because variance of the functional connectivity (how well the networked locations are synchronized) has been shown to correlate with behavioral changes [92]. Also, the raw optical intensity measurement traces may be used as additional inputs to the SVM. Whether accuracy improves upon their inclusion will be examined.

Human Subject Trial Validation Test Plans

We will investigate the agreement between the measured optical signals (both [Hb] and intensity) and behavioral measures (such as reaction time and response error rate) to validate the above-described system with a human subject trial.

We will monitor portions of the ATN and DMN networks with fNIRS to determine the accuracy with which we can classify attentional state (on-task/accurate or off-task/inaccurate) during task performance, using the fNIRS signals alone. Known states

and classifier accuracy will be determined by behavioral measures indicating performance decrement due to lapses in attention.

Thus far, the ability to discriminate periods of time during which a subject is engaged or not engaged in a cognitive task has been shown with accuracy of 71 percent \pm 3 percent, and potentially up to 88 percent, using two locations and minimal signal processing, and given clean, within-subject, withinsession training data [88]. The implementation of real-time signal processing and state classification for attentional performance monitoring will be optimized further with additional fNIRS trials.

For these trials, optical signals will be collected and relative hemoglobin concentrations will be calculated for each of four locations at 6.25 Hz with a 16-source-channel four-detector Imagent system and customized probes (ISS, Inc., Champaign, IL). These will be the four locations on the right-side as shown in Figure 4. Two channels will be used at each location (one for the confounding physiological measurements). This will use half of the available source channels, with a lack of headgear appropriate for detector-sharing being the limiting factor.

This data will be exported to a serially networked computer running in-house custom software, which will calculate the changes in [Hb] based on the optical intensity changes, subtract the physiological contributions and remove motion artifact. Activation is indicated by concurrent increases in [HbO] and decreases in [HbR]. The temporal correlation of the activations in each signal with those in the others will also be calculated. Each of the four fNIRS time traces will be input to a Support Vector Machine (SVM). The temporal correlations may be used as additional SVM inputs, or to qualify probe localization, based on expected within-network correlation and cross-network anti-correlation. Tasks will be presented to the subjects at a frequency which is filtered out of the fNIRS signals to remove task effects. The time traces will have different characteristics depending on the location of the optode (which network it is monitoring), and the attentional condition (working accurately, or resting/making errors). The output will be one label classifying all the data for that time period as attending or not attending (a binary classification). In the future, greater levels of classification using Support Vector Regression or multiclass SVM, and input feature optimization, can be explored.

The SVM will require training and known state labels. Each subject will spend a few minutes alternately performing tasks requiring attention and resting. For binary classification, a working state will dictate the application of "attending/on-task" labels, while a resting state will dictate the application of "not attending/off-task" labels. For three-state classification, accurate task responses will dictate the application of "not attending" labels, and a resting state will dictate the application of "resting/off-task" labels. These known labels will be applied to the training data, and the SVM will be trained. The same subject will then perform a task (making errors or not) or rest, and the SVM will be blind to the true condition. The SVM will classify the new fNIRS signals according to the characteristics shared with trained accurate, inaccurate or rest signals. The output predicted classification label will be compared to known labels (based on behavioral measures) to calculate accuracy.

SVM optimization will be accomplished by selecting kernel parameters which produce the best classification accuracy using within-subject training data. SVM parameters are discussed in the "Practical Considerations for SVM implementation" section below. In future work, whether training will be generally applicable to different tasks may be investigated by attempting to classify attentional state during one task (such as a more complex, operationally-relevant task) using training data obtained during the performance of another task.

In simultaneous fNIRS-fMRI testing, SVMs will be employed for both the fMRI [61] and the fNIRS state classification. The subject's behavioral responses to the task over time (such as their error rate and reaction time) will be recorded to determine the known labels and thus the accuracy of the SVM output labels. Accurate subject responses will dictate the application of "attending" labels, while inaccurate responses will dictate the application of "not attending" labels. These known labels will be applied similarly to the classification for the fNIRS-only trials. When optical signal patterns are produced that are similar to those with an "attending" label, a classification prediction of "attending" is expected. This is

expected to correlate with more accurate behavioral responses because of the behavioral relevance of the ATN and DMN network activations we are measuring. Classification with fMRI data can potentially be done using many mm-sized voxels across the whole brain as feature inputs. For a more fair comparison, the fMRI signals used for the classification will be restricted with a spatial mask to those from the four cortical tissue volumes accessible to the fNIRS probes being used (essentially the outer few mm of the brain beneath and between that source and detector). Simultaneous fNIRS-fMRI trials are required to ensure the comparison of the classifications based on the same hemodynamic activations, which may be influenced by physiological variations and subject motivation, effort and response strategy.

Practical Considerations for SVM Implementation

When using any SVM library to perform classification on a data set, several choices must be made by the researcher prior to training. These are:

- The value of the regularization parameter *C*.
- The type of transformation kernel, K(x,y).
- The values of any parameters of K(x,y).

Several commonly used transformation kernels are:

Туре	Form: $K(x,y) =$	Parameter(s)
Polynomial	$(\boldsymbol{x} \cdot \boldsymbol{y} + 1)^p$	$p \in \mathbb{Z}^+$
Radial Basis Function	$\exp\left\{-\gamma \left\ \boldsymbol{x}-\boldsymbol{y}\right\ ^{2}\right\}$	$\gamma \in \mathbb{R}^+$
Sigmoidal	$\tanh(\kappa x \cdot y - \delta)$	$x, \delta \in \mathbb{R}$

Note that a linear SVM is just a particular case of a polynomial kernel. It has been noted that a radial basis function is often a suitable first guess for SVM kernel selection when no prior knowledge is available regarding the separability of the feature space [100]. If the desired accuracy is not achieved using a radial basis function, then another kernel type should then be selected. Using a radial basis function as the SVM kernel (which is most likely for this work, and has been piloted [88] using LIBSVM [101]) requires a choice of the non-negative parameter γ . Note that selecting this kernel parameter is similar in nature to specifying the inverse variance of a Gaussian distribution function. Simultaneously, one must also select the error tolerance regularization parameter *C*. Small values of *C* discount errors in the training data to produce a generalizable smooth decision boundary, at the risk of classifier accuracy. Thus, in practical application, the fidelity of the training data which represent the states of interest becomes very important.

Best known practices in the machine learning literature to date dictate a uniformly or logarithmically spaced grid search for (C, γ) such that the cross-validation accuracy of the training data is maximized. Cross-validation is a procedure in which the training data is partitioned into small sets of equal size. The SVM is then, in turn, trained using each set and validated using the remaining sets. The overall accuracy percentage is tracked and returned. Finding the optimal SVM parameters in this manner is computationally expensive, but for a single class of SVM problems with the same type of input data these parameters often do not need to change. It is our working assumption that for a given individual executing the same task, the SVM parameters (C, γ) may be computed once (following the use of initial control tasks as training data) and may remain constant for the individual. Thus, values for these parameters are best determined by running sets of similar data when computational time is available, looking for convergence upon a range which consistently produces acceptable results for a given type of input data in a given situation. Future research should explore adaptive techniques for the identification of optimal (C, γ) in the context of classifying fNIRS data in an online setting, perhaps using evolutionary algorithms

or simulated annealing. If such techniques are demonstrated to perform well, SVM would become more adaptable to categorization under changing operational circumstances.

Classification accuracy would be improved by such SVM parameter optimization. Accuracy should also be improved by proper automated processing to clean the signals of physiological confounds and motion artifact. This is especially important for the training data. Automated lost signal rejection and improved headgear together would reduce the negative effects of gaps and exposure to ambient light. SVM feature weighting can guide the determination of which input data (Hb or raw optical probe traces, or functional connectivity correlations) are most important to achieving high classification accuracy. Generally, increasing the number of SVM input features should improve accuracy, but it is not helpful to include redundant or noisy signals which do not contribute useful information to the classifier. This is important for the optimization of the number of probe locations, as we aim to both maximize accuracy and minimize the necessary hardware on the head.

Future Research

Other Potential Research Applications

fNIRS is relevant to optimizing human effectiveness in a broad range of safety-critical operational activities. For example, monitoring the default mode network is relevant to performance decrement due to fatigue. Slow reaction times, particularly after total sleep deprivation, were associated with greater activity in the default mode network [102], which should be deactivated during vigilant task engagement. Also, activation of the default mode network might be used as an idle state detector for brain-computer interface applications [36].

Monitoring attention is relevant to cognitive decrement in extreme and stressful environments [103]. Also, attention is relevant to motor skill learning [26, 27]. As increased skill evolves into rote or automated activity, executive control process activation is reduced [41]. Further, quantifying attention over time could be used to differentiate goal neglect from actual skill decrement. During performance of attention-demanding tasks, a lack of attention may explain a drop in performance compared to actual skill loss. At the work overload extreme, executive "top-down" attentional resource limits may be reached if sensory inputs are overloaded with incoming information. Performance may drop despite attention to task, or attention may decrease as efforts are abandoned.

Aside from monitoring the default mode network or attentional regions, other cognitive states may be explored in a similar manner by monitoring different regions on the head than those identified for this particular work. If fMRI literature indicates regions of interest in superficial cortex, fNIRS may be useful for that application. Finally, similar to electroencephalography and fMRI [30, 61, 104-106], fNIRS can be used in biofeedback self-training systems.

Steps to Real World Use

If the planned simultaneous fNIRS-fMRI trials are successful, this system will have been demonstrated in a laboratory environment. Much development remains to be completed prior to use in realistic environments. Steps in this direction include: completing headgear prototyping, further automation of signal calculations for online processing, evaluation and classifier parameter selection, reducing classifier training needs, testing the system with increasingly complex tasks and in increasingly realistic environments, showing generalizability across behavioral tasks and physiological states, and performing tests with subjects relevant to the true end user population (such as trained pilots). Even sitting upright instead of lying in the fMRI scanner is a step in the "real world" application direction due to the increasing contributions from Mayer waves for blood pressure regulation from supine to sitting to standing [36]. fMRI studies represent an important opportunity to anchor fNIRS studies, especially considering the shared sensing of localized hemodynamic responses. However, "peoples' performance in [artificial experimental tasks] might not be representative of their behavior and beliefs in the real world"

[107]. This motivates comparisons as well to EEG studies, considering the shared advantage of more ecologically-valid studies due to the non-invasive and portable nature of these two techniques.

Much defense-sponsored cognition work with fNIRS has been undertaken for such reasons. Certainly, however, the shortcomings of existing fNIRS headgear hold back highly realistic studies. Sweat, impacts, motion and temperature changes are only some of many variables and relevant field conditions that will come out of real-life human use that may not be fully accounted for until they are thoroughly experienced in multiple experiments. "Laboratory studies conceived and interpreted in isolation from real-world experience may do far worse than fail to generalize back to the natural environment; they may generate fundamental misunderstandings of the principles of human attention" [108]. Indeed a careful balance must be struck between rigorous, controlled experiments in the laboratory, and validation in real-world environments.

Appendix: Introduction to Support Vector Machines

Support Vector Machines (SVM) are a class of supervised learning methods developed from the statistical learning theory of Vapnik and Chervonenkis. The modern application-driven theory of SVMs was formulated at Bell Laboratories during the 1990s.

Assume that we are given a sample of recorded and categorized data $\{(x_1, y_1), \dots, (x_n, y_n)\}$, where each x_1 represents an input vector belonging to a systems feature space, and y_i represents a corresponding categorical labeling. For simplicity, assume that we are only interested in binary classification, so that y_i

 $\in \{-1,1\}$ represents two categories of interest. An illustration of a prototypical problem in \mathbb{R}^2 is shown in

Figure 5. The aim of SVM is to formulate an optimal decision function $f(x_i)$ to classify input data as belonging to one of these two categories. To minimize the risk of misclassification, f is formulated such that the boundary between the two classification regions is maximized. This principle is illustrated in Figure 6. For this example, it was assumed that the optimal decision function was a linear classifier, i.e.,

 $f(x_i) = \begin{cases} -1 \text{ if } \mathbf{w} \cdot x_1 + b > x_2 \\ 1 \text{ otherwise} \end{cases}$. For the ideal case of completely linearly separable data in *n* dimensions, the

linear SVM problem takes the form of a (convex) quadratic problem:

minimize:
$$\frac{1}{2} \| \boldsymbol{w} \|_2^2$$

subject to: $y_i (\langle \boldsymbol{w}, \boldsymbol{x}_i \rangle + b) \ge 1 \forall i$

Here the objective function restricts the norm of *w* to regularize the problem, and the constraints guarantee fidelity to the classification problem. In practice, training data gathered through real world processes may not be linearly separable simply due to measurement errors. In this case, slack variables $\xi_i \ge 0$ must be introduced into the problem to allow for a tunable amount of error in the solution. The problem then becomes:

minimize:
$$\frac{1}{2} \| \boldsymbol{w} \|_2^2 + C \sum_{i=1}^n \xi_i$$

subject to: $y_i (\langle \boldsymbol{w}, \boldsymbol{x}_i \rangle + b) \ge 1 - \xi_i \forall i$

where *C* is a regularization parameter controlling the tradeoff between finding a hyperplane that separates the data well and one which maximizes the margin between the two categories. Finally, in the most general case where the feature space is not linearly separable (even without measurement errors), it is assumed that the decision function involves some transformation function $\phi(x_i)$ that maps input data into a new (possibly infinite dimensional) feature space where linear SVM is applicable. The SVM problem then has the form:

minimize:
$$\frac{1}{2} \|\boldsymbol{w}\|_2^2 + C \sum_{i=1}^n \xi_i$$

subject to: $y_i (\langle \boldsymbol{w}, \boldsymbol{\phi}(\boldsymbol{x}_i) \rangle + b) \ge 1 - \xi_i \forall i$



Figure 5.—An example of a linearly repeatable, binary classified data set in the plane.



This problem has a more computationally tractable dual formulation given by:

minimize:
$$\frac{1}{2} \boldsymbol{a}^T \boldsymbol{Q} \boldsymbol{a} - \sum_i a_i$$

subject to: $\boldsymbol{y}^T \boldsymbol{a} = 0, 0 \le a_i \le C \forall i$

Where Q is the $n \times n$ positive semi-definite matrix $Q_{i,j} = y_i y_j K(x_i, x_j)$ with $K(x_i, x_j) = \phi(x_i)^T \phi(x_j) = \langle \phi(x_i), \phi(x_j) \rangle$. After solving the dual problem numerically, the decision rule becomes:

$$f(\mathbf{x}) = \operatorname{sgn}\left(\sum_{i=1}^{n} y_i a_i \mathbf{K}(\mathbf{x}_i, \mathbf{x}) + b\right)$$

Note that we need not know ϕ explicitly for either the minimization problem or the solution formulation; only a function K (called the transformation kernel) which computes inner products within the transformed space. This problem statement and solution form is the so-called *C*-Support Vector Classification (*C*-SVC) formulation. Alternate formulations exist, such as the v-Support Vector Classification (v-SVC) and Distribution SVM (1-class SVC), with each specifying constrained optimization problems similar to above, but with alternate specifications of regularization parameters.

For our work, the *C*-SVC formulation was used, with all computations executed using the Python programming language bindings for the open-source LIBSVM library. LIBSVM numerically solves the *C*-SVC dual problem using a Sequential Minimal Optimization type iterative decomposition algorithm. The stopping rule dictates that the iteration may terminate when the Karush-Kuhn-Tucker optimality condition is satisfied. This algorithm has been shown to be efficient and numerically stable both theoretically and in practice [109].

Aside from LIBSVM [101], several other open-source SVM libraries exist for *C*-SVC type SVM classification, such as SVM^{*light*} and mySVM. The documented capabilities, scripting language bindings, and researcher feedback from these libraries are very similar to LIBSVM. At the present time, it is unknown if any performance differences exist between these libraries and LIBSVM.

References

- 1. Oken, B.S., M.C. Salinsky, and S.M. Elsas, *Vigilance, alertness, or sustained attention: physiological basis and measurement*. Clinical Neurophysiology, 2006. **117**(9): p. 1885-1901.
- Schmorrow, D.D. and L.M. Reeves, 21(st) century human-system computing: Augmented cognition for improved human performance. Aviation Space and Environmental Medicine, 2007. 78(5): p. B7-B11.
- 3. Snow, M., et al., Service Test and Evaluation Report. Phase IV. DARPA Augmented Cognition, Improving Warfighter Information Intake Under Stress. 2006.
- 4. Schnell, T., et al., *Improved Flight Technical Performance in Flight Decks Equipped with Synthetic Vision Information System Displays.* International Journal of Aviation Psychology, 2004. **14**(1).
- 5. Pope, A., Bogart, EH, Bartolome, DS., *Biocybernetic system validates index of operator engagement in automated task.* Biological Psychology, 1995. **40**: p. 187-195.
- 6. Arenth, P.M., J.H. Ricker, and M.T. Schultheis, *Applications of Functional Near-Infrared Spectroscopy (fNIRS) to neurorehabilitation of cognitive disabilities.* Clinical Neuropsychologist, 2007. **21**(1): p. 38-57.
- 7. Bunce, S.C., et al., *Functional near-infrared spectroscopy An emerging neuroimaging modality*. Ieee Engineering in Medicine and Biology Magazine, 2006. **25**(4): p. 54-62.
- 8. Gibson, A.P., J.C. Hebden, and S.R. Arridge, *Recent advances in diffuse optical imaging*. Physics in Medicine and Biology, 2005. **50**(4): p. R1-R43.
- 9. Gratton, E., et al., *Measurement of brain activity by near-infrared light*. Journal of Biomedical Optics, 2005. **10**(1).
- 10. Boas, D.A., A.M. Dale, and M.A. Franceschini. *Diffuse optical imaging of brain activation: approaches to optimizing image sensitivity, resolution, and accuracy.* in *Conference on Mathematics in Brain Imaging.* 2004. Los Angeles, CA.
- 11. Schroeter, M.L., et al., *Investigating the post-stimulus undershoot of the BOLD signal A simultaneous fMRI and fNIRS study*. Neuroimage, 2006. **30**(2): p. 349-358.
- 12. Steinbrink, J., et al. Illuminating the BOLD signal: combined fMRI-fNIRS studies. in International School on Magnetic Resonance and Brain Function. 2005. Erice, Italy.
- 13. Obrig, H. and A. Villringer, *Beyond the visible Imaging the human brain with light*. Journal of Cerebral Blood Flow and Metabolism, 2003. **23**(1): p. 1-18.
- 14. Strangman, G., D.A. Boas, and J.P. Sutton, *Non-invasive neuroimaging using near-infrared light*. Biological Psychiatry, 2002. **52**(7): p. 679-693.
- 15. Emir, U.E., C. Ozturk, and A. Akin, *Multimodal investigation of fMRI and fNIRS derived breath hold BOLD signals with an expanded balloon model*. Physiological Measurement, 2008. **29**(1): p. 49-63.
- 16. Huppert, T.J., et al., *Quantitative spatial comparison of diffuse optical imaging with blood oxygen level-dependent and arterial spin labeling-based functional magnetic resonance imaging.* Journal of Biomedical Optics, 2006. **11**(6).
- 17. Kleinschmidt, A., et al., *Simultaneous recording of cerebral blood oxygenation changes during human brain activation by magnetic resonance imaging and near-infrared spectroscopy*. Journal of Cerebral Blood Flow and Metabolism, 1996. **16**(5): p. 817-826.
- 18. Strangman, G., et al., A quantitative comparison of simultaneous BOLD fMRI and NIRS recordings during functional brain activation. Neuroimage, 2002. **17**(2): p. 719-731.
- 19. Li, L., et al. Design and evaluation of a simultaneous fNIRS/ERP instrument art. no. 643429. in Conference on Optical Tomography and Spectroscopy of Tissue VII. 2007. San Jose, CA.
- 20. Moosmann, M., et al., *Correlates of alpha rhythm in functional magnetic resonance imaging and near infrared spectroscopy*. Neuroimage, 2003. **20**(1): p. 145-158.
- 21. Boas, D.A., et al., *The accuracy of near infrared spectroscopy and imaging during focal changes in cerebral hemodynamics*. Neuroimage, 2001. **13**(1): p. 76-90.

- 22. Franceschini, M.A., et al., *Diffuse optical imaging of the whole head*. Journal of Biomedical Optics, 2006. **11**(5).
- 23. Murphy, K., et al., *The impact of global signal regression on resting state correlations: Are anti-correlated networks introduced?* Neuroimage, 2009. **44**(3): p. 893-905.
- 24. Mesquita, e.a., *Resting state functional connectivity of the whole head with near-infrared spectroscopy*. Biomedical Optics Express, 2010. **1**(1): p. 324-336.
- 25. Zhang, Q., E. Brow, and G. Strangman, *Adaptive Filtering for global interference cancellation and real-time recovery of evoked brain activity: a Monte Carlo simulation study.* Journal of Biomedical Optics, 2007. **12**(4): p. 044014-1 044014-12.
- 26. Hatakenaka, M., et al., *Frontal regions involved in learning of motor skill A functional NIRS study*. Neuroimage, 2007. **34**(1): p. 109-116.
- 27. Leff, D.R., et al., *Changes in prefrontal cortical behaviour depend upon familiarity on a bimanual co-ordination task: An fNIRS study.* Neuroimage, 2008. **39**(2): p. 805-813.
- 28. Peck, E., Lalooses, F, Chauncey, K. Framing Meaningful Adaptation in a Social Context. in ACM CHI 2011 Workshop: Brain and Body Interfaces: Designing for Meaningful Interaction, May 8th 2011. 2011.
- 29. Hirshfield, L.M., et al., *This is Your Brain on Interfaces: Enhancing Usability Testing with Functional Near-Infrared Spectroscopy*, in *ACM CHI 2011, Session: Brain & Bio-sensor Interactions*. 2011: Vancouver, BC, Canada. p. 372-383.
- 30. Cowings, P., *Psychophysiology of Spaceflight.*, in 14th IAA Humans In Space Symposium, Living in Space: Scientific, Medical and Cultural Implications. 2003: Banff, Alberta, Canada.
- 31. Callaway, E. *Tiny scanner may monitor astronauts' mental health* 2008 03 July 2008]; NSBRI grant for fNIRS sensor]. Available from: <u>http://space.newscientist.com/article/dn14247-brain-breathalysers-may-scan-astronauts-for-stress.html</u>.
- 32. Drummond, S.P.A., et al., *Compensatory recruitment after sleep deprivation and the relationship with performance.* Psychiatry Research-Neuroimaging, 2005. **140**(3): p. 211-223.
- 33. Nebel, K., et al., *On the neural basis of focused and divided attention*. Cognitive Brain Research, 2005. **25**(3): p. 760-776.
- 34. Vohn, R., et al., *Management of attentional resources in within-modal and cross-modal divided attention tasks: An fMRI study.* Human Brain Mapping, 2007. **28**(12): p. 1267-1275.
- 35. Coyle, S.M., T.E. Ward, and C.M. Markham, *Brain-computer interface using a simplified functional near-infrared spectroscopy system.* Journal of Neural Engineering, 2007. **4**(3): p. 219-226.
- 36. Matthews, F., et al., *Hemodynamics for braincomputer interfaces*. Ieee Signal Processing Magazine, 2008. **25**(1): p. 87-94.
- 37. Kojima, T., et al., *Measurement of train driver's brain activity by functional near-infrared spectroscopy (fNIRS)*. Optical and Quantum Electronics, 2005. **37**(13-15): p. 1319-1338.
- Solovey, E., Lalooses, F, Chauncey, K, Weaver, D, Parasi, M, Matthias Scheutz, M, Sassaroli, A, Fantini, S, Schermerhorn, Girouard, PA, Jacob, RJK., Sensing Cognitive Multitasking for a Brain-Based Adaptive User Interface, in CHI 2011, Session: Brain & Bio-sensor Interactions. 2011: Vancouver, BC, Canada. p. 383-392.
- 39. Joanette, Y., et al., *Neuroimaging investigation of executive functions: evidence from fNIRS*. PSICO, 2008. **39**(3): p. 267-274.
- 40. Fan, J., et al., *The activation of attentional networks*. Neuroimage, 2005. 26(2): p. 471-479.
- 41. Gilbert, S.J. and P.W. Burgess, *Executive function*. Current Biology, 2008. 18(3): p. R110-R114.
- 42. Posner, M.E., Cognitive Neuroscience of Attention. 2004, New York, NY: Guilford Press.
- Fox, M.D., et al., *The human brain is intrinsically organized into dynamic, anticorrelated functional networks*. Proceedings of the National Academy of Sciences of the United States of America, 2005. 102(27): p. 9673-9678.
- 44. Weissman, D.H., et al., *The neural bases of momentary lapses in attention*. Nature Neuroscience, 2006. **9**(7): p. 971-978.

- Eichele, T., et al., *Prediction of human errors by maladaptive changes in event-related brain networks*. Proceedings of the National Academy of Sciences of the United States of America, 2008. 105(16): p. 6173-6178.
- 46. O'Connell, R.G., et al., *Uncovering the Neural Signature of Lapsing Attention: Electrophysiological Signals Predict Errors up to 20 s before They Occur.* Journal of Neuroscience, 2009. **29**(26): p. 8604-8611.
- 47. Byrne, E.A. and R. Parasuraman, *Psychophysiology and adaptive automation*. Biological Psychology, 1996. **42**(3): p. 249-268.
- 48. Karatekin, C., D.J. Marcus, and J.W. Couperus, *Regulation of cognitive resources during sustained attention and working memory in 10-year-olds and adults.* Psychophysiology, 2007. **44**(1): p. 128-144.
- 49. Duncan, J. and A.M. Owen, *Common regions of the human frontal lobe recruited by diverse cognitive demands*. Trends in Neurosciences, 2000. **23**(10): p. 475-483.
- 50. Hugdahl, K., et al. Brain activation measured with fMRI during a mental arithmetic task in schizophrenia and major depression. in 7th Annual Meeting of the Organization-for-Human-Brain-Mapping. 2001. Brighton, England.
- 51. Sarter, M., W.J. Gehring, and R. Kozak, *More attention must be paid: The neurobiology of attentional effort.* Brain Research Reviews, 2006. **51**(2): p. 145-160.
- 52. Sharp, D.J., et al., *The neural correlates of declining performance with age: Evidence for agerelated changes in cognitive control.* Cerebral Cortex, 2006. **16**(12): p. 1739-1749.
- 53. Schweiger, M., et al., *Image reconstruction in optical tomography in the presence of coupling errors*. Applied Optics, 2007. **46**(14): p. 2743-2756.
- 54. Jasper, H., Progress and problems in brain research. J Mt Sinai Hosp N Y, 1958. 25(3): p. 244-53.
- 55. Jurcak, V., D. Tsuzuki, and I. Dan, 10/20, 10/10, and 10/5 systems revisited: Their validity as relative head-surface-based positioning systems. Neuroimage, 2007. **34**(4): p. 1600-1611.
- 56. Okamoto, M., et al., *Multimodal assessment of cortical activation during apple peeling by NIRS and fMRI*. Neuroimage, 2004. **21**(4): p. 1275-1288.
- 57. Sato, H., et al., *Within-subject reproducibility of near-infrared spectroscopy signals in sensorimotor activation after 6 months.* Journal of Biomedical Optics, 2006. **11**(1).
- 58. Martinos Center for Biomedical Imaging *NIRS-DOT Visiting Fellowship Course*. 2007; Available from: <u>http://www.nmr.mgh.harvard.edu/martinos/training/NIRS-DOTcourse.php</u>.
- 59. Abdelnour, A.F. and T. Huppert, *Real-time imaging of human brain function by near-infrared spectroscopy using an adaptive general linear model.* Neuroimage, 2009. **46**(1): p. 133-143.
- 60. Mantini, D., et al., *Electrophysiological signatures of resting state networks in the human brain*. Proceedings of the National Academy of Sciences of the United States of America, 2007. **104**(32): p. 13170-13175.
- 61. LaConte, S.M., S.J. Peltier, and X.P.P. Hu, *Real-time fMRI using brain-state classification*. Human Brain Mapping, 2007. **28**(10): p. 1033-1044.
- 62. Izzetoglu, K., et al., *Functional optical brain imaging using near-infrared during cognitive tasks*. International Journal of Human-Computer Interaction, 2004. **17**(2): p. 211-227.
- 63. Cruz, C., et al., *Clockwise and counterclockwise rotating shifts: Effects on sleep duration, timing, and quality.* Aviation Space and Environmental Medicine, 2003. **74**(6): p. 597-605.
- 64. Huppert, T.J., et al., *HomER: a review of time-series analysis methods for near-infrared spectroscopy of the brain.* Applied Optics, 2009. **48**(10): p. D280-D298.
- Lloyd-Fox, S., A. Blasi, and C.E. Elwell, *Illuminating the developing brain: The past, present and future of functional near infrared spectroscopy*. Neuroscience and Biobehavioral Reviews, 2010. 34(3): p. 269-284.
- 66. Orihuela-Espina, F., et al., *Quality control and assurance in functional near infrared spectroscopy* (*fNIRS*) experimentation. Physics in Medicine and Biology, 2010. **55**(13): p. 3701-3724.
- 67. ISS, I. *Functional Brain Imaging System Imagent*. [html] 2008; product information]. Available from: <u>http://www.iss.com/Products/imagent/index.html</u>.

- 68. Wen, X., et al., *In vivo skin optical clearing by glycerol solutions: mechanism*. Journal of Biophotonics, 2010. **3**(1-2): p. 44-52.
- 69. Harrivel, A., et al. *Toward Improved Headgear for Monitoring with Functional Near Infrared Spectroscopy*. in 15th Annual Meeting of the Organization for Human Brain Mapping. 2009. San Francisco, CA: NeuroImage.
- 70. Tucker, D.M., *Spatial sampling of head electrical fields the Geodesic Sensor Net*. Electroencephalography and Clinical Neurophysiology, 1993. **87**(3): p. 154-163.
- 71. Boas, D.A., et al., *Improving the diffuse optical imaging spatial resolution of the cerebral hemodynamic response to brain activation in humans*. Optics Letters, 2004. **29**(13): p. 1506-1508.
- 72. Strangman, G., M.A. Franceschini, and D.A. Boas, *Factors affecting the accuracy of near-infrared spectroscopy concentration calculations for focal changes in oxygenation parameters*. Neuroimage, 2003. **18**(4): p. 865-879.
- 73. Kawaguchi, H. and E. Okada. *Evaluation of image reconstruction algorithm for near infrared topography by virtual head phantom art. no.* 662906. in *Conference on Diffuse Optical Imaging of Tissue*. 2007. Munich, Germany.
- 74. Hillman, E.M.C., et al., *Depth-resolved optical imaging and microscopy of vascular compartment dynamics during somatosensory stimulation*. Neuroimage, 2007. **35**(1): p. 89-104.
- 75. Okada(b), E. and D.T. Delpy. *Near-infrared light propagation in an adult head model. II. Effect of superficial tissue thickness on the sensitivity of the near-infrared spectroscopy signal.* in *Biomedical Topical Meeting of the Optical-Society-of-America.* 2003. Miami Beach, Fl.
- 76. Hoshi, Y., et al., *Reevaluation of near-infrared light propagation in the adult human head: implications for functional near-infrared spectroscopy.* Journal of Biomedical Optics, 2005. **10**(6).
- 77. Duncan, A., et al., *Measurement of cranial optical path length as a function of age using phase resolved near infrared spectroscopy*. Pediatric Research, 1996. **39**(5): p. 889-894.
- 78. Cannestra, A.F., et al., *Temporal spatial differences observed by functional MRI and human intraoperative optical imaging*. Cerebral Cortex, 2001. **11**(8): p. 773-782.
- 79. Liu, H.L., et al., *Determination of optical-properties and blood oxygenation in tissue using continuous NIR light.* Physics in Medicine and Biology, 1995. **40**(11): p. 1983-1993.
- 80. Huppert, T.J., S.G. Diamond, and D.A. Boas, *Direct estimation of evoked hemoglobin changes by multimodality fusion imaging*. Journal of Biomedical Optics, 2008. **13**(5): p. Article No.: 054031.
- 81. Izzetoglu, M., et al., *Functional near-infrared neuroimaging*. Ieee Transactions on Neural Systems and Rehabilitation Engineering, 2005. **13**(2): p. 153-159.
- 82. MacFarlane, e.a., Improved fNIRS Using a Novel Brush Optrode, in the Optical Society's (OSA) 94th annual meeting, Frontiers in Optics (FiO). 2010: Rochester, N.Y.
- 83. InfraScan, I.H.B.D. *InfraScan, Inc.* [cited 2008 November 25]; Infrascanner[™] is a hand-held, non-invasive, near-infrared (NIR) based mobile imaging device to detect brain hematoma at the site of injury within the "golden hour".]. Available from: <u>http://www.infrascanner.com/</u>.
- 84. Newswise. *Researchers Develop First Handheld Device to Detect Brain Hematoma*. Realizing the importance of finding hematoma as soon as possible after the injury, a team of Drexel University biomedical engineers has created the InfraScanner(tm), the first handheld device that medical professionals can use to detect brain hematoma at the accident scene.]. Available from: http://www.newswise.com/articles/view/518934/.
- 85. Filas, R.W., B.H. Johnson, and C.P. Wong. *Index-matching elastomers for fiber optics*. in *Electronic Components Conference*, 1989. Proceedings., 39th. 1989. Houston, TX, USA.
- 86. Ding, H.F., et al., *Refractive indices of human skin tissues at eight wavelengths and estimated dispersion relations between 300 and 1600 nm*. Physics in Medicine and Biology, 2006. **51**(6): p. 1479-1489.
- 87. Yates, T.D., et al., *Time-resolved optical mammography using a liquid coupled interface*. Journal of Biomedical Optics, 2005. **10**(5): p. Article No.: 054011.

- 88. Harrivel, A., et al. Monitoring attentional state using functional near infrared spectroscopy: A pilot study. in 17th Annual Meeting of the Organization for Human Brain Mapping. 2011. Quebec City, Canada.
- 89. Lawrence, N.S., et al., *Multiple neuronal networks mediate sustained attention*. Journal of Cognitive Neuroscience, 2003. **15**(7): p. 1028-1038.
- 90. Raichle, M.E., et al., *A default mode of brain function*. Proceedings of the National Academy of Sciences of the United States of America, 2001. **98**(2): p. 676-682.
- 91. Raichle, M.E. and A.Z. Snyder, *A default mode of brain function: a brief history of an evolving idea*. Neuroimage, 2007. **37**(4): p. 1083-90; discussion 1097-9.
- 92. Kelly, A.M.C., et al., *Competition between functional brain networks mediates behavioral variability*. Neuroimage, 2008. **39**(1): p. 527-537.
- 93. Harrivel, A., A. Hylton, and P. Tin, A System for Attentional State Detection with Functional Near Infrared Spectroscopy, in International Conference on Human-Computer Interaction in Aerospace. 2010: Cape Canaveral, Florida.
- 94. Kineses, Z.T., et al., *Model-free characterization of brain functional networks for motor sequence learning using fMRI*. Neuroimage, 2008. **39**(4): p. 1950-1958.
- 95. Weng, S.J., et al., Alterations of resting state functional connectivity in the default network in adolescents with autism spectrum disorders. Brain Research, 2009. **1313**: p. 202-214.
- 96. Uddin, L.Q., et al., Functional Connectivity of Default Mode Network Components: Correlation, Anticorrelation, and Causality. Human Brain Mapping, 2009. **30**(2): p. 625-637.
- 97. Steinstrater O., S.J., Frank A., Jansen A., and Knecht S., *Transcranial magnetic stimulation and language: how variable are our stimulation sites?* Neuroimage, 2001. **13**: p. S257.
- 98. Fair, D.A., et al., A method for using blocked and event-related fMRI data to study "resting state" functional connectivity. Neuroimage, 2007. **35**(1): p. 396-405.
- 99. Greicius, M.D., et al., *Functional connectivity in the resting brain: A network analysis of the default mode hypothesis.* Proceedings of the National Academy of Sciences of the United States of America, 2003. **100**(1): p. 253-258.
- 100. C. W. Hsu, C.C.C., C. J. Lin. A Practical Guide to Support Vector Classification. 2003; Available from: <u>http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.6.3096</u>.
- 101. Chang, C.-C., Lin, Chih-Jen LIBSVM : a library for support vector machines. 2001.
- 102. Drummond, S.P.A., et al., *The neural basis of the psychomotor vigilance task*. Sleep, 2005. **28**(9): p. 1059-1068.
- 103. Lieberman, H.R., et al., *The fog of war: Decrements in cognitive performance and mood associated with combat-like stress.* Aviation Space and Environmental Medicine, 2005. **76**(7): p. C7-C14.
- 104. Decharms, R.C., *Applications of real-time fMRI*. Nature Reviews Neuroscience, 2008. **9**(9): p. 720-729.
- 105. Hodges, J., For Langley Inventors, It's Mind Over Golf, in NASA Langley Researcher News, May 11, 2009. 2009.
- 106. Hodges, J., 'Mindshift' Biofeedback Gaming Technology, in NASA Langley Researcher News, September 3, 2010. 2010.
- 107. Smilek, D., et al., *Metacognitive errors in change detection: Missing the gap between lab and life.* Consciousness and Cognition, 2007. **16**(1): p. 52-57.
- 108. Kingstone, A., et al., *Attention, researchers! It is time to take a look at the real world.* Current Directions in Psychological Science, 2003. **12**(5): p. 176-180.
- 109. Cristianini, N. and J. Shawe-Taylor, An introduction to support vector machines: and other kernelbased learning. 2000: Cambridge University Press.

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Functional Near Infrared Spectroscopy (fNIRS) is an emerging neuronal measurement technique with many advantages for application in operational and training contexts. Instrumentation and protocol improvements, however, are required to obtain useful signals and produce expeditiously self-applicable, comfortable and unobtrusive headgear. Approaches for improving the validity and reliability of fNIRS data for the purpose of sensing the mental state of commercial aircraft operators are identified, and an exemplary system design for attentional state monitoring is outlined. Intelligent flight decks of the future can be responsive to state changes to optimally support human performance. Thus, the identification of cognitive performance decrement, such as lapses in operator attention, may be used to predict and avoid error-prope states. We propose							
that attentional performance may be monitored with fNIRS through the quantification of hemodynamic activations in cortical regions which are part of functionally-connected attention and resting state networks. Activations in these regions have been shown to correlate with behavioral performance and task engagement. These regions lie beneath superficial tissue in head regions beyond the forehead. Headgear development is key to reliably and robustly accessing locations beyond the hairline to measure functionally-connected networks across the whole head. Human subject trials using both fNIRS and functional Magnetic Resonance Imaging (fMRI) will be used to test this system. Data processing employs Support Vector Machines for state classification based on the fNIRS signals. If accurate state classification is achieved based on sensed activation patterns,							
INIRS will be shown to be useful for monitoring attentional performance. 15. SUBJECT TERMS							
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