Brain Mapping of Sound Stimulation

PDSB 2020 – Group 5
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1. ABSTRACT

EEG data obtained from 24 volunteers was used to understand the effect of musical and non-musical auditory stimuli in brain activity. Both non-musicians and musicians were submitted to aural stimuli (monaural, binaural and musical) and the data collected was studied with the goal of developing brain mapping and neuromodulation tools, since changes in the emotional and cognitive conditions could be associated with distinct auditory perceptions. The raw data provided was preprocessed through the application of a FIR filter and the removal of artifacts by using independent component analysis.

The results of musician EEG recordings were then compared with the recordings of non-musicians, visually, through topographic maps, and quantitively using statistical tests, to determine whether being a musician develops higher sensitivity and perception levels. Regarding monaural stimulation, musicians presented slightly more intense beta activity in the frontal region, and there was no statistical difference. With binaural stimulation, beta frontal activity was more intense in musicians and the overall frequency differences were statistically significant. When testing for music with or without lyrics both low-beta and high-beta frequencies were present in higher levels in the volunteers who were musicians. Thus, musicians seem to be more stimulated and more highly involved while listening to music.

Additionally, the results of musicians for distinct types of stimuli were also compared to understand if the complexity of musical sounds determines a more complex brain reaction. Some significant variations were found between the response of musicians and non-musicians, and more complex musical sounds proved to induce a more intense response in musicians as well. Therefore, the conclusions obtained were coherent with the expected results.

2. PROBLEM AND MOTIVATION

Different auditory stimuli result in effects that vary significantly from each other, which is thought to be a valuable tool to potentially increase neuroplasticity and assist in the development of neuromodulation techniques.

The alertness of an individual – asleep, relaxed, or alert and focused - is linked to the dominant frequency of their brainwaves. This knowledge can be applied to non-invasive neurostimulation procedures (brainwave synchronization), that can be useful to improve the quality of life, treat health conditions and/or improve cognitive capacity. As an example, the slower delta waves (0.5 Hz – 4 Hz) are the frequencies associated with deep sleep, which are often unattainable after a hectic busy day of work. Through the application of binaural beats, individuals are able to reach a specific frequency of brainwaves quicker, including delta activity, thus, inducing deeper states of sleep. [1]

By better understanding the brain stimulation that results from the application of auditory stimuli, it is possible to generate topographic maps of the head and quantify the response patterns of several individuals to each stimulus. Since music is widely known for being a powerful method for emotional communication, capable of producing a range of different responses in the listener, it is particularly interesting to verify if the distinctive characteristics between musicians and non-musicians implicate differences in musical perception. However, the scientific study of the arts is immensely intricate due to the complexity of human perception of patterns and qualities [2], thus, relying on statistical evaluations to provide relevant conclusions.

The data used in this assignment was obtained from a series of electroencephalography acquisitions from 24 volunteers, 12 musicians and 12 non-musicians. Different types of stimuli were selected, namely monaural, binaural, structured musical sounds with no lyrics and structured musical sounds with lyrics, and the responses of the two groups were compared.

3. BACKGROUND AND RELATED WORK

The electroencephalogram represents a biological signal that is the recorded electrical activity of the brain obtained from electrodes placed over the scalp. Neurons are the functional unit of the nervous system and specialize in generating and conducting electrical impulses. The resting potential of a neuronal cell (-30 to -90 mV) is determined by the imbalance of electrical charges between their interior and their surroundings. Due to the opening of specific ion channels, the membrane potential becomes more positive than it is at resting potential, thus the membrane is said to be depolarized and an action potential is generated and propagated.

The potential generated by one single neuron is obviously very difficult to detect in a reliable manner without having direct contact with it. However, the activity of large groups of neurons that are simultaneously active can be detected. Action potentials are essential for cell-to-cell communication, since they propagate throughout the length of the axon until they reach the synaptic terminal and induce the release of neurotransmitters that lead to the subsequent depolarization of adjacent cells through axon-dendrite interactions.

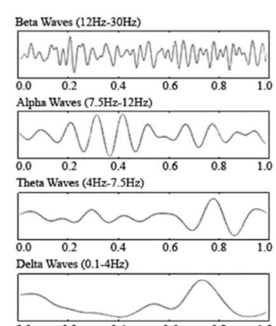

Figure 1 – Typical EEG waveforms [3]

To increase the spatial resolution of this procedure, multiple electrodes are used in well-established standardized configurations such as the International 10-20 System. The name 10-20 refers to the positions of the electrodes along the midline of the scalp placed at 10%, 20%, 20%, 20%, 20% and 10% of the total nasion-inion distance.

Five main frequency bands can be found on EEG signals: delta rhythm (0.5 to 4 Hz), present in deep sleep and relaxed states; theta rhythm (4 to 8 Hz), related to memory and cognitive functions; alpha rhythm (8 to 12 Hz), that increases when the subject's eyes are closed; and beta rhythm (12 – 30 Hz), associated with concentration and active thinking.

Table 1:Division of Volunteers in 2 categories: musicians and non-musicians

Non-Musicians	***Musicians***
FDHI_9874	KTNS_8416
FDWF_6874	LEHA_6437
FOIW_4458	LMKJ_2267
FOPK_2381	SIUY_9971
FRUY_8958	THMN_2001
GTSH_9767	TYQA_3821
HAOK_0267	URTJ_9455
HFJE_9847	USOI_9896
HJPA_2156	WDQI_8823
JGKE_9847	WQHJ_0023
KALP_9263	XNOA_2289
KGND_7465	ZMAP_0116

4. APPROACH AND UNIQUENESS

4.1 Material

The data analyzed consists of EEG signals recorded at the Evolutionary Systems and Biomedical Engineering Lab of the Systems and Robotics Institute (LaSEEB-ISR, Instituto Superior Técnico) by Marco Miranda, in the master thesis study "Mapeamento das Alterações EEG com Estimulação Auditiva".

The master thesis study involved fifty-four healthy volunteers that were divided in two groups - musicians (M) and non-musicians (NM). The criteria for being considered a musician was based on the answers to a survey presented which consisted of three questions: 1) if you have musical training; 2) if you know how to play a musical instrument; 3) if you write music. To be considered a musician, the volunteer must respond positively to at least two questions or only to question 3).

The EEG signals were acquired using a standard 21-electrode cap and following the 10-20 International System for EEG electrode placement, with 250 Hz sampling frequency recording. The EEG signals were recorded using the *Somnium*™ software and after the signal acquisition the data was exported to the EDF format (European Data Format) and the name of each EDF file corresponding to each volunteer was codified.

The signal acquisition was performed on each volunteer while listening to three sequences of aural stimuli (EA). Each sequence was made of 17 antestimuli, 17 audio tags (pure frequency of 20Hz that starts 5 seconds before each EA and has a duration of 2 seconds) and 17 EA with 10 seconds each, and had a total duration of approximately 9 minutes. For this project, the data analyzed corresponds to the monaural and binaural EA of sequence 1 and the the structured musical stimulum (EME) and structured musical stimulum with vocals (EMEV) of sequence 3.

The data made available for the hereby described project corresponds to the recording of 24 of the original 54 volunteers, 12 musicians and 12 non-musicians, as shown in Table 1.

4.2 Methods

The schematic shown in Figure 2 represents the pipeline of the steps adopted for the pre-processing and analysis of the EEG signals.

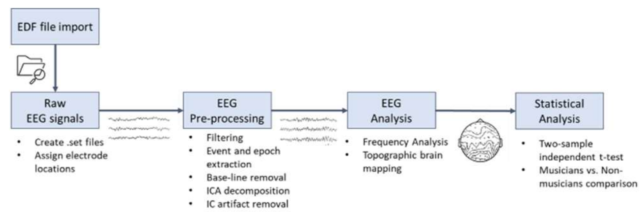

Figure 2 – Pipeline of the methodology steps adopted.

Electrode locations

The collected EEG signals were imported into EEGLAB using the Biosig plugin (pop_biosig.m). For each EDF file there is a .set file. Electrode channel locations were estimated using the MNI coordinate file for the BEM dipfit template model, using the EDF channel labels. The respective function for this procedure is called pop_chanedit.m. In Figure 3 is represented the main head model that was used.

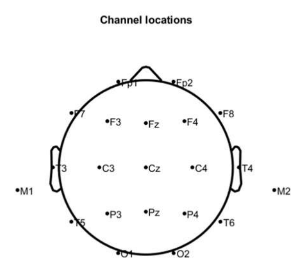

Figure 3 - Electrode/channel locations used by EEGLAB.

Filtering

The whole EEG signal from each individual was filtered using a two-way least-squares FIR filter (firls.m). The default option of EEGLAB is to perform the FIR filtering with order 3×(Sampling frequency)/(Low-cutoff frequency).. To filter the data, the 0.5-30Hz bandpass frequencies were used. In Figure 13 is presented the frequency and phase responses of the filter, with order 3×250/0.5=1500.

Event and epoch extraction

According to the audio file provided in the EDF files it was possible to retrieve the time intervals where the sound stimuli were given. Using the EEGLAB tools for event and epoch extraction, the EEG set files were segmented and organized by epochs. Under the experimental procedure, the epochs do not represent repeated trials of the same stimulus, but trials from the same type of stimulus, which are given in the audio sequences. Events were separated in monaural, binaural, EME and EMEV. Each epoch was extracted from -3 to 10 seconds in relation to the beginning of the stimulus event, in order to use the EEG signal previous to the stimulus as a reference.

Baseline removal

EEGLAB removes the baseline from the epochs automatically. It consists of the removal of the mean offset and it is generally applied to the epoch signal right before the stimulus (-3 to 0 seconds).

ICA decomposition

Independent Component Analysis (ICA) is a valuable computational tool to perform blind source separation, which allows the estimation of additive components of a multivariate signal, such as the EEG. In the special case of EEG, numerous electrical sources are responsible for the electrical signals recorded in the scalp, including brain activity from neurons. However, artifacts may arise by other electrical sources, such as skeletal muscle activation (e.g. blink or eye movement) or cardiac muscle activity (pulse artifact) and such artifacts can affect many EEG channels throughout the acquisition. By performing ICA, it is possible, to some extent, to isolate these specific electrical sources and reconstruct the signal without them. This is accomplished by manipulating an ICA weight matrix that is computed in the process.

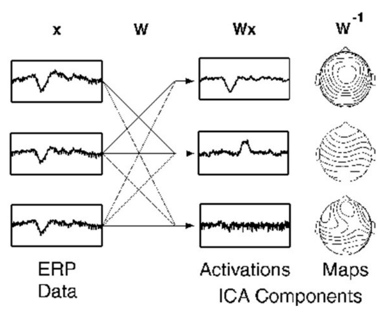

Figure 4 - Representation of the ICA process, in which a multivariate signal x is decomposed in independent components Wx with a weight matrix W. The inverse of the weight matrix can be used to build topographical maps of the different activity sources.

After pre-processing the data, it is possible to begin further analysis and to extract meaningful features that can support the experimental objectives. A common approach to distinguish two different groups within an experiment is to make a frequency analysis. Different contents of frequency bands can indicate different mental status and therefore, it is possible to extract some conclusions about the subjects. Also, by looking at the distribution of frequency bands across the brain, and performing brain mapping, one can associate specific areas of interest to the respective intensity of physiological functions or mental states.

Frequency analysis

Frequency analysis of the EEG channels was made using the pwelch function of MATLAB, that performs a Discrete Fourier Transform (DFT) to obtain a Power Spectral Density (PSD), using Welch's technique. The analysis used a Hamming window with a length of an eighth of the signal's length and it computed the DFT with 50% overlap between samples and the default number of DFT points. An example of the computed power spectral density in the range 0-30Hz is presented in Figure 5.

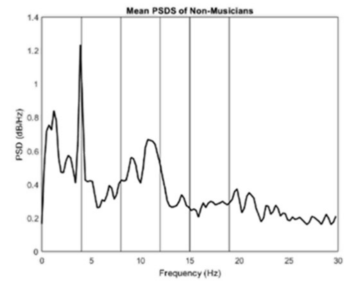

Figure 5 - Example of the Power Spectral Density of a group. The vertical lines separate the different bands analyzed (delta, theta, alpha, low-beta, beta and high-beta).

Topographic brain mapping

The power spectral density values for each channel and for a single trial, were generated using the MATLAB function pwelch. Then, the MATLAB function TriScatteredInterp was used to create a scattered linear data interpolant, with specified data point locations corresponding to the channel locations. Then the 3D topographic map was generated. The x and y axis represent the x and y values of the electrode locations. The z axis represents the average power spectrum density of the EEG signal within a certain frequency band and across a specific group of trials. The 2D topographic map was obtained from the projection of the 3D topographic map into the xy plane. (Figure 6)

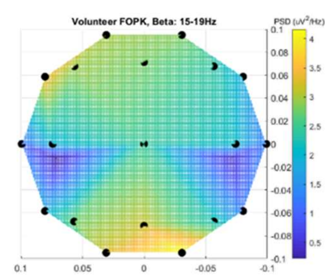

Figure 6 - *2D topographic map. Electrode O2 is identified in red.*

Statistical Analysis

Although frequency and brain mapping are useful to assess the main features in subjects, in order to validate the differences between a sample of the two groups, it was necessary to perform a statistical analysis. Assuming the populations of musicians and non-musicians are normally distributed, a two-sample independent t-test was used to assess the differences between the means of the groups' distribution. The MATLAB function to perform the statistical test was ttest2, and to assess whether the populations had equal variances, the MATLAB function used was vartestn, where a Levene's test with significance level α=5% was performed. The code for the implementation is in statistical_test.m script. The null hypothesis H0 was defined as considering the mean of the PSD frequency bands of the two groups equal. The frequency bands considered for the statistical test were the delta, theta, alpha, low-beta, beta and high-beta frequency bands and the frequencies ensemble (0-30Hz).

5. RESULTS AND CONTRIBUTIONS

To understand how different sounds influence cognitive responses in musicians and non-musicians, topographic maps of the head for both groups of volunteers were plotted using the corresponding average power spectral density function and two-sample independent T-tests were performed to understand if the variations between EEG recordings of musicians and non-musicians were statistically relevant.

For monaural stimuli, the topographic maps obtained for both groups were very similar and the t-test resulted in the acceptance of the null hypothesis, indicating that the variations between the responses of the two groups were not statistically significant.

However, for binaural stimuli, musical stimuli with no voices and musical stimuli with voices, the topographic maps obtained were increasingly different in that order and the t-test resulted in the rejection of the null hypothesis for several of the frequency bands, suggesting that the differences in the perception of the stimuli between the two groups of volunteers are statistically relevant.

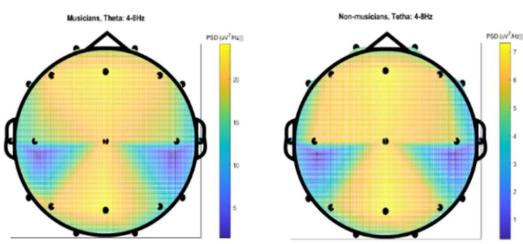

Figure 7 - Topographic maps displaying the presence of theta frequencies in the average musician and in the average non-musician in response to a structured musical sound with no voices (SEQ3 – EA12)

The average power spectral density functions for musicians revealed higher amplitudes and more intense peaks throughout than the non-musicians PSD functions for all of the trials.

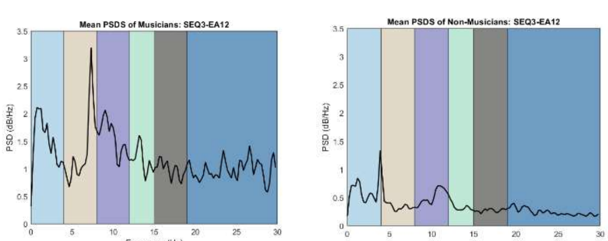

Figure 8 - Comparison between the PSD functions of musicians (left) and non-musicians (right) in response to a structured musical sound with no voices (SEQ3 – EA12)

To further explore the impact of the EA stimuli in the brain activity, the difference in the response patterns of musicians to a musical sound with no voices and a musical sound with voices was also analyzed in order to conclude if more complex musical sounds trigger more complex cognitive processes.

The topographic maps of the head of the average musician are presented below (Figure 4) for the trials with musical sound with no voices and for the trials with musical sound with voices, for the three main alertness-related brain rhythms – theta, alpha, and beta.

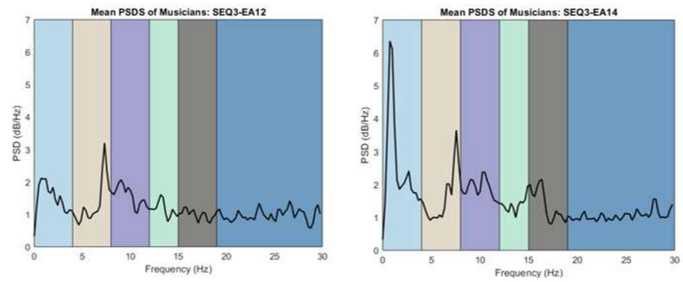

Figure 9 - Comparison between the PSD functions of musicians for EME stimuli (left) and EMEV stimuli (right)

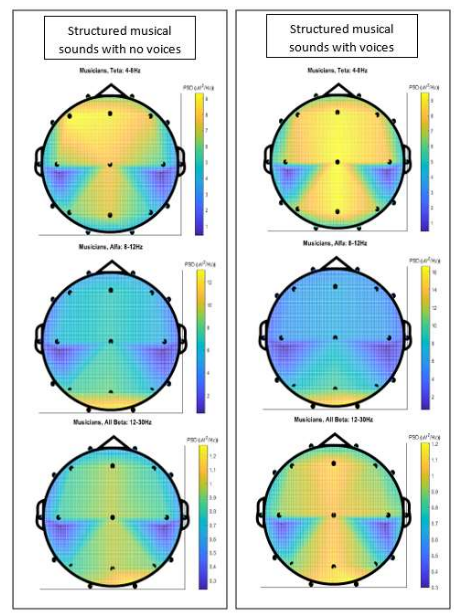

Figure 10 - Topographic maps displaying the presence theta, alpha and beta frequencies in the average musician in response to a structured musical sound with no voices (SEQ3-EA12) and in response to a structured musical sound with voices (SEQ3-EA14).

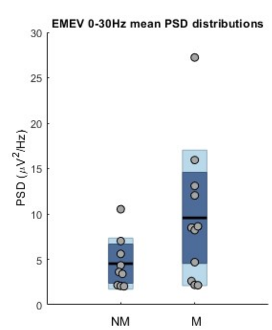

Figure 11 - Average PSD distributions for musicians and non-musicians for structured musical stimuli with voices. H0 rejected.

The trials performed with music containing lyrics resulted in an average power density distribution for these three types of frequency higher than in the trials with music with no voices. This finding reveals that more complex musical sounds trigger a more evident reaction in the brains of musicians.

The PSD functions obtained from the average of all musicians for these two different trials (Figure 6) also reveal more intense peaks in the delta, theta and beta regions and higher overall amplitudes for alpha frequencies. However, the null hypothesis was not rejected since the average power spectral density is similar for the two sets of trials and the test does not consider the spatial distribution of the frequencies – Figure 12.

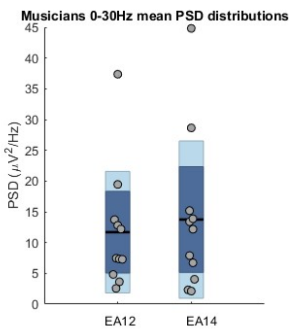

Figure 12 - *Average PSD distributions for musicians' trials for EA12 (EME) and EA14 (EMEV).* *H0 not rejected.*

6. DISCUSSIONS AND CONCLUSIONS

The analysis of topographic maps of the head and statistical testing provided relevant information regarding the differences between the response patterns of musicians and non-musicians. Throughout this work, it was confirmed that the cognitive and emotional perception of musicians is sharper than that of non-musicians. For monaural and binaural auditory stimuli, the variations in the power distribution for all the relevant frequency ranges are mild, however the null hypothesis H0 that considered that both distributions were equal was rejected for the binaural-based trials, indicating a bigger discrepancy between the two groups than in the monaural-based trials.
Regarding the musical stimuli made available for the realization of this project, only two kinds were analyzed – musical stimuli with no voices and musical stimuli with voices. It was uncovered that differences between the two groups were statistically relevant for both auditory stimuli, indicating that musicians seem to be more stimulated and more highly involved while listening to music. Statistical testing confirmed this conclusion, since the null hypothesis was rejected for several of the frequency ranges for these two types of trials.
The brain response to music within musicians was also studied further by analyzing the difference in the recorded EEG activity for the two types of musical stimuli previously mentioned, with the goal of understanding if more complex musical sounds trigger more complex cognitive processes and, therefore, more intense brain activity within musicians. This was confirmed through the analysis of topographic maps of the head. However, statistical testing did not support this conclusion, since the T-test used evaluates the average of the two sets of results and does not consider the spatial distribution of the frequencies.
The results obtained are highly affected by the preprocessing techniques applied to the raw EEG data. The removal of independent components associated to artifacts was performed manually, which might induce some errors since the group is inexperienced in this type of analysis. Moreover, the reduced number of participants in the study also contributes to a substantial statistical error, and the incomplete or inexistent trials for some of the subjects that had to be eliminated reduced the available sample even further.
By increasing the cohort and acquiring more repetitions of each trial, the recordings can be averaged, facilitating the removal of artifacts, and increasing the statistical significance of the results.

7. REFERENCES

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