A Review of Past and Future Near-Infrared Spectroscopy Brain Computer Interface Research at the PRISM Lab

Larissa C. Schudlo, *IEEE and EMBS Student Member*, Sabine Weyand, *IEEE and EMBS Student Member*, and Tom Chau, *IEEE Senior Member*

***Abstract* — Single-trial classification of near-infrared spectroscopy (NIRS) signals for brain-computer interface (BCI) applications has recently gained much attention. This paper reviews research in this area conducted at the PRISM lab (University of Toronto) to date, as well as directions for future work. Thus far, research has included classification of hemodynamic changes induced by the performance of various mental tasks in both offline and online settings, as well as offline classification of cortical changes evoked by different affective states. The majority of NIRS-BCI work has only involved able-bodied individuals. However, preliminary work involving individuals from target BCI-user populations is also underway. In addition to further testing with users with severe disabilities, ongoing and future research will focus on enhancing classification accuracies, communication speed and user experience.**

I. Introduction

Brain computer interfaces (BCIs) can provide individuals with severe motor impairments with a means of communicating and interacting with their environment using only their cognitive activity [1]. Near-infrared spectroscopy (NIRS) is a non-invasive optical imaging technique that measures hemodynamic brain activity. In the past decade, NIRS has gained increasing attention as an access modality in BCIs. NIRS-BCIs are a key topic of investigation at the Pediatric Rehabilitation Intelligent Systems Multidisciplinary (PRISM) lab at the University of Toronto.

This paper reviews the past NIRS-BCI work conducted at the PRISM Lab, and provides insight into the current and future research directions. Section II describes the past work. To date, we have published a total of 13 papers exploring single-trial classification of NIRS signals measured from the anterior prefrontal cortex (aPFC) [2]–[13]. Section III describes the ongoing and future NIRS-BCI research at the PRISM lab, aimed at improving classification accuracies, communication speed and user experience.

II. Past Research

Single-trial classification of NIRS signals for BCI applications can either be performed offline, immediately following the completion of data collection, or online, as the data are collected. Offline classification is typically used to establish suitable approaches for specific classification problems. Online classification is needed for real-time communication and control.

BCIs can also be categorized as either ‘active’, ‘reactive’ or ‘passive’ [14]. In an active system, the user is required to purposefully produce changes in their brain activity using a BCI control task to indicate intent. Alternatively, a reactive system monitors the user’s natural response in reaction to an external stimulus. A passive BCI monitors spontaneous brain state to derive contextual user information. A classification accuracy of 70% is often cited as the accepted minimum threshold for effective communication with a BCI [15].

At this time, research conducted at the PRISM lab has included studies involving able-bodied participants exploring active and reactive BCIs in an offline setting, and active online BCIs. An offline case-study including a client with motor impairments has also been conducted. Table 1 summarizes the studies conducted to date.

A. *Active NIRS-BCIs – Offline Analysis*

To date, our NIRS-BCI studies have largely concentrated on the development of actively controlled systems. A key focus of this research area has been the suitability of different cognitive tasks for BCI control. Mental arithmetic (MA) [2]–[5], [8] and the Verbal Fluency Task (VFT) [9] have proven to be potent mental tasks for driving an NIRS-BCI, with average offline accuracies ranging between 71.2 ± 3.3% and 76.1 ± 8.4% in differentiating these tasks from rest or a control condition. Mental singing (MS) has also been considered for NIRS-BCI use [4] but differentiation from rest has only reached an average rate of 62.7 ± 9.3%, suggesting that a BCI driven by MS may not be suitable for all users. However, MS can be effective in a 2-class synchronous BCI when used together with MA. In differentiating these two tasks, an average classification accuracy of 77.2 ± 7.0% was obtained with 10 individuals [2]. The possibility of a 3-state BCI supporting MA, MS and rest was also considered by Power *et al.*, who were able to differentiate the 3 classes at an average adjusted accuracy of 56.2 ± 8.7%, well above levels of random chance [6].

Perhaps the variability in success with the different tasks can be attributed to the unique cognitive faculties invoked by each task. While MA and VFT utilize one’s working memory, MS heavily relies on an emotional response, which may be more challenging to induce in some individuals. Further exploration of new cognitive tasks for NIRS-BCI control is needed. In addition to evaluating BCI control tasks, other aspects of an NIRS-based communication pathway have been explored, but to a lesser extent.

L.C Schudo, S. Weyand and T. Chau are with the Bloorview Research Institute, Holland Bloorview Kids Rehabilitation Hospital, Toronto, Ontario, Canada and the Institute of Biomaterials and Biomedical Engineering, University of Toronto, Ontario, Canada (T Chau phone: 416-425-6220, ext. 3515; fax: 416-425-1634; e-mail: tom.chau@utoronto.ca).

Communication speed is a significant concern for hemodynamic-based BCIs. Due to the inherent 5-8s post-stimulus latency of the hemodynamic response, most studies have employed a 20s response interval [2]–[5], [8], [9]. However, post-hoc analyses have suggested that shorter durations, such as 15 or 10s, may be feasible for some individuals [4], [8]. A shortened response interval would not only improve communication rates, but would also decrease the mental demand placed on the BCI user.In terms of signal classification, various offline alternatives have been considered, with linear discriminant analysis being the most prevalent choice [3]–[9].

B. Active Hybrid BCIs with NIRS – Offline Analysis

NIRS measurements can be used simultaneously with other modalities to potentially improve classification accuracies. Motivated by the enhanced results achieved by combining NIRS with electroencephalography (EEG) [16], [17], Faress *et al.* explored the development of an active hybrid BCI driven by the VFT that combines NIRS and Transcranial Doppler Ultrasonography (TCD) [9]. TCD is a non-invasive modality that measures blood flow velocity in the cerebral arteries of the brain. With the multi-modal TCD-NIRS system, VFT and post-activation rest were differentiated offline at an average accuracy of 86.5 ± 6.0% across 9 participants. Comparatively, average accuracies of 76.1 ± 9.9% and 79.4 ± 10.3% were achieved using only NIRS and TCD, respectively. Classification accuracies achieved with the multimodal NIRS-TCD system were significantly higher than those obtained using either of the measurement modalities alone for five of the nine participants.

C. Reactive NIRS-BCIs – Offline Analysis

For some individuals, performing a specific cognitive task to exert BCI control may not be feasible. Alternatively, NIRS can be used to detect functional intent by classifying evoked, rather than induced modulations in cortical activity. To this end, NIRS-based detection of emotions has been explored using musically- [12] and visually- [10] induced affective states. With both forms of induction, positive and negative emotional states were discriminated at rates, on average, greater than 70%. The possibility of evaluating subjective preference through the classification of NIRS signals has also be considered [13]. These initial results demonstrate great potential in using NIRS to automatically detect an individual's response to external events through a hemodynamic response alone. However, reactive NIRS-BCI development is still in its infancy. To advance this type of BCI, the robust differentiation of multiple levels of emotional valence and arousal will need to be achieved.

D. Active NIRS-BCIs – Online Analysis

Although the majority of NIRS-BCI studies have exclusively analyzed data offline, progress has been made towards online classification of hemodynamic activity, an imperative for real-world communication and control. Online systems provide a single instance of classifier training (unlike cross-validation in an offline analysis) and offer user feedback. An offline comparison of various online classifier training paradigms found that although a sufficient amount of training data could be collected over multiple sessions, including test session-specific training data resulted in improved online testing results [5]. This type of training paradigm was tested in an online system driven by MA, with the provision of user feedback in terms of a dynamic topographic map representing prefrontal hemodynamic activity [7]. An average online accuracy of 77.4 ± 10.5% was achieved across 2 sessions, which aligns with previous offline results [8]. MS has also been tested in an online

TABLE 1. SUMMARY OF RESULTS. Accuracies represent average classification rates across all study participants. MA = Mental Arithmetic, MS = Mental Singing, VFT = Verbal Fluency Task. [Hb], [HbO, and [tHb] = deoxygenated, oxygenated, and total hemoglobin, respectively. HMM = Hidden Markov Models, LDA = Linear Discriminant Analysis, ANN = Artificial Neural Networks, SVM = Support Vector Machine.

	Paper	States Differentiated	No. Subjects	Accuracy (%) (mean ± std dev)	NIRS Features	Classifier
active offline	Power 2010	MA *vs* MS	10	77.2 ± 7.0	AC intensity	HMM
	Power 2011	MA *vs* rest, MS *vs* rest	8	71.2 ± 3.3 - MA *vs* rest 62.7 ± 9.3 - MS *vs* rest	Slope of AC intensity	LDA
	Power 2012	MA *vs* rest	1	71.1	Slope of [Hb] & [HbO]	LDA
	Power 2012	MA *vs* MS *vs* rest	8	56.2 ± 8.7	Slope of AC intensity	LDA
	Faress 2013	VFT *vs* control state	9	86.5 ± 6.0 - hybrid 76.1 ± 8.4 - NIRS	Slope of [Hb], [HbO] & [tHb]	LDA
active online	Chan 2012	MA *vs* rest	10	63.0 ± 18.9	[Hb] and [HbO]	ANN
	Schudlo 2014	MA *vs* rest	10	77.4 ± 10.5	Slope of [Hb], [HbO] & [tHb]	LDA
passive offline	Tai 2008	positive *vs* negative emotions	10	84.6 ± 8.2	Mean, skewness, kurtosis, total signal energy of [Hb] & [HbO]	LDA, SVM
	Moghimi 2012	positive *vs* negative emotions	10	71.9 ± 8.2	Laterality, mean, slope, coefficient of variation, amplitude change of [Hb] & [HbO]	LDA

system with user feedback in the form of a dynamic bar graph depicting the instantaneous (continuous-valued) classifier output [11]. Although an average accuracy of 63.0 ± 18.9% was achieved in this 2-session study, these online results are comparable to those achieved offline under a similar task paradigm [4].

Though the online NIRS-BCI results achieved so far are encouraging, there is potential for improvement. Because an online system provides feedback, it affords the user an opportunity to learn and improve control over their hemodynamic activity. It is possible that with continued practice (via longer online studies), online results could eventually exceed those obtained offline. Additionally, with more proficient control over one's cortical activity, the response interval or classifier training time could be reduced without significant losses in system performance.

E. Client Case Study – Offline Analysis

Limited research has been conducted with the target user population (*i.e.* non-verbal individuals with severe motor impairments). Target BCI users include individuals with, for example, amyotrophic lateral sclerosis, severe cerebral palsy (CP), high-level cervical spinal cord injuries, or severe muscular dystrophies [1]. In a case study, Power and Chau investigated the potential of an NIRS-BCI with an individual with Duchene muscular dystrophy (DMD) [3]. The 20-year old participant underwent two data collection sessions in which NIRS measurements were taken during MA performance and rest. The two mental states were differentiated at an average offline accuracy of 71.1%. This classification rate is in line with previous studies on able-bodied participants [4], suggesting that an NIRS-BCI driven by MA may be suitable for individuals with neuromuscular disorders. Additional investigations with individuals with DMD and other types of motor impairments are warranted.

III. Ongoing & future Research directions

There are currently several ongoing and future research directions being explored by members of the PRISM lab including: investigating new task combinations, exploring personalized mental task selection, weaning off mental tasks to achieve voluntary self-regulation, moving beyond a binary choice paradigm, measuring from brain areas other than the PFC, and more thorough testing with client populations.

A. Investigating New Tasks & Task Combinations

Many researchers have used MA [2], [4], [5], [7], [8], [18], or motor imagery [18]–[20] for NIRS-BCI control. These tasks appear to be repeatedly chosen since they have consistently proven to induce significant hemodynamic changes for a majority of study participants. Single-trial classification of VFT and MS have also been well explored [2], [4], [9], [11]. However, from a usability perspective, these tasks may not be suited to all individuals during long-term BCI use, especially if they are not particularly enjoyable to the user. A larger collection of user-friendly and effective NIRS-BCI control tasks would expand the versatility of this technology. Other tasks that are known to induce a measureable hemodynamic response include: mental rotation [21], relaxing with counting [22], thinking of happy thoughts [10], and focused attention [23].

B. Exploring Personalized Mental Tasks

In addition to exploring new prescribed task combinations, there is ongoing research on the development of a more user-specific BCI, which allows users to choose their own personalized mental tasks. Use of individually-optimized control tasks has been previously considered in EEG-BCI work [24], and exploration of this approach in an NIRS-based pathway is merited. This research is motivated by the high inter-subject variability in the hemodynamic response and mental task preferences of users. A BCI that allows users to choose their own tasks could be significantly easier to use than one that only supports prescribed mental tasks. Additionally, a personalized BCI may be more enjoyable to use, and in turn result in greater user satisfaction and adoption. A study is currently underway where users are asked to select their preferred BCI control tasks based on performance and ease of use ratings.

C. Weaning from Mental Tasks to Voluntary Self-Regulation of Cortical Activity

Research investigating actively-controlled NIRS-BCIs has primarily focused on using mental tasks to control the system. However, it is possible that users can be weaned off these specific tasks and achieve 'self-regulation', i.e., voluntary control of their cortical activity. Previous EEG-BCI studies have shown that users were able to voluntarily control their physiological signals without the need to perform a particular mental task [25]. Perhaps self-regulation of cortical activity can also be achieved using feedback of NIRS measurements. A BCI driven by voluntary self-regulation could require a lower workload, be more intuitive, and be easier to use than a BCI controlled by specific mental tasks. A study investigating the feasibility of using a neurofeedback-based training paradigm to transition from mental task performance to self-regulation of one's hemodynamic activity is currently underway.

D. Moving Beyond Binary Classification

To date, single-trial classification of NIRS signals has primarily focused on 2-class problems, such as differentiating a task from rest. As NIRS-BCI research advances, it is desirable to increase the number of control channels accessible to users. A BCI that supports 3 or more states would facilitate faster communication. Though the results for a 3-class system obtained by Power *et al.* [6] are encouraging, improvements are necessary for effective communication. Transitioning from binary to ternary classification comes with several challenges, such as determining suitable mental task combinations, and overcoming higher misclassification probabilities.

E. Considering Other Brain Regions

For classification of higher-level cognitive tasks and affective states, NIRS measurements have primarily been taken from the aPFC. This region plays a key role in decision- making, working memory and emotional response. However, mental activities often activate multiple brain regions, rather than a single, isolated area. This could be exploited in an NIRS-BCI. Considering areas other than or in addition to the aPFC may improve classification rates, especially if different tasks activate distinct brain regions. Indeed, others have begun considering multiple brain regions for NIRS-BCIs [18] and further exploration of optimal task and brain region combinations is warranted.

F. Continued Testing with Potential BCI Users

NIRS-BCI studies involving target user populations have been limited in both number and participant size. It cannot be assumed that the results obtained with able-bodied adults will extend to client populations[26]. NIRS data collection with clinical populations may present unique challenges. Subject movement is a particular concern [3]. For users prone to movement, such as individuals with severe hyperkinetic CP, motion artifact correction must be deployed to salvage data and limit user frustration. However, many of the motion correction algorithms proposed for NIRS signals to date cannot be implemented in real-time. Online artifact correction will be essential for thorough testing on different target user populations. Other concerns with clinical testing of NIRS-BCIs include the suitability of certain BCI control tasks, visual requirements of a system's interface, and participant recruitment.

REFERENCES

[1] J. Wolpaw and N. Birbaumer, "Brain-computer interface technology: a review of the first international meeting," *IEEE Trans. Rehabil. Eng.*, vol. 8, no. 2, pp. 164–173, 2000.

[2] S. D. Power, T. H. Falk, and T. Chau, "Classification of prefrontal activity due to mental arithmetic and music imagery using hidden Markov models and frequency domain near-infrared spectroscopy," *J. Neural Eng.*, vol. 7, no. 2, pp. 1–9, 2010.

[3] S. D. Power and T. Chau, "Automatic single-trial classification of prefrontal hemodynamic activity in an individual with Duchenne muscular dystrophy.," *Dev. Neurorehabilitation*, vol. 16, no. 1, pp. 67–72, Jan. 2013.

[4] S. Power, A. Kushki, and T. Chau, "Towards a system-paced near-infrared spectroscopy brain-computer interface: differentiating prefrontal activity due to mental arithmetic and mental singing from the no-control state.," *J. Neural Eng.*, vol. 8, no. 6, p. 066004, 2011.

[5] S. D. Power, A. Kushki, and T. Chau, "Intersession consistency of single-trial classification of the prefrontal response to mental arithmetic and the no-control state by NIRS.," *PloS One*, vol. 7, no. 7, p. e37791, Jan. 2012.

[6] S. D. Power, A. Kushki, and T. Chau, "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*, vol. 5, no. 1, p. 141, 2012.

[7] L. C. Schudlo and T. Chau, "Dynamic topographical pattern classification of multichannel prefrontal NIRS signals : II . Online differentiation of mental arithmetic and rest," vol. 11, pp. 1–14, 2014.

[8] L. C. Schudlo, S. D. Power, and T. Chau, "Dynamic topographical pattern classification of multichannel prefrontal NIRS signals," *J. Neural Eng.*, vol. 10, no. 4, p. 046018, Aug. 2013.

[9] A. Faress and T. Chau, "Towards a multimodal brain-computer interface: combining fNIRS and fTCD measurements to enable higher classification accuracy.," *NeuroImage*, vol. 77, pp. 186–94, Aug. 2013.

[10] K. Tai and T. Chau, "Single-trial classification of NIRS signals during emotional induction tasks: towards a corporeal machine interface.," *J. Neuroengineering Rehabil.*, vol. 6, p. 39, Jan. 2009.

[11] J. Chan, S. Power, and T. Chau, "Investigating the need for modelling temporal dependencies in a brain–computer interface with real-time feedback based on near infrared spectra," *J. Infrared Spectrosc.*, vol. 20, no. 1, p. 107, 2012.

[12] S. Moghimi, A. Kushki, S. Power, A. M. Guerguerian, and T. Chau, "Automatic detection of prefrontal cortical response to emotionally rated music using multi-channel near-infrared spectroscopy," *J. Neural Eng.*, vol. 9, no. 026022, p. 8, 2012.

[13] S. Luu, "Decoding subjective preference from single-trial near-infrared spectroscopy signals," *J. Neural Eng.*, vol. 6, no. 1, p. 016003, 2008.

[14] T. O. Zander and C. Kothe, "Towards passive brain–computer interfaces: applying brain–computer interface technology to human–machine systems in general," *J. Neural Eng.*, vol. 8, no. 2, p. 025005, Apr. 2011.

[15] A. Kubler, V. K. Mushahwar, L. R. Hochberg, and J. P. Donoghue, "BCI meeting 2005-workshop on clinical issues and applications," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 14, no. 2, pp. 131–134, 2006.

[16] S. Fazli, J. Mehnert, J. Steinbrink, G. Curio, A. Villringer, K.-R. Müller, and B. Blankertz, "Enhanced performance by a hybrid NIRS-EEG brain computer interface.," *NeuroImage*, vol. 59, no. 1, pp. 519–29, Jan. 2012.

[17] G. Pfurtscheller, B. Z. Allison, C. Brunner, G. Bauernfeind, T. Solis-Escalante, R. Scherer, T. O. Zander, G. Mueller-Putz, C. Neuper, and N. Birbaumer, "The hybrid BCI," *Front. Neuroprosthetics*, vol. 4, p. 30, 2010.

[18] M. Stangl, G. Bauernfein, J. Kurzmann, R. Scherer, and C. Neuper, "A haemodynamic brain-computer interface based on real-time classification of near infrared spectroscopy signals during motor imagery and mental arithmetic," *J. Infrared Spectrosc.*, vol. 21, no. 3, p. 157, 2013.

[19] S. M. Coyle, T. E. Ward, and C. M. Markham, "Brain–computer interface using a simplified functional near-infrared spectroscopy system," *J. Neural Eng.*, vol. 4, no. 3, pp. 219–226, Sep. 2007.

[20] R. Sitaram, H. Zhang, C. Guan, M. Thulasidas, Y. Hoshi, A. Ishikawa, K. Shimizu, and N. Birbaumer, "Temporal classification of multichannel near-infrared spectroscopy signals of motor imagery for developing a brain-computer interface," *NeuroImage*, vol. 34, no. 4, pp. 1416–1427, 2007.

[21] C. Herff, D. Heger, F. Putze, J. Hennrich, O. Fortmann, and T. Schultz, "Classification of mental tasks in the prefrontal cortex using fNIRS.," *Conf. Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. IEEE Eng. Med. Biol. Soc. Conf.*, pp. 2160–3, Jul. 2013.

[22] N. Naseer and K.-S. Hong, "Functional near-infrared spectroscopy based discrimination of mental counting and no-control state for development of a brain-computer interface.," *Conf. Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. IEEE Eng. Med. Biol. Soc. Conf.*, vol. 2013, pp. 1780–3, Jul. 2013.

[23] K. Izzetoglu, H. Ayaz, A. Merzagora, M. Izzetoglu, P. a. Shewokis, S. C. Bunce, K. Pourrezaei, A. Rosen, and B. Onaral, "The Evolution Of Field Deployable fNIR Spectroscopy From Bench To Clinical Settings," *J. Innov. Opt. Health Sci.*, vol. 04, no. 03, pp. 239–250, Jul. 2011.

[24] E. V. C. Friedrich, R. Scherer, and C. Neuper, "The effect of distinct mental strategies on classification performance for brain–computer interfaces," *Int. J. Psychophysiol.*, vol. 84, no. 1, pp. 86–94, Apr. 2012.

[25] A. Kübler, B. Kotchoubey, T. Hinterberger, N. Ghanayim, J. Perelmouter, M. Schauer, C. Fritsch, E. Taub, and N. Birbaumer, "The thought translation device: a neurophysiological approach to communication in total motor paralysis," *Exp. Brain Res. Exp. Hirnforsch. Expérimentation Cérébrale*, vol. 124, no. 2, pp. 223–232, Jan. 1999.

[26] E. W. Sellers and E. Donchin, "A P300-based brain-computer interface: Initial tests by ALS patients," *Clin. Neurophysiol.*, vol. 117, no. 3, pp. 538–548, 2006.