Harnessing Physiological Responses to Improve NIRS-Based Brain-Computer Interface Performance

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Abstract—**This study investigated the inclusion of physiological responses due to mental activity tasks as complementary information for improved-performance brain-computer interfaces (BCI) based on near-infrared spectroscopy (NIRS). Cortical hemodynamic responses due to music imagery tasks, combined with physiological responses, were collected from six able-bodied participants. Hidden Markov models (HMM) were used to model the normative physiological and hemodynamic responses of the individual at rest. A normalized log-likelihood measured was proposed for automated detection of music imagery events, which in turn, were used as BCI control signals. Experimental results suggest that improved performance is attained once physiological signals are incorporated into the BCI design. More specifically, improvements of 13% and 7% were observed in system sensitivity and specificity, respectively. These results suggest that physiological signals can be used to enhance the performance of NIRS-based BCIs and thus provide a more reliable communicative channel for individuals with severe motor impairments.**

I. Introduction

Individuals with severe motor disabilities necessitate the use of access technologies, or human-machine interfaces, to translate user intentions into useful control signals. Eye gaze [1], head [2], and tongue control devices [3] are a few examples of such technologies. However, these require some degree of voluntary motor control and are therefore unsuitable for locked-in individuals who lack any functional motor or speech skills. These individuals often have full cognitive awareness but are unable to make their non-functional bodies respond appropriately to their intentions. Brain-computer interfaces (BCI) have been shown to be reliable access solutions for such individuals [4].

Near-infrared spectroscopy (NIRS) has recently been investigated as a non-invasive method of measuring cortical hemodynamic responses for BCI design [5]. NIRS operates by determining the properties of a substance by transmitting near-infrared electromagnetic radiation (650 nm - 950 nm wavelengths) through the substance and comparing the intensities of the returning and incident light. BCIs based on NIRS technologies image the brain to harness hemodynamic responses resultant from mental activity. More specifically, certain mental activities (e.g., music imagery) cause changes in regional concentrations of oxygenated and deoxygenated hemoglobin due to an increase in blood flow and metabolic demands, hence altering the optical properties of the brain. Since the amount of light absorbed versus the fraction reflected is mostly dependent on the concentrations of such hemoglobins, hemodynamic responses can be assessed via NIRS [6]. This response has been shown to have a latency of 5-8 seconds post voluntary activation and can be measured from the prefrontal cortex [7].

Previous studies have shown that music imagery can elicit [8] and enhance [9] the intense emotional responses required to activate the prefrontal cortex [7]. Furthermore, prefrontal hemodynamic responses to imagined singing of subject-selected music have been observed by functional magnetic resonance [10]. Similarly, physiological responses such as changes to electrodermal activity and respiration rate have been shown to be elicited by cognitive tasks similar to those used by NIRS-BCI systems (i.e., music imagery) [11], [12]. As a consequence, the purpose of this study was to investigate the potential of incorporating physiological responses to improve NIRS-based BCI performance.

Four non-invasively acquired physiological signals were explored, namely, electrodermal activity, skin temperature, respiration rate, and heart rate. Physiological responses were collected in combination with hemodynamic responses as participants performed a music imagery task. The developed system made use of hidden Markov models to distinguish between baseline (i.e., rest) and music imagery events; such discrimination was used to develop BCI control signals. Experiments with six participants showed that improved BCI performance was attained once physiological and hemodynamic responses were combined.

The remainder of this paper is organized as follows. Section II provides a description of the proposed system. Section III presents the study protocol and the obtained experimental results. Discussion and conclusions are presented in Sections IV and V, respectively.

II. System Description

Figure 1 illustrates the overall design of the proposed system. Hemodynamic responses (HemoR) in the prefrontal cortex were collected simultaneously with four physiological modalities, namely electrodermal activity (EDA), skin temperature (ST), respiration rate (RR), and heart rate (HR), while the participant sat quietly at rest (baseline) and while the participant performed a task which consisted of alternating between rest and music imagery (test). Baseline data was used to train user-specific reference hidden Marokov models (HMM) representative of the normative physiological and hemodynamic responses of the participant at rest. Test data was scored against the reference HMMs via a log-likelihood

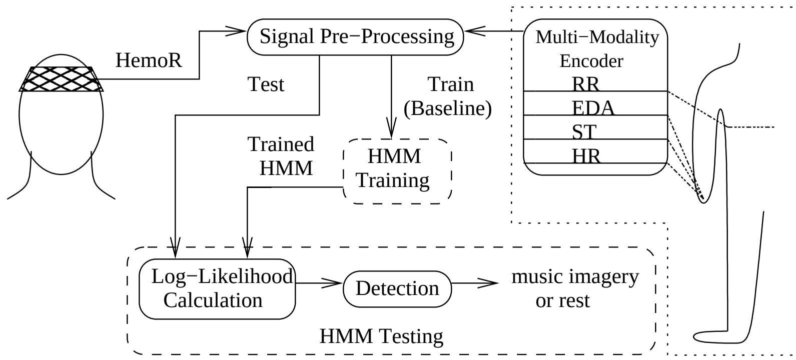

Fig. 1. Study overview – Cortical hemodynamic responses (HemoR) were collected using NIRS technology with a custom-designed headband while electrodermal activity (EDA), skin temperature (ST), heart rate (HR), and respiration rate (RR) were collected by a multi-modality encoder. Responses were collected from participants while they sat at rest (used for HMM training) and while they performed rest-plus-music imagery tasks (used for system testing). BCI control signals were generated based on the detected music imagery events.

measure which was then used for automatic music imagery detection; detection of such events could be used as control signals for BCI usage. A detailed description of the system is provided in the subsections to follow.

A. Measurement of Hemodynamic Responses

Near-infrared spectroscopy was used to measure the hemodynamic response in the frontopolar cortex, the superior portion of the orbitofrontal cortex, and the medial sections of the dorsolateral prefrontal cortex via the Imagent Function Brain Imaging System from ISS Inc. Sixteen light sources (eight at 690 nm and eight at 830 nm) delivered 110-MHz modulated light to the forehead which was returned to two photomultiplier tube detectors at a demodulated cross-correlation frequency of 5kHz. The light sources were multiplexed to avoid cross-signal contamination resulting in an effective sampling rate of 31.25 Hz. A fast Fourier transform was applied to the collected signals and DC data components (relative amplitude at 0 Hz) were output.

B. Measurement of Physiological Responses

The four physiological signals were recorded simultaneously using the ProComp Infiniti multi-modality encoder from Thought Technology at a sampling frequency of 256 Hz. All sensors were placed on the participant's non-dominant hand. Electrodermal activity was measured from two 10 mm diameter Ag-AgCl surface electrodes attached with adhesive collars on the medial phalanges of the index and middle fingers. Medial phalanges were chosen as they represent a region of the skin containing a high density of sweat glands. A constant 0.5 V was applied between the two electrodes. Skin temperature was measured using a thermal sensor on the distal phalange of the fifth finger. Heart rate was computed from the interbeat intervals of the blood volume pressure waveform obtained with a photoplethysmograph sensor. Lastly, respiration rate was measured by positioning a piezoelectric belt around the thoracic area; stretching due to expansion and contraction of the chest were converted into voltages.

C. Signal Pre-Processing

Physiological signal pre-processing consisted of downsampling to 31.25 Hz and noise reduction via fifth order lowpass Butterworth filters with cutoff frequencies at 0.2, 0.1, 1.2, and 0.3 Hz for EDA, ST, RR, and HR signals, respectively. NIRS signals, in turn, were denoised using wavelet-based filters as suggested by the work described in [6]. Filtering was performed via a 12-level decomposition using the Daubechies-12 wavelet and consisted of the reconstruction of the approximation wavelet coefficients with either the last three, four, or five detail coefficients (henceforth termed 3-, 4-, or 5-detail filters, respectively).

D. Hidden Markov Models

Hidden Markov models (HMM) have been commonly used for applications such as speech recognition and are not detailed here; the reader is referred to [13] for a full discussion. In this study, HMMs were used to model the normative hemodynamic and physiological responses of an individual at rest. During music imagery tasks, it is expected that the investigated NIRS and physiological signals deviate from the observed baseline responses and such deviations can be used for BCI control. To explore the benefits of harnessing physiological responses, HMMs were trained on NIRS signals alone and on NIRS combined with physiological signals.

To allow for a user-centred BCI design [14], different HMM parameters, such as number of states (Q) and number of full-covariance Gaussian components (M) in the Gaussian mixture output distributions, were explored on a per-participant basis. Model parameters, including state transition and initial state probabilities and output distribution parameters, were computed via the commonly used expectation-maximization algorithm summarized in [13]. Pilot experiments suggested that the following "$Q-M$" HMM configurations provided a balance between system performance and model complexity: $Q = 4$, $M = 1,2$, or 3, or $Q = 2, M = 1$, or 2.

E. Automatic Music Imagery Detection

By training HMMs on baseline data, a log-likelihood measure could be used for automatic music imagery detection.

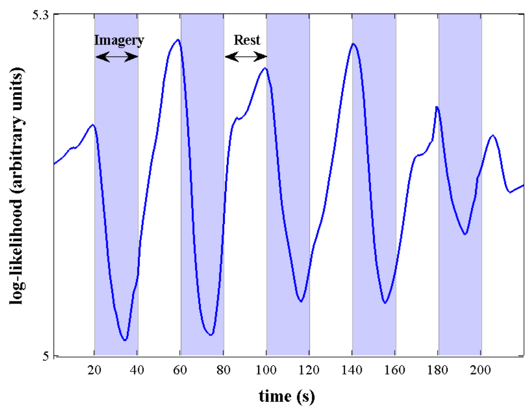

Fig. 2. Log-likelihood temporal series computed from test data consisting of alternating rest (unshaded) and imagery (shaded) periods.

More specifically, higher log-likelihood values were indicative that the observed responses (either hemodynamic alone or hemodynamic combined with physiological) were similar to those observed during rest. Lower log-likelihood values, in turn, suggested that the observed responses deviated from rest and could indicate controlled mental activity. Figure 2 depicts a representative log-likelihood temporal series with the expected increases during rest (unshaded regions) and decreases during music imagery (shaded regions).

Due to the nature of the log-likelihood function, complex machine learning algorithms were not necessary for music imagery detection. In lieu, simple changes in the sign of the slope (from positive to negative) of the log-likelihood function were used for imagery detection. To minimize the effects of mind wandering, music imagery events were detected only if a decrease in log-likelihood was sustained for a minimum of 5 seconds. Log-likelihood values were computed for different window lengths ranging from $l = 1-15$ seconds and for different window overlaps ranging from $s = 0.3-1$ seconds; normalization was performed based on the investigated window length. The use of different window sizes and overlap was motivated by the differences in reaction times among participants which may have been due to factors such as mental alertness, innate reaction times, and familiarity with the procedure.

III. Experimental Results

This section describes the data collection protocol and performance metrics used, as well as reports the obtained experimental results.

A. Data Collection

Six able-bodied participants (four female, two male) with a mean age of 28.5 ± 11.6 years were recruited. Ethics approval for this study was obtained from the affiliated institutes and participants freely consented to participate. The study consisted of four sessions completed on two separate days. Two sessions were baseline trials, each 130 seconds in duration, wherein the participant was sitting at rest in a neutral state of mind and was instructed to focus on their breathing. The remaining two sessions were test trials, each 220 seconds in duration, wherein the participant alternated between 20 second rest and music imagery intervals (see Fig. 2); interval transitions were cued by a light tap on the arm. Each test trial started and ended with rest intervals and each participant performed music imagery on self-selected songs which elicited emotions of the same valency (i.e., ”happy” or ”sad”).

B. Performance Metrics

Two performance metrics were used to gauge system performance, sensitivity and specificity. Sensitivity measured how accurately expected imagery events were detected, whereas specificity measured how accurately expected rest intervals were identified. The measures were computed as

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP+FN}} \times 100\%, \quad (1)$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN+FP}} \times 100\%, \quad (2)$$

where TP and TN referred to true positives and true negatives, respectively; FP and FN referred to false positives (erroneous BCI activation) and false negatives (undetected music imagery).

For the NIRS-trained HMMs, an expected imagery interval (true positive) was detected if a sustained slope decrease in the log-likelihood series occurred within the first 13 seconds of an imagery interval. This grace period compensated for the latencies in the hemodynamics-driven signal, which can be upwards of eight seconds [5], and the participant's reaction time to begin imagery upon being cued, which was found to be around five seconds in pilot experiments. For the physiologically enhanced NIRS-trained HMMs, this grace period was shortened to 7.5 seconds as physiological responses were found in pilot experiments to posses shorter latencies (on average 3.5 ± 0.9 seconds) relative to hemodynamic responses. If no activation was detected within this window, an incorrectly identified rest interval was classified and a false negative was observed. Activations detected in expected rest intervals were deemed false positives while expected rest intervals with no activations were classified as true negatives.

C. Quantitative Results

Table I reports per-participant sensitivity (labeled “sens”) and specificity (labeled “spec”) values obtained with the NIRS-driven and NIRS-plus-physiological HMM-based BCI paradigms. To allow for a user-centred BCI design [14], optimal combinations of filter detail d, HMM parameters (Q and M), and log-likelihood window l and overlap s sizes were obtained on a per-participant basis. As can be seen, system sensitivity is significantly increased once physiological responses are incorporated into the BCI design ($p < 0.1$, t-test). Specificity is also improved, although not as significantly ($p < 0.3$). Overall, average increases of approximately 13% and 7% were observed for sensitivity and specificity measures, respectively.

TABLE I

PER-PARTICIPANT COMPARISON OF THE PERFORMANCES OBTAINED WHEN USING HMMS TRAINED ON ONLY NIRS SIGNALS AND THOSE TRAINED WITH NIRS-PLUS-PHYSIOLOGICAL SIGNALS. AVERAGE AND STANDARD DEVIATION ("ST. DEV.") VALUES, COMPUTED OVER THE SIX PARTICIPANTS, ARE ALSO REPORTED.

	NIRS Only		Physio & NIRS	
Subject	**Sens**	**Spec**	**Sens**	**Spec**
1	80.0	92.0	83.3	100.0
2	100.0	58.0	100.0	91.7
3	80.0	58.0	77.5	66.7
4	50.0	100.0	80.0	91.7
5	80.0	83.0	100.0	50.0
6	90.0	75.0	100.0	100.0
mean	**80.0**	**77.7**	**90.1**	**83.3**
st. dev.	**16.7**	**17.4**	**11.0**	**20.4**

IV. DISCUSSION

To customize the physiologically enhanced NIRS-based BCI for each participant, a calibration session with known imagery and rest intervals would be required to determine optimal log-likelihood and HMM parameters. This optimization process could be performed with minimal intervention by an outside party, similar to the calibration session required by existing commercially-available speech recognizers. Furthermore, since only normative baseline data was required for HMM training, as opposed to baseline and imagery data required by competing BCIs, the calibration session could be relatively short on the order of tens of seconds.

The simplicity of the proposed system lies in the nature of the cognitive task employed and its ability to elicit both hemodynamic and physiological responses. Traditional BCIs use only a single modality and therefore may limit the participant's ability to control the interface. By harnessing the physiological responses that simultaneously occur with the hemodynamic responses, a more comprehensive view of the participant's response to the cognitive task was observed and thus the output control signal was more representative of the participant's intent.

Although the delay in detecting activations is not ideal for online activities, e-book reading or television remote controlling may be suitable applications. Further studies may investigate the use of different combinations of physiological signals which would be more appropriate for individuals with a disability (e.g., individuals with spinal cord injury who may not benefit from using the electrodermal response [11]). Furthermore, the hemodynamic and/or physiological signals may be responsive to environmental noise and therefore may require compensation strategies to differentiate between voluntary and involuntary responses.

V. CONCLUSIONS

This study proposed a physiologically enhanced NIRS-based BCI system. Subject-specific hidden Markov models trained on NIRS-driven hemodynamics responses and four independent physiological responses, namely, electrodermal activity, skin temperature, respiration rate, and heart rate, were used to differentiate between two cognitive states: rest and music imagery. Experimental results with NIRS-trained HMMs showed sensitivity and specificity values of (80.0 $\pm$ 16.7)% and (77.7 $\pm$ 17.4)%, respectively. By including the physiological responses, sensitivity and specificity increased to (90.1 $\pm$ 11.0)% and (83.3 $\pm$ 20.4)%, respectively, resulting in performance gains of 13% and 7%. These promising results motivate further investigations of using physiological responses to improve the performance of traditional BCI systems, in particular for individuals in the target population.

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