Biomed Eng Lett (2014) 4:223-230
DOI 10.1007/s13534-014-0156-9

REVIEW ARTICLE

Recent Functional Near Infrared Spectroscopy Based Brain Computer Interface Systems: Developments, Applications and Challenges

Phillips V Zephaniah and Jae Gwan Kim

Received: 4 September 2014 / Revised: 22 September 2014 / Accepted: 25 September 2014

Abstract
Functional Near Infrared Spectroscopy (fNIRS) based Brain Computer Interface (BCI) systems have grown in popularity in the last years, and has shown itself as a useful tool in developing portable and convenient BCI systems. The purpose of this review paper is to highlight the recent developments, applications, and challenges that research groups have achieved in the field of fNIRS-BCI. We will show how fNIRS can be paired with another modality (i.e. EEG, fTCD, etc.) to drastically improve classification accuracy. From there, we will discuss the recent achievements in classification techniques researchers have had with fNIRS or a combined fNIRS modality. Finally, we will look at how fNIRS-BCI systems are used to enhance human-robot interactions and assistive technologies. Throughout our review paper, we will note challenges groups have had with their studies, as to provide a framework for future research topics for the fNIRS-BCI community.

Keywords fNIRS, Near infrared spectroscopy, NIRS, BCI, Brain computer interface, Classification

INTRODUCTION

The research dedicated to functional near infrared spectroscopy (fNIRS) has grown tremendously over the years as researchers continue to push the limits of how fNIRS can provide functional insight into the brain. Researchers have realized the advantages of fNIRS such as portability, low cost, noninvasiveness, and real time data acquisition to administer many different brain studies [1]. A recent review paper, dedicated to twenty years of fNIRS studies, is a generous resource of where fNIRS research has been and where it is going [2]. Fig. 1 from Boas *et al*. review paper shows an eye catching statistic, that the number of fNIRS paper has grown exponentially over the years. A specific area that we believe this review paper glosses over is the work being done for fNIRS-based brain computer interface (BCI). As we will show, there is a lot of research and development being done in this field. This review is intended to highlight the recent developments and achievements in the field of fNIRS-BCI. Most importantly, we have the intention to gather issues that different research groups have had in implementing fNIRS-BCI. By collecting current issues, we hope to provide a framework to guide the future research dedicated to fNIRS-BCI.

fNIRS is a noninvasive technique utilizing the optical window of light and tissue interactions, between 700–1000 nm, to provide hemodynamic concentration changes, specifically in the case of oxyhemoglobin and deoxyhemoglobin [3]. The relationship of oxyhemoglobin and deoxyhemoglobin concentration in a stimulated brain can play an important role of understanding how the brain works [4] and also how to improve the fNIRS signal [5]. fNIRS has always been particularly susceptible to interference such as motion artifacts, global interference, and subject's hair. Thus many statistical procedures thus many statistical procedures have been implemented to remove these issues [6]. It has been our observation that many fNIRS measurements are taken at the prefrontal cortex. The prefrontal cortex has the advantage of being free of hair, easy to access [7], pivotal in the execution of mental task [8] and a strong indicator of a user's cognitive or emotional state [9]. fNIRS systems can be developed in a

Phillips V Zephaniah, Jae Gwan Kim
School of Information and Communication, Gwangju Institute of Science and Technology, Gwangju 500-712 Republic of Korea

Jae Gwan Kim (✉)
Department of Medical System Engineering, Gwangju Institute of Science and Technology, Gwangju 500-712 Republic of Korea
Tel : +82-62-715-2220 / Fax : +82-62-715-2204
E-mail : jaekim@gist.ac.kr

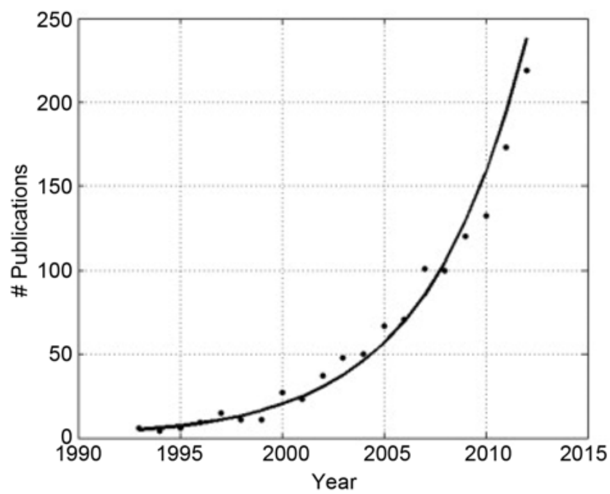

Fig. 1. Growth of fNIRS publications per year. Reproduced with permission from Elsevier [2].

time and frequency domain, or with a continuous wave system. Many differences lie between the systems with an important distinction being that continuous wave systems can only acquire relative hemodynamic concentration changes. That being said, there is a much larger prevalence of continuous wave systems in brain research studies, due to two reasons: the system's simplicity in design and construction, and the large number of commercial continuous wave products available [10].

Countless research of fNIRS studies of the brain has shown that this technique is more than capable of understanding mental diseases in depth. Recently, fNIRS has been particularly helpful in understanding illnesses such as posttraumatic stress disorder (PTSD) [11], schizophrenia [12], Alzheimer's [13], and attention deficit hyperactivity disorder (ADHD) [14]. Researchers have made significant strides with fNIRS in identifying how disorders effect the brain hemodynamics. Fig. 2 shows the hemodynamics of a control group and a group with PTSD working through a digit span task [11]. Figs. 2a and 2b shows an example of hemodynamics of a healthy subject in a forward and backward digit span task, respectively and Figs. 2c and 2d show the contrasting hemodynamics for a subject with PTSD in a forward and backward digit span task, respectively. The graph shows the fluctuation of hemodynamics during the three phases of working memory in order to execute complex cognitive tasks: encoding, maintenance, and retrieval. The important conclusion from these graphs is that subjects with

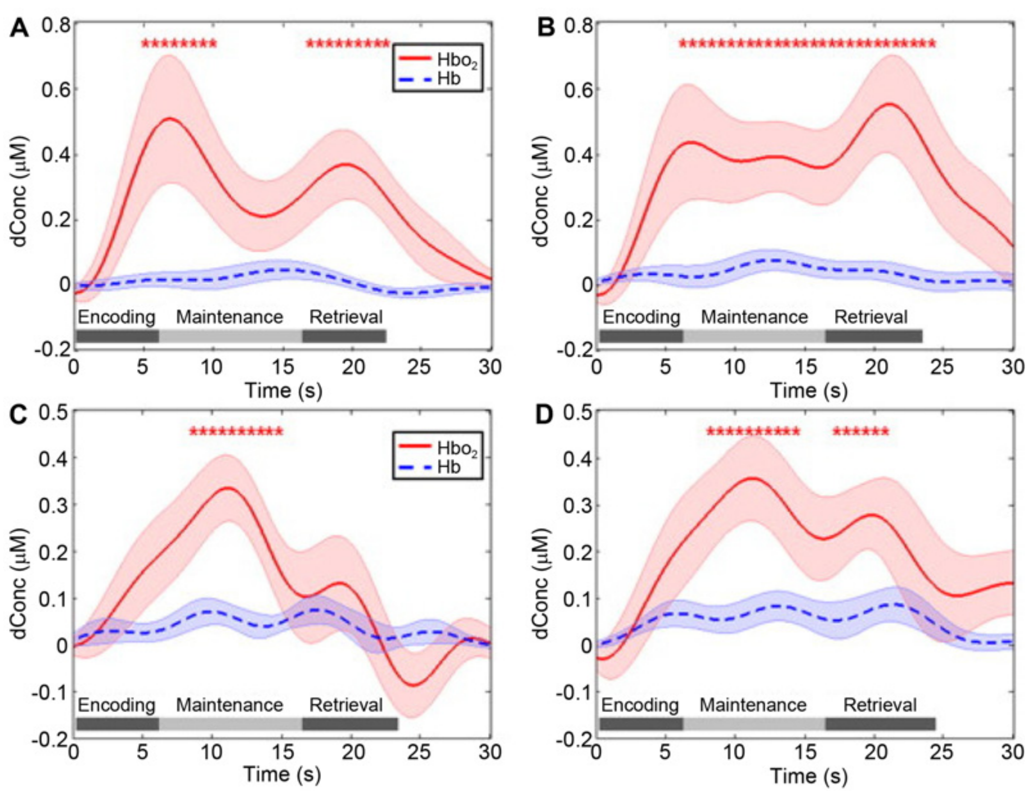

Fig. 2. (a) Mean hemodynamic changes for healthy subjects in a forward digit span task. (b) Mean hemodynamic changes for healthy subjects in a backward digit span task. (c) Mean hemodynamic changes for subjects with PTSD during a forward digit span task. (d) Mean hemodynamic changes for subjects with PTSD during a backward digit span task. The * indicates point on the graph in which the hemodynamic changes are significantly different from baseline. The shaded area indicates standard error. Reproduced with permission from Elsevier [11].

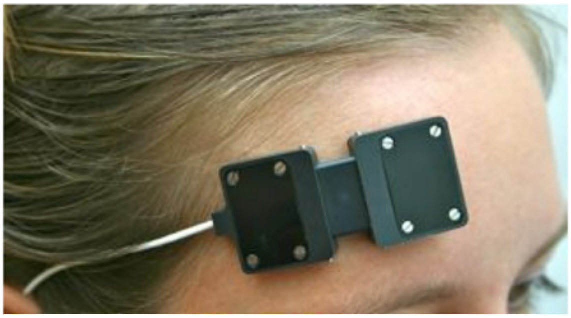

Fig. 3. PortaLite Commercialized fNIRS System. Reproduced with permission from Artinis Medical Systems (http://www.artinis.com/).

PTSD show the most activity in the maintenance phase of working memory and a dip in the retrieval phase. This is compared to healthy subjects that have a strong peak around encoding and retrieval. As we can see, these hemodynamic changes are important in understanding how PTSD effects the brain. While success for fNIRS has been developed for these mental illnesses, it is the significant progress of fNIRS-BCI that warrants our special attention.

BCI is the communication to the outside environment through the use of neural signals. It is often used in order for subjects to regain control of the environment around them, even though they may not have the ability to do so [15]. BCI is particularly helpful in achieving accurate communication for subjects who are "locked in" with disabilities such as amyotrophic lateral sclerosis (ALS) [16]. BCI systems have been developed with modalities such as fNIRS, Electroencephalography (EEG), Magnetoencephalography (MEG), functional Magnetic Resonance Image (fMRI) [17] or hybrid BCI systems such as fNIRS-EEG and EEG-ECG [18]. Even though fNIRS has the limitation of only being able to measure the slower vascular response of the brain [3], it is our belief that its ease of use and portability makes it ideal for fast commercialization of a BCI system. Fig. 3 shows an example of a commercialized wireless fNIRS sensor to be used for brain functional studies. This is just an example of a sensor that shows convenience and portability that would make it ideal for a BCI system.

In order to understand the recent research of fNIRS based BCI, we will look at research dedicated to the following: fNIRS BCI systems, fNIRS BCI Classification, and fNIRS for human-robot interactions (HRI) and assistive devices. Finally, we make note of issues that recent published papers had with their fNIRS-BCI studies, in hopes that this review paper can serve as a central repository for unanswered questions in the fNIRS-BCI research community.

fNIRS BCI SYSTEMS

One of the first fNIRS based BCI systems were employed by Coyle *et al*. [19], which led further work in utilizing the fNIRS signal for use as a "Mindswitch" [20]. The Mindswitch paradigm or the simple classification of an activated brain from Coyle *et al*. [20] is crucial in fNIRS and EEG combined BCI system. As defined by Pfurtscheller *et al*. [18], an activated brain is when the oxyhemoglobin concentration change can be classified from a state different than when at rest [18]. This implies that the user wants to engage in the BCI system. Coyle *et al*. were able to achieve high classification results but like many studies after it, their results were limited by noise of the fNIRS signal and the naturally slow hemodynamic response of the body. Since that time, development of fNIRS BCI systems have improved. There has been a development of a completely online classification fNIRS BCI system [21]. There has also been reports of fNIRS BCI systems successfully achieving brain communication for subjects suffering locked in states (i.e ALS) [22] and even outperforming EEG in classification accuracy [23].

The development of fNIRS BCI has seen to be most effective when combined with other modalities such as EEG. The problem with sole EEG systems is that classification

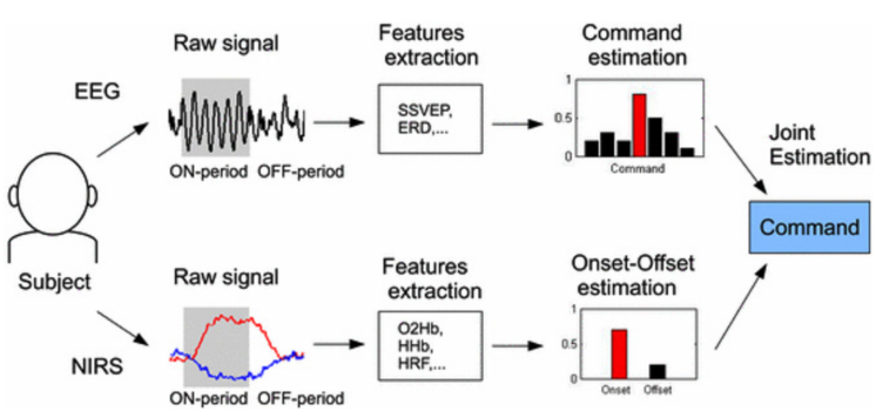

Fig. 4. Basic workflow of EEG and NIRS hybrid BCI System. Reproduced with permission from IEEE [24].

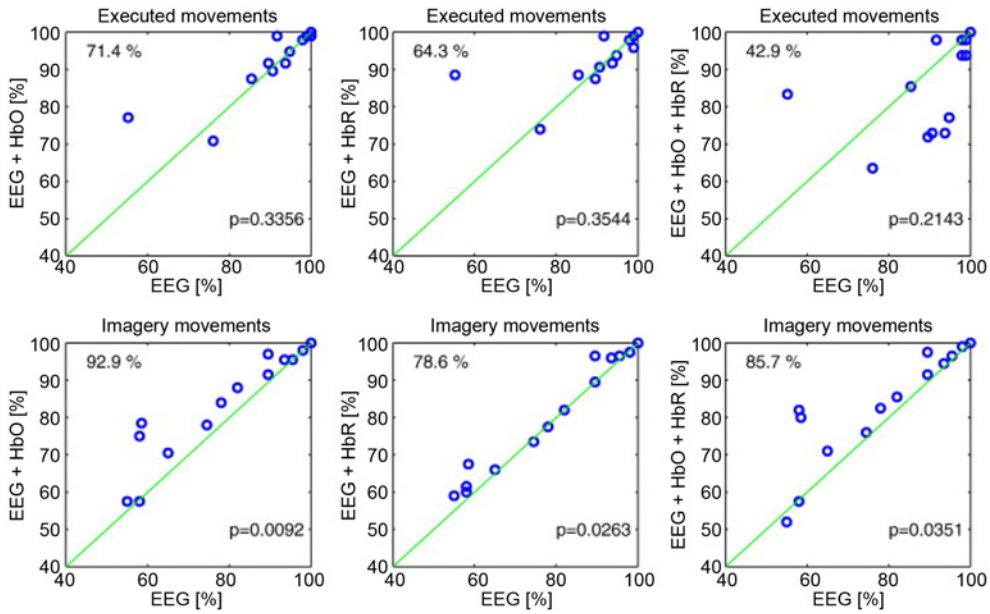

Fig. 5. A comparison of classification accuracy for real and imagery movements, between EEG and EEG with a fNIRS signal The green line marks an equal classification accuracy between the two. Points above the green line would indicate in an improvement of classification accuracy when combining EEG with a hemodynamic signal. The p value indicates the level of significance between the two classification, and the percentage represents how many subjects showed an improvement with combined EEG classification over only EEG. Reproduced with permission from Elsevier [28].

becomes difficult with short training task epochs and that the EEG signal is innately noisy and hard to discriminate between a task and rest period [24]. The development of these hybrid systems have begun with bulky EEG and fiber based fNIRS systems [25, 26] to a more recently developed fully integrated and wireless EEG-fNIRS system [27].

A general flow of fNIRS and EEG hybrid systems can be seen in Fig. 4 provided by Tomita *et al*. [24]. By using fNIRS, there is an overall improvement classification of steady state visual evoked potential in the brain, and a better discrimination of an active and inactive brain state [24]. This active and inactive brain state is essentially the "Mindswitch" paradigm mentioned before. The discrimination of an active and inactive brain state with fNIRS and EEG classification of imagery tasks has turned BCI illiterate users becoming high performance BCI users [28]. Fig. 5 shows the improvement of classification that Fazli *et al*. achieved between only the EEG signal and classification with the EEG signal and a hemodynamic response. The green diagonal line represents equal classification rate between EEG and a combined EEG and fNIRS signal. As we can see, most points lie above the green diagonal, indicating better classification with EEG and the fNIRS signal. The percentage on each graph indicate what percentage of subjects saw an improvement in classification by including the fNIRS signal. In addition, there has been findings that fNIRS and the hybrid fNIRS and EEG system has allowed for accurate self-paced BCI instead of relying on

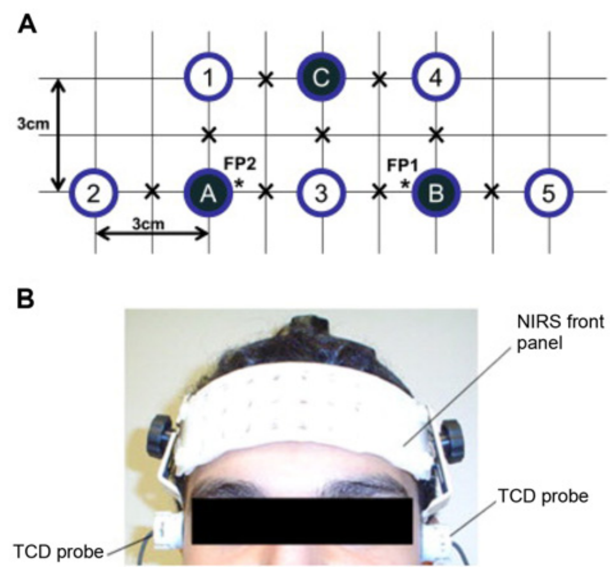

Fig. 6. (a) NIRS source-detector arrangement. Detectors (A, B, C) are solid circles. Source fiber (1, 2, 3, 4, 5) are represented by open circles. The approximate location of the NIRS channel is marked by an x. The location of FP1 and FP2 are denoted by * (b) Image of custom NIRS-TCD probe holder. Reproduced with permission from Elsevier [32].

cued tasks, a more realistic scenario for BCI use in daily life [29, 30]. This shows the enhancements in classification that hybrid BCI's have made. They have transitioned from experiments where the time of intended mental imagery task are known to systems that are more aware of the user's mental state and can discern changes in mental states at any moment.

fNIRS and EEG BCI systems aren't the only type of hybrid fNIRS BCI system that is currently being developed. fNIRS along with the inclusion of biosignals (i.e. ECG, skin conductance response, and blood pressure) has been used to improve the classification of motor execution tasks [31]. Another recent example by Faress *et al*. [32] has shown that a combination of fNIRS and function transcranial Doppler sonography (fTCD) was able to achieve higher linear discriminate analysis (LDA) classification rate, from 76.1% (fNIRS only) and 79.4% (TCD only) to 86.5% (fNIRS and TCD), by combining the hemodynamic changes along with blood velocity to indicate an activated and post activated brain [32]. Fig. 6 shows the geometry of the fTCD and fNIRS combined BCI system.

fNIRS BCI CLASSIFICATION

The work regarding fNIRS-BCI has shown that the concept of classification will always remain a pivotal issue when trying to develop BCI systems. In this section, we want to highlight what type of work researchers have done in classifying the fNIRS signal. We also want to show the different techniques that have been used to improve the accuracy or reduce the time lag that is associated with classifying an activated brain with fNIRS.

Besides just the "Mindswitch" classification of an activated brain, researchers have recently been able to use fNIRS with EEG systems to accurately classify executed movement that distinguished between forward, backward, left, and right movements [33]. Also, fNIRS has been able to differentiate emotional/mental states [34] and a task's degree of mental workload for the user [7]. An interesting study looked at the best mental tasks that give the best accuracy for classification. Testing many different mental tasks, they had found the combination of right hand motor imagery and mental multiplication, along with the combination of mental multiplication and mental figure rotation are both good tasks for determining an activated brain [35]. The findings that mental multiplication and arithmetic as an inducer of discernable brain activity has been backed up by other studies [36].

As we mentioned, the time lag from the vascular response makes it difficult to develop a very responsive fNIRS BCI system [20]. To combat this, researchers have been working on detecting an activated brain sooner. By classifying using the different features from the fNIRS signal (i.e. oxyhemoglobin and deoxyhemolgobin, concentration, channel contrast to noise ratio, signal history etc.), the fNIRS signal time lag was reduced, but they did not obtain a consistent set of features across subjects [37]. The acquisition of a "fast" fNIRS signal remains an open question for fNIRS BCI.

Another important topic in fNIRS BCI classification is training. It has been shown that additional training leads to stronger event-related desynchronization (ERD) brain signals and better classification accuracy [38]. The paper, "*Intersession Consistency of Single-Trial Classification of the Prefrontal Response to Mental Arithmetic and the No-Control State by NIRS*" (Power *et al*. [30]), sheds light on the many issues when it comes to training. This includes training in the same session versus different sessions and the optimal number of training samples [39]. They observed that responses from session to session varied due to factors such as fatigue and motivation. However, task habituation did not have any effect on the classification rates. Finally, the group has shown that intersession classification is much better than classifying from a different session (Fig. 7). Their conclusion is that fNIRS classification is ultimately a trade-off between convenience and accuracy. Higher accuracy can come from a single session with plenty of training samples collected before each BCI system use, however at the discomfort of the user. It is our belief that this tradeoff of convenience versus accuracy is not acceptable for a realistic fNIRS-BCI to be implemented. More work must be done in order to come to a better median between the two.

A key to enhanced classification may come from the reduction of noise and global interference, a known issue that degrades the quality of the fNIRS signal [34, 40]. One solution to this is the use of a short and long distance detector, also known as the "corrected NIRS signal." The short detector will only detect the global noise which can be removed from the long distance detector to get a better

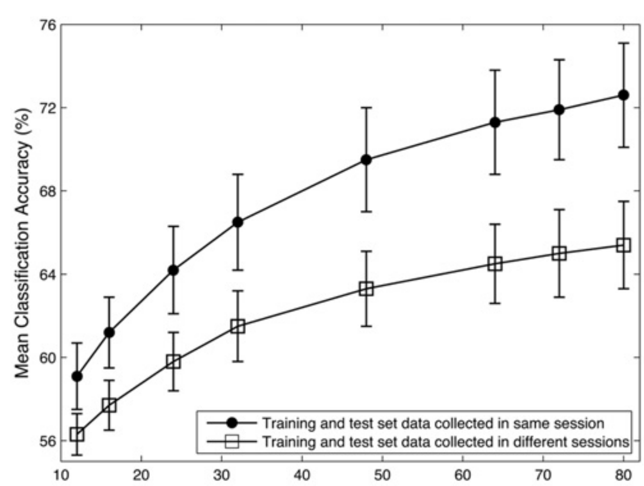

Fig. 7. Comparison of mean classification accuracy with the number of samples in the training set. Source: Power *et al*. [39].

estimate of the signal stemming only from the brain [41]. Research is continually being done to optimize the geometry of the source and detector. It has been found that both single and multichannel detectors are susceptible to added noise, however measurement and processing methods involving multichannel detectors were more robust in reducing the noise in the signal [42]. Independent component analysis and principle component analysis have also been successful in removing the global interference noise that can be found in the short detector [43]. However, the issue of global interference and noisy signals will always remain at the forefront of fNIRS studies and enhanced methods need to be continually developed in order to remove fluctuations from the scalp, and cerebral spinal fluid.

fNIRS FOR HUMAN ROBOT INTERACTION AND ASSISTIVE DEVICES

In this section, we will discuss a few of the recent examples of the application of the fNIRS signal. Besides classifying imagined or executed tasks, the fNIRS signal can be applied to enhance HRI and assistive driving devices. Human robot interaction and fNIRS is a rapidly growing research area, as researchers use the functional changes of the brain to understand and enhance user experience with robots, especially for mental rehabilitation purposes [44]. Recently, through fNIRS and EEG signals alone, developers have enabled control of a humanoid robot [45]. To pinpoint the activation of the brain during external stimuli, researchers have looked at the subject's brain response when a robotic hand is moved [46], which could be important in neuro rehabilitation.

The application of fNIRS signal for human robot interactions or the more generalized human computer interaction (HCI) has had its share of issues. Strait *et al*. [34] had found that fNIRS' motion artifacts and lack of robust signal processing method interfered with their ability to accurately enhance HCI [34]. For example, for tasks lasting longer than one minute, the activation could not be differentiated from the rest time. Finally, it has been found that the fNIRS signal could not return to a normal or pretask state after stimulation, which created a very unreliable signal [34]. This implies that the fNIRS signal may not be well equipped to classify a subject who is undergoing many different tasks. Both of these scenarios: highly varied tasks and long task times, greatly degrades the fNIRS signal even though they are likely scenarios that users may encounter.

There also has been work in using fNIRS to communicate to driving assistance devices. Research has been done to interpret the brain activity of senior citizens during car driving, in order to understand brain activity patterns based on human movements. They were able to have results relating activation of specific parts of the brain to movement perception during driving tasks. This study has achieved promising results and bolsters the hopes of using fNIRS for a driverless car or a system that can aid the task of driving for senior citizens [47].

SUMMARY

The intent of this review paper was to show the recent developments and applications for fNIRS BCI. The portability and convenience of fNIRS gives it tremendous potential of being a way for implementing BCI systems for the masses. Previous works in fNIRS have shown the ability to provide detailed functional changes of the brain and to help in the understanding of brain disorders [11-14]. BCI systems are the next logical step for fNIRS in utilizing the functionality of the brain in order to communicate with the outside environment. A good example of a real life BCI system is one that is self-paced, rather than cued [29]. In addition, hybrid fNIRS-EEG BCI systems have improved classification results and have turned illiterate BCI users into well performing users [18, 28]. As our examples of fNIRS BCI systems have shown, there has been tremendous progress since Coyle *et al*. [19] work and fNIRS is now a feasible BCI solution.

This paper has provided many examples of fNIRS BCI systems that have been able to recognize the user's mental state and whether a brain is active. However, there are still many open issues left in the fNIRS community. In our opinion, there should be additional research for online systems that are more focused on self-paced BCI paradigms, and optimization of the fNIRS signal to reduce time lag and noise. However, the fNIRS signal is degraded with long task times and task variability [34] which is a realistic situation for BCI. To target these issues, we must continually improve fNIRS signal processing methodology. The fNIRS signal can tell a lot about the functional changes of the user [5] and has a large feature space to work with [37], yet we have found few publications that utilizes all the information fNIRS has to offer. It is also our belief that the "fast" fNIRS signal, or early detection of the activated brain state of the user, can greatly improve the reliability and pragmatism of fNIRS BCI to be implemented for disabled patients. From our research, we believe a "fast" fNIRS signal can be achieved by the optimization of the signal feature space paired with the right mental tasks and training sessions [35-37]. Optimization in this area will be crucial in order to develop a more robust fNIRS BCI system.

Finally, the issue of fNIRS-BCI user training is remains a largely unanswered and interesting question for the BCI community. As it is well known, BCI training is critical in high performance BCI systems, but how a user is trained is widely varied and often cumbersome to administer. The work trying to understand and optimize training for fNIRS BCI has shown that it is ultimately a dispute of convenience versus accuracy [39], with no happy solution. It would be ideal to have a lot of training data to improve classification accuracy, however it comes at the inconvenience of the user. Understanding and perfecting the fNIRS training period will be a critical step in the development of fNIRS BCI, and we predict that more work will be done in this area.

ACKNOWLEDGEMENTS

This work was partially supported by the National Research Foundation of Korea (NRF) Grants (NRF-2012K1A2B1A03000757, NRF-2013R1A1A2013625) and a grant from the institute of Medical System Engineering (iMSE) in the GIST.

CONFLICT OF INTEREST STATEMENTS

Phillips VZ declares that he has no conflict of Interest in relation to the work in this article. Kim JG declares that he has no conflict of Interest in relation to the work in this article.

REFERENCES

[1] Ferrari M, Quaresima V. A brief review on the history of human functional near-infrared spectroscopy (fNIRS) development and fields of application. NeuroImage. 2012; 63(2):921-35.
[2] Boas DA, Elwell CE, Ferrari M, Taga G. Twenty years of functional near-infrared spectroscopy: introduction for the special issue. NeuroImage. 2014; 85(Pt 1):1-5.
[3] Villringer A, Chance B. Non-invasive optical spectroscopy and imaging of human brain function. Trends Neurosci. 1997; 20(10):435-42.
[4] Buxton RB, Frank, LR. A model for the coupling between cerebral blood flow and oxygen metabolism during neural stimulation. J Cereb Blood Flow Metab. 1997; 17(1):64-72.
[5] Cui X, Bray S, Reiss AL. Functional near infrared spectroscopy (NIRS) signal improvement based on negative correlation between oxygenated and deoxygenated hemoglobin dynamics. NeuroImage. 2010; 49(4):3039-46.
[6] Tak S, Ye JC. Statistical analysis of fNIRS data: a comprehensive review. NeuroImage. 2014; 85(Pt 1):72-91.
[7] Derosière G, Mandrick K, Dray G, Ward TE, Perrey S. NIRS-measured prefrontal cortex activity in neuroergonomics: strengths and weaknesses. Front Hum Neurosci. 2013; doi:10.3389/fnhum.2013.00583.
[8] Hoshi Y, Tamura M. Near-infrared optical detection of sequential brain activation in the prefrontal cortex during mental tasks. NeuroImage. 1997; 5(4 Pt 1):292-7.
[9] Doi H, Nishitani S, Shinohara K. NIRS as a tool for assaying emotional function in the prefrontal cortex. Front Hum Neurosci. 2013; doi:10.3389/fnhum.2013.00770.
[10] Scholkmann F, Kleiser S, Metz AJ, Zimmermann R, Mata Pavia J, Wolf U, Wolf M. A review on continuous wave functional near-infrared spectroscopy and imaging instrumentation and methodology. NeuroImage. 2014; 85(Pt 1):6-27.
[11] Tian F, Yennu A, Smith-Osborne A, Gonzalez-Lima F, North CS, Liu H. Prefrontal responses to digit span memory phases in patients with post-traumatic stress disorder (PTSD): a functional near infrared spectroscopy study. NeuroImage Clin. 2014; 4:808-19.
[12] Chou PH, Koike S, Nishimura Y, Kawasaki S, Satomura Y, Kinoshita A, Takizawa R, Kasai K. Distinct effects of duration of untreated psychosis on brain cortical activities in different treatment phases of schizophrenia: a multi-channel near-infrared spectroscopy study. Prog Neuropsychopharmacol Biol Psychiatry. 2014; 49:63-9.
[13] Kito H, Ryokawa A, Kinoshita Y, Sasayama D, Sugiyama N, Ogihara T, Yasaki T, Hagiwara T, Inuzuka S, Takahashi T, Genno H, Nose H, Hanihara T, Washizuka S, Amano N. Comparison of alterations in cerebral hemoglobin oxygenation in late life depression and Alzheimer's disease as assessed by near-infrared spectroscopy. Behav Brain Funct. 2014; doi:10.1186/1744-9081-10-8.
[14] Araki A, Ikegami M, Okayama A, Matsumoto N, Takahashi S, Azuma H, Takahashi M. Improved prefrontal activity in AD/HD children treated with atomoxetine: a NIRS study. Brain Dev. 2014; doi:10.1016/j.braindev.2014.03.011.
[15] Pfurtscheller G, Flotzinger D, Kalcher J. Brain-computer interface-a new communication device for handicapped persons. J Microcomput Appl. 1993; 16(3):293-9.
[16] Nijboer F, Sellers EW, Mellinger J, Jordan MA, Matuz T, Furdea A, Halder S, Mochty U, Krusienski DJ, Vaughan TM, Wolpaw JR, Birbaumer N, Kübler A. A P300-based brain-computer interface for people with amyotrophic lateral sclerosis. Clin Neurophysiol. 2008; 119(8):1909-16.
[17] Min BK, Marzelli MJ, Yoo SS. Neuroimaging-based approaches in the brain–computer interface. Trends Biotechnol. 2010; 28(11):552-60.
[18] Pfurtscheller G, Allison BZ, Brunner C, Bauernfeind G, Solis-Escalante T, Scherer R, Zander TO, Mueller-Putz G, Neuper C, Birbaumer N. The hybrid BCI. Front Neurosci. 2010; doi:10.3389/fnpro.2010.00003 .
[19] Coyle S, Ward T, Markham C, McDarby G. On the suitability of near-infrared (NIR) systems for next-generation brain–computer interfaces. Physiol Meas. 2004; 25(4):815-22.
[20] Coyle SM, Ward TE, Markham CM. Brain-computer interface using a simplified functional near-infrared spectroscopy system. J Neural Eng. 2007; 4(3):219-26.
[21] Naseer N, Hong MJ, Hong KS. Online binary decision decoding using functional near-infrared spectroscopy for the development of brain-computer interface. Exp Brain Res. 2014; 232(2):555-64.
[22] Gallegos-Ayala G, Furdea A, Takano K, Ruf CA, Flor H, Birbaumer N. Brain communication in a completely locked-in patient using bedside near-infrared spectroscopy. Neurology. 2014; 82(21):1930-2.
[23] Birbaumer N, Gallegos-Ayala G, Wildgruber M, Silvoni S, Soekadar SR. Direct brain control and communication in paralysis. Brain Topogr. 2014; 27(1):4-11
[24] Tomita Y, Vialatte FB, Dreyfus G, Mitsukura Y, Bakardjian H, Cichocki A. Bimodal BCI using simultaneously NIRS and EEG. IEEE T Biomed Eng. 2014; 61(4):1274-84.
[25] Cooper RJ, Everdell NL, Enfield LC, Gibson AP, Worley A, Hebden JC. Design and evaluation of a probe for simultaneous EEG and near-infrared imaging of cortical activation. Phys Med

Biol. 2009; 54(7):2093-102.
[26] Lareau E, Lesage F, Pouliot P, Nguyen D, Le Lan J, Sawan M. Multichannel wearable system dedicated for simultaneous electroencephalography/near-infrared spectroscopy real-time data acquisitions. J Biomed Opt. 2011; doi:10.1117/1.3625575.
[27] Safaie J, Grebe R, Moghaddam HA, Wallois F. Toward a fully integrated wireless wearable EEG-NIRS bimodal acquisition system. J Neural Eng. 2013; doi:10.1088/1741-2560/10/5/056001.
[28] Fazli S, Mehnert J, Steinbrink J, Curio G, Villringer A, Müller KR, Blankertz B. Enhanced performance by a hybrid NIRS-EEG brain computer interface. NeuroImage. 2012; 59(1):519-29.
[29] Koo B, Lee HG, Nam Y, Kang H, Koh CS, Shin HC, Choi S. A hybrid NIRS-EEG system for self-paced brain computer interface with online motor imagery. J Neurosci Methods. 2014; doi:10.1016/j.jneumeth.2014.04.016.
[30] Power SD, Kushki A, Chau T. Automatic single-trial discrimination of mental arithmetic, mental singing and the no-control state from prefrontal activity: toward a three-state NIRS-BCI. BMC Res Notes. 2012; doi:10.1186/1756-0500-5-141.
[31] Zimmermann R, Marchal-Crespo L, Edelmann J, Lambercy O, Fluet MC, Riener R, Wolf M, Gassert R. Detection of motor execution using a hybrid fNIRS-biosignal BCI: a feasibility study. J Neuroeng Rehabil. 2013; doi:10.1186/1743-0003-10-4.
[32] Faress A, Chau T. Towards a multimodal brain-computer interface: combining fNIRS and fTCD measurements to enable higher classification accuracy. NeuroImage. 2013; 77:186-94.
[33] Khan MJ, Hong MJ, Hong KS. Decoding of four movement directions using hybrid NIRS-EEG brain-computer interface. Front Hum Neurosci. 2014; doi:10.3389/fnhum.2014.00244
[34] Strait M, Scheutz M. What we can and cannot (yet) do with functional near infrared spectroscopy. Front Neurosci. 2014; doi:10.3389/fnins.2014.00117.
[35] Hwang HJ, Lim JH, Kim DW, Im CH. Evaluation of various mental task combinations for near-infrared spectroscopy-based brain-computer interfaces. J Biomed Opt. 2014; doi:10.1117/1.JBO.19.7.077005.
[36] Schudlo LC, Chau T. Dynamic topographical pattern classification of multichannel prefrontal NIRS signals: II. Online differentiation of mental arithmetic and rest. J Neural Eng. 2014; doi:10.1088/1741-2560/11/1/016003.
[37] Cui X, Bray S, Reiss AL. Speeded near infrared spectroscopy (NIRS) response detection. PLoS ONE. 2010; doi:10.1371/journal.pone.0015474.
[38] Kaiser V, Bauernfeind G, Kreilinger A, Kaufmann T, Kübler A, Neuper C, Müller-Putz GR. Cortical effects of user training in a motor imagery based brain-computer interface measured by fNIRS and EEG. NeuroImage. 2014; 85(Pt 1):432-44.
[39] Power SD, Kushki A, Chau T. Intersession consistency of single-trial classification of the prefrontal response to mental arithmetic and the no-control state by NIRS. PLoS One. 2012; doi:10.1371/journal.pone.0037791.
[40] Zhang Q, Strangman GE, Ganis G. Adaptive filtering to reduce global interference in non-invasive NIRS measures of brain activation: How well and when does it work? NeuroImage. 2009; 45(3):788-94.
[41] Saager RB, Telleri NL, Berger AJ. Two-detector corrected near infrared spectroscopy (C-NIRS) detects hemodynamic activation responses more robustly than single-detector NIRS. NeuroImage. 2011; 55(4):1679-85.
[42] Scholkmann F, Metz AJ, Wolf M. Measuring tissue hemodynamics and oxygenation by continuous-wave functional near-infrared spectroscopy-how robust are the different calculation methods against movement artifacts? Physiol Meas. 2014; 35(4):717-34.
[43] Virtanen J, Noponen T, Meriläinen P. Comparison of principal and independent component analysis in removing extracerebral interference from near-infrared spectroscopy signals. J Biomed Opt. 2009; doi:10.1117/1.3253323.
[44] Shibata T. Therapeutic seal robot as biofeedback medical device: qualitative and quantitative evaluations of robot therapy in dementia care. Proc IEEE. 2012; 100(8):2527-38.
[45] Honda, ATR and shimadzu jointly develop brain-machine interface technology enabling control of a robot by human thought alone. http://world.honda.com/news/2009/c090331Brain-Machine-Interface-echnology/. Accessed 30-Sep-2014.
[46] Chang PH, Lee SH, Gu GM, Lee SH, Jin SH, Yeo SS, Seo JP, Jang SH. The cortical activation pattern by a rehabilitation robotic hand: a functional NIRS study. Front Hum Neurosci. 2014; doi:10.3389/fnhum.2014.00049
[47] Shimizu S, Inoue H, Nara H, Tsuruga T, Miwakeichi F, Hirai N, Kikuchi S, Watanabe E, Kato S. Basic study for new assistive technology based on brain activity during car driving. J Robot Mechatron. 2014; 26(2):253-60.