Multi-Modal Integrated Mini-QEEG Solution with Results, Training Protocols and Neurofeedback in Real-time

Francisco Marques-Teixeira[1], Horácio Tomé-Marques[1], João Andrade[1] and João Marques-Teixeira[1,2]

[1]Neurobica, Neurobios - Instituto de Neurociências, Rua Agostinho de Campos, 369, 4200-015, Porto, Portugal
[2]Laboratory of Neuropsychophysiology, University of Porto, Rua Alfredo Allen, 4200-135, Porto, Portugal

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Abstract: Many Neurofeedback softwares allow clinicians to develop modular protocols. Some even allow to be performed quantitative Electroencephalography (QEEG) analysis. However, an all-in-one solution does not exist, with built-in decision tree, that permits to perform a QEEG analysis, apply a protocol decision, and perform subsequent iterated mini-QEEG analysis, and subsequente protocol decisions and training, in the same system. Our application, besides being able to make the identification of the brain dysfunctional patterns concerning its electrophysiology, and accurately choose the Neurofeedback training protocols to apply, performs real-time Neurofeedback. We compared our system with a conventional EEG and QEEG system in a proof of concept rational, obtaining an average Pearson Correlation Coefficient of 0.89 regarding the dysfunctional patterns and protocols, as well as remitted dysfunctional patterns. In conclusion, our application is pervasive, scalable and potentially ubiquitous. And it can be extended into multiple and different consumer fields.

1   INTRODUCTION

This extended abstract aims to present the model behind an application for Neurofeedback (NF) training. Our model purposes a multi-modal integrated mini quantitative Electroencephalography (mini-QEEG) solution with results, training protocols and NF in real-time. Firstly, we present the theory behind brain performance optimization and how it differs from clinical NF. Secondly, we present how this theory can be applied to our software architecture model and how the system architecture is organized. To finalize, we present some preliminary results on how this system is as accurate and valid as a conventional clinical EEG and NF system.

Neurofeedback is a brain performance technique that uses processes of operant conditioning which leads to self-regulation of brain activity (Ute Strehl, 2014). Recent studies suggest that EEG Neurofeedback represents feasible and promising a tool for therapeutic interventions, and cognitive enhancement (Enriquez-Geppert et al, 2017), and that critical brain dynamics can be modulated with closed-loop stimulation in an automatic, involuntary fashion (Zhigalov et al, 2016).

We developed an application that processes EEG signal from 16 channels in real-time, computes metrics, e.g., power, frequency, phase, for each electrode,

and, according to inter- and intra-hemispheric physiological ratios and asymmetries of the main frequency bands (theta, alpha and beta), it assesses the main dysfunctional brain electrophysio-logical patterns in each user, and the main Neurofeedback protocols to perform according to a severity order.

We also programmed a decisional tree that assesses the success of each Neurofeedback session and outputs which protocol of the list should be done afterwards, up to 10 sessions per protocol. A user's block is composed of 3 protocols and, in the end of the block, another QEEG is automatically registered for verification of the overall improvement. If the improvement is satisfactory according to a defined threshold, the training is finished. However, if not, another block of 1 Neurofeedback protocol (up to 10 sessions) is recommended. The program repeats this process until the improvements are satisfactory.

2   METHODS

To develop this application, we have used the Processing Software, based in Java, to write and compile all the code.

The system architecture was based on a fixed main steps model:

1. Pre-processing: EEG signal Processing;

2. Post-processing: metrics computation;

3. QEEG: rules and protocols decisional tree;

4. Neurofeedback: mini-QEEG and training analysis

5. Validation of the whole application and extracted metrics.

For the first (1) step, we applied Fast Fourier Transform (FFT), with a 0.98 Hz resolution, to 16 scalp electrodes (Fp1, Fp2, Fz, F3, F4, Cz, C3, C4, T3, T4, Pz, P3, P4, O1, O2, Oz (this channel is represented as the average between O1 and O2). We use linked-ears reference and ground is located on AFz site. Based on the frequency spectrum, a known lead-off detection current and Ohm's Law, we also compute the impedance in each electrode.

For the second (2) process, we computed the spectral power for each electrode and for different frequency bins and frequency-bands, in real-time.

We also developed a blink and jaw clench detection routine. When one of these events is detected, the software assumes the value of the referred metrics as the result of the linear interpolation of the last 4 values computed.

For the third (3) process of this work, we computed dysfunctional patterns, such as dysfunctional power ratios, asymmetries inter-hemispheric and intra-hemispheric, among others.

These dysfunctional patterns were based in deviations of the normal brain electrophysiology, grouped as instabilities (frontal alpha asymmetry, frontal beta asymmetry, antero-posterior beta inversion) (Davidson, 1979, 2004; Harmon-Jones, 2004; Minnix et al., 2004; Nitschke, et al., 2004; Sutton and Davidson, 1997; Wiedemann et al., 1999), disconnection (disrupted Hibeta at T3 and/or T4) (Coan and Allen, 2004), blocking (disrupted Hibet:beta ratio at Fz and/or Pz, also known as Swingle ratio) (Swingle and Paul, 2015); hot temporals (high percentage of beta and hibeta at T3 and/or T4), and dystonus (hypertonus and hypotonus) (Hagemann, 2004).

Our software has a table of rules of dysfunctional patterns grouped according to the groups referred above and every-time there is a ratio that is inverted or not-present the rule is turned-on, thus, the dysfunctional pattern is considered.

Our software ranks the dysfunctional patterns of the user according to an serial order, based on their score, and link that dysfunctional order to a specific training protocol. As soon as a NF training session is completed, the efficiency of the protocol is automatically assessed by a mini-QEEG, in such a way that

the program will decide if the user will need to train the same protocol again or will jump to the next one in the serial order. In this application, the minimum training sessions per protocol are 6 sessions and the maximum are 10 sessions. Each training block is composed by 3 training protocols and each block has a minimum of 18 sessions (3x6) and a maximum of 30 sessions (3x10).

In the end of each block, the program performs a post-block QEEG to assess the success of the training. If the overall dysfunctional patterns are not corrected, the client will be indicated to do another block, this process being repeated until the dysfunctional patterns normalize. All the computation is done instantaneously.

For the fourth (4) process, we have programmed a real-time feedback related to a base-line measured in each training session that indicates the positive and negative feedback to be given to the user according to the dysfunctional pattern rule (reinforce or inhibit a certain frequency band in specific electrodes). This feedback is adaptive relative to a moving base-line, of 60 seconds, that dictates its difficulty level. Thus, we created a generative feedback, according to the level of the user's learning.
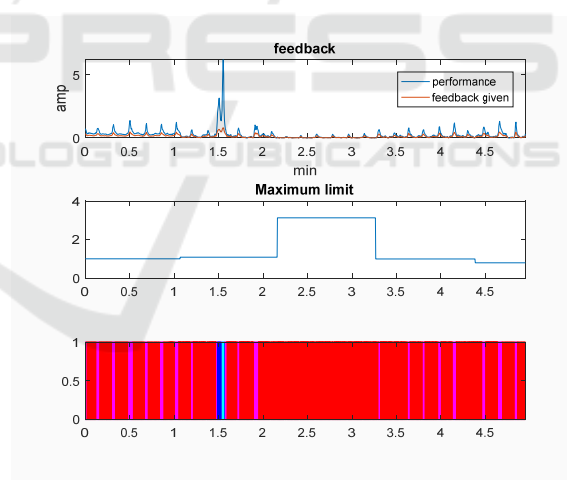

Figure 1: Example of the generative adaptation of the feedback of one user. First plot – user's performance in blue and feedback given in orange. Second plot – Maximum limit used to compute the feedback. Third plot – feedback given (from worst to best: red, pink, dark blue, light blue). We can see that the maximum limit goes up because the metric being trained rises in the moving base-line. Thus, the user stops receiving a positive feedback because now the level is more difficult. Then, since it became "too hard", the maximum limit drops down again, and the user starts receiving more positive feedback again.

To validate (5) this application:

1) we compared it to a standard QEEG system;

2) and perform NF sessions to assess the training efficiency of the system.

Regarding the QEEG system comparison we used the Neuronic E8.5 system (neuronicsa.com) for the EEG registration and the Neuroguide software (appliedneuroscience.com) for editing and processing EEG data.

We have made 4 recordings with 4 different users, 3 males and 1 female, mean age 34,75, with eyes closed. Each recording is composed by 2 consecutive 1 minute acquisitions using Neurobica (our system) and Neuronic. The same electro-cap (http://electro-cap.com) was used with both systems and only the connections to the EEG acquisition system was changed, so all the practical physical conditions were maintained for both systems. We verified the impedances with Neurobica, maintaining their values below 10 KΩ before recording the signal.

Regarding the clinical validation of the NF training, 1 user made 11 sessions of approximately 5 minutes, in two days (6 in the first and 5 in the following day). All sessions were done with the same NF protocol (based on the reinforcement of β band in F3 channels relatively to F4) to study its metric evolution with the training.

3 RESULTS

In this section, we present the preliminary results for the comparison of the metrics (a) computed with the Neuronic system and ours (b) as well as the Neurofeedback training results.

3.1 Systems Comparison

Figure 3 shows the comparison between the results of the 2 sets of one minute acquisitions, Neuronic and Neurobica, for the four users included in the study. This comparison was done based on the values computed for the metrics corresponding to the dysfunctional patterns scores. Neuronic values were computed offline, after acquisition, using MATLAB (www.mathworks.com), and Neurobica results were computed online by our application.
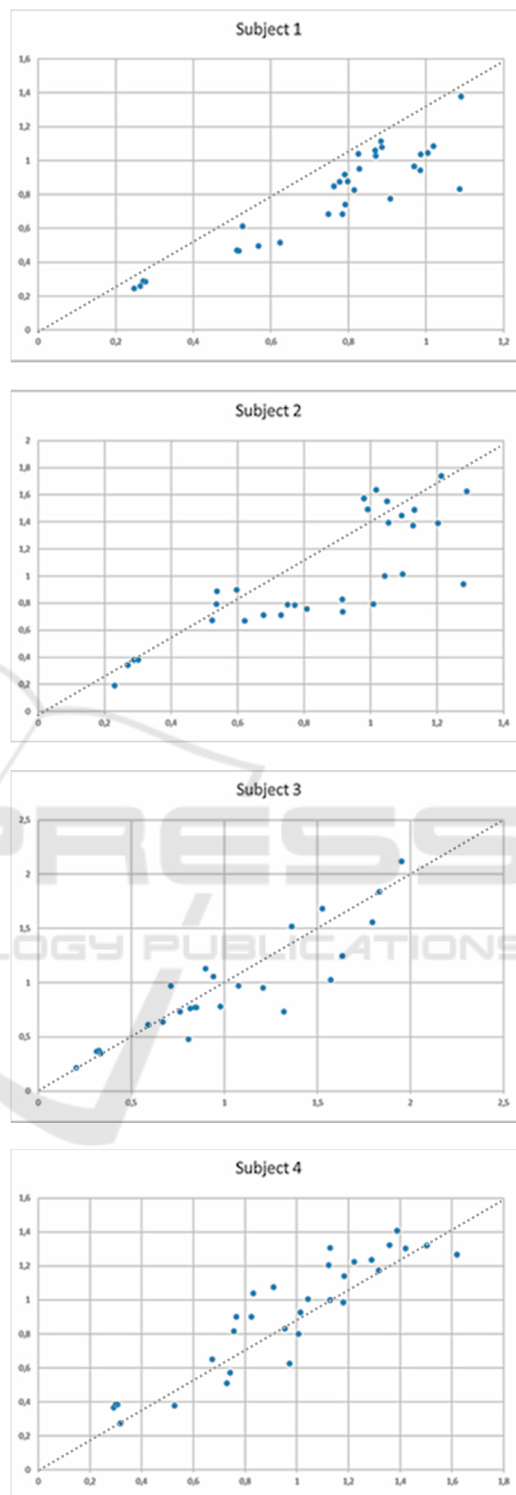

Figure 2: Comparison between results computed after offline processing of Neuronic acquisition (x axis) and online processing during Neurobica acquisition (y axis).
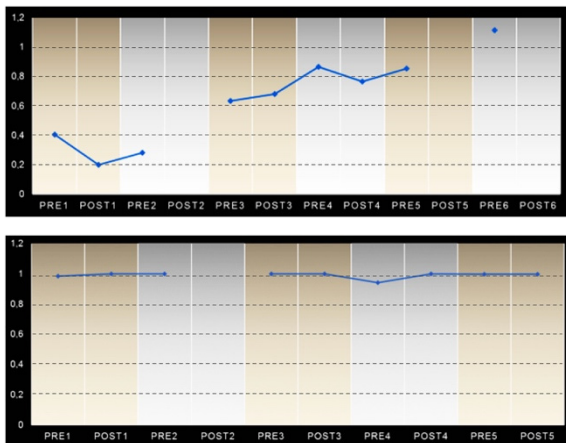
Figure 3: Dysfunctional pattern metric score across NF training sessions in the first (above) and second (below) days. Some values are missing because they were not recorded. Optimal value should be above 1. In the beginning of the first day, the score is significantly below that value. It rises as the sessions are made, until it reaches a value higher than 1. In the second day, it maintains its value around 1.

As it can be seen in the plots of the correlation results are statistically significant (for all users, p-value < 0.001), with an average Pearson Correlation Coefficient of 0.89.

3.2 Neurofeedback Training

For preliminary assessment of NF training efficiency, one users spent two consecutive afternoons performing NF with the same protocol. Each NF session lasted for 5 minutes and small breaks between sessions were made. The specific dysfunctional pattern metric relative to the protocol was computed before and after NF training. Figure 3 shows this metric evolution across time in the two afternoons of training.

4 DISCUSSION

4.1 Systems Comparison

The preliminary results indicate that the online analysis performed by the Neurobica system is strongly correlated with the offline analysis made after the acquisition with Neuronic, which leads us to suggest that we are measuring and computing reliable data.

4.2 Neurofeedback Training

Neurofeedback training preliminary results are very

satisfying and encouraging because they show the effectiveness of the NF training in the regularization of the dysfunctional pattern metric score, in the first day. They also show that, after regularized, the metric stabilizes in the following day. This is an important conclusion relatively to Neurofeedback effectiveness in general and more studies based on this approach are going on, with more users and different follow-up periods.

4.3 Future Work

For this work, we programmed all the metrics and ratios computation. Efforts are being made for in the future to work on the mining of all the intra and inter user data in a local server. During this process, all the data will be returned to the users in a dashboard with the following information: 1) scheme of the training sessions accomplished according with the training proposed by the application that self-organizes according to the success in the correction of the dysfunctional patterns; 2) information about the training protocol used in each session and how was the evolution of the metrics and rations of that protocol; 3) information about the dysfunctional patterns assesses in the QEEG of each user; 4) topographic maps of the respective metrics and ratios of each user; 5) we are also working on the assessment of cognitive performance improving, symptom reduction and behavioural and well-beingness changes after the Neurofeedback training and ; 6) we are preparing the extension this pilot study to more subjects in order to accomplish the final validation of this integrated system.

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