Resting-awake EEG amplitude modulation can predict performance of an fNIRS-based neurofeedback task

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***Abstract* - Affective neurofeedback emerges as an innovative approach to relieve symptoms of psychiatric disorders. However, some users are unable to control these systems and are named neurofeedback illiterates. In this paper, we propose a cross-modality approach to predict affective neurofeedback illiteracy using electroencephalography (EEG) amplitude modulation measures. Thirty-one subjects were submitted to five-minute resting state protocol with EEG records, followed by functional near-infrared spectroscopy (fNIRS)-based affective neurofeedback task. EEG amplitude modulation measures were extracted from the resting block and correlated with the task performance. The gamma-m-alpha modulation from one channel presented a negative correlation with performance (ρ=-0.639, p=0.006). When used as input for a support vector regression model, this feature predicted performance with a mean absolute error of 13.78%. Our findings suggest this cross-modality feature is related to the affective lateralization effect, as well as with the EEG-hemodynamics coupling during resting-state. This feature might be a promising tool to predict performance and choose the best strategy for future therapeutics using affective neurofeedback.**

Keywords - *affective neurofeedback, fNIRS, EEG amplitude modulation, performance predictor*

I. Introduction

Affective neurofeedback uses neurophysiological signals to detect affective states and convert this information into computer commands [1]. One of the therapeutic uses of affective neurofeedback is to control abnormal neural activities associated to psychiatric disorders and possibly relief symptoms severity and lead to clinical improvement in patients with the major depressive disorder, obsessive-compulsive disorder, schizophrenia, addiction, personality disorders [2, 3].

Neurofeedback users require some time to learn to self-regulate their brain activity and achieve the desired control of the technique [4, 5]. This learning period may be several minutes up to several weeks, as already observed in longitudinal studies [6, 7]. However, even with long periods of training, explicit instruction and improvements in experiment protocol and signal processing, it is expected that some subjects, healthy or disabled, will present poor control performances [8]. These are examples of "non-performers," or "illiterates," which can comprise up to 50% of potential neurofeedback users [9, 10]. For these cases, the best option to attain proficiency would be switching to another neurofeedback approach [5, 8, 10].

During the last few years, an intense debate has risen about possible predictors for this lack of ability to control different protocols of NF [10]. While some studies evaluated the relation of the mental strategy used to gain control of the neurofeedback and its accuracy [11, 12], others correlated psychological aspects with performance, such as the self-confidence [13], frustration [4] and concentration [14]. Using different neurophysiological predictors, the accuracy of motor imagery and sensorimotor rhythms task performance in untrained participants was predicted from resting state EEG acquisition [15]. Complementarily, functional [16] and structural [17] neuroimaging were also used as performance predictors.

In this paper, we propose to use a cross-modality approach, evaluating an electrophysiological predictor for hemodynamic-based neurofeedback. Amplitude modulation features [18] are computed from the EEG signals acquired during the pre-task resting-state block and correlates these values with the performances of functional near-infrared spectroscopy (fNIRS)-based neurofeedback task. The choice of the EEG amplitude modulation metrics is based on previous studies reporting a linear correlation between the alpha modulations and the blood flow through grey matter [19-21].

II. METHODS AND MATERIALS

A. Participants

Thirty-one healthy participants (age: 25.71±3.32 years, 15 male), all undergraduate or graduate students, volunteered for the study and provided written consent; ethics approval was obtained from The Research Ethics Committee of the Federal University of ABC. Participants declared no history of neurological or psychiatric diseases and had normal or corrected-to-normal vision.

B. fNIRS-based affective neurofeedback

The affective neurofeedback task consisted of two blocks of five minutes of continuous resting-state (before and after the neurofeedback test), intermediated by two combinations of training/test blocks with 10/11 trials (Figure 1) containing visual instructions/feedback each, respectively. During the training and test blocks, subjects were instructed to remember autobiographical memories with positive affect context or to remain relaxed (rest with eyes opened), depending on the stimuli presented on the screen. Data from each training block was used to train a Linear Discriminant Analysis (LDA) model, which was used to provide feedback to the participant during each test block.

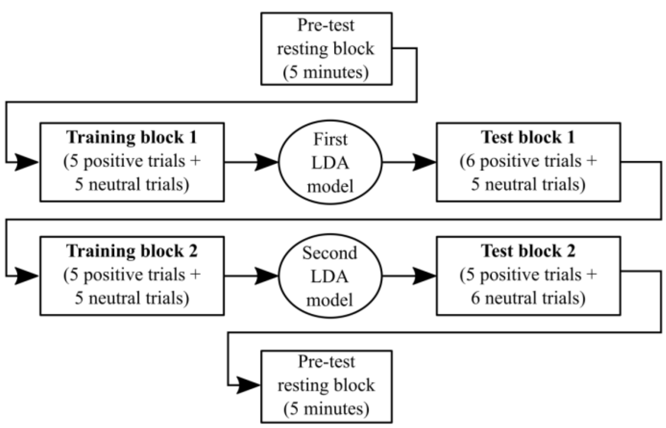

Fig. 1. Experimental flowchart.

Deoxyhemoglobin and oxyhemoglobin concentrations of thirty-two fNIRS channels recorded using the NIRScout System (NIRx Medical Technologies, LLC. Los Angeles, California) were used as inputs for the neurofeedback. For this, real-time signal processing was performed every second, with a band-pass (0.01-0.2 Hz) filter in both time series to remove noises related to the heartbeat (0.8~1.2 Hz), respiration (0.3Hz) and Mayor waves (<0.01). Deoxyhemoglobin and oxyhemoglobin concentrations were then computed, averaged and used as inputs to the LDA model. We arranged all fNIRS channels in an elastic band covering the frontotemporal and occipital regions (Figure 2).

Finally, the "performance" measure reported here corresponds to the number of trials during the test blocks where the user achieved minimum control of the system (i.e., maintained the instructed affect during at least 15 s from a total of 30 s per trial).

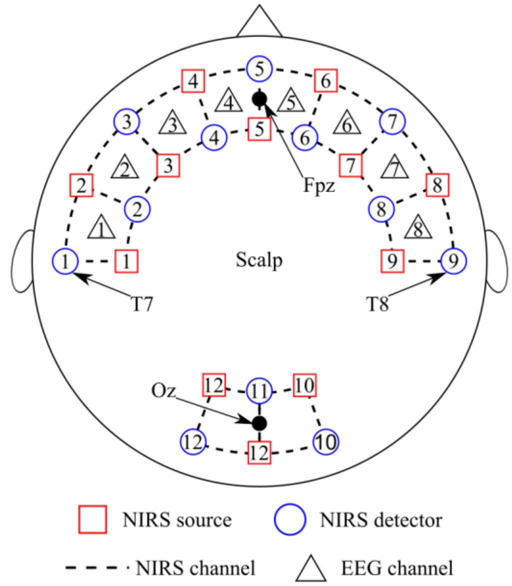

Fig. 2. EEG and NIRS channels over the scalp.

C. EEG capture and pre-processing

Eight EEG channels were recorded using a 72-channel QuickAmp amplifier system (Brain Products GmbH, Germany), with the reference and ground electrodes positioned in each earlobe (Figure 2). The sampling frequency was 500 Hz, and no filters were applied during acquisition.

The pre-task resting block (5 minutes) was segmented from the raw data, and band-pass filtered between 0.1-100 Hz by a second order Butterworth filter. Then, we applied the wavelet-enhanced independent components analysis (wICA) for artifact correction [22-24]. For this, signals were decomposed into eight independent components (ICs) and the wavelet transform applied to each IC. In sequence, wavelet thresholds were selected to differentiate between neural and artefactual coefficients, and the inverse wavelet transform was applied to these thresholds, retrieving ICs with only neural activity. Finally, the artifact-free EEG data were reconstructed using the wavelet-corrected ICs [22-24]. After the manual evaluation, the IC artifact detection threshold was set to 1.6 and the cleaning artifact tolerance to 1.4. These thresholds are responsible for detecting components with artifacts and the artifact magnitude, respectively [22].

D. EEG amplitude modulation computation

As previously mentioned, there is growing evidence that brain activity modulation is possibly related to the cerebral blood flow, in particular, the "alpha modulations" [19-21]. With this in mind, we propose here a novel feature for predicting the performance of fNIRS-based affective neurofeedback using these alpha modulations. Figure 3 depicts the signal processing steps involved in its computation.

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First, temporal series from all channels were decomposed into five classic spectral bands, called: delta (0.1-4.0 Hz), theta (4.0-8.0 Hz), alpha (8.0-12.0 Hz), beta (12.0-30.0 Hz) and gamma (30.0-100.0 Hz). The temporal amplitude envelope of each sub-band signal is then computed using the Hilbert transform [25].

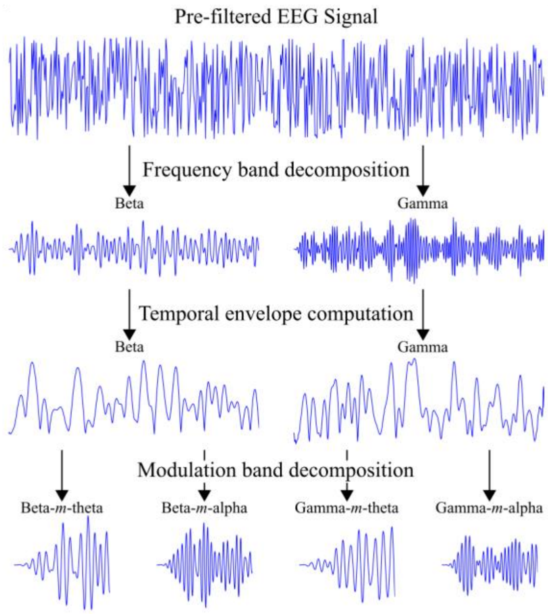

Fig. 3. Signal processing steps comprised in the calculation of EEG amplitude modulation.

However, due to the Bedrosian's theorem [26], the envelope signal can only contain modulation frequencies up to the maximum frequency of its originating signal. Additionally, the present study focused mainly on the alpha band modulations but also included the theta modulations due to a common discussion about the limit regarding theta and alpha bands. Thus, we maintained only the beta and gamma bands for the following steps. To quantify the rate of change of the sub-band temporal envelope, each envelope was decomposed into two modulation bands, called: m-theta (4.0-8.0 Hz) and m-alpha (8.0-12.0 Hz). To distinguish between the original frequency and the modulation bands, we use the notation "original frequency band - m - modulation band" (e.g., beta-m-alpha).

Finally, each modulation band is converted into a single value by an average moving window of 20 s in the power time series, with 50% of overlapping. Thus, at the end of the computation, each participant had an average value for each amplitude modulation, in each channel. In other words, 32 features per subject.

E. Correlation analysis and support vector regression

Spearman correlation coefficient was computed for each amplitude modulation, in each channel, to correlate its values with the vector of performances. Then, a permutation test was applied with 10^6 permutations for each channel and modulation band, to compare the obtained correlation values with the randomly by chance obtained correlations. Finally, the resulting p-values (significance level of 0.05) were corrected for 32 multiple comparisons (8 channels x 4 modulation bands) using Bonferroni approach.

The Channel4-gamma-m-alpha feature (the one with highest absolute correlation and significant p-value) was then used as input to a regression model to predict neurofeedback performance (e.g., the percentage of trials where the user achieved a minimum control of the system). The induced model was a Support Vector Regression (SVR) with a radial bias function kernel [27]. The choice for the SVR algorithm was based on its non-parametric approach, allowing the use of a non-linear kernel, as well as its strategy to minimize the generalization error. This induction was performed using a leave-one-participant-out (LOPO), were the SVR model was tested using the participant-out, and trained using the remaining participants. This procedure was repeated until all participants were used as the testing set. Then, we evaluated the performance of the SVR model using the mean absolute error (MAE), which is the average distance between the observed and predicted performances.

III. Results

The sample included in this analysis presented performances ranging from 10 to 100% (mean ± standard deviation = 67.74 ± 24.18%).

A. Amplitude modulation and performance

Figure 4 presents a heat map corresponding to the Spearman correlation coefficients between the neurofeedback performance and each modulation band in each channel. The Channel4-gamma-m-alpha feature presented a significant negative correlation with performance ($\rho = -0.639$, $p = 0.006$). In other words, the lower the amplitude modulation in this channel better is the performance of the user. Although other features also presented relatively high absolute correlation values, such as Channel4-beta-m-theta ($\rho = -0.420$, $p = 0.622$) and Channel8-gamma-m-theta ($\rho = -0.347$, $p = 1.000$), none of them reached the significance level.

B. Predictive performance

To illustrate the predictive performance of the Channel4-gamma-*m*-alpha feature, it was used as input to the SVR model. Figure 5 shows the relation between the predicted and observed performances of each participant. The MAE of the model was 13.78%, and the figure presents the error of each predicted value as the diameter of the corresponding circle. As examples, the highest absolute error was 64.26% while the lowest absolute error was 1.23%.

IV. Discussion

A. Lateralization effect

The presence of significant correlation with performance in only one channel (approximately over the right frontopolar region) is expected. A classical effect in affective neuroscience studies using EEG is the presence of some level of asymmetry, or the so-called lateralization, regarding the frontal channels [28]. This effect is commonly related to the prefrontal and orbitofrontal cortices, structures possibly recorded by the EEG channels and highly involved in the emotion and motivation brain circuits [28]. Even more, previous studies also reported the resting-state lateralization (recorded with fNIRS) as good predictors of the cortical responsiveness to emotions [29].

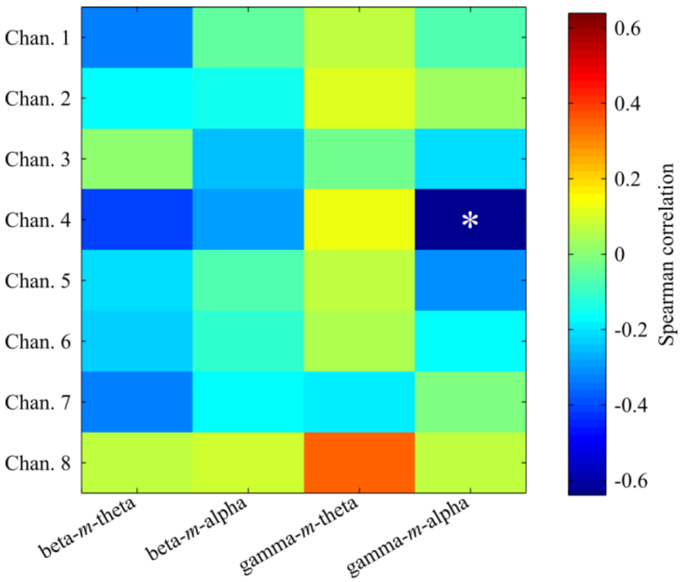

Fig. 4. Spearman correlations between the neurofeedback performance and each amplitude modulation in each channel. Hot colors represent positive correlations, while cold colors represent negative correlations.

B. *EEG and hemodinamics*

This cross-modality approach (EEG predictor for a fNIRS task) might seem unexpected at first sight. However, numerous recent studies suggest some level of relation between electroencephalographic and hemodynamic measures. For example, the EEG activity appears to be related with the blood-oxygen-level-dependent (BOLD) signal in functional magnetic resonance imaging (fMRI) measures, where low-frequency hemodynamics present an equivalent alpha activity [30], mainly in the frontal and parietal regions [31]. Also, simultaneous records revealed that the resting-state levels of oxyhemoglobin concentration are temporarily succeeded by alpha and beta power peaks in some brain areas [32]. Thus, since both measures are temporally and spatially related at some level, this cross-modality predictor may indeed be explored.

Besides, considering the original frequency of the relevant features, the gamma rhythm seems to be correlated with the self-referential resting-state network [33], which includes the medial ventral prefrontal cortex, the pregenual anterior cingulate, the hypothalamus and the cerebellum [34]. This characteristic is compatible with the targeting areas of this experiment, where the neurofeedback is focused on the prefrontal cortex and the self-induction of autobiographical memories with emotional context.

C. *Signal quality measure*

Another consideration of the significant correlation and its accuracy as a performance predictor is the possibility of a non-biological reason for these results. It is known that EEG is much more susceptible to biological (artifacts) and non-biological (environmental and instrumental noises) interferences [35]. Thus, during multimodal experiments, the EEG signal might present substantial evidence to the quality level, such as those related to the cap preparation (positioning, skin cleanness and conductivity, muscular contraction, head movements or heart rate interference). These noise sources, although less evident in fNIRS records, are crucial to the reliability of the results [36, 37].

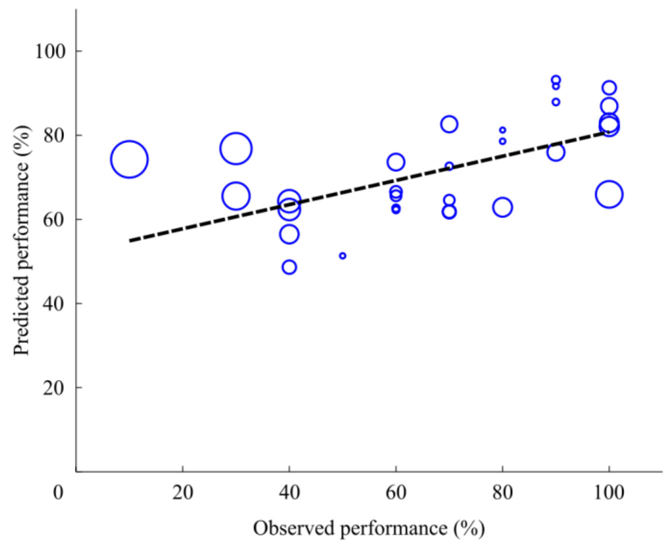

Fig. 5. Predicted performances achieved by the Support Vector Regression using the 'chan-4-gamma-*m*-alpha' feature. Each circle represent one participant, and the diameter of the circle is proportional to corresponding error. The dotted line corresponde to the line of best fit.

In this context, future research should explore if these pre-task EEG measures compose a biological predictor of literacy, or a noise evaluator to guarantee the experimental quality.

V. Conclusion

In this paper, we presented a cross-modality feature for neurofeedback performance prediction. The feature, termed "EEG amplitude modulation," measures the rate with which resting-state EEG sub-band signals are modulated. Our experimental setup showed that the alpha modulation is highly correlated with the affective neurofeedback performance, and achieved a satisfactory predictive performance with a low level of errors. This automated predictor has the potential to assist future experimenters to evaluate potential users of the studied neurofeedback method, or to adopt an alternative neurofeedback approach to the predicted illiterate users.

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