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Automatic detection of a prefrontal cortical response to emotionally rated music using multi-channel near-infrared spectroscopy

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Abstract
Emotional responses can be induced by external sensory stimuli. For severely disabled nonverbal individuals who have no means of communication, the decoding of emotion may offer insight into an individual's state of mind and his/her response to events taking place in the surrounding environment. Near-infrared spectroscopy (NIRS) provides an opportunity for bed-side monitoring of emotions via measurement of hemodynamic activity in the prefrontal cortex, a brain region known to be involved in emotion processing. In this paper, prefrontal cortex activity of ten able-bodied participants was monitored using NIRS as they listened to 78 music excerpts with different emotional content and a control acoustic stimuli consisting of the Brown noise. The participants rated their emotional state after listening to each excerpt along the dimensions of valence (positive versus negative) and arousal (intense versus neutral). These ratings were used to label the NIRS trial data. Using a linear discriminant analysis-based classifier and a two-dimensional time-domain feature set, trials with positive and negative emotions were discriminated with an average accuracy of 71.94% ± 8.19%. Trials with audible Brown noise representing a neutral response were differentiated from high arousal trials with an average accuracy of 71.93% ± 9.09% using a two-dimensional feature set. In nine out of the ten participants, response to the neutral Brown noise was differentiated from high arousal trials with accuracies exceeding chance level, and positive versus negative emotional differentiation accuracies exceeded the chance level in seven out of the ten participants. These results illustrate that NIRS recordings of the prefrontal cortex during presentation of music with emotional content can be automatically decoded in terms of both valence and arousal encouraging future investigation of NIRS-based emotion detection in individuals with severe disabilities.

1. Introduction

Emotions are patterns of experience, perception, action and communication that can be animated in response to physical and social encounters (Keltner and Gross 1999). Some theories suggest that emotions can be manifested as a result of human interactions with the surrounding environment (Frijda and Mesquita 1994, Lazarus 1991, Campos *et al* 1989), which result in physiological changes (Oatley *et al* 2006) such as the modulation of central and peripheral nervous system

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activity (Blood and Zatorre 2001, Herrmann *et al* 2003, Baumgartner *et al* 2006, Collet *et al* 1997, Sinha *et al* 1992, Krumhansl 1997). These changes may facilitate the identification of emotional state in non-verbal individuals with severe disabilities who may have no other means of expression. Of particular appeal is the detection of affective responses through brain activity monitoring, as there is no requirement for voluntary motor control. Indeed, computer-based detection of emotional responses may enhance 'implicit' communication about the user in human–computer interaction systems (Cowie *et al* 2001). Affective computing has long been touted for its potential for more realistic and user-accommodating interactions (Picard 2000). An emotionally aware system stands to benefit non-verbal individuals with severe disabilities by estimating their emotional state in the absence of more direct means of interaction (e.g. speech and gestures). In turn, knowledge of the patient's affective state may help to mitigate care-giver stress and facilitate treatment decisions in a timely fashion (Happ 2000).

Various brain circuits including parts of the limbic system and amygdala are responsible for perception of emotional stimuli (Panksepp and Bernatzky 2002, Siegel and Edinger 1981, LeDoux 2001). In addition, the frontal region of the human brain is involved in regulating emotional response to sensory input (Rolls 2000, Davidson 2004, 1992). For example, severity of the depressive symptomatology in patients following stroke lesions was reported to be significantly correlated with proximity of the lesion to the frontal pole (Robinson *et al* 1984). Moreover, left and right frontal activations were also found in response to watching video clips inducing positive and negative emotional responses, respectively (Wheeler *et al* 1993). Activations in the orbito-frontal and ventral prefrontal cortex in response to highly pleasurable self-selected music excerpts have also been reported (Blood and Zatorre 2001).

Among various brain measurement modalities such as electroencephalography (Niedermeyer and Da Silva 2005), positron emission tomography (Ter-Pogossian *et al* 1980), magnetoencephalography (Hämäläinen *et al* 1993) and magnetic resonance imaging (Bushong 1988), near infra-red spectroscopy (NIRS) is particularly well suited to long-term bedside monitoring of prefrontal cortex activity. NIRS involves the optical measurement of changes in oxygenated (HBO_2) and deoxygenated hemoglobin (HHb) concentrations in regional cerebral blood flow (Jobsis 1977, Villringer *et al* 1993). Being an optical modality, NIRS measurements are not susceptible to electrogenic artifacts such as electrooculograms and electromyograms.

NIRS has been used previously to detect emotional responses in the prefrontal cortex. Recent findings with emotionally laden visual stimuli have confirmed the presence of prefrontal cortex activations detectable by NIRS (Herrmann *et al* 2003, Yang *et al* 2007, Hoshi *et al* 2011). Likewise, in the context of automatic emotion detection, Tai and Chau (2009) were able to differentiate between prefrontal responses to affective pictures and baseline activity on a single-trial basis with an average of 75% accuracy. However, the perception of visual stimuli may require gaze fixation and the control of the eye muscles responsible for keeping the eyes open. Therefore, individuals with severe disabilities who possess little or no voluntary muscle control, possibly concomitant with vision impairment, may not be able to observe visual stimuli. However, evidence suggests that aural stimuli, the perception of which requires no voluntary muscle control, can also elicit a pre-frontal response (Blood and Zatorre 2001, Blood *et al* 1999, Boso *et al* 2006). Previous findings indicate that when used as a BCI control task, active music imagery (mental singing) can be differentiated from the rest state and mental math with accuracies significantly above chance (Power *et al* 2010, Falk *et al* 2011, Guirgis *et al* 2010). However, NIRS-based automatic detection of passive prefrontal responses to affective aural stimuli remains unexplored to date.

In this study, we examined the feasibility of automatically detecting emotional responses to aural stimuli by near-infrared spectroscopic interrogation of the prefrontal cortex. Music in particular is recognized for its ability to induce an emotional response in a wide array of individuals (Meyer 1956). The emotional content of music is known to be perceived across cultures (Fritz *et al* 2009) and distinguished by children as young as 6 years of age (Dalla Bella *et al* 2001). In fact, music has been frequently used as an emotional auditory stimulus (Koelsch 2005, Kreutz *et al* 2008, Hopyan *et al* 2006, Spackman *et al* 2005, Gerrards-Hesse *et al* 1994). In this paper, music excerpts were thus used for inducing affective brain activity.

2. Methods

2.1. Participants

We recruited ten able-bodied volunteers (five females, five males, age: 25 ± 2.7 years). The participants reported to have normal hearing, and normal or corrected-to-normal vision. The recruitment criteria excluded individuals with reported cardiovascular diseases, metabolic disorders, history of brain injury, respiratory conditions, drug and alcohol-related and psychiatric conditions. Participants were instructed to refrain from caffeine and alcohol consumption 5 h prior to the study. Volunteers had an average of 5.5 years of past music training. Ethics approval was obtained from the Bloorview Research Institute research ethics board and all participants provided informed written consent.

2.2. Stimuli

The stimuli were composed of 78 researcher-selected and 6 participant-selected musical pieces. All music segments were 45 s in duration. The excerpts included lyrical and non-lyrical pieces. The lyrics were in different languages (English, French, Italian and Spanish) to reduce potential effects of brain activation due to mental singing. The 78 standard music pieces were chosen by two researchers from different genres of music (classical, rock, jazz and pop). Specifically, candidate pieces were assessed in terms of their valence characteristics as suggested by the tone, rhythm and lyrics (where applicable). Note that the researcher assessments were used solely to ensure an approximately uniform representation of music between

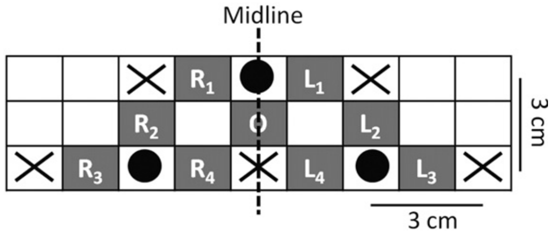

Figure 1. The layout of light sources (circles) and detectors (Xs). The vertical line denotes the anatomical midline. The annotated shaded areas correspond to recording locations.

Onset beep	Brown noise	Aural stimuli	Brown noise	Offset Beep	Participant Rating
2 sec.	10 sec.	45 sec.	5 sec.	2 sec.	N/A

Figure 2. Trial sequence.

valences (positive versus negative). The actual data analysis described in section 2.5 relied solely on participant ratings of valence and arousal. For the participant-selected pieces, participants chose *a priori* three pieces of music that personally induced intense positive emotions (joy or excitement) and three that induced intense negative emotions (sadness). The control acoustic stimulus was Brown noise (BN). User feedback in our pilot studies indicated that this type of noise was subjectively more pleasant than white noise at the same sound pressure level (Vossa and Clarke 1978).

2.3. Measurements

An Imagent Functional Brain Imaging System from ISS Inc. (Champaign, IL) was used for NIRS measurements. A custom-made rubber polymer (3M 9900 series) headgear held three light detectors and ten light sources in place over the forehead, as depicted in figure 1. At each ‘X’ location in figure 1, two light sources, one at 830 nm and the other at 690 nm, were co-located. This layout had been previously used for prefrontal cortex monitoring in Power *et al* (2010) and provided readings at the nine shaded locations in figure 1. With data from two wavelengths, this configuration yielded 18 different channels of light intensity readings. The midpoint of the headgear was aligned to anatomical midline (as estimated by the position of the participant’s nose), while the lower edge of the headgear sat just above the eyebrows. Light sources were modulated at 110 MHz and the detector amplifiers were modulated at 110.05 MHz which led to a cross-correlation frequency of 5 kHz. The data were sampled at 31.25 Hz. During a complete cycle of all ten sources, each source illuminated the surface for 1.6 ms during which eight acquisitions were made. A fast Fourier transform (FFT) was applied to the average of the eight waveforms to obtain an estimate of ac and dc intensities as well as the phase delay (Power *et al* 2010). The dc light intensities were used to determine HHb and HBO_2 concentrations.

2.4. Procedures

Each participant attended four sessions, which occurred on separate days, no more than four weeks apart. In each session, participants completed three blocks with optional breaks between blocks. Each block consisted of 12 consecutive trials: four trials with positively valenced songs (one of which was a participant-selected song), four trials with negatively valence songs (one of which was a participant-selected song) and four BN trials. Within a block, the music and BN trials were pseudo-randomized, such that two BN trials never occurred consecutively while positively and negatively valenced songs appeared in no apparent order. The same pseudo-random sequence of trials was employed for all participants.

Figure 2 depicts a trial sequence. In each trial, the participant listened to 10 s of BN, followed by a 45 s auditory stimulus (music or BN), and finally 5 s of BN. The sound level was faded in and out at the beginning and end of the trial, respectively, to reduce the risk of eliciting a startle. At the end of each trial, the participant rated the intensity and valence of their emotional experience using a nine-level self-assessment Manikin (Morris 1995). The beginning and end of each trial was marked by an audible tone. The participants were instructed to close their eyes when they heard the initial tone, and to open their eyes upon hearing the second tone.

2.5. Data analysis

- *Pre-processing procedure.* Low-frequency artifacts such as respiration, heart rate and the Mayer wave were filtered using a type II third order Chebychev low pass filter with a cut-off frequency of 0.1 Hz (normalized stop-band edge frequency of 0.032 and stop-band ripple of 50 dB down from the peak pass-band value) (Power *et al* 2011). The 830 nm and 630 nm light intensities at each of the nine recording sites were used to calculate HBO_2 and HHb concentrations via the modified Beer–Lambert law (Cope 1991, Duncan *et al* 1995), which resulted in 18 channels of concentration data.

  To reduce the effects of initial device calibration, the concentration time series were normalized within each experimental block against the mean in the same block.
- *Features.* Two genres of features were considered: laterality features and single-channel features. All features were extracted from HBO_2 and HHb concentrations. Table 1 summarizes the features used. Single-channel features were calculated at each of the nine interrogation locations and consisted of the mean, slope and coefficient of variation of the concentration signals during the 45 s aural stimuli period, as well as the change in the average concentration from the preceding baseline period to the task period. The slope was determined by fitting a line using linear regression to all data points in the 45 s trial window and calculating the corresponding slope. The coefficient of variation was determined by finding the ratio of the variance to the mean over the course of the trial. Such features have previously characterized task-based activation in the prefrontal cortex (Power *et al* 2011, Tai and Chau 2009, Naito *et al* 2007). In total, there were 4 features/location $\times$ 9 locations $\times$ 2 chromophore concentrations = 72 single-channel features.

Table 1. Summary of features used in the analysis.

Feature type	Features
Laterality features	Lateral slope ratio (LSR) = right concentration slope/left concentration slope Lateral absolute mean difference (Δ LM) = |left concentration mean − right concentration mean|
Single channel-based features	Stimuli period mean (M) Stimuli period slope (S) Coefficient of variation (CV) Mean difference between signal and noise (ΔM) = stimuli period mean − preceding noise period mean

The two laterality features quantified differences in activity between the left and the right sides, and thus were calculated for each of the four pairs of interrogation locations symmetrical about the midline (i.e. 1L-1R, 2L-2R, 3L-3R and 4L-4R in figure 1). Laterality features included the ratio of the concentration signal slopes, and the difference in the average signal values, between corresponding left and right channels. The inclusion of these features was motivated by physiological findings that confirm lateralized activations in response to emotional stimuli (Wheeler *et al* 1993, Davidson 1992, Altenmüller *et al* 2002). In total, there were 2 features/channel pair × 4 channel pairs × 2 chromophore concentrations = 16 laterality features.

- *Classification procedures*. For each trial, 65 s of data were extracted, including the 45 s stimulus period and the preceding (10 s) and subsequent (5 s) BN periods. The trials with BN were set aside, and the rest of the data were partitioned according to arousal and valence ratings. For the analysis of arousal, the 48 highest rated trials (out of 96 trials with music) over all four sessions were selected. For the valence component, the 24 highest positively rated and 24 highest negatively rated trials across all four sessions (out of 96 trials with music) were selected. The high arousal (HA), positive valence (PV), negative valence (NV) and BN trials were labeled accordingly. Note that arousal and valence labeling were performed independently (Nhan and Chau 2010, Russell 1980).

A classifier based on the linear discriminant analysis (LDA) (Duda *et al* 2001) was used to solve two different two-class classification problems (HA versus BN and PV versus NV). Comparing the two valence categories (i.e. PV and NV) individually with the BN was not feasible due to the difference in sample sizes ($n_{HV} = n_{LV} = 24$, $n_{BN} = 48$). The classification accuracy was estimated using the average of 50 independent iterations of tenfold cross-validation. The classification accuracy was defined as the ratio of the number of correctly classified samples over the size of the testing data. Due to the differences in prefrontal activation in different participants, feature selection was performed to select a subset of the feature set that best separated the two classes for each participant. To measure separability, we used the Fisher score which is (Duda *et al* 2001) defined as the ratio of the difference between the mean of features extracted from each class under investigation to the sum of variances of features from each class on the training data. The Fisher score for each feature was calculated and the top two features with the highest score were selected for classification. Adjusted classification accuracy was defined as the average of classifier sensitivity and specificity in each iteration of classifier evaluation shown in (1). Adjusted accuracy was more suitable for unbalanced datasets where the number of samples belonging to the two classes was different (Zeng *et al* 2002, Manoharan *et al* 2008):

$$\text{adjusted accuracy} = \frac{1}{2}\left(\frac{\text{true positives}}{\text{true positives} + \text{false negatives}} + \frac{\text{true negatives}}{\text{true negatives} + \text{false positives}}\right) \quad (1)$$

3. Results

Figure 3 depicts normalized sample concentration recordings from all recording locations for participant 3. Figures 3(a) and (b) are recordings during a music excerpt rated as highly arousing and strongly positive, whereas figures 3(c) and (d) are normalized sample recordings from one of the most arousing but most negatively rated trials. Recordings during a sample BN trial are provided for comparison in both cases. Some immediate patterns are evident. For both HBO_2 plots, we notice a general increase in concentration (hyper-oxygenation), illustrated in figures 3(a) and (c). The hyper-oxygenation occurs at different points in time during exposure to various auditory stimuli. In both positive- and negative-rated trials depicted in figure 3, a decrease in the HHb concentration following hyper-oxygenation is observed which is consistent with previous findings of functional NIRS studies (Obrig *et al* 1996, Meek *et al* 1995). The valenced responses are visibly distinct from the sample BN response (light gray traces).

The average classification accuracies for the valence (PV versus NV) and arousal (HA versus BN) classification problems are reported in tables 2 and 3, respectively, for each participant. The best accuracy averaged over all participants was obtained with two-dimensional feature sets for both HA versus BN (71.93%), and PV versus NV (71.94%) classification problems. Tables 2 and 3 also summarize the different features selected by the feature selection algorithm for each classification problem and each participant. As seen, the optimal feature set was different for each participant.

The spatial distribution of features leading to the best accuracies are marked in figure 4 for the HA versus BN and PV versus NV classification problems. In these figures, the

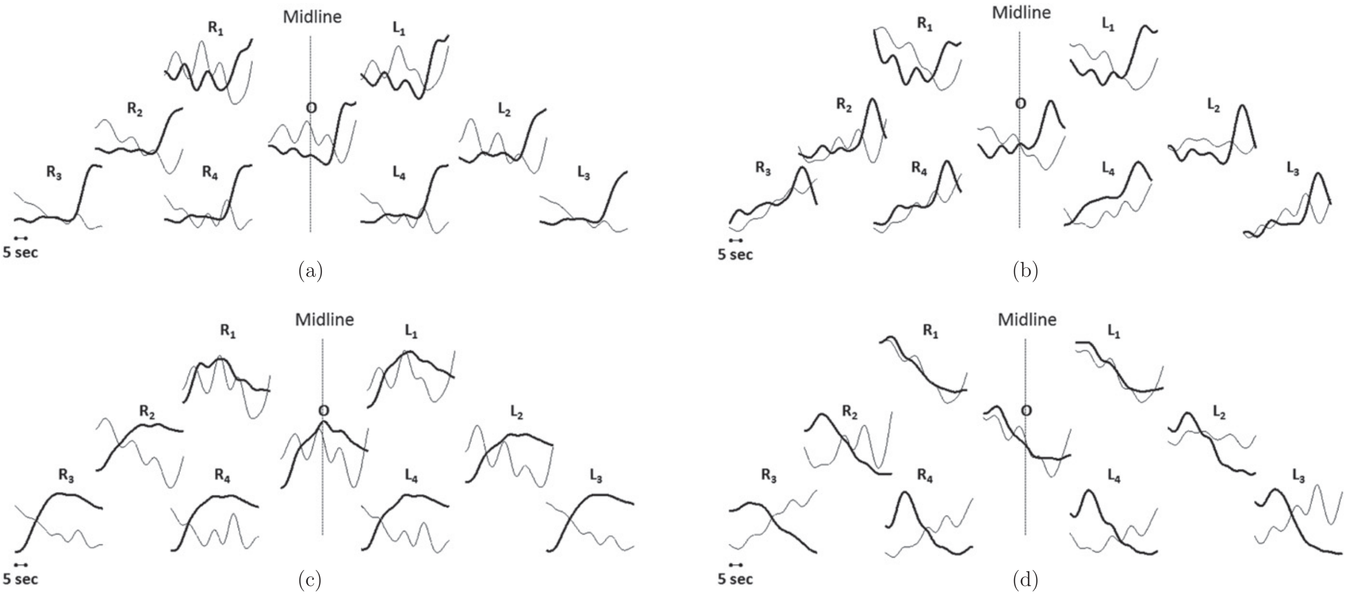

Figure 3. (a and c) Normalized HBO_2 concentration signals at different recording locations while (b) and (d) are the corresponding normalized HHb concentration signals. The dark lines represent normalized signals corresponding to highly valenced, HA stimuli while the lighter gray line depicts normalized concentrations during BN presentation to the same participant. The same BN sample is illustrated for both positively and negatively valenced examples. (a) HbO_2 concentration for positively valenced stimulus. (b) HHb concentration for positively valenced stimulus. (c) HBO_2 concentration for negatively valenced stimulus. (d) HHb concentration for negatively valenced stimulus.

Table 2. Classification accuracy in % for each participant when classifying HA versus BN. Feature types corresponding to the best-average accuracy are also presented for each participant (M = stimulus period mean; ΔM = stimulus period mean − preceding noise period mean; LSR = lateral slope ratio; ΔLM = lateral mean difference; S = slope, CV = coefficient of variation.

Participants	Gender	HA versus BN% (two features)	Features chosen
1	M	90.21 ± 1.72	ΔM
2	F	76.91 ± 1.04	ΔM
3	F	78.67 ± 3.31	ΔM
4	F	67.57 ± 2.01	M, S
5	F	69.04 ± 1.91	ΔM, CV
6	M	58.12 ± 2.55	S
7	M	61.71 ± 2.43	S, ΔM
8	F	71.16 ± 1.08	S
9	M	70.17 ± 3.93	ΔM
10	M	75.72 ± 1.28	ΔM
Average		**71.93 ± 9.09**	

Table 3. Classification accuracy in % for each participant when classifying PV versus NV. Feature types corresponding to the best average accuracy are also presented for each participant (M = stimulus period mean; ΔM = stimulus period mean − preceding noise period mean; LSR = lateral slope ratio; ΔLM = lateral mean difference; S = slope, CV = coefficient of variation.

Participants	Gender	PV versus NV% (two features)	Features chosen
1	M	75.20 ± 4.22	ΔM, M
2	F	77.73 ± 2.09	LSR, S
3	F	63.28 ± 4.30	LSR, M
4	F	67.76 ± 2.83	LSR, ΔM
5	F	77.57 ± 4.10	ΔM
6	M	63.04 ± 3.67	ΔM, M
7	M	62.00 ± 3.46	S,CV
8	F	86.91 ± 2.87	ΔM
9	M	76.99 ± 5.11	ΔM, M
10	M	68.96 ± 6.55	S,M
Average		**71.94 ± 8.19**	

magnitude of a rectangular area is directly proportional to the frequency at which the feature in question was selected at a specific recording site across all participants. The vertical line represents the anatomical midline. The values are based on the feature set dimensionality resulting in the highest average classification accuracy.

Figure 5 illustrates how the adjusted classification accuracy (i.e. average of classification sensitivity and specificity) averaged across all participants changes as trials with lower arousal ratings are compared to BN. Similarly, figure 6 depicts how adjusted accuracy changes when different ranges of positively and negatively rated trials are compared. Comparisons ranged from the highest negative trials (top 12) versus the highest positive trials (top 12) to all positively rated trials classified against all negatively rated trials. In both figures 5 and 6, the average adjusted accuracy across participants exceeds the chance level.

4. Discussion

- *Classification accuracy*. The objective of this study was to detect the brain response to emotionally laden music by monitoring the prefrontal hemodynamics manifested as changes in the HBO_2 and HHb concentrations. Visual inspection of the concentration waveforms in figure 3 supports the choice of discriminatory features (e.g. mean

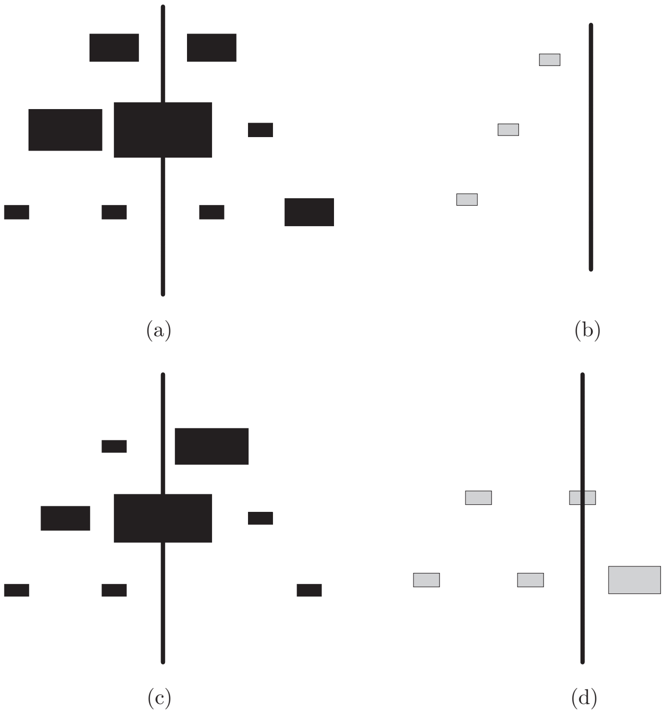

Figure 4. Location of features resulting in the best overall accuracy. Each rectangle is located over a recording site. The size of the rectangle is proportional to the number of features selected from the corresponding location. The vertical line denotes the anatomical midline (HA = high arousal; BN = Brown noise; PV = positive valence; NV = negative valence). (a) HBO_2, HA versus BN. (b) HHb HA versus BN. (c) HBO_2, PV versus NV. (d) HHb, PV versus NV.

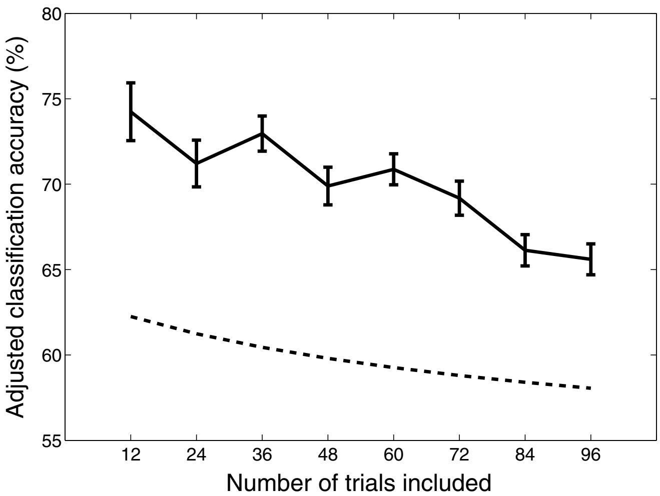

Figure 5. Adjusted classification accuracy (averaged across participants with the standard deviation bar shown) versus the number of trials included for classification against BN trials, after sorting all trials based on ratings of arousal in descending order (e.g. accuracies reported for the 12 trials are the result of classifying the 12 highest-rated arousal trials against all trials with BN). The dashed line marks the upper limit of the 95% confidence interval around the chance level computed based on the appropriate number of trials (Müller-Putz *et al* 2008).

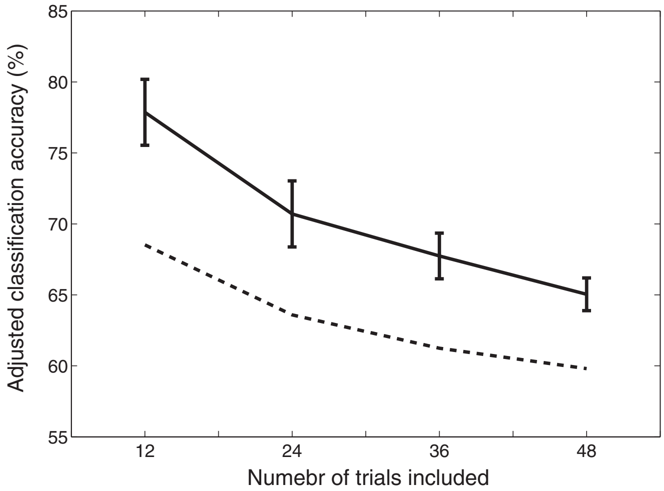

Figure 6. Adjusted classification accuracy (averaged across participants with the standard deviation bar shown) versus the number of trials included for classification, after sorting all trials based on ratings of PV and NV in descending order (e.g. accuracies reported for 12 trials are the result of classifying the 12 most positively rated trials against the 12 most negatively rated trials). The dashed line marks the upper limit of the 95% confidence interval around the chance level computed based on the appropriate number of trials (Müller-Putz *et al* 2008).

and slope). Emotional arousal in response to music was classified against the BN response with an average accuracy of 71.93% while emotional valence (i.e. positive or negative) was differentiated with 71.94% accuracy. These findings indicate that the emotional content of music induces differential patterns of activity in the prefrontal cortex, detectable algorithmically by NIRS.

As reported in tables 2 and 3, classification accuracies varied across participants, corroborating previous findings of individual differences in emotional reactivity (Rothbart and Derryberry 1981, Buss and Plomin 1975). As can be seen in tables 2 and 3, accuracies above the chance level were achieved for nine out of ten participants in the HA versus BN classification problem ($\alpha = 0.05$), while in the PV versus NV scenario, accuracies for seven out of ten participants exceeded chance ($\alpha = 0.05$)[6].

One of the concerns when investigating emotional experience using the PFC activity is the possibility of activation due to the emotion induction task requirements as opposed to the emotions induced (Herrmann *et al* 2003). However, figure 5 illustrates how the average-adjusted accuracy degrades as trials with increasingly lower arousal rating are compared against BN. Therefore, the difference in the task requirements (e.g. attentional demands), when presenting music compared to BN presentation, is unlikely to be responsible for classification accuracy. Similarly, in figure 6, the average-adjusted accuracies degrade as trials with increasingly lower PV and NV ratings are classified against each other. This decrease in the adjusted accuracies is expected due to potential similarities between trials rated at the lower

[6] Note that for a two-class problem, the 95% confidence intervals ($\alpha = 0.05$) for 48 and 24 trials per class are 50 ± 9.80 and 50 ± 13.59, respectively (Müller-Putz *et al* 2008).

positive and lower negative ends of valence (approaching the neutral state).

According to figure 4, which depicts the recording sites corresponding to features selected across all participants, the spatial distribution of the features resulting in the best overall accuracy was bilateral. This finding is consistent with the bilateral physiological substrates that are responsible for the perception of valence in the prefrontal cortex (Davidson 1992). Nonetheless, in three out of ten participants, unilateral activation was most discriminatory as laterality features were among those selected for solving the valence classification problem (see table 3).

- *Diversity in the music database.* Previous studies have reported regional brain activity modulation due to specific characteristics of music such as rhythm, timbre and major/minor chords (Kuck *et al* 2003, Samson 2003, Pallesen *et al* 2005). In these studies, the investigators varied selected music characteristics while carefully controlling for others. Other studies, focusing on emotion induction, have used diverse music databases (e.g. self-selected music pieces) to ensure successful elicitation of emotional reactions (Blood and Zatorre 2001, Schmidt and Trainor 2001). In the current study, the second approach was used.

  The variability of arousal and valence ratings for a given piece of music across participants (i.e. the same music excerpt rated differently among participants) suggests that the observed brain activity was indeed attributable to emotional experiences. Moreover, the variability in ratings among participants implies that the classification algorithm was not likely biased toward specific musical characteristics.
- *Challenges.* Due to the limited number of samples, only two dimensions of emotion (valence and arousal) were considered. Although these measures are informative, they fail to capture more specific emotional labels. For example, fear and sadness can both be rated as negatively valenced and high in arousal. In order to differentiate more specifically among emotional labels, other dimensions of emotion such as occurrence (eruptive versus gradually arising) and dominance (complete control versus no control over the situation) need to be considered (Wundt and Judd 1907).

  Special care was devoted to standardize headgear placement across all four sessions, which in turn should have minimized instrumentation inconsistencies. However, differences in the shape of the skull may have led to variabilities in the brain regions monitored in different participants. Therefore, the present results preclude conclusions about the specific brain regions that were activated.

  The human response to emotional stimuli may be affected by emotional sensitivity. In fact, Petrides and Furnham (2003) have shown that individuals with high trait emotional intelligence respond faster and show more sensitivity in an emotion induction paradigm. Including a measure of emotional sensitivity in addition to the self-reported ratings might have helped to explain the inter-subject variability in classification accuracies.

  Previous studies of emotion have indicated gender differences as an important factor in emotional response (Marumo *et al* 2009, Yang *et al* 2007). However, the limited number of participants did not allow further investigations of gender-related differences in the emotional response. Future studies with larger sample sizes need to be devised to investigate the effects of gender in emotion-induced prefrontal hemodynamic response.

5. Conclusion

This study exploited hemodynamic activity to automatically decode prefrontal cortical responses to emotionally laden music. Arousal and valence components of emotion were automatically detected with accuracies higher than 70% using multichannel near-infrared spectroscopy and linear discriminant classifiers with two judiciously selected signal features. These findings encourage future development of automatic methods of emotion detection in individuals with severe disabilities who have no expressive communication.

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