Subject-independent decoding of affective states using functional near-infrared spectroscopy

Lucas R. Trambaiolli[1,*], Juliana Tossato[2], André M. Cravo[2], Claudinei E. Biazoli Jr.[2], João R. Sato[2]

[1] Division of Basic Neuroscience, McLean Hospital - Harvard Medical School, Boston, USA
[2] Center for Mathematics, Computing and Cognition, Federal University of ABC, São Bernardo do Campo, Brazil
* Corresponding author: lucasrtb@gmail.com

Abstract: Affective decoding is the inference of human emotional states using brain signal measurements. This approach is crucial to develop new therapeutic approaches for psychiatric rehabilitation, such as affective neurofeedback protocols. To reduce the training duration and optimize the clinical outputs, an ideal clinical neurofeedback could be trained using data from an independent group of volunteers before being used by new patients. Here, we investigated if this subject-independent design of affective decoding can be achieved using functional near-infrared spectroscopy (fNIRS) signals from frontal and occipital areas. For this purpose, a linear discriminant analysis classifier was first trained in a dataset (49 participants, 24.65±3.23 years) and then tested in a completely independent one (20 participants, 24.00±3.92 years). Significant balanced accuracies between classes were found for positive vs. negative (64.50±12.44%, $p<0.01$) and negative vs. neutral (67.75±14.45%, $p<0.01$) affective states discrimination during a passive elicitation condition consisting in viewing affective-loaded images. For an active elicitation condition, in which volunteers were instructed to recollect personal affective experiences, significant accuracy was found for positive vs. neutral affect classification (71.00±17.93%, $p<0.01$). In this last case, only three fNIRS channels were enough to discriminate between neutral and positive affective states. Our results highlight fNIRS as a feasible technique for subject-independent affective decoding, reaching significant classification accuracies of affective states using only a few but biologically relevant features.

Keywords: Functional near infrared spectroscopy, Affective decoding, Multivariate analysis, Brain decoding, Affective states

1. Introduction

Multivariate brain decoding (MBD) allows the inference of mental states based on diverse features of brain signals (Haynes and Rees, 2006). In comparison to conventional analytic methods, this approach has the advantage of considering the various brain regions simultaneously, thus providing information on the neural networks of interest as a whole (Kubilius et al., 2015). One particular application of MBD is to identify emotional

or affective experiences to develop brain-computer interfaces or neurofeedback protocols (Mühl et al., 2014). The clinical application of affective neurofeedback is particularly interesting since it can enable patients to volitionally control abnormal neural activities associated with psychiatric disorders, leading to brain connectivity reorganization and the relief of symptom severity (Kim and Birbaumer, 2014).

Conventional clinical neurofeedback approaches are based on subject-specific designs (Kim and Birbaumer, 2014). In other words, the patient is first submitted to an initial screening to create a calibration database for the neurofeedback algorithm and, later, starts the proper neurofeedback training. However, although reliable to the participant's neural data, this initial step leads to long sessions that might increase physical and mental exhaustion and, consequently, reduce the therapeutic benefits (Sulzer et al., 2013). Thus, ideally, therapeutic affective neurofeedback should be trained with the first set of volunteers and applied with little or no calibration to new individuals. However, the subject-independent identification of mental states remains an open technical challenge (Haynes and Rees, 2006).

Subject-independent emotional classifications have been previously reported on facial and body expressions (Mariooryad and Busso, 2013, Tan et al., 2016), and voice tone (Mariooryad and Busso, 2013). A critical limitation of those studies is that volunteers can easily handle the records used in order to achieve the desired result, even without changing their affective states. Moreover, such exclusively behavioral measures do not provide neural information, which is crucial to a properly designed neurofeedback system. Thus, investigations using neurophysiological records such as electrophysiology (EEG) and functional magnetic resonance imaging (fMRI) should foster the development of affective interfaces. Using EEG data, for example, different studies using a subject-independent design combined several features and classifiers to predict the affect experienced by new participants, achieving accuracies between 70 and 95% (Lin et al., 2010, Bozhkov and Georgieva, 2014, Georgieva et al., 2015, Ramaraju et al., 2015). Using fMRI data, accuracy varied from 60% to 80% depending on the number of voxels (from 2000 to 4000) included as predictors (Baucom et al., 2012).

Another challenge for fostering clinical affective neurofeedback applications is the high-cost and limited mobility of the so far most accurate imaging measurements (such as those acquired using fMRI or MEG) (Sulzer et al., 2013). In this context, functional Near-Infrared Spectroscopy (fNIRS) emerges as an attractive neuroimaging technique for MBD-based affective discrimination. This method is based on low-energy light detectors and transmitters for measuring the light absorption through the cortical surface (Villringer et al., 1993). It makes possible to investigate local changes in the concentrations of oxy and deoxyhemoglobin in response to functional brain activity, similarly to the widely applied fMRI BOLD effect (Steinbrink et al., 2006). Furthermore, fNIRS presents a good trade-off between spatial and temporal resolutions, with low susceptibility to instrumental and biological noise when compared to EEG, and considerably lower cost and higher portability than fMRI (Nishitani and Shinohara, 2013). Affective-related experiments are

benefited from fNIRS usage due to its reliability to record the prefrontal cortex activation, as well as allowing both restricted and naturalistic emotion-related experiments (Nishitani and Shinohara, 2013, Bendall et al., 2016, Pinti et al., 2018). With this in mind, several studies showed a significant subject-specific offline prediction of affective states using different fNIRS protocols (Tai and Chau, 2009, Hosseini et al., 2011, Köchel et al., 2011, Trambaiolli et al., 2018b, Hu et al., 2019).

Using a fronto-occipital fNIRS setup, our research group achieved 80 to 95% of within-subject affective classification accuracy (Trambaiolli et al., 2018b), and developed a functional subject-specific neurofeedback protocol (Trambaiolli et al., 2018a). Here, considering the above-mentioned technical challenges for subject-independent affective decoding, we aimed to evaluate whether these fronto-occipital fNIRS signals provide enough information to the subject-independent offline classification of affective states. To achieve this goal, we collected two independent datasets with passive and active affective elicitation tasks. The passive elicitation condition was based on a set of International Affective Pictures System (IAPS) images that were thought to induce positive, negative or neutral affective states (Lang et al., 1997). Critically, those images were selected in order to balance the arousal dimension for the different valences. In the active elicitation condition, participants were instructed to imagine personal situations with positive, negative or neutral affective contexts. We expected decoding performances higher than the chance level when comparing two different affective states in each elicitation condition. Also, based on the affective-workspace model (Edelman, 1989, Barrett and Bliss-Moreau, 2009), we expected the relevant information used in classification to come from nodes of neural networks mainly comprising frontal and occipital areas (Lindquist et al., 2012, Lindquist et al., 2015).

2. Methods

2.1. Participants

Forty-nine healthy participants (25 female, 24.65±3.23 years) were enrolled in the first part of the experiment. Inclusion criteria were no previous (self-reported) diagnosis of neurological (ICD-10: G00-G99) and/or psychiatric disorders (ICD-10: F00-F99), and normal or corrected-to-normal vision. All participants were attending college or graduated and provided written informed consent to participate in this study.

Two years later, a second (and independent) sample of twenty healthy participants (10 female, 24.00±3.92 years) was collected by a different researcher, and in a separate laboratory (at the same university). The inclusion criteria and the experimental protocol were equal to the first sample. For both cases, ethical approval was obtained from the local Ethics Committee, and no payment was provided to the participants, according to the national rules.

2.2. Functional NIRS acquisition

fNIRS measurements were conducted using the NIRScout System (NIRx Medical Technologies, LLC. Los Angeles, California) using an array of optodes (12 light sources and 12 detectors) covering the prefrontal, temporal and occipital areas. Optodes were arranged in an elastic band, with nine sources and nine detectors positioned over the frontal and temporal regions, and three sources and three detectors over the occipital region. Four positions of the International 10-20 System were adopted as reference points during the setup: sensors 1 and 9 were positioned approximately over the T7 and T8 locations, respectively, while the Fpz and Oz positions were in the center of channels 5-5 and 11-11, respectively, as shown in Figure 1. The source-receptor distance was 30 mm for adjacent optodes, and the used wavelengths were 760 and 850 nm. Signals obtained from the thirty-two channels were measured with a sampling frequency of 5.2083 Hz (determined by the maximum sampling frequency of the equipment - 62.5 Hz - divided by the number of sources - 12) using the NIRStar 14.0 software (NIRx Medical Technologies, LLC. Los Angeles, California).

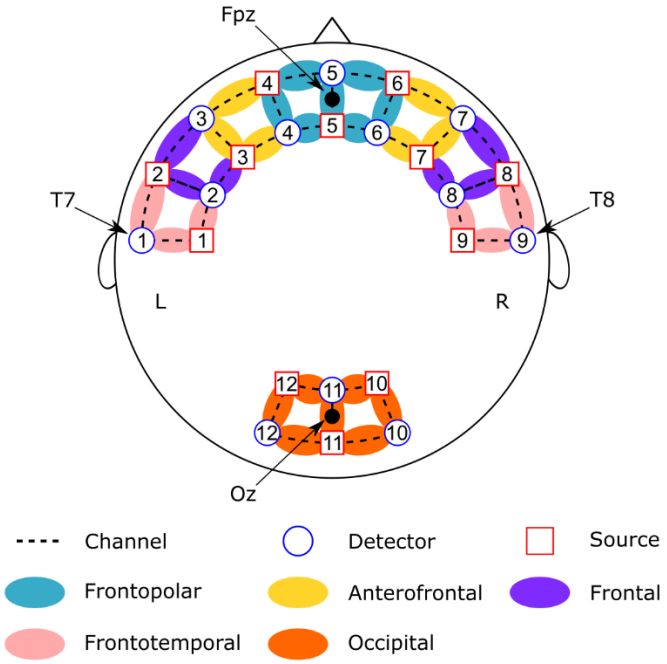

Figure 1 - Channel configuration. Red circles represent sources; blue circles represent the detectors and dotted lines the channels. Colors show channel positions according to the International 10-20 system.

2.3. Experimental protocol

During the test, participants sat in a padded chair with armrest, positioned 1-meter distance in front of a monitor. They were asked to remain relaxed, with hands within sight resting on the armrests or the table. They were also requested to avoid eye movements,

as well as any body movement. The recording room remained dark during registration and subject used earplugs.

2.3.1. Block of passive elicitation

For the block of passive elicitation of affect, we used images available on the international affective picture system (IAPS) catalog (Lang et al., 1997). First, images were filtered according to their average values of arousal and then were ranked according to their valence values. We selected the 30 pictures with higher average values of valence, the 30 with lowest values and 60 of intermediate values, as follows:

- Positive pictures (Valence = 7.884±0.220; Arousal = 5.036±0.448): 1811, 2057, 2080, 2209, 5210, 5830, 7200, 2040, 2058, 2091, 2340, 5700, 5833, 7330, 1440, 2045, 2070, 2150, 2347, 5825, 5910, 7502, 1710, 2050, 2071, 2165, 2550, 5829, 5982, 8420;
- Negative pictures (V = 2.007±0.183; A = 5.549±0.339): 2375.1, 3101, 3261, 9181, 9322, 9560, 2703, 3180, 3301, 9185, 9326, 9571, 2095, 2800, 3191, 3350, 9253, 9332, 2205, 3016, 3225, 9040, 9300, 9421, 2345.1, 3062, 3230, 9140, 9301, 9433;
- Neutral pictures (V = 5.234±0.060; A = 3.770±0.813): 2122, 2514, 5520, 7019, 7182, 7550, 2191, 2635, 5531, 7021, 7207, 7632, 2211, 2702, 5532, 7043, 7242, 7830, 1122, 2308, 2745.1, 5533, 7052, 7248, 8065, 1350, 2377, 2850, 5740, 7053, 7249, 1616, 2381, 2870, 5920, 7058, 7365, 1675, 2385, 2880, 6910, 7062, 7497, 1820, 2487, 5395, 7001, 7080, 7500, 1908, 2495, 5471, 7014, 7090, 7506, 2102, 2499, 5510, 7017, 7100.

This block consisted of twenty trials (5 for positive stimuli, 10 for neutral and 5 for negative). For the first 2 seconds of each trial, a white cross was presented in the center of a blank screen. During the next 30 seconds, a new figure was displayed every 5 seconds, totaling six randomly selected figures per trial corresponding to the desired affective class (Figure 2). Presenting a group of images with the same valence ensures the maintenance of cognitive engagement (Tie et al., 2009) and the required duration to achieve the peak of oxygen concentration change relative to baseline (Schroeter et al., 2006). At the end of the trial, a new screen was presented asking the participant to assign a score from 1 to 9 for the subjective valence (1 – extremely negative valence; 9 – highly positive valence) and subjective arousal (1 – lower arousal; 9 – higher arousal) experiences. After this, a blank screen appears for a random duration between 2-4 seconds and participants were instructed to blink and/or move in this period but not in the other phases.

2.3.2. Block of active elicitation

The block of active elicitation of affect (affective imagination) consisted of twenty trials (5 trials for positive affect, 5 for negative affect and 10 for resting with eyes open,

also called as neutral affect). Each trial started with a baseline period of a blank screen with a white cross in the center. After 2 seconds, the instruction (representing the desired emotion) appeared to the left of the display, remaining on the screen for 2 s (Figure 2). The instruction consisted of either a green arrow pointing up (positive affect), a red arrow pointing downward (negative affect) or a blue circle (neutral affect). For 30 seconds after the instruction was presented, the screen remained unchanged, corresponding to the participant's affective imagination period. At the end of the trial, a new screen was presented asking the participant to assign a score from 1 to 9 for the subjective valence (1 – extremely negative valence; 9 – highly positive valence) and subjective arousal (1 – lower arousal; 9 – higher arousal) experiences. After this, a blank screen appears for a random duration between 2 to 4 seconds and participants were instructed to blink and/or move in this period.

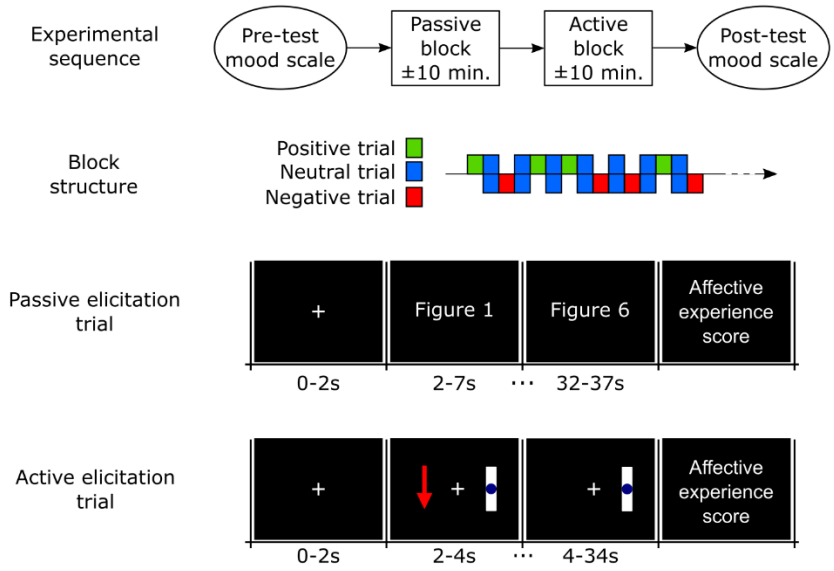

Figure 2 - Visual stimuli order in passive and active elicitation trials. The order of trials into the block is random, but always alternating neutral trials with positive and negative affect trials.

2.4. Data analysis

2.4.1. Preprocessing

Preprocessing was performed using Matlab (Mathworks, MA, USA) with the nirsLAB v2014.12 toolbox (NIRx Medical Technologies, LLC. Los Angeles, California). Each participant's raw data were digitally band-pass filtered by a linear-phase FIR filter (0.01-0.2 Hz) to filter noises due to heart beat (0.8~1.2 Hz), respiration (0.3 Hz) and Mayor waves (<0.01) (Naseer and Hong, 2013, Naseer et al., 2014). Then each wavelength was detrended by their respective whole length record (without segmentation), and the

variation in concentration of oxyhemoglobin and deoxyhemoglobin were calculated by the Beer-Lambert law (differential pathlength factor set to 7.25 and 6.38, respectively) (Essenpreis et al., 1993). Each concentration curve was then segmented into the 30 s of interest of each trial, for all studied conditions.

The mean concentration of oxyhemoglobin and deoxyhemoglobin for each segment was calculated for each channel using the average of moving 2s-window means with 50% overlap. Thus, each subject's database was composed of 64 features of average concentration (32 channels × 2 chromophores) in 20 experimental conditions (10 neutral trials + 5 positive trials + 5 trials), for both blocks.

2.4.2. Machine learning procedure

To decode affective states across databases, we used the Linear Discriminant Analysis (LDA) implementation provided by the BCILAB toolbox (Kothe and Makeig, 2013) with its default parameters. This analysis was divided in two main steps represented in Figure 3.

First, we performed an LDA-based feature selection using the whole feature space from the first experimental sample (49 participants) (steps in blue in Figure 3). The LDA model searches for a linear projection of multivariate observations to univariate ones (Fisher, 1936). Thus, it is possible to use the eigenvalues of the within-class covariance matrix in LDA (which contain most of the relevant information) as a measure of feature relevance (Sato et al., 2009). To reduce the number of features used during classification, we first ranked the absolute eigenvalues from all features, and then created different subsets selecting the best 5 to 100% (with steps of 5%) features with highest eigenvalues (in other words, one subset using the top 5% features, another subset using the top 10%, and so on).

For each obtained feature subset, projections of the training and testing datasets described by the selected features only are built using the first (49 participants) and second (20 participants) experimental samples, respectively (steps in red in Figure 3). Then, we evaluated the predictive performance on each corresponding test set. This approach was applied to evaluate affective conditions in pairs, following "Positive versus Neutral", "Negative vs. Neutral" and "Positive vs. Negative" combinations, for blocks of passive and active elicitation separately. Here we followed this binary approach since many current neurofeedback protocols are mainly based on two-class designs (Hamilton et al., 2011, Johnston et al., 2011, Brühl et al., 2014, Zotev et al., 2013, Young et al., 2014, Hamilton et al., 2016, Trambaiolli et al., 2018a).

To evaluate the prediction performance in each comparison, we calculated the decoding accuracy as (trials correctly classified from first class + trials correctly classified from second class)/2. This approach avoids the potential unbalance of sample size in each comparison, and this random result should be 50%.

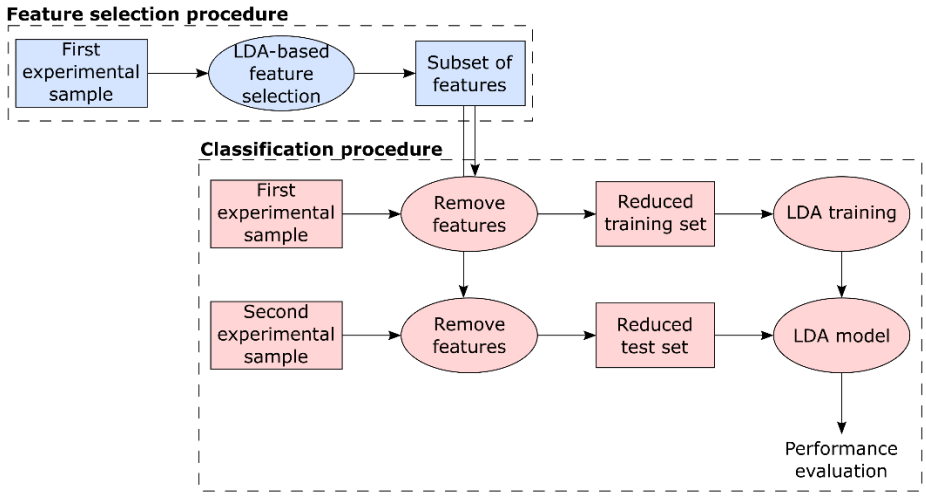

Figure 3 - Machine learning procedure: Initially, we performed an LDA-based feature selection using the first experimental sample (49 subjects). Then, based on these selected features, we created training and test sets for the LDA classifier using the first (49 subjects) and second (20 subjects) experimental samples, respectively.

2.4.3. Statistical analysis

Considering that the results here presented are sum-based proportions, and no ceiling-effect was observed, these data assume approximately normal distributions. Thus, here we applied parametric t-tests to evaluate our results.

First, the subject scores of valence and arousal of the second database were evaluated by a two-sample t-test. The comparisons used the mean values of valence and arousal assigned during positive, negative and neutral trials. This procedure was repeated for both elicitation blocks. The p-values were Bonferroni corrected for multiple comparisons (2 subjective measures × 3 comparisons of conditions × 2 elicitation blocks).

The significance of classification accuracy of each comparison was evaluated by a one sample t-test, comparing the prediction performance from all participants in this comparison against chance level (50%). Each result was independently adjusted by using the Bonferroni correction for 120 multiple comparisons (20 different percentages of features × 3 comparisons of conditions × 2 elicitation blocks = 120).

3. Results

3.1. Subjective scores of Arousal and Valence

Table 1 presents the mean subjective scores of arousal and valence relative to the positive, negative and neutral conditions, during both active and passive elicitation. Moreover, the corrected p-values of each comparison are also presented.

Table 1 - In the first half of the table, mean ± standard-deviation of subjective scores (ranging from 1 to 9) assigned by each subject of the second database during negative, neutral and positive trials. In the second half, p-values of the comparison between the scores assigned for each trial type.

Mean subjective scores		
	Valence	*Arousal*
Passive elicitation		
Negative	2.52±1.38	6.05±1.34
Neutral	5.11±0.73	2.71±1.29
Positive	6.79±0.92	4.82±1.60
Active elicitation		
Negative	2.57±0.97	5.85±1.71
Neutral	4.84±0.24	2.09±1.39
Positive	7.20±0.77	5.67±1.75
Statistical comparisons (p-values)		
	Valence	*Arousal*
Passive elicitation		
Positive vs. Negative	<0.01	0.14
Positive vs. Neutral	0.02	1.00
Negative vs. Neutral	<0.01	<0.01
Active elicitation		
Positive vs. Negative	<0.01	1.00
Positive vs. Neutral	<0.01	<0.01
Negative vs. Neutral	<0.01	<0.01

Valence scores presented significant differences for all the comparisons. It is relevant, however, that no significant difference of the arousal scores was found during “Positive vs. Negative” comparisons, as well as during “Positive vs. Neutral” comparison during the passive block.

3.2. Classification results

LDA accuracy boxplots are presented in Figure 4. Classification accuracy for passive elicitation significantly exceeded chance level in “Positive vs. Negative” comparisons, with highest result as 64.50±12.44% (mean ± standard-deviation, $p<0.001$) using 20% of features (12 channels), and in “Negative vs. Neutral” comparisons (67.75±14.45%, $p<0.01$, 40% of features – 25 channels). No significant differences were found for “Positive vs. Neutral” comparisons.

During active elicitation comparisons, “Positive vs. Neutral” accuracies were greater than chance level, and the highest result was 71.00±17.95% ($p<0.001$) using only 5% of the features (3 channels). No significant differences were found for “Positive vs. Negative” and “Negative vs. Neutral” comparisons.

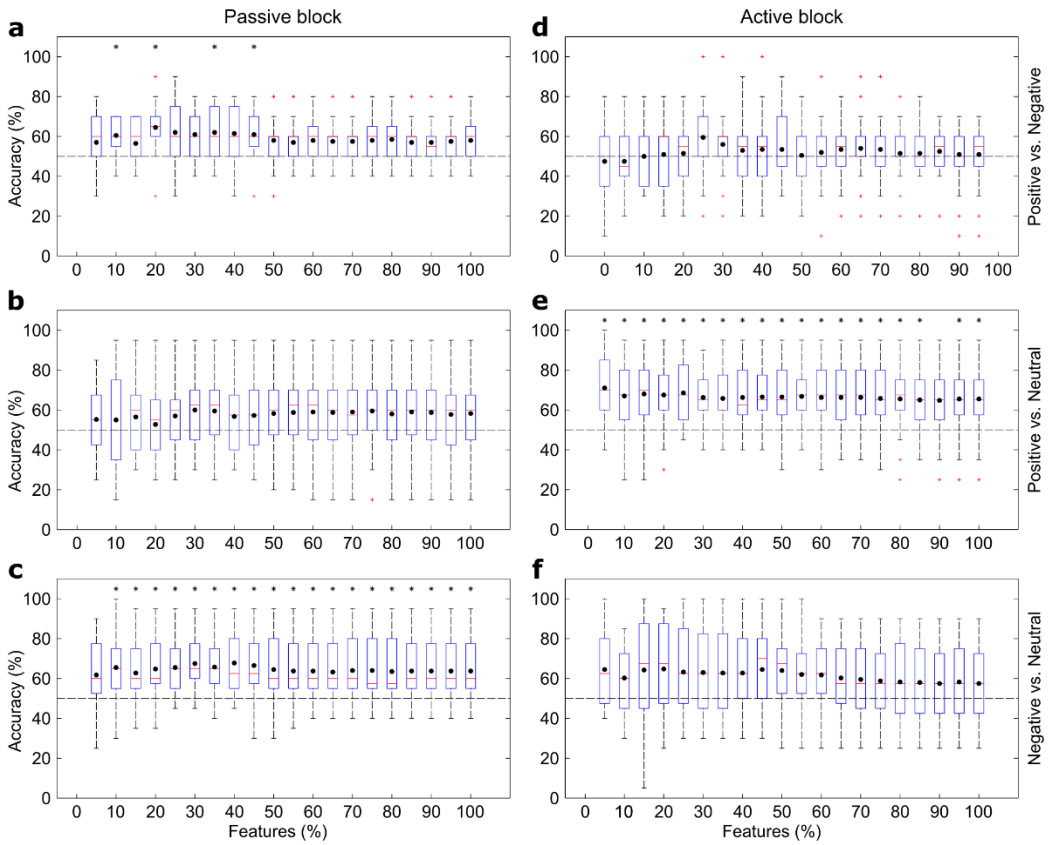

Figure 4 - Box plots showing the results using the LDA classifier and different feature subsets. (A) presents the “Positive vs. Negative”, (B) the “Positive vs. Neutral”, and (C) the “Negative vs. Neutral” comparisons for passive elicitation block, while (D-F) follows the same order for active elicitation block. Black dots present the means, red lines the medians, red crosses the outliers and black asterisks the statistical difference for chance level ($p<0.05$).

3.3. Relevant channels

In Figure 5, the channels selected in each of the highest significant results previously reported are shown alongside their respective weights assigned by the classifier. The location of the channels follows the same order shown in Figure 1.

Among the “Positive vs. Negative” classification during the passive elicitation block, the highest accuracy was achieved using 12 features. Nine of these features correspond to information about the deoxyhemoglobin concentration. According to the 10-5 EEG electrode positioning system (Oostenveld and Praamstra, 2001), four channels are approximately at the frontopolar area, two at the anterofrontal area, and three at the occipital area. Complementary, three features included information about the oxyhemoglobin concentration at the frontopolar (two channels) and the occipital (one) areas.

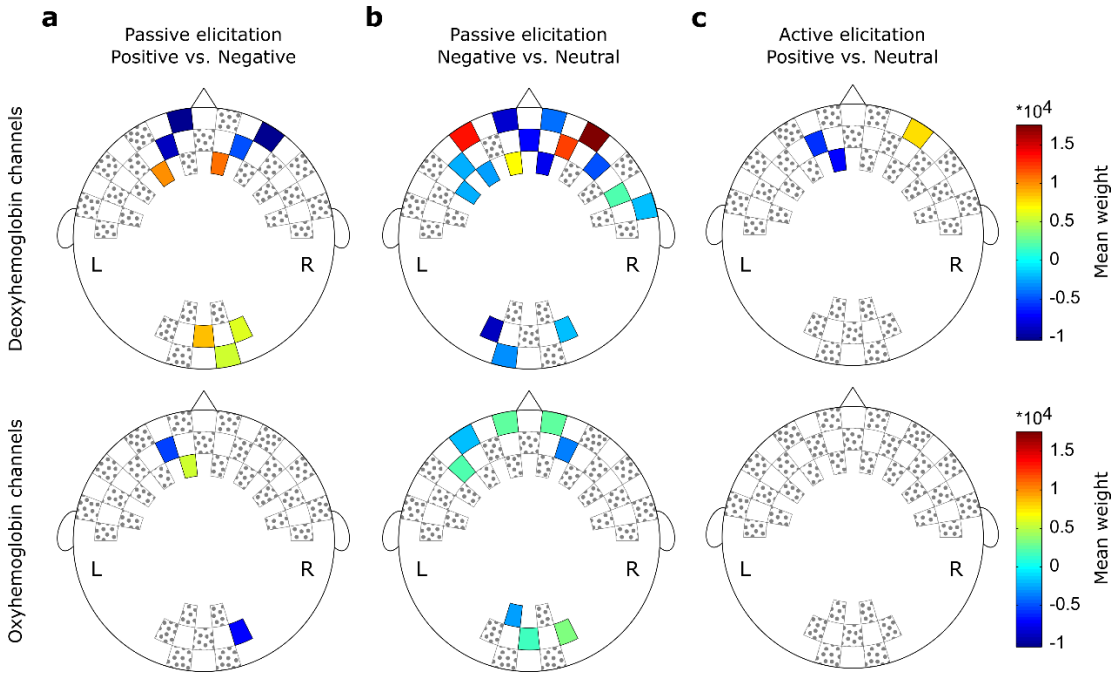

Figure 5 - Weights assigned by the LDA classifier for each feature during the (A) "Positive vs. Negative" comparisons using 20% of features and (B) "Negative vs. Neutral" comparisons using 40% of features. In (C), the weights for each feature during the "Positive vs. Neutral" comparisons using 5% of features. Hottest colors indicate positive weights while cooler colors indicate negative weights. Channels filled with gray dots were not used during the test.

For the “Negative vs. Neutral” classification during the passive elicitation, 25 channels carried relevant information: six frontopolar, five anterofrontal, two frontal, one frontotemporal and three occipital channels for the deoxyhemoglobin concentration; and three frontopolar, two anterofrontal and three occipital channels for the oxyhemoglobin concentration.

Finally, the “Positive vs. Neutral” decoding during the active elicitation block used only three channels to achieve the highest performance: two frontopolar and one anterofrontal. These channels provided information about the deoxyhemoglobin concentration.

4. Discussion

4.1. Affective decoding

First, it is essential to highlight the absence of statistical significance in the subjective arousal score during the “Positive vs. Negative” comparisons. In addition to the significant difference in the valence scores, it suggests that any classification result in these comparisons is exclusively related to valence differences between positive and negative affect. Further, during both “Positive vs. Neutral” and “Negative vs. Neutral”

comparisons, statistical differences were found for valence and arousal scores. It is expected that Positive and Negative present differences in arousal and valence when compared to absent affective content (Neutral). Some studies suggest valence and arousal not as two orthogonal dimensions, but as a single V-shaped dimension (Kuppens et al., 2013). Accordingly, these two dimensions cannot be separated in most of the emotional stimuli systems (for example, the International Affective Pictures System) (Lang, 2005, Barrett and Bliss-Moreau, 2009). Given this, we have demonstrated that it is possible to detect distinct patterns of hemodynamic activity generated by different affective valence elicitation tasks. Our results also provide evidences for the feasibility of decoding affective states in a new, untested subject, based on a model trained in previously collected and independent dataset.

For the decoding of passively elicited affective states, only the accuracies for “Positive vs. Negative” and “Negative vs. Neutral” comparisons were higher than chance level. This finding is in line with previous inter-subject studies using the IAPS database to decode affective states, but with fMRI (Baucom et al., 2012). The decoding of active elicitation, on the other hand, presented significant accuracy for the “Positive vs. Neutral” condition exclusively. For potential neurofeedback applications, self-regulation of neural activity related to a specific affective task are desirable (Birbaumer et al., 2013, Kim and Birbaumer, 2014). In cases where potential users present increased levels of negative emotions and decreased levels of positive emotions (Gross and Muñoz, 1995), improving the neural and cognitive discrimination between Positive and Neutral states might be clinically relevant (Trambaiolli et al., 2018a).

In a qualitative evaluation, some participants described, after the experiment, that the negative affect induced by the pictures presented during the passive block was more intense than the positive one. Negative figures into the IAPS catalog are mainly related to death, malnutrition, sickness, poverty, and disgust (Lang et al., 1997), which are more consensual than the content of some positive stimuli, such as babies, pets or beaches. Moreover, some studies suggest that processing negative stimuli are more demanding in the brain (Ito et al., 1998), which might generate more clear signals to our classifiers than the neural processing of positive stimuli. On the other hand, the participants also described that the positive imagery during active condition was more natural to achieve and more intense than the negative representation.

4.2. Relevant features and the neural networks of affect

For both passive elicitation results, relevant features included both fNIRS derived oxyhemoglobin and deoxyhemoglobin concentrations measures. In fact, each chromophore is expected to provide different and complimentary information. Deoxyhemoglobin is thought to be an indicator of functional activation and is more directly related to the fMRI BOLD signal (Song et al., 2006, Steinbrink et al., 2006), while a recent work found a correlation between oxyhemoglobin signal and the EEG band power

variation in cortical regions (Pfurtscheller et al., 2012). Other decoding experiments also reported both hemoglobin concentrations as relevant for classification (Tai and Chau, 2009). These results suggest a non-redundancy of these measures.

In accordance with two meta-analyses of neuroimaging data in affective tasks, we found that occipital areas signals were among the relevant features for classification (Lindquist et al., 2012, Lindquist et al., 2015). Additionaly, fNIRS studies also described activation of the occipital cortex during affective stimulation (Alpers et al., 2005, Herrmann et al., 2008). Minati and colleagues, for example, found increased occipital response to positive and negative affects relative to neutral pictures of the same database we have used (IAPS) (Minati et al., 2009). Moreover, it is interesting to note that the classifier assigned high absolute weights for a considerable number of channels from frontopolar and anterofrontal regions. A frontal lateralization of activity during the experience and regulation of emotional responses is a classical effect (Ahern and Schwartz, 1985, Ochsner and Gross, 2005, Balconi and Mazza, 2010, Balconi et al., 2011). However, a more broad theoretical account of affective processing, affective workspace hypothesis, states that activity patterns of the same core neural network could implement both positive and negative affective responses (Edelman, 1989, Barrett and Bliss-Moreau, 2009). Our application of MDB, which considers distributed brain activity, is in line with the theoretical assumptions of such model. Frontal regions, which were consistently relevant for classification in our experiments, superpose to the network nodes that have been proposed as core regions of the affective neural workspace (Barrett et al., 2007, Lindquist et al., 2012).

4.3. Subject-independent designs

fNIRS-based affective neurofeedback protocols were recently applied to healthy (Sakatani et al., 2013, Trambaiolli et al., 2018a) and psychiatric populations (Ehlis et al., 2018), including patients with schizophrenia (Storchak et al., 2019), autism disorder (Liu et al., 2016), and attention-deficit/hyperactivity disorder (ADHD) (Marx et al., 2015, Hudak et al., 2017). However, all these protocols have subject-specific designs which require training blocks or calibration trials for every experimental session. In addition to the expected duration of the setup preparation, these demands can act as stressors for patients presenting anxiety symptoms, or cause physical and mental fatigue shortly after the initial blocks (Sulzer et al., 2013). Consequently, patients may not achieve their best performance, or the therapeutic benefits associated with the protocol. All these aspects make the investigation of subject-independent fNIRS protocols a timely research topic.

Critically, classification accuracies presented in this paper are lower than those presented in our previous subject-specific study (Trambaiolli et al., 2018b). However, the performance drop during subject-independent designs is an expected effect due to the inter-subject variability of anatomy, level of stress, rest, among others. For example, Robinson and colleagues report more than 10% of performance reduction from a subject-

dependent to a subject-independent fNIRS-based motor imagery neurofeedback (Robinson et al., 2016).

Also, the mean accuracy for “Positive vs. Neutral” discrimination in the active condition was slightly over the 70% threshold suggested by the brain-computer interface and neurofeedback communities as sufficient to perform device control and communication (Tai and Chau, 2009, McFarland et al., 2006). This is a crucial finding since the differentiation between the active elicitation of positive affect and a neutral (resting-state) condition is the state of the art of hemodynamic-based neurofeedback protocols applied to both health and psychiatric populations (Johnston et al., 2011, Zotev et al., 2011, Zotev et al., 2013, Moll et al., 2014, Young et al., 2014, Trambaiolli et al., 2018a). It is also important to emphasize that this result was reached using only three channels. Considering future applications, the use of only three channels means shorter setup procedure, lower instrumental and computational costs and the possibility of even more portable systems.

4.4. Limitations and future perspectives

Despite the controls we implemented in our experimental design, collection and analysis, several limitations should be recognized. First, although fNIRS signal is mainly related to the near-infrared light absorption into the cortical surface, it also encompasses peripheral responses, including changes in skin, muscular and cranial blood flow and the aerobic process of energy consumption related to muscle contractions (Nishitani and Shinohara, 2013). Consequently, some authors refer to fNIRS applications for control of devices such as corporeal machine interfaces (Tai and Chau, 2009). As this constitutes one fundamental issue of this method, further validation using this approach is warranted. Here, one approach that could be explored in future studies is the use of short-separation channels to filter systemic hemodynamic fluctuations from non-neural sources (Gagnon et al., 2014, Brigadoi and Cooper, 2015).

However, even with these limitations, we reinforce the advantages of fNIRS compared to other neuroimaging techniques in implementing MBD systems. Particularly, the portability, benefit-cost relation and the good balance between spatial and temporal resolutions makes fNIRS especially suitable for this purpose (Nishitani and Shinohara, 2013). In fact, these aspects create a solid base for an increasing number of studies using fNIRS for MBD of motor, cognitive, and more recently for decoding of affective states (Tai and Chau, 2009, Hosseini et al., 2011, Trambaiolli et al., 2018b). Cognitive previous applications include subject-independent decoding of semantic experiences (Zinszer et al., 2017) or audiovisual processing (Emberson et al., 2017). Additionally, the portability of fNIRS systems allow a fast evolution of naturalistic experiments targeting real-world applications (Falk et al., 2010, Balardin et al., 2017), such as affective neurofeedback systems for therapeutic purposes (Trambaiolli et al., 2018a).

Finally, we used minimal preprocessing steps, classifying fNIRS data using the mean changes in oxy and deoxyhemoglobin concentrations as features. This approach was used in order to test fNIRS based MDB of affective state with the least assumptions possible, to avoid introducing spurious artifact in the signal and to test the feasibility for posterior real-time analysis (Coyle et al., 2007, Sitaram et al., 2007). In comparison, recent studies identified that combining the mean hemoglobin concentration with other temporal and time-frequency features improves the decoding accuracies reaching values close to 90% in within-subject decoding (Tai and Chau, 2009, Naseer et al., 2016a, Naseer et al., 2016b). Therefore, future studies should also evaluate the effect of different feature extraction techniques to the inter-participants MBD of affective states.

5. Conclusion

Our results demonstrated that fNIRS is a suitable tool for inter-participants multivariate brain decoding of affective states. The accuracy in discriminating positive from neutral self-generated affects was significant and above the threshold desired for effective control of brain-computer interfaces. Thus, the construction of fNIRS-based BCI or neurofeedback devices should be attempted.

Acknowledgements

The authors thank Guilherme A. Z. Moraes (NIRx) and Jackson Cionek (Brain Support Brazil) for the technological support.

Compliance with Ethical Standards

Funding: This study was funded by Federal University of ABC, Coordination for the Improvement of Higher Education Personnel (CAPES), and São Paulo Research Foundation (FAPESP - grant numbers 2015/17406-5, 2017/05225-1, 2018/21934-5 and 2018/04654-9)

Conflict of Interest: The authors declare no conflict of interest.

Ethical approval: All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

Informed consent: Informed consent was obtained from all individual participants included in the study.

References

AHERN, G. L. & SCHWARTZ, G. E. 1985. Differential lateralization for positive and negative emotion in the human brain: EEG spectral analysis. *Neuropsychologia,* 23**,** 745-755.

ALPERS, G., HERRMANN, M., PAULI, P. & FALLGATTER, A. 2005. Emotional arousal and activation of the visual cortex: A near infrared spectroscopy analysis. *Journal of Psychophysiology,* 19.

BALARDIN, J. B., ZIMEO MORAIS, G. A., FURUCHO, R. A., TRAMBAIOLLI, L., VANZELLA, P., BIAZOLI JR, C. & SATO, J. R. 2017. Imaging brain function with functional near-infrared spectroscopy in unconstrained environments. *Frontiers in human neuroscience,* 11**,** 258.

BALCONI, M., BORTOLOTTI, A. & GONZAGA, L. 2011. Emotional face recognition, EMG response, and medial prefrontal activity in empathic behaviour. *Neuroscience Research,* 71**,** 251-259.

BALCONI, M. & MAZZA, G. 2010. Lateralisation effect in comprehension of emotional facial expression: a comparison between EEG alpha band power and behavioural inhibition (BIS) and activation (BAS) systems. *Laterality: Asymmetries of Body, Brain and Cognition,* 15**,** 361-384.

BARRETT, L. F. & BLISS-MOREAU, E. 2009. Affect as a psychological primitive. *Advances in experimental social psychology,* 41**,** 167-218.

BARRETT, L. F., MESQUITA, B., OCHSNER, K. N. & GROSS, J. J. 2007. The experience of emotion. *Annu. Rev. Psychol.,* 58**,** 373-403.

BAUCOM, L. B., WEDELL, D. H., WANG, J., BLITZER, D. N. & SHINKAREVA, S. V. 2012. Decoding the neural representation of affective states. *Neuroimage,* 59**,** 718-727.

BENDALL, R. C., EACHUS, P. & THOMPSON, C. 2016. A brief review of research using near-infrared spectroscopy to measure activation of the prefrontal cortex during emotional processing: the importance of experimental design. *Frontiers in human neuroscience,* 10**,** 529.

BIRBAUMER, N., RUIZ, S. & SITARAM, R. 2013. Learned regulation of brain metabolism. *Trends in cognitive sciences,* 17**,** 295-302.

BOZHKOV, L. & GEORGIEVA, P. Classification models of emotional biosignals evoked while viewing affective pictures. 2014 4th International Conference On Simulation And Modeling Methodologies, Technologies And Applications (SIMULTECH), 2014. IEEE, 601-606.

BRIGADOI, S. & COOPER, R. J. 2015. How short is short? Optimum source–detector distance for short-separation channels in functional near-infrared spectroscopy. *Neurophotonics,* 2**,** 025005.

BRÜHL, A. B., SCHERPIET, S., SULZER, J., STÄMPFLI, P., SEIFRITZ, E. & HERWIG, U. 2014. Real-time neurofeedback using functional MRI could improve down-regulation of amygdala activity during emotional stimulation: a proof-of-concept study. *Brain topography,* 27**,** 138-148.

COYLE, S. M., WARD, T. E. & MARKHAM, C. M. 2007. Brain–computer interface using a simplified functional near-infrared spectroscopy system. *Journal of neural engineering,* 4**,** 219.

EDELMAN, G. M. 1989. *The remembered present: a biological theory of consciousness*, Basic Books.

EHLIS, A. C., BARTH, B., HUDAK, J., STORCHAK, H., WEBER, L., KIMMIG, A. C. S., KREIFELTS, B., DRESLER, T. & FALLGATTER, A. J. 2018. Near-Infrared Spectroscopy as a New Tool for Neurofeedback Training: Applications in Psychiatry and Methodological Considerations. *Japanese Psychological Research,* 60**,** 225-241.

EMBERSON, L. L., ZINSZER, B. D., RAIZADA, R. D. & ASLIN, R. N. 2017. Decoding the infant mind: Multivariate pattern analysis (MVPA) using fNIRS. *PloS one,* 12**,** e0172500.

ESSENPREIS, M., ELWELL, C., COPE, M., VAN DER ZEE, P., ARRIDGE, S. & DELPY, D. 1993. Spectral dependence of temporal point spread functions in human tissues. *Applied optics,* 32**,** 418-425.

FALK, T. H., GUIRGIS, M., POWER, S. & CHAU, T. T. 2010. Taking NIRS-BCIs outside the lab: towards achieving robustness against environment noise. *IEEE Transactions on Neural Systems and Rehabilitation Engineering,* 19**,** 136-146.

FISHER, R. A. 1936. The use of multiple measurements in taxonomic problems. *Annals of eugenics,* 7**,** 179-188.

GAGNON, L., YÜCEL, M. A., BOAS, D. A. & COOPER, R. J. 2014. Further improvement in reducing superficial contamination in NIRS using double short separation measurements. *Neuroimage,* 85**,** 127-135.

GEORGIEVA, O., MILANOV, S., GEORGIEVA, P., SANTOS, I. M., PEREIRA, A. T. & SILVA, C. 2015. Learning to decode human emotions from event-related potentials. *Neural Computing and Applications,* 26**,** 573-580.

GROSS, J. J. & MUÑOZ, R. F. 1995. Emotion regulation and mental health. *Clinical psychology: Science and practice,* 2**,** 151-164.

HAMILTON, J. P., GLOVER, G. H., BAGARINAO, E., CHANG, C., MACKEY, S., SACCHET, M. D. & GOTLIB, I. H. 2016. Effects of salience-network-node neurofeedback training on affective biases in major depressive disorder. *Psychiatry Research: Neuroimaging,* 249**,** 91-96.

HAMILTON, J. P., GLOVER, G. H., HSU, J. J., JOHNSON, R. F. & GOTLIB, I. H. 2011. Modulation of subgenual anterior cingulate cortex activity with real-time neurofeedback. *Human brain mapping,* 32**,** 22-31.

HAYNES, J.-D. & REES, G. 2006. Neuroimaging: decoding mental states from brain activity in humans. *Nature Reviews Neuroscience,* 7**,** 523.

HERRMANN, M. J., HUTER, T., PLICHTA, M. M., EHLIS, A. C., ALPERS, G. W., MÜHLBERGER, A. & FALLGATTER, A. J. 2008. Enhancement of activity of the primary visual cortex during processing of emotional stimuli as measured with event-related functional near-infrared spectroscopy and event-related potentials. *Human Brain Mapping,* 29**,** 28-35.

HOSSEINI, S. H., MANO, Y., ROSTAMI, M., TAKAHASHI, M., SUGIURA, M. & KAWASHIMA, R. 2011. Decoding what one likes or dislikes from single-trial fNIRS measurements. *Neuroreport,* 22**,** 269-273.

HU, X., ZHUANG, C., WANG, F., LIU, Y.-J., IM, C.-H. & ZHANG, D. 2019. fNIRS Evidence for Recognizably Different Positive Emotions. *Frontiers in human neuroscience,* 13.

HUDAK, J., BLUME, F., DRESLER, T., HAEUSSINGER, F. B., RENNER, T. J., FALLGATTER, A. J., GAWRILOW, C. & EHLIS, A.-C. 2017. Near-infrared spectroscopy-based frontal lobe neurofeedback integrated in virtual reality modulates brain and behavior in highly impulsive adults. *Frontiers in human neuroscience,* 11**,** 425.

ITO, T. A., LARSEN, J. T., SMITH, N. K. & CACIOPPO, J. T. 1998. Negative information weighs more heavily on the brain: The negativity bias in evaluative categorizations. *Journal of personality and social psychology,* 75**,** 887.

JOHNSTON, S., LINDEN, D., HEALY, D., GOEBEL, R., HABES, I. & BOEHM, S. 2011. Upregulation of emotion areas through neurofeedback with a focus on positive mood. *Cognitive, Affective, & Behavioral Neuroscience,* 11**,** 44-51.

KIM, S. & BIRBAUMER, N. 2014. Real-time functional MRI neurofeedback: a tool for psychiatry. *Current opinion in psychiatry,* 27**,** 332-336.

KÖCHEL, A., PLICHTA, M. M., SCHÄFER, A., LEUTGEB, V., SCHARMÜLLER, W., FALLGATTER, A. J. & SCHIENLE, A. 2011. Affective perception and imagery: a NIRS study. *International Journal of psychophysiology,* 80**,** 192-197.

KOTHE, C. A. & MAKEIG, S. 2013. BCILAB: a platform for brain–computer interface development. *Journal of neural engineering,* 10**,** 056014.

KUBILIUS, J., BAECK, A., WAGEMANS, J. & DE BEECK, H. P. O. 2015. Brain-decoding fMRI reveals how wholes relate to the sum of parts. *Cortex,* 72**,** 5-14.

KUPPENS, P., TUERLINCKX, F., RUSSELL, J. A. & BARRETT, L. F. 2013. The relation between valence and arousal in subjective experience. *Psychological Bulletin,* 139**,** 917.

LANG, P. J. 2005. International affective picture system (IAPS): Affective ratings of pictures and instruction manual. *Technical report*.

LANG, P. J., BRADLEY, M. M. & CUTHBERT, B. N. 1997. International affective picture system (IAPS): Technical manual and affective ratings. *NIMH Center for the Study of Emotion and Attention,* 1**,** 39-58.

LIN, Y.-P., WANG, C.-H., JUNG, T.-P., WU, T.-L., JENG, S.-K., DUANN, J.-R. & CHEN, J.-H. 2010. EEG-based emotion recognition in music listening. *IEEE Transactions on Biomedical Engineering,* 57**,** 1798-1806.

LINDQUIST, K. A., SATPUTE, A. B., WAGER, T. D., WEBER, J. & BARRETT, L. F. 2015. The brain basis of positive and negative affect: evidence from a meta-analysis of the human neuroimaging literature. *Cerebral Cortex,* 26**,** 1910-1922.

LINDQUIST, K. A., WAGER, T. D., KOBER, H., BLISS-MOREAU, E. & BARRETT, L. F. 2012. The brain basis of emotion: a meta-analytic review. *The Behavioral and brain sciences,* 35**,** 121.

LIU, N., CLIFFER, S., PRADHAN, A. H., LIGHTBODY, A., HALL, S. S. & REISS, A. L. 2016. Optical-imaging-based neurofeedback to enhance therapeutic intervention in adolescents with autism: methodology and initial data. *Neurophotonics,* 4**,** 011003.

MARIOORYAD, S. & BUSSO, C. 2013. Exploring cross-modality affective reactions for audiovisual emotion recognition. *IEEE Transactions on affective computing,* 4**,** 183-196.

MARX, A.-M., EHLIS, A.-C., FURDEA, A., HOLTMANN, M., BANASCHEWSKI, T., BRANDEIS, D., ROTHENBERGER, A., GEVENSLEBEN, H., FREITAG, C. M. & FUCHSENBERGER, Y. 2015. Near-infrared spectroscopy (NIRS) neurofeedback as a treatment for children with attention deficit hyperactivity disorder (ADHD)—a pilot study. *Frontiers in human neuroscience,* 8**,** 1038.

MCFARLAND, D. J., ANDERSON, C. W., MULLER, K.-R., SCHLOGL, A. & KRUSIENSKI, D. J. 2006. BCI meeting 2005-workshop on BCI signal processing: feature extraction and translation. *IEEE transactions on neural systems and rehabilitation engineering,* 14**,** 135-138.

MINATI, L., JONES, C. L., GRAY, M. A., MEDFORD, N., HARRISON, N. A. & CRITCHLEY, H. D. 2009. Emotional modulation of visual cortex activity: a functional near-infrared spectroscopy study. *Neuroreport,* 20**,** 1344.

MOLL, J., WEINGARTNER, J. H., BADO, P., BASILIO, R., SATO, J. R., MELO, B. R., BRAMATI, I. E., DE OLIVEIRA-SOUZA, R. & ZAHN, R. 2014. Voluntary enhancement of neural signatures of affiliative emotion using FMRI neurofeedback. *PloS one,* 9**,** e97343.

MÜHL, C., ALLISON, B., NIJHOLT, A. & CHANEL, G. 2014. A survey of affective brain computer interfaces: principles, state-of-the-art, and challenges. *Brain-Computer Interfaces,* 1**,** 66-84.

NASEER, N. & HONG, K.-S. 2013. Classification of functional near-infrared spectroscopy signals corresponding to the right-and left-wrist motor imagery for development of a brain–computer interface. *Neuroscience letters,* 553**,** 84-89.

NASEER, N., HONG, M. J. & HONG, K.-S. 2014. Online binary decision decoding using functional near-infrared spectroscopy for the development of brain–computer interface. *Experimental brain research,* 232**,** 555-564.

NASEER, N., NOORI, F. M., QURESHI, N. K. & HONG, K.-S. 2016a. Determining optimal feature-combination for LDA classification of functional near-infrared spectroscopy signals in brain-computer interface application. *Frontiers in human neuroscience,* 10**,** 237.

NASEER, N., QURESHI, N. K., NOORI, F. M. & HONG, K.-S. 2016b. Analysis of different classification techniques for two-class functional near-infrared spectroscopy-based brain-computer interface. *Computational intelligence and neuroscience,* 2016.

NISHITANI, S. & SHINOHARA, K. 2013. NIRS as a tool for assaying emotional function in the prefrontal cortex. *Frontiers in human neuroscience,* 7**,** 770.

OCHSNER, K. N. & GROSS, J. J. 2005. The cognitive control of emotion. *Trends in cognitive sciences,* 9**,** 242-249.

OOSTENVELD, R. & PRAAMSTRA, P. 2001. The five percent electrode system for high-resolution EEG and ERP measurements. *Clinical neurophysiology,* 112**,** 713-719.

PFURTSCHELLER, G., DALY, I., BAUERNFEIND, G. & MÜLLER-PUTZ, G. R. 2012. Coupling between intrinsic prefrontal HbO2 and central EEG beta power oscillations in the resting brain. *PLoS One,* 7**,** e43640.

PINTI, P., AICHELBURG, C., GILBERT, S., HAMILTON, A., HIRSCH, J., BURGESS, P. & TACHTSIDIS, I. 2018. A review on the use of wearable functional near-infrared spectroscopy in naturalistic environments. *Japanese Psychological Research,* 60**,** 347-373.

RAMARAJU, S., IZZIDIEN, A. & ROULA, M. A. The detection and classification of the mental state elicited by humor from EEG patterns. 2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), 2015. IEEE, 1472-1475.

ROBINSON, N., ZAIDI, A. D., RANA, M., PRASAD, V. A., GUAN, C., BIRBAUMER, N. & SITARAM, R. 2016. Real-time subject-independent pattern classification of overt and covert movements from fNIRS signals. *PloS one,* 11**,** e0159959.

SAKATANI, K., TAKEMOTO, N., TSUJII, T., YANAGISAWA, K. & TSUNASHIMA, H. 2013. NIRS-based neurofeedback learning systems for controlling activity of the prefrontal cortex. *Oxygen Transport to Tissue XXXV.* Springer.

SATO, J. R., FUJITA, A., THOMAZ, C. E., MARTIN, M. D. G. M., MOURÃO-MIRANDA, J., BRAMMER, M. J. & JUNIOR, E. A. 2009. Evaluating SVM and MLDA in the extraction of discriminant regions for mental state prediction. *NeuroImage,* 46**,** 105-114.

SCHROETER, M. L., KUPKA, T., MILDNER, T., ULUDAĞ, K. & VON CRAMON, D. Y. 2006. Investigating the post-stimulus undershoot of the BOLD signal—a simultaneous fMRI and fNIRS study. *Neuroimage,* 30**,** 349-358.

SITARAM, R., ZHANG, H., GUAN, C., THULASIDAS, M., HOSHI, Y., ISHIKAWA, A., SHIMIZU, K. & BIRBAUMER, N. 2007. Temporal classification of multichannel near-infrared spectroscopy signals of motor imagery for developing a brain–computer interface. *NeuroImage,* 34**,** 1416-1427.

SONG, A. W., HUETTEL, S. A. & MCCARTHY, G. 2006. Functional neuroimaging: Basic principles of functional MRI. *Handbook of functional neuroimaging of cognition,* 2**,** 22-52.

STEINBRINK, J., VILLRINGER, A., KEMPF, F., HAUX, D., BODEN, S. & OBRIG, H. 2006. Illuminating the BOLD signal: combined fMRI–fNIRS studies. *Magnetic resonance imaging,* 24**,** 495-505.

STORCHAK, H., HUDAK, J., HAEUSSINGER, F. B., ROSENBAUM, D., FALLGATTER, A. J. & EHLIS, A.-C. 2019. Reducing auditory verbal hallucinations by means of fNIRS neurofeedback-A case study with a paranoid schizophrenic patient. *Schizophrenia research,* 204**,** 401.

SULZER, J., HALLER, S., SCHARNOWSKI, F., WEISKOPF, N., BIRBAUMER, N., BLEFARI, M. L., BRUEHL, A. B., COHEN, L. G., DECHARMS, R. C. & GASSERT, R. 2013. Real-time fMRI neurofeedback: progress and challenges. *Neuroimage,* 76**,** 386-399.

TAI, K. & CHAU, T. 2009. Single-trial classification of NIRS signals during emotional induction tasks: towards a corporeal machine interface. *Journal of neuroengineering and rehabilitation,* 6**,** 39.

TAN, J.-W., ANDRADE, A. O., LI, H., WALTER, S., HRABAL, D., RUKAVINA, S., LIMBRECHT-ECKLUNDT, K., HOFFMAN, H. & TRAUE, H. C. 2016. Recognition of intensive valence and arousal affective states via facial electromyographic activity in young and senior adults. *PloS one,* 11**,** e0146691.

TIE, Y., SUAREZ, R. O., WHALEN, S., RADMANESH, A., NORTON, I. H. & GOLBY, A. J. 2009. Comparison of blocked and event-related fMRI designs for pre-surgical language mapping. *Neuroimage,* 47**,** T107-T115.

TRAMBAIOLLI, L. R., BIAZOLI, C. E., CRAVO, A. M., FALK, T. H. & SATO, J. R. 2018a. Functional near-infrared spectroscopy-based affective neurofeedback: feedback effect, illiteracy phenomena, and whole-connectivity profiles. *Neurophotonics,* 5**,** 035009.

TRAMBAIOLLI, L. R., BIAZOLI, C. E., CRAVO, A. M. & SATO, J. R. 2018b. Predicting affective valence using cortical hemodynamic signals. *Scientific reports,* 8**,** 5406.

VILLRINGER, A., PLANCK, J., HOCK, C., SCHLEINKOFER, L. & DIRNAGL, U. 1993. Near infrared spectroscopy (NIRS): a new tool to study hemodynamic changes during activation of brain function in human adults. *Neuroscience letters,* 154**,** 101-104.

YOUNG, K. D., ZOTEV, V., PHILLIPS, R., MISAKI, M., YUAN, H., DREVETS, W. C. & BODURKA, J. 2014. Real-time FMRI neurofeedback training of amygdala activity in patients with major depressive disorder. *PloS one,* 9**,** e88785.

ZINSZER, B. D., BAYET, L., EMBERSON, L. L., RAIZADA, R. D. & ASLIN, R. N. 2017. Decoding semantic representations from functional near-infrared spectroscopy signals. *Neurophotonics,* 5**,** 011003.

ZOTEV, V., KRUEGER, F., PHILLIPS, R., ALVAREZ, R. P., SIMMONS, W. K., BELLGOWAN, P., DREVETS, W. C. & BODURKA, J. 2011. Self-regulation of amygdala activation using real-time fMRI neurofeedback. *PloS one,* 6**,** e24522.

ZOTEV, V., PHILLIPS, R., YOUNG, K. D., DREVETS, W. C. & BODURKA, J. 2013. Prefrontal control of the amygdala during real-time fMRI neurofeedback training of emotion regulation. *PloS one,* 8**,** e79184.