A review of functional Near-Infrared Spectroscopy measurements in naturalistic environments

Paola Pinti[1,2a], Clarisse Aichelburg[2], Sam Gilbert[2], Antonia Hamilton[2], Joy Hirsch[1,3,4,5b], Paul Burgess[2], Ilias Tachtsidis[1a]

[1] Department of Medical Physics and Biomedical Engineering, University College London, UK
[2] Institute of Cognitive Neuroscience, University College London, UK
[3]Departments of Psychiatry, [4]Neuroscience, and [5]Comparative Medicine, Yale School of Medicine, New Haven, CT, USA

Correspondence concerning this article should be sent to: Paola Pinti, Department of Medical Physics and Biomedical Engineering, University College London, UK (E-mail: p.pinti@ucl.ac.uk)

Abstract

The development of novel miniaturized wireless and wearable functional Near-Infrared Spectroscopy (fNIRS) devices have paved the way to new functional brain imaging that can revolutionize the cognitive research fields. Over the past few decades, several studies have been conducted with conventional fNIRS systems that have demonstrated the suitability of this technology for a wide variety of populations and applications, to investigate both the healthy brain and the diseased brain. However, what makes wearable fNIRS even more appealing is its capability to allow more ecologically-valid measurements in everyday life scenarios that are not possible with other gold-standard neuroimaging modalities, such as functional Magnetic Resonance Imaging. This can have

[a]The author is supported by the Wellcome Trust (104580/Z/14/Z).
[b]The author is the principal investigator on and supported by the following grants from the US National Institute of Health: NIH 5 R01 MH107513; NIH 5 R01 MH111629; NIH 5 R01 HD 090153.

a huge impact on the way we explore the neural bases and mechanisms underpinning human brain functioning.

The aim of this review is to provide an overview of studies conducted with wearable fNIRS in naturalistic settings in the field of cognitive neuroscience. In addition, we present the challenges associated with the use of wearable fNIRS in unrestrained contexts, discussing solutions that will allow accurate inference of functional brain activity. Finally, we provide an overview of the future perspectives in cognitive neuroscience that we believe would benefit the most by using wearable fNIRS.

Keywords

fNIRS, wearable, ecological, cognitive neuroscience

1. Introduction

Understanding and identifying the relationships between human behaviour and cognitive processes represented the main goal of cognitive neuroscientists over the past century. Historically, neuropsychological assessments were conducted investigating the effect of task manipulations on participants' performance and behavioural variables (e.g., response times, accuracy, etc.), with cognitive models built on the basis of the outcome of the cognitive tests. Neuropsychological tests were - and still are - often used as a support for diagnostic purposes, e.g. for the early detection of cognitive disabilities such as Alzheimer's (Spooner & Pachana, 2006). However, there is not always a univocal correspondence between a certain stimulus and behaviour, and behavioural variables might not be enough in characterizing some cognitive functions (Poldrack, 2006). Nowadays, the field of cognitive neuroscience concerns itself with mapping information

processing models of the *mind* onto the structural and operational (e.g., electrical, metabolic, hemodynamic) features of the *brain*. This has been enabled by neuroimaging technologies currently available to neuroscientists, such as neurovascular-based techniques (i.e., functional magnetic resonance imaging (fMRI), functional near-infrared spectroscopy (fNIRS), positron-emission-tomography (PET)), and electromagnetic techniques (i.e., electroencephalography (EEG) and magnetoencephalography (MEG)). In classical neuroimaging investigations, participants are required to undertake a timely rigid constructed experimental procedure involving one or many different types of stimuli that intend to elicit a behaviour that can be associated with particular brain regions. Often, the experimental paradigm used to elicit the mental processing (e.g., showing a long series of single words one at a time) does not require the participant to be engaged in a mental task that is very similar to one that would typically be encountered in everyday life. Indeed, as neuroimaging is done within the tight constraints of the neuroimaging laboratory and instrument, everyday life behaviour cannot be exactly replicated. For example, interactions with other people (including physical ones), and complex integrative tasks such as serial multitasking where a person is swapping between very different tasks such as cooking or shopping (Burgess, 2015). These situations are hard to mimic in e.g. an fMRI scanner. In fact, fMRI as well as PET and MEG impose significant physical constraints, given the fact that measurements are taken with participants restrained in a scanner. Moreover, all these techniques are highly susceptible to motion artifacts and/or cannot be brought outside the lab, thus not being suitable for use on freely-moving subjects and in everyday life. These issues limit the questions that can be asked, and raise the question of the ecological validity of the results. For these reasons, a neuroimaging method which can be used while people perform almost any activity that

they would in everyday life, especially over lengthy durations, opens up the possibility of asking very different scientific questions, especially exploratory ones. Moreover, the method can, if used appropriately, decrease the possibility of an error of scientific inference in mapping mind to brain.

A solution for monitoring the neural correlates of daily life activities can be achieved by wearable fNIRS devices. fNIRS is one of the most recent neuroimaging technique and, over the past few decades, it has rapidly grown to become an invaluable and powerful tool for neuroscientists and clinicians to monitor changes in brain tissue oxygenation and hemodynamic (Boas, Elwell, Ferrari & Taga, 2014). fNIRS utilises near-infrared (NIR) light (650-1000 nm) to measure the concentration changes of oxygenated (HbO_2) and deoxygenated (HbR) haemoglobin, taking advantage of the different absorption spectra of the two chromophores in the NIR wavelength range. When a brain region becomes metabolically active, there is an oversupply of cerebral blood flow (CBF) to meet the increase in oxygen demand; this is reflected by an increase in ΔHbO_2 and a decrease in ΔHbR (i.e., the hemodynamic response) and is an indicator of functional brain activity (Scholkmann et al., 2014). fNIRS measurements are performed by placing a certain number of NIR light sources, shining light into the brain, and optical detectors, collecting the back-scattered light, onto the participants' head. The transmitted and the back-scattered light are usually guided through fibre optics connected to the main recording unit of the fNIRS system. Most of the conventional fNIRS instruments are quite heavy and big in size, and need carts to be transported (Scholkmann et al., 2014). Thanks to the recent technological advancements, more portable and miniaturized fNIRS devices were developed. This new generation of wearable devices allow participants to freely and naturally move in the environment without tight physical restraints. These systems are

battery-powered, wearable and data can be either stored on the wearable recording unit or transmitted wirelessly to a laptop.

The availability of this novel technology, paves the way to new neuroscientific investigations that can now be performed in more naturalistic and ecologically-valid settings, with people free to walk and interact with the environment as they would do in real-life. The aim of this review is to give an overview of the studies performed so far with wearable fNIRS devices in the field of cognitive neuroscience in more naturalistic situations. In this framework, we also aim at discussing (i) the challenges associated with the use of fNIRS on freely moving subjects, focusing on the analysis approaches and limitations, (ii) provide recommendations for successful use of the technology in naturalistic situations, and (iii) discuss the possible future directions.

2. Overview of wearable fNIRS systems

The last decade has seen a trend towards the development of miniaturized and wearable fNIRS devices. Such systems are based on the continuous-wave (CW) NIRS technology (Scholkmann et al., 2014), and overcome the issues and restrictions related to bulky fibre optic bundles, usually by having LEDs directly coupled to the head and flexible headbands holding sources and detectors. In addition, these instruments are battery operated, being more portable and allowing measurements in everyday life scenarios with minimal restraints; data are usually stored in the device itself or sent to a PC through wireless communication.

Concerning the number of channels, this depends on the number of sources and detectors the device is equipped with. A channel is composed by one source and one detector, and represents the measurement point, i.e., the investigated brain tissue volume

located at half of the source-detector distance and at a depth of around half the source-detector distance (Patil, Safaie, Moghaddam, Wallois, & Grebe, 2011). The first wearable system implementing wireless telemetry was limited by the number of optodes (i.e., light source or detector), having one detector and one light source, resulting in one measurement channel, and permitting the monitoring of very limited brain regions (Hoshi & Chen, 2002; Shiga, Yamamoto, Tanabe, Nakase, & Chance, 1997). Significant progress was made subsequently, and more sophisticated devices were developed and validated, with a higher number of channels (e.g., 16 (Ayaz et al., 2013), 20 (Piper et al., 2014), 22 (Atsumori et al., 2009), 32 (Muehlemann, Haensse, & Wolf, 2008)) to meet the need for higher head coverage for different functional investigations. For example, one of the first portable optical brain imagers (Chance, Luo, Nioka, Alsop, & Detre, 1997) was improved and extended from one to 16 channels (4 LEDs light sources and 10 detectors; sampling frequency=2 Hz) at Drexel University (Ayaz et al., 2013), allowing now the monitoring of both dorsal and inferior frontal cortical areas. Additionally, the palm-sized wireless system described by Muehlemann et al. (2008) can measure up to 32 channels at a sampling frequency of 100 Hz. Channels configuration and number can be easily adapted on individual's needs using systems with modular optodes (Funane et al., 2017; Chitnis et al., 2016a). More recently, multi-distance, eight- and four-wavelength systems were implemented (Chitnis et al., 2016b; Wyser, Lambercy, Scholkmann, Wolf, & Gassert, 2017), permitting the monitoring of changes in both brain hemodynamics (ΔHbO_2, ΔHbR) and metabolism (oxidized cytochrome-c-oxidase ($\Delta oxCCO$)), at different depths, and with a scalable number of channels, thanks to the modular optodes design (Wyser et al., 2017). In addition, the availability of short-separation channels in the system presented by Wyser et al. (2017) improves the signals' quality by

automatically removing the influence of systemic physiological changes originating at the more superficial layers of the head (Tachtisdis & Sholkmann, 2016). Wearable solutions integrating simultaneous EEG and fNIRS measurements were proposed as well (Lareau et al., 2011; Safaie, Grebe, Moghaddam, & Wallois, 2013), taking advantage of the suitability of fNIRS for multimodal imaging. However, to date, in order to minimize the power consumption and have a miniaturized and light wearable device that functions for long time periods, the number of channels is still limited when compared to conventional fNIRS instruments that can reach whole head coverage.

From 2009, several companies began to commercialize wearable and wireless fNIRS devices. The systems available so far in the market were reviewed by Quaresima and Ferrari (2016) (NOTE: in addition to the list provided by the authors, a newer system, the *Brite23*, has been recently introduced by *Artinis, The Netherlands*, with 23 channels, a maximum sampling rate of 100 Hz, wireless data transmission and possible hyperscanning configuration). In Table 1, we expanded the information provided by Quaresima and Ferrari (2016) with additional details on the available systems.

Table 1. Overview of the features of the commercially available wireless and wearable fNIRS systems (adapted from Quaresima and Ferrari (2016)).

Device	Company, Country	Probed brain region	Fibreless	Wavelengths	SD separation
Brite23	Artinis, The Netherlands	Whole PFC		760, 850 nm	35 mm
OctaMon	Artinis, The Netherlands	PFC		760, 850 nm	35 mm (26 mm for babies)
PortaLite	Artinis, The Netherlands	Custom		760, 850 nm	30, 35, 40 mm

Hb-13N	Astem, Japan	PFC	X	770, 830 nm	2, 4, 20, 30 mm (spatially resolved)
Pocket NIRS HM	Dynasense Inc., Japan	PFC	X	735, 810, 850 nm	30 mm
fNIRS Imager 1200M	fNIRS Devices LLC., USA	PFC	X	730, 850 nm	2.5 mm
WOT-100	Hitachi, Japan	PFC	X	705, 830 nm	30 mm
WOT-220	Hitachi, Japan	PFC	X	705, 830 nm	30 mm
WOT-HS	Hitachi, Japan	PFC	X	705, 830 nm	21.2, 30 mm
HOT-1000	Hitachi, Japan	PFC	X	810 nm	10, 30 mm
Genie	MRRA Inc., USA	INF	INF	700, 850 nm	DOT
NIRSport	NIRx Medical Technologies, LLC, USA	Custom		760, 850 nm	Custom
NIRSIT	Obelab, Korea	PFC	X	780, 850 nm	15, 21.2, 30, 33.5
LIGHTNIRS	Shimadzu, Japan	Custom		780, 805, 830 nm	30 mm
SPEEDNIRS	Shimadzu, Japan	Custom		780, 805, 830 nm	30 mm
OEG-16	Spectratech Inc., Japan	PFC	X	770, 840 nm	30 mm
OEG-16 ME	Spectratech Inc., Japan	PFC	X	770, 840 nm	30 mm
OEG-17APD	Spectratech Inc., Japan	Custom		770, 840 nm	30 mm
OEG-SpO2	Spectratech Inc., Japan	PFC	X	770, 840 nm	30 mm
Techen Wireless	TechEn Inc., USA	INF	INF	INF	INF

Abbreviations: SD= source-detector; PFC = Prefrontal cortex; DOT = Diffuse optical tomography; INF= Information not found.

Twenty devices are currently commercially available, with different number of channels (from 1 to 496) and sampling frequencies (1-100 Hz). The majority of them implement wireless data transmission and allow the synchronization of multiple devices

(up to 7) for hyperscanning measurements (i.e., simultaneous recording of brain activity of two or more individuals (Babiloni & Astolfi, 2014)). High-density (i.e., more dense set of source-detector pairs (Eggebrecht et al., 2012)) optical tomography systems for the prefrontal cortex are available as well, with 204 and 496 channels (Quaresima & Ferrari, 2016), that allows the performance of DOT measurements, with several measurements at different depths that improves the lateral and depth resolution (Eggbrecht et al., 2012, Zhao & Cooper, 2017). Most of the instruments are designed for measuring only the prefrontal cortex (Table 1), mainly to maximize the functioning duration of the system, and the optical components are usually connected to a small processing and recording/transmitting unit holding the battery, usually carried through a backpack (Figure 1).

Figure 1. Examples of wireless and wearable fNIRS devices in unrestrained situations. Panel A shows a fibreless system (WOT-100, Hitachi, Japan) monitoring the prefrontal cortex outside the lab. A black cap is used to prevent detectors saturation. In panel B, a wearable device equipped with fibres (LIGHTNIRS, Shimadzu, Japan) measuring over

the motor cortices is presented, where wires are connected to the control unit carried through a backpack (Photo courtesy of *Shimadzu, Japan*).

Most instruments have fixed source-detector separations, typically 3 cm for adult studies. Two DOT systems are available and allow measurement of brain activity at different depths, while two systems permit the adjustment of source-detector separations with custom configurations. The majority of the instruments use two wavelengths to resolve oxy- and deoxy- haemoglobin concentrations, except the *Pocket NIRS HM* from *Dynasense* and the *SPEEDNIRS* and *LIGHTNIRS* from *Shimadzu* that use three-wavelengths to account for the scattering, and the WOT-1000 from Hitachi, which uses only one wavelength to resolve total-haemoglobin. Eleven of the available systems are completely fibreless and optical components are directly coupled to the head (Table 1; see Figure 1 A for an example); the others use shorter and lighter wires than conventional fNIRS systems to guide the light that are connected to the control unit (see Figure 1 B for an example), still allowing for free movement. To prevent detector saturations in case of outdoor use, shading caps are available (Figure 1 A); alternatively, some devices implement a reference detector measuring the ambient light that is used to correct for stray light.

3. Literature Review

A literature review of research articles using wearable fNIRS devices in more ecologically-valid cognitive experiments was carried out in order to identify the most common applications of wireless fNIRS in the field of cognitive neuroscience so far, and to set the starting point for our discussions and future directions. More precisely, we focused on the studies employing the new class of wearable and/or wireless devices in

unrestrained contexts with freely-moving participants while undertaking a cognitive task. The search procedure was performed using the PubMed database, manual search from articles references and the publication surveys available on the Society for functional Near Infrared Spectroscopy website (http://fnirs.org/publications/nirs-niri-publications/). For database searching, we used the keywords functional near-infrared spectroscopy, fNIRS, wireless, portable, wearable, and brain. Articles were selected on the basis of the following inclusion criteria:

1. Original research papers published on peer-reviewed journals until September 2017. Review papers and conference proceedings were excluded.
2. Papers involving task-evoked functional activity experiments with a cognitive task performed on freely moving participants and not in a typical laboratory setup (usually, seated and interacting with a computer only).
3. Articles employing wearable fNIRS devices to measure brain activity in response to cognitive tasks. Papers using conventional fNIRS instrumentation were excluded.

In case of multiple cognitive tasks examined within the same paper, only the ones involving the use of wearable fNIRS devices, and with freely-moving subjects were considered. Ten original research papers were included in the present review. Following the procedure adopted by Herold et al. (2017), from articles' full-texts we collected information concerning the application of wireless fNIRS (e.g., population, and experimental protocol), the pre-processing, and the statistical analysis of fNIRS data. In the following sections, we present the approaches adopted in the reviewed studies with additional details, providing an overview of the application of wearable fNIRS (Table 2),

and data acquisition (Table 3), data pre-processing (Table 4) and statistical inference (Table 5).

3.1. Population and experimental protocol

The majority of the studies (Table 2) included in the present review were performed on a cohort of healthy young adults (Atzumori et al., 2010; Balardin et al., 2017; McKendrick et al., 2016; McKendrick, Mehta, Ayaz, Scheldrup, & Parasuraman, 2017; Mirelaman et al., 2014; Pinti et al., 2015; Takeuchi et al., 2016) and two on healthy older adults (Maidan et al., 2016; Takeuchi et al., 2016). Two papers examined individuals with neurological deficits such as Parkinson's Disease (Maidan et al., 2016; Nieuwhof et al., 2016), and one included individuals with mild cognitive impairments (Doi et al., 2013).

Table 2. Summary of the populations investigated in the reviewed articles and overview of the experimental protocols.

First author	**Population** (n= number of participants; age in years ± SD)	**Experimental protocol**		
		Behavioural task	**Conditions**	**Study design** Number of blocks; block duration
Atsumori et al. 2010	- Healthy young adults (n=6; 29.7 ± 3.3)	- NW - DTW + attention demanding task	- Rest - Control (NW) - Task	- 1 block; 20 s. - 6 blocks; 10 s. - 5 blocks; 10 s.
Balardin et al. 2017	- Healthy young adults (n=1; 30)	- Playing table tennis	- Rest - Forehand - Predictable - Unpredictable	- 10 blocks; 30 s. - 10 blocks; 20 s. - 10 blocks; 20 s. - 10 blocks; 20 s.
	- Healthy young adults (n=1; 26)	- Continuous monitoring in everyday life	- Everyday life activities	- Continuous; 4 h.
Doi et al. 2013	- MCI old adults (n=16; 75.4 ± 7.2)	- NW - DTW + verbal letter fluency task	- Pre-task rest - Task - Rest	- 3 blocks; 10 s. - 3 blocks; 20 s. - 3 blocks; 30 s.
Maidan et al. 2016	- Old adults with Parkinson's Disease (n=68; 71.6 ± 0.9); - Healthy old adults (n=28; 70.4 ± 0.9)	- NW - DTW + serial subtraction - DTW + negotiating obstacles	- Rest - Task	- 5 blocks; 20 s. - 5 blocks; 30 s.

McKendrick et al. 2016	- Healthy young adults (n=20; 18-29)	- DTW + auditory 1-back task - DTW + scenery probe	- Rest - Task	- 47 blocks; minimum 15 s. - 37 blocks; 60 s. - 10 blocks; 30 s.
McKendrick et al. 2017	- Healthy young adults (n=13; mean=22; range 19-31)	- Sitting + auditory 1-back task - DTW indoor + auditory 1-back task - DTW outdoor + auditory 1-back task	- Task	- 4 blocks; 120 s. - 2 blocks: 120 s. - 2 blocks, 120 s.
Mirelaman et al. 2014	- Healthy young adults (n=23; 30.9 ± 3.7)	- NW - DTW + counting forward - DTW + serial subtraction - Standing + serial subtraction	- Rest - Task	- 6 blocks; 20 s. - 5 blocks; 30 s/30 m.
Nieuwhof et al. 2016	- Old adults with Parkinson's Disease (n=12; 70.1 ± 5.4)	- DTW + counting forward - DTW + serial subtraction - DTW + reciting digit span	- Rest - Task	- 6 blocks; 20 s. - 5 blocks; 40 s.
Pinti et al. 2015	- Healthy young adults (n=1; 24)	- DTW + ongoing task - DTW + PM	- Rest - Ongoing task	- 2 blocks; 60 s. - 2 blocks; ~5 min. - 1 block; ~5 min.

			- Non-social PM task - Social PM task	- 1 block; ~5 min.	
Takeuchi et al. 2016	- Healthy young adults (n=16; 25.9 ± 4.4) - Healthy old adults (n=15; 71.7 ± 3.3)	- DTW + playing *Touch the numbers*	- Rest - Task	- 6 blocks; 30 s. - 15 blocks; 10 s.	

Abbreviations: NW = Normal walking; DTW = Dual-task walking; MCI = Mild cognitive impairment; PM = Prospective memory.

All the studies examined in this review (Table 2) involved a motor-cognitive dual-task walking (DTW) protocol, in which participants were asked to perform a secondary cognitive task while walking. For instance, in the study of Atsumori et al. (2010), the secondary task was an attention demanding task (ball-carrying) that was carried out while walking. Other cognitive tasks employed in addition to walking involved serial subtractions (Maidan et al, 2016; Mirelaman et al., 2014; Nieuwhof et al., 2016), counting forward (Mirelaman et al., 2014; Nieuwhof et al., 2016), reciting a series of digits (digit span (Nieuwhof et al., 2016), a verbal letter fluency task (Doi et al., 2013) and playing a game on a smartphone (Takeuchi et al., 2016). A table tennis task was used by Balardin et al. (2017) to investigate the feasibility of wearable and wireless fNIRS in case of moderate levels of motion. Whilst the above-mentioned studies were performed in indoor environments, more interestingly four studies (Balardin et al., 2017; McKendrick et al., 2016; McKendrick et al., 2017; Pinti et al., 2015) were carried out outside in everyday life contexts. Balardin et al. (2017) monitored changes in prefrontal cortex activity during the execution of everyday life actions. The study by McKendrick et al. (2016) aimed at investigating situation awareness and mental workload on people during navigation of a college campus using a hand-held display, or an augmented reality wearable display while simultaneously performing a visual perception or an auditory 1-back task. More recently, the auditory 1-back was repeated on participants while sitting, walking indoor and walking outdoor around a busy college campus (McKendrick et al., 2017). Pinti et al. (2015) investigated the neural correlates of a prospective memory (PM) task conducted in the streets of London on freely-moving subjects with no particular restrictions and no preparation of the environment (Pinti et al., 2015).

Typical block design experiments (i.e., conditions are repeated over time and spaced out by rest periods) are usually employed except for the papers by Pinti et al. (2015) and Balardin et al. (2017), where continuous monitoring with minimum task repetitions were adopted. For instance, in Pinti et al. (2015) conditions were repeated twice while in most neuroscience experimental investigations blocks and events are repeated multiple times (e.g., 10 or more). This was done to mimic real-life situations as much as possible and to have more ecologically-valid cognitive tasks. Rest periods are usually represented by normal walking (NW, i.e., walking with no secondary task) conditions (Atsumori et al., 2010; McKendrick et al., 2016; Pinti et al., 2015; Takeuchi et al., 2016), standing while performing a secondary task (Pinti et al., 2015) or standing still (Balardin et al., 2017; Doi et al., 2013; Maidan et al., 2016; McKendrick et al., 2017; Mirelaman et al., 2014; Nieuwhof et al., 2016).

3.2. Data acquisition

Cortical hemodynamic responses (Table 3) were usually investigated over the pre-frontal cortex (PFC) since this region is easily accessible, and most of the commercially available system allows the monitoring of only frontal regions (Atsumori et al., 2010; Doi et al., 2013; Maidan et al., 2016; McKendrick et al., 2016; McKendrick et al., 2017; Mirelaman et al., 2014; Nieuwhof et al., 2016; Pinti et al., 2015; Takeuchi et al., 2016). In one study, supplementary motor and primary motor cortex were probed instead during a table tennis task (Balardin et al., 2017).

Table 3. Summary of the fNIRS devices and data acquisition features.

First author	fNIRS data acquisition				
	Wavelengths	**Number of channels**	**Source-detector separation**	**Cortical brain region**	**Sampling frequency**
Atsumori et al. 2010	- 754 and 830 nm	- 22	- 30 mm	- PFC	- 5 Hz
Balardin et al. 2017	- 760 and 850 nm	- 23 - 22	- 30 mm	- PFC - supplementary motor and primary motor cortex	- 7.81 Hz
Doi et al. 2013	- 770 and 840 nm	- 16	- 30 mm	- PFC	- 1.54 Hz
Maidan et al. 2016	- 760 and 850 nm	- 6	- 30, 35, 40 mm	- PFC	- 10 Hz
McKendrick et al. 2016	- 730 and 850 nm	- 4	- Not reported	- PFC	- 4 Hz
McKendrick et al. 2017	- 730 and 850 nm	- 4	- Not reported	- PFC	- 4 Hz
Mirelaman et al. 2014	- 760 and 850 nm	- 6	- Not reported	- PFC	- 10 Hz
Nieuwhof et al. 2016	- 760 and 850 nm	- 6	- 30, 35, 40 mm	- PFC	- 10 Hz

Pinti et al. 2015	-	705 and 830 nm	-	16	-	30 mm	-	PFC	-	5 Hz
Takeuchi et al. 2016	-	705 and 830 nm	-	16	-	30 mm	-	PFC	-	5 Hz

Abbreviations: PFC = Prefrontal cortex

3.3. Data pre-processing

The pre-processing of fNIRS data is a crucial step as the results of statistical analyses strongly rely on the quality of the data. It is thus extremely important to reduce the impact of physiological noises, motion artifacts and slow drifts present in the fNIRS signals. Table 4 summarizes the details of the pre-processing steps adopted in the reviewed studies to de-noise fNIRS data.

Table 4. Summary of the steps adopted for the fNIRS data pre-processing.

First author	fNIRS data pre-processing			
	DPF	**Motion artifact correction**	**Filtering**	**Additional steps**
Atsumori et al. 2010	- N/A	- Not performed	- Not performed	- Baseline correction
Balardin et al. 2017	- Not reported	- Not performed	- BP filter [0.01 0.2] Hz	- Down-sampling to 1 Hz
Doi et al. 2013	- Not reported	- Not performed	- LP filter 0.05 Hz	- Baseline correction
Maidan et al. 2016	- Not reported	- Wavelet-based	- BP filter [0.01 0.14] Hz	- CBSI; Baseline correction
McKendrick et al. 2016	- Not reported	- Not performed	- LP FIR filter, 20^{th} order, 0.1 Hz	- Baseline correction
McKendrick et al. 2017	- Not reported	- Not performed	- LP FIR filter, 20^{th} order, 0.1 Hz	- Baseline correction
Mirelaman et al. 2014	- Not reported	- Not performed	- LP FIR filter, 0.14 Hz	- Baseline correction
Nieuwhof et al. 2016	- Constant (6.0)	- MARA	- LP Butterworth filter, 0.1 Hz	- Baseline correction
Pinti et al. 2015	- N/A	- Wavelet-based	- BP Butterworth filter, 3^{rd} order, [0.008 0.2] Hz	- Down-sampling to 1 Hz; CBSI

Takeuchi et al. 2016	-	N/A	-	Not performed	- Moving average - BP filter [0.01 0.5] Hz	-	Baseline correction

Abbreviations: DPF = differential path length factor; BP = Band-pass; LP = low-pass; CBSI = correlation-based signal improvement; FIR = finite impulse response; MARA = movement artifact reduction algorithm.

3.4. Data analysis

The presence of functional activation in the investigated brain regions was statistically assessed (Tak & Ye, 2014) in most of the studies using the averaging method, i.e. averaging signal segments across task and rest periods, and inferring functional brain activity on the basis of the difference between task and rest mean values (Atsumori et al., 2010; Doi et al., 2013; Maidan et al., 2016; McKendrick et al., 2016; McKendrick et al., 2017; Mirelaman et al., 2014; Nieuwhof et al., 2016; Takeuchi et al., 2016).

Table 5. Overview of the analysis of fNIRS data.

First author	fNIRS analysis		
	Method	**Activation parameter**	**Time used for the analysis**
Atsumori et al. 2010	- Averaging + *t*-test	- HbO_2 and HbR	- 6 – 32 s after the start of the task
Balardin et al. 2017	- GLM + *t*-test - CWT	- HbO_2	- Entire task block - 1 min
Doi et al. 2013	- Averaging + *t*-test	- HbO_2	- Entire task block
Maidan et al. 2016	- Averaging + Linear mixed model	- HbO_2	- Entire task block
McKendrick et al. 2016	- Averaging + Generalized and linear mixed model	- HbO_2 and HbR	- Entire task block
McKendrick et al. 2017	- Averaging + Generalized and linear mixed model	- HbO_2 and HbR	- Entire task block
Mirelaman et al. 2014	- Averaging + RM ANOVA - CWT	- HbO_2	- Entire task block
Nieuwhof et al. 2016	- Averaging + Wilcoxon signed-rank test	- HbO_2 and HbR	- Entire task block
Pinti et al. 2015	- N/A	- HbO_2 and HbR	- Entire task period
Takeuchi et al. 2016	- Averaging + ANOVA	- HbO_2	- Entire task block

Abbreviations: GLM = General linear model; CWT = Continuous wavelet transform; RM ANOVA = Repeated measures analysis of variance analysis.

One paper adopted the General Linear Model (GLM) approach instead, i.e. fitting the fNIRS data with task-related regressors modelling the theoretical hemodynamic response to the assigned cognitive task (Balardin et al., 2017). Continuous Wavelet Transform (CWT) was used in 2 articles to investigate the functional connectivity between brain regions (Balardin et al., 2017; Mirelaman et al., 2014).

4. Challenges and way forward

When recording fNIRS data in unrestrained contexts and on mobile people, there are some methodological issues that need to be considered and addressed. In this section, we discuss and summarize the technology limitations (Table 6), providing some suggestions to overcome these issues, and to get meaningful fNIRS data and results.

Table 6. Summary of the challenges associated with using fNIRS in naturalistic settings and recommended solutions.

Challenge		**Solution**
Body movements	Motion artifacts	Correct through: - Wavelet-based filtering - tPCA
	Optical decoupling	- Properly secure the fNIRS probes to the head
Sunlight/Detector saturation		- Protecting caps - Device with ambient light detector
Signals' quality deterioration/ Channels inclusion criteria		- Visual inspection of signals - Exclude channels without heart rate oscillations - Exclude channels with CV>15% - Exclude non-measuring channels (e.g. flat lines)

Systemic changes	- Include longer rest periods (e.g., 2 min) - Band-pass filtering (NOTE: this removes some of the physiological noises, e.g. heart rate and respiration, but it is not effective in removing task-evoked systemic changes) - Measure additional physiological signals - Monitor participants' movements (accelerometer or GPS) - Report results of ΔHbO_2 and ΔHbR
Statistical inference/ Unstructured protocols	- Apply AIDE

Abbreviations: tPCA = targeted principal component analysis; SNR = Signal-to-noise ration; CV = coefficient of variation.

4.1. Body movements

In order to arrive at a correct neuroscientific conclusion, it is necessary to record good quality fNIRS data. However, the signals' quality can be deteriorated by several factors. If we consider recording neuroimaging data on freely moving people, the first concern relates to the execution of body and head movements. In fact, although fNIRS is more tolerant to movements, and wearable devices are miniaturized and even more robust than conventional fNIRS instruments, motion artifacts are more likely to occur when participants are walking rather than sitting on a chair, as they are allowed to move freely and perform a wider range of movements. For example, motion errors can corrupt fNIRS signals with shifts from baseline values (Figure 2 A, green shaded areas) or fast and narrow spikes (Brigadoi et al., 2014), characterized by a positive correlation between HbO_2 and HbR (Figure 2 A, yellow shaded areas).

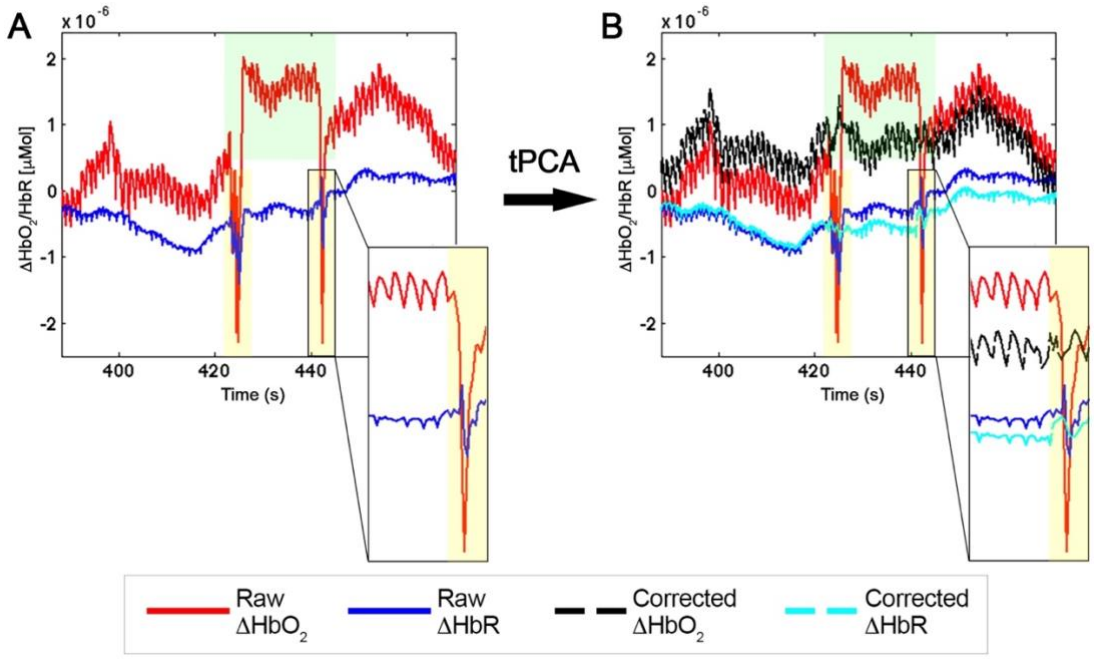

Figure 2. Example of motion artifacts in raw fNIRS signals (A) as shifts from baseline values (green shaded areas) and fast spikes (yellow shaded areas), where HbO_2 and HbR are correlated. Panel B shows the effect of the application of the tPCA approach for the correction of motion errors. HbO_2 and HbR become anti-correlated after being properly corrected. Data refer to the study by Pinti et al., 2015.

To date, several methods are available to identify and correct for motion artifacts (Scholkmann, Spichtig, Muehlemann, & Wolf, 2010), and were reviewed by Brigadoi et al. (2014). Among these, the wavelet-based (Molavi & Dumonts, 2012) and the targeted principal component analysis (tPCA) approaches (Yücel et al., 2014) appeared to be the most effective. In Figure 2 B, we show the effectiveness of tPCA to correct both baseline shifts (green shaded areas) and higher-frequency spikes (yellow shaded areas). In the latter, the physiological anti-correlation between HbO_2 and HbR typical of functional activity (Obrig et al., 2000) is effectively restored. Only 3 of the reviewed papers included the correction of motion errors. Since correcting for such artifacts was demonstrated to be better than rejecting corrupted trials (Brigadoi et al., 2014), we suggest employing one of the available correction techniques, and especially the wavelet-based filtering or tPCA

(Table 6), as part of the pre-processing flow. Head movements can also lead to a loss of coupling between the optodes and the head that further deteriorates signals' quality. In case of poor optical coupling, no physiological signals are sampled and time-series are only constituted of white-noise (Figure 3 A), characterized by a constant power spectral density (PSD). The fNIRS probes thus have to be securely attached to the head, with good contact with the skin.

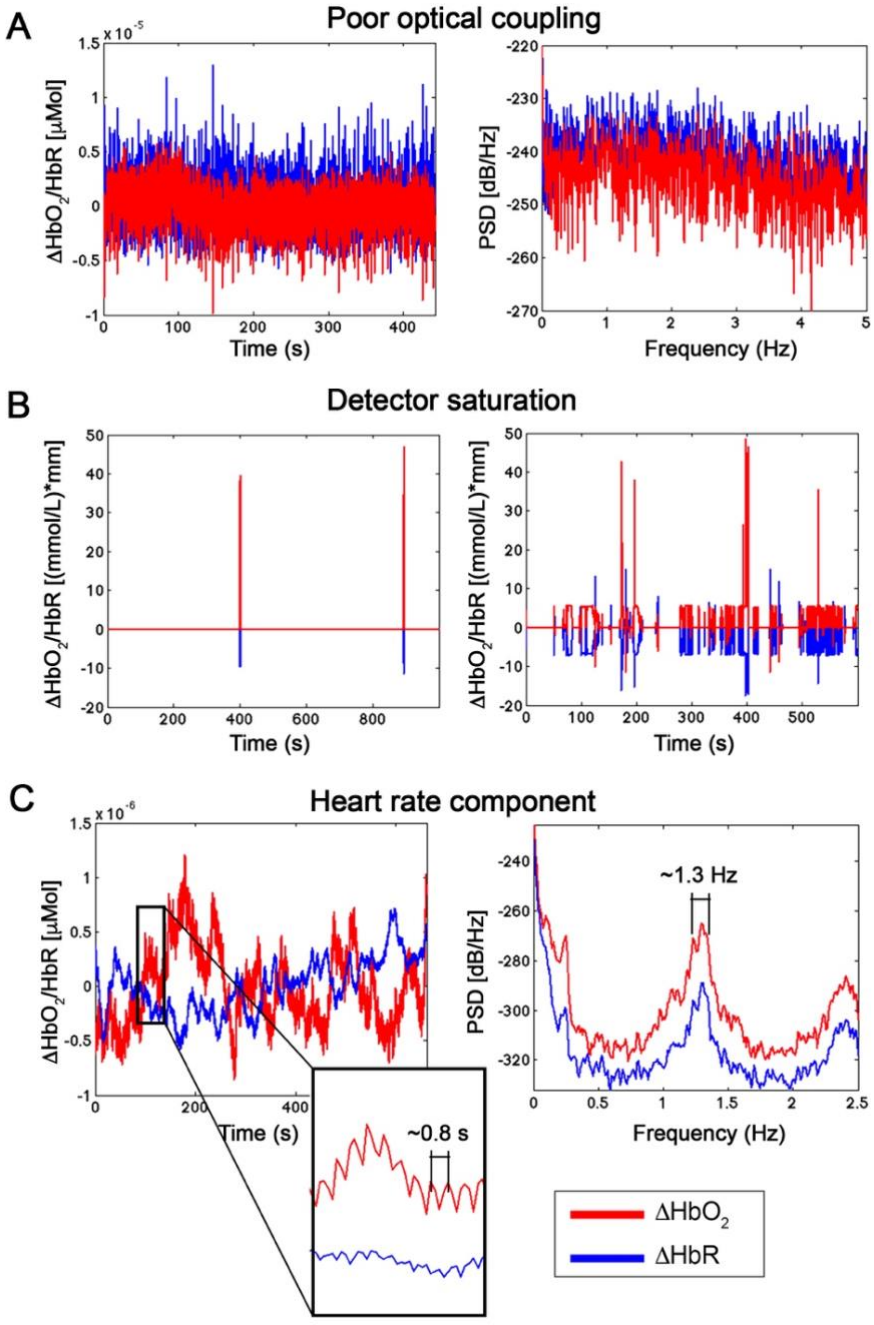

Figure 3. Example ΔHbO_2 and ΔHbR in absence of a good coupling between the optodes and the head (A). This is reflected by the presence of only white noise, with a constant PSD. Data were in-house collected on the visual cortex using the Hitachi ETG-4000 during the presentation of a flashing checkerboard. In panel B, examples of channels corrupted by sunlight are shown, with consequent detector saturation. Data refer to the study by Pinti et al., 2015. The quality of fNIRS data can be assessed evaluating the presence of heart beat oscillations (C), visible both in the time- and in the frequency-domain. Data correspond to resting-state signals in-house recorded over the PFC using the Hitachi WOT-system.

In addition, when using fNIRS in outdoor environments, optical detectors should be protected from the stray sunlight. In this case, the detectors will be overexposed and measured intensity signals will appear as flat lines or be full of spikes with non-physiological amplitudes (Figure 3 B). Detector overexposure and saturation can be prevented using light-shielding caps/hats (Figure 1 A; McKendrick et al., 2016, 2017; Pinti et al., 2015) or detectors with very high dynamic range or using fNIRS devices that incorporate a reference detector measuring only the ambient light that is then subtracted from the other channels' signals(e.g., *Brite23* and *Octamon* from *Artinis*, Table 1). In order to identify noisy channels due to poor coupling or not-measuring channels due to detectors saturation, we highly recommended to (i) visually inspect the recorded signals and (ii) assess channels' quality using more objective measures e.g. following the approach proposed by Piper et al. (2014) based on the coefficient of variation (CV) of the signals, excluding those channels with CV values higher than 15%. Signals' quality can be evaluated checking for the presence of the heart beat oscillation (~0.6 - 1 s) in the time-series, especially in ΔHbO_2, or a frequency peak in the range ~1 - 1.5 Hz in the PSD of the signal (Figure 2 C). This ensures that physiologically meaningful components are measured.

4.2. Systemic interferences

To improve the accuracy of functional investigations through fNIRS, the influence of physiological confounding factors need to be taken into consideration as well. In fact, fNIRS signals are contaminated by components of systemic origin that are not related to neuronal activity and that can lead to false positives and/or false negatives when inferring functional activity (Tachtsidis & Scholkmann, 2016). These physiological changes can

arise both at the intra- and extra-cerebral compartments of the head, and can be both spontaneous and evoked by the cognitive task (Scholkmann et al., 2014). A large amount of variability in fNIRS signals can thus be represented by changes in breathing rate, heart rate, carbon dioxide (CO_2) in the blood, blood pressure, vasomotor and autonomic regulations (Holper, Scholkmann, & Wolf, 2014; Kirilina et al., 2012; Rowley et al., 2006; Scholkmann, Gerber, Wolf, & Wolf, 2013; Tachtsidis et al., 2004; Tong, Hocke, & Licata, 2012). We expect the effect of systemic interferences to be even more pronounced in case of physical activity. For example, rapid posture changes (e.g., from laying down to standing up) can induce venous pooling or orthostatic hypotension (Balardin et al., 2017). In addition, walking can lead to changes in e.g. heart and breathing rates. In Figure 4, we show examples of heart rate (A) and breathing rate (B) signals recorded during the experiment performed by Pinti et al. (2014).

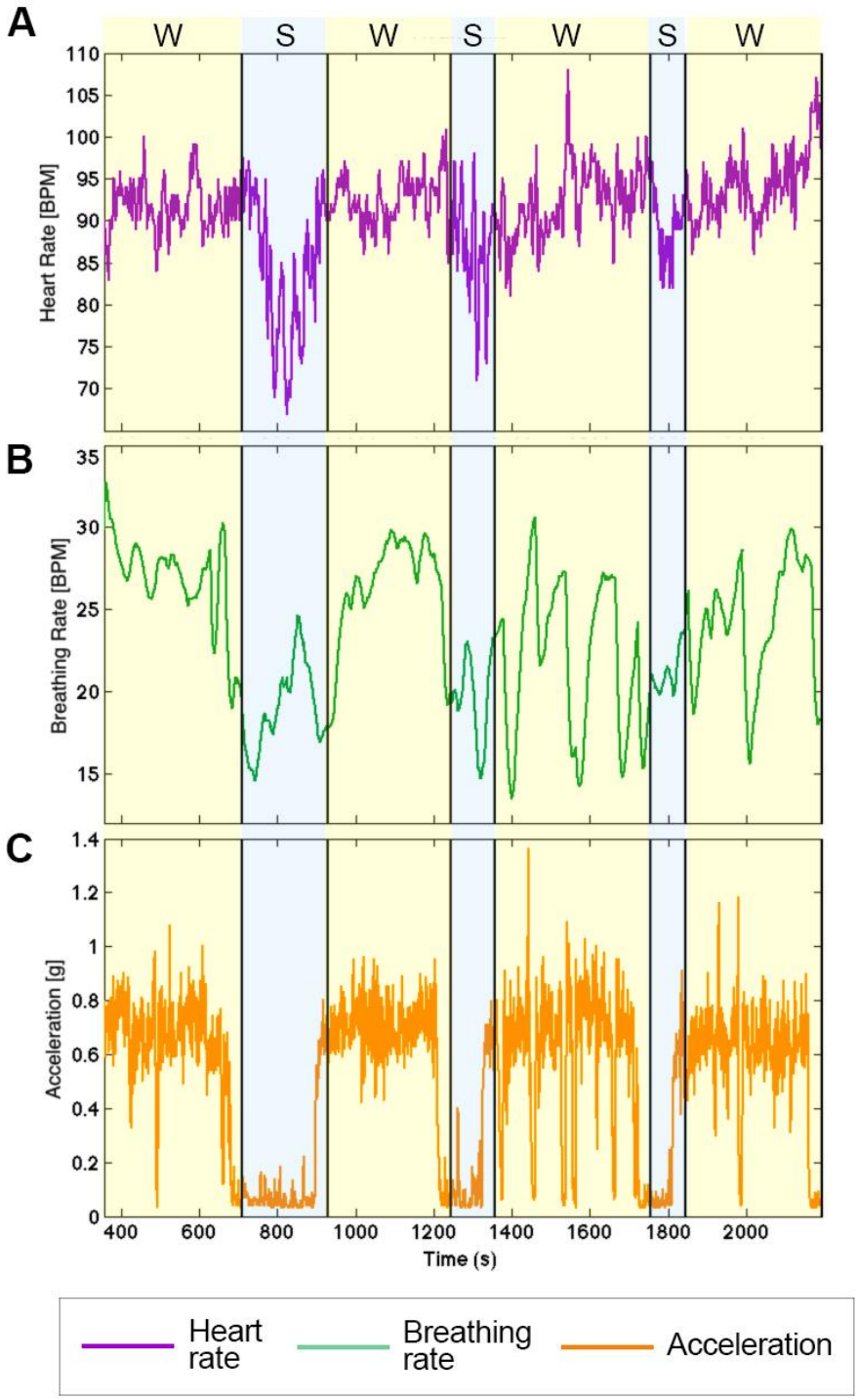

Figure 4. Heart rate (A), breathing rate (B), and acceleration (C) data referring to one participant undertaking the experiment described in Pinti et al. (2014). Yellow shaded areas indicate the conditions involving walking (W), while blue shaded areas represent the phases in which the participant was standing (S).

Walk-related changes can be observed in both signals when passing from experimental conditions involving walking (W; yellow shaded areas, lasting ~6 min) to standing conditions (S; blue shaded areas, lasting ~3 min), with increases and decreases in both heart rate and breathing rate levels.

Measuring acceleration (Figure 4 C) or GPS data can help in the interpretation of physiological and hemodynamic changes, providing information on participants' movements (e.g., walk vs. stand, speed). Walking for long periods can cause fatigue with consequent systemic changes that alter the brain hemodynamic responses. As shown in Figure 5, changes in breathing rate exhibits trends very similar to concentration signals, and in particular ΔHbO_2 (Kirilina et al., 2012; Tachtsidis & Scholkmann, 2016), both when the participant is walking (W; yellow shaded areas) and standing (S; blue shaded areas). To reduce fatigue, longer rest periods lasting a few minutes are recommended (Herold et al., 2017), to allow physiological and hemodynamic variables to reach their baseline values.

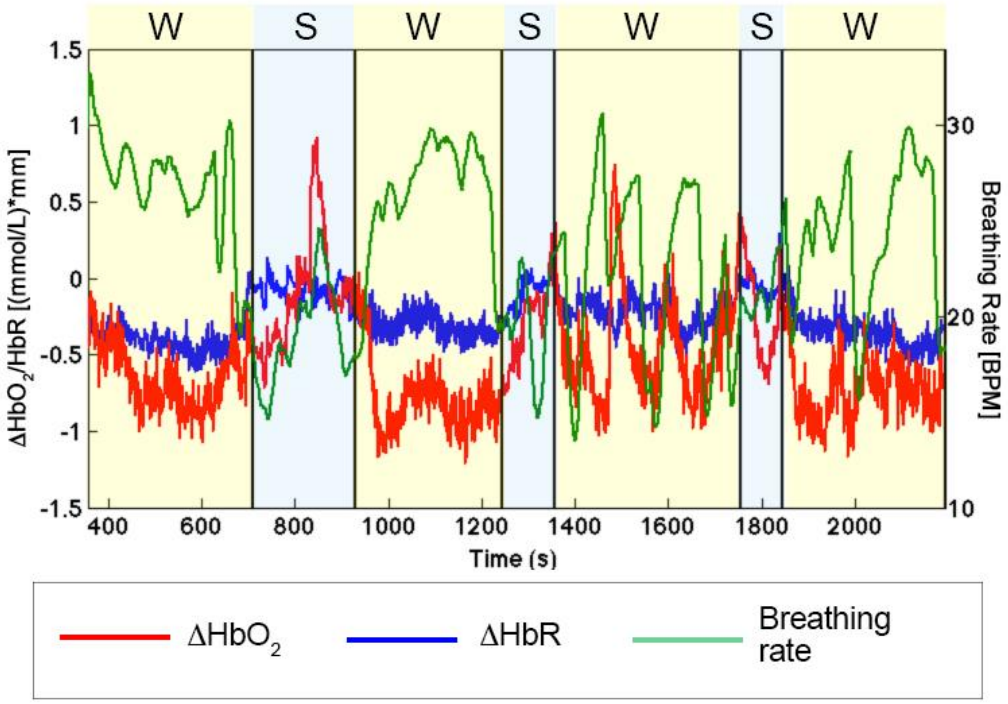

Figure 5. Breathing rate and unpre-processed concentration changes in oxy- and deoxy-haemoglobin referring to one participant undertaking the experiment described in Pinti et al. (2014). Yellow shaded areas indicate the conditions involving walking (W), while blue shaded areas represent the phases in which the participant was standing (S).

Different methods were proposed so far to reduce the impact of these components (Scholkmann et al., 2014). One of the most straightforward is to filter the fNIRS signals in specific frequency bands, preserving the functional activity range and excluding the noise frequencies. In the reviewed studies, low-pass filters are more often used. However, fNIRS signals can also include slow trends related to instrumental noise and/or very low frequency vasomotion regulations (<0.1 Hz). We thus recommend to use low-pass filters together with high-pass filters (i.e., band-pass filters) to remove both slow trends and higher frequency physiological noises (e.g., heart rate (~1 Hz)). Attention should be paid in the choice of the cut-off frequencies to ensure that only the noise components are filtered out. Additionally, the use of short-separation (SS) channels was demonstrated to

be effective in removing the extra-cerebral signals components (e.g., superficial skin blood flow) from long-separation channels (Gagnon et al., 2012). SS channels are created by placing a light source very close to a detector, usually at less than 1 cm distance, and record data from the extra-cerebral tissue. However, such superficial signal regression techniques (Funane et al., 2014, Gagnon et al., 2012) require a larger number of optodes, as each long separation channel must be combined with a short separation channel as close as 1.5 cm (Gagnon, Yücel, Boas, & Cooper, 2014). This is not fully possible with most of the commercially available wearable devices since the number of channels is still limited compared to conventional systems and are designed to maximize the investigation of the cortical tissue. Superficial regression can, to date, be performed with DOT devices (e.g., *Genie* from *MMRA*, and *NIRSIT* from *Obelab*, Table 2) that have a denser array of optodes, with the possibility of sampling from SS channels. Other approaches based on independent component analysis (ICA) (Kohno et al., 2007), principal component analysis (PCA; Zhang Y. et al., 2005), Bayesan filtering (Scarpa et al., 2011) and anti-correlation maximization (CBSI; Cui, Bray, & Reiss, 2010) have been proposed as well. Currently, the most effective methodology able to separate systemic components from fNIRS cortical signals (Scholkmann et al., 2014) is to combine fNIRS measurements with systemic physiological data (e.g., mean blood pressure, heart rate, scalp blood flow). These systemic signals can be e.g. used as additional regressors in the GLM analysis of fNIRS data (Tachtsidis et al., 2010; Kirilina et al., 2012) or combined with ICA to identify the components to remove (Patel, Katura, Maki, & Tachtsidis, 2011). Only one of the studies we reviewed (Pinti et al., 2015) monitored changes in heart rate and breathing rate, and none included SS channels signal regression or PCA/ICA approaches. However, we recommend measuring physiological signals alongside fNIRS for a more effective

reduction of systemic interferences. In fact, thanks to the feasibility of fNIRS for multimodal monitoring, this can be easily performed through the use of wearable physiological monitors (e.g., chest straps; Pinti et al., 2015) that do not interfere with the optical equipment and with participants' movements.

4.3. Statistical analysis

Concerning the statistical analysis of fNIRS data, the most common method to infer functional brain activity from fNIRS signals is to use averaging or GLM approaches (see Tak & Ye (2014) for a review). Both methods require the knowledge of the timeline of events, which are pre-established and known in conventional experimental protocols structured as typical block- or event-related design paradigms. However, the analysis is not so immediate in case of unstructured experimental protocols, where brain activity is continuously monitored with minor control over the presentation of stimuli. For instance, in the work by Pinti et al. (2015), functional brain activity over the PFC was measured during the execution of an unstructured prospective memory task. In that case, participants were asked to respond and "fist bump" in greeting particular targets (either certain people or stationary objects) located in the testing area. However, the onsets of functional events associated with those actions were not pre-established as in typical block or event-related design experiments, and were very difficult to identify from the analysis of video recordings of participants' behaviour. In fact, the peaks of hemodynamic responses (i.e., increase in ΔHbO_2 and decrease in ΔHbR) are expected to occur ~6 s after the stimulus onset (Scholkmann et al., 2014); however, non-synchronous hemodynamic responses to the targets' fist bumping were observed (Figure 6 A, arrows), where the ΔHbO_2 and ΔHbR peaks were anticipated of ~15 s.

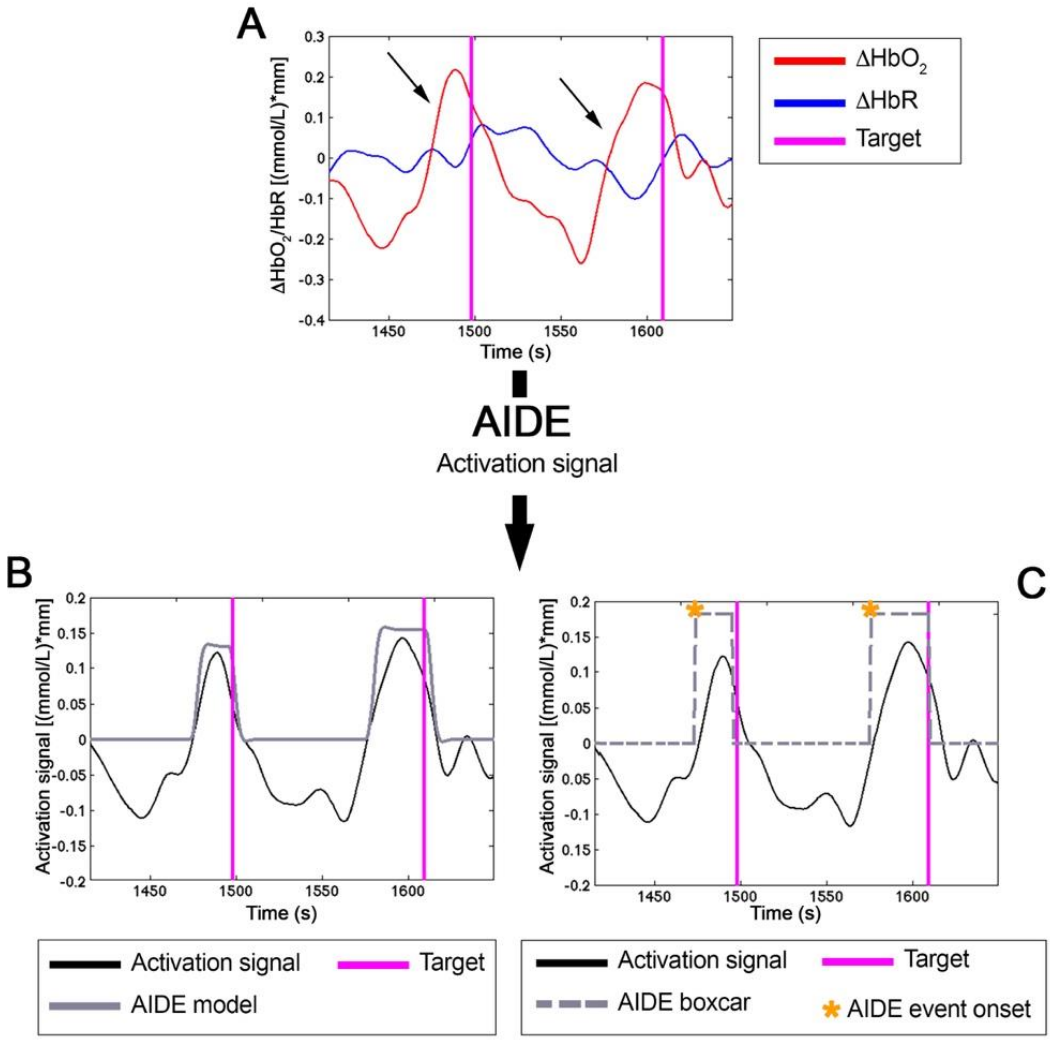

Figure 6. Example of ΔHbO_2 and ΔHbR signals referring to one participant undertaking the experiment described in Pinti et al. (2015) (A). Magenta lines represent the time point in which the participant fist bumped two targets in the experimental area. Panel B shows the resulting activation model resulting from the application of AIDE (black line; Pinti et al., 2017), corresponding to the best fit with the activation signal (red line). The corresponding boxcar (black line) and the identified event onsets (orange asterisks) are illustrated in panel C. The estimated functional events occur ~20 s before the participant reached the targets (magenta lines).

This means that, in this case, functional events are more likely to occur when the participant spotted/approached the target (i.e., intention retrieval) rather than actually fist bumped it (i.e., intention realization). Recovery or prediction of the onset of the event

corresponding to the moment when the participant retrieves the intention is extremely difficult from the video recordings or even impossible. This is also true when brain activity is continuously monitored during everyday life activities as in the study by Balardin et al. (2017), and it is very hard to match fNIRS signal changes to participants' behaviour. For instance, the authors investigated the inter-hemispherical functional connectivity using 1 min sliding window over the 4 hours continuously recorded fNIRS data. The spectrogram of the time-varying connectivity revealed a frequency peak of 0.002 Hz that, however, could not be linked to any of the daily activities. To overcome the issues related to the identification of functional events in unstructured protocols, an alternative approach was proposed by Pinti et al. (2017). The authors developed and validated a novel algorithm based on the GLM fitting procedure, called AIDE (Automatic IDentification of functional Events) that recovers the onsets of functional events directly from fNIRS data with good accuracy. This method is applied to an 'activation signal' computed combining oxy- and deoxy- haemoglobin signals through the CBSI approach (Cui et al., 2010), in order to work on one signal containing information on both ΔHbO_2 and ΔHbR, reducing at the same time the impact of systemic interferences. Functional events (both the onset and duration) are determined identifying the activation model (i.e., the convolution of a boxcar representing the timeline of the events with the hemodynamic response function) that gives the best fit with the activation signal (Pinti et al., 2017). AIDE thus takes the opposite approach than conventional neuroimaging analysis techniques, and does not make any assumption on the timings of functional events. In this way, no hypotheses and assumptions have to be made, and functional events can be identified also in case of experimental protocols with no particular structure. In Figure 6 B-C, are presented the results of the application of AIDE to the example of Figure 6 A.

More precisely, Figure 6 B shows the activation model (black line) giving the best fit with the activation signal (red line) that best describes the occurrence of functional trends (i.e., increase in the activation signal). The corresponding boxcar, representing the timeline of functional events, is reported in Figure 6 C (black line). In agreement with the visual inspection of signals that suggested anticipated hemodynamic responses, functional events (Figure 6 C, orange asterisks) actually happened ~20 s before the participant reached the targets (Figure 6 C, magenta lines). This confirms that functional events occur during the intention retrieval process rather than in correspondence of the intention realization.

To increase the strength of the statistical inference results and to formulate more accurate conclusions, we also recommend reporting results for both ΔHbO_2 and ΔHbR. In fact, functional activation corresponds to an increase in ΔHbO_2 and decrease in ΔHbR (Obrig et al., 2000). Changes in oxyhemoglobin are very often used as the marker to assess functional activity because of its high-contrast changes. However, this signal has been demonstrated to be strongly influenced by systemic changes (Kirilina et al., 2012), and can give rise to global and poorly localized hemodynamic responses (Zhang X., Noah, & Hirsch, 2016). On the contrary, ΔHbR is less affected by confounding factors (Kirilina et al., 2012) and a more robust indicator of brain activity, giving more localized and specific results (Hirsch, Zhang X., Noah & Ono, 2017).

5. Discussion

Over the last few decades, fNIRS has rapidly become a powerful method to image brain activity and investigate cognitive functions that cannot be studied in artificial contexts such as an fMRI scanner (e.g., social interactions (Hirsch et al., 2017), motor

control (Herold et al., 2017), neurodevelopment (Lloyd-Fox, Blasi, & Elwell, 2010)). The boundaries of these neuroscientific investigations can now be further extended thanks to the availability of wearable fNIRS instrumentation (Quaresima & Ferrari, 2016), allowing the monitoring of brain functioning in even more ecologically-valid scenarios and in outdoor environments (Balardin et al., 2017; McKendrick et al., 2016; McKendrick et al., 2017; Pinti et al., 2015) with mobile participants. In fact, these systems are miniaturized, more portable and thus lighter respect to conventional fNIRS devices, thanks to the absence of heavy and long optical fibres. Participants are now allowed to move and walk more freely in the environment without remarkable physical restraints usually imposed by standard instrumentations. This new class of devices was firstly introduced to the market less than 10 years ago (Quaresima & Ferrari, 2016), but only over last couple of years their use in more naturalistic situations and unconstrained environments is increasing. With this review, we aimed to givean overview of the state-of-the-art of the application of this novel wearable fNIRS technology in cognitive neuroscience, with participants freely moving in the environment while engaged in a cognitive task.

To date, most of the studies were conducted in conventional laboratory settings, and involved the monitoring of PFC hemodynamics during a dual-task walking test (Table 2) with basic cognitive tasks (e.g., N-back task, digit span, verbal fluency task, serial subtractions, playing a game on a smartphone). Experimental protocols were structured as typical block-designed paradigms, and common statistical inference approaches (e.g., averaging, GLM; Tak & Ye, 2014) were employed to analyse fNIRS data (Table 5). Nevertheless, even though these studies adopted standard approaches for neuroimaging, they have contributed some major findings. First, they have demonstrated

the feasibility of wearable fNIRS in assessing functional brain activity to tasks performed during walking. This sets the basis for future applications in real-world contexts since we continuously carry out dual-task walking (DTW) actions in our everyday life. Second, the new class of fNIRS devices are well tolerated not only by healthy adults, but also by patients with neurological deficits and mild cognitive impairment. This opens the way to new applications in clinical settings such as for neurorehabilitation. Third, it was proven that the new class of fNIRS devices are able to investigate the interplay between gait and higher cognitive and cortical control mechanisms in case of clinical patients. For instance, this is particularly important in the case of Parkinson's disease as the monitoring of these patients during DTW tasks can help in explaining their difficulties in performing two tasks at the same time or gait failures in everyday life (Maidan et al., 2016). Research on walking is not only relevant in clinical populations. In our modern society, using smartphones while walking has become ubiquitous. Takeuchi et al. (2016) explored the cognitive-motor interference that can lead to increased risk of falling. Participants had to complete a game on their phone while walking and the investigators measured PFC activity using a wireless fNIRS device. This study further highlights the efficacy of wireless fNIRS in an ecological valid task, especially when investigating complex behaviour involving simultaneous motor and cognitive tasks.

The studies by Balardin et al. (2017), McKendrick et al. (2016, 2017), and Pinti et al. (2015) were conducted in outdoor environments and in situations mirroring everyday life contexts. McKendrick et al. (2016, 2017) took a neuroergonomic approach to assess mental workload and situation awareness while following a route in real-world scenarios. To this goal, the authors employed a block design functional protocol and fNIRS data analysis could be carried out through approaches commonly used in the

analysis of neuroimaging data, such as block averaging (Tak & Ye, 2014). However, this is not the case of unstructured experimental protocols, such as those used in the studies by Pinti et al. (2015) and Balardin et al. (2017), where continuous monitoring and no stimuli repetitions were adopted instead. Alternative approaches must be taken, such as using AIDE (Pinti et al., 2017) to recover and identify functional events directly from fNIRS data with no a-priori assumptions. Whilst some precautions related to the use of fNIRS in challenging situations need to be taken into account (see Section 5), these studies have demonstrated the feasibility of wearable fNIRS in effectively monitoring functional brain activity on people freely moving in outdoor settings while carrying out tasks as they would normally do in real life.

6. Future directions

In this section we describe some of the possible applications in the field of cognitive neuroscience that we believe they would benefit the most from the use of wearable fNIRS.

The new neuroscience of TWO: Hyperscanning with fNIRS

One clear advantage for fNIRS as a technique for the study of human brain-cognition relationships is in the study of social interaction. This is because the typical environment of e.g. a MRI or PET scanner precludes naturalistic or normal social behaviour, limiting the questions that can be asked, and raising the question of the ecological validity of the results.

It is widely appreciated that organizational principles of neural coding underlying interpersonal and social interactions are critically understudied relative to their

importance for understanding basic human behavior in both healthy and psychiatric conditions (Cui, Bryant, & Reiss, 2012; Frith, 2008; Hasson, Ghazanfar, Galantucci, Garrod, & Keysers, 2012; Schilbach, 2014). This barrier to investigation reflects the technical difficulties acquiring neural imaging data simultaneously on two or more interacting individuals. More precisely, there are two related challenges that face researchers currently working to understand the social brain, and both can potentially be ameliorated by the use of wearable fNIRS. These are (1) the ecological validity, and (2) the second-person neuroscience. While current fNIRS hyperscanning studies all use tethered systems with seated participants (Scholkmann, Holper, Wolf & Wolf 2013), the extension of hyperscanning to wearable fNIRS would allow us to monitor brain activity during a much wider range of social activities including dance, teaching, large scale collaborative tasks, even sports. For example, a recent study used wireless EEG to track brain-to-brain synchrony in classrooms (Dikker et al., 2017); similar studies with fNIRS might provide more detailed information on the engagement of different brain systems during teaching and learning interactions.

Recent investigations of interpersonal interactions between two or more persons now lead the way toward a new neuroscience of natural cross-person communication (Babiloni & Astolfi, 2014; Scholkmann et al., 2013). The investigation of dynamic social interactions between two individuals extends the fundamental unit of behaviour from a single brain to a two-brain unit, the dyad, and the focus is on communication protocols within the unit. Further to this, rapidly fluctuating facial expressions and subtle interaction-related movements that are transmitted and received during natural social interactions are poorly resolved by conventional experimental methods, thereby highlighting the significant advantages to hyperscanning (Schilbach, 2014). This

advantage is illustrated in several recent studies. For example, although the salience of eyes in communication is well acknowledged, the evidence is primarily based on single brain studies and viewing static pictures often with direct vs indirect gaze (Allison, Puce, & McCarthy, 2000; Ethofer, Gschwind, & Vuilleumier, 2011). However, a recent hyperscanning study of live eye-to-eye contact with fNIRS confirms a previously unappreciated critical role for real interaction via eye contact in natural interpersonal interactions (Hirsch et al., 2017). General linear models and functional connectivity findings within and across-brains revealed natural eye-to-eye effects greater than viewing static pictures of faces. These neural differences include canonical language regions, and suggest that eye-to-eye contact engages active neural systems associated with social engagement. The advantages of real-time hyperscanning in the context of the interactive brain hypothesis promise a new level of understanding of the neural processes that underlie social behaviour. Cross-brain synchrony between specific neural regions may become foundational hallmarks of interpersonal communication that enable a new window of opportunity to investigate social connections. For example, indices of affiliation, conduits for emotional contagion, diagnostic indicators of developmental social disorders and psychiatric conditions such as depression, anxiety and schizophrenia, may be developed and understood using hyperscanning in natural situations.–These foundational findings and the forward trajectories are early entry points toward a new neuroscience of TWO that emerges from hyperscanning based on fNIRS.

fNIRS and Virtual Reality (VR)

A further benefit of fNIRS is that it can potentially be combined with virtual reality (VR) or augmented reality to give full experimental control of a participant's

experience in a dynamic environment. Common VR headsets (e.g., Oculus Rift) can be modified to combine with an fNIRS frontal cortex recording system, or fNIRS can be used in conjunction with a CAVE VR system in which the virtual environment is present on all the walls surrounding the participant and is seen in 3D with 3D glasses. Studies in fMRI examined how participants in VR respond to threat stimuli (McCall, Hildebrandt, Bornemann & Singer, 2015) and if they show prosocial behaviour in an emergency (Pan & Slater, 2011). If these VR scenarios were combined with fNIRS, we could understand the neural mechanisms underlying these behaviours.

fNIRS as a tool of driving research

The potential of fNIRS is also particularly striking for everyday behaviours that simply cannot be investigated in the laboratory, such as driving a car. Liu, Pelowski, Pang, Zhou, and Cai (2016) reviewed fNIRS as a tool for driving research, evaluating different models of fNIRS devices, paradigms employed and key findings, as well as comparing to fMRI/EEG research. While various studies used fNIRS in driving simulators, others used fNIRS in real cars (see Liu et al. (2016) for a review). fNIRS allowed the investigation of various risk factors in driving such as fatigue, distraction, ageing (for further details see Liu et al., 2016). The authors are convinced that fNIRS proved itself as a useful method in driving research. Further research can address changes in brain activations in other regions than PFC, such as temporal cortex, parietal and pre-motor areas. Moreover, other risk factors can be explored, such as inexperience, unexpected events, distractions, alcohol and with passengers. Lastly, the authors highlight the recent introduction of time-course measurements, which will allow exploring real-time, dynamic activation changes during driving.

fNIRS for neuroeconomics and neuroergonomics research

Other applications could involve multimodal monitoring in everyday life contexts. Kopton and Kenning (2014) evaluated the potential of fNIRS in neuroeconomics research. They argue that the interdisciplinary research field of 'neuroeconomics' was the result of investigating neurophysiological processes of economic decision making using methods such as fMRI, EEG, electrodermal activity (EDA) and eye-tracking. However, recent challenges in neuroeconomics necessitate measuring situational factors outside the laboratory and in the 'real-world'. These methodological demands can only be met with flexible and mobile technologies such as wearable fNIRS. The review describes not only lab-based experiments using wireless fNIRS with high ecological validity, but also evaluate the reliability of wireless fNIRS in field experiments (Kopton & Kenning, 2014). The authors conclude that even though few neuroeconomic studies employed mobile fNIRS to date, the fruitfulness of fNIRS in neuroeconomics outside the laboratory is irrefutable.

Additionally, neuroergonomics would massively benefit from the use of wearable fNIRS on mobile participants. Neuroergonomics is defined as the study of the human brain functioning during physical or cognitive activities at work and in everyday life settings (Parasuraman, 2011). This discipline integrates theories and models from different fields, such as ergonomics and neuroscience, to investigate the relationship between brain functions and technologies and settings in complex daily activities (Mehta & Parasuraman, 2013; Mandrick, Chua, Causse, Perrey & Dehais, 2016). It also aims to assess and monitor mental workload in everyday life situations in order to reduce human errors and mental workload while increasing human performance (Mandrick et al., 2016).

Neuroergonomics is different from conventional neuroscience as it investigates cognition in response to work, and requires the possibility to measure brain activity in naturalistic environments such as in the workplace (Mehta & Parasuraman, 2013). Therefore, conventional neuroimaging techniques such as fMRI and PET are not well suited for neuroergonomics research in everyday life scenarios given the physical restrictions that they impose on participants. On the contrary, wearable fNIRS can help in overcoming these issues, allowing the monitoring of brain activity on freely moving subjects. This is particularly important in neuroergonomics, as stated by Mehta and Parasuraman (2013), as bodily movements are necessary for physical ergonomics studies and for research on embodied cognition that requires people to move and interact with real-world environments.

fNIRS for the study of prefrontal cortex function

There is another sizeable subfield of cognitive neuroscience where the necessity is just as great but perhaps less immediately obvious. This is the study of prefrontal cortex function. The arguments around this topic are quite complex, and have emerged from over 100 years of research. But we will try to summarise it here very briefly. The starting point is that most theorists agree that the prefrontal cortex supports a range of mental processes which operate in a 'supervisory' (Shallice, 1988) or 'executive' fashion over other processes which are more 'informationally encapsulated' (e.g. Coltheart, 1999). Informational encapsulation means that a cognitive system is relatively dedicated to affecting a particular behaviour or dealing with a particular type of stimulus. Informationally encapsulated mental resources, such as basic visual, motor, language or sensory processing and so forth, enable 'automatic processing' (Schneider & Shiffrin,

1977), that is fast and well-rehearsed. By contrast, many of the mental processes that are thought to be supported by prefrontal cortex operate in a slow 'controlled processing' fashion. This executive processing takes several forms, and operates across a wide range of situations, but an overall aim of the executive system is to deal with novel or difficult situations, and create new ways of behaving to deal with them (see Gilbert and Burgess (2008) for an introduction to executive function theory). Successful operation of the PFC executive system will mean that the next time that situation is encountered the individual will find it less novel, and their behavioural response will be quicker and less effortful, since they will now know what to do. In this way, the job of the prefrontal cortex executive system is, in effect, to make itself redundant. The principle here is easy to understand. But what might be less obvious is that studying such a cognitive system presents very specific methodological challenges (for review see Burgess, 1997). For instance: (1) the *construct validity* (i.e. the degree to which you are measuring what you intend to measure) of a cognitive task that intends to elicit executive processing typically decreases with the number of trials that are given. So, multiple repetition of the same problem or stimuli as is common in neuroimaging (or psychometric) studies risks missing the critical processing that one wishes to detect. (2) Construct validity can also be seriously compromised by putting the participant in a situation which *directly* signals to the participant that a 'controlled processing' mode should be entered. This is because one of the roles of prefrontal cortex processes is to monitor the environment and switch into 'controlled processing' mode if required. This kind of signal tends to be given if you put a participant in highly unfamiliar – perhaps even slightly intimidating - environment. This may be one reason why some executive tasks that mimic 'real-world' situations were shown to be more sensitive in detecting frontal lobe dysfunction in neurological patients

than those that are administered in the clinic and are quite confrontational in their format (see Burgess et al., (2006) and Burgess and Stuss (in press) for review). (3) A related feature is that some subregions of PFC (especially rostral PFC) are specifically involved in dealing with 'open-ended' situations, i.e. problems where there are many possible solutions and one has to decide for oneself which one to take. (4) Further, much of the processing that PFC supports is 'stimulus-independent', i.e. is not strongly linked to the presentation of a stimulus (Gilbert, Frith & Burgess, 2005). An extreme example is mind-wandering. But there are many other forms of stimulus-independent thought, such as maintaining an intention to act in the future while being occupied with another task (known as *prospective memory*). These four features of situations which tap processing supported by the prefrontal cortex (novel, not clearly signalling that controlled processing is required; open-endedness, and requiring stimulus-independent thought) are very common features of situations in everyday life. But they are not typically strong features of a neuroimaging experiment where an experimenter asks a person to lie down in a scanner, concentrate on what they are about to be shown, and then are shown a series of near-identical stimuli to which a very limited number of responses are instructed to be made. Compare that with the richness of these four features in the situation where a person is going shopping in a mall that is unfamiliar to them, where they have to decide for themselves what is best to buy and where, remembering to carry out many different errands while they are there, and e.g. remembering not to exceed the parking meter time allowance. For these reasons, in the field of human neuropsychology, naturalistic tasks with good 'ecological validity' were developed for use in detection of executive dysfunction in neurological patients with frontal lobe damage (e.g. Shallice & Burgess (1991); Castiel, Alderman, Jenkins, Knight, & Burgess (2012)). Not only has this had

obvious clinical benefit in terms of being able to quantify deficits which could previously not be measured, but it also led to several theoretical discoveries (e.g. the role of rostral PFC in multitasking, prospective memory, and time perception; see Burgess & Wu (2013) for review). The new developments with fNIRS offer the possibility of following an analogous path in moving from measurement in the clinic or laboratory, to measurement in "real life", thus permitting much more accurate measurement of the processes of interest, with the attendant promise of new discoveries about the functions that the frontal lobes support.

7. Conclusion

Over recent years, the focus of cognitive neuroscientists shifted significantly towards the monitoring of brain activity in 'real life', especially when investigating those cognitive functions that might be difficult to study in a highly artificial experimental environment. Therefore, a neuroimaging method that allows us to monitor brain activity actually in a naturalistic environment is an obvious starting point, and matters of construct validity and ecological validity subsequently become a secondary concern. We now have the possibility to monitor brain activity in everyday life thanks to the availability of new instruments such as wearable fNIRS systems. In addition, new methods were developed that we can use to analyse fNIRS data recorded during naturalistic experiments. Whilst these novel techniques provide the capacity to measure effectively functional brain activity in more ecologically-valid contexts, careful consideration needs to be taken when using wearable fNIRS. For instance, the impact of systemic interferences is more pronounced in freely moving subjects. To date, the technology is also still limited by the degree of head coverage and whole-head measurements cannot yet be performed.

In summary, the reviewed studies laid the foundations to future neuroscientific investigations with wearable fNIRS devices in more ecologically-valid contexts and in outdoor environments, starting from the basics and demonstrating the feasibility of the new generation of wearable fNIRS with a series of proof-of-principle experiments. Having demonstrated the strengths and the limitations of this new technology, we believe that wearable fNIRS can find application in many different fields, addressing questions that cannot be investigated with previous technologies. It seems possible now with recent technological and conceptual developments in fNIRS that neuroimaging for cognitive neuroscience can now move ‘from lab to life’.

References

Allison, T., Puce, A., & McCarthy, G. (2000). Social perception from visual cues: role of the STS region. *Trends Cogn Sci, 4*(7), 267-278.

Atsumori, H., Kiguchi, M., Obata, A., Sato, H., Katura, T., Funane, T., & Maki, A. (2009). Development of wearable optical topography system for mapping the prefrontal cortex activation. *Review of Scientific Instruments*, *80*(4), 043704.

Atsumori, H., Kiguchi, M., Katura, T., Funane, T., Obata, A., Sato, H., ... & Kubota, K. (2010). Noninvasive imaging of prefrontal activation during attention-demanding tasks performed while walking using a wearable optical topography system. *Journal of biomedical optics*, *15*(4), 046002-046002.

Ayaz, H., Onaral, B., Izzetoglu, K., Shewokis, P. A., McKendrick, R., & Parasuraman, R. (2013). Continuous monitoring of brain dynamics with functional near infrared spectroscopy as a tool for neuroergonomic research: empirical examples and a technological development. *Frontiers in human neuroscience*, *7*.

Babiloni, F., & Astolfi, L. (2014). Social neuroscience and hyperscanning techniques: past, present and future. *Neuroscience & Biobehavioral Reviews*, *44*, 76-93.

Balardin, J. B., Morais, G. A. Z., Furucho, R. A., Trambaiolli, L., Vanzella, P., Biazoli Jr, C., & Sato, J. R. (2017). Imaging brain function with functional near-infrared spectroscopy in unconstrained environments. *Frontiers in human neuroscience*, *11*.

Boas, D. A., Elwell, C. E., Ferrari, M., & Taga, G. (2014). Twenty years of functional near-infrared spectroscopy: introduction for the special issue.

Brigadoi, S., Ceccherini, L., Cutini, S., Scarpa, F., Scatturin, P., Selb, J., ... & Cooper, R. J. (2014). Motion artifacts in functional near-infrared spectroscopy: a comparison of motion correction techniques applied to real cognitive data. *Neuroimage*, *85*, 181-191.

Burgess, P. W. (1997) Theory and methodology in executive function research. In: P. Rabbitt (Ed.) Theory and Methodology of Frontal and Executive Function, 81-116. Hove, U.K.: Psychology Press.

Burgess, P. W., Alderman, N., Forbes, C., Costello, A., Coates, L. M-A., Dawson, D. R., Anderson, N. D., Gilbert, S. J., Dumontheil, I. and Channon, S. (2006) The case for the development and use of "ecologically valid" measures of executive function in experimental and clinical neuropsychology. *Journal of the International Neuropsychological Society*, 12, 1-16.

Burgess, P. W. & Wu, H-C. (2013) Rostral prefrontal cortex (Brodmann area 10): metacognition in the brain. (2013) Chapter 31 in: Principles of frontal lobe function, 2nd edition (Editors: Donald T. Stuss & Robert T. Knight), 524-534. New York: OUP.

Burgess, P. W. (2015). Serial multitasking: from lab to life. In J. Fawcett, E. F. Risko & A. Kingstone (Eds.), The Handbook of Attention, chapter 19, 443-462. MIT Press.

Burgess, P.W. and Stuss, D.T. (in press) Fifty years of frontal lobe research: impact on assessment. *Journal of the International Neuropsychological Society*.

Castiel, M., Alderman, N., Jenkins, K., Knight, C., Burgess, P. W. (2012) Use of the Multiple Errands Test – Simplified Version in the assessment of suboptimal effort. *Neuropsychological Rehabilitation*, 22 (5), 734-751.

Chance, B., Luo, Q., Nioka, S., Alsop, D. C., & Detre, J. A. (1997). Optical investigations of physiology. A study of intrinsic and extrinsic biomedical contrast. *Philosophical Transactions of the Royal Society of London B: Biological Sciences*, *352*(1354), 707-716.

Chitnis, D., Cooper, R. J., Dempsey, L., Powell, S., Quaggia, S., Highton, D., ... & Everdell, N. L. (2016a). Functional imaging of the human brain using a modular, fibre-less, high-density diffuse optical tomography system. *Biomedical optics express*, *7*(10), 4275-4288.

Chitnis, D., Airantzis, D., Highton, D., Williams, R., Phan, P., Giagka, V., ... & Elwell, C. E. (2016b). Towards a wearable near infrared spectroscopic probe for monitoring concentrations of multiple chromophores in biological tissue in vivo. *Review of Scientific Instruments*, *87*(6), 065112.

Coltheart, M. (1999). Modularity and cognition. *Trends in Cognitive Sciences*, 3(3), 115-120.

Cui, X., Bray, S., & Reiss, A. L. (2010). Functional near infrared spectroscopy (NIRS) signal improvement based on negative correlation between oxygenated and deoxygenated hemoglobin dynamics. *Neuroimage*, *49*(4), 3039-3046.

Cui, X., Bryant, D. M., & Reiss, A. L. (2012). NIRS-based hyperscanning reveals increased interpersonal coherence in superior frontal cortex during cooperation. *Neuroimage*, *59*(3), 2430-2437.

Dikker, S., Wan, L., Davidesco, I., Kaggen, L., Oostrik, M., McClintock, J., ... & Poeppel, D. (2017). Brain-to-brain synchrony tracks real-world dynamic group interactions in the classroom. *Current Biology*, *27*(9), 1375-1380.

Doi, T., Makizako, H., Shimada, H., Park, H., Tsutsumimoto, K., Uemura, K., & Suzuki, T. (2013). Brain activation during dual-task walking and executive function among older adults with mild cognitive impairment: a fNIRS study. *Aging clinical and experimental research*, *25*(5), 539-544.

Eggebrecht, A. T., White, B. R., Ferradal, S. L., Chen, C., Zhan, Y., Snyder, A. Z., ... & Culver, J. P. (2012). A quantitative spatial comparison of high-density diffuse optical tomography and fMRI cortical mapping. *Neuroimage*, *61*(4), 1120-1128.

Ethofer, T., Gschwind, M., & Vuilleumier, P. (2011). Processing social aspects of human gaze: A combined fMRI-DTI study. *Neuroimage*, *55*(1), 411-419.

Frith, C. D. (2008). Social cognition. *Philosophical Transactions of the Royal Society B, 363*(1499), 2033-2039.

Funane, T., Kiguchi, M., Atsumori, H., Sato, H., Kubota, K., & Koizumi, H. (2011). Synchronous activity of two people's prefrontal cortices during a cooperative task measured by simultaneous near-infrared spectroscopy. *Journal of biomedical optics*, *16*(7), 077011-077011.

Funane, T., Atsumori, H., Katura, T., Obata, A. N., Sato, H., Tanikawa, Y., ...& Kiguchi, M. (2014). Quantitative evaluation of deep and shallow tissue layers' contribution to fNIRS signal using multi-distance optodes and independent component analysis. *Neuroimage*, 85, pp. 150-165.

Funane, T., Numata, T., Sato, H., Hiraizumi, S., Hasegawa, Y., Kuwabara, H., Hasegawa, K., Kiguchi, M. (2017). Rearrangeable and exchangeable optical module with system-on-chip for wearable functional near-infrared spectroscopy system. *Neurophotonics*, 5(1), 011007.

Gagnon, L., Cooper, R. J., Yücel, M. A., Perdue, K. L., Greve, D. N., & Boas, D. A. (2012). Short separation channel location impacts the performance of short channel regression in NIRS. Neuroimage, 59(3), pp. 2518-2528.

Gagnon, L., Yücel, M. A., Boas, D. A., & Cooper, R. J. (2014). Further improvement in reducing superficial contamination in NIRS using double short separation measurements. Neuroimage, 85, pp. 127-135.

Gilbert, S. J., Frith, C. D. & Burgess, P. W. (2005). Involvement of rostral prefrontal cortex in selection between stimulus-oriented and stimulus-independent thought. *European Journal of Neuroscience,* 21, 1423-1431.

Gilbert, S.J. & Burgess, P.W. (2008) Executive function. *Current Biology*, 18(3), R110-4.

Hasson, U., Ghazanfar, A. A., Galantucci, B., Garrod, S., & Keysers, C. (2012). Brain-to-brain coupling: A mechanism for creating and sharing a social world. *Trends in Cognitive Science, 16*(2), 114-121.

Herold, F., Wiegel, P., Scholkmann, F., Thiers, A., Hamacher, D., & Schega, L. (2017). Functional near-infrared spectroscopy in movement science: a systematic review on cortical activity in postural and walking tasks. *Neurophotonics, 4*(4), 041403.

Hirsch, J., Zhang, X., Noah, J. A., & Ono, Y. (2017). Frontal temporal and parietal systems synchronize within and across brains during live eye-to-eye contact. *NeuroImage*.

Holper, L., Scholkmann, F., & Wolf, M. (2014). The relationship between sympathetic nervous activity and cerebral hemodynamics and oxygenation: A study using skin conductance measurement and functional near-infrared spectroscopy. *Behavioural brain research, 270*, 95-107.

Hoshi, Y., & Chen, S. J. (2002). Regional cerebral blood flow changes associated with emotions in children. *Pediatric neurology, 27*(4), 275-281.

Kirilina, E., Jelzow, A., Heine, A., Niessing, M., Wabnitz, H., Brühl, R., ... & Tachtsidis, I. (2012). The physiological origin of task-evoked systemic artefacts in functional near infrared spectroscopy. *Neuroimage, 61*(1), 70-81.

Kohno, S., Miyai, I., Seiyama, A., Oda, I., Ishikawa, A., Tsuneishi, S., ... & Shimizu, K. (2007). Removal of the skin blood flow artifact in functional near-infrared spectroscopic imaging data through independent component analysis. *Journal of biomedical optics*, 12(6), pp. 062111-062111.

Kopton, I. M., & Kenning, P. (2014). Near-infrared spectroscopy (NIRS) as a new tool for neuroeconomic research. *Frontiers in human neuroscience, 8*.

Lareau, E., Lesage, F., Pouliot, P., Nguyen, D., Le Lan, J., & Sawan, M. (2011). Multichannel wearable system dedicated for simultaneous electroencephalography/near-infrared spectroscopy real-time data acquisitions. *Journal of biomedical optics*, 16(9), 096014-096014.

Liu, T., Pelowski, M., Pang, C., Zhou, Y., & Cai, J. (2016). Near-infrared spectroscopy as a tool for driving research. *Ergonomics*, *59*(3), 368-379.

Lloyd-Fox, S., Blasi, A., & Elwell, C. E. (2010). Illuminating the developing brain: the past, present and future of functional near infrared spectroscopy. *Neuroscience & Biobehavioral Reviews*, *34*(3), 269-284.

Maidan, I., Nieuwhof, F., Bernad-Elazari, H., Reelick, M. F., Bloem, B. R., Giladi, N., ... & Mirelman, A. (2016). The role of the frontal lobe in complex walking among patients with Parkinson's disease and healthy older adults: an fNIRS study. *Neurorehabilitation and neural repair*, *30*(10), 963-971.

Mandrick, K., Chua, Z., Causse, M., Perrey, S., & Dehais, F. (2016). Why a Comprehensive Understanding of Mental Workload through the Measurement of Neurovascular Coupling Is a Key Issue for Neuroergonomics?. *Frontiers in human neuroscience*, *10*.

McCall, C., Hildebrandt, L. K., Bornemann, B., & Singer, T. (2015). Physiophenomenology in retrospect: Memory reliably reflects physiological arousal during a prior threatening experience. *Consciousness and cognition*, *38*, 60-70.

McKendrick, R., Parasuraman, R., Murtza, R., Formwalt, A., Baccus, W., Paczynski, M., & Ayaz, H. (2016). Into the wild: neuroergonomic differentiation of hand-held and augmented reality wearable displays during outdoor navigation with functional near infrared spectroscopy. *Frontiers in human neuroscience*, *10*.

McKendrick, R., Mehta, R., Ayaz, H., Scheldrup, M., & Parasuraman, R. (2017). Prefrontal hemodynamics of physical activity and environmental complexity during cognitive work. *Human Factors*, *59*(1), 147-162.

Mehta, R. K., & Parasuraman, R. (2013). Neuroergonomics: a review of applications to physical and cognitive work. *Frontiers in human neuroscience*, *7*.

Mirelman, A., Maidan, I., Bernad-Elazari, H., Nieuwhof, F., Reelick, M., Giladi, N., & Hausdorff, J. M. (2014). Increased frontal brain activation during walking while dual tasking: an fNIRS study in healthy young adults. *Journal of neuroengineering and rehabilitation*, *11*(1), 85.

Molavi, B., & Dumont, G. A. (2012). Wavelet-based motion artifact removal for functional near-infrared spectroscopy. *Physiological measurement*, *33*(2), 259.

Muehlemann, T., Haensse, D., & Wolf, M. (2008). Wireless miniaturized in-vivo near infrared imaging. *Optics express*, *16*(14), 10323-10330.

Nieuwhof, F., Reelick, M. F., Maidan, I., Mirelman, A., Hausdorff, J. M., Rikkert, M. G. O., ... & Claassen, J. A. (2016). Measuring prefrontal cortical activity during dual task walking in patients with Parkinson's disease: feasibility of using a new portable fNIRS device. *Pilot and feasibility studies*, *2*(1), 59.

Obrig, H., Wenzel, R., Kohl, M., Horst, S., Wobst, P., Steinbrink, J., ... & Villringer, A. (2000). Near-infrared spectroscopy: does it function in functional activation studies of the adult brain?. *International Journal of Psychophysiology*, *35*(2), 125-142.

Pan, X., & Slater, M. (2011). Confronting a moral dilemma in virtual reality: a pilot study. In *Proceedings of the 25th BCS Conference on Human-Computer Interaction*, British Computer Society, 46-51.

Parasuraman, R. (2011). Neuroergonomics: Brain, cognition, and performance at work. *Current directions in psychological science*, *20*(3), 181-186.

Patel, S., Katura, T., Maki, A., & Tachtsidis, I. (2011). Quantification of systemic interference in optical topography data during frontal lobe and motor cortex activation: an independent component analysis. *Oxygen Transport to Tissue XXXII*, 45-51.

Patil, A. V., Safaie, J., Moghaddam, H. A., Wallois, F., & Grebe, R. (2011). Experimental investigation of NIRS spatial sensitivity. *Biomedical optics express*, *2*(6), 1478-1493.

Poldrack, R. A. (2006). Can cognitive processes be inferred from neuroimaging data?. *Trends in cognitive sciences*, *10*(2), 59-63.

Pinti, P., Aichelburg, C., Lind, F., Power, S., Swingler, E., Merla, A., ... & Tachtsidis, I. (2015). Using fiberless, wearable fNIRS to monitor brain activity in real-world cognitive tasks. *Journal of visualized experiments: JoVE*, (106).

Pinti, P., Merla, A., Aichelburg, C., Lind, F., Power, S., Swingler, E., ... & Tachtsidis, I. (2017). A novel GLM-based method for the Automatic IDentification of functional Events (AIDE) in fNIRS data recorded in naturalistic environments. *NeuroImage*, *155*, 291-304.

Piper, S., Krüger, A., Koch, S. P., Mehnert, J., Habermehl, C., Steinbrink, J., & Schmitz, C. H. (2014). A Wearable Multi-channel NIRS Imaging System for Brain Imaging in Freely Moving Subjects. *Charité University Medicine Berlin, Department of Neurology*.

Quaresima, V., & Ferrari, M. (2016). Functional Near-Infrared Spectroscopy (fNIRS) for Assessing Cerebral Cortex Function During Human Behavior in Natural/Social Situations: A Concise Review. *Organizational Research Methods*, 1094428116658959.

Rowley, A. B., Payne, S. J., Tachtsidis, I., Ebden, M. J., Whiteley, J. P., Gavaghan, D. J., ... & Delpy, D. T. (2006). Synchronization between arterial blood pressure and cerebral

oxyhaemoglobin concentration investigated by wavelet cross-correlation. *Physiological measurement*, *28*(2), 161.

Safaie, J., Grebe, R., Moghaddam, H. A., & Wallois, F. (2013). Toward a fully integrated wireless wearable EEG-NIRS bimodal acquisition system. *Journal of neural engineering*, *10*(5), 056001.

Scarpa, F., Brigadoi, S., Cutini, S., Scatturin, P., Zorzi, M., Dell'Acqua, R., & Sparacino, G. (2011). A methodology to improve estimation of stimulus evoked hemodynamic response from fNIRS measurements. Engineering in Medicine and Biology Society, EMBC, 2011 Annual International Conference of the IEEE, pp. 785-788.

Scholkmann, F., Spichtig, S., Muehlemann, T., & Wolf, M. (2010). How to detect and reduce movement artifacts in near-infrared imaging using moving standard deviation and spline interpolation. *Physiological measurement*, *31*(5), 649.

Scholkmann, F., Gerber, U., Wolf, M., & Wolf, U. (2013). End-tidal CO_2: an important parameter for a correct interpretation in functional brain studies using speech tasks. *Neuroimage*, *66*, 71-79.

Scholkmann, F., Kleiser, S., Metz, A. J., Zimmermann, R., Pavia, J. M., Wolf, U., & Wolf, M. (2014). A review on continuous wave functional near-infrared spectroscopy and imaging instrumentation and methodology. *Neuroimage*, *85*, 6-27.

Shallice, T. (1988). From Neuropsychology to Mental Structure. New York: Cambridge University Press.

Shallice, T. and Burgess, P. W. (1991) Deficits in strategy application following frontal lobe damage in man. *Brain*, 114**,** 727-741.

Shiga, T., Yamamoto, K., Tanabe, K., Nakase, Y., & Chance, B. (1997). Study of an algorithm based on model experiments and diffusion theory for a portable tissue oximeter. *Journal of biomedical optics*, *2*(2), 154-161.

Schilbach, L. (2014). On the relationship of online and offline social cognition. *Frontiers in Human Neuroscience, 8*, 278.

Schneider, W., & Shiffrin, R. M. (1977). Controlled and automatic human information processing: I. Detection, search, and attention. *Psychological Review*, 84, 1-66.

Spooner, D. M., & Pachana, N. A. (2006). Ecological validity in neuropsychological assessment: a case for greater consideration in research with neurologically intact populations. *Archives of clinical neuropsychology*, *21*(4), 327-337.

Tachtsidis, I., Elwell, C. E., Leung, T. S., Lee, C. W., Smith, M., & Delpy, D. T. (2004). Investigation of cerebral haemodynamics by near-infrared spectroscopy in young healthy volunteers reveals posture-dependent spontaneous oscillations. *Physiological measurement*, *25*(2), 437.

Tachtsidis, I., Koh, P. H., Stubbs, C., & Elwell, C. E. (2010). Functional optical topography analysis using statistical parametric mapping (SPM) methodology with and without physiological confounds. Oxygen Transport to Tissue XXXI, pp. 237-243.

Tachtsidis, I., & Scholkmann, F. (2016). False positives and false negatives in functional near-infrared spectroscopy: issues, challenges, and the way forward. *Neurophotonics*, *3*(3), 031405-031405.

Tak, S., & Ye, J. C. (2014). Statistical analysis of fNIRS data: a comprehensive review. *Neuroimage*, *85*, 72-91.

Takeuchi, N., Mori, T., Suzukamo, Y., Tanaka, N., & Izumi, S. I. (2016). Parallel processing of cognitive and physical demands in left and right prefrontal cortices during smartphone use while walking. *BMC neuroscience*, *17*(1), 9.

Tong, Y., Hocke, L. M., & Licata, S. C. (2012). Low-frequency oscillations measured in the periphery with near-infrared spectroscopy are strongly correlated with blood oxygen level-dependent functional magnetic resonance imaging signals. *Journal of biomedical optics*, *17*(10), 1060041

Wyser, D. G., Lambercy, O., Scholkmann, F., Wolf, M., & Gassert, R. (2017). Wearable and modular functional near-infrared spectroscopy instrument with multidistance measurements at four wavelengths. *Neurophotonics*, *4*(4), 041413.

Yücel, M. A., Selb, J., Cooper, R. J., & Boas, D. A. (2014). Targeted principle component analysis: a new motion artifact correction approach for near-infrared spectroscopy. *Journal of innovative optical health sciences*, *7*(02), 1350066.

Zhao, H., & Cooper, R. J. (2017). Review of recent progress toward a fiberless, whole-scalp diffuse optical tomography system. *Neurophotonics*, *5*(1), 011012.

Zhang, X., Noah, J. A., & Hirsch, J. (2016). Separation of the global and local components in functional near-infrared spectroscopy signals using principal component spatial filtering. *Neurophotonics*, *3*(1), 015004.

Zhang, Y., Brooks, D. H., Franceschini, M. A., & Boas, D. A. (2005). Eigenvector-based spatial filtering for reduction of physiological interference in diffuse optical imaging. *Journal of biomedical optics*, 10(1), pp. 011014-01101411.