Chapter 3

The Use of Functional Near-Infrared Spectroscopy in Neuroergonomics

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INTRODUCTION

Functional Near Infrared Spectroscopy (fNIRS) is a multiwavelength optical technique: originally developed for the clinical monitoring of tissue oxygenation,[1] it eventually evolved into a useful tool for functional neuroimaging studies.[2–4] The technology has advanced and a variety of fNIRS instruments have been developed to monitor changes in local cerebral oxygenation by measuring the concentration changes of both deoxygenated hemoglobin (deoxy-Hb) and oxygenated hemoglobin (oxy-Hb). Various types of brain activities, such as motor and cognitive activities, have been studied using fNIRS.[5–11]

fNIRS has become increasingly popular for functional neuroimaging studies due to its portability and relatively low cost. It measures hemodynamic changes in the brain in a similar fashion to functional magnetic resonance imaging (fMRI), but fNIRS is quiet (no operating sound), provides higher temporal resolution, does not restrict participants to a confined space, and does not require the participant to lie down. These qualities make fNIRS an ideal candidate for monitoring brain-activity-related hemodynamic changes not only in laboratory settings but also under working conditions and in more ecologically valid environments. Although fNIRS is not immune to all noise caused by motion artifacts, and the failure to remove such noise adequately may lead to biased or false results, fNIRS is more tolerant to motion artifacts induced by the movement of the head compared to fMRI[12] and has even been used in experiments that require participants to exercise. Real-time applications, such as brain–computer interface scenarios, benefit most from algorithms that can both process data in real time and lead to acceptable results using only current and past data points.

This chapter introduces fNIRS principles, signal processing, and analysis techniques as well as representative applications. An introductory overview of these concepts and video tutorial from theory to practice are given in Ayaz et al.[13]

MEASURE

Physiological and Physical Principles

Typically, an optical apparatus consists of a light source by which the tissue is radiated and a light detector that receives light after it has interacted with the tissue. Biological tissues are relatively transparent to light in the near-infrared range between 700 and 900 nm. Photons that enter the tissue undergo two different types of interaction, absorption and scattering. Within the near-infrared range of light, the two primary absorbers are oxy-Hb (HbO2) and deoxy-Hb (Hb).

By measuring optical density (OD) changes at two wavelengths, the relative change of oxy-Hb and deoxy-Hb versus time can be obtained using the modified Beer–Lambert law (MBLL).[14] OD at a specific input wavelength (λ) is the logarithmic ratio of input light intensity (I_{in}) and output (detected) light intensity(I_{out}). OD is also related to the concentration (c) and molar extinction coefficient (ε) of chromophores, the corrected distance (d) of the light source and detector, and a constant attenuation factor (G):

$$\mathrm{OD}_\lambda = \log\left(\frac{I_{in}}{I_{out}}\right) \approx \varepsilon_\lambda \cdot c \cdot d + G \tag{3.1}$$

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Having the same I_{in} at two different time instances and detected light intensity during baseline (I_{rest}) and performance of the task (I_{test}), the difference in OD is:

$$\Delta \mathrm{OD}_{\lambda} = \log\left(\frac{I_{\mathrm{rest}}}{I_{\mathrm{test}}}\right) = \varepsilon_{\lambda}^{\mathrm{HB}} \cdot \Delta c^{\mathrm{HB}} \cdot d + \varepsilon_{\lambda}^{\mathrm{HBO_2}} \cdot \Delta c^{\mathrm{HBO_2}} \cdot d \tag{3.2}$$

Measuring the OD at two different wavelengths gives:

$$\begin{bmatrix} \Delta \mathrm{OD}_{\lambda 1} \\ \Delta \mathrm{OD}_{\lambda 2} \end{bmatrix} = \begin{bmatrix} \varepsilon_{\lambda 1}^{\mathrm{HB}} d & \varepsilon_{\lambda 1}^{\mathrm{HBO_2}} d \\ \varepsilon_{\lambda 2}^{\mathrm{HB}} d & \varepsilon_{\lambda 2}^{\mathrm{HBO_2}} d \end{bmatrix} \begin{bmatrix} \Delta c^{\mathrm{HB}} \\ \Delta c^{\mathrm{HBO_2}} \end{bmatrix} \tag{3.3}$$

This equation set can be solved for concentrations if the 2 x 2 matrix is nonsingular. Typically, the two wavelengths are chosen within 700–900 nm where the absorption of oxy-Hb and deoxy-Hb are dominant as compared to other tissue chromophores, and below and above the isosbestic point (~805 nm where absorption spectrums of deoxy- and oxy-Hb cross each other) to focus the changes in absorption to either deoxy-Hb or oxy-Hb, respectively. A historical perspective of the MBLL and its application in fNIRS is available.[4,15–18]

PROCESSING

This subsection introduces the typical signal preprocessing pipeline for raw fNIRS signals before they can be used for analysis. Preprocessing of raw signals is needed to eliminate various types of noise and contaminants that are present in the signals; they can be caused by physiological factors (such as cardiac- and respiration-related signal components), sensor coupling (detector saturation and low light), or motion artifacts. Processing algorithms have been developed for both detection and elimination of contaminated segments prior to analysis, and also for the removal of noise or artifacts to clean the signals. Processing can be applied to light intensity measures as well as hemoglobin signals in both time-series for each channel separately or spatially, or across channels at each time instance. The rest of this subsection discusses each major contamination type and the processing it needs.

Motion Artifacts

When the fNIRS sensors, light sources, and/or detectors slide from their original attached location or lose contact with the skin due to head motion, unexpected sudden bursts or spikes can occur in the fNIRS measurements. Furthermore, if the light source loses coupling with the skin, the detector may record either very low values (since no light may pass through it) or extremely high intensities due to the reflected light from the skin (instead of through the tissue underneath) that can cause momentary saturation. Similar saturation effects may occur if the detector is dislodged and loses contact with the skin, causing the penetration of ambient light. Head movement can further cause changes in the pressure applied to the sensor pad or to the light sources and detectors. These changes may allow more photons to enter the tissue, temporarily varying the detected light intensity.

Other than the visual inspection of data for possible motion artifacts, there are a growing number of motion artifact detection and removal algorithms to automate noise detection and eliminate subjectivity.[19–25] Most of these algorithms are developed and modeled for oxy-Hb, deoxy-Hb, and blood volume (oxy-Hb+deoxy-Hb) data,[20,22,26] while the remaining algorithms perform analysis on raw intensity measurements.[19,21,25] It may be most appropriate to perform the algorithms for motion artifact detection and removal on raw measurements to prevent the propagation of error, bias, and cross-talk between hemodynamic signals. In one thesis[27] a method based on combined temporal independent component analysis (ICA) and principal component analysis (PCA) was proposed and implemented on raw intensity measurements collected at two wavelengths and a dark current condition. A spatial PCA-based filtering algorithm was proposed[21] to exploit the property whereby a motion artifact has an intense and correlated effect on a large area of a near-infrared spectroscopy sensor. In its most simplistic approach, raw data processing is typically limited to low-pass or band-pass filtering to remove high-frequency components or exclude the data altogether if it is an irrecoverable case. However, low-pass or band-pass filtering cannot fully eliminate outliers or spikes that are usually much higher than optical signal levels. It is important to identify these motion-corrupted regions objectively in the time-series data. A recent statistical filtering approach, called sliding-window–motion–artifact–rejection (SMAR) has been developed[19] that uses a covariant of a variation-based approach to identify motion-related artifacts. SMAR does not require a priori knowledge, such as a training dataset from a specific subject or experimental protocol. The algorithm is suitable for use in real time during an experiment since it is causal and simple, and requires practically no computational run-time cost. SMAR is a popular method in the typical signal-processing pipeline to assess signal quality and eliminate contaminated signal segments or channels.

Superficial Layers

Through various Monte Carlo simulations it has been shown that fNIRS is able to measure changes in the hemodynamic response within a banana-shaped volume of underlying tissue between the light source and the detector. The depth of penetration is a fraction of the source–detector distance, and the tissue structure is usually taken as approximately half the source–detector separation for the adult human head.[28,29] Thus within the sampled volume and in addition to the hemodynamic changes originating from the cortical brain layer, there could be additional signal contributions to the overall fNIRS measurements from the superficial head layers of skin/scalp, skull, and cerebrospinal fluid (CSF). Specifically, as compared to the skull and CSF, the skin/scalp layer has more vasculature, and hence hemodynamic changes in this layer can result in additional confounding signals to the targeted cerebral hemodynamic response in fNIRS measurements. However, the amount of signal contribution from the skin layer to the cerebral hemodynamic response is still controversial.[30,31] Study findings[32] suggest that task-related hemodynamic responses disappeared when skin blood flow was occluded. Further evaluation by the authors concluded that a major part of the task-related changes in the oxy-Hb concentration in the forehead was due to task-related changes in the skin blood flow. In a later study,[33] results indicate that skin blood flow influenced both short and long source–detector separation measurements. Contrary to these findings, other studies have shown that measurements obtained from larger source–detector separations (used to guarantee the penetration to cortical brain regions) showed significant task-dependent differences, whereas shorter source–detector separations for measurements obtained only from superficial layers did not show any significant differences.[31,34,35]

Several studies have investigated and proposed appropriate optode configurations and various algorithms to eliminate such potential confounding signals from the skin/scalp layer. As an outcome of these studies, an almost universal agreement has been achieved suggesting the implementation of short and long source–detector separations in hardware configurations. Here, separate measurements originating only from superficial layers can be simultaneously acquired from the short separations. These measurements can then be used as reference signals in the elimination of skin effects from the long separations when extracting cerebral hemodynamic responses. For the elimination of the skin effect with the use of reference signal measurements, algorithms range from signal component elimination techniques (i.e., PCA and ICA) to spatial filtering (i.e., common average rejection).[30,36–38]

Physiological Signals

fNIRS can measure the hemodynamic response related to neuronal activity through the mechanism of neurovascular coupling. In addition to changes related to cognitive activity, fNIRS measurements can also capture hemodynamic signals based on other physiological sources such as heart pulsation, blood pressure, and respiration. Due to their natural rhythm, these almost-periodic signals occupy certain frequency bands that typically arise outside the frequency content of the hemodynamic response related to cognitive activity. In general, separation of such signals is performed using simple frequency selective filters. These additional physiological signals are usually treated like artifacts, and hence removed from fNIRS measurements and eliminated from the overall cognitive activity monitoring study. However, measurement of such signals from different origins using a single sensor can provide insights into different processes in the human body (i.e., information on heart rate variability and respiration rate), forming another powerful aspect of fNIRS monitoring. Similarly, as proposed in various studies, very low-frequency oscillations are sometimes considered as physiological artifacts and frequency selective filters are used to eliminate such effects. Mayer waves, which occur due to arterial blood pressure and have a frequency range centered around ~0.1 Hz, can overlap with the frequency band of hemodynamic response related to cognitive activity and can be a more problematic physiological artifact. Care should be taken if frequency selective filters are to be used for their elimination so that signal content related to cognitive activity is not suppressed in the process. In addition to simple frequency selective filters, more sophisticated methods proposed for the elimination of physiological signals include the curve-fitting method, adaptive, Wiener, and Kalman filtering techniques, least-squares regression algorithms, ICA, and RETROICOR.[39–48]

ANALYZE

There are multiple instrumentation approaches developed for fNIRS, reviewed by Ferrari and Quaresima.[8] Most commercial systems currently available are continuous wave (CW), and for these conversion of fNIRS intensity measurements to relative changes in hemodynamic response in terms of oxy-Hb and deoxy-Hb is usually performed using the previously explained MBLL. There are several parameters given in Eq. (3.3), such as molar extinction coefficients, ε and corrected distance, d for each wavelength used and each chromophore being extracted, that are necessary to be able to perform a matrix inversion. In CW fNIRS applications these parameters are usually taken as constants and must be known a priori.

For molar extinction coefficients there are tabulated values for each chromophore of interest at various wavelengths within the near-infrared range.[14] Corrected distance (d) is linearly related to source–detector separation (sd) scaled by differential pathlength factor (DPF) as $d = \text{sd} \times \text{DPF}$. In addition to individual differences, it has been shown that DPF depends on various factors including source–detector separation, wavelength, head location, age, gender, and even oxygen saturation due to differences in layer thickness and tissue composition.[28,49–52]

Other than the aforementioned constants in CW fNIRS applications, changes in oxy-Hb and deoxy-Hb are obtained relative to a baseline condition. Since comparisons between subject groups, optode locations, or task conditions are made using these relative changes, it is important to design a test protocol with appropriate baseline intervals, usually taken as relaxation/resting periods in between the task periods to allow the cognitive state to return to similar levels. These local baseline regions can then be used in MBLL conversions to obtain changes in the hemodynamic response in the task condition relative the baseline region immediately preceding the task. Note that this operation also corresponds to common baseline correction methods (subtracting the mean of the local baseline region from the following task period data epoch) applied to oxy-Hb and deoxy-Hb data obtained relative to a global baseline region collected at the beginning of the task.

In general, hemodynamic response to neuronal activity is explained through a mechanism called neurovascular coupling, such that neuronal activity causes an increase in oxygen and glucose consumption which then leads to an increase in cerebral blood flow. During the brief period of neuronal activation seen in evoked response studies, this oversupply of oxygen forms the basis of expected changes in hemodynamics as measured by fNIRS, where an increase in oxy-Hb is concomitant with a decrease in the deoxy-Hb time series[6,53] This has been compared to and validated by the blood-oxygenation-level-dependent response obtained by fMRI. Even though the relationship between neural activity and vascular response is usually taken as linear, various nonlinearities have also been noted[54,55] which can be more pronounced in block designs with continuous or rapid presentation of trials. Nevertheless, to reduce dimensionality, statistical comparisons between task conditions, head locations, or subject groups are performed on features extracted from oxy-Hb and deoxy-Hb traces instead of using whole data epochs. Such features involve data values or time components such as the average, maximum or minimum values, time to peak, or full width half maximum. Features extracted from fNIRS measurements are not only used in statistical comparisons but have been recently utilized in machine-learning algorithms for automated classification of healthy and diseased groups or between various conditions.[56–58]

APPLICATIONS

This section highlights select applications of fNIRS in neuroergonomics, listing just a few to represent a growing and diverse array of application areas.[59] The main application domain is related to the human–machine/technology frontier. The efficiency and safety of complex high-precision human–machine systems present in aerospace and robotic surgery are closely related to the cognitive readiness, ability to manage workload, and situational awareness of their operators. Subjective operator reports and physiological and behavioral measures are not sufficiently reliable to monitor the cognitive overload that can lead to adverse outcomes. A key feature of the concept of mental workload (which reflects how hard the brain is working to meet task demands) is that it can be dissociated from behavioral performance data. While experienced human operators can maintain performance at required levels through increased effort and motivation or strategy changes, even in the face of increased task challenge, sustained task demands eventually lead to performance decline unless the upward trend in mental workload can be used to predict subsequent performance breakdown. Consequently, it is important to assess mental workload independent of performance measures during training and operational missions. Neuroergonomic approaches based on measures of human brain hemodynamic activity can provide sensitive and reliable assessments of human mental workload in complex training and work environments. fNIRS is a field-deployable noninvasive optical brain-monitoring technology that provides a measure of cerebral hemodynamics within the prefrontal cortex in response to sensory, motor, or cognitive activation. The following examples examine the relationship of the hemodynamic response in the prefrontal cortex to levels of expertise, mental workload state, and task performance in a variety of application areas.

Aerospace: Cognitive Workload Assessment of Air Traffic Controllers

In a collaborative project, Drexel Optical Brain Imaging Team incorporated fNIRS in a study at the FAA's William J. Hughes Technical Center Human Factors Laboratory where certified controllers were monitored while they managed realistic air traffic control (ATC) scenarios under typical and emergent conditions.[60] The primary objective was to use neurophysiological measures to assess cognitive workload and the usability of new interfaces developed for ATC systems. Throughout the study, certified professional controllers completed ATC tasks with different interface settings and controlled difficulty levels for verification. The results indicated that brain activation as measured by fNIRS provides a valid measure of mental workload in this realistic ATC task[60] (Fig. 3.1).

FIGURE 3.1 Control workstations with high-resolution radarscope, keyboard, trackball, and direct keypad access (left). Operators in the study performing ATC tasks in front of workstations with a fNIRS sensor pad on their foreheads (right).

Aerospace: Expertise Development With Piloting Tasks

Another longitudinal study investigated expertise development with practice in a variety of settings, including of use of complex piloting tasks. fNIRS was used to investigate the relationship of the hemodynamic response in the anterior prefrontal cortex to changes in level of expertise and task performance during learning of simulated unmanned aerial vehicle (UAV) piloting tasks.[60,61] Novice participants with no prior UAV piloting experience participated in a 9-day training program where they used flight simulators to execute real-world maneuvers. Each day, self-reported measures (with NASA TLX), behavioral measures (task performance), and fNIRS measures (prefrontal cortex activity indicating mental effort on task) were recorded. Participants practiced approach and landing scenarios while piloting a virtual UAV (Fig. 3.2). The scenarios were designed to expose novice subjects to realistic and critical tasks for a UAV ground operator directly piloting an aircraft. Results indicate that the level of expertise does appear to influence the hemodynamic response in the dorsolateral/ventrolateral prefrontal cortices. As such, measuring activation in these attentional and control areas relative to task performance can provide an index of level of expertise and illustrate how task-specific practice influences the learning of tasks (Fig. 3.2).

Healthcare: Cognitive Aging

Decline in gait performance is common in aging populations and can result in increased risk of mortality and morbidity, frequent hospitalizations, and in general poorer quality of life.[62–64] Recent epidemiological, cognitive, and neuroimaging studies suggest that gait is influenced by higher-order cognitive and cortical control mechanisms. However, neural underpinnings of gait are still not well understood or studied.

We investigated neural correlates of locomotion in elderly populations by monitoring brain activity in the dorsolateral prefrontal cortex (PFC) using fNIRS (fNIRS Imager 1000, fNIR Devices, Potomac, MD) in a large cohort of elderly participants (age > 65) while they performed real on-the-ground walking tasks with or without a cognitive interference task of letter generation in a longitudinal study for 5 years ("Central Control of Mobility in Aging [CCMA]" project at Albert Einstein College of Medicine, Yeshiva University, Bronx, NY).

FIGURE 3.2 Low-fidelity flight simulator with unmanned vehicle remote-piloting tasks while operator prefrontal brain activity is monitored with fNIRS.

Our initial pilot study on 11 young and 11 elderly participants indicated that oxygenation levels are increased in the PFC in a dual-task condition (walking while talking—WWT) as compared to a single task (normal walking—NW) in both young and old individuals, but young individuals showed greater increases in PFC oxygenation levels as compared to old participants, suggesting that older adults may underutilize the PFC in attention-demanding locomotion tasks.[65] Reproducible measurements of task-related changes in oxygenation levels found increased PFC activity in WWT as compared to NW in a large cohort of nondemented and ambulatory elderly adults ($n = 348$) in the Central Control of Mobility in Aging (CCMA) study.[66–68] Moreover, elevated PFC oxygenation levels were shown to be maintained throughout the course of WWT but not during NW, since WWT is a dual-task condition and hence more cognitively demanding. In addition, increased oxygenation levels in the PFC were related to better gait and cognitive performance during WWT, consistent with compensatory reallocation models. The individual and combined effects of gender and perceived stress on gait velocity and PFC oxygenation levels during locomotion were studied,[62] and higher levels of perceived task-related stress were found to be associated with more difficulties in negotiating the demands of dual-task walking as well as attenuation of brain oxygenation patterns under attention-demanding walking in older men. Subjective and objective measures of fatigue in the context of the established dual-task walking paradigm[69] indicated that worse perceptions of fatigue were associated with an attenuated increase in oxygenation levels from NW to WWT. In addition to these findings in healthy aging, our studies identified differences in brain activity levels in elderly people with various disease conditions, such as diabeties, neurological gait abnormalities, Parkinsonian syndromes, and MS.[70–74] Findings indicated that higher oxygenation levels during WWT among individuals with peripheral neurological gait abnormalities were associated with worse cognitive performance but faster gait velocity. Patients with Parkinsonian syndromes manifested higher PFC activation to maintain postural stability. Similarly, oxygenated hemoglobin levels were increased in persons with MS compared to controls while walking to compensate for decreased efficiency, whereas presence of diabetes was associated with poorer walking performance and attenuated brain response. With the implementation of fNIRS, our findings have provided more information on neural underpinnings of mobility in aging with or without disease conditions, which can have further implications for risk assessment and interventions in incident mobility impairments and falls.

CONCLUSION

Mobile fNIRS sensors enable monitoring brain activity out of the lab and in ecologically valid settings. Neuroergonomic uses for such fNIRS technology include continuous and ubiquitous measurement of brain function at work and at home. This has the potential to change the way we work and interact with technology and each other. fNIRS technology is still evolving, with ongoing hardware and processing improvements that are making fNIRS systems more portable, more reliable, and more affordable. Ultraportable wearable fNIRS sensors are expected to break the limitations of traditional neuroimaging approaches that previously imposed barriers on experimental protocols, data-collection settings, and task conditions at the expense of ecological validity. As the youngest neuroimaging modality, fNIRS has already reached a level that addresses and benefits real-world problems and industry challenges. As fNIRS technology further matures and enhances its capability, new areas of application will emerge, opening new research directions as well as routine-use cases for industry and home settings.

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