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Quantitative EEG for Brain-Computer Interfaces

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1. Introduction

This paper attempts to give different examples of applications of quantitative EEG for the realization of Brain-Computer Interfaces. Particularly we think that neurotechnologies for Brain-Computer Interface (BCI) based on electroencephalography (EEG) offer advanced tools of interest for other research and application fields. EEG BCI technologies are based on the electrical nature of brain activity. EEG BCI captures user state or intent via electrical signals recorded on the scalp and maps them into computer or device commands. As the reader can imagine such a process goes through an intermediate process of quantification. We explain in the following chapter some of these techniques.

We describe in Section 2 two of the most classical paradigms used in Brain-Computer Interfaces for communication. The so-called P300 paradigm is often used in BCI for spelling purposes. We detail here its relationship to attentional processes and the way it can be measured. Moreover we discuss so-called Steday-State Visual Evoked Responses (SSVEP), which are elicited while observing a flickering light source.

Affective Computing is an emerging field within BCI that involves detecting the emotional content within the subjects' brain activity. Arousal, workload, and stress can be studied through EEG quantitative analysis. We describe in Section 3 different developments and experimental works we have conducted in this field.

Neuro-feedback (NF) is a type of user feedback that uses real time displays of electroencephalography measurements of brain activity features. Quantitative EEG has been extensively used in this therapeutical field. EEG features are extracted and displayed allowing the user to modulate their temporal evolution. This results in neuromodulatory techniques based on neuro-feedback training with therapeutic applications, which are detailed in Section 4 on hand of Attention Deficit Hyperactivity Disorder. We finally give in Section 5 some conclusions to this overview.

2. Event Related Potentials for BCI

2.1. *P300 as a tool for attention measurement*

We recall in this section the quantification of attention in mental processes as described in [1]. Brain-Computer Interfaces have been using a particular paradigm based on attentional processes denoted as P300 [2] [3] for communication. The main idea of the experimental paradigm is that when a external stimuli raises the attention of a subject, a characteristic brain waveform appears [4]. A typical P300 waveform or complex is formed by a negative peak at approximately 200 ms followed by a positive one of larger amplitude at 300 ms. The peak at 300 ms, which is formed by two different components, can be used for attentional studies. Particularly the component of the P300 event-related potential, which originates in the frontal part of the brain, is associated with attention mechanisms during task processing, whereas the one found in the tempo-parietal part relates to memory processes [5]. We propose in this communication to extend the observation of peripheral muscle activity [1] with the measurement of such brain activity. We expect from this paradigm shift to get a more direct access to attentional processes as originated in the brain. This could lead to a more objective quantification of the relationship between e.g. creativity and attention.

Particularly we describe our work with the so-called rapid serial visual presentation (RSVP) paradigm [6]. Such experimental set-up proposes to show a sequence of images to the experimental subjects. The images are shown at a high presentation rate between 100 and 1000 ms. The time between stimuli has an influence in the P300 amplitude as shown in [5]. In such a set-up the subject is instructed to consciously detect a particular image in the sequence. Each time this image appears her brain activity shows the so-called P300 waveform. We describe here the results obtain in such a set-up.

Three different subjects went through the RSVP of 500 natural images in sets of 10 different pictures at a rate of 10 per second. The subjects were told to detect 1 particular image in each of the sets. While this image to be detected is denoted as the target stimuli, the remaining ones in the set are the non-target. Each image of a 10 set gilts as target image 5 times for each subject. While undergoing the experimental paradigm, the brain activity of the subject was monitored through an electroencephalography (EEG) device using 32 different channels placed following the 10-20 standard positioning.

In order to conduct the data analysis we have used the methodology described in [8], which uses an ensemble of Support Vector Machines. The first stage of this methodology includes filtering the data in the band 0.1 to 10 Hz, decimating the obtained signals, and cutting the intervals of 667 ms duration after stimuli presentation. We exemplary show the grand averages of the waveforms obtained on all target stimuli in Figure 1. We have selected here the channels presenting the best response by visual inspection, and use them later in the classification. It is worth mentioning that the latency of the peak corresponding to the P300 appears delayed w.r.t. usual value at 300 ms due to the complexity of the stimuli used in the experiment.

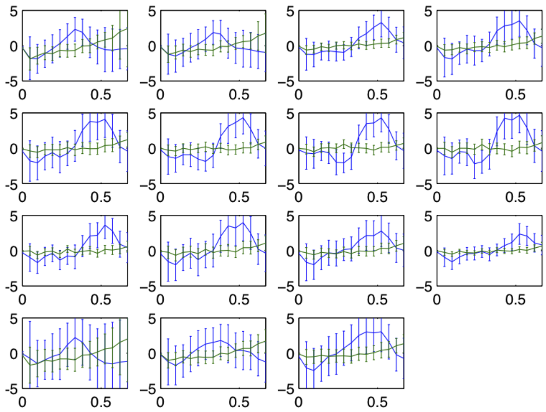

Figure 1. Grand averages with standard error bars of signals obtained with target (blue) vs. non-target (green) stimuli in electrode positions Fp1, AF3, T7, C3, CP1, CP5, P7, P3, CP6, CP2, C4, T8, Fp2, Fz, Cz (from top-left to bottom-right).

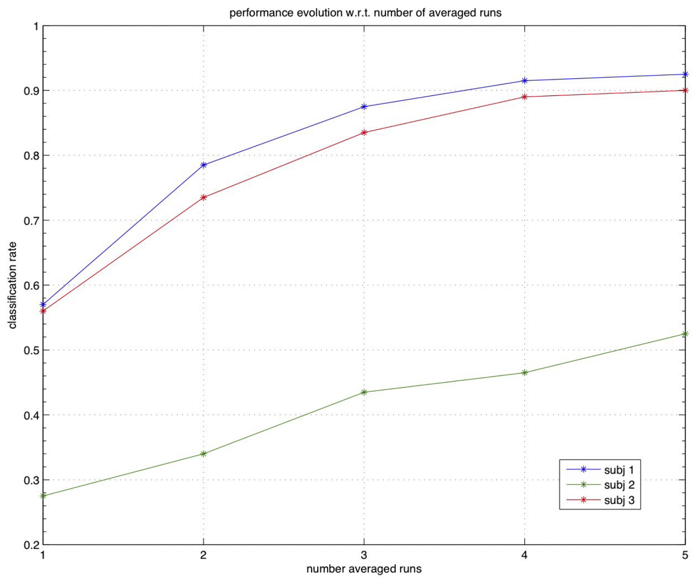

Figure 2. Classification performance of the methodology used herein when averaging the classification results over different runs for the 3 different experimental subjects (see legend).

After the signals have been pre-processed and reduced to 15 component feature vector per channel, we concatenate each channel feature and deliver it to a set of 10 classifiers in order to measure the classification performance . Here the goal is to discriminate between target and non-target images based on the P300 waveforms. We use as performance the classification rate, i.e. the percentage of right classified stimuli. Such a classification can be used to characterize the attentional process that leads each subject to detect the presence of the target images. As in the case of the feature vectors (see Figure 1), the classification result will improve when averaging the detection of several results. Hence we characterize the performance in a plot that depicts the classification rate with respect to the number of averaged classification outputs, i.e. the number of times an image has to be shown to a subject in order to present a classifiable P300 waveform. The result is given in Figure 2. As it can be observed the methodology gives excellent performance for 2 out of 3 subjects. The poor performance in Subject2 could already be observed in his grand average plots, which do not show a clear distinction between target and non-target stimuli. Such a poor performance could be due to a lack of attention during the experimental task.

The results described in this section, i.e. a characterization of the P300 wave in form of its latency and amplitude, and its classification performance can be used for the objective measurement of attentional psychophysical features.

2.2. STEADY-STATE VISUAL EVOKED POTENTIALS

In recent years, there has been increased interest in using steady state visual evoked potentials (SSVEP) in brain computer interface (BCI) systems. The SSVEP approach currently provides the fastest and most reliable communication, making it the ideal BCI paradigm. SSVEP-based BCIs offer two main advantages over BCIs based on other electrophysiological sources: i) have higher information transfer rate, and ii) require shorter calibration time [37].

SSVEP is a resonance phenomenon arising mainly in the visual cortex when a person is focusing their visual attention on a light source flickering with a frequency from 1 to 100 Hz [38]. When SSVEP is elicited, it is manifested as oscillatory components in the user's EEG, especially in the signal from the primary visual cortex [39]. SSVEP-based BCIs can be classified into three categories depending on the specific stimulus sequence modulation in use: time modulated VEP (t-VEP) BCIs, frequency modulated VEP (f-VEP) BCIs, and pseudorandom code modulated VEP (c-VEP) BCIs [40].

BCI systems based in f-SSVEP have been the approach most commonly used in BCI research. In f-SSVEP based systems each target is flashed at a unique frequency generating resonance response that can be measured in the EEG as oscillatory components matching the repetitive visual stimulation (RVS) frequency and its harmonics. It is when SSVEP is elicited its response is characterized by an energy increase at the RVS frequency and its harmonics that is also phase-locked with the stimulus [41].

Frequency is a crutial property of the RVS. SSVEP is elicited when a person is focusing their visual attention on a light source flickering with a frequency ranging from 1 to 100 Hz [38]. SSVEP response has a strong subject and RVS frequency dependency and therefore, for practical SSVEP-based BCI systems construction, it is recommendable to tune this parameter for each subject under evaluation in order to obtain a large SSVEP response. The choice of the flickering frequency determines which cortical network synchronizes to the flickering frequency [42] and therefore the electrode or combination of electrodes in which the SSVEP response appears.

Figure 3: User controlling an SSVEP-based BCI application with four degrees of freedom

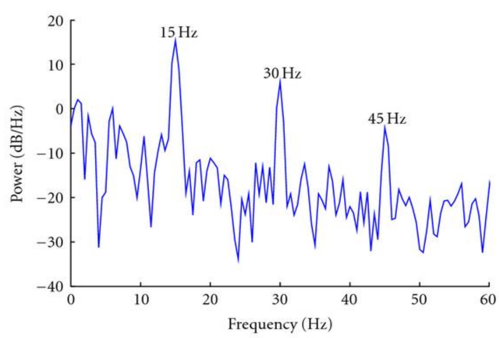

Figure 4: SSVEP power response for a 15Hz stimulation frequency[45]. SSVEP manifests oscillations at the stimulation frequency and higher harmonics.

Practical SSVEP based BCI systems in general are compound of several targets consisting of RVS sources flickering at different frequencies. When the system detects the elicited response corresponding to one of the frequencies under evaluation it carries out the associated action. Two main types of SSVEP based BCI paradigms exists: asynchronous and synchronous. Synchronous, also known as cued-paced BCI paradigms do not consider de possibility that the user does not wish to communicate. RVS is always present and the SSVEP response continuously evaluated. Although these BCIs are relatively easy to use and develop , they are impractical for many in many real-world settings [43].

Asynchronous or self-paced BCI, user can interact with the BCI at their leisure, without worrying about well defined time frames [44]. In this case the system detects when the user wants to interact with the BCI switching on the stimulation sources during a short time defined period. During this period the user focus his attention on the target whose associated action wants to carry out. After the stimulation the response of the target frequencies is evaluated determining which one was responsible of eliciting the evoked potential.

3. Affective computing: Novel Brain Computer Interfaces

The effect of emotional and affective states of the user on Human Computer Interaction systems has been widely studied [18][19][20]. Moreover, the impact of affective states on BCI systems performance has also been studied [21][22], proving the importance of incorporating mechanisms for dealing with affective states on the realization of Brain-Computer Interfaces. Affective computing methodologies and techniques have been used to develop BCI systems in which taking into account the affective state of the user improved the performance [46][47].

We present in the following sections our works on emotion detection from EEG and stress detection from EEG that can be applied to the realization of advanced BCI systems incorporating affective computing to achieve high levels of performance.

3.1. Arousal-valence detection

Following the dimensional approach to model emotions, we can take the valence state of the subject as the first dimensional state, and the arousal state of the subject, as the second. For the sake of the detection's method, these two dimensions are usually considered to be independent. Therefore, the emotional state on each of them is measured separately, having valence and arousal a variety of proposed detection methods each.

The detection of arousal using EEG has been widely published proposing different methodologies. However, the most common approaches are those that make use the relation between asymmetric frontal cortical activity and the valence state [25]. Studies show that on positive-valence states, the left hemisphere of the brain cortex present higher activity with regards to right hemisphere, whereas on negative-valence states, the right hemisphere presents higher activity with regards to the left one [26] [27]. Moreover, according to newer publications, this asymmetric activation is stronger or specific to the frontal cortex [28].

In order to measure the activation of each hemisphere or region, some works take profit of the reported evidence that the brain activity is inversely related to the preeminence of the alpha (8-12Hz) frequency band of a EEG signal. On low brain activity periods the alpha band increases it's power with regards to other bands, and vice versa [29].

To compute the asymmetric activation of right and left hemisphere, power on alpha band is computed on right and left hemisphere, obtaining what is commonly called alpha-asymmetry: alpha power on right hemisphere minus alpha power on left hemisphere. Positive values of this value will respond to greater activity of left hemisphere with regards right hemisphere and, therefore, correspond to positive valence states. On the contrary, negative values of alpha-asymmetry will correspond to negative valence state.

Following this asymmetry-based approach, we developed a valence state detector based on EEG. Placing the electrodes on the right and left hemisphere locations for the frontal and prefrontal cortex, we average the alpha activation of the electrodes located on the right hemisphere and the electrodes of the left hemisphere. The difference between the averaged activations of the right hemisphere and the averaged activations of the left hemisphere is taken as value corresponding to the valence state of the subject.

While for valence most of the methodologies share a clear approach based on asymmetric activation, the different methodologies to detect the arousal state from brain activity take a high variety of approaches. Arousal states have traditionally been detected from the reactions of the autonomic nervous system through the monitoring of heart rate, skin temperature or galvanic skin response. However, more recently brain activity has also been used to detect arousal. Some publications related high mental workloads with high arousal states [30], and low mental states and boredom with low arousal [31]. Other publications relate event-related reactions on different bands ands locations of the brain to arousal. Variances of event-related synch and desynchronization on alpha (8-12Hz) and theta (4-8Hz) bands in different areas of the brain to different arousal states induced by pictures have been reported [32]. Also gamma bands (30-65Hz) have been reported to present higher activation regarding high arousal states [33].

Following the mental-load approach, we developed an arousal state detector based on EEG. Taking profit to the reported activation of beta bands on higher work-loads, we take the ratio between the beta activation and alpha activation to compute the ratio of activation versus deactivation. This ratio will correspond to the arousal state of the arousal in our detection.

3.2. A qEEG platform for visualizing emotional features

In this section we present an EEG-based system for tracking emotions in real-time, build upon the application programming interface (API) for the Enobio® electrophysiological sensor[1]. It is based on the valence-arousal framework [23], a representation in which the arousal dimension measures how dynamic the emotional state is, and the valence is a global measure of the positive or negative feeling associated with the state.

The graphical user interface consists of a control panel (Figure 5), in which the user can configure the Enobio® setup, and an emotion visualization panel (Figure 6), in which the detected emotions are shown in real-time.

1 http://neuroelectrics.com/enobio

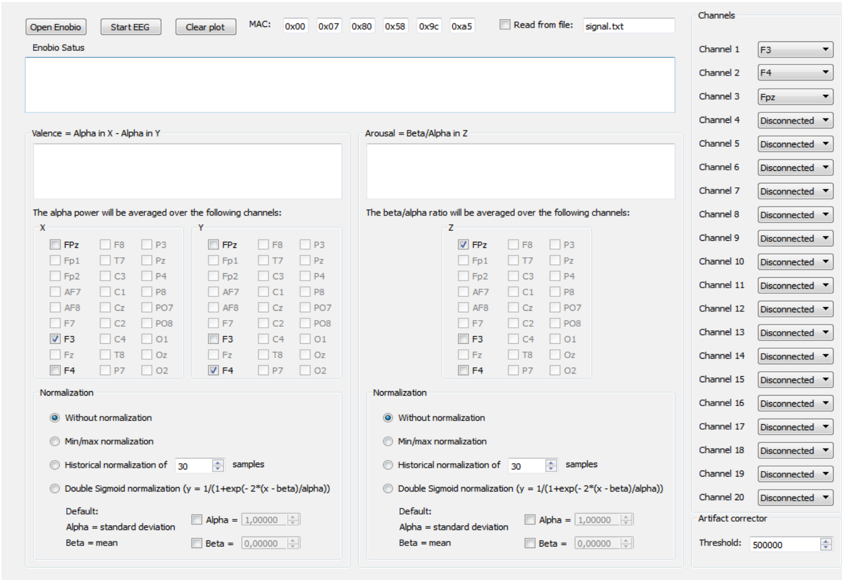

Figure 5. Control panel

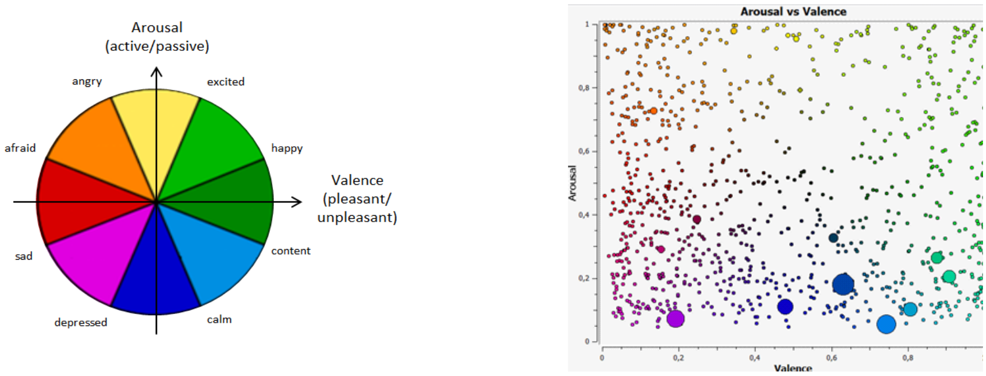

Figure 6. Plutchik color scheme (lrft) and its usage in the visualization panel (right).

The control panel allows the user to configure the electrode positions that will be used to compute the valence and arousal values. Moreover the power in the alpha and beta bands will be averaged over the selected channels for each element in the valence and arousal calculation, as following:

$$Valence = \frac{1}{I}\sum_{i=1}^{I} P_{alpha}(channel_i) - \frac{1}{J}\sum_{j=1}^{J} P_{alpha}(channel_j)$$

$$Arousal = \frac{1}{K}\sum_{k=1}^{K} P_{beta}(channel_k) / P_{alpha}(channel_k) \quad ,$$

where $P_{alpha}(channel_i)$ and $P_{beta}(channel_i)$ are the power in the alpha and beta bands in the *i*-th channel, and *I*, *J* and *K* are the number of selected channels for each element. The user can also select among four normalization methods applied to the valence and arousal values: (1) the range normalization; (2) the historical normalization, in which the minimum and maximum are computed only over the last L samples; (3) the Sigmoid normalization, where sigmoid parameters can be set up; and (4) no normalization.

The emotion visualization panel consists of a two-dimensional plot in which the valence and arousal are represented in the horizontal and vertical axis, respectively. Such a representation was proposed by Russel [13]. Every time a valence-arousal pair is computed, an emotion is represented with a circle in its corresponding position, color and size. The position of the circle depends on the values of the valence and arousal, while the color of the circle is set according to a color scheme derived from Plutchik [24] (Figure 6), and the size of the circle is determined by the recentness of the sample –the more recent the sample, the bigger the circle; as time goes by, the size of the older samples becomes smaller. The resulting system outputs a new emotion every 0.4 seconds, taking into account that the Enobio outputs 500 samples per second and that the values of valence and arousal are computed every block of 200 samples.

3.3. *Stress detection*

According to [9], “Psychological Stress" occurs when an individual perceives that environmental demands tax or exceed his or her adaptive capacity. In this work we focus on this type of stress and applied a protocol in which several tasks were designed to induce different level of stress to the participants. The protocol included a baseline recording, a reading task (low stress), a stroop test, an arithmetic task (medium stress) and finally a false blood sample test (high stress). In the first part of our work, we applied averages over the 12 participants of our EEG features.

Following the Rel model of emotions [13], the “stress” emotion is characterized by a negative valence and a positive arousal, which can be placed in a line over the orange and plae blue sectors of the diagram given in Figure 6. Based on the literature (for example [10], [11] and [12]), we see that Alpha Asymmetry is related with the valence dimension of emotions while Beta/Alpha ratio is related with the arousal dimension. In our work we have focused on these 2 EEG features and in order to extract them we used 3 EEG channels (F7, F8 and Cz as reference).

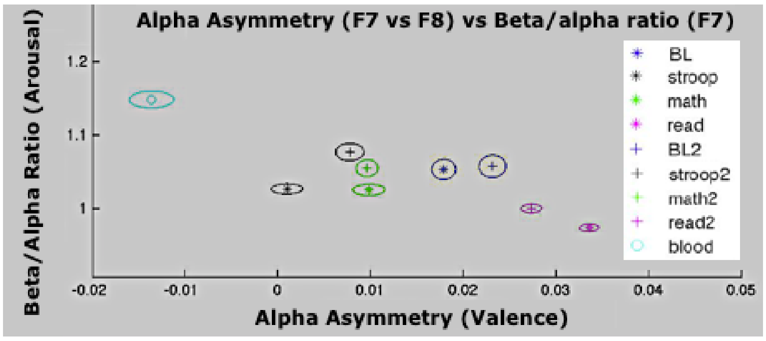

Figure 7: Average over subjects of the Beta/Alpha ratio and the Alpha asymmetry for each one of the tasks of our protocol.

The results shown in Figure 7 are as expected: our low stress tasks have higher valence and lower arousal, while our high stress task has the opposite behavior. The medium stress tasks fall in between.

In the next step of our work and in order to study the possibility of detecting stress levels on a subject to subject basis, we applied machine learning techniques in order to train a classifier (Linear Discriminant Analysis) using a leave-one-subject approach. In this case we obtain a performance as high as 88% between Baseline and Fake Blood Sample task, 72% between Stroop Test and Blood Sample and finally 83% between Baseline and Stroop.

The conclusion of this study is that EEG can be used to extract stress level, and interestingly enough is that only 3 EEG channels are needed, making the system unobtrusive. More over this system has the capacity to work in real time, making it very suitable for augmented reality, neurofeedback applications and for Stress Management Therapies.

4. Therapeutical usage of qEEG and BCI: Neurofeedback for attention deficit hyperactivity disorder

Attention deficit hyperactivity disorder (ADHD) is the most common psychiatric disorder in children (2% to 5%) [14] and is generally diagnosed in children who exhibit attention difficulties, impulsive behaviors, and extreme levels of hyperactivity. Also, children with ADHD frequently exhibit a variety of physical problems such as headaches and immune system deficiencies, resulting in frequent illnesses.

For over 50 years and increasingly more since 1990s, Ritalin and amphetamine derivates have been used to treat ADHD worldwide [15]. Even considered as safe drugs, they have frequent side effects, e.g. appetite suppression, abdominal pain, insomnia, headache, and anorexia [16]. Neurofeedback (NF) therapy opens new possibilities for ADHD care providing an adverse side effect free treatment. Electroencephalography (EEG) measures the electric currents in the brain reflecting the function of certain brain activities. Since 1970s studies have revealed specific ADHD patterns measured in the EEG. The goal of EEG Biofeedback training is to teach ADHD patients how to alter these abnormal patterns. During neurofeedback treatment children learn how to self-regulate these patterns usually by playing videogames. Attention and alertness levels are transformed into game commands encouraging the patient to operate at desired levels. Neurofeedback training has many therapeutic applications including attention deficit hyperactivity disorder (ADHD). Creative states and meditation patterns can also be found in the EEG and be trained in the same way as a clinical neurofeedback application.

4.1. *EEG Patterns*

The most common pattern found in ADHD is the excess slow wave activity in the frontal regions [16]. There are numerous other ways of looking at sub-types of ADHD based on EEG band power analysis. Excess theta activity is the most common type, as reflected in theta-beta ratios using single channel [17]. There can also be excess alpha activity usually in the lower alpha range (8-10Hz). The goal of EEG Biofeedback training is to teach the child how alter these abnormal brain waves normalizing the EEG activity.

Band power meditation patterns can also be found in the EEG. Significantly increased theta power was found during nondirective meditation while there was also a significant increase in alpha power [35]. Professionally significant enhancement of music and dance performance and mood has followed training with an EEG-neurofeedback protocol which increases the ratio of theta to alpha waves using auditory feedback with eyes closed [36].

4.2. BrainSurfer: NE Neurofeedback application

BrainSurfer, a flexible general porpoise, fully configurable neurofeedback application, developed by Neuroelectrics®, aiming to address ADHD treatment requirements. The application has been designed in order to satisfy both experienced researchers and clinician needs. BrainSurfer monitores the temporal power evolution of customized frequency bands fulfilling almost every neurofeedback band power based training protocol. BrainSurfer uses Enobio® in its 8 channel version, a wearable , wireless electrophysiology sensor system for the recording of EEG, which makes it simple and quick to set-up the device montage, it also provides the added advantage of not having the patient attached to the measuring device. BrainSurfer performs robust band power calculation in real-time. Signal processing stages include filtering, referencing, eye artifact correction, windowing and power spectral density extraction. The calculated power feature is presented to the clinician/researcher allowing him to monitor its temporal evolution and used to command the patient's video game application.

BainSurfer gives the possibility of automatically configuring the NF application parameters for most ADHD popular training protocols including the ones previously described. Experienced users have also the chance of fully configuring the application setting.

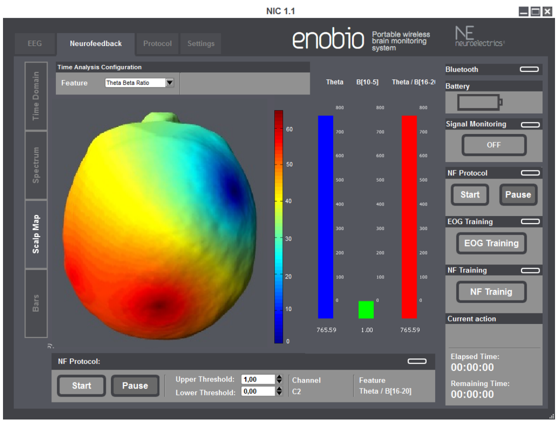

Figure 8: ADHD feature QEEG

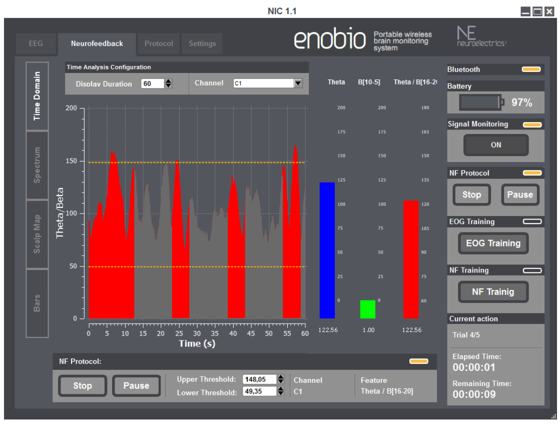

Figure 9: ADHD temporal feature monitoring

During the neurofeedback training the operator is able to follow in real time the calculated feature evolution. BrainSurfer feature monitoring includes temporal feature evolution (Figure 9), PSD and bar representation. Quantitative Electroencephalography (QEEG) (Figure 8) of the feature at every connected electrode is also presented. Quantitative Electroencephalography (QEEG) of the feature at every connected electrode is also presented. Brain surfer also provides simple statistics of the performance of both training trials and the entire training session, definitely useful to follow the treatment evolution. Current neurofeedback clinical applications such as BrainSurfer can be easily configured to calculate meditation and creative state features boosting the possibilities of creativity neurofeedback.

5. Conclusions

The paper presented herein describe different neurotechnologies to be used for the quantification of the brain activity. All types of techniques take as starting point the electrical nature of such activity. Brain-Computer Interfaces based on the detection of Event Related Potentials like the P300 or the SSVEPs described herein and the detection of affects can be used for the objective measurement of cognitive processes. Different parameters of the P300 waveform and its detection can be used to quantify attentional processes. SSVEPs used the reaction to flickering stimulation sources as reflected in the brain activity. Moreover we have described different technologies for the measurement of arousal, valence, and stress. All these interface paradigms relay on quantification techniques to be exploited in other research and application fields.

Moreover neurofeedback, which is based on the real-time application of quantitative techniques on brain activity, is used to modify the dynamics of brain activity. The presented neurofeedback application can be tuned to monitor in real-time different brain rhythms. This measurement goes thence into the control loop of the visual feedback mechanism. The modulatory action of these technologies in therapy has not been exploited in correspondence with its potential. We expect the following years to witness its full development.

6. References

[1] Friedman, Ronald S., Ayelet Fishbach, Jens Förster, and Lioba Werth. "Attentional priming effects on creativity." Creativity Research Journal 15, no. 2-3 (2003): 277-286.

[2] Fazel-Rezai, R., Allison, B.Z., Guger, Ch., Sellers, E.W., Kleih, S.C., Kübler, A. (2012) P300 brain computer interface: current challenges and emerging trends. Frontiers in Neuroengineering 5: 14), p. 14.

[3] Farwell, L., and Donchin, E.(1988). Talking off the top of your head: toward a mental prosthesis utilizing event-related brain potentials. Electroencephalogr. Clin. Neurophysiol. 70, 510–523.

[4] Gray, H. M., Ambady, N., Lowenthal, W. T., & Deldin, P. (2004). P300 as an index of attention to self-relevant stimuli. Journal of Experimental Social Psychology, 40(2), 216-224.

[5] Polich, J. (2007). Updating P300: an integrative theory of P3a and P3b. Clinical neurophysiology: official journal of the International Federation of Clinical Neurophysiology, 118(10), 2128.

[6] Acqualagna, L., Treder, M. S., Schreuder, M., & Blankertz, B. (2010). A novel brain-computer interface based on the rapid serial visual presentation paradigm. In Conf. Proc. IEEE Eng. Med. Biol. Soc 1, pp. 2686-2689).

[7] Guger, C., Krausz, G., Allison, B. Z., & Edlinger, G. (2012). Comparison of dry and gel based electrodes for P300 brain–computer interfaces. Frontiers in Neuroscience, 6.

[8] Rakotomamonjy, A., & Guigue, V. (2008). BCI competition III: dataset II-ensemble of SVMs for BCI P300 speller. Biomedical Engineering, IEEE Transactions on, 55(3), 1147-1154.

[9] Sheldon Cohen, Denise Janicki-Deverts, and Gregory E. Miller. Psychological stress and disease. JAMA: The Journal of the American Medical Association, 298(14):1685-1687, October 2007.

[10] I. H. Gotlib, C. Ranganath, and J. P. Rosenfeld. Frontal EEG alpha asymmetry, depression, and cognitive functioning. Cognition and Emotion, 12(3):449-478, 1998.

[11] Richard S. Lewis, Nicole Y. Weekes, and Tracy H. Wang. The eect of a naturalistic stressor on frontal eeg asymmetry, stress, and health. Biological Psychology, 75(3): 239 -247, 2007. ISSN 0301-0511.

[12] Qing Zhang and Minho Lee. Fuzzy-gist for 4-emotion recognition in natural scene images. pages 1-8, 2010.

[13] James A. Russel (1980). A Circumplex Model of Affect. J. Personality and Social Psychology 39 (6) 1161-1178

[14] American Psychiatric Association (1994). Diagnosis and Statistical Manual of Mental Disorders, Washington.

[15] Werner Van den Bergh (2010), Neurofeedback (EEG-Biofeedback) (BMED Press LLC). In Neurofeedback and state regulation in ADHD, a therapy whithout medication. Corpus Christi, Texas.

[16] Lydia Thompson and Michael Thompson (2009). QEEG and neurofeedback for assessment and effective intervention. Quantitative EEG and neurofeedback, advance theory and applications (2nd ed.), Elsevier.

[17] Monastra, V. Lubar, J. F. Linden (1999). Assesing attention deficit hyperactivity disorder via quantitative electroencephalography: An initial validation study. Neuropsychology. Endicott, New York.

[18] Partala, T., & Surakka, V. (2004). The effects of affective interventions in human–computer interaction. Interacting with computers, 16(2), 295-309.

[19] Brave, S., & Nass, C. (2002). Emotion in human-computer interaction. The human-computer interaction handbook: fundamentals, evolving technologies and emerging applications, 81-96.

[20] Cowie, R., Douglas-Cowie, E., Tsapatsoulis, N., Votsis, G., Kollias, S., Fellenz, W., & Taylor, J. G. (2001). Emotion recognition in human-computer interaction. Signal Processing Magazine, IEEE, 18(1), 32-80.

[21] Birbaumer, N. (2006). Breaking the silence: brain–computer interfaces (BCI) for communication and motor control. Psychophysiology, 43(6), 517-532.

[22] Curran, E. A., & Stokes, M. J. (2003). Learning to control brain activity: a review of the production and control of EEG components for driving brain–computer interface (BCI) systems. Brain and cognition, 51(3), 326-336.

[23] P. J. Lang. (1995). The Emotion Probe: Studies of Motivation and Attention. Am. Psychologist, 50(5):372–385.

[24] Plutchik, R. (1994). The Psychology and Biology of Emotion. Harper Collinns, New York

[25] Harmon-Jones, E., Gable, P. A., & Peterson, C. K. (2010). The role of asymmetric frontal cortical activity in emotion-related phenomena: A review and update. *Biological psychology*, *84*(3), 451-462.

[26] Sackeim, H. A., Greenberg, M. S., Weiman, A. L., Gur, R. C., Hungerbuhler, J. P., & Geschwind, N. (1982). Hemispheric asymmetry in the expression of positive and negative emotions: neurologic evidence. *Archives of Neurology*,*39*(4), 210.

[27] Robinson, R. G., & Price, T. R. (1982). Post-stroke depressive disorders: a follow-up study of 103 patients. *Stroke*, *13*(5), 635-641.

[28] Schutter, D. J., van Honk, J., d'Alfonso, A. A., Postma, A., & de Haan, E. H. (2001). Effects of slow rTMS at the right dorsolateral prefrontal cortex on EEG asymmetry and mood. *Neuroreport*, *12*(3), 445-447.

[29] Cook, I. A., O'Hara, R., Uijtdehaage, S. H., Mandelkern, M., & Leuchter, A. F. (1998). Assessing the accuracy of topographic EEG mapping for determining local brain function. n *Electroencephalography and clinical neurophysiology*,*107*(6), 408-414.

[30] Brookhuis, K.A., De Waard, D., 2001. Assessment of drivers' workload: performance, subjective and physiological indices. In: Hancock, P., Desmond, P. (Eds.), Stress, Workload and Fatigue: Theory, Research and Practice. Lawrence Erlbaum, New Jersey, pp. 321–333.

[31] Kroemer, K., Kroemer-Elbert, E., 2001. Ergonomics: How to Design for ease and Efficiency, Prentice-Hall.

[32] Aftanas, L. I., Varlamov, A. A., Pavlov, S. V., Makhnev, V. P., & Reva, N. V. (2002). Time-dependent cortical asymmetries induced by emotional arousal: EEG analysis of event-related synchronization and desynchronization in individually defined frequency bands. Int. *Journal of Psychophysiology*, *44*(1), 67-82.

[33] Keil, A., Müller, M. M., Gruber, T., Wienbruch, C., Stolarova, M., & Elbert, T. (2001). Effects of emotional arousal in the cerebral hemispheres: a study of oscillatory brain activity and event-related potentials. *Clinical Neurophysiology*,*112*(11), 2057-2068.

[34] Nitsche, M. A., Cohen, L.G., Wassermann E. M., Priori, A., Lang, N., Antal, A., Paulus, W., Hummel, F., Boggio, P. S., Fregni, F., & Pascual-Leone, A. (2008). "Transcranial direct current stimulation: State of the art 2008". Brain Stimulation 1(3), 206–23.

[35] Lagopoulos, J., Xu, J., Rasmussen, I., Vik, A., Malhi, G. S., Eliassen, C. F., ... & Ellingsen, Ø. (2009). Increased theta and alpha EEG activity during nondirective meditation. The Journal of Alternative and Complementary Medicine, 15(11), 1187-1192.

[36] Gruzelier, J. (2009). A theory of alpha/theta neurofeedback, creative performance enhancement, long distance functional connectivity and psychological integration. Cognitive processing, 10, 101-109.

[37] M. Cheng, X. Gao, S. Gao, and D. Xu. Design and Im- plementation of a Brain-Computer Interface With High Transfer Rates. IEEE Transactions on Biomedical En- gineering, 49(10):1181–1186, 2002.
[38] G. Dornhege, J. D. R. Millan, T. Hinterberger, and D. J. M. eds., Toward Brain-Computer Interfacing (Neural Information Processing). The MIT Press, September 2007
[39] C. Veigl, C. Weiß, D. Ibanez, A. Soria-Frisch, A. Carbone: Model-based Design of Novel Human-Computer Interfaces - The Assistive Technology Rapid Integration and Construction Set (AsTeRICS), 4th IEEE Biosignals and Biorobotics Conference (ISSNIP 2013), Rio de Janeiro (Brasil), 18-20 February 2013.
[40] VEP-Based Brain-Computer Interfaces: Time, Frequency, and Code Modulations, Bin G Y, Gao X R, Wang Y J, et al. , IEEE Computational Intelligence Magazine. 2009, 4(4): 22-26
[41] Mason, S., Bashashati, A., Fatoure-chi, M., Navarro, K., Birch, and G., A comprehensive survey of brain interface technology designs. Annals of Biomedical Engineering, vol. 35, no. 2, pp. 137–169, February 2007.
[42] Y. Wang, X. Gao, B. Hong, C. Jia, and S. Gao. Brain- Computer Interfaces Based on Visual Evoked Poten- tials. IEEE Engineering in Medicine and Biology Mag- azine, 27(5):64–71, 2008.
[43] Graimann, B., Allison, B., & Pfurtscheller, G. (2010). Brain–computer interfaces: A gentle introduction. In Brain-Computer Interfaces (pp. 1-27). Springer Berlin Heidelberg.
[44] Mason, S. G., & Birch, G. E. (2000). A brain-controlled switch for asynchronous control applications. Biomedical Engineering, IEEE Transactions on, 47(10), 1297-1307.
[45] Zhu, D., Bieger, J., Molina, G. G., & Aarts, R. M. (2010). A survey of stimulation methods used in SSVEP-based BCIs. Computational intelligence and neuroscience, 2010, 1.
[46] Garcia–Molina, G., Tsoneva, T., & Nijholt, A. (2013). Emotional brain–computer interfaces. International Journal of Autonomous and Adaptive Communications Systems, 6(1), 9-25.
[47] Chanel, G. (2009). Emotion assessment for affective computing based on brain and peripheral signals. University of Geneva.