Computer Brain Interface - Pattern Mining

PDSB - GROUP 6

Carlota de Macedo Santos[1], Manuel Madeira[1], Maria Teresa Parreira[1] and Sofia Guterres[1]

Abstract— **A Computer-Brain Interface (CBI) approach is an alternative of great interest to the current Brain-Computer Interface (BCI) methods. This is achieved by creating a system that adapts to the user through reliable pattern recognition. EEG recordings of four subjects from an evoked potential stimulus experiment were available and processed via a battery of techniques in line with current research practice, in both time and frequency domains. The responses to auditory stimuli (simple beeps and complex sounds) were analyzed with the aim of identifying a consistent stimulus response. In general, and following the 10-20 EEG numeration system, channels C3 and C4 showed a more intense activity both on the time and frequency domains, during and after the stimuli. Channels F3, F4, P3 and P4 were also activated in a less pronounced manner while channels O1 and O2 are associated with the lower brain activity. Higher frequencies were found in the complex sounds (5-20 Hz), while for the beeps, the main frequencies remain in lower ranges (0-5 Hz). Furthermore, different patterns of activation were noticed for different regions. Correlation Analysis showed that there is usually no significant correlation among the EEG records obtained in different moments (before, during, after). For the same moment, however, the correlation is typically high. Between individuals, significant correlations rarely occur. Given limitations in data size and quality, no robust conclusions could be drawn from this study and further investigation using more strict protocols and more data is advised.**

Keywords — **Computer-Brain Interface, Auditory Stimuli, Evoked Potentials, Power Spectral Density, EEG Rhythms, Correlation Analysis, Machine Learning, Pattern Recognition.**

I. INTRODUCTION

A brain-computer interface is a system created to be independent on the brain's normal output pathways of peripheral nerves and muscles; brain activity is measured and properly converted into an artificial output that replaces, restores, enhances, supplements and/or improves natural Central Nervous System (CNS) output[1], thus providing alternative methods for communication and control for people with severe motor disabilities. These systems are a fast-growing emergent technology as signal processing algorithms and increased computing power have reduced the need for bulky equipment. In this view, BCIs have been explored in applications as diverse as security, lie detection, alertness monitoring, education, art, and human augmentation [2].

However, one of the main limitations of the current BCI methods is the duration of the process of adaptation of the subject to the paradigm, as it requires training in order to generate an adequate response. Thus, a way around this limitation would be to have a BCI system adapting directly to the user by discovering which are the patterns that the user can reproduce and that the system can reliably recognize - a Computer-Brain Interface (CBI) approach.

When visual stimuli, the most common type of stimuli used in BCIs, cannot be used to produce a response measurable and classifiable by electroencephalography (EEG), such as in cases of completely locked-in syndrome (CLIS) (where there is loss of all volitional control over muscles, including eye-muscles) or in amyotrophic lateral sclerosis (ALS), whose consequence is, among others, sight deterioration, conventional, visual stimuli-based BCIs are not an option and therefore an auditory stimuli based CBI becomes a very enticing approach. Furthermore, these nonvisual paradigms are very promising for the detection or even communication with patients who are diagnosed with a disorder of consciousness (DOC) [1], in which little or no capacity for behavioral expression makes the assessment of the patients cognitive function and awareness extremely challenging; distinguishing DOC from CLIS is also demanding, as both situations are, from a motor point of view, very similar - leading to misdiagnose rates of up to 40% [3]. The current work consists of an attempt at finding patterns within auditory responses that indicate the possibility of using a CBI system for communication or diagnosis.

Two approaches to a potential CBI system can be taken: extracted features can either be as universal as possible, in order to accommodate inter-subject variability, or the system can have a built-in EEG-based identification which aims to differentiate among individuals performing the same requested task and, therefore, feature extraction needs to capture the particular response traces of an individual. In order cover the two approaches and investigate their feasibility, intra-subject and inter-subject response variability were assessed - the first, aiming to find patterns of response to distinctive stimuli, in order to evaluate the possibility of stimuli recognition through EEG analysis (*e.g.* whether the response to the sound of a thunder or the sound of a laughter induce distinguishable patterns in a channels or set of channels of EEG); the second, in order to investigate if a less-personalized CBI system for communication is achievable, via assessing what correlations, if any, can be established within the responses of a group of individuals to certain acoustic stimuli, as well as assessing what sounds could potentially induce less

[1]Bioengineering Department, Instituto Superior Técnico, Universidade de Lisboa.

inter-subject variability. The main advantage of this last technique would be the ability to use machine learning techniques for pattern mining and feature extraction for better performance in classifiers.

The chosen approach concerns a battery of signal processing techniques, adequate and whose outcomes have been validated for use in EEG signals, to assess what are the individual patterns of response in 4 subjects to "beep" sounds of different frequencies and to 6 complex sounds (such as thunder, birds, or laughing). The possibility of having distinguishable, recognizable responses to auditory stimuli from different natures was investigated. Finally, the results from the individual analysis were compared, to evaluate similarity in response and assess the universality of CBI systems.

II. THEORETICAL BACKGROUND

A. Electroencephalography to record brain activity

1) Basic Principle of EEG recording and Instrumentation: Electroencephalography is a technique used to represent the electrical activity of the brain. This cortical activity is generated due to excitatory and inhibitory postsynaptic potentials developed by cell bodies and dendrites of pyramidal neurons. External stimuli can generate signals that may be recorded on the scalp using surface electrodes [4] and, in this sense, scalp EEG is an average of the multifarious activities of small cortical zones beneath the electrode.

In clinical practice, several channels are recorded simultaneously from various locations on the scalp for comparative analysis of the activities of different regions on the brain. The electrodes are displayed according to an electrode placement 10-20 system, dictated by the International Federation of Societies for Electroencephalography and Clinical Neurophysiology, as outlined in Fig.II.1.

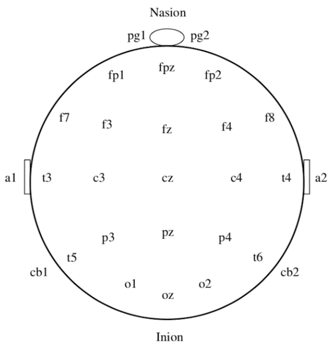

Fig. II.1. The 10-20 system electrode placement for EEG recording: *pg*(nasopharyngeal); *a* (auricular); *fp* (prefrontal); *f* (frontal); *p* (parietal); *c* (central); *o* (occipital); *t* (temporal); *cb* (cerebellar); *z* (mid line); odd numbers on the left side of the subject and even numbers on the right side of the subject [4].

2) EEG rhythms: EEG signals exhibit several patterns of rhythmic or periodic activity, EEG rhythms, that can be related with physiological and mental processes. These rhythms, namely α, γ, δ, θ and β, have really well defined frequency ranges:

- Delta (δ): $0.5 \leq \mathrm{f} < 4$ Hz;
- Theta (θ): $4 \leq \mathrm{f} < 8$ Hz;
- Alpha (α): $8 \leq \mathrm{f} \leq 13$ Hz;
- Beta (β): $13 < \mathrm{f} < 30$ Hz;
- Gamma (γ): $30 < \mathrm{f} < 80$ Hz.

In typical EEG recordings it is possible to distinguish these different frequency bands in the time domain. An example of "pure" frequency bands recordings is represented on Fig.II.2.

The alpha rhythm is the principal resting rhythm of the brain; it is common in wakeful, resting adults, especially in the occipital area. Auditory tasks with the eyes closed lead to strong alpha waves, which are suppressed when the eyes are open [4]. As alpha waves are replaced by slower rhythms at various stages of sleep, theta waves appear at the beginning stages of sleep and delta waves appear at deep-sleep stages. The presence of delta or theta (slow) waves in a wakeful adult may be considered to be abnormal [4].

The beta rhythm is considered to be related to responses induced by various types of sensory input or stimuli, active sensory processes involving attention, and short-term memory processes [4]. Thus, in evoked potential experiment with external stimuli, it is expected to have an enhancement of these rhythms. High-frequency gamma waves, on the other hand, appear as background activity in tense and anxious subjects [4] but are usually discarded in the analysis as they are embedded with noise.

Hence, the presence or absence of expected waves underlines an abnormal situation. Indeed, focal brain injury or tumors lead to slower waves in the corresponding regions and the presence of a left-right rhythmic asymmetry could indicate disturbances in cortical pathways. Hence, analyzing the distribution pattern of the waves throughout the experiment is normally performed as a type of feature extraction.

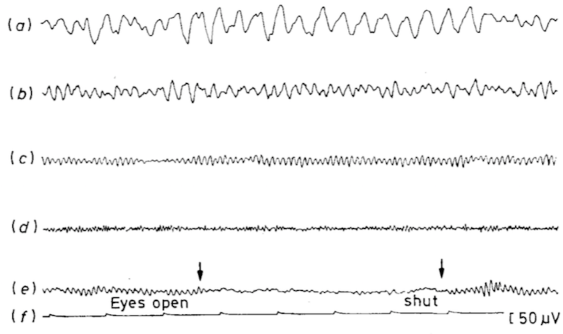

Fig. II.2. From the top to the bottom: (a) δ wave; (b) θ wave; (c) α wave; (d) β wave; (e) blocking of the α wave by eye opening. [4].

3) Importance of Signal Processing in EEG signals: Biomedicine represents an important and highly fertile area for the application of conventional digital signal processing techniques and for the development of new robust algorithms, as it consists on the recording of the physiological activity of organisms. Signal processing is deeply embedded in medical equipment and plays a crucial role when it comes to medical data analysis and significant information extraction.

Taking the aforementioned into account, one must have in mind that EEG signals are a combination of multifarious and non stationary activity of many small zone of cortical surface beneath each electrode.Thus, it is a low amplitude signal with high sensitivity to electrical noise as electrode measurement contains a 50-60 Hz noise picked up by electrode leads nearby power sources.

Furthermore, it has a high propensity to artifacts. Indeed, patient's motion (ocular, cardiac, respiratory...) or the electrical environment (electrodes impedance and connectivity, wire motion, cross talks and contamination at the sources, along the paths or at the site of acquisition) deeply affect the recorded signals. In this view, signal processing is an important step to acquire a signal that can be analyzed in an accurate manner.

B. Computer Brain Interface and evoked potentials

1) General Overview using EEG bio signals: CBI exploits the fact that certain aspects of brain activity are linked to specific mental states and processes, called "signatures" or "features". A CBI is a combination of techniques for recording brain activity, extracting and processing signatures, and translating aspects of the signature into computer commands, which are fed back to the user. Its operation can be summed up in a few steps, named below and depicted in Fig.II.3:

1) Acquisition of signal from the brain.
2) Preprocessing raw data.
3) Signature/feature extraction.
4) Feature classification.
5) Translation of the classified signature/feature into computer commands.
6) Application interface for the actual application design.

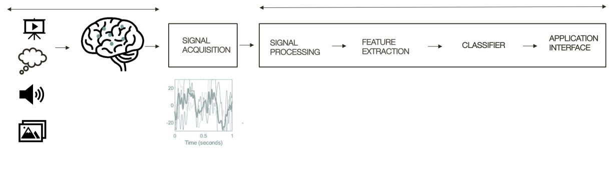

Fig. II.3. General representation of a CBI system. Retrieved from Abhang *et al.* (2016) [2]

One of the critical steps in the design of CBI applications based on EEG is to process and analyzed such EEG signals in real-time, in order to identify the mental state of the user. The stage of extraction of characteristics is probably the most critical step in the processing of signal EEG as it is related with maximizing the potential success of the classification stage. With CBI, there are 3 main sources of information that can be used to extract features from EEG signals:

1) Spatial information through selecting specific EEG channels with a higher differential response to a determined stimulus.
2) Temporal information helping describing how the relevant signal varies with time with a determined stimulus.
3) Spectral information helping understanding how the power in some relevant frequency bands varies with a determined stimulus.

2) CBI and Evoked Potential Experiments: BCI and CBI paradigms can be used to assess brain functionality, in cases such as the occurrence of a stroke[5], by analyzing evoked potentials (EPs), typical of EEG signals. EPs are electrical signals measured from the scalp after the stimulation rendered by some external, known and standardized stimulus and can be of visual, auditory or somatosensory nature. There are several types of event-related potentials (ERP) - which imply both EP and brain responses prompted by cognitive processes evolved by external stimuli or precursory mechanisms for motor action - that can be used to detect responses to stimuli in a EEG signal. The P300 ERP is a positive voltage deflection of the electro-cortical potential that 300-500 ms post-stimulus as a result of attending or responding to target, task-relevant, visual, auditory, or somatosensory stimuli. This ERP is one of the most popular examples of CBI and BCI in communication and a true evidence of the potential of these systems.

Alternatively, an auditory evoked potential (AEP) is an electrical signal elicited from the brain while an auditory stimulus is presented in a time-locked manner. AEP signal consists of reproducible positive or negative peaks, latency, amplitude and behavioral correlation. AEPs are much smaller in amplitude compared to the EEG signals and can either be steady-state, if the auditory stimulus has a fast rate (thus the AEP overlaps with the immediate stimuli response) or transient, which avoids the overlap by using a slow-rate stimulus. Currently, AEPs are widely employed to test auditory function, and used as an important diagnostic tool in infant hearing screening [6]. The proper identification and/or classification of ERPs allows for a functioning interface using EEG signals. Therefore, investigating the feasibility of a auditory-based CBI system calls for an extensive stage of processing of raw data, in order to establish which patterns on an EEG signal exhibit the most potential for a practical application of the proposed technology.

C. Neuro-physiology of Human Cortex

In order to understand and analyze the effects of auditory stimuli in the brains encoded response, it is important to highlight that the physical vibration (referred as sound) is encoded in a nervous impulse. During this encoding step, the cochlea plays a major role as an efficient frequency analyzer [1]. Its abundant nerve supply allows for the impulses to be taken to the brain stem by afferent pathways. Reaching the temporal Lobe, the information is processed [7].

As it will be discussed further, other parts of the cortex are important during the stimulus information processing. In fact, the parietal cortex is of great relevance when it comes to perception of acoustic space and sensory information processing to enhance behaviorally relevant features for movement planning. Moreover, the frontal cortex facilitates attention to incoming stimuli from the primary sensory regions and integrates complex perceptual information from sensory, the parietal and temporal association cortices to plan appropriate behavioral responses to external and internal stimuli [8], [9].

III. MATERIALS AND METHODS

A. Available data

EEG recordings of four subjects (AC, BZ, JL and WN) were available. The electrodes were placed on the subjects' scalp according to the international 10-20 system. A total of nine channels were recorded: F3, F4, P3, P4, C3, Cz, C4, O1, and O2, as well as two reference channels (M1 and M2), and two electrooculogram (EOG) channels (Fp1 and Fp2).

Each subject was exposed to different types of stimuli: auditory and visual [2]. In the scope of the present research, the responses to real auditory stimuli are analyzed. The available sounds were ”beep” sounds of 1kHz, 2kHz, and 3kHz, which are repeated twelve times each, as well as six multi-frequency sounds (boom, ringing, crying, laughing, birds and thunder sounds), which are repeated three times each.

Given the availability of recordings for nine channels, a multi-channel analysis was performed. The results were analyzed for each channel and among channels, with the aim of identifying a consistent stimulus response. Furthermore, an inter-subject analysis was also carried out. The software used for processing and analysis was *Matlab*.

B. Pre-processing of the EEG signals

Before any processing of the signal was performed, the available EEG channels were filtered. The first step was applying a notch filter to remove the clear 50Hz power-line interference that had been picked up by electrode leads nearby power sources, as verified in the spectrum. Secondly, a Butterworth band-pass filter, with cut-off frequencies of 0.5Hz and 30Hz, was designed in order to remove most of the high-frequency noise in the signal, as well as the DC component, while keeping the frequencies of interest for analysis of the EEG.

The following step was removing the eye movement/blinking artifacts, that would deeply affect further analysis. Since these ocular artifacts (OA) are usually present in the same frequency band as the EEG (low-frequency band), and their shape is also spike-like [10], the estimation of clean EEG signals from contaminated ones is a very delicate and complex process. Many methods have been proposed for the removal of OA. In the present research, two different approaches have been tested: the Wavelet Transformation (WT) analysis and Independent Component Analysis (ICA).

Wavelet Transformation analysis starts by decomposing the single-channel EEG signals into a predetermined number of sub-bands, each corresponding to a specific range of frequencies. If the goal is removing high frequency noise, some of the lower-level coefficients can be set to zero. When aiming to remove OAs, however, due to the frequency superimposition of these artifacts with the EEG signal, some thresholding technique might be required [10], [11], where wavelet coefficients in low-frequency bands can be corrected by a thresholding function before signal reconstruction. However, choosing an adequate thresholding function can be very difficult and inconsistent[10], making this method impossible to generalize, which is a major drawback for the automatic removal of artifacts. Therefore, after performing 6-level decomposition on the available channels for one subject (BZ), using a Daubechies 4 wavelet (*'db4'*), and confirming that most of the present artifacts were superimposed with the EEG signal in the low-frequency bands, this method was discarded. The results after reconstruction are, nonetheless, depicted in Fig. A.1.

Independent Component Analysis is the most common Blind Source Separation (BSS) method for artifact removal [12], [10]. ICA estimates a matrix of sources from a given matrix of observations (in equal number). These independent components (”sources”) are assumed to be statistically independent and the recorded EEG signals are assumed to be a linear combination of them [12]. The components which correspond to artifacts are then identified and removed, and the reconstructed signal is obtained by remixing the remaining components [13]. Since this method has been shown to be very efficient and seems to be promising for automatic artifact removal, it was elected as the strategy to remove OA in the available EEG data, in spite of some *a priori* limitations, such as the low number of available EEG channels. For each subject, the estimated EEG sources were correlated with the Fp1

[1]the basiliar membrane responds resonantly to highest frequencies at the basal end and to progressively lower frequencies as one progresses toward the apical end.

[2]real and imaginary taks were asked

and Fp2 channels, and those with the highest correlation were discarded before the remixing process. The results (as illustrated in Fig. A.2 for subject BZ) seem to be satisfactory for most EEG channels. Besides removing some of the eye movement artifacts, ICA also removes some of the high-energy components of the signal.

C. Processing of the filtered EEG data

After appropriate pre-processing of the EEG data, and because the exact time stamps of the auditory stimuli were readily identified, the data was segmented in 3 epochs for each stimulus: 1 second before the stimulus, the duration of the stimulus, and 1 second after. Then, Synchronized Averaging of the signals was performed. This is a commonly used time-domain technique for the removal of random noise when we are in the presence of multiple repetitions of the event of interest[4]. However, a small number of realizations will most likely not improve the Signal-to- Noise Ratio (SNR) of the data. As a matter of a fact, in the present research, since only 12 repetitions of the *beep* sounds were available for each subject and each frequency, and only 3 repetitions were available for any of the other sound stimuli, Synchronized Averaging did not result in a output meaningful for analysis.

As an alternative, an estimate of the Power Spectral Density (PSD) of each epoch was obtained and, for each channel and each stimulus, the average of the available PSDs was obtained. The PSD or Fourier spectrum represents a density function of signal energy versus frequency [4], *i.e.* reveals which are the most representative frequencies present by those who have a higher energy. The PSDs were computed using *Matlab*'s function *pwelch*[3], which estimates the spectrum of the signal using Welch's overlapped segment averaging estimator: the signal is divided in (if possible) 8 long segments with 50% overlap, each of which is windowed with a Hamming window; the periodograms are then averaged to obtain the PSD estimate.

Additionally, the Short Time Fourier Transform (STFT) of the EEG signals was computed for one of the subjects. This method allows for the analysis of non-stationary signals in short windows [4], providing the variation of the signals' spectra over time. However, the results were inconclusive and therefore this analysis was discarded.

After obtaining the appropriate PSD estimates, the spectral difference between the epochs before and during, during and after, and before and after the stimuli was computed. This is a simple subtraction of the spectra for the designated intervals, which allows for the visualization of the changes in the spectra during the stimuli.

In order to quantify the variations in the spectra of the signal before, during, and after each stimulus, the computation of the relative power of each of the EEG's frequency bands of interest - δ (0.5 to 4 Hz), θ (4 to 8 Hz), α (8 to 13 Hz) and β (13 to 30 Hz) - was performed. To this end, the function *relpower.m* was created. It receives a PSD and the sampling frequency, and returns the relative power of each frequency band by computing the relative area under the PSD curve of each of them (using *Matlab*'s *trapz*). The created function was then applied to each epoch (before, during, and after) of every stimulus.

Finally, with the aim of understanding the dependence of the stimulus response between channels and in order to compare similarities among auditory signals, a correlation analysis was carried out, with the main aim of understanding the comparative temporal evolution for each of the individuals analyzed and the similarity of responses among individuals for each moment (before, during and after the sound). For the temporal analysis, only the "beep" sounds were considered as consequence of having a duration of exactly 1 second; the responses recorded during the signal were compared with the responses preceding the beginning of the sound (duration: 1 second) and proceeding its end (duration: 1 second). For the inter-subject analysis, all the sounds were used with the expectation of identifying regular and reproducible patterns. Those correlation coefficients were computed using *Matlab*'s *corrcoef*.

Topographical maps were also created in order to better visualize the areas activated during the stimuli and the difference in activation a the different segments.

IV. RESULTS AND DISCUSSION

A. Comparing different techniques of Signal Processing

As mentioned previously, several techniques of signal processing were performed, in order to assess the effect of the auditory stimuli on the cerebral activity, translated in the EEG signal. Indeed, signals' decompositions in time, power spectral densities, power spectral differences and relative powers of frequency bands of interest were completed. The means of the power spectral densities and signal decompositions in time a repetitions for the different stimuli were also achieved.

However, the aforementioned methods do not have the same significance for the present analysis. In fact, as a low number of repetitions was performed, the mean of the signal in time is not of great interest, as it is highly dependent on irregular spikes. For instance, in the channel C4 (and globally for the remaining ones) of the subject AC, the mean signal during the "boom"' stimuli has an irregular pattern due to the first repetition (Fig. A.3).

Regarding relative powers, spectral densities and spectral density differences, the information provided by the three methods is globally redundant. Thus, for further analysis, relative powers will be considered, when it comes to the extraction of important results, for their simpler interpretation and quantification.

[3]`https://nl.mathworks.com/help/signal/ref/pwelch.html`

B. Electroencephalography: a Mirror of the Brain's Activation

Knowing that EEG signals measure electrical activity of the pyramidal cells of the brain, the amplitude of the signal and its major frequencies are of great interest to understand which areas are more active during the auditory stimulation.

As a global overview, during and after the stimulus, the channels C3 and C4 show a more intense activity both on the time and frequency domains, displaying more pronounced amplitudes[4]. Channels F3, F4, P3 and P4 are also activated in a less pronounced manner and channels O1 and O2 are the electrodes associated with the lower brain activity. The present analysis is supported by the literature and by general knowledge about the cortex and its functional areas. Indeed, having in mind the 10-20 system for EEG sensors' placement and considering similar surveys regarding auditory stimulation, temporal cortex (auditory cortex) should concentrate the higher activation focus, *i.e* T3, C3, T4, C4[5] [14]. This is illustrated in Fig. IV.1.

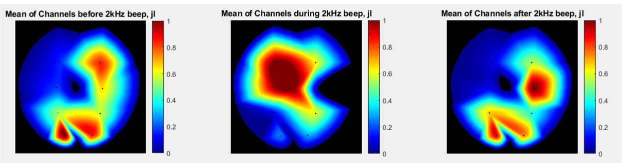

Fig. IV.1. Changes in power before (left), during (middle) and after (right) for bird sounds, for subject JL.

Regarding the frontal cortex, as previously introduced, since it is paired with attention, decision and anticipation, one can understand its activation by the high level of focus of the participants, and by the will of anticipating the stimulus, as it was a repetitive activity. However, its activation should be dominant before the stimulus, and this is not always verified in the present experiment, when compared to other areas' activations. Nevertheless, with exception of subject WN, a higher activation is noticed for the repetitions 2 and 3 of complex sounds, supporting the aforementioned supposition.

Moreover, as previously mentioned, the occipital cortex, as it is associated with the visual pathways, is related with lower activity levels and with high contamination signals, caused by electrical conduction between electrodes that can produce activity in less active zones [15].

Furthermore, the parietal activation, as it is correlated with emotions and with the analysis of behaviorally relevant environmental aspects, is more present in the complex sounds than in the "beep" stimuli. This phenomenon can be explained by the fact that the previously mentioned stimuli are related with emotions such as sadness or happiness, that induce an electrical activation in this part of the brain. However, with the exception of subject JL, this difference is not pronounced.

C. Comparing response to distinct auditory stimuli

As explained in Section III, two main types of stimuli were used: beeps of different frequencies (1 kHz, 2 kHz, 3 kHz) and more complex sounds, that can be classified, according to their emotional content, as pleasant (birds, laughing), neutral (ringing) and unpleasant (thunder, boom, crying).

1) Spectral Analysis: Comparing the response to beeps and to sounds, it is important to point out that, regarding the spectra, higher frequencies, with considerable amplitude, are found in the complex sounds (5-20 Hz), while for the beeps the main frequencies remain in lower ranges (0-5 Hz). This can be observed in the PSD plots (as illustrated in Figs. IV.2 and IV.3, for subject WN), where a shift of the main lobe for higher frequencies can be noted; this observation is supported by the remaining spectral analysis methods.

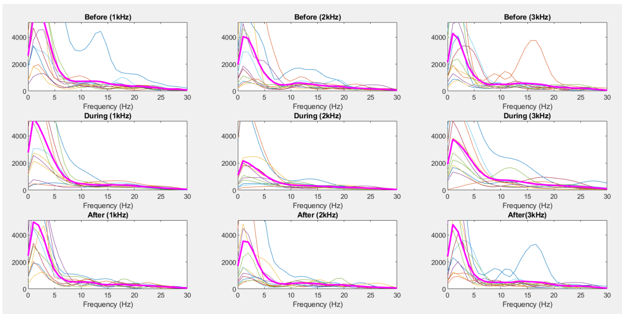

Fig. IV.2. PSD plots for the "beep" sounds, channel C3 of subject WN. The thinner lines represent the individual PSDs, and the thicker magenta line is their average.

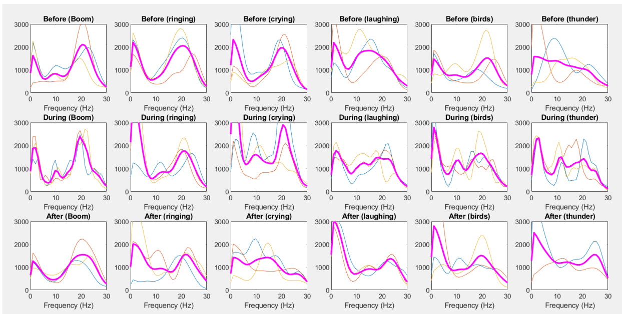

Fig. IV.3. PSD plots for the different sounds, channel C3 of subject WN. The thinner lines represent the individual PSDs, and the thicker magenta line is their average.

2) Relative Power analysis: θ and β waves show no regular evolution pattern over channels and stimuli

[4]The analysis was based on the mean signal created and channels with abnormal variations inherent to artifacts or noise were discarded as it would have affect the overall evolution of the signal a time or frequency

[5]Indeed, as in the present analysis no T3 or T4 channels data were provided, C3 and C4 were the electrodes closer to the temporal lobe, thus concentrating the higher activation among the electrodes provided.

for both types of excitation (Fig. A.5 illustrates this observation). The only exception is for the beep signal response in subject WN, in which the theta rhythms globally increase (see Fig.A.6). It seems to be inconsistent with the literature as it is referred that β rhythms are associated with learning, attention and memory, being highly present in the temporal and central lobes, thus an increase of these waves during the diverse stimuli was anticipated. Moreover, as mentioned before, γ waves were not analyzed because the filtering of the signal was made below its frequency range, and, actually, there are still today controversies on its activity meaning and its study is still not predominant.

Regarding the α and θ rhythms, different activity pattern were observed and differ between the two type of stimuli.

Indeed, for Beeps, looking at the frequency domain globally, processed data suggests that there is a decrease of δ wave during the stimulus, followed by an increase after the stimulus. This decrease is especially stressed for the 2 and 3 Hz stimuli and can be observed in Fig.A.4. This is confirmed by the PSD plots that show a global shift to the right side of the image during the stimuli situation in comparison with the before stimuli situation. Subjects AC and WN also show a significant increase of α rhythm during the stimulus (see Fig.A.7). It seems to be quite abnormal, as these waves are usually present in a relaxing setting with the eyes closed. However, due to the absence of information about the experiment, one cannot predict if the participant were listening to the sounds with eyes open or closed.

For the sounds, there is a general increase of the δ wave during the stimulus, followed by a decrease to the basal activity value. This can be understood as the existence of intermittent activity into frontal and temporal cortex. However, some exceptions are noticed in subject JL but one has to take into account that the low number of repetitions influences the results and can lead to wrongful conclusions. Subject JL also showed a high alpha activity during the experiment. Moreover, correlating the present analysis with the literature, alpha asymmetry for pleasant and unpleasant were expected[14] but that could not be observed, even if overall changes in relative power were noticed due to the stimuli. Moreover, it was expected that relaxing sounds, such as birds, to have higher alpha during the stimulus [16]. Again, this was not confirmed.

3) Feature extraction and uniform response across individuals: Recent research, concerning binary beats, found that frequency has an impact on the mental state captured by the EEG signal [17]. Concerning the Beeps and observing the signals obtained over time, however, there seems to be no consistent data about which frequency causes a broader impact on the EEG signal. Regarding the three stimuli, the 1 kHz seems to have a more coherent response over all the channels, namely for AC. Additional readings also mentioned that, for extremely high and extremely low frequency ranges of beeps, the power spectral density usually shows higher amplitudes [16]. However, in the present experiment, the tested frequencies are all situated in the comfortable range perceived by the Human species, thus, the aforementioned fact cannot be verified.

The high level of intra and inter-subject variability reported was also noticed for the complex sounds experiment. It is supported by a survey based on the assessment of a biometric system for recognition based on EEG and auditory stimulus [18] in which the different signatures, in response to a stimulus, varies due to the morphology and plasticity of individuals and also varies for the same subject in different days or repetitions of the same stimulus.

One must also take into consideration that analyzing the relative power of the δ waves is unreliable for a robust and accurate classifier design. The high relative power observed for delta waves in general might indicate that low frequency noise or artifacts were not properly removed. This fact jeopardizes the analysis and, therefore, the conclusions drawn based on these observations are less reliable and must be interpreted in a qualitative rather than a quantitative way.

On this note, in an effort to backup our findings with unbiased measures of similarity, a quantitative study of variability was achieved using Correlation Analysis.

D. Correlation Analysis Results

1) Temporal Evolution: The temporal evolution results for one of the individuals (AC) and for one of the "beep" sounds are represented on Fig. IV.4; Fig. IV.6 results from processing the data in Fig. IV.4, levelling it according to [19]:

- $0 \leq abs(C_{i,j}) < 0.3$ - negligible correlation;
- $0.3 \leq abs(C_{i,j}) < 0.5$ - low correlation;
- $0.5 \leq abs(C_{i,j}) \leq 1$ - moderate to very high correlation.

where $abs(C_{i,j})$ stands for the absolute value of the corresponding correlation coefficient.

As far as these results are concerned, it is possible to state that there is usually no significant (moderate to very high) correlation among the EEG records obtained in different moments. In the rare occasions when the EEG recording has significant correlations in channels belonging to different moments, it often happens that one of the channels involved is one of the occipitals (O1 or O2).

Regarding the correlations obtained from the EEG records at the same moment, the amount of significant correlations is extremely high (almost every pair of channels shows significant correlation and the few which don't vary from individual to individual, from sound to sound and from moment to moment). Consequently, this generally high correlation among channels corroborates what is one

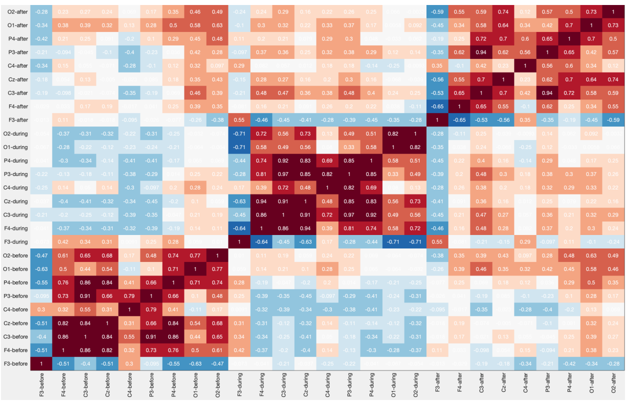

Fig. IV.4. Correlation coefficients obtained among channels, considering the EEG records for three different moments: 1 second before the beginning of the sound, during the sound and 1 second after the end of the signal. Individual: AC. Sound: Beep-1kHz

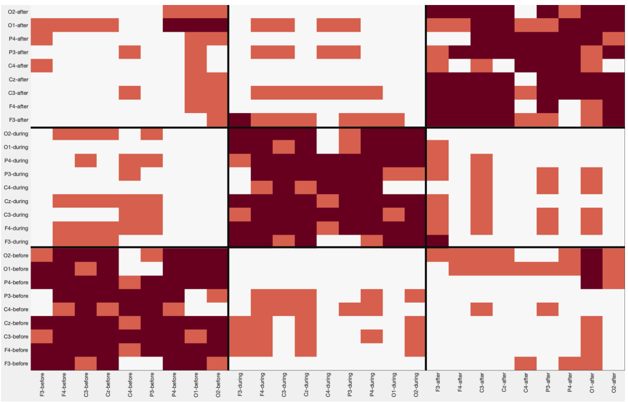

Fig. IV.5. Correlation results obtained among channels, considering the EEG records for three different moments: 1 second before the beginning of the sound, during the sound and 1 second after the end of the signal. This figure results from Fig.IV.4, by levelling it according to [19]: white - negligible correlation; light red - low correlation; dark red - high correlation. Individual: AC. Sound: Beep-1kHz

of the surface EEG technique main limitations: its low ability to isolate responses from different brain regions, due to decreased conductance and sensitivity, which leads to the interference of responses of neighboring regions in each electrode.

2) Inter-subject Analysis: The inter-subject analysis results for one of the moments ("before") and for one of the sounds ("1 kHz") are represented on Fig. IV.6. This figure shows the results after processing the data as previously demonstrated, according to [19].

The first relevant result to point out is that the correlations for channels belonging to the same individual are usually significant (almost every pair of channels shows significant correlation and the rare ones which don't display it vary from moment to moment, from sound to sound and from individual to individual).

Regarding correlations between individuals, it is possible to understand that significant (moderate to very-high) correlations rarely occur. Moreover, the variation of the number of correlations across moments shows an

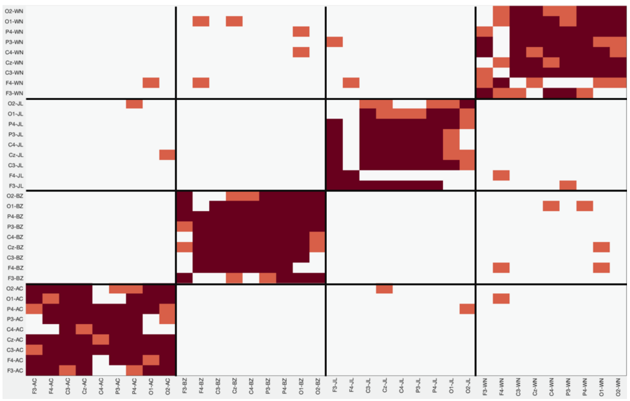

Fig. IV.6. Correlation results obtained among channels, considering the EEG records for three different moments: 1 second before the beginning of the sound, during the sound and 1 second after the end of the signal. This figure results from Fig.IV.4, by levelling it according to [19]: white - negligible correlation; light red - low correlation; dark red - high correlation. Sound: Beep-1kHz. Moment: Before.

interesting behaviour: for "beep" sounds the number of low correlations among individuals increases from the "before" moment to the "during" moment and decreases from the "during" moment to the "after" moment, whilst for more complex sounds it decreases from the "before" moment to the "during" moment and increases from the "during" to the "after" moment. This can be related with the fact that the "beep" signals consist of a pure frequency, triggering a common response among individuals (leading to the observed low correlations), while for more complex sounds (having much more than one frequency), the response triggered is a less typical one and very subject-specific.

V. CONCLUSION, LIMITATIONS AND FURTHER RESEARCH

A. Conclusions in the scope of Computer Brain Interface and Pattern Mining

In spite of the use of techniques usually adequate to such little amounts of data (*e.g.* synchronous averaging), we were able to find results consistent with literature and, consequently, with what was expected to be observed. Nevertheless, a robust intra and inter-subject variability analysis was one of the most complicated steps in this study. Regarding EEG recordings, generally C3 and C4 channels have more activity, which can be explained by their closeness to the temporal (auditory) cortex where response to sound is more evident; electrodes P3 and P4 follow C3 and C4 in terms of brain activity, for the same reasons. This fact is especially evident for complex sounds recordings, due to the association of the parietal cortex with emotions (which the multi-frequency sounds naturally trigger). F3 and F4 electrodes are next in the activity scale, namely on the recordings just before the beginning of the sounds, as a result of this region having an association with the anticipation of a known and repetitive stimulus. Finally, O1 and O2 are the electrodes which show a lower brain activity, since this region is more commonly related with responses to visual stimulation.

As far as the correlation analysis is concerned, it is possible to conclude that there is a significant correlation among channels belonging to the EEG recordings of the same individual and a mainly negligible correlation among data from different individuals, for a given sound and moment. A significant correlation among channels belonging to the EEG recordings of the same moment and a mainly negligible correlation among channels belonging to EEG recordings of different moments, for a given sound and individual were also found.

Another interesting finding in this work is related with the heterogeneity found between the brain response to "beep" sounds and to complex sounds: the response to "beep" sounds has dominant low frequency components (0-5Hz), while the response to complex sounds shows a significant shift towards higher frequencies (5-20Hz). The analysis of the relative power of each frequency band also displayed this heterogeneity: the response to "beep" sounds showed a decrease in δ waves during the auditory stimuli, with a more coherent response to the "beep" of 1 kHz, while the response to more complex sounds showed an increase on that frequency band. Finally, through the correlation analysis it was possible to verify that the number of low correlations for signals of different individuals (for a given moment and a given sound) increased during the "beep" auditory stimuli in comparison with the number of low correlations observed before and after it, while for complex sounds the opposite occurred and that number actually decreased.

B. Limitations of the experimental protocol

The experimental protocol used for data acquisition constitutes the main limitation to its success rates. For example, we could verify that the protocol description provided is, in fact, not performed (*e.g.* the interval between stimuli is not of constant duration). Additionally, the conception of the protocol itself results in intrinsic constraints to the accomplishment of meaningful conclusions of this work.

First, one should mention the method of acquiring data: noninvasive EEG is a more practical and safe method when compared to invasive or partially invasive acquisition techniques such as Electrocorticography (ECoG); however, noninvasive acquisition produces poor signal resolution because the skull dampens signals, dispersing and blurring the electromagnetic waves created by the neurons[2]; therefore, there is a low data transfer rate and low signal strength, leading to low signal-to-noise ratio which hinders fine feature extraction. The placement of the electrodes is also a debatable aspect - the fact that no temporal electrodes were included in the acquisition of auditory responses increases the probability of loss of meaningful data for the analysis, as that is possibly one of the areas subjected to more evident changes.

The low amount of repetitions of each type of auditory stimulus is a great obstacle to meaningful feature extraction, as well as meaningful comparisons and conclusions. In order to find consistencies in the results, the amount of responses analyzed should surpass 100 [15]. With a total amount of 36 "beep" repetitions (12 for each frequency) and 3 repetitions of each type of sound, significance in analysis is severely impaired.

Inter-subject variability analysis is hampered by the fact that the EEG of only four subjects is collected. Because the number of "samples" is so little, slight variations in aspects such as electrode conduction will largely influence the signal processing methods used for this type of analysis, thus compromising the results. This means that neither findings of high inter-subject correlation nor low correlation can be extrapolated for future implementations of CBIs, as the collection of data from a higher number of subjects could largely influence our findings.

C. Limitations of signal processing methods

The limitation of a low number of repetitions of each signal is particularly prominent for signal processing. When there are only 3 repetitions of a stimulus, an outlier response (*e.g.* one particularly affected by noise) will greatly influence the output of a processing technique and thus the analysis and findings (can be seen in Fig.A.7). Therefore, the results of the multi-frequency sounds should be carefully interpreted with respect to the raw samples used. On this note, it is important to mention that the sounds are hard to identify; the laughing and crying sound are hardly distinguishable as such, which jeopardizes the occurrence of an emotional response to this stimuli that could help discern responses between sounds of different nature.

Regarding pre-processing steps, only ocular artifacts were removed, since there is no data on EMG or ECG which would allow for the removal of these artifacts using techniques such as ICA. On that note, even though ICA is a standard approach in EEG signal processing, this technique often requires a larger amount of channels in order to perform well, given that the amount of sources identified is limited to the amount of input channels. Of course, the removal of any sort of artifacts, as well as the filtration of the signals, due to the inability to carry out perfect noise removal, will always involve the risk of removal of physiologically meaningful information from the signal.

Even though some of the most popular paradigms in non-visual stimuli based CBI are P300 paradigms, in which the discriminating stimuli is a sound[7] or even the direction of the sound [20], with the advantage of the P300 signal being independent from learning and being quickly and robustly classifiable [1], in this work we were not able to perform a P300 analysis, as there were no discriminating stimuli and the subjects all knew the protocol beforehand.

D. Further research

The dataset and number of responses to stimuli in the present work was insufficient for the application of machine learning techniques in processing steps. With enough samples of response to distinct auditory stimuli, these techniques could have been used to build a classifier, able to capture the main features of the response to each type of sound and identify what was being listened to.

An interesting direction of research for an even more inclusive CBI technology (*i.e.* one who considers the patients' physical limitations) would be to use, instead of visual or auditory stimuli, imaginary ones. This implies an investigation of the way in which baseline activity in auditory or other sensory areas of the cortex is modulated by attention or when generating mental images/sounds provides a valuable way of probing their functional connectivity and contributions to conscious experience without having to use an external stimulus. With enough training data, it would be possible to identify and even differentiate among imagined stimuli, thus allowing for the implementation of a classifying system which could be used for communication. One of the greatest advantages of this technology would be the lack of need for externally induced responses - here, the stimuli is generated by the user itself. One the other hand, it implies the presence of a minimal level of cognitive potential, in order to generate a measurable response, as well as an adequate level of concentration from the user. Additionally, research on this topic demands very strict data collection protocols, because it is necessary to control exactly when the subject imagines/recollects the stimulus.

References

[1] S. C. Kleih, T. Kaufmann, C. Zickler, S. Halder, F. Leotta, F. Cincotti, F. Aloise, A. Riccio, C. Herbert, D. Mattia, and A. Kbler, "Chapter 2 - out of the frying pan into the firethe p300-based bci faces real-world challenges," in *Brain Machine Interfaces: Implications for Science, Clinical Practice and Society* (J. Schouenborg, M. Garwicz, and N. Danielsen, eds.), vol. 194 of *Progress in Brain Research*, pp. 27 – 46, Elsevier, 2011.

[2] P. A. Abhang, B. W. Gawali, and S. C. Mehrotra, "Chapter 8 - braincomputer interface systems and their applications," in *Introduction to EEG- and Speech-Based Emotion Recognition* (P. A. Abhang, B. W. Gawali, and S. C. Mehrotra, eds.), pp. 165 – 177, Academic Press, 2016.

[3] C. Schnakers, A. Vanhaudenhuyse, J. Giacino, M. Ventura, M. Boly, S. Majerus, G. Moonen, and S. Laureys, "Diagnostic accuracy of the vegetative and minimally conscious state: Clinical consensus versus standardized neurobehavioral assessment," *BMC Neurology*, vol. 9, p. 35, Jul 2009.

[4] R. M. Rangayyan, *Biomedical Signal Analysis, Second Edition*. Wiley - IEEE Press, 2015.

[5] S. Silvoni, A. Ramos-Murguialday, M. Cavinato, C. Volpato, G. Cisotto, A. Turolla, F. Piccione, and N. Birbaumer, "Brain-Computer Interface in Stroke: A Review of Progress," *Clinical EEG and Neuroscience*, vol. 42, no. 4, pp. 245–252, 2011. PMID: 22208122.

[6] M. P. Paulraj, K. Subramaniam, S. B. Yaccob, A. H. B. Adom, and C. R. Hema, "Auditory evoked potential response and hearing loss: a review," vol. 9, pp. 17–24, 2015.

[7] D. Klobassa, T. Vaughan, P. Brunner, N. Schwartz, J. Wolpaw, C. Neuper, and E. Sellers, "Toward a high-throughput auditory p300-based braincomputer interface," *Clinical Neurophysiology*, vol. 120, no. 7, pp. 1252 – 1261, 2009.

[8] G.H.PatelB.J.HeM.Corbetta, *Encyclopedia of Neurosciences*. Academic Press, 2 ed., 2009.

[9] R. T. A. L. J.Neville, "Electroencephalography and clinical neurophysiology," vol. 50, pp. 112–124, 2010.

[10] B. Yang, K. Duan, C. Fan, C. Hu, and J. Wang, "Automatic ocular artifacts removal in EEG using deep learning," *Biomedical Signal Processing and Control*, vol. 43, pp. 148–158, 2018.

[11] H.-A. T. Nguyen, J. Musson, F. Li, W. Wang, G. Zhang, R. Xu, C. Richey, T. Schnell, F. D. McKenzie, and J. Li, "Eog artifact removal using a wavelet neural network," *Neurocomputing*, vol. 97, pp. 374–389, 2012.

[12] J. Minguillon, M. A. Lopez-Gordo, and F. Pelayoa, "Trends in eeg-bci for daily-life: Requirements for artifact removal," *Biomedical Signal Processing and Control*, vol. 31, pp. 407–418, 2017.

[13] C. Burger and D. J. van den Heever, "Removal of eog artefacts by combining wavelet neural network and independent component analysis," *Biomedical Signal Processing and Control*, vol. 15, pp. 67–79, 2015.

[14] T. M. N. B. W. R. M. S. Dirk T. Hettich, Elaina Bolinger, "EEG Responses to Auditory Stimuli for Automatic Affect Recognition," *Frontiers in Neurosciences*, 2016.

[15] S. W. D. S. Pegah Tayaranian Hosseini, Steven Bell, "Induced activity in eeg in response to auditory stimulation," *Elsevier-Biomedical Signal Processing and Control*, pp. 31–42, 2015.

[16] S. G. Renu Bhoria, "A Study of the effect of sound on EEG," *International Journal of Electronics and Computer Science Engineering*, 2015.

[17] J. C. A. N. Juti Naraballobh, Dusit Thanapatay, "EEG-Based Analysis of Auditory Stimulus in a Brain-Computer Interface," *International Conference of Information and Communication Technology for Embedded Systems*, 2015.

[18] A. K. S. M. S. Vinothkumar .D, Mari Ganesh Kumar, "Task-Independent EEG based Subject Identification using Auditory Stimulus," 2018.

[19] M. MM, "Statistics corner: A guide to appropriate use of correlation coefficient in medical research," *Malawi Med J.*, vol. 24(3), pp. 69–71, 2012.

[20] M. Schreuder, B. Blankertz, and M. Tangermann, "A New Auditory Multi-Class Brain-Computer Interface Paradigm: Spatial Hearing as an Informative Cue," *PLOS ONE*, vol. 5, pp. 1–14, 04 2010.

APPENDIX

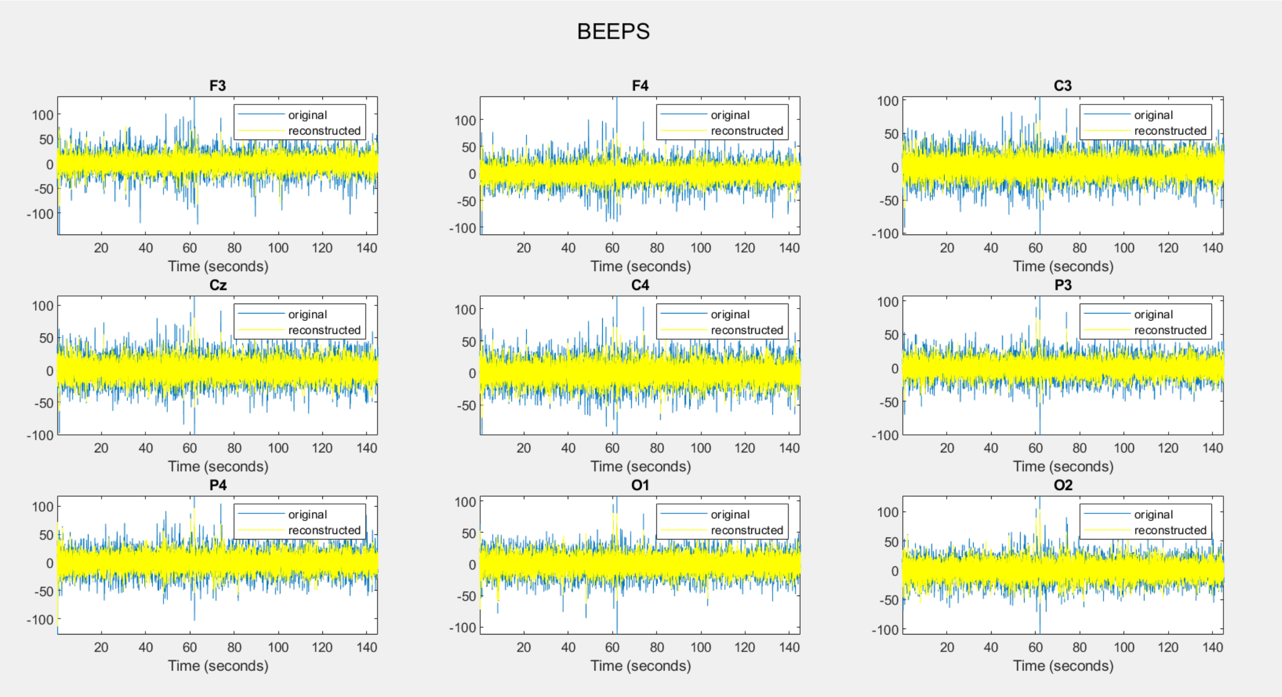

Fig. A.1. Results of noise removal using WT analysis (BZ). The EOG artifacts were not successfully removed, as their frequency band is superimposed with that of the signal. The original (blue) and reconstructed (yellow) signals are plotted.

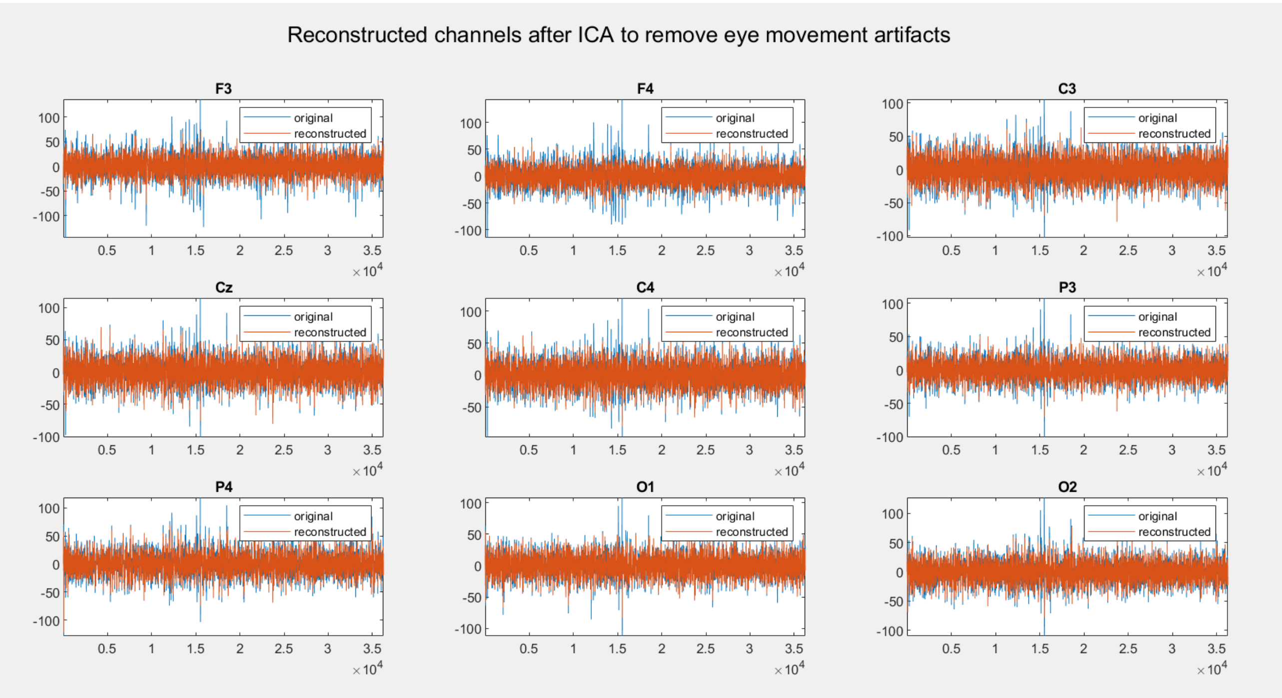

Fig. A.2. Results of the application of ICA for eye artifact removal (BZ). The original (blue) and reconstructed (red) signals are plotted.

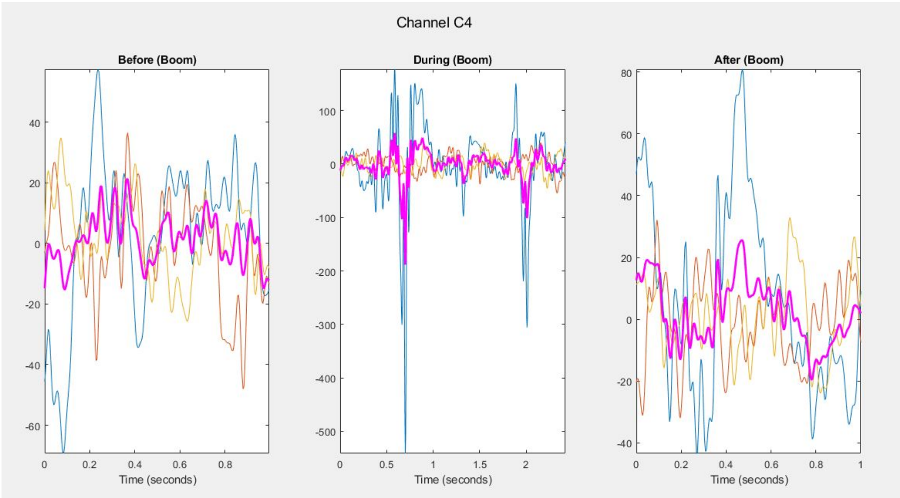

Fig. A.3. Time-domain plots for the "boom" sound, channel C4 of subject AC. During the sound, it's possible to observe an abnormal response in the first repetition (blue line).

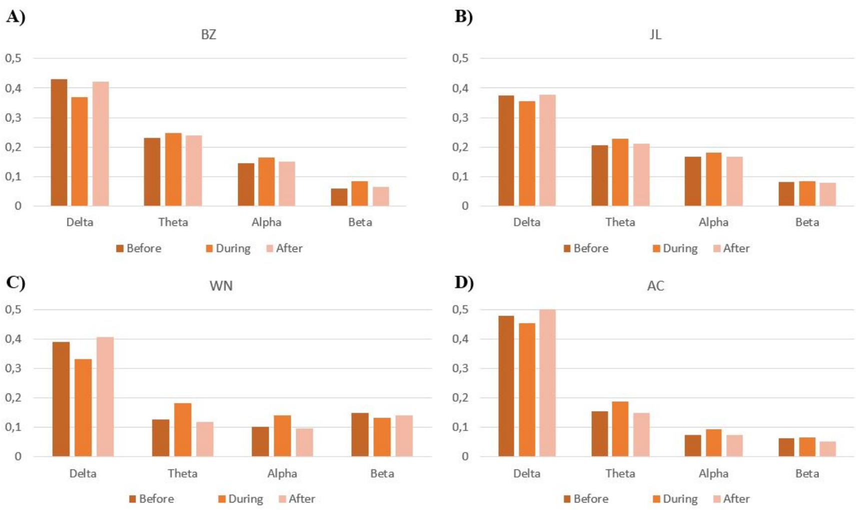

Fig. A.4. Relative power of each frequency band of interest ($\delta, \theta, \alpha, \beta$) for the 3 kHz beep sounds all four subjects. A) BZ B) JL C) WN D) AC. In all subjects, decrease of the relative power of the delta waves can be observed.

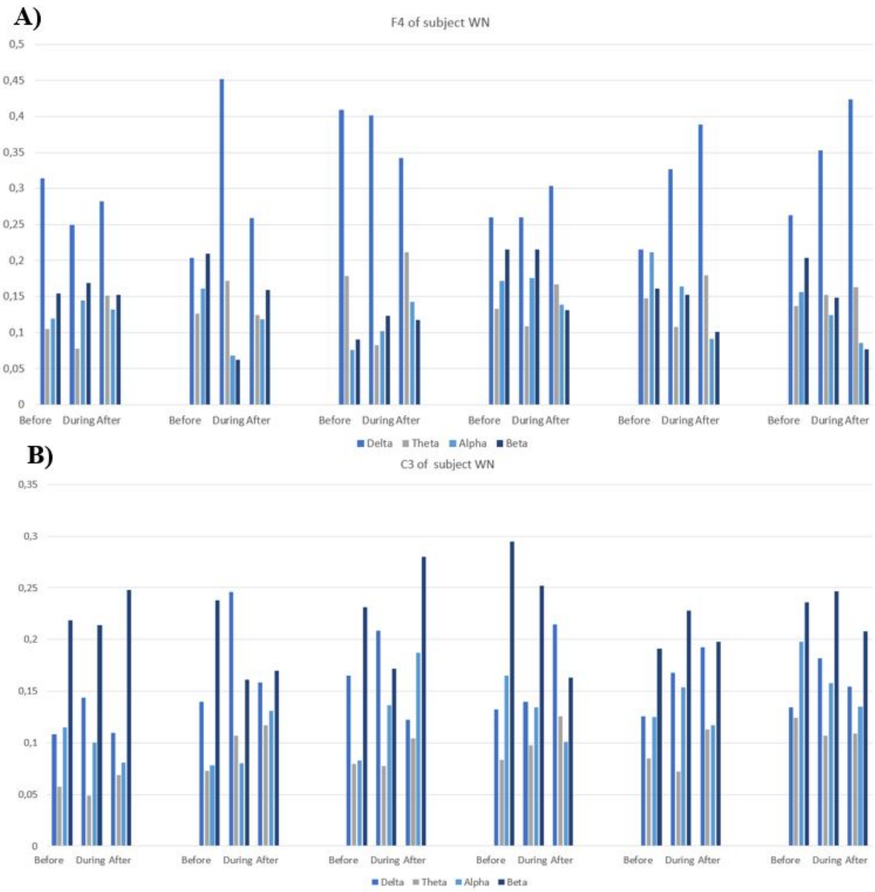

Fig. A.5. Relative power of each frequency band of interest ($\delta, \theta, \alpha, \beta$) for the multi-frequency sounds in subject WN A) Channel F4, where delta activity is predominant but doesn't have a pattern of activation among distinct signals. B) Channel C3, where beta activity is predominant but, again, no pattern of activation among distinct signals can be observed.

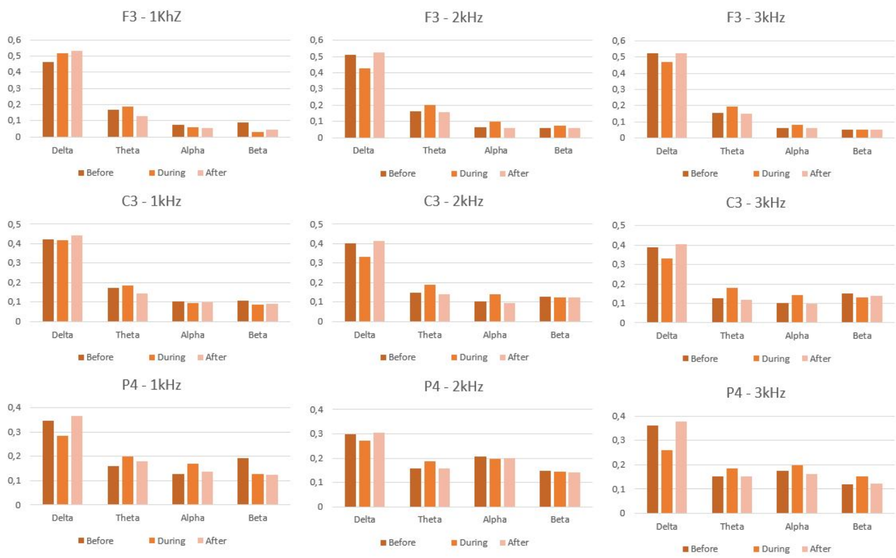

Fig. A.6. Relative power of each frequency band of interest ($\delta, \theta, \alpha, \beta$) for the beep sounds in subject WN. Left to right: 1kHz,2kHz,3kHz. Top to bottom: channels F3,C3,P4. The increase of the theta waves can be observed among all stimuli and all channels.

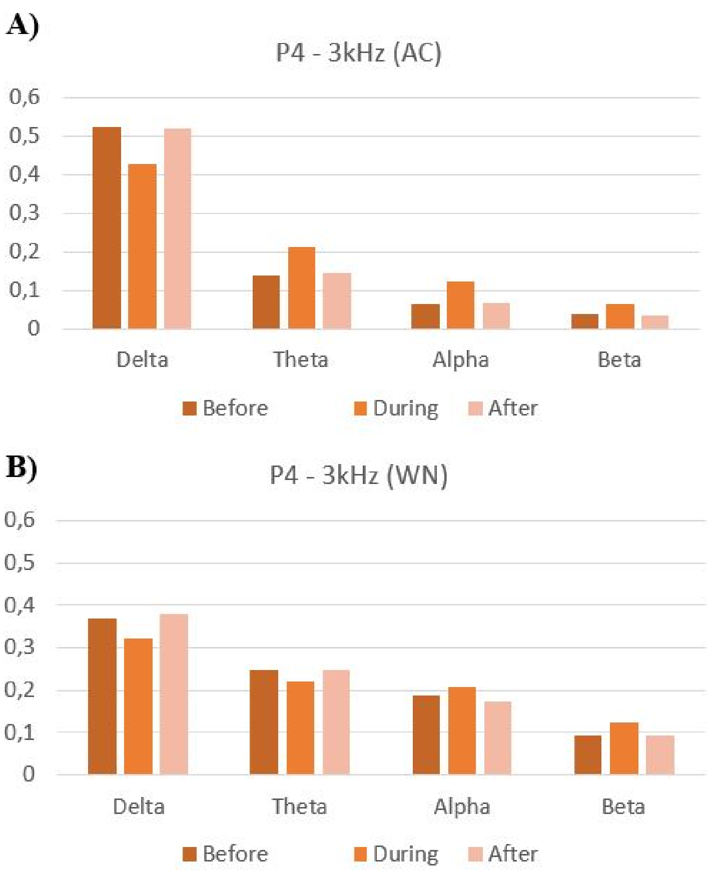

Fig. A.7. Relative power of each frequency band of interest ($\delta, \theta, \alpha, \beta$) for the 3kHz beep sounds. A) subject AC; B) subject WN. The increase of the alpha waves during the stimulus can be observed.