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ELECTROENCEPHALOGRAM PATTERNS WITH THE PRESENCE OF AN UNKNOWN MUSICAL STIMULUS

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Abstract
The cerebral activity presents different behaviors in different situations and levels of consciousness, especially under musical stimulation. Signals of the central nervous system may disclose bioelectrical patterns, since listening to rhythmic sequences activates specific brain areas. In this paper, we analyze 42 neurologically normal Brazilian individuals, submitted to musical stimulation based on a procedure consisting of three different steps, during which the volunteer is kept with closed eyes. The first step is associated with the preliminary control silence period, without any stimulus, as the volunteer remains at rest. The second step consisted of unknown music stimulation. Finally, the third step involves post-music rest. Quantitative signal analysis computes the power spectrum time variations. Results point out stronger changes in gamma and high gamma waves (30 – 100 Hz). Even though the clinical rhythms (0 – 30 Hz) change throughout the whole period of the experiment, quantitative differences at gamma and high gamma bands are remarkably greater. Particularly, when comparing the initial silent period and the final post-stimulation silent one, bioelectrical differences are only highlighted by gamma and high gamma rhythms. In consequence, this paper points out that the EEG analysis of cognitive issues related to musical perception cannot disregard gamma and high gamma waves.

Keywords: Electroencephalography. Musical Stimulus. Time-frequency Analysis.

1. Introduction

Several physiological and pathological phenomena can be linked to the brain waves with frequencies above the classical clinical range (1 – 30 Hz). Particularly, for epilepsy, these waves may enable the diagnosis of pathological conditions (Engel and Silva 2012). Recent non-invasive studies report that the surface electroencephalography (EEG) provides information at frequencies above 30 Hz since these signals are not considered just an artifact to be discarded (Telenczuk et al. 2011). It is known that, whereas classical brain waves are associated with inhibitory functions, gamma oscillations within 30 - 80 Hz range disclose cortical activation and may be related to information processing, awareness perception, and memory maintenance (Herrmann et al. 2016; Freeman and Quiroga 2013). Especially, EEG oscillations contribute to different cognitive functions, depending on their topographic location and their parameters, such as amplitude, frequency, phase, or coherence (Herrmann et al. 2016). Several studies have suggested the correlation of brain states with frequency band power distribution throughout the skull. For example, the highest frequencies (such as gamma and high gamma) can act as biomarkers for mapping neuronal sets of the temporal region during memory and/or attention tasks (Kucewicz et al. 2017). On the other hand, the alpha frequency power is inversely correlated with attention in general, thus, characterizing the resting state (Kay et al. 2012).

The biological processing of musical stimulus in the brain takes place firstly in the auditory cortex, which is located in the posterior superior part of the temporal lobe, inside the lateral sulcus. In this region, limbic, striatal, and mesencephalic structures are distributed. For this reason, the mesolimbic striated dopaminergic system encodes the musical reward (Clark et al. 2014). It modulates the connectivity of the *nucleus accumbens* (reward and pleasure pathway) to the auditory cortical area, as well as to other regions of the brain involved in the perceptual analysis and in music evaluation (Clark et al. 2014; Calabrò et al. 2015). Bioelectrical signals of the central nervous system (CNS) provide informational characteristics in response to emotional states (Lin et al. 2010) since when listening to rhythmic sequences, the basal ganglia and supplemental motor area are activated (Bauer et al. 2015).

In order to establish the relationship between music and brain dynamics, it is necessary to study the emotional profile of individuals following the musical stimulus, based on the EEG (Pan et al. 2013). In Balasubramanian et al. (2018), theta rhythm energy during stimulation was higher compared to the periods without stimuli, as volunteers were exposed to their favorite songs. Gomes et al. (2018) pointed out significant cerebral activation in the left hemisphere, when positive feelings were reported by the listeners. On the other extreme, there was much more activation in the right hemisphere as unpleasant feelings were elicited by the stimulus. Banerjee et al. (2016) found an increase of alpha power in EEG signals, when volunteers are stimulated by joyful music. As seen in Schaefer et al. (2013), the more complex stimuli are, in terms of notes, lyrics, rhythms; more significant is the central processing of information. In Nakamura et al. (1999), EEG was recorded in normal volunteers. This study highlights that the beta rhythm power of the posterior cerebral region was higher at the moment of musical stimulation when compared to the other recording periods. Wang et al. (2016) studied the relationship between brain activity and musical characteristics in the time domain, pointing out specific patterns in brain activity related to different types of musical stimulation. In Kumagai et al. (2017), cortical activation was assessed following three distinct types of musical stimulus. Cortical responses were stronger for unknown music employed during the stimulation. Finally, Khosrowabadi and Rahman (2010) showed that the application of particular tools to the EEG signal, e.g., K-nearest neighbor, helps to identify different EEG characteristics under different musical stimulus.

Nowadays, research on musical stimulation focusing on rehabilitation has become a quite promising field, because this art stimulates cognitive, affective, and motor-sensory processes (Thaut and Hoemberg 2016). However, from the Brazilian literature, there are few articles investigating musical stimulation analysis based on unknown or unfamiliar songs. Concerning this literature lack, international studies present even a smaller number of articles that explicitly consider gamma and high gamma bands in the EEG analysis. Therefore, in the present work, EEG records of neurologically healthy volunteers were analyzed under the stimulus of unknown music, in order to assess quantitative changes in the EEG following such stimulation, particularly at the higher frequency waves (30 – 100 Hz).

2. Material and Methods

This study involved 42 neurologically healthy individuals, in the sense that they did not present any history of previous neurological pathologies, also excluding those making use of neurological medication during at least one year previously the EEG recording. The inclusion criteria were: 1 - to be able to listen to musical stimulation with clarity; 2 – use of an unknown musical stimulus, with respect to the volunteer; 3 - the musical stimuli caused "positive" emotions such as joy, hope, energy, humor (reported at the end of the recording following an interview). The Protocol number 1.716.960 of the Human Research Ethics Committee (HREC), Federal University of Uberlandia (UFU), Brazil, has formally authorized this research.

All signals were recorded by a biomedical signal amplifier, including a digital filter 1 - 100 Hz, with a notch filter and the sampling frequency equal to 1 k Hz. A total of 20 electrodes plus two references were used, arranged according to the 10-20 system.

A particular protocol was employed in all registers, involving three sequential steps, during which the volunteer remained lying down, at rest and eyes closed all the time. The first one is called “Eyes Closed” (EC), during which the volunteer remained quiet, in silence, for 60 seconds. During the second one, “Music” (MU), the volunteer remained still at rest, but he/she was stimulated by a piece of unknown music for a period of 60 seconds, the National Anthem of Japan. The music was played through a small soundbox, positioned at 60 centimeters far from the volunteer's head, with a volume equal to 50 dB. The third step of the protocol is called “Post Music” (PM), during which the volunteer is recorded exactly under the same conditions of EC, for 60 seconds. It should be highlighted that all volunteers were stimulated with the same music. According to an interview performed with each volunteer previous the recording, all of them were unaware of such music, so that to assure its characteristic of unknown and unfamiliar stimulation. After stimulation, a quick interview was performed with all volunteers, to check emotions elicited by the stimulation. We have retained just recordings tied to positive emotions, such as hope, enthusiasm, joy, goodwill.

These recordings were analyzed by two neurologists, considering the following criteria: A) Quality of the EEG tracing, avoiding visual artifacts; B) Recording of at least one minute with closed eyes under silence, one minute of musical stimulation, and one minute of post-stimulation under silence, so that each event should necessarily take 60 seconds. After careful analysis of neurologists, each signal was submitted to spectral filtering involving the Fourier transform to minimize cardiac and muscle interference. Therefore, the records of this study can be considered free of artifacts.

EEG signal analysis commonly involves the power spectral density (PSD) calculus (Freeman and Quiroga 2013), and this enables to assess the behavior of signal power both for clinical rhythms (ranging from 1 to 30 Hz), as well as for higher frequency waves (gamma and high gamma rhythms) (Schomer and Silva 2011). In this paper, the EEG signal of volunteers was divided into three parts or events, named EC, MU, and PM. The quantitative analysis considered all 20 electrodes for all volunteers. Each event was segmented into the amount of 60 segments of one second. Subsequently, the PSD was calculated for each segment. These calculations were combined into three sub-groups: Clinical Rhythms, considering the range of frequency 1 up to 30 Hz; Gamma Rhythms, ranging from 30 up to 80 Hz (excluding values of 58 to 62 Hz); and Super-gamma Rhythms, at frequency levels from 80 up to 100 Hz.

Considering a sub-group of cerebral rhythm, PSD values were organized into time-frequency matrices, with frequency values arranged in lines, and columns composed of the chronological contributions of the segments. The matrices were normalized so that the PSD values ranged from 0 to 100, as shown by Eq. 1, named Normalized Power Signal (NPS).

$$NPS_x a(b,f) \; = \frac{S_x a(b,f)}{\mathrm{Max}(S_x a)} \qquad (1)$$

Wherein: $NPS_x a(\mathrm{b},f)$ - Normalized Matrix of PSD, for electrode x, estimated for the event a, at both segments, in cerebral frequency, f. $S_x a(f) -$ Power spectral density of segment (b), at frequency (f), associated with event (a) [W/Hz], scalar. $S_x a(b,f) -$ Power Spectral Density Matrix, wherein the lines represent the frequency values (f), and the columns refer to segments (b) [W/Hz]. $Máx(S_x a)$ – Maximum amplitude calculated after analysis of all elements of the matrix $S_x a$ [W/Hz], thus leading to a scalar value.

Data generated by (1) were stored in matrices, for each electrode of the EEG signal. Thus, the descriptive statistical analysis was applied in order to characterize each channel, taking into account the 42 individuals. Median and standard deviation values were estimated over NPS values of each event, and, from the median values, a final matrix was generated, resulting in frequency ranges from 1 up to 100 Hz, including all temporal contributions of the EC, MU, and PM events.

In order to check if the NPS behavior changes before, during, and after musical stimulation, a comparison test was applied. Thus, the Mann-Whitney test was chosen since it is a nonparametric tool. The confidence index used was α = 0.05. As the p-values are calculated based on the test, it is possible to assess if data were statistically equal (p-value greater than 0.05), or if they were different (p-value less than 0.05).

The final data matrix of each electrode was divided into three sections, according to the frequency range of interest, so that the results could be analyzed in a suitable way. Therefore, three sub-matrices were created: matrix including information from 1 up to 30 Hz, representing the standard EEG clinical analysis band; matrix with data tied to the rang from 30 up to 80 Hz, representing the gamma band; and matrix including results from 80 up to 100 Hz, representing the High gamma rhythm. It should be noticed that, for all these sub-matrices, the chronological order of the events was held (starting with EC, then following MU, and PM), and for each event, a time-frequency diagram was drawn employing a color scale, which summarized the NPS information. Blue color or close to that color indicates low NPS values, whereas reddish or close to that shade indicates high amplitude NPS.

3. Results and Discussion

For all the subsequent analyses, we consider just one single pair of electrodes selected within each topographic region. They were F3 - F4 in the frontal region, C3 - C4 in the central region, T5 - T6 in the temporal region, P3 - P4 in the parietal region, and O1 - O2 in the occipital region. All this represents five symmetric pairs of electrodes in a total amount of 20, involving both the right and left hemispheres. In consequence, each pair refers to a particular cortical region, thus leading to topographic information on cerebral music processing.

Table 1 shows the mean and standard deviation of the NPS tied to the clinical band (1 to 30 Hz). In this table, each line refers to an electrode, summing up ten lines, and the first three columns, from the left to the right, are tied to events (EC, MU, and PM, respectively). The last three columns point out the result of the comparison test, showing the p-value result. Tables 2 and 3, which are similar to Table 1, present similar information as Table 1, but on the gamma and high gamma rhythms, respectively. It should be noticed that the p-value result was represented by asterisks (*) in the tables (Tables 1, 2, and 3), indicating that there was a significant statistical difference; or by the inequality "> 0.05", disclosing that the comparison led to similar statistical results. It is important to point out that the greater the number of asterisks, the smaller the p-value, therefore the greater the statistical difference.

Within a clinical range (1 to 30 Hz), the NPS results in Table 1 show that the values arise from the MU event. In fact, they are higher than those tied to both EC and PM events. This finding just excludes the F4 electrode, wherein NPS was higher in the EC event. Regarding a statistical comparison between NPS values of EC and MU events, the results present remarkable differences. A quite similar finding arises when MU and PM events are compared to each other. Therefore, Table 1 yields that the NPS quantifier may be considered an ineffective measurement for distinguishing EC, MU, and PM events, in the context of classical cerebral rhythms.

Table 2 shows the NPS values associated with the gamma rhythm. It is important to notice that the values are almost equal, regardless of the electrodes. Clearly, EC, MU, and PM events could be considered quite different from each other in terms of NPS within the gamma band. In each comparison, few electrodes presented a p-value greater than 0.05, in other words, almost all electrodes are different from each other. In addition, NPS amplitudes, during the EC event, seem to be lower than those values obtained in MU, which disclose a strong cerebral response to the musical stimulation measured in the gamma rhythm. One of the possible explanations for this fact is that this musical stimulus is uncommon for Brazilian volunteers.

Table 3 summarizes results related to the high gamma rhythm 80 - 100 Hz. In the literature, it is known that high gamma rhythms are triggered by different types of neural generators, and these high-frequency responses are produced by the auditory cortex (Engel and Silva 2012). Also, Table 3 shows that NPS amplitudes within the high gamma range were lower with respect to those obtained in Tables 1 and 2. The general behavior of the electrodes is similar throughout the scalp. A significant difference between NPS values takes place in most of the electrodes as the events evolve, and results in Table 3 are quite similar in behavior with respect to the gamma rhythm in Table 2.

Table 1. Results of statistical analysis for clinical rhythms performed for the different events (EC, MU, PM).

Clinical Rhythms (1 – 30 Hz)						
	Mean ± Standard Deviation			p-value		
Electrode	Eyes Closed	Music	Post Music	EC x MU	EC x PM	MU x PM
F3	180.87 ± 9.00	189.09 ± 9.31	177.99 ± 8.69	***	> 0.05	***
F4	184.07 ± 8.77	182.09 ± 6.56	178.87 ± 8.19	> 0.05	**	*
C3	179.18 ± 8.14	190.67 ± 8.17	179.23 ± 7.61	***	> 0.05	***
C4	188.00 ± 7.91	201.75 ± 8.43	184.46 ± 8.02	***	*	***
T5	173.44 ± 7.14	177.41 ± 8.61	176.75 ± 7.24	*	*	> 0.05
T6	170.68 ± 7.53	181.44 ± 7.47	172.62 ± 8.02	***	> 0.05	***
P3	172.57 ± 8.27	181.67 ± 6.45	178.86 ± 7.64	***	***	*
P4	178.54 ± 8.70	182.59 ± 8.73	175.32 ± 7.70	*	> 0.05	***
O1	166.65 ± 8.10	175.47 ± 7.87	173.91 ± 7.74	***	***	> 0.05
O2	165.98 ± 7.45	170.50 ± 8.06	166.75 ± 7.05	*	> 0.05	*

Significant statistical difference: * p-value < 0.05. ** p-value < 0.005. *** p-value < 0.0005.

Based on the NPS matrices divided into rhythms, 10 time-frequency diagrams were assembled for all rhythms, leading to the following results: Figure 1 for the clinical range (1 to 30 Hz), Figure 2 for the gamma range (30 to 80 Hz), and Figure 3 depicts the high gamma rhythm (80 to 100 Hz). Each of these figures contains ten images, (a) to (j), arranged in two columns, each column referring to a cerebral hemisphere. In addition, each line is associated with a particular brain region. Each Time-Frequency diagram presents information that varies between the maximum and minimum amplitude of NPS values for each situation, with blue colors indicating low amplitudes, and reddish tones indicating high values. It is important to notice that, considering a time-frequency diagram, all estimated NPS information for EC, MU and PM are arranged sequentially. In consequence, the analysis of these results, should not only consider in which frequencies there are NPS peaks, but also should take into account the chronological order, to assess possible differences between the pre-stimulus signal (EC), the stimulus (MU), and the post-stimulus (PM).

Table 2. Results of statistical analysis for gamma rhythms performed for the different events (EC, MU, PM).

Gamma (30 – 80 Hz)						
	Mean ± Standard Deviation			p-value		
Electrode	Eyes Closed	Music	Post Music	EC x MU	EC x PM	MU x PM
F3	52.42 ± 1.05	55.54 ± 0.89	53.21 ± 1.04	***	***	***
F4	54.14 ± 1.40	54.46 ± 1.16	53.25 ± 1.18	>0.05	**	***
C3	53.90 ± 1.16	58.68 ± 1.12	55.91 ± 1.07	***	***	***
C4	56.48 ± 1.37	60.84 ± 1.15	55.28 ± 1.19	***	***	***
T5	51.60 ± 1.12	53.41 ± 1.11	53.97 ± 1.02	***	***	**
T6	50.77 ± 1.31	54.35 ± 1.29	52.34 ± 1.06	***	***	***
P3	51.73 ± 1.25	54.40 ± 1.04	54.92 ± 1.20	***	***	*
P4	53.03 ± 1.17	54.90 ± 1.15	52.68 ± 1.27	***	>0.05	***
O1	48.49 ± 1.01	51.10 ± 1.22	50.84 ± 0.96	***	***	>0.05
O2	48.04 ± 1.05	50.46 ± 1.11	48.79 ± 1.05	***	***	***

Significant statistical difference: * p-value < 0.05. ** p-value < 0.005. *** p-value < 0.0005.

Table 3. Results of statistical analysis for high gamma rhythms performed for the different events (EC, MU, PM).

High Gamma (80 – 100 Hz)						
	Mean ± Standard Deviation			p-value		
Electrode	Eyes Closed	Music	Post Music	EC x MU	EC x PM	MU x PM
F3	14.28 ± 0.46	15.12 ± 0.49	14.43 ± 0.42	***	*	***
F4	14.90 ± 0.54	14.84 ± 0.43	14.59 ± 0.45	>0.05	**	**
C3	14.76 ± 0.45	16.05 ± 0.50	15.20 ± 0.41	***	***	***
C4	15.36 ± 0.53	16.61 ± 0.48	14.96 ± 0.50	***	***	***
T5	14.02 ± 0.40	14.49 ± 0.40	14.62 ± 0.38	***	***	>0.05
T6	13.73 ± 0.45	14.68 ± 0.45	14.10 ± 0.47	***	***	***
P3	14.14 ± 0.47	14.79 ± 0.46	14.98 ± 0.48	***	***	*
P4	14.56 ± 0.47	14.96 ± 0.44	14.40 ± 0.48	***	>0.05	***
O1	13.09 ± 0.38	13.66 ± 0.51	13.61 ± 0.39	***	***	>0.05
O2	12.99 ± 0.37	13.65 ± 0.37	13.16 ± 0.41	***	*	***

Significant statistical difference: * p-value < 0.05. ** p-value < 0.005. *** p-value < 0.0005.

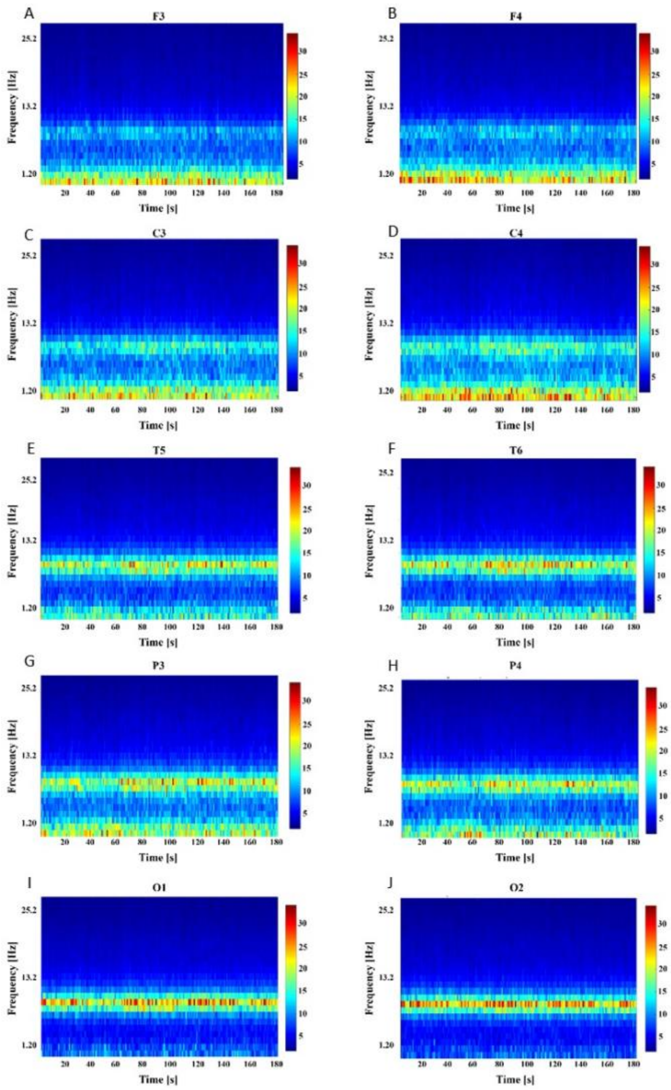

Figure 1. Time-Frequency diagrams of Clinical Rhythms. Each image within this Figure represents the behavior of the NPS over time, considering that the first 60 seconds refer to the 'Eyes Closed' situation, the next 60 seconds are related to the 'Music' situation and the last 60 seconds are from 'Post Music'. A – electrode F3; B – electrode F4; C – electrode C3; D – electrode C4; E – electrode T5; F – electrode T6; G – electrode P3; H – electrode P4; I – electrode O1; J – electrode O2. The vertical axis is measured as a percentage (%) of the total power, and the horizontal axis is measured in seconds, within the range 0-180s.

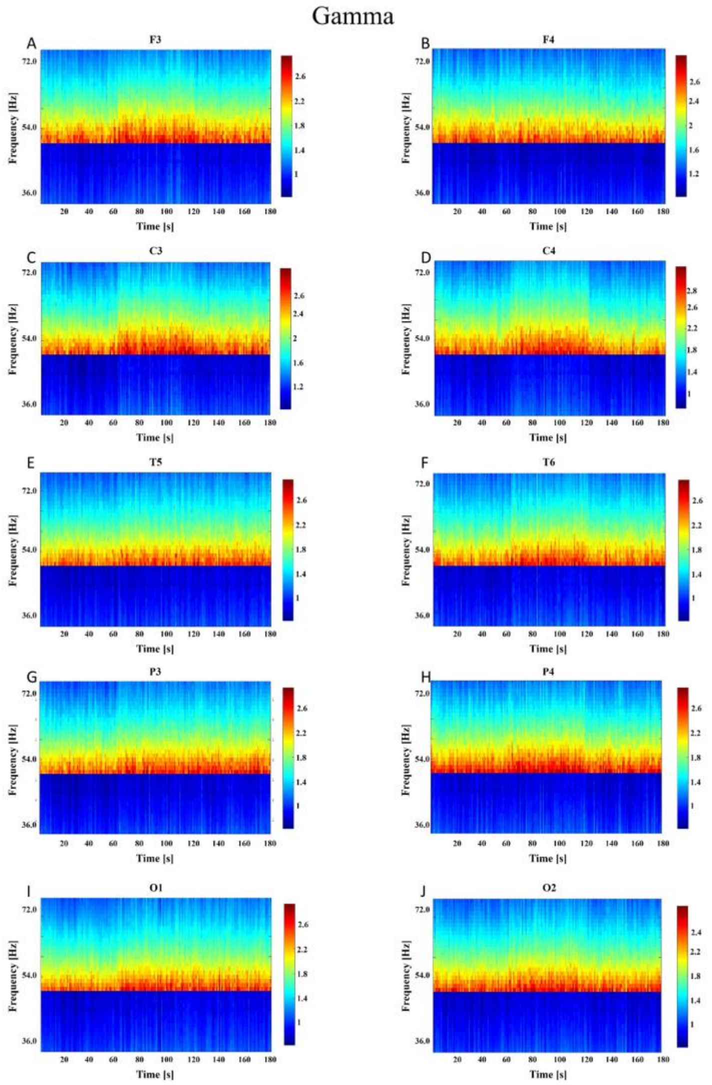

Figure 2. Time-Frequency diagrams of Gamma Rhythm. Each image within this Figure represents the behavior of the NPS over time, considering that the first 60 seconds refer to the 'Eyes Closed' situation, the next 60 seconds are related to the 'Music' situation and the last 60 seconds are from 'Post Music'. A – electrode F3; B – electrode F4; C – electrode C3; D – electrode C4; E – electrode T5; F – electrode T6; G – electrode P3; H – electrode P4; I – electrode O1; J – electrode O2. The vertical axis is measured as a percentage (%) of the total power, and the horizontal axis is measured in seconds, within the range 0-180s.

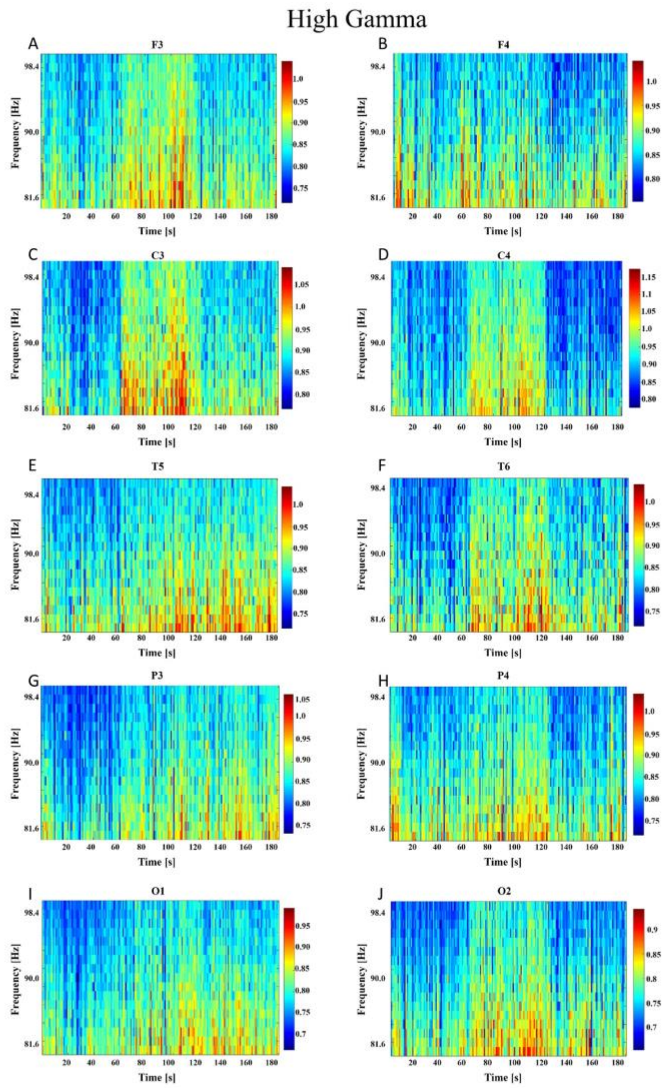

Figure 3. Time-Frequency diagrams of High Gamma Rhythm. Each image within this Figure represents the behavior of the NPS over time, considering that the first 60 seconds refer to the 'Eyes Closed' situation, the next 60 seconds are related to the 'Music' situation and the last 60 seconds are from 'Post Music'. A – electrode F3; B – electrode F4; C – electrode C3; D – electrode C4; E – electrode T5; F – electrode T6; G – electrode P3; H – electrode P4; I – electrode O1; J – electrode O2. The vertical axis is measured as a percentage (%) of the total power, and the horizontal axis is measured in seconds, within the range 0-180s.

Figure 1 enables the analysis of NPS over time, in terms of the Delta to Beta rhythms, considering the three events. Although time variations of NPS cannot be sharply assessed by simple visual analysis, it is possible to check that NPS amplitudes for Delta and Alpha rhythms are higher than those tied to other rhythms, for all electrodes. Specifically, for some electrodes, e.g., C4, T5, and P3, NPS amplitude raises for the Alpha rhythm as stimulation takes place, which is not verified before and after such stimulation. Considering the tracks of Figure 1 related to the Theta and Beta bands, one can perceive differences in NPS throughout the events.

The low amplitude of NPS measured during the EC event with respect to the MU event may be associated with a strong cerebral response to musical stimulation, particularly in the gamma and high gamma rhythms. One of the possible reasons for this may be related to the music being unfamiliar to the population. In fact, Calabrò et al. (2015) discuss that exists some dependence among the interactions between the cortex and specific or non-specific areas of the thalamic nucleus. Basic cognition is "fed" by recurrent electrical activity between the cortex and the thalamus at gamma-band frequencies. In order to establish some sort of working memory, even it lasts a very short period; this recurrent activity must take place for the consciousness to occur. In addition, the cingulate cortex is also considered important, which is part of the limbic lobe, involved in emotional formation and processing, selective attention (anterior cingulate cortex), learning, and memory (long-term potentiation). The cingulate cortex is also important for executive function. Therefore, it is noted that, regardless of the volunteer's feelings elicited by the music, this response to the stimulus becomes strong during the stimulation period.

The study of Banerjee et al. (2016), which analyzed the clinical band and the gamma rhythms through nonlinear techniques, depicted significant differences of the EEG signal in presence of the musical stimulus. The article considered 10 healthy Indian volunteers, who underwent stimulation of two different styles of Indian music, a cheerful one (raga Chhayanat) and a sad one (raga Darbari). Each stimulus was presented for 3 minutes, including some periods without music. Assessing the increase of alpha power, it was also noticed greater excitement in all the volunteers when they were stimulated by the joyful music. After removing this stimulus, alpha power remained high for a few moments, in accordance with the results reported in our article. In the case of theta and gamma waves, no significant changes were assessed in Banerjee et al. (2016). However, the author did not compare the intensity of the gamma power statistical change for the various events of his experiment, with the changes of the same quantifier considering clinical rhythms. On the other hand, this article compares all the brain waves, showing that the NPS values in PM still maintain high amplitude within gamma and high gamma bands.

Finally, all the other studies in the literature discussed similar research to the present article, but always restricting the analysis to the clinical brain waves (1 - 30 Hz). In Kumagai et al. (2017), cortical activation was measured utilizing the EEG signal analysis in the presence of musical stimuli of three types: familiar, unknown, and a type that mixes notes of familiar musical stimuli with notes of unknown musical stimuli. The EEG signals were analyzed from eight healthy volunteers. The cortical responses associated with the unknown music led to stronger quantitative changes than in the case of the familiar stimulus, which agrees quite well with our results. On the other hand, the study of Bajoulvand et al. (2017) considers 16 EEG records from healthy volunteers, which were submitted to four distinct musical stimuli, lasting 2 minutes each. This study concludes that the more familiar the music is to the listener, the more significant the quantitative change in the EEG signal behavior.

After performing EEG recordings of 20 healthy volunteers stimulated by classical musical pieces (Hook and Mozart sonatas), for two minutes each, Martínez-Rodrigo et al. (2017) concluded that different stimulus led to changes in the Theta and Alpha rhythms, based on main components analysis. Particularly, for Mozart's sonata stimulation, it is noticed an increase in Delta and Alpha power throughout the cerebral cortex. Similar results were reported in Maity et al. (2015), wherein 10 EEG records of healthy young volunteers were studied, stimulated by Indian music called *tanpura*, which aids relaxation. Over 2 minutes of recording, both Delta and Alpha power increased during the musical stimulus. Results close to Table 1 are reported in this article.

Concerning the discussion presented in the previous paragraph, several other articles report a significant power increase only in the Alpha band during musical stimulation, regardless of the stimulus type. In Kay et al. (2012), 40 healthy individuals were assessed, divided into 2 groups, one group stimulated with self-selected songs by the volunteers, whereas the other group did not listen to any music. EEG and magnetic resonance imaging were simultaneously recorded, and alpha rhythm power increased for the first group. In Schaefer et al. (2013), 10 volunteers undergone two distinct musical stimuli (instrumental music and complex music, i.e., including lyrics, notes, and rhythms) over several minutes, and they were simultaneously submitted to memorization tasks. Concerning Vijayalakshmi et al. (2010), EEG records were performed in 10 volunteers submitted to a meditation song. It was outlined that the amplitude of the Alpha wave increases during and/or after the musical stimulus, as well as it is assessed an increase in the relaxation and in the concentration attained by the volunteers. The article of Cong et al. (2013) outlines the increase of Alpha power during musical stimulation, highlighting the relevant Alpha and Theta oscillations in the occipital area while the stimulus is applied. In this study, performed with 14 right-handed people, the stimulation with modern tango style lasted 8.5 minutes, results pointed out the intense Alpha activity during musical stimulation. A similar result was assessed in Figure 1, presenting the time-frequency diagrams of the clinical rhythms from 1 up to 30 Hz for the temporal, parietal, and occipital regions. They clearly disclose high NPS amplitudes associated with MU, with respect to the other events.

Furthermore, according to the literature, different emotions evoked by the musical stimulation can be associated with the topographic location of the bioelectrical activity. For example, in Gomes et al. (2018), 30 healthy volunteers were submitted to four different types of musical stimuli. Several different kinds of feelings such as joy, sadness, fear, and rage were elicited. For positive feelings, such as joy and enthusiasm, significant brain activation was assessed in the left hemisphere; on the other hand, for unpleasant feelings, intense activation in the right hemisphere was assessed. Particularly, when the music was considered fun, there was a significant increase in Alpha power when compared to the other frequencies.

Furthermore, in the context of EEG applied for emotional studies, Tandle et al. (2016) analyzed 41 people, stimulated by a classical Indian instrumental music raga Bhairavi, which were divided into two distinct groups: people who appreciated music (group 1) versus a group of people who did not like it (group 2). For the first group, the left hemisphere showed a significant increase in Theta power, as periods before and during musical stimulation were compared to each other, with respect to the right hemisphere. In consequence, pleasant emotions were evoked in people of the first group. On the other hand, in this article, wherein all volunteers reported positive feelings elicited by unknown music, an increase in signal power during musical stimulation was assessed in the left frontal lobe, represented by the F3 electrode (see Table 1 and Figure 1). By contrast, in the right lobe, signal power decreased during musical stimulation, according to Table 1. In consequence, our findings agree with the results reported in Tandle et al. (2016).

4. Conclusions

This work analyzed the musical stimulation of 42-Brazilian neurologically normal individuals through a piece of unknown music, for which most volunteers report positive emotions as a consequence of the stimulation. Our analysis made use of the time-frequency diagram, thus considering the cognitive process dynamics. Whereas in the literature most articles consider samples of 10 individuals and perform standard spectral analysis. Although only one article considers the EEG beyond 40 Hz; our work explicitly studies the 1 - 100 Hz rhythms.

Considering a total amount of 30 comparisons in each cerebral rhythm (see Tables 1, 2, and 3), it is clear that 27 changes of significant magnitude take place in the gamma and high gamma bands. In consequence, higher frequencies present a more intensive pattern of bioelectrical activity than the clinical band. In summary, considering clinical rhythms (1 - 30 Hz), gamma (30 - 80 Hz), and high gamma (80 - 100 Hz) waves, the last two rhythms led to the best results in the detection of the musical stimulus. Consequently, it is possible to clearly distinguish the behavior of the brain before, during, and after this stimulus by analyzing the range 30 – 100 Hz. This conclusion can be easily visualized in the time-frequency diagrams of Figure 3, referring to the high gamma band. This specific behavior is inherent to the whole cerebral cortex since the changes were assessed at almost all electrodes.

The time-frequency diagrams outlined important details of the musical stimulation process. For the clinical rhythms, it was assessed a significant change of the delta power in the frontal and central regions, as well as intense variation of alpha power in the temporal, occipital, and parietal regions. These experimental conclusions agree quite well with almost all articles in the literature. In the gamma range, more significant changes were observed around frequencies 50 and 70 Hz.

This whole set of results points out that research associated with complex cognitive phenomena, such as musical perception, should include gamma and high gamma rhythms. A clear example of this conclusion can be seen in Table 1 and Figure 1, wherein we cannot clearly realize almost any change of NPS amplitudes within the 1-30 Hz clinical range during EC and PM events. Consequently, it is impossible to differentiate these two events from the bioelectric point of view, only considering the classic Delta to Beta rhythms. On the other hand, it must be considered the practical difficulty associated with the very low amplitudes related to the gamma and high gamma rhythms. In fact, our experimental results pointed out that the NPS of the clinical rhythms is clearly higher than gamma NPS, which in turn is higher than high gamma NPS.

Although this study is innovative, it is necessary to consider a greater number of volunteers, in order to achieve better statistical accuracy. Further studies may be performed considering different types of sound stimuli, and it is interesting to correlate EEG analysis with the feelings reported by each volunteer during stimulation. In consequence, quantitative patterns of EEG could be related to particular emotions or to specific music styles.

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References

BAJOULVAND, A., et al. Analysis of folk music preference of people from different ethnic groups using kernel-based methods on EEG signals. *Applied Mathematics and Computation*. 2017, **307**, 62-70. https://doi.org/10.1016/j.amc.2017.02.042

BALASUBRAMANIAN, G., et al. Music induced emotion using wavelet packet decomposition—An EEG study. *Biomedical Signal Processing and Control*. 2018, **42**, 115-128. https://doi.org/10.1016/j.bspc.2018.01.015

BANERJEE, A., et al. Study on Brain Dynamics by Non Linear Analysis of Music Induced EEG Signals. *Physica A: Statistical Mechanics and its Applications*. 2016, **444**, 110-120. https://doi.org/10.1016/j.physa.2015.10.030

BAUER, A.K.R., KREUTZ, G. and HERRMANN, C.S. 2015. Individual musical tempo preference correlates with EEG beta rhythm. *Psychophysiology*. 2015, **52**(4), 600-604. https://doi.org/10.1111/psyp.12375

CALABRÒ, R.S., et al. Neural correlates of consciousness: what we know and what we have to learn! *Neurological Sciences*. 2015, **36**(4), 505-513. https://doi.org/10.1007/s10072-015-2072-x

CLARK, C.N., DOWNEY, L.E. and WARREN, J.D. Music biology: All this useful beauty. *Current Biology*. 2014, **24**(6), 234-237. https://doi.org/10.1016/j.cub.2014.02.013

CONG, F., et al. Linking brain responses to naturalistic music through analysis of ongoing EEG and stimulus features. *IEEE Transactions on Multimedia*. 2013, **212**(1), 1060 -1069. https://doi.org/10.1109/TMM.2013.2253452

ENGEL, J. and DA SILVA, F.L. High-frequency oscillations – Where we are and where we need to go. *Progress in Neurobiology*. 2012, **98** (3), 316-318. https://doi.org/10.1007/978-1-4614-4984-3

FREEMAN, W. and QUIROGA, R.Q. *Imaging Brain Function With EEG: Advanced Temporal and Spatial Analysis of Electroencephalographic Signals*. New York: Springer, 2013. Available from: https://doi.org/10.1007/978-1-4614-4984-3

GOMES, P., PEREIRA, T. and CONDE, J. Musical emotions in the brain-a neurophysiological study. *Neurophysiology Research*. 2018, **1**(1), 12–20.

HERRMANN, C.S., et al. EEG oscillations: From correlation to causality. *International Journal of Psychophysiology*. 2016, **103**, 12-21. https://doi.org/10.1016/j.ijpsycho.2015.02.003

KAY, B.P., et al. Moderating effects of music on resting state networks. *Brain Research*. 2012, **1447**, 53-64. https://doi.org/10.1016/j.brainres.2012.01.064

KHOSROWABADI, R. and RAHMAN, A.W.B.A., 2010. Classification of EEG correlates on emotion using features from Gaussian mixtures of EEG spectrogram. In: *Proceeding of the 3rd International Conference on Information and Communication Technology for the Moslem World (ICT4M)*. Singapore: IEEE, pp. 102-107. Available from: https://ieeexplore.ieee.org/document/5971942

KUCEWICZ, M.T., et al. Dissecting gamma frequency activity during human memory processing. *Brain*. **140**(5), 1337-1350, 2017. https://doi.org/10.1093/brain/awx043

KUMAGAI, Y., ARVANEH, M. and TANAKA, T. Familiarity Affects Entrainment of EEG in Music Listening. *Frontiers in Human Neuroscience*. 2017, **11**, 1-8. https://doi.org/10.3389/fnhum.2017.00384

LIN, Y.P., et al. EEG-based emotion recognition in music listening. IEEE Transactions on Biomedical Engineering. 2010, **57**(7), 1798-1806. Available from: https://ieeexplore.ieee.org/document/5458075

MAITY, A.K., et al. Multifractal Detrended Fluctuation Analysis of alpha and theta EEG rhythms with musical stimuli. Chaos, Solitons and Fractals. 2015, **81**, 52-67. https://doi.org/10.1016/j.chaos.2015.08.016

MARTÍNEZ-RODRIGO, A., et al. Neural Correlates of Phrase Rhythm: An EEG Study of Bipartite vs. Rondo Sonata Form. *Frontiers in Neuroinformatics*. 2017, **11**(9), 1-9. https://doi.org/10.3389/fninf.2017.00029

NAKAMURA, S., et al. Analysis of music-brain interaction with simultaneous measurement of regional cerebral blood flow and electroencephalogram beta rhythm in human subjects. *Neuroscience Letters*. 1999, **275**(3), 222-226. https://doi.org/10.1016/S0304-3940(99)00766-1

PAN, Y., et al., 2013. Common frequency pattern for music preference identification using frontal EEG. In: *6th International IEEE/EMBS Conference on Neural Engineering*. San Diego: IEEE, pp. 505–508. Available from: https://ieeexplore.ieee.org/document/6695982

SCHAEFER, R.S., DESAIN, P. and FARQUHAR, J. Shared processing of perception and imagery of music in decomposed EEG. *NeuroImage*. 2013, **70**, 317-326. https://doi.org/10.1016/j.chaos.2015.08.016

SCHOMER, D.L. and SILVA, F.H.L. *Niedermeyer's Electroencephalography: Basic Principles, Clinical Applications, and Related Fields*. New York: Oxford University Press, 2011.

TANDLE, A., et al., 2016. Study of valence of musical emotions and its laterality evoked by instrumental Indian classical music: An EEG study. In: *International Conference on Communication and Signal Processing, ICCSP*. India: IEEE, pp. 327–331. Available from: https://ieeexplore.ieee.org/document/7754149

TELENCZUK, B., et al. High-frequency EEG covaries with spike burst patterns detected in cortical neurons. *Journal of Neurophysiology*. 2011, **105**(6), 2951-2959. https://doi.org/10.1152/jn.00327.2010

THAUT, M.H. and HOEMBERG, V. *Handbook of Neurologic Music Therapy*. 1st ed. New York: Oxford University Press, 2016.

VIJAYALAKSHMI, K., SRIDHAR, S. and KHANWANI, P. 2010. Estimation of effects of Alpha music on EEG components by time and frequency domain analysis. In: *International Conference on Computer and Communication Engineering, ICCCE*, Kuala Lumpur: IEEE, pp. 11–13. Available from: https://ieeexplore.ieee.org/document/5556761?part=1

WANG, D., et al., 2016. Exploiting ongoing EEG with multilinear partial least squares during free-listening to music. In: *IEEE 26th International Workshop on Machine Learning for Signal Processing*, Salerno: IEEE, pp. 1–6. Available from: https://ieeexplore.ieee.org/document/7738849

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