Functional Near-Infrared Spectroscopy in Human-Robot Interaction

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Functional near-infrared spectroscopy (fNIRS) is a promising new tool for research in human-robot interaction (HRI). The technology has already been used for brain-robot interfaces to affect robots' behaviors and as an evaluation tool for assessing brain activity during interactions. In this survey, we provide a comprehensive literature review of published research on fNIRS from various communities to assess its utility in HRI. We discuss four exemplary applications in more detail and also list several challenges that need to be overcome for fNIRS to be an effective tool in realistic HRI settings.

Keywords: human-robot interaction (HRI), functional near-infrared spectroscopy (fNIRS), near-infrared spectroscopy (NIRS), brain imaging, neuroimaging, brain-robot interface (BRI), human-machine interaction (HMI), brain-computer interface (BCI), brain-machine interface (BMI)

1. Introduction

One of the main goals of research in human-robot interaction (HRI) is to develop interaction principles and algorithms that will allow humans and robots to interact effectively. Information exchange between humans and robots is thus at the heart of HRI (Goodrich & Schultz, 2007), with the primary communication channels being visual, auditory, and tactile. Recently, researchers have started to explore the brain-robot interface (BRI) as an additional information channel for robots to gain more direct access to physiological changes in the human brain and thus, ideally, to be able to better estimate and respond to the human's cognitive activity.

Electroencephalography (EEG) is among the most widely used technologies in the psychological and brain sciences, as well as in human-computer interaction (HCI) and related fields. While it provides high temporal resolution and thus allows for tracking of processes that change quickly (e.g., see the work on event-related potentials), it has the disadvantage of poor spatial resolution and signal-to-noise ratio. Similarly, while *functional magnetic resonance imaging* (fMRI) provides high spatial resolution, it does so at the expense of poor temporal resolution and restricted subject mobility and interaction paradigms. The magnetic field limits the possible ways human subjects can interact with their environments; for example, in HRI experiments with fMRI, subjects are typically asked to either interact with imagined robots or are shown the robots before being placed in the

scanner. In comparison, *functional near-infrared spectroscopy* (fNIRS) is a newer neuroimaging technology that combines some of the advantages of fMRI (i.e., localization but in lower spatial resolution) with those of EEG (i.e., portability enabled by a free range-of-motion head mount with wireless tethering).[1]

Researchers have repeatedly described functional near-infrared spectroscopy as portable (at least *potentially*), affordable, non-invasive and, most importantly, as a useful tool for brain-computer interfaces (Girouard et al., 2009; Hirshfield et al., 2009; Solovey et al., 2012; Kawaguchi et al., 2011; Zimmerman et al., 2011). Thus, it is not surprising that there is an expanding body of research utilizing fNIRS in HRI settings and more general HCI contexts (see Tables 2 and 3). In fact, in HRI two distinct usage patterns have begun to emerge with respect to fNIRS: (1) as an input channel that allows robots to alter their behavior based on human brain activity and (2) as a measurement tool for evaluating interactions between humans and robots (cf. Kawaguchi et al. 2012).

Together, the properties of fNIRS and its possible applications make it an exciting and promising new technology for HRI. Unfortunately, the literature on fNIRS is dispersed across many publication outlets in the HRI, HCI, neuroimaging, and brain-computer interface (BCI) communities. Moreover, the overall success of employing fNIRS in HRI settings is currently unclear as a consequence of inconsistencies in published results within and between these fields. Hence, the goal of this survey is twofold: (1) to provide the first comprehensive overview of fNIRS in HRI, and (2) to provide an analysis across multiple fields of the utility and potential of fNIRS in HRI research, with particular focus on naturalistic and unconstrained interactions and environments. We start with a review of the technology, followed by a comprehensive survey of its applications to HRI, detailing selected studies as exemples. We then discuss the challenges of using fNIRS in HRI and point to future directions for research to overcome those challenges.

Figure 1. fNIRS sensors secured to forehead with a tight cap tethered to ISS OxiplexTS tissue oximeter next to the laptop computer.

2. Functional near-infrared spectroscopy (fNIRS)

Functional near-infrared spectroscopy is a technique for measuring changes in blood-oxygenation level. Its use as a neuroimaging tool has been growing since the 1990s (Chance et al., 1993; Hoshi & Tamura, 1993, 1997; Villringer et al., 1993). A number of fNIRS instruments have been developed, using a variety of techniques for assessing changes, including frequency domain, continuous wave, and time-resolved spectroscopy. Of these techniques, continuous-wave fNIRS has seen the most adoption in HRI. These instruments are based on the modified Beer-Lambert law, relating changes in hemoglobin concentration to changes in light intensity (Hoshi, 2011b). A review of the commer-

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[1] A community has formed around the technology (see `fnirs.org`), activities of which include a biennial meeting.

cially available continuous-wave fNIRS instruments and a summary of their technical details can be found in (Scholkmann et al., 2013).

As a technique that indirectly computes a measurement of cortical activation, fNIRS is a neuroimaging methodology most similar to fMRI. By measuring hemodynamic and metabolic events, fNIRS non-invasively gauges regional cortical activation (Gratton et al., 2001). The change in hemoglobin concentration due to neural activity is called the "hemodynamic response" and is measureable with fNIRS due to the differences in molar absorptivity of hemoglobin. As the hemodynamic response is a secondary response to neuronal activity, it lags behind the triggering neuronal events by 1-2 seconds. This response peaks about 5 seconds after the onset of the stimulus and then dips back down as homeostasis is reestablished. The details of the blood-oxygen-level-dependent hemodynamic response are extremely important to understand before one can best apply the fNIRS technique to any domain. The literature on hemodynamics (e.g., Matthews & Pearlmutter 2008; Steinbrink et al. 2006) and fMRI (e.g., Huettel et al. 2009) is especially relevant.

Biological tissue is transparent to light in the near-infrared range between 700-1000 nm. Measurements of the ratio of oxygenated to deoxygenated hemoglobin are obtained through the coupling of infrared light emission and detection. LED or laser light – the source – is emitted and carried through a fiber optic bundle to the skin, where it travels at an angle into the brain. The photons follow a banana-shaped path through the skin, skull and cerebral cortex to be caught by a photo-detector positioned several centimeters away. Source-detector distances between 3 and 4 cm are sensitive to the hemodynamic changes within the top 2-3 mm of the cortex. This sensitivity extends laterally 1 cm (perpendicular to the axis created by the source and the detector) on both sides. Since oxygenated and deoxygenated hemoglobin are both chromophores that absorb light in the near-infrared range, regional changes in hemoglobin concentration can be calculated based on wavelength-dependent changes in light attenuation (Irani et al., 2007).

Sensors are usually positioned against specific portions of the head in order to target specific regions of the brain via multiple channels (light source-frequency pairings; see Lloyd-Fox et al. 2010 for more details concerning probe channels and source-detector pairs). These sensors are attached by various means including caps, headbands, and mechanical supports. Most sensors are tethered by cables that extend back to the fNIRS instrument (see Figure 1). There are also wireless, portable versions of fNIRS devices in development (Bozkurt et al., 2005; Yurtsever, Kepics, & Bozkurt, 2003; Yurtsever, Bozkurt, et al., 2003). It is common practice to seat participants and instruct them to minimize any movement, or to even physically stabilize/support them, in order to avoid so-called "motion artifacts," i.e., unwanted signal changes (due to fNIRS' sensitivity to motion) caused by the participant's movements (Coyle et al., 2007) (cf. Section 4.1). [2]

3. Current applications of fNIRS in HRI

There are two predominant ways in which fNIRS is used as a tool in HRI research: as a *transducer* and as an *evaluation tool* (see Table 1). In either case, the human performs a task (e.g., interacts with a robot) while wearing the fNIRS probes. The principle difference between the two paradigms is what happens to that signal once it reaches the computer for processing (see Figure 2).

The use of fNIRS as a transducer of cerebral blood flow into an actionable signal for the robot effectively amounts to the brain-robot interface, a tool for converting a user's neural activity into a sequence of robot commands or actions. Several HRI and HCI studies have pursued this line of application, summarized in Table 2 and Table 3, with varying amounts of success. For example, the BRI has been used for transforming the brain activity of movement-oriented thoughts (e.g., "turn

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[2]A useful visual aid for those new to the technology can (at the time of this writing) be found at: `http://images .lingvistika.org/w/images/f/f1/NIRS_activation_movie.gif`

Table 1: fNIRS Paradigms

Paradigm	Signal Processing	Primary Application(s)
Evaluation Tool	Offline	Event/task-onset detection; region-specific activation
Transducer	Online	Brain-computer and brain-robot interfaces

to the left") into motion directives (Y. Matsuyama et al., 2010) and for transforming imagined or actual grasping of the hand into movement of a robotic arm (Tsunashima et al., 2009; Yanagisawa et al., 2010, 2012). Similarly, it has been used for converting brain activity during the application of isometric force into robot motion via force estimation models (Tsubone et al., 2007, 2008). While it has not yet been demonstrated, the transduction of more complex thoughts such as "*retrieve the package from the mail room*," into commands for a robot is part of the long-term vision for this technology.
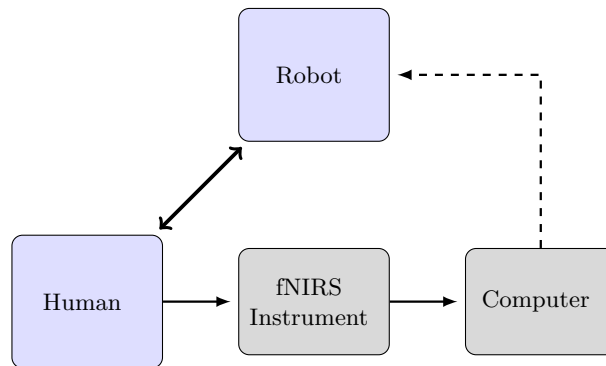

Figure 2.   During HRI (represented by the bold double-headed arrow) information is passed from the human wearing the fNIRS probes to the instrument and then on to a computer for on- or offline processing. In the online case (e.g., BRI), the processed information can be used to influence the robot's behavior (shown as the dotted line from *computer* to *robot*). In the offline case data are preserved on the computer for later evaluation.

As an evaluation tool, fNIRS enables offline analyses and inferences about cortical activity. Data recorded during a task are preserved and subsequently inspected or visualized by the experimenter. Fortunately, this paradigm faces fewer signal processing challenges than real-time applications do. Examples of the evaluation tool paradigm include investigations of moral decision-making, sustained attention, and robot-assisted therapy. While fNIRS could be positioned to measure blood flow in most regions of the cerebral cortex (regardless of paradigm), it has been primarily employed to monitor portions of the frontal lobe including the pre-frontal cortex (PFC) and the motor cortices. The phenomena that have garnered the most fNIRS-oriented attention from the community include, but are not limited to *cognitive workload*, *intention*, *multitasking*, *attention*, *movement execution*, *imagined movement*, and *problem solving*. Table 2 provides a comprehensive list of fNIRS-oriented studies and research programs in HRI with brief summary descriptions.

In the following section we describe both fNIRS application paradigms in HRI in more detail by providing prototypical examples of each.

Table 2: Publications of fNIRS in HRI. Research groups with multiple publications on the same topic are listed by first author and year on the same line. Type (E) indicates fNIRS used as an evaluation tool and type (T) indicates fNIRS used as a transducer. A single asterisk (*) indicates that probes were positioned according to the international 10-20 system for EEG; double asterisks (**) indicate probe placement of the international 10-10 system.

PUBLICATIONS	TYPE	TOPIC	REGION
Aoki 2011, 2012; Suzuki 2011	E	physiological responses to robot cultural greetings	M1, BA44 *
Caproni 2009	T	toward interface for robotic surgery	CP3, CP4 **
Kawaguchi 2011, 2012; Shibata 2012	E	evaluation of robot-assisted therapy with seal robot	frontal lobe
Matsuyama, H. 2009	T	direct motion control of humanoid robot	F4, F7 (working memory) *
Matsuyama, Y. 2010	T	humanoid robot control with heterogeneous biosignals	unspecified
Nozawa 2010, 2009	E	developing autonomous adaptive agent for maintaining interaction	PFC
Okumura 2007	T	toward brain-robot interface	PFC, PMC
Solovey 2012	T	cognitive load classification for adaptive robot autonomy	anterior PFC
Strait 2013	E	evaluating moral decision-making in human-agent interaction	PFC
Tsubone 2007, 2008	T	robot arm control with force estimation model	M1, PM (motor) *
Yanagisawa 2010, 2012; Tsunashima 2009	T	control of robotic arm with imagined and actual grasping	motor cortex
Zimmerman 2011	T	brain-body-robot interface for stroke rehabilitation	PMC; M1 (motor) *

Table 3: Publications of fNIRS in HCI. These publications were selected for breadth and with the criterion that research topics have direct parallels to or or are useful for HRI. In some cases only the most recent publication of an author or research group is displayed. Type (E) denotes fNIRS used as an evaluation tool and type (BCI) denotes research toward a brain-computer interface. An asterisk indicates that probes were positioned according to the international 10-20 system for EEG.

AUTHOR(S)	YEAR	TYPE	TOPIC	REGION
Abdelnour & Huppert	2009	E;BCI	real-time predictive model of neural activity	motor cortex
Ayaz et al.	2011	E	cognitive load during virtual maze task	PFC
Ayaz et al.	2012	E	workload during complex cognitive and visuomotor tasks	PFC
Coyle et al.	2007	BCI	single-channel control system, "Mindswitch"	C3; C4 (motor) *
Girouard et al.	2013	E	passive BCI using real-time fNIRS classifications	PFC
Herrmann et al.	2008	E	neural correlates of alertness	frontal lobe
Hirshfield et al.	2011	E	cognitive load under different user interfaces	PFC
Hoshi & Tamura	1997	E	cognitive load while solving math problems	bilateral PFC
Izzetoglu; K. et al.	2004	E	cognitive state during complex task	PFC
Khoa & Nakagawa	2009	BCI	distinguishing brain activities, toward BCI	frontal lobe
Menda et al.	2010	E;BCI	enhancing UAV operator training, evaluation	PFC
Morihiro et al.	2009	E	cognitive load during motor-task learning	left PMC to SMC *
Raganatha et al.	2005	BCI	toward BCI for direct control	C3; C4 (motor) *
Sassaroli et al.	2008	BCI	classifying cognitive load state	PFC
Sitaram et al.	2007	BCI	temporal classification; BCI for cursor control	C3; C4 (motor) *
Solovey et al.	2011	BCI	detecting cognitive multitasking state	PFC
Takano et al.	2010	BCI	virtual maze navigation	PFC

3.1 fNIRS as Transducer

BRI for ergonomic robotic surgery. Caproni and colleagues used fNIRS with the goal of building a better robotic surgery console (Caproni et al., 2009). Their work investigates potential solutions to the challenges inherent in minimally invasive robotic surgery. The ergonomics of robotic surgical consoles have become increasingly important as the field of medical robotics expands and develops. Caproni et al. (2009) researched a more natural and ergonomic method for providing relevant input to the surgical console by using fNIRS *in situ* as the means for HRI. This methodology is motivated by evidence that fNIRS can pick out *discrete patterns of activation* potentially relatable to the surgeon's intentions in a normal, unrestricted environment (Leff et al., 2007, 2008). The ultimate goal of the system is to confirm action intention, predict surgical errors, and assess psychological stress in real time.

Caproni et al. (2009) report an experiment conducted with two participants in which they utilize a continuous-wave fNIRS instrument to image the centro-parietal lobe. Participants were instructed through two paradigms — motor-imagery and non-motor-imagery — to imagine moving an on-screen object in the specified direction (left, right, up, down, toward, and away). The obtained data was then used to conduct task simulations that employed different fNIRS channel selections, machine learning classifiers, and aggregation policies. Classification accuracy (in simulation) of the *optimal* configurations across data from both participants ranged from 55% to 67% (chance = 16.7%). That is, in simulation the system was moderately capable of retroactively differentiating (offline) cerebral blood flow during imagined moves in one of six directions.

While these results are promising, they also highlight the difficulty of processing and classifying fNIRS signals. Contributions of this research to the field include fNIRS data acquired from the centro-parietal lobe, a novel method of fNIRS feature-selection, and in-depth performance analysis of some widely-used machine learning approaches to fNIRS signal classification. It is important to note that the authors explicitly describe their study as exploratory and state that it may have benefited from a larger sample size.

BRI for robot motion control. H. Matsuyama and colleagues (2009) created a BRI for controlling a humanoid robot via working memory activation. Their study was a preliminary attempt at capturing cerebral activation during problem solving for direct robot control. Participants in the study were measured with a 35-channel continuous-wave fNIRS instrument while they solved arithmetic problems. The authors developed an algorithm for detecting activation change in the regions of the brain responsible for working memory (F4 and F7 by the international 10-20 system for EEG probe placement). Their BRI sent a primitive motion command to a small humanoid robot when it detected changes in CBF that coincided with arithmetic problem-solving. In other words, the participant worked on the arithmetic problem, which caused increased activation in working memory, which in turn was detected via fNIRS in real-time and transduced into a motion command for the robot.

While the fNIRS-BRI in their publication was both simple and domain-specific, it was an effective demonstration of how an fNIRS-based interface can serve to initiate actions in a robot. However, this work also exposed two main shortcomings of fNIRS that are obstacles for its employment in some HRI domains: response delays and limited-time operation. For the first, note that hemodynamic changes in oxygenated hemoglobin concentration level take place over several seconds (Coyle et al., 2007). The time between a participant beginning the arithmetic problem and the transmission of the control signal varied from a few seconds to over fifteen seconds in experiments reported by H. Matsuyama et a. (2009) . This delay was due to the inherent slowness of the hemodynamic response to cognitive activity. The authors identified an *initial dip* – the initial increase in deoxygenated hemoglobin that occurs much faster than changes in oxygenated and total hemoglobin – as a feature of the hemodynamic response that might help mitigate this problem and thereby allow much

earlier triggered control signals. However, they emphasize that the *initial dip* of the signal is weak and difficult to detect in real time. The second problem is also well-known in the literature, namely that detecting task-onsets is much simpler in a short window of the fNIRS signal (10s - 45s) than characterizing the signal over longer periods of time (cf. Section 4).

Other research groups have also investigated the feasibility of the fNIRS-BRI for motion control. Examples include a system for robot control via heterogeneous biosignals (Y. Matsuyama et al., 2010), a brain-body-robot interface for stroke rehabilitation (Zimmerman et al., 2011), and robot arm control via activation of the motor cortex (Tsubone et al., 2008; Yanagisawa et al., 2012). The region of interest in most of these motion-control studies is the motor cortex as the eventual goal is to design interfaces that facilitate robot motion control via imagined or actual motion of the human body. Moreover, the motor cortex has distinct advantages compared to other regions of the brain for employing fNIRS: it is only responsible for the various components of movement – planning, control, execution – and it is more optically accessible (Leff et al., 2011).[3]

3.2   fNIRS as Evaluation Tool

Robot-assisted therapy.   Animal-assisted therapy uses animal interaction for therapeutic means. Kawaguchi and colleagues (2012) used Paro, the robotic seal, together with fNIRS in order to assess the effectiveness of HRI for therapy . Paro was designed to coexist with people in their natural environments. It has soft white fur and a natural feel. The surface is touch-sensitive as well, permitting contact measurement. In a novel approach to animal-assisted therapy, Kawaguchi et al. (2012) conducted an experiment in which 10 participants interacted with Paro while wearing fNIRS sensors. They used a continuous-wave fNIRS instrument with 35 channels, and sensors were positioned primarily on the frontal lobe area of the participants. Each participant interacted with Paro while it was turned on and while it was turned off. The authors compared cerebral blood flow during rest to both types of interaction with Paro.

Results showed significant differences in the activation of some channels between rest and the Paro tasks. When Paro was off, they observed that both sides of the frontal lobe speech area were activated in addition to the motor areas. They inferred that these activations were due to (1) participants talking to Paro when it was switched off and (2) to the need to interact *intentionally* with a non-responsive robot. When Paro was on, they found activation in the left side of the speech area while participants spoke to Paro. Moreover, activation in both sides of the Sylvian fissure indicated recognition of emotional gesture expression.

Kawaguchi et al. (2012) concluded that interaction with the switched-on Paro was natural since participants responded physiologically to Paro's emotional gesture expression. Additionally, interaction with the switched-off Paro could be experienced as unnatural and intentional (i.e., forced). Their research supports fNIRS as an evaluation tool for detecting and characterizing interaction between humans and robots via imaging of the frontal lobe.

Engagement during HRI. Nozawa and Kondo (2010) demonstrated a promising approach to sustainable HRI by endowing robots with intrinsic motivation . They introduced a new robot model capable of learning about and behaving with respect to a human partner by satisfying its own intrinsic motivation. In their evaluation study, human participants interacted with three different types of robots in a virtual setting (including the intrinsically-motivated robot) and were monitored with fNIRS in order to assess the effect of each agent type on their cognitive state. They were told to maintain correct posture in order to minimize motion artifacts. Each of the 24 participants interacted with each of the 3 robots for 15 minutes. Twelve of the participants were monitored with a 22-channel CW-fNIRS instrument and probes were positioned on their foreheads in order to target the

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[3]Video demos of preliminary experiments with fNIRS-BCI and BRI can be found at `http://youtu.be/bYdJWdPn` `_LI` and `http://youtu.be/A_xRbwii7Cs`.

prefrontal cortex.

Participants rated their interaction with the intrinsically-motivated adaptive agent as more charming, enjoyable, and sustainable than their interactions with the other two agents. Information-theoretic analysis of the interactions suggested that a balanced information transfer between the robot and the human is important for sustainable interaction. The standard deviations of oxygenated hemoglobin signals at each channel were compared between 11 participants. Nozawa and Kondo (2010) found statistically significant differences in the activation variability of one channel (out of 22) after averaging results over all participants. This channel overlaps the dorsolateral prefrontal cortex, which is involved in both the control and sustaining of attention. They thus concluded that the intrinsically-motivated agent was successful in continuously affecting the participants' level of attention.

While their research provides some support for the offline analysis of fNIRS data to evaluate a subject's level of engagement, it also highlights the need for a standard of inference about these data – specifically in regard to statistical tests and probe-region mappings. On the other hand, it is one of the few studies that investigates the hemodynamic response beyond the task-onset period, as each trial is 15 minutes in duration.

Other instances of fNIRS used as an evaluation tool in HRI leave open the possibility for integration with other brain imaging technologies. Strait et al. (2013) use fNIRS in the search for measurable neural correlates to decision-making, ascribed agency, and emotional valuation . Participants in part one of their study were put in charge of a fictional "emergency evacuation" scenario in which they had to choose which entities to transport to safety. Candidates included robots and humans among several controls. They demonstrated that fNIRS is capable of measuring activation related to moral decision-making in the PFC, with the caveat that in order to confirm this interpretation of results, an integrated fNIRS-fMRI study would be necessary. Multimodal evaluation is an ideal strategy for confirming the correlation of regional activation to external phenomena, and this kind of evaluation contributes toward a mapping useful for the entire fNIRS community (and to the fMRI community, in this case).

4.   Challenges of using fNIRS in HRI

The previous section showcased prototypical examples of fNIRS in HRI, which intended to serve as proof-of-concept studies that fNIRS can be successfully utilized both as a component of an interface device and as an evaluation tool in HRI. However, most previous and current applications have encountered significant challenges that were, in most cases, not sufficiently addressed. The goal of this section is to discuss the most pressing roadblocks for the wide use of fNIRS in HRI (see Table 4 for a collection of technical papers and reviews about fNIRS). The aim here is to provide the aspiring fNIRS user in HRI with key fundamental characteristics of the technology and a list of potential pitfalls that need to be avoided and overcome.

4.1   Signal Processing

As already mentioned, motion artifacts degrade and transform the fNIRS signal. These artifacts can be caused by (1) movement of the sensors on the skin altering the angle of transmitted and reflected light, (2) bodily movements, especially of the face, altering blood flow, and (3) head orientation (M. Izzetoglu et al., 2005; Matthews & Pearlmutter, 2008; Robertson et al., 2010; Sassaroli et al., 2008; Wolf et al., 2007). Attempts at combating these effects include chin rests and mechanical supports (Coyle et al., 2007) (which are often not feasible in realistic HRI settings) as well as specific signal processing filters.

Unfortunately, most current filtering techniques cannot be effectively utilized in real time. In some cases this is because parameter selection depends upon relative knowledge of the signal within

each time-slice (e.g., standard deviation of signal amplitude). Not only has the use of absolute parameters been shown to be less accurate than the use of relative parameters, but there are also major hurdles for computing absolutes, which include signal drift and inter-participant neurological differences (Coyle et al., 2007; Matthews & Pearlmutter, 2008). Moreover, adequately filtering for motion artifacts can require manual inspection of the signal, which is subject to human error and bias and must be performed post-experiment. There are, however, more promising recent proposals for real-time motion artifact filtering in natural environments including techniques such as adaptive general linear models (Abdelnour & Huppert, 2009), Wiener filters (Devaraj, 2004), and Kalman filters (M. Izzetoglu et al., 2010).
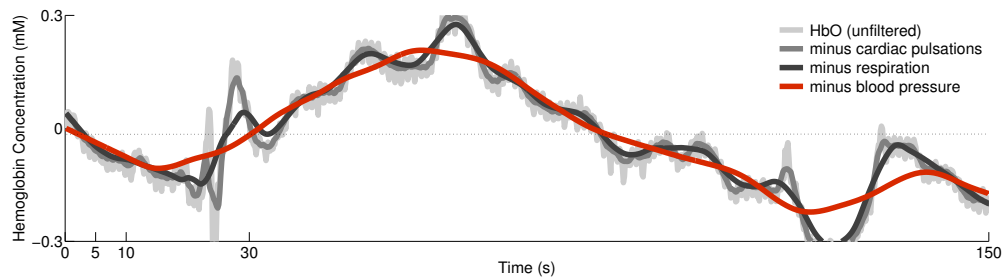

Figure 3. Filtering of cardiac pulsation, respiration, and blood pressure artifacts from a raw oxygenated hemoglobin (HbO) signal.

Separating task-related from unrelated cortical activity and signal noise is also difficult (if not impossible) in some cases. The PFC, for example, is a bustling metropolis of executive functions (Koechlin et al., 1999) and it is unlikely that it is possible to discriminate among the various parallel ongoing processes in this area. Moreover, fNIRS is sensitive to systemic physiological artifacts such as Mayer waves and those from respiration, blood pressure, and cardiac pulsation (see Figure 3) (Cui et al., 2010; Fekete et al., 2011; Matthews & Pearlmutter, 2008; Ye et al., 2009). While filtering techniques for these artifacts are published, the literature demonstrates major inconsistencies in both recognizing the need for and utilizing them. Hence, all of these factors confound inferences about characteristics of the signal, specifically characteristics attributable to the task (i.e. not present during rest).

Another complication arises from the fact that in some cases extra-cerebral blood flow is measured instead of or in addition to cerebral blood flow by continuous-wave devices; that is, measurements reflect absorbance changes in the superficial layers and the skin instead of just in the cerebral tissue (Coyle et al., 2007). Continuous-wave measurements are derived from the Modified Beer-Lambert law, the commonly used equation for expressing the relationship between light intensities and chromophore concentrations. These measurements have indeed been shown to be sensitive to changes in extra-cerebral blood flow (Hoshi, 2011b; Kohl-Bareis et al., 2002; Liu et al., 1995; Sato et al., 2007). This sensitivity can obfuscate task-related activity and potentially lead to incorrect interpretations of the signal.

4.2 Hemodynamic Response

Some experiments have attempted to distinguish patterns in CBF during different types of task, e.g., during a difficult and an easy game (Girouard et al., 2009; Sassaroli et al., 2008; Solovey et al., 2011, 2012). However, it is unclear whether consistent distinctions can be made between two types of tasks, or even between a task and the prior/subsequent resting period, for all the reasons discussed

Table 4: Recent fNIRS-related technical and review publications. Papers are referenced by first author. In most cases only the most recent publication of the author is referenced.

AUTHOR(S)	YEAR	TOPIC
Ayaz et al.	2010	motion artifact filtering with sliding-window
Bozkurt et al.	2005	portable system for bedside monitoring of newborns
Butti et al.	2007	interpreting fNIRS with generalized linear models
Cui et al.	2010	NIRS signal improvement
Cutini et al.	2011	new method for probe placement
Devaraj, A.	2004	motion artifact removal for real-wold applications
Fekete et al.	2011	signal noise reduction and statistical inference
Ferrari & Quaresima	2012	history of fNIRS development and fields of application
Hoshi, Y.	2011	issues, obstacles and techniques
Hoshi, Y.	2011	diffuse optical tomography approach
Hoshi, Y.	2009	basic theory, limitations, future prospects
Hu et al.	2013	reduction of fNIRS trial-to-trial signal variablity
Huppert et al.	2009	time-series analysis methods
Izzetoglu, M. et al.	2010	motion artifact cancellation with Kalman filtering
Izzetoglu, M. et al.	2007	assessing human performance and cognitive activities
Izzetoglu, M. et al.	2005	motion artifact cancellation with Weiner filtering
Kirilina et al.	2012	task-evoked systemic artifacts in fNIRS
Leff et al.	2011	imaging the cerebral cortex during motor tasks
Lloyd-fox et al.	2010	fNIRS for infant monitoring
Matthews et al.	2008	signal processing challenges
Plichta et al.	2007	retest reliability of event-related fNIRS
Robertson et al.	2010	evaluation of motion artifact removal methods
Sano et al.	2012	adaptive hemodynamic response function
Scholkmann et al.	2013	continuous-wave fNIRS instrumentation and methodology
Schultheis et al.	2008	signal interference, artifacts in realistic settings
Solovey et al.	2008	signal interference, artifacts in realistic settings
Uchida et al.	2010	optode configuration in diffuse optical tomography
Xu et al.	2011	motor classification with wavelets and SVM for BCI
Ye et al.	2009	statistical mapping for fNIRS
Yurtsever et al.	2003	portable continuous-wave fNIRS instrument
Zhang et al.	2010	BCIs from the perspective of industrial robotics

above. Furthermore, it is unclear how reliably and quickly any such distinction could be made since even the *onset* of vascular change lags 1-2 seconds behind the neural activation that caused it (Gratton et al., 2001; Irani et al., 2007). Real-time systems which intend to dynamically act on rapid cognitive changes must address this inherent trait since it otherwise limits the applicability of fNIRS to slow-changing (on the order of several seconds) cognitive phenomena. Another potential limitation is the way the hemodynamic response changes over longer periods of time. Most previous fNIRS research in HCI and HRI has been limited to task-onset detection in 10-45 second windows. The signal over longer time spans has gone largely uninvestigated.

4.3 Probe Placement and Reproducibility

Sensors must be attached securely in order to avoid creating motion artifacts that degrade the fNIRS signal. One research group reported that the method of connecting the optodes to the subject's head actually had the greatest bearing on system performance because of its substantial effect on signal

quality (Coyle et al., 2007). The quality of the fNIRS signal is additionally affected by dark skin pigmentation (Wassenaar & Brand, 2005) and hair caught between the sensor and scalp (Coyle et al., 2007).

While a first step toward imaging specific regions of the brain with fNIRS is to use a probe-placement framework like the international 10-20 system for EEG (Niedermeyer & Silva, 2004), there is no guarantee precisely which regions are measured (Hoshi, 2011b; Plichta et al., 2007). These frameworkis rely on anatomical landmarks for placing sensors and so are inherently inexact across participants. There is also variation in precise function-location mappings between partici-pants. Furthermore, re-positioning the probe set on an individual is prone to error and even millime-ter movements of the probe set can lead to centimeter shifts in whole channel position (Plichta et al., 2007). A potential countermeasure is to use MRI scans and neuro-navigational tools to ensure a con-stant positioning of the probe set, but this strategy eliminates some of the core advantages of fNIRS, namely portability, simplicity and cost (see Plichta et al. 2007 for a discussion of the reliability and replicability of fNIRS measurements).

4.4 Statistical Analysis and Inference

There is currently no standard, established method for performing statistical analyses of fNIRS signals; rather, each researcher is left to his or her own approach. Parametric tests like the analysis of variance are the dominant technique, but there is insufficient discussion as to the validity of these tests (e.g., whether a normal distribution can be assumed for the signal). As a result, it is unclear whether the inferences drawn from statistical analyses will be equally upheld by the research community. Fortunately, several recent efforts have been made toward supplying universal tools for statistical analysis and inference, including NIRS-SPM Ye et al. 2009 and the NIRS Analysis Package Fekete et al. 2011.

Furthermore, it is difficult to make definitive claims about *precisely* what fNIRS is measuring. Just because a property of an fNIRS signal correlated with levels of cognitive load, for instance, does not guarantee that cognitive load was being measured. This point is more than just one of semantics; rather, in one case the correlation might hold up while in another the *actual* process responsible for the association might be absent. Moreover, a correlation for one subject in one experiment does not imply correlation across subjects and experimental replications (e.g., it is possible that whatever is directly measured by fNIRS in one particular task in a particular region of the brain only correlates with the experimental task one time in the one particular individual tested). Additionally, correlations alone do not establish causal relations, which are necessary for explanations of effects and often required for generalizations across tasks.

Replications are also especially sensitive to probe positioning where differences of mere mil-limeters could lead to the absence of a correlation (Hoshi, 2011b; Plichta et al., 2007). While it is tempting to characterize CBF during a task as a direct measure of the task, it actually includes co-occurring neural activity and cognitive phenomena that could just as well be responsible for, or obscuring, the relevant activity.

The meaning and significance of the information coming from the fNIRS signal is important for both the BRI and its evaluative use. It is usually unclear exactly what the signal *means* in terms of the cognitive processes that are (at least in part) responsible for its characteristics. In order for inferences to consistently hold true within and between research groups, it is imperative that information about the fNIRS signal be put in community-wide contexts. Such contextual mechanisms might include scales for inferring degrees of activation (e.g.,the levels of cognitive workload inferable from the signal over time).

4.5   Hardware and Environment

Additional complications arise due to fNIRS hardware and environmental conditions. For one, because probes need to be placed on the subject's head and connected to a processing device (either through wires or through a wireless tether), there are range and mobility limitations imposed on the kinds of interactions that can be performed. This is especially limiting of proximate interactions (e.g., situated social robotics experiments). Moreover, in some cases, the subject's hair may entirely prevent appropriate probe placements and thus prevent fNIRS from being used (as shaving the head is usually not an option). Ambient light and changes of lighting conditions in the environment also poses potential problems as they can alter the signal-to-noise ratio. In most cases this can be addressed with thick opaque covers (e.g., headbands, helmets, etc.) that protect the probes.

5.   Discussion

The exploration of fNIRS as a tool in HRI research and the evaluation of its potential have already begun, as demonstrated by the above exemplary studies (enhancing interactions during robotic surgery, triggering robotic actuation, assessing animal-assisted therapy with robots, and assessing engagement and attention). Yet, given the many challenges with fNIRS that remain to be addressed (as described in the previous section), it seems premature to consider fNIRS ready for realistic (i.e., *real-time*) HRI applications. In an effort to provide ways forward for researchers in HRI we delineate best practices, research avenues, and paradigms.

We described two ways of utilizing fNIRS: as a tool for evaluation and as a transducer. These two categories are not hard and fast; rather, they exist as a convenient way of thinking about practical applications. There are other concrete distinctions between fNIRS usage patterns in HRI, the most important being that of offline vs. online (real-time) signal processing. The prototypical application of fNIRS as an evaluation tool has emerged as an offline post-hoc analysis of a signal recorded during some notable period (the experiment stimulus). On the other hand, the application of fNIRS as a transducer has emerged as real-time conversion or monitoring of a signal. Table 1 formalizes these prototypes: as an offline evaluation tool, fNIRS has been used to identify the *onset* of neural activation from a "task" (e.g., solving an arithmetic problem, seeing a visual stimulus), and to discern regional activation during an extended interaction, e.g., activation of the speech areas in Kawaguchi et al.'s (2011, 2012) Paro study. As a transducer, fNIRS drives BCIs and BRIs of both the direct control and passive variety.

The following list defines paradigm-independent best research practices for any application of fNIRS to HRI (and related fields):

- *Probe placement*: effective, consistent placement that ensures no hair caught between the probes and the forehead, no movement of the probes, and constant contact with scalp. Application should also adhere to a standard framework for probe placement (e.g., 10-20 system for EEG).

- *Limited subject movement and motion*: support for the subject's head as well as verbal instructions to minimize movement. Relatedly, contortion of the facial muscles (e.g., frowning, smiling, talking, etc.) can produce signal artifacts (Chenier & Sawan, 2007).

- *Skin pigmentation*: awareness of and accounting for fNIRS' decreased ability to determine tissue oxygen saturation in subjects with dark skin pigmentation (Wassenaar & Brand, 2005).

- *Ambient light*: safe-guarding for ambient light can be accomplished with dark, opaque materials like headbands, helmets, and swim caps that cover the sensors (and hold them in place).

- *Appropriate Filtering*: filtering of regular artifacts from the fNIRS signal, including those caused by Mayer waves, cardiac and respiration patterns, and subject and probe motion (cf. Section 4.1).

- *Inference and Processing*: use of fNIRS-specific peer-reviewed statistical techniques and signal processing packages.[4]

The above guidelines are important for optimizing the signal-to-noise ratio, reliability of data, and legitimacy of inferences about those data.

There are fortunately some domains where fNIRS could already be rather straightforwardly deployed. Candidates include any type of HRI domain where human motion can be significantly restricted and environmental conditions can be controlled (such as in the case of a human operator situated at a computer screen in an indoor environment) and where monitoring the human can lead to some performance improvement (either by just collecting data about the human for post-hoc processing or by directly adapting robot behavior during task performance). This includes mixed-initiative human-robot teams where robots would benefit from being better-informed about the physiological state of their human teammates allowing them to make better and more informed decisions (e.g., regarding task allocations, behavior adaptations, and verbal communication). Such tasks include coordinated search and rescue missions, remote deep-sea and space exploration, military exercises, unmanned aerial vehicle (UAV) operation, and many others (see Goodrich & Schultz 2007 for a complete survey of HRI problem domains). In particular, fNIRS might be able to help address one of the important open problems in HRI: how to provide interfaces and mechanisms to allow a single operator to control multiple robots (e.g., human cognitive workload measured by fNIRS during multi-robot interactions could be used be used to dynamically adjust the autonomy of these robots; for early efforts, see Solovey et al., 2012)).

However, fNIRS might find wider and more immediate use as a component in evaluative studies that face fewer of the technical and adoption obstacles than using fNIRS as a transducer: integrated interfaces, whether for direct control or passive input, require real-time signal processing and complex inference architectures using machine learning or statistical techniques to extract meaningful classifications from the raw signal. Evaluation studies do not necessitate on-board real-time processing of the fNIRS signal; the signal can be processed offline, off-board, after the interaction.

The properties of the hemodynamic response should also influence application avenues for fNIRS in HRI. Since the *onset* of the vascular response lags behind the neural stimulus by 1-2 seconds, fNIRS is not suited for rapid (subsecond time scale) reaction to cognitive events. Instead, fNIRS might be better suited to detection of minute-by-minute state changes over sustained periods (i.e., slower-changing cognitive phenomena). However, there are still many obstacles to overcome even for this kind of application (cf. Section 4.1), and it is necessary to integrate knowledge of regional hemodynamics *over time* to design appropriate applications.

Overall, current HRI research using fNIRS (as summarized in Table 2) shows a trend of applying fNIRS to the motor cortex, although the reasons for this trend are not entirely clear. In part it seems to be due to the fact that the motor cortex is responsible for fewer, localizable functions and is more optically accessible compared to other regions like the PFC (Koechlin et al., 1999; Leff et al., 2011). It also might be due to the increasing interest in assistive robotics where fNIRS can be used

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[4]See http://fnirs.org/software/ for links to software developed for fNIRS imaging and processing.

to control robotic actuators (e.g., directional movements of a robotic wheelchair). However, other application domains are also very promising, such as using the physiological response recorded by fNIRS as a measurement of engagement with robots (e.g., in elder care or educational settings). In fact, there are several open avenues for research and contribution that are key to advancing fNIRS in HRI, including the following:

- *Probe-placement frameworks*: either adaptation of existing EEG frameworks into fNIRS-specific probe-placement mappings or development of entirely new frameworks.

- *Datasets*: fNIRS data recorded during specific interactions (including rest) for the training of algorithms and community vetting, comparison, and integration.

- *Replications*: the replication of existing experiments to extend and/or assess replicability and reliability of fNIRS-related claims.

- *Real-time event and task classification*: online techniques for effectively distinguishing between task-induced cognitive states (for BCI/BRI). Extensive evaluation of these techniques is necessary to support claims.

- *Real-time filters*: algorithms and software packages for the filtering of signal artifacts in real time (especially motion artifacts).

- *Portable instruments*: wireless, user-wearable fNIRS devices for use in free-roaming interactions.

- *Predictive architectures*: mechanisms for overcoming the limitations imposed by hemodynamics on using fNIRS for subsecond detection and inference.

- *Multimodal mappings*: data from integration of fNIRS with other brain sensing technologies like fMRI or EEG for confirming inferences about stimulus-activation correlations.

Research efforts on these fronts are mutually complementary and invaluable to the development of fNIRS as a tool for HRI.

6.   Conclusion

Functional near-infrared spectroscopy is a promising new technology for the HRI community and there is a wide range of areas to which brain-imaging seems to be applicable within and outside HRI. fNIRS has already been used for HRI research (including robot-assisted therapy, problem solving, multitasking, ergonomics, engagement, attention, limb-control and rehabilitation, intention, and others), both as a BRI to control robot behavior and as an evaluation tool for ascertaining the nature of human-robot interactions. However, several significant challenges remain to be addressed before fNIRS can become a more widely useful, practical tool for HRI research. These challenges include context-dependent hardware concerns, signal inference, interface design, robust signal processing, properties of the hemodynamic response, effective probe placement, and developing statistical analysis and inference tools. While many of the difficulties with fNIRS have been recognized, there is currently a dearth of follow-up studies to address them. It is thus our hope that this survey will prompt researchers to actively engage in fNIRS-related HRI research that can help overcome the current challenges to make fNIRS a genuinely and consistently useful tool to the HRI community.

Acknowledgments

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