PREFERRED MUSIC EFFECT ON HUMAN BRAIN USING FUNCTIONAL NEAR-INFRARED SPECTROSCOPY

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Master thesis

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Contents

1. Summary

The following thesis develops a scientific experiment in the field of neuroscience, applicable to the innovative world of neuromarketing and even also applicable in the clinical psychological field.

The aim of the research is to determine if the music preferred by a subject generates different brain activity in the prefrontal cortex of the brain compared to classical music or white noise. To do this, an experiment has been done with 11 subjects, who have listened to different audio tracks without any distraction.

The methods used in this study have been, on the one hand, functional near-infrared spectroscopy to obtain the data of the subjects and, on the other hand, a statistical analysis of variances in the means. Previously, the data has been preprocessed using lowpass and highpass filters and moving averages. Both the preprocessing and the analysis have been carried out using the statistical software R.

The statistical results of the study show different activity generated in the prefrontal cortex by the preferred music to classical music or to the resting status. However, at a qualitative level, a similar behaviour has been observed in subjects under the stimulus of preferred music or white noise. The most important conclusion that has been obtained is the clear reduction of brain activity when subjects have been under classical music stimulus.

Future studies should be conducted in order to determine the effect of white noise on the brain, as well as that of an unpleasant sound compared to a pleasant one.

2. Introduction

2.1. Goals and Hypothesis

The following research's principal purpose of study is understanding the effect of music in the human brain. Specifically, the presented research is elaborated aiming to analyze weather the music preferred by a subject evokes a greater activation in the human's brain in comparison of other music or even noise samples.

Thereby, all the approach and development of this research thesis is grounded in a fundamental question that gives meaning and form to all the approaches. The question is the following: Does the music that we like activate our brain more than other audio stimulus?

The human beings coexist with music at all times. It is an art that makes us enjoy of pleasant times, stimulates us to remember past facts or even makes us share emotions in group songs or live concerts. However, even that it seems quite natural, it is produced through complex and surprising neuronal mechanism. Because of that, science world always comes up with that question.

We listen to music already from the crib or even in the gestation process. Babies, in the first months of life, have the capacity to respond to melodies even before than to a verbal communication from their parents (Judy Plantinga, Laurel J. Trainor, 2009). Soft music sounds relax them. It is known, for example, that premature kids that can't sleep are benefited by their mother's heartbeat or imitating sounds (Katherine Rand, Amir Lahav, 2014).

Music is considered among the elements that cause more pleasure in life. It releases dopamine in the brain as food, sex or drugs do. All of them are stimulus that depend of a subcortical brain circuit in the limbic system, that is to say, that system formed by brain structures that manage physiological responses to emotional stimulus; in particular, caudate and accumbens nucleus and their connection with the pre-frontal area (Del Arco A, Mora F., 2008). The studies that show activation to those mentioned stimulus reveal an important overlap within the areas, suggesting that all of them activate a common system.

As mentioned above, pre-frontal cortex (PFC) of the brain is one of the brain areas affected by music stimulus. By the use of functional near-infrared spectroscopy (fNIRS), changes in the blood flow of the PFC can be measured.

Later, in section 4, the relation of fNIRS imaging and brain activation is extensively explained, however, this brief explanation is needed to understand in this introduction the hypothesis that will be studied. Using an fNIRS device owned by Takahashi's Lab among several subjects, this research aims to detect significant difference in the PFC blood flow to preferred music stimulus, testing the following hypothesis.

2.1.1. Hypothesis

Preferred music has a different effect on PFC blood flow than classical music or resting status within subjects.

It is important to remark the time limitation of the study. When working with human beings, one of the most difficult phase in the research is to define properly how the experiment will be performed, and sometimes, this phase requires some iterations until finally it fulfills the requirements expected. This research has been developed in a time frame of 6 months, which has been enough as a first approach to the case, but could perfectly be continued in order to get more accurate data.

2.2. Motivation

Neuroscience has traditionally had the goal of understanding how the nervous system work. Both at functional and structural level, this discipline tries to understand how the brain is organized. During the last years, studies have gone beyond, not only trying to understand how brain works, but also the repercussion that it has on our conducts, thoughts and emotions.

The development of new techniques has been of great help inside this field in order to be able to carry out experimental studies. Neuroimaging studies have facilitated the task of relating concrete structures with different functions, using a very useful tool for this purpose: infrared-ray spectroscopy. As an engineer, it is always interesting to understand and make profit of technological tool, and even more if its outputs can directly be measured and analyzed.

However, all the technologies learned during my different academic career projects, have been normally applied through software programs to system simulations or in prototypes. The fact of performing a research with human beings gives a realistic context to it, which, in a certain way, position this thesis nearer to a practical field but also challenges the study since human behavior is less predictive than any machine.

On the other hand, any scientific research involves an extensive statistical analysis since, as mentioned before, human behavior is complex and it is not trivial to find the best way to treat the data gathered in the experiment. As an engineer of this new era in which companies tend to emphasize the use of all the data they can collect around their environment, it is crucial to improve my analytical skills, and this thesis is a great opportunity for doing it.

In addition, throughout my academic years, I have studied subjects related to innovation and business management. This study consists of an experiment that can be perfectly placed in the recent field of neuromarketing, because this study or similar can help define advertising campaigns or the atmosphere of a local, choosing a certain type of music in order to capture the attention of consumers.

Finally, being a musician gives this research a special interest, since it helps me understand why people can change his emotions by the simple fact of listening to music they like. Emotion, expression, social skills, mind theory, linguistic and mathematics abilities, motor and visuospatial abilities, decision taking, autonomy, creativity, emotional and cognitive flexibility, everything converges simultaneously in the shared musical experience. People sing and dance together in all cultures. We know we do it today and we will continue doing it in the future. We can imagine that our ancestors did it, around the fire, thousands of years ago. We are what we are with music and because of music, neither more nor less.

3. Theoretical Framework

As mentioned in the introduction, this project is based on a study about human beings. During the realization of this research, a great part of the time has been invested in understanding why is PFC the area of the brain studied and on what fundamentals the use of fNIRS technology is based. The main objective of this section is then to summarize the information processed in order to give a theoretical framework to the readers.

3.1. Brain cortex structure and its functions

The cerebral cortex is divided into four areas or lobes: frontal, temporal, parietal and occipital, each of which is responsible for different functions. At the same time, the brain is also divided into two hemispheres: the right, which helps us think creatively and the left, which encourages us to think in a much more logical way. Therefore, it has a frontal lobe on the right side and a frontal lobe on the left side. In this study we will focus attention on one of them: the frontal lobe. The frontal lobe is the largest area of the brain.

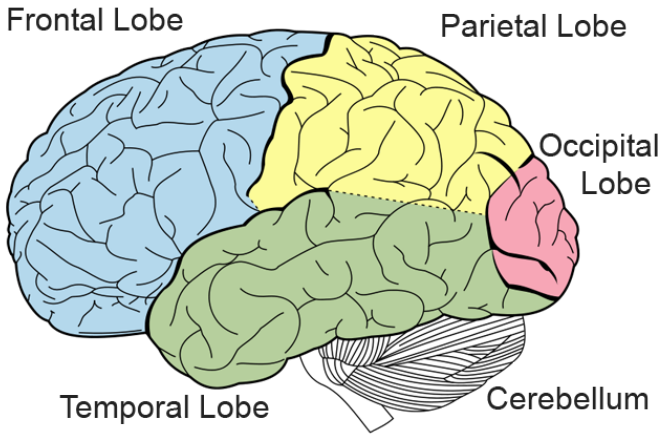


Figure 3.1.1. Lobe structure of the brain

The frontal lobe is located in the most anterior part of the cerebral cortex, and in front of the parietal lobe. This lobe is comprehended as the most prominent lobe in humans, due to its specific functions and because it occupies a third of our total brain. In other species, its volume is much lower.

It is considered that our personality resides in the frontal lobes, which is also where emotions are handled, problem solving, reasoning, planning and other functions. The frontal lobes are linked to the sensory and memory centers throughout the brain. His main job is to allow us thinking about things and determine how to use the information found in another part of the brain.

Without going into detail, the different areas of the frontal lobe and their functions are listed below (Sanides, 1964). Later, the PFC will be detailed, since it is the area studied in this investigation:

- Primary motor cortex: motor control.
- Premotor cortex: motor planning, speech motor planning (Broca's area).
- Frontal eye field: as its proper name says, eye controlling.
- Prefrontal Cortex:
    - Dorsolateral prefrontal region: planning, judgment, temporal organization, self-care, motor programming.
    - Orbitofrontal region: social perception, attention, **control of emotion**, behavior guided by reward / punishment.
    - Mediofrontal region: decrease in motor activity, spontaneity, speech, prosody, increase in response latitude, perseverance.

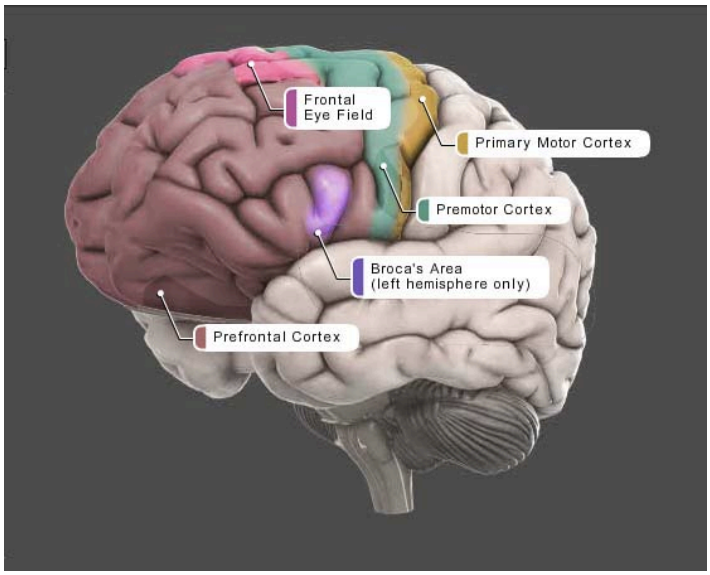


Figure 4.1.2. Frontal lobe structure

The PFC is the most frontal portion of the frontal lobes and manages complex cognitive processes such as memory, planning, reasoning and problem solving (Roberts, 1998) . This area helps us establish and maintain objectives, stop negative impulses, organize events in the order of time and form our personality.

It is especially developed in hominids and is related to the development of complex cognitive processes involved in decision-making, which has led to its association with personality and social behavior.

Numerous clinical and experimental studies (see Section 4.2.) have shown the involvement of the frontal lobes in emotions, especially in a specific area: the orbitofrontal cortex (OFC). The OFC is an area located in the ventral medial region of the PFC.

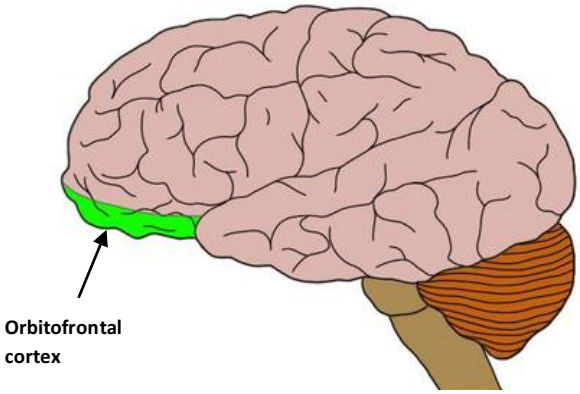


Figure 3.1.3. Location of OFC

Because of its connections with regions of the frontal cortex and other cerebral structures, the OFC (or ventromedial part of the PFC) contains information on frontal behavioral planning and sensory processing of the environment, which allows it to act on the development of certain behaviors and physiological responses.

The objective then of this section has been to break down the parts of the human brain until arriving at the region studied in this investigation, since it is in charge of the processing of emotions: the OFC.

3.2. Music effect on the brain

Music is originated through vibrations produced by an instrument, by the voice or another source. These waves are transported through the air and enter the ear. Where three small bones located in the middle amplify the sound waves and then are converted into electrical impulses that are transmitted to the brain by means of the auditory nerves.

It is at that moment when the brain comes to interpret these electrical impulses as "sound". Where tonality, rhythm and lyrics are interpreted in different areas of the brain.

With the passage of time, music can improve linguistic skills, creativity and happiness. It also helps reduce anxiety and pain, causes rapid healing and increases optimism (Conrad, 2010). And it also helps to heal some neurological diseases such as Alzheimer's (Camilla N. Clark, Jason D. Warren, 2015), Parkinson's (Raglio, 2015) and Autism (Ruth James, Jeff Sigafoos, Vanessa A. Green, Peter B. Marschick, 2014).

Music can affect your mood anywhere, as in your car, your office or your home. It can even contribute to how you feel inside a mall store and influence your decision to buy. The large retail chains have long opted to control every aspect of the environment to impact the experience of the buyer. This often results in an increase in sales.

In a study conducted in 2014 (Kielstra, 2016) at a Dutch restaurant, the lighting and music of the place was deliberately manipulated while monitoring the behaviour of the diners. Its authors demonstrated that music can affect the perception, feelings and the buying pattern of clients, influencing their mood. In total, the expense was increased by 20% when the place was

set with classical music, as opposed to Pop or Jazz music. People felt more comfortable, happy and calm. Even, the evaluation of place and service increased in these circumstances, because the mood of the diners was more positive.

It is also demonstrated that music affects the brain in terms of memory (Jäncke, 2008), learning, attention (Fuyima Mori, Fatemeh Azadi Naghsh, Taro Tezuka, 2014) and emotion (Jäncke, 2008). In this work we focus on emotion, since we are studying the OFC (Soria-Urios G, Duque P, García Moreno JM, 2011).

Listening to music creates peaks of emotions that increase the amount of dopamine, a neurotransmitter that helps control the reward and pleasure centers of the brain. They also help to process other emotions such as fear, sadness, resentment and pain, even when they are present at the subconscious level.

Many are the studies that have already been made using music stimulus in the PFC. For example, the effect of different music genre's samples was demonstrated to cause different concentrations in blood flow variation (Marcelo Bigliassi, Vinicius Barreto-Silva, Thiago Ferreira Dias Kanthack, Leandro Ricardo Altimari, 2014). More in detail, significant differences in PFC activation were studied with classical and techno music audio stimuli (Marcelo Bigliassi, Umberto Leon-Dominguez, Leandro Altimari, 2015). Music preferences in young and elderly individuals were also detected through PFC hemodynamics (Ono, 2017). Also, an experiment using film clips as visual and audio stimuli was conducted, also proving its effect on PFC (Jose Leon-Carrion, Jesus Damas, Kurtulus Izzetoglu, Kambiz Pourrezai, Juan Francisco Martín-Rodríguez, Juan Manuel Barroso y Martin, Maria Rosario Dominguez-Morales, 2006).

Finally, it is important to state that this research has only been conducted within male subjects, in order to prevent the possible effect of gender difference when stimulating the PFC, already shown in previous researches (Bigliassi, Barreto-Silva, Altimari, Vandoni, Codrons, Buzzachera, 2015; Yang H, Zhou Z, Liu Y, Ruan Z, Gong H, Luo Q, Lu Z, 2007).

3.3. Functional near-infrared spectroscopy fundamentals

Understanding how the brain works is one of the great unknowns of nature. This study has become one of the great challenges at the beginning of the 21st century as reflected by the BRAIN initiatives in the United States or the HUMAN BRAIN PROJECT of the European Commission through large-scale projects such as the Human Connectome Project.

The observation of brain activity is carried out by means of neuroimaging whose history goes back to 1924 when Hans Berger obtained the first encephalographic signal (EEG). Since then, other ways of making neuroimaging have emerged, such as functional magnetic resonance (MRI-BOLD) or positron emission tomography (PET), among others, with different strengths and weaknesses. In 1977, Jobsis laid the first stone for another neuroimaging modality based on irradiation and sensing of infrared light: neuroimaging by functional infrared spectroscopy (fNIRS).

The word "spectroscopy" derives from the Latin root spectrum (appearance, image) and the Greek word skopia (see). This definition is rather descriptive of the spectroscopic measurement itself; for example: see a slight image from a sample.

Since its origins in the 70s to the present, NIRS technology has evolved enormously, being considered today a powerful sensor for the qualitative and quantitative analysis in the agro-alimentary, pharmaceutical, chemical industry, and in certain applications in medicine, environment, etc.

Near-infrared spectroscopy or NIRS (near-infrared spectroscopy) is an optical non-invasive diagnostic method that uses the absorption or reflection of a certain wavelength produced by the different functional groups found in the tissues.

In order to understand the principles of fNIRS, it is mandatory to review NIRS. Technically speaking, the NIRS involves a beam of light that when interacting with biological material produces electromagnetic radiation in the form of waves in the range of 600 to 1000 nm (Alessandro Torricelli, Davide Contini, Antonio Pifferi, Mattero Caffini, Rebecca Re, Lucia Zucchelli, Lorenzo Spinelli, 2014) within the near-infrared spectrum, allowing it to penetrate into a sample and be absorbed or reflected. This reflected wave is analysed and can provide information about the sample as geometry of the object, size, distribution and composition. This allows us to know various physiological variables in real time such as Oxygen saturation and oxygenation index in any tissue. In this study, the information obtained are the changes in oxyhemoglobin (HbO2) and deoxyhemoglobin (Hb) summed, using a wavelength of 800 nm.

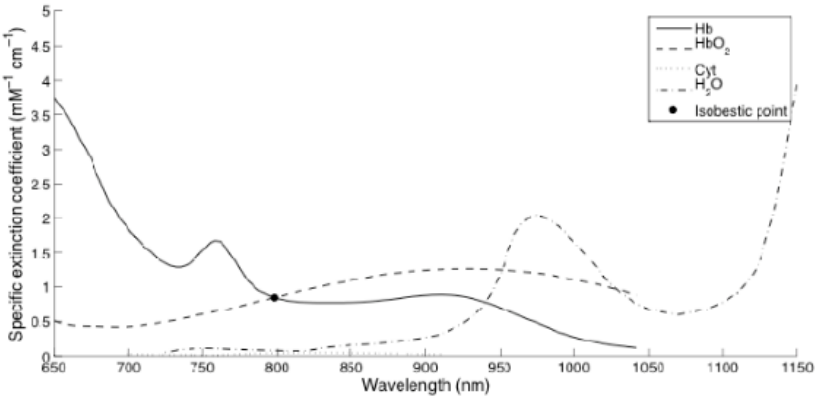


Figure 3.3.1. Absorption spectra for Hb and HbO_2

In the neuroimaging field fNIRS uses light to monitor noninvasively tissue hemodynamic and oxidative metabolism. The two most common brain areas where light is emitted are the primary motor cortex and the prefrontal cortex. Considering the different functions of the frontal lobe mentioned in section 4.2., signals corresponding to motor execution and motor imagery tasks are acquired from the motor cortex; whereas those corresponding to mental arithmetic, mental counting, emotions, etc. are acquired from the prefrontal cortex. Different emitter-detector configurations have been used in these two areas, however, the emitter-detector distance is usually kept within a specific range, as it plays an important role in fNIRS measurement. For instance, if emitter-detector distance is increased, then imaging depth is also increased. To measure hemodynamic response signals from the cortical areas, an emitter-detector separation of around 3 cm is suggested. A separation of less than 1 cm might contain only skin-layer contribution, whereas that of more than 5 cm might result in weak and therefore unusable signals (Noman Naseer, Keum-Shik Hong, 2015).

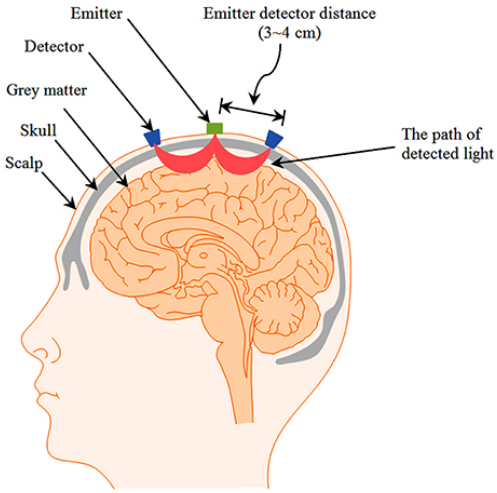


Figure 3.3.2. Example of emitter-detector pairs showing the paths of light

4. Methods

4.1. Subjects

For this study, 11 healthy volunteers (all males), aged 19-26 years, participated in the study. Before the tests, all of the procedures were explained. As mentioned in the previous section, female subjects were avoided in order to prevent the possible effect of gender difference when stimulating the PFC, already shown in previous researches (Marcelo Bigliassi, Umberto Leon-Dominguez, Leandro Altimari, 2015; Yang H, Zhou Z, Liu Y, Ruan Z, Gong H, Luo Q, Lu Z, 2007).

It is important to mention that, due to lack of time, all the adults were recruited from, Takahashi's Lab the laboratory I have been working with. However, none of them were involved in the research so the subjects were neutral. Also, they were offered an economic compensation in exchange for their efforts.

4.2. Experimental design

In order to better understand the following section, the hypothesis to be studied already mentioned in the Introduction is recalled below.

Hypothesis

Preferred music has a different effect on PFC blood flow than classical music or resting status within subjects.

As we can see, in this study an intra-subject (within subjects) test has been conducted. The fundamental characteristic of this design is that the same subjects go through all the experimental conditions. Comparisons are made between conditions and for them the measurements of each subject in each condition are used. We define an intra-subject design as a way to study the behavior of the same group of people under different conditions.

On the other hand, a between-subjects design could have been developed. In a between-subjects design, the various experimental treatments are given to different groups of subjects. The main advantage of intra-subject design over between-subjects design is that it requires fewer participants, making the process much more agile and less complicated in terms of resources. Due to the lack of time already mentioned, this advantage is very valuable.

For example, if you want to test four conditions with four groups of 30 participants it becomes difficult to manage and expensive. Using a group, which is tested with all four conditions, is much easier. Facility is not the only advantage, since a well-planned intra-subject design allows researchers to control the effect on individuals much more easily and reduce the possibility that individual differences distort results.

A disadvantage of this research design is the problem of drag effects, since the first test negatively influences the following ones. Two examples of this, with opposite effects, are fatigue

and practice. In a long experiment, with many conditions, the participants may be tired and completely fed up with the fact that the researchers are intrusive, ask them questions and press them to take the tests. This may decrease your performance in the last study.

On the other hand, the effect of the practice could mean that they feel more confident and successful after the first condition, simply because the experience has made them feel more confident to do the tests. As a result, in many experiments a counterweight design is recommended, where the order of treatments varies, although this is not always possible.

However, none of the examples described are applicable to our experiment, because in our case, the subject must only evaluate each audio, which is a non-exhaustive task and its practice does not influence.

All of the subjects were asked two days before the experiment to think about 3 songs that they really liked. Songs could be in any language and any music genre. The only requirement was that the music piece had to generate in them a very pleasant or motivational status. Once the subjects selected their preferred songs, they would forward a paper with those detailed.

On the other hand, two classical songs were selected in order to induce a calm stimulus in the subjects (Marcelo Bigliassi, Umberto Leon-Dominguez, Leandro Altimari, 2015). The songs used were 'Air on G String' from Johann Sebastian Bach and 'Nocturne op.2 No.2' from Frédéric Chopin, both of them played at 50 beats per minute approximately.

Finally, white noise was generated through Audacity software. In technical terms white noise can be described as noise whose amplitude is constant throughout the audible frequency range. A useful analogy is that of white light, which as we all know from school, contains all the colors(frequencies) combined together. White noise is used in the experiment since it blends the external sounds (lab members chattering, doors, etc.) into the overall background noise, so your brain pays less attention to those sounds. Therefore, white noise it is reproduced in order to obtain baseline values and evaluate resting status.

After collecting all the different audio pieces, an audio sample was recorded for every different subject using Audacity (Audacity Team, Pittsburgh, PA, USA). Each audio sample was composed with 90 seconds of each of the songs detailed by the subjects, as well as from the classical songs and also from the generated white noise audio. Before each of the 90 seconds tracks, 10 seconds of white noise was placed in order to later obtain the baseline values. Also, 20 silent seconds were placed after each track in order to allow the subject evaluate it. The pattern of the audio samples is shown in Figure 5.2.1. Volume level of each track was normalized and maximum peaks allowed were of 12 dB.

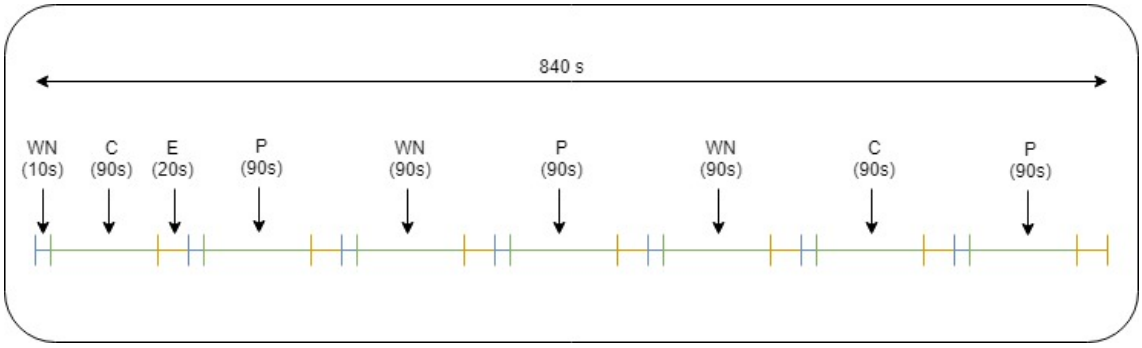


Figure 4.2.1. Audio sample pattern. White noise(WN), Classical (C), Evaluation(E), Preferred(P)

The subjects were seated in a comfortable reclining chair and the experiment was explained to them. Then, a two channel fNIRS device (HOT-1000, NeU Corporation, Japan) was placed on their foreheads with the light emitter situated approximately at 1cm over the eyebrows. The device contains one light emitter for each hemisphere of the brain and two detectors for each light emitter. Based on the principles explained in section 4.3., the cortical oxygenation in both hemispheres of the PFC was quantified. An image of the device and more specifications can be found on annex 9.4.

On the other hand, noise-cancellation Hi-Fi headphones (HD 25-C II, Sennheiser, Germany) were also placed on the subjects. The 840s audio sample was reproduced through an iPhone, always at the same volume level, ensuring that all subjects were under the same circumstances.

Participants were asked to stay still with their eyes focused on a fixation cross while listening to the audio sample in order to prevent motion effect in the brain blood flow, except after each 90s track, since they needed to evaluate each track.

Figure 4.2.2. Subject prepared for doing experiment

The evaluation was performed using Visual Analog Scale (VAS), a tool used to help a person evaluate the intensity of certain sensations and feelings, normally used for clinical purpose to measure pain. The visual analog scale for pain is a straight line in which one end means absence of pain and the other end means the worst pain imaginable. The patient marks a point on the line that matches the amount of pain he feels (Valerie SL Williams, Robert J Morlock, Douglas Feltner, 2010). It can be used to choose the correct dose of an analgesic. An example of VAS scale for pain is shown in figure 5.2.2.

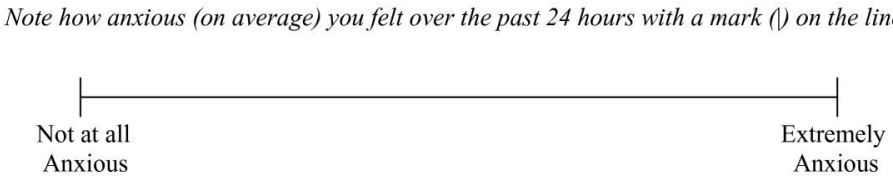


Figure 4.2.3. Example of VAS scale for anxiety evaluation

VAS was chosen for this experiment as evaluation method since it allows the participant to express their feelings without being rational and therefore, the time required for the evaluation is short. An example of VAS evaluation from one of the subjects is provided in the annex 9.3.

4.3. Pre-processing

For the pre-processing as well as for the data analysis, open-source integrated development environment RStudio (Boston, MA, USA) has been used, based on R programming language. Many other software packages as SPSS or Matlab could have been used, however, due to personal interest and future expectations RStudio was the one selected. All the code related to the pre-processing and the analytical steps detailed in the following sections has been self-developed and can be found in annex 9.1, with a brief explanation of each of the different blocks.

The fNIRS device was connected through Bluetooth® to an iOS application called HOT-Measurement, also developed by NeU Corporation (various screenshots from HOT-Measurement app are presented in the Annexes). Once each subject was evaluated, a CSV was generated with specific relevant data at 10 Hz and also non-relevant data that was not used.

From each CSV, only the left and right channels with a 3cm distance from the light emitter raw data and the left and right channels with raw data already processed by HOT-Measurement were loaded in the workspace. Also, from the 11 subjects that volunteered, 3 had to be discarded since the data collected had interspersed empty gaps due to a failure in the application.

In order to simplify and express as clear as possible the pre-processing developed, an example with one of the subject's data will be used as support.

Raw data

First of all, it is convenient to show the starting point of the data with which the research has worked. Since it is the first plot, it is important to clarify that the X axis corresponds to the number of measures, and since we are working with a 10Hz sampling frequency and the test has a duration of 840 seconds, we can see the limit at 8400 measures. Also, vertical dotted lines are added to the graph in order to represent the audio pattern.

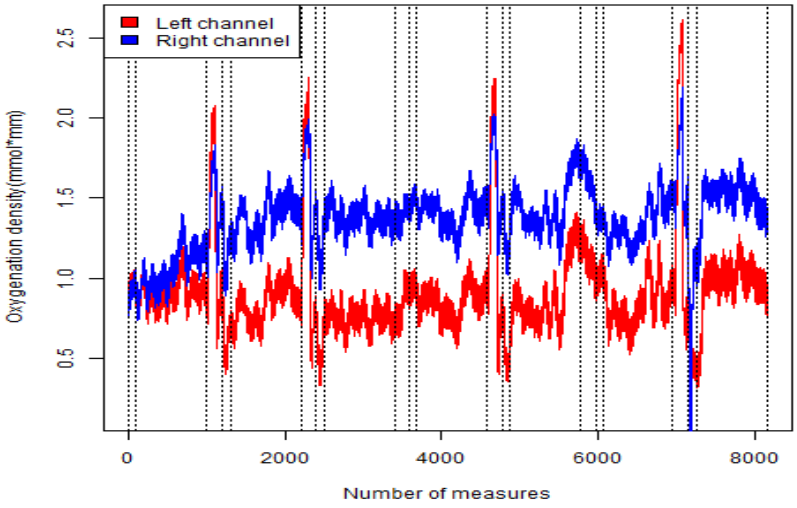


Figure 4.3.1. Left and right channels of subject 4 raw data of 3cm detector

As we can see in Figure 5.3.1., there is too much noise and a possible trend that must be removed for the further analysis. Also, we can see a significant increase of oxygenation in the intervals where the subject evaluated the track (20 seconds windows). This is mainly caused by the motion effect of the participant's head. The 3rd and 5th evaluation windows don't show this peak, since the track to be evaluated was white noise and the subject considered that it was not necessary.

Filtered data

In order to remove instrument noises, motion artifacts and other interferences, a filter in order to remove high frequencies must be designed and applied (Santosa H, Hong MJ, Kim SP, Hong KS, 2013). For that, a 20th-order low-pass filter with a normalized cut-off frequency of 0.1Hz using Hamming window was applied. The filter design was mainly obtained from previous researches already made mentioned in section 4.2.

On the other hand, since the further statistical analysis would be based on the difference respect the baseline values, it was necessary to remove the trend by removing the components of the lowest frequencies. Therefore, a 5th order Butterworth high-pass filter with cut-off

frequency of 2.5/60 Hz was designed and applied. In this case, the filter design was facilitated by a Mr. Kojima, a lab colleague who had been working with the same fNIRS device.

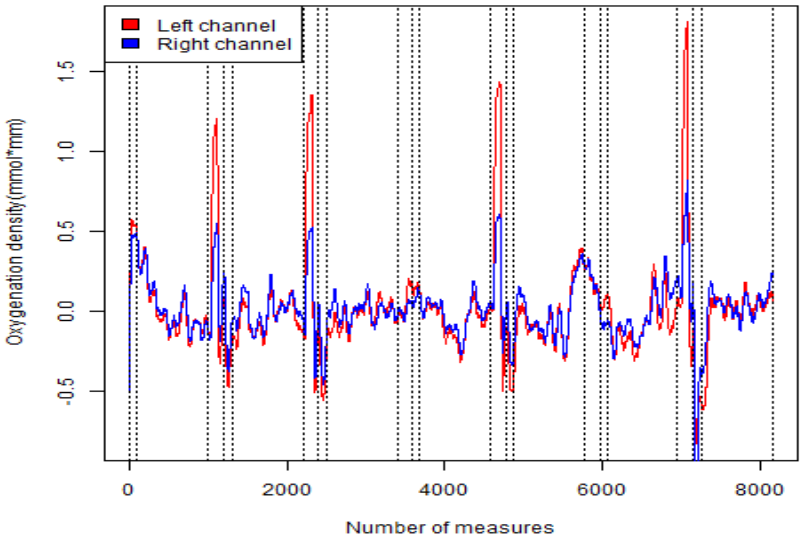


Figure 4.3.2. Left and right channels of subject 4 filtered data of 3cm detector

Scaled and smoothed data

In order to smooth the data removing volatility, 5th order moving-average windows have been applied.

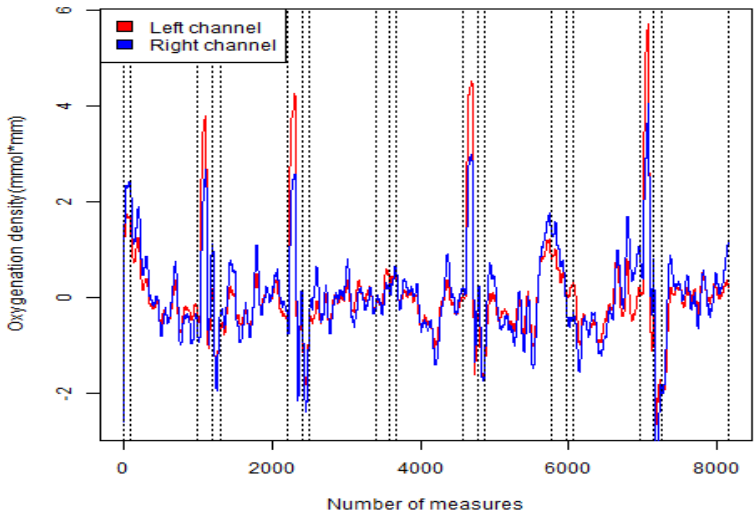


Figure 4.3.3. Left and right channels of subject 4 filtered, smoothed and scaled data of 3cm detector

As it has been mentioned in the introduction, the hypothesis to be studied is performed within subjects. Therefore, a Z-score normalization has been applied in order to remove the mean and the standard deviation for each data set.

In the following graph, a comparison between the raw data pre-processed by the steps described and by HOT-Measurement App for the left channel can be seen. Differences can be seen, especially in the trend. In the further sections, the reasons for having used the detailed self-processing method will be detailed, but mainly is because of normality of data.

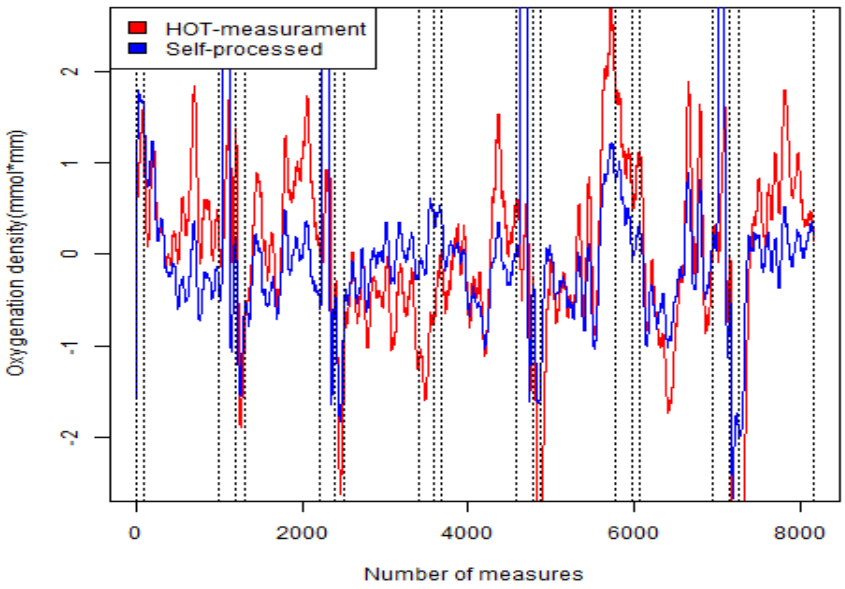


Figure 4.3.4. Left channel of subject 4 comparison, between self-processed data and HOT-Measurement App processed data

Data sampling

Finally, the last part of the pre-processing involved breaking the data into the different tracks that composed each audio sample and group them by channel and subject. Since all the audio samples followed the same pattern, this step consisted on simply subsetting the data taking into account the time pattern shown in Figure 5.2.1. and grouping them in a data frame.

4.4. Data analysis

When performing a statistical analysis, it is highly important to choose correctly an appropriate statistical test according to your question and the data you have. In our case, the two first characteristics we can state of our data are that its nature is numerical and the existence of more than two groups in each data set (Barun K Nayak, 2011).

One-Way ANOVA

With this two characteristics, the first statistical test that comes into our minds is the analysis of variance (ANOVA). One-way ANOVA is a statistical technique that indicates whether two variables, one independent and one dependent, are related based on whether the means of the dependent variable are different in the categories or groups of the independent variable. That is, it indicates if the means between two or more groups are similar or different.

For example, if we compare the number of children between the groups or levels of social class: those that are lower class, working class, middle-low class, upper-middle class and upper class. That is, we will check through ANOVA if the variable "number of children" is related to the variable "social class". Specifically, it will be analyzed if the average number of children varies according to the level of social class to which the person belongs. If the means of the dependent variable are equal in each group or category of the independent variable, the groups do not differ in the dependent variable, and therefore there is no relationship between the variables. In contrast, and following the example, if the means of the number of children are different between the levels of social class is that the variables are related.

When applying one-way ANOVA, a test called F and its significance are calculated. The F or F-test statistic (called F in honour of the Ronald Fisher statistic) is obtained by estimating the variation of the means between the groups of the independent variable and dividing it by the estimation of the variation of the means within the groups.

$$F = \frac{\left(\frac{RSS_0 - RSS_1}{m}\right)}{\left(\frac{1 - RSS_0}{n-k}\right)}$$

The calculation of the F statistic is somewhat complex to understand, but basically what it does is to divide the variation between the groups by the variation within the groups. If the means between the groups vary a lot and the average within a group varies little, that is to say, the groups are heterogeneous among them and similar internally, the value of F will be higher, and therefore, the variables will be related.

In conclusion, the more the means of the dependent variable differ between the groups of the independent variable, the higher the value of F. If we do several ANOVA analyses of one factor, the one with F higher will indicate that there are more differences and for both a stronger relationship between the variables.

The significance of F will be interpreted as the probability that this value of F is due to chance. Following a confidence level of 95%, the most used in social sciences, when the significance of F is less than 0.05, the two variables are related.

Factor design

In this study, the goal is to identify changes in the brain activity depending on the audio stimulus and its evaluation. With that purpose, various factors have been designed, all of them related to the characteristics of the audio track:

- **Audio track:** defines which is the audio track played for that data. The levels for that factor are: C1, P1, W1, P2, W2, C2, P3.
- **Subject:** defines the participant to whom data belongs to.
- **VAS:** defines the numerical evaluation given by the subject to that audio track.
- **VAS factorized:** defines the numerical evaluation given by the subject converted to a categorical scale. The conversion used was the following:

VAS	VAS Factorized
14-12	A
12-10	B
10-8	C
8-6	D
6-4	E
4-2	F
2-0	G

Table 4.4.4.1. Factorization of VAS numerical evaluation

- **Audio type:** defines what type of audio is the audio track played. The different levels are: C (classical), P (preferred), W (white noise).

As mentioned in section 5.3, the data was subsetted into samples corresponding to the audio pattern. For this analysis, only the data corresponded to a 90s audio track was stored in the matrix. Therefore, only 7 levels of audio track are needed. The structure of the data matrix would be the one described in Table 5.4.1:

Brain activity	Audio track	Subject	VAS	VAS factorized	Audio Type
Numerical	Categorical	Categorical	Numerical	Categorical	Categorical
	7 levels	8 levels		7 levels	3 levels

Table 4.4.1. Structure of data matrix for each channel

Once the ANOVA matrix is built, the next step is to check if the data fulfills the requirements needed in order to perform ANOVA analysis. This statistical test belongs to the group of parametric tests.

Parametric vs non-parametric tests

Parametric tests assume statistical distributions underlying the data. Therefore, some validity conditions must be met, so that the result of the parametric test is reliable. In our case, ANOVA test will be reliable only if each data sample fits a normal distribution and if the variances are homogeneous.

Non-parametric tests should not conform to any distribution. They can therefore be applied even if parametric validity conditions are not met.

The advantage of using a parametric test instead of a non-parametric test is that the former has more statistical power than the latter. In other words, a parametric test has a greater capacity to lead to a rejection of the null hypothesis. Most of the time, the p value associated with a parametric test is less than the p-value associated with its non-parametric equivalent executed on the same data. On the other hand, non-parametric tests are more robust than parametric tests, that is to say, they are valid in a wider range of situations.

Parametric tests often have their non-parametric equivalents. Therefore, the next step is to check if our data meets normality and homoscedasticity (variances are homogeneous) conditions required for ANOVA.

Normality

The normality tests, also called normality contrasts, aim to analyze how much the distribution of the observed data differs from what was expected if they came from a normal distribution with the same mean and standard deviation. Two strategies can be differentiated: those based on graphic representations and hypothesis testing.

In this research, both strategies have been followed. However, due to the data sample size, hypothesis testing is very likely to reject normality of the data. Since the sample size is large, statistical hypotheses tests have a large power, and hence any small difference between our distribution and the null distribution (normal distribution) is meaningful and leads to the rejection of the null hypothesis.

The test used has been Kolmogorov-Smirnov. It is considered as a null hypothesis that the data do come from a certain distribution and as an alternative hypothesis that they do not. The p-value of these tests indicates the probability of obtaining a distribution like the one observed if the data really come from a population with a certain distribution. The distribution tested in this case, is obviously a normal distribution. In table 5.4.3, we can see the p-values obtained for this test.

	Sub1	Sub2	Sub3	Sub4	Sub5	Sub6	Sub7	Sub8
Left Channel	4.41E-05	4.10E-07	1.61E-06	0	0	8.04E-11	3.28E-09	0
Right Channel	0	1.05E-11	2.46E-12	0	0	0	1.55E-11	0
Left Channel HOT-Measurement App processed	0	1.76E-11	0	0	0	0	0	0
Right Channel HOT-Measurement App processed	0	1.42E-08	0	0	0	0	2.75E-10	0.000774

Table 4.4.3. P-values for Kolmogorov-Smirnov test for each subject data and each channel

As already foreseen, the normality assumption has been rejected through hypothesis testing. The second phase in this step is to analyse graphically our data. For that, histograms with a normal distribution curve superimposed on the graph are used.

On one hand, figures 5.4.1 and 5.4.2 shows us that data processed by ourselves follow a likely normal distribution:

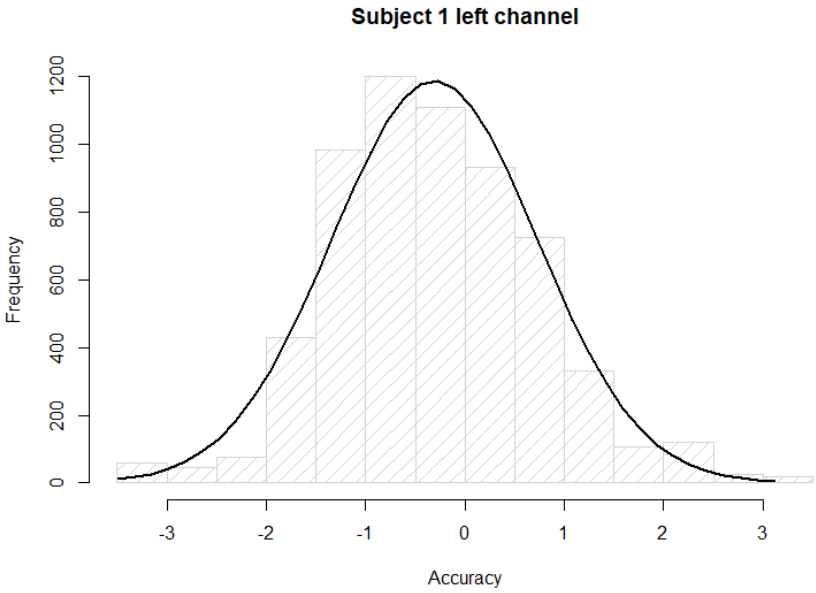


Figure 4.4.1. Histogram of subject 1 left channel processed data

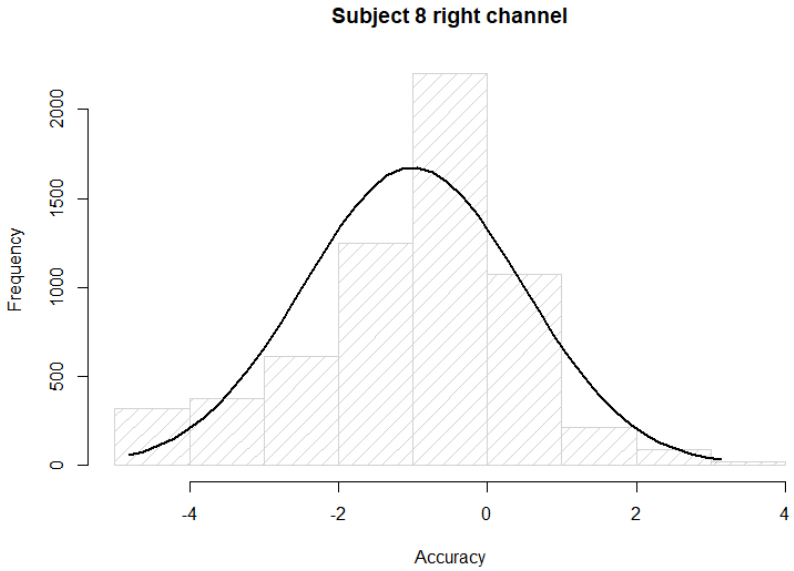


Figure 4.4.2. Histogram of subject 8 right channel processed data

On the other hand, figures 5.4.3 and 5.4.4 show that data already processed by HOT-Measurement App does not follow a normal distribution. Therefore, from now on, we will only focus on data treated with pre-processing strategy mentioned in section 5.3.

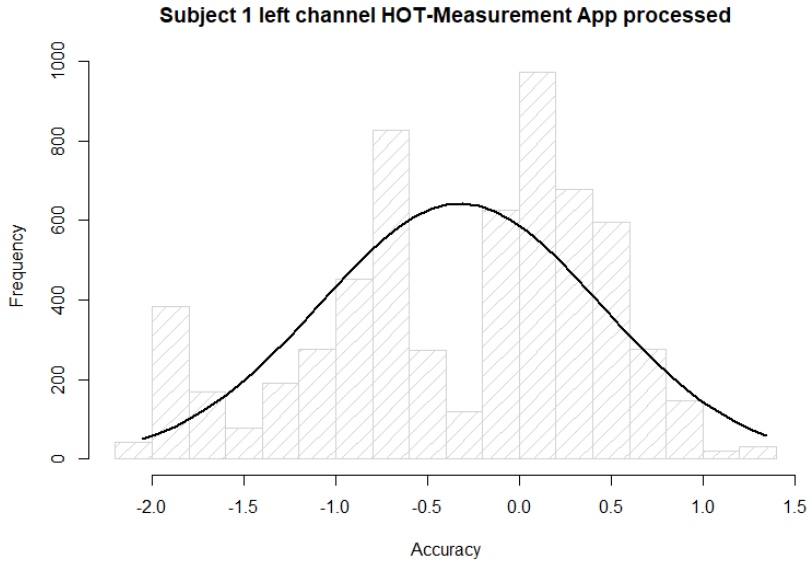


Figure 4.4.3. Histogram of subject 1 left channel HOT-Measurement App processed data

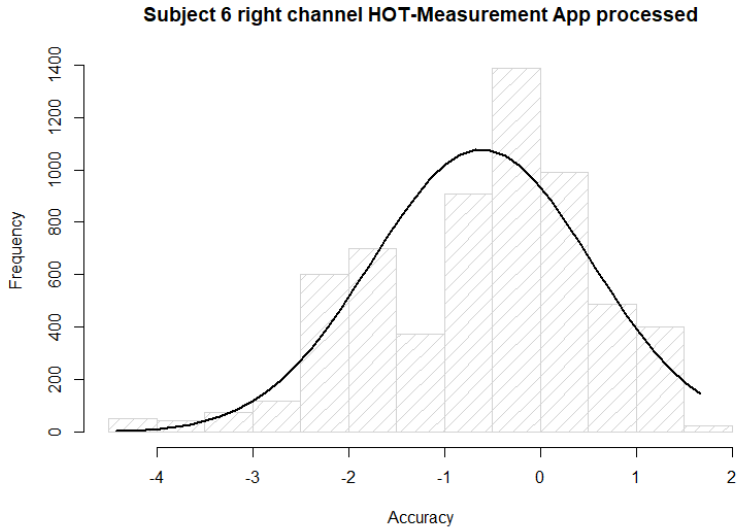


Figure 4.4.4. Histogram of subject 6 right channel HOT-Measurement App processed data

The conclusion is that, for self-processed data, we could use parametric tests since the data sample size is very large. However, as it can be seen below, homoscedasticity condition is not met and non-parametric tests shall be used even the data distribution. That is why, from now on, only self-processed data will be used and each of both channels will be named as left and right hemispheres.

Homoscedasticity

Homocedasticity is a characteristic of a linear regression model that implies that the variance of errors is constant over time. The word homocedasticity can be broken down into two parts, homo (equal) and cedasticity (dispersion). In such a way that, if we unite these two words adapted from the Greek, we would obtain something like the same dispersion or the same dispersion. In a simple view, figure 5.4.5 represents the difference between both characteristics:

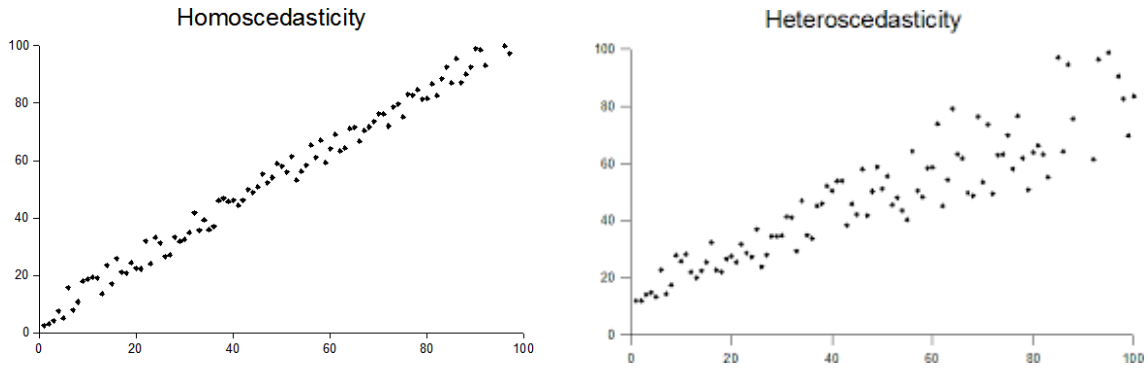


Figure 4.4.5. Difference between homoscedastic and heteroscedastic data

In this case, homoscedasticity was tested through Breusch-Pagan test. The idea of this test is to check if you can find a set of Z variables that serve to explain the evolution of the variance of the random perturbations, estimated this from the square of the errors of the initial model on which it is tried to verify if it exists or not heteroscedasticity. In this case, with a p-value smaller than our cutoff for significance 0.05, the null hypothesis of homoscedasticity will be rejected. The following table shows the results for the test of the linear model Brain value ~ VAS factorized:

	Sub1	Sub2	Sub3	Sub4	Sub5	Sub6	Sub7	Sub8
Left Hemisphere	5.52E-154	1.14E-176	1.29E-71	2.77E-104	2.32E-150	5.95E-66	1.11E-119	3.40E-197
Right Hemisphere	1.32E-303	2.16E-206	1.19E-72	1.64E-30	5.76E-249	1.21E-26	0	3.90E-170

Table 4.4.4. P-values for Breusch-Pagan test for each subject data and left and right channels

The conclusion obtained then through this test was the restriction of using only non-parametric models. As mentioned above, almost every parametric test has its non-parametric equivalent. ANOVA's non-parametric most famous tests are Welch's ANOVA and Kruskal-Wallis test. In our case, the test used will be Welch's ANOVA, since it allows heteroscedasticity but assumes normality. Kruskal-Wallis, on the contrary, assumes homoscedasticity but allows non-normality.

Welch's ANOVA

Welch's ANOVA compares two means to see if they are equal. It is an alternative to the Classic ANOVA and can be used even if your data violates the assumption of homogeneity of variances.

Welch's test should be run in all cases where data is normally distributed but violates the assumption of homogeneity of variance. ANOVA (and the non-parametric alternative Kruskal-Wallis) are very unstable for these situations, producing Type I error rates that are:

- Conservative for large sample sizes and
- Inflated for small sample size.

Welch's ANOVA is fast becoming the go-to method out of the three. For normal, different-variance, and balanced data (i.e. same-size samples), Welch's has the most power and the lowest type I error rate. However, classic ANOVA still performs the best when data is normal, equal-variance, and is either balanced or unbalanced.

The main idea of Welch's F-test is to use a weight w_i in order to reduce the effect of heterogeneity. This weight is based on the sample size (n_i) and the observed variance (s_i^2) for the group in question (in our case, it would be VAS factor if we want to correct the results seen in Kolmogorov-Smirnov test):

$$w_i = \frac{n_i}{s_i^2}$$

Then the adjusted grand mean ($\bar{Y}_{welch}$) can be calculated based on a weighted mean for each group:

$$\bar{Y}_{welch} = \frac{\sum_{i=1}^{r} w_i \bar{Y}_{i.}}{\sum_{i=1}^{r} w_i} \qquad \text{where } \bar{Y}_{i.} \text{ is the sample mean for } i\text{th group; } i=1,\ldots,r$$

Treatment sum of squares ($SSTR_{welch}$) and treatment mean squares ($MSTR_{welch}$) are:

$$SSTR_{welch} = \sum_{i=1}^{r} w_i (\bar{Y}_{i.} - \bar{Y}_{welch})^2$$

$$MSTR_{welch} = \frac{SSTR_{welch}}{r-1}$$

The next step is to calculate a term called lambda (Λ), based again on weights:

$$\Lambda = \frac{3 \sum_{i=1}^{r} \frac{(1 - \frac{w_i}{\sum_{i=1}^{r} w_i})^2}{n_i - 1}}{r^2 - 1}$$

The test statistic to be used between the alternatives is:

$$F^*_{welch} = \frac{SSTR_{welch}/(r-1)}{1 + \frac{2\Lambda(r-2)}{3}} \sim F_{r-1,1/\Lambda}$$

The alternatives conclusions considered in Welch's F-test are same as the traditional F-test:

$$H_0: \mu_1 = \mu_2 = \cdots = \mu_r$$

$$H_a: \text{not all } \mu_i \text{ are equal}$$

Finally, the decision rule to control the level of significance at α is:

$$\text{If } F^* \leq F_{(1-\alpha;\, r-1,1/\Lambda)}, \text{ conclude } H_0$$

$$\text{If } F^* > F_{(1-\alpha;\, r-1,1/\Lambda)}, \text{ conclude } H_a$$

Although Welch's F-test is an adaptation of the F-test and supposed to be more reliable when the assumption of homogeneity of variance was not met, the disadvantage is it has fewer degrees of freedom than the F-test ($1/\Lambda \leq n_t - r$). Thus Welch's F-test is less powerful than the F-test. And since the weight factor is highly related to the sample sizes and the observed variances ($w_i = \frac{n_i}{s_i^2}$), when the number of observations is small, the results of the Welch's F-test may be quite unstable.

Games-Howell post hoc test

A very common analysis to do after an analysis of variances is to determine which are the groups that are most differenced. The most famous test for this phase is Tukey's test, however, it is a parametric test that assumes both normality and homoscedasticity. Hence, in this research a non-parametric equivalent test was performed: Games-Howell post hoc test.

The test was designed based on Welch's degrees of freedom correction and uses Tukey's studentized range distribution, denoted q. The Games-Howell test is performed on the ranked variables similar to other nonparametric tests.

In the next section, the results obtained from Welch's ANOVA and Games-Howell post hoc test are presented and discussed.

5. Results

5.1. Boxplot analysis and outliers treatment

As a first step, in order to interpret the results, it is convenient to perform a graphical analysis. For that, box and whisker plots will be used. Normally used in descriptive statistics, boxplots are an excellent way to quickly examine one or more sets of data graphically. Although they appear primitive compared to a Histogram or a Density Plot, they have the advantage of occupying less space, which is useful when comparing distributions among many groups or data sets.

Here are the types of observations one can make when viewing a box and whisker diagram:

- What are the key values, such as: the average, the 25th percentile, etc.
- If there are outliers and what are their values.
- If the data is symmetric.
- How closely the data is grouped.
- If the data is skewed and if so, in what direction.

The first pair of boxplots shown in figure 6.1.1 represent the brain activity of each subject for both hemispheres of the brain.

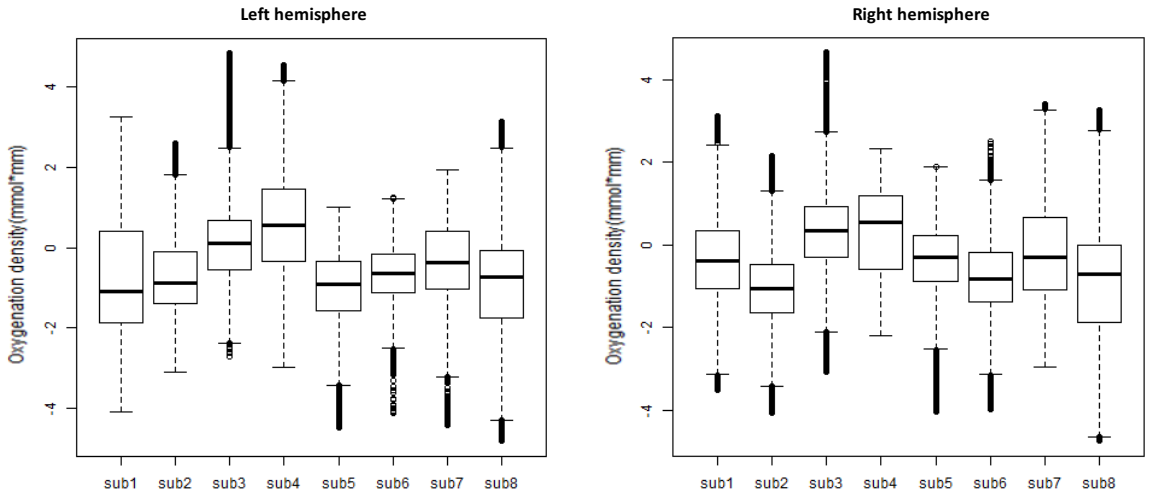


Figure 5.1.1. Boxplot of brain activity for left and right hemispheres categorized by subject

As it can be seen, there is a significant difference in the brain activity for each subject. However, this difference is not a concern to the study, since the interested analysis relies on the effect caused by the VAS evaluation factor and the baseline of each subject is the same for every factor.

The second pair of boxplots shown in figure 6.1.2 represent the brain activity of all subjects together for both hemispheres of the brain. The data is categorized by the factorized evaluation given by the subjects.

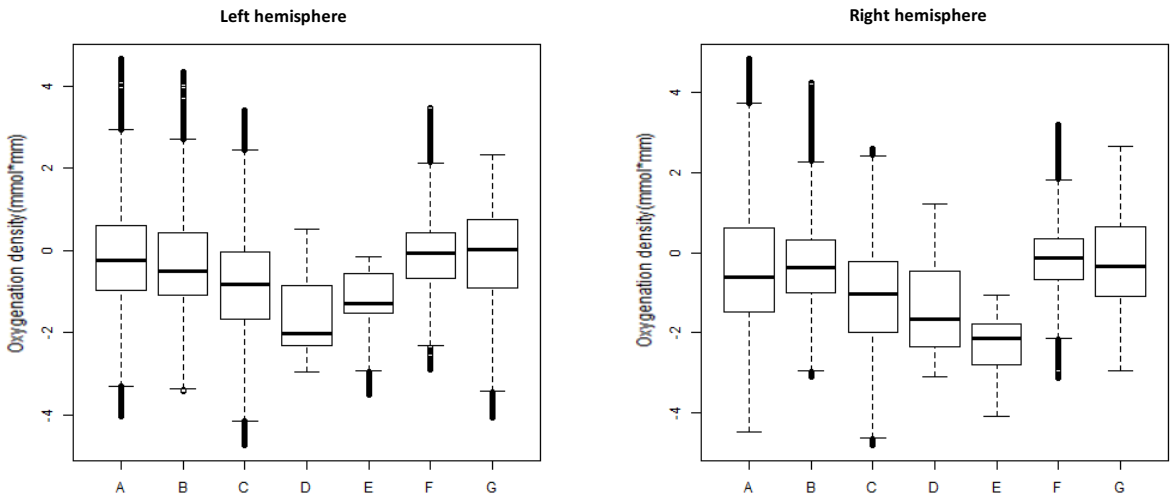


Figure 5.1.2. Boxplot of brain activity for left and right hemispheres categorized by VAS evaluation factorized

The interpretation of these boxplots is very interesting, since a clear trend can be identified. As it can be seen, both sides of the brain show a reduction of brain activity for the intermediate evaluations. That is to say, the brain seems to present a higher activity for preferred music or white noise.

Also, boxplots for individual subjects data sets are shown below. These are also categorized by the VAS evaluation factorized.

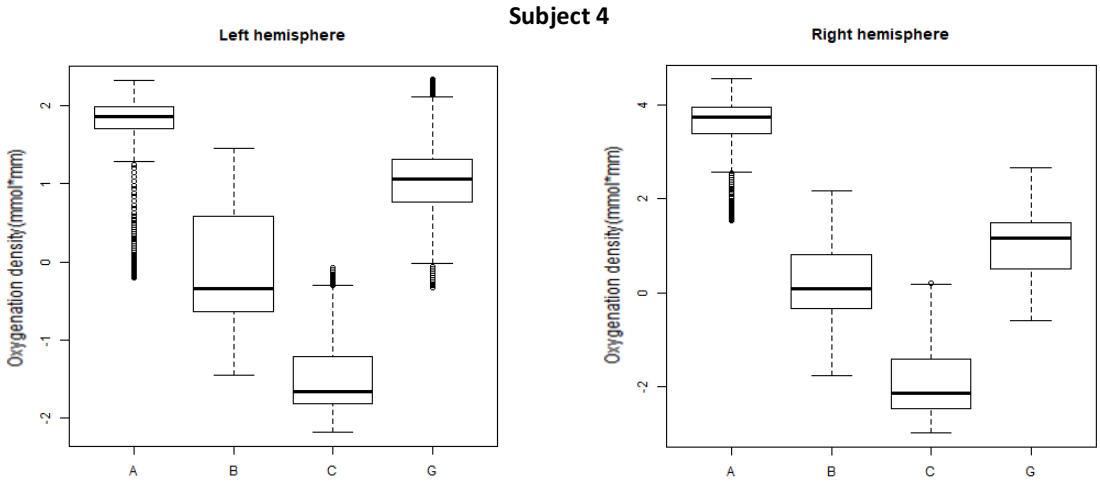


Figure 5.1.3. Boxplot of brain activity for left and right hemispheres from Subject 4 categorized by VAS evaluation factorized

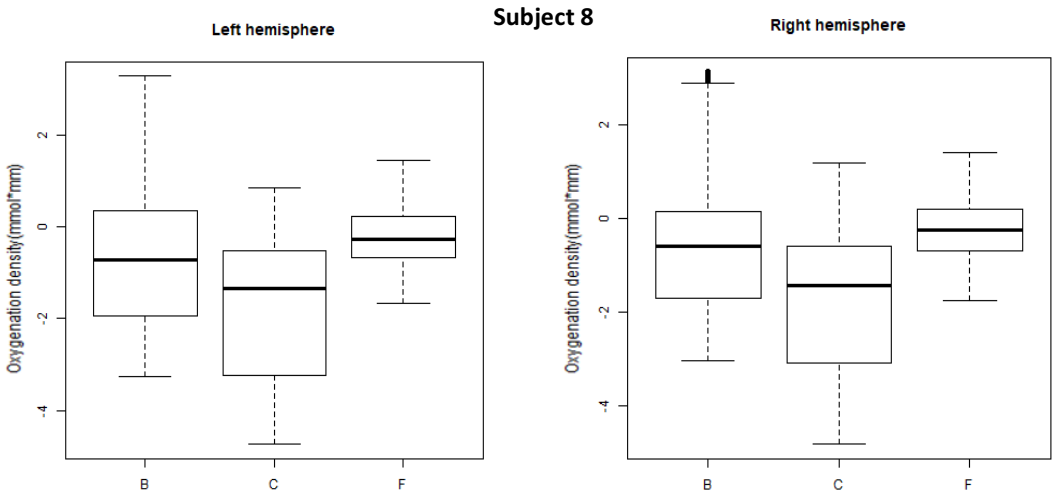


Figure 5.1.4. Boxplot of brain activity for left and right hemispheres from Subject 8 categorized by VAS evaluation factorized

Both in figures 6.1.3 and 6.1.4, it can clearly be seen a similar pattern to the one shown in figure 6.1.1. As mentioned above, subjects tend to show a lower brain activity only of intermediate evaluations.

Finally, boxplots with data categorized by the audio type are shown. Figure 6.1.5 represent the data for all the subjects together.

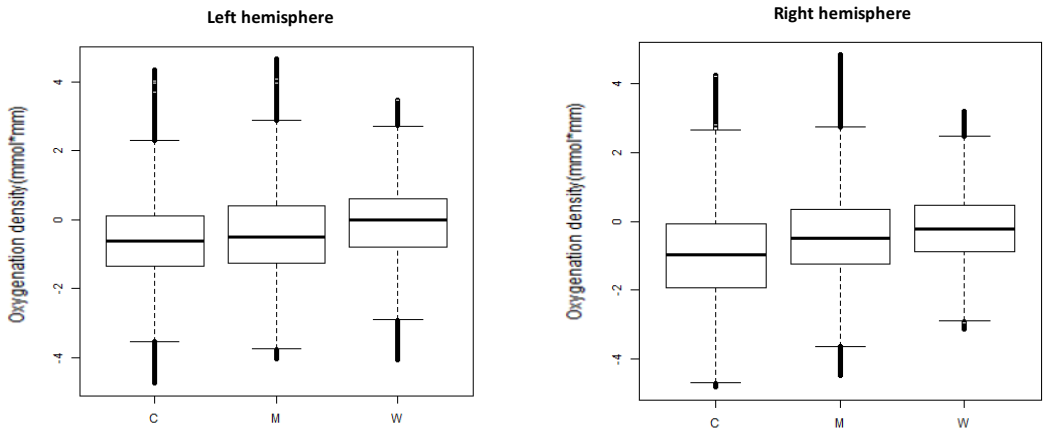


Figure 5.1.5. Figure 5.1.2. Boxplot of brain activity for left and right hemispheres from all the subjects categorized by audio type

It can be observed a smoother variance among the different audio types. This change is caused due to a reduced number of factors and hence, data is more compressed. Nevertheless, the pattern shows also the lower brain activity for the calm music, which normally will be related to intermediate VAS score.

Finally, individual boxplot pairs for separate subjects datasets are shown in figures 6.1.6 and 6.1.7.

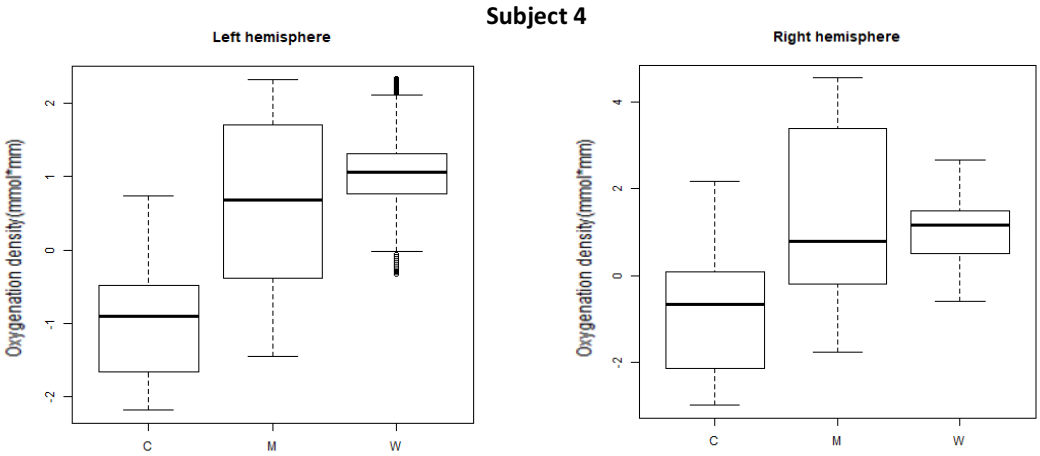


Figure 5.1.6. Boxplot of brain activity for left and right hemispheres from Subject 4 categorized by audio type

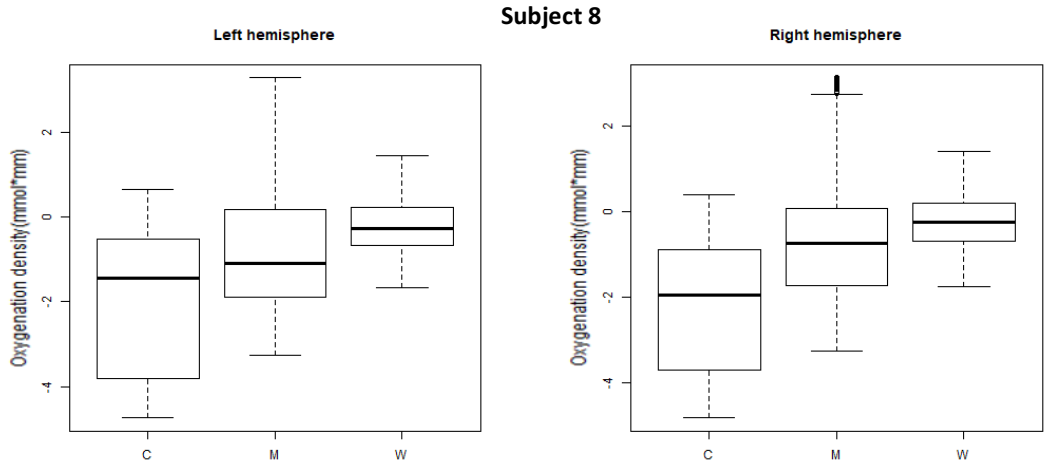


Figure 5.1.7. Boxplot of brain activity for left and right hemispheres from Subject 8 categorized by audio type

In this case, the variance is not so reduced since the number of factors is quite similar. For subject 4 it varies only for 1 less factor and for subject 8 the number of factors is the same. Another time it can be seen the same pattern, where calm music stimulates the lowest brain activity. In the annex 9.2, individual boxplots for all the subjects can be found.

If we take a look at the previous boxplots, we can see that most of them present outliers. Atypical or outlier cases are called those observations with characteristics different from the others. These type of cases can't be characterized categorically as beneficial or problematic but they must be considered in the context of the analysis and the type of information that can provide should be evaluated.

Their main problem is that they are elements that may not be representative of the population being able to seriously distort the behaviour of statistical contrasts. On the other hand, although being different from most of the sample, may be indicative of the characteristics of a valid segment of the population and, consequently, a signal of the lack of representativeness of the sample.

Outliers may appear for different causes. It could be due to an error in the measurement process, an extraordinary event or sometimes there is just no specific reason. In this study, the outliers do not appear to have any specific reason. In this cases, the best to do is to perform the analysis with and without those observations aiming to analyse its influence over the results.

In this study, the same analysis steps have been conducted with and without outliers. The observations considered have been considered as outliers if they are 1.5 times bigger from the first quartile or 1.5 time smaller than the third quartile. The results for both cases show an almost exact pattern, so, in order to not miss any data, outliers will be considered in the study.

In the following sections, statistical tests will be conducted in order to analyse deeper the conclusions obtained graphically via the boxplots.

5.2. Welch's ANOVA

As mentioned above, this section and the following one will show the results on the statistical tests already described in section 5.4.

In order to test whether there is significant difference between the means of each data group, Welch's ANOVA has been conducted. As a first step, the data from all the subjects has been treated together, categorized by the VAS evaluation factorized and the nature of the audio (classical, preferred or white noise).

	VAS factorized	Audio Type
Left hemisphere	0	3.45515E-289
Right hemisphere	0	0

Table 5.2.1. P-values for Welch's ANOVA test categorized by VAS evaluation factorized and Audio Type

Clearly we can reject the null hypothesis of no difference between means. That is to say, there is a significant difference between means for data categorized by each subject evaluation and the audio nature.

A second analysis has been conducted within each subject. As has been done with the whole data of the subjects previously, the analysis has been done by categorizing the data according to the evaluation and the nature of the audio.

	Sub1	Sub2	Sub3	Sub4	Sub5	Sub6	Sub7	Sub8
Left Hemisphere	6.70E-210	6.21E-225	2.27E-44	0	2.21E-250	1.75E-166	4.10E-187	6.42E-319
Right Hemisphere	1.62E-286	2.00E-224	7.74E-27	0	1.51E-190	2.41E-283	1.06E-59	0

Table 5.2.2. P-values for Welch's ANOVA test categorized by VAS evaluation factorized for each subject

	Sub1	Sub2	Sub3	Sub4	Sub5	Sub6	Sub7	Sub8
Left Hemisphere	1.97E-323	1.13E-286	0	0	3.80E-246	1.39E-252	2.03E-228	0
Right Hemisphere	0	2.44E-319	0	0	1.15E-191	4.56E-231	8.20E-164	0

Table 5.2.3. P-values for Welch's ANOVA test categorized by audio type for each subject

Again, the null hypothesis can be rejected so we can ensure a difference of brain activity in each subject depending on the evaluation or the audio type.

5.3. Games-Howell Post Hoc Test

As mentioned in section 5.4, after identifying difference amongst means for each group of data, a post hoc test in order to determine which are the groups with a bigger difference should be performed. Hence, the last piece of this section is destined to Games-Howell Post Hoc Test.

In the following table, the results of a first Games-Howell test are shown. The groups to be compared are categorized by VAS evaluation factorized, and we can see the results for both hemispheres.

	Left Hemisphere		**Right Hemisphere**	
VAS evaluation factorized	Mean difference	P-Value	Mean difference	P-Value
C-A	-0,783545665	1,01E-08	-0,771675636	3,36E-08
E-A	-1,121815179	0	-1,928624182	3,75E-11
G-A	-0,022866429	0,893460784	0,10426062	0,000149497
B-A	-0,249308155	3,40E-08	-0,022624055	0,943685598
D-A	-1,387564371	0	-1,01941117	0
F-A	0,012790752	0,991834374	0,186797508	4,72E-09

E-C	-0,338269514	0	-1,156948546	0
G-C	0,760679236	3,39E-08	0,875936256	3,39E-08
B-C	0,53423751	3,39E-08	0,749051581	3,29E-08
D-C	-0,604018706	0	-0,247735535	2,77E-07
F-C	0,796336417	1,97E-08	0,958473144	1,93E-08
G-E	1,09894875	0	2,032884802	0
B-E	0,872507024	5,89E-13	1,906000127	1,51E-13
D-E	-0,265749192	5,43E-08	0,909213011	0
F-E	1,134605931	2,18E-13	2,11542169	3,27E-13
B-G	-0,226441726	2,24E-08	-0,126884675	2,19E-08
D-G	-1,364697942	0	-1,123671791	3,65E-13
F-G	0,035657181	0,347536352	0,082536888	7,84E-06
D-B	-1,138256216	1,44E-13	-0,996787115	3,72E-13
F-B	0,262098907	8,93E-09	0,209421563	1,00E-08
F-D	1,400355123	7,52E-13	1,206208679	0

Table 6.3.1. Games-Howell post hoc test results categorized by VAS evaluation for both hemispheres

P-values highlighted on the table identify the pair of groups which don´t present a significate mean difference. It is important to mention that for the left hemisphere, there is no significant difference for brain activity related to audio samples evaluated either with the highest score (A) or the lowest ones (F-G). Also, note that in the right hemisphere, there is no significant difference for the highest scores (A-B).

In order to perform a simple graphical analysis of the test results, a bar chart has been created for both hemispheres, representing the absolute mean difference between each pair of VAS evaluation groups.

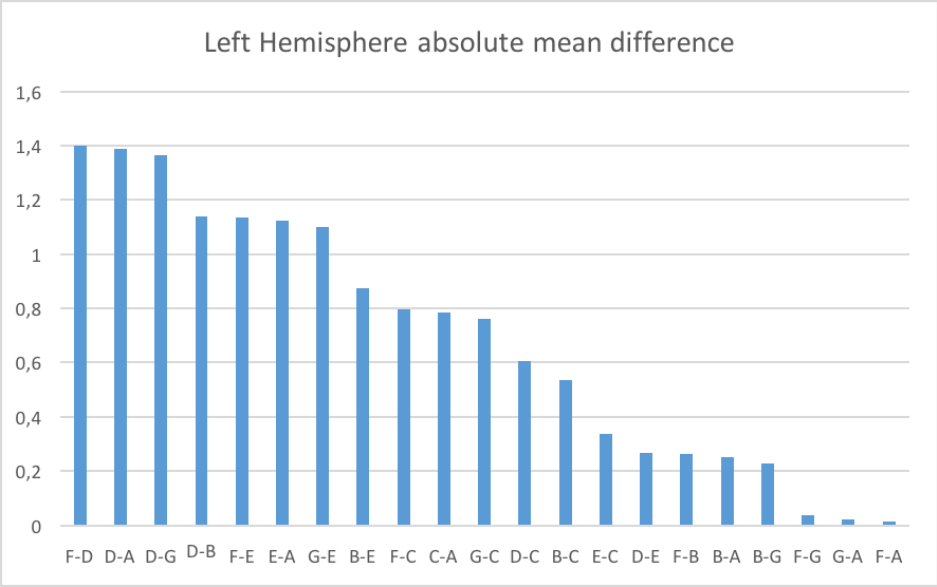


Figure 6.3.1. Bar chart representing absolute mean differences for left hemisphere

As already observed in section 6.1, the biggest differences remain lowest evaluations (F-G) and medium evaluations (D-E) and highest evaluations (A-B) with also medium evaluations (D-E).

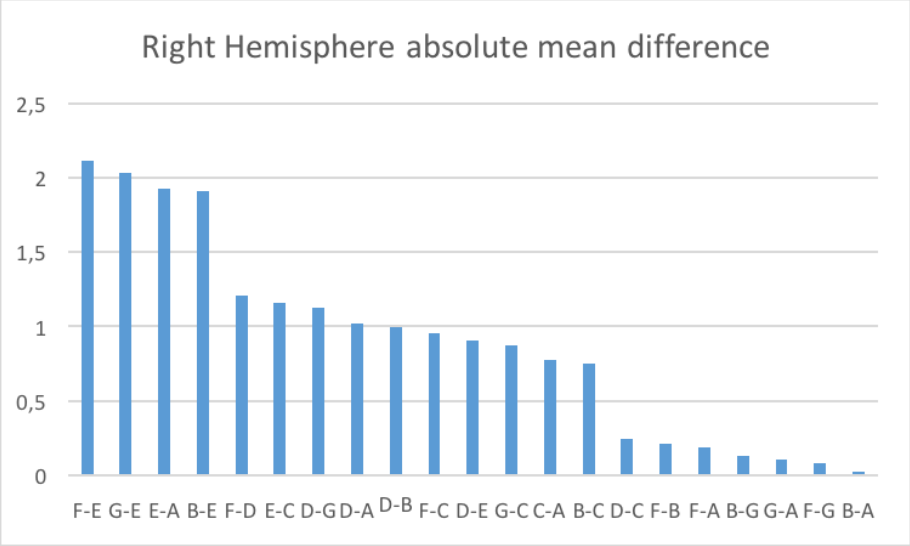


Figure 6.3.2. Bar chart representing absolute mean differences for right hemisphere

In Figure 6.3.2, again the same pattern can be observed, with medium evaluation pairs with highest and lowest showing the biggest differences.

Finally, the same post hoc analysis has been performed using the audio type in order to categorize the data collected from all the subjects. In Table 6.3.3, the results of the test can be observed.

	Left Hemisphere		Right Hemisphere	
Audio type	**Mean difference**	**P-Value**	**Mean difference**	**P-Value**
M-C	0,225887705	0	0,59396885	0
W-C	0,506199019	0	0,791713124	0
W-M	0,280311315	0	0,197744274	0

Table 6.3.2. Games-Howell post hoc test results categorized by audio type for both hemispheres

In this case, all the groups show significant mean difference, so statistically it is not possible to make any assumptions regarding the experiment. That is to say, there is proven difference of brain activity between each audio type stimulus, however, since every pair show significant mean difference, there are no clear assumptions as previously seen in Table 6.3.1.

As previously done, in order to analyze the test graphically, bar charts have been elaborated for both hemispheres.

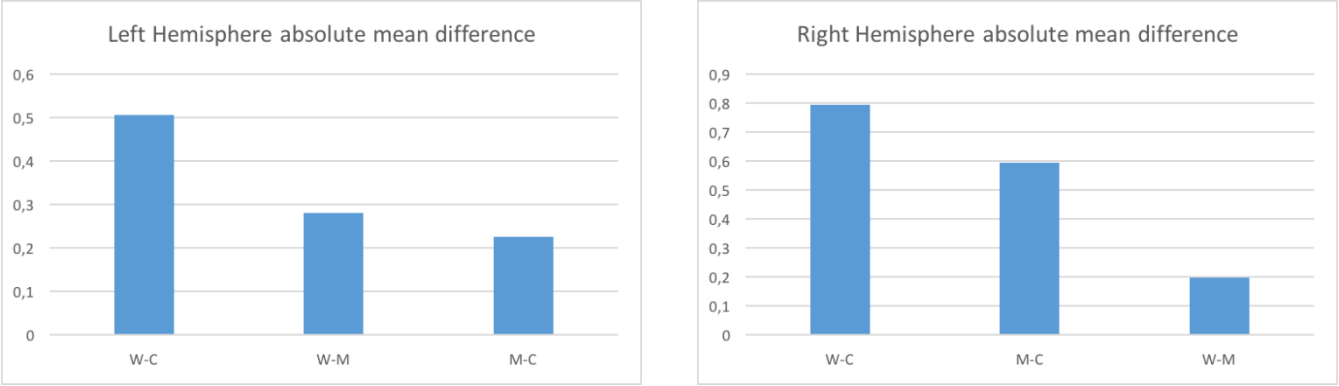


Figure 6.3.3. Bar chart representing absolute mean differences for left and right hemisphere, categorized by audio type

Both hemispheres show a biggest difference in brain activity for white noise and calm music audio stimulus. However, right hemisphere differs from the left one, since it presents a more notable difference between calm and motivational music.

6. Conclusions

During the past months in the elaboration of this research, several concepts have been assimilated, analysed and finally put into practice.

The goal of this study was none other than to conduct an experiment in order to demonstrate the effect of music on the brain, specifically in the PFC, because as shown in section 4, music is capable to stimulate the brain through its three basic components (rhythm, melody and lyrics).

The demonstration has been based around the formulation of one only hypothesis: *Preferred music has a different effect on PFC blood flow than classical music or resting status within subjects.* From this, the experiment explained in section 5 has been designed.

Thus, throughout the section 6, significant differences in brain activity have been observed by categorizing the data according to the VAS evaluation and the type of audio sample reproduced. As shown in Figure 6.3.3, white noise and preferred music have caused a similar effect on PFC activity, unlike calm music. Hence, a clear and interesting conclusion can be obtained: classical music stimulates a lower brain activity on the PFC than preferred music or white noise.

However, the results of the statistical tests show significant differences between the three types of audio. Therefore, accepting or rejecting the hypothesis in this study is complicated. On the one hand, it is true that preferred music causes a different effect on the PFC, but, on the other hand, white noise has stimulated a similar level of brain activity to the preferred music, and that was not the expected behaviour. Thus, the hypothesis is considered valid, but questions that should be investigated later are opened.

The first issue is the fact that the audios evaluated with the lowest score have generated levels of activity in the PFC similar to the preferred music. A possible future experiment would be to evaluate subjects with unpleasant sounds and compare them with pleasant sounds.

On the other hand, it is worth questioning whether white noise really calms the human being, as had been clarified in section 5 and demonstrated in previous investigations.

Finally, mention that, even if the project's time limit has been satisfactorily met through the design of the intra-subject experiment, a larger sample size would have strongly supported the formulated and validated hypothesis.

7. Acknowledgements

I would first like to thank my thesis advisor Professor Makoto Takahashi of the Graduate School of Engineering at Tohoku University. The door to Prof. Takahashi office was always open whenever I ran into a trouble spot or had a question about my research or writing. He consistently allowed this paper to be my own work, but steered me in the right direction whenever I needed it.

I would also like to thank my buddy Mr.Kon. Since the day I arrived at the laboratory, he has helped me in many ways, be it academic or personal, always with a smile in his face.

Also, I really appreciate all the laboratory members for their will to participate in my research. In special, I would like to thank Mr.Kojima and Mr.Ogawa, since they have helped me when I was in doubts on how to proceed.

Finally, I must express my very profound gratitude to my parents and to my brother and sister for providing me with unfailing support and continuous encouragement throughout my years of study and through the process of researching and writing this thesis. This accomplishment would not have been possible without them. Thank you.

8. Annexes

8.1. R Code

```
raw_csvs <-
list(fuga,hamataki,kojima,kon_3,ryota,ibata,nonoyama,ohara) # list of
raw data csvs
subjects_names <-
c('sub1','sub2','sub3','sub4','sub5','sub6','sub7','sub8')


# Visual analogue scale data

CH16_vas <- c(6.1,11.1,0,10.3,0,5.6,12)*10/14
sub1_vas <- c(8.3,13.5,1,13.7,1,4.9,12.7)*10/14
sub2_vas <- c(8.7,11.4,1,6.8,1,12.1,11.4)*10/14
sub3_vas <- c(9.2,13,3,13.6,2.4,10.5,13.8)*10/14
sub4_vas <- c(8.3,10.8,1,11.2,1,9.3,12.4)*10/14
sub5_vas <- c(12.1,12.9,1,13,0.8,9.3,13.1)*10/14
sub6_vas <- c(10.8,11.2,3.4,9.8,3,12.4,11.3)*10/14
sub7_vas <- c(9,10.9,2.5,11.3,1.5,9.2,10.8)*10/14
sub8_vas <- c(9.2,10.7,2.2,10.6,2.3,9.8,11.5)*10/14
vas_list <-
list(sub1_vas,sub2_vas,sub3_vas,sub4_vas,sub5_vas,sub6_vas,sub7_vas,su
b8_vas)

# Visual analogue scale factorized
# 14-12 : A
# 12-10 : B
# 10-8  : C
# 8-6   : D
# 6-4   : E
# 4-2   : F
# 2-0   : G


CH16_vas_f <- c('E','B','G','B','G','E','A')
sub1_vas_f <- c('C','A','G','A','G','E','A')
sub2_vas_f <- c('C','B','G','D','G','B','B')
sub3_vas_f <- c('C','A','F','A','F','B','A')
sub4_vas_f <- c('C','B','G','B','G','B','A')
sub5_vas_f <- c('B','A','G','A','G','C','A')
sub6_vas_f <- c('B','B','F','C','F','A','B')
sub7_vas_f <- c('C','B','F','B','G','C','B')
sub8_vas_f <- c('C','B','F','C','F','C','B')
```

```
vas_list_f <-
list(sub1_vas_f,sub2_vas_f,sub3_vas_f,sub4_vas_f,sub5_vas_f,sub6_vas_f
,sub7_vas_f,sub8_vas_f)


# Time frame
CH16_limits <-
c(1,102,1005,1194,1286,2187,2390,2490,3379,3578,3663,4566,4759,4859,57
53,5951,6060,6955,7152,7253,8155)
limits <-
c(1,100,1000,1200,1300,2200,2400,2500,3400,3580,3680,4580,4770,4870,57
70,5970,6070,6950,7150,7250,8150)

# Create matrix with audio sample lenghts
samples_CH16 <- matrix(nrow=20, ncol=2)
for (i in 1:length(CH16_limits)-1) {samples_CH16[i,1] = limits[i];
samples_CH16[i,2] = CH16_limits[i+1]}

samples <- matrix(nrow=20, ncol=2)
for (i in 1:length(limits)-1) {samples[i,1] = limits[i]; samples[i,2]
= limits[i+1]}

# filter subjects data and z-scale data from each csv for each channel

l3_bw <- list()
r3_bw <- list()
l_processed <- list()
r_processed <- list()
library(seewave) #for butterworth filter
library(signal) #for fir_filter
library(forecast) #for moving average

lowpass <- fir1(n=20,w=0.1,type='low',window = hamming(21))
highpass <- fir1(n=20,w=1/815,type='high',window = hamming(21))


for (i in c(1:length(raw_csvs))) {
  l3_bw[[i]] <-
scale(ma(bwfilter(filter(lowpass,raw_csvs[[i]]$density_l3_raw),n=5,fro
m=1/60/2.5,f=10),order=5))
  l3_bw[[i]] <- l3_bw[[i]][complete.cases(l3_bw[[i]]),]
  r3_bw[[i]] <-
scale(ma(bwfilter(filter(lowpass,raw_csvs[[i]]$density_r3_raw),n=5,fro
m=1/60/2.5,f=10),order=5))
  r3_bw[[i]] <- r3_bw[[i]][complete.cases(r3_bw[[i]]),]
  l_processed[[i]] <- scale(raw_csvs[[i]]$leftBrain_value)
  r_processed[[i]] <- scale(raw_csvs[[i]]$rightBrain_value)
```

```
}

data <- list(l3_bw,r3_bw,l_processed,r_processed)

#break data into samples
data_sampled <- rep(list(rep(list(list()),length(raw_csvs))),4)

for(t in c(1:length(data))){
  for(s in c(1:length(raw_csvs))){
    for (i in 1:nrow(samples)) {
      data_sampled[[t]][[s]][[i]] <-
data[[t]][[s]][samples[i,1]:samples [i,2]]

    }
  }
}


library(stats)
library(onewaytests) #welch's test
library(lmtest) #bptest



#create columns with VAS scores for ANOVA analysis
vas_list_columns <- list()
for (i in c(1:length(vas_list))){
    vas_list_columns[[i]] <- rep(vas_list[[i]][1],880)
  for (t in c(2:length(vas_list[[i]]))){
    vas_list_columns[[i]] <-
append(vas_list_columns[[i]],rep(vas_list[[i]][t],880))
  }
}

#create columns with VAS scores factorized for ANOVA analysis
vas_list_columns_f <- list()
for (i in c(1:length(vas_list_f))){
  vas_list_columns_f[[i]] <- rep(vas_list_f[[i]][1],880)
  for (t in c(2:length(vas_list_f[[i]]))){
    vas_list_columns_f[[i]] <-
append(vas_list_columns_f[[i]],rep(vas_list_f[[i]][t],880))
  }
}

#create column with Motivational vs Classical vs White
audio_type <- c('C','M','W','M','W','C','M')
audio_type_vector <- c()
```

```
for(i in c(1:length(audio_type))){
  audio_type_vector <-
append(audio_type_vector,rep(audio_type[i],880))
}
audio_type_column <- rep(audio_type_vector,8)


anova_list_split <- rep(list(list()),4)
anova_matrix <- matrix(ncol=6)
colnames(anova_matrix) <-
c('values','ind','subject','vas','vas_f','audio_type')
anova_list <- rep(list(anova_matrix),4)



#create anova matrixes for between and within subject analysis
for (i in c(1:length(data_sampled))){
  for (t in c(1:length(data_sampled[[1]]))){
      C1 <- data_sampled[[i]][[t]][[2]][1:880] -
mean(data_sampled[[i]][[t]][[1]][3:length(data_sampled[[i]][[t]][[1]])
])
      P1 <- data_sampled[[i]][[t]][[5]][1:880]-
mean(data_sampled[[i]][[t]][[4]])
      W1 <- data_sampled[[i]][[t]][[8]][1:880]-
mean(data_sampled[[i]][[t]][[7]])
      P2 <- data_sampled[[i]][[t]][[11]][1:880]-
mean(data_sampled[[i]][[t]][[10]])
      W2 <- data_sampled[[i]][[t]][[14]][1:880]-
mean(data_sampled[[i]][[t]][[13]])
      C2 <- data_sampled[[i]][[t]][[17]][1:880]-
mean(data_sampled[[i]][[t]][[16]])
      P3 <- data_sampled[[i]][[t]][[20]][1:880]-
mean(data_sampled[[i]][[t]][[19]])
      subject_1 <- cbind.data.frame(C1,P1,W1,P2,W2,C2,P3)
      stacked_subject <- cbind.data.frame(stack(subject_1),subject =
as.vector(rep(subjects_names[t],6160))) #add subject name
      stacked_vas <- cbind.data.frame(stacked_subject,vas =
as.vector(vas_list_columns[[t]])) #add vas score
      stacked_vas_f <- cbind.data.frame(stacked_vas,vas_f =
as.vector(vas_list_columns_f[[t]])) #add vas score factorized
      stacked_type <- cbind.data.frame(stacked_vas_f, audio_type =
as.vector(audio_type_vector))
      anova_list_split[[i]][[t]] <- stacked_type
      anova_list[[i]] <-
rbind.data.frame(anova_list[[i]],stacked_type)
```

```
      anova_list[[i]]$ind <- factor(anova_list[[i]]$ind)
      anova_list[[i]]$subject <- factor(anova_list[[i]]$subject)
      anova_list[[i]]$vas_f <- factor(anova_list[[i]]$vas_f)
      anova_list[[i]]$audio_type <- factor(anova_list[[i]]$audio_type)
      anova_list[[i]] <-
anova_list[[i]][complete.cases(anova_list[[i]]),]
    }
}

# Between subjects: obtain pv matrix and csv's for anova and welch's
anova, kolmogorov and breusch pagan tests
anova_pv_matrix_between <- matrix(nrow =4,ncol=2)
colnames(anova_pv_matrix_between) <- c('ind','subject')
ks_pv_matrix_between <- matrix(nrow =4)
bp_pv_matrix_between <- matrix(nrow=4)
welch_pv_matrix_between <- matrix(nrow=4,ncol=2)
colnames(welch_pv_matrix_between) <- c('vas_f','audio_type')
for (i in c(1:length(anova_list))){
    anova_pv_matrix_between[i,1] <-
summary(aov(anova_list[[i]]$values~anova_list[[i]]$ind))[[1]][["Pr(>F)
"]][1]
    anova_pv_matrix_between[i,2] <-
summary(aov(anova_list[[i]]$values~anova_list[[i]]$subject))[[1]][["Pr
(>F)"]][1]
    welch_pv_matrix_between[i,1] <-
welch.test(values~vas_f,anova_list[[i]])$p.value
    welch_pv_matrix_between[i,2] <-
welch.test(values~audio_type,anova_list[[i]])$p.value
    ks_pv_matrix_between[i] <-
ks.test(anova_list[[i]]$values,rnorm(length(anova_list[[i]]$values),me
an(anova_list[[i]][complete.cases(anova_list[[i]]),]$values)))$p.value
    bp_pv_matrix_between[i] <-
bptest(anova_list[[i]]$values~anova_list[[i]]$subject)$p.value
  }
write.csv(anova_pv_matrix_between, file =
'anova_between_subjects.csv')
write.csv(welch_pv_matrix_between, file =
'welch_between_subjects.csv')
write.csv(ks_pv_matrix_between, file = 'ks_between_subjects.csv')
write.csv(bp_pv_matrix_between, file = 'bp_between_subjects.csv')
#anova & bp between subjects for subject and genre with vas score
vas_pv_matrix_between <- matrix(nrow=2,ncol=2)
colnames(vas_pv_matrix_between) <- c('ind','subject')
rownames(vas_pv_matrix_between) <- c('anova','bptest')
vas_pv_matrix_between[1,1] <-
summary(aov(anova_list[[1]]$vas~anova_list[[1]]$ind))[[1]][["Pr(>F)"]]
[1]
```

```
vas_pv_matrix_between[1,2] <-
summary(aov(anova_list[[1]]$vas~anova_list[[1]]$subject))[[1]][["Pr(>F
)"]][1]
vas_pv_matrix_between[2,1] <-
bptest(anova_list[[1]]$vas~anova_list[[1]]$ind)$p.value
vas_pv_matrix_between[2,2] <-
bptest(anova_list[[1]]$vas~anova_list[[1]]$subject)$p.value
write.csv(vas_pv_matrix_between, file =
'anova&bp_vas_between_subjects.csv')

#Within subjects: obtain pv matrix and csv's for anova and welch's
anova, kolmogorov and breusch pagan tests
anova_pv_matrix_within <- matrix(ncol = length(data_sampled[[1]]),nrow
=4)
ks_pv_matrix_within <- matrix(ncol = length(data_sampled[[1]]),nrow=4)
bp_pv_matrix_within <- matrix(ncol=length(data_sampled[[1]]),nrow=4)
welch_pv_matrix_within <-
matrix(ncol=length(data_sampled[[1]]),nrow=4)
for (i in c(1:length(anova_list_split))){
  for (t in c(1:length(anova_list_split[[1]]))){
    anova_pv_matrix_within[i,t] <-
summary(aov(anova_list_split[[i]][[t]]$values~anova_list_split[[i]][[t
]]$ind))[[1]][["Pr(>F)"]][1]
    welch_pv_matrix_within[i,t] <-
welch.test(values~vas_f,anova_list_split[[i]][[t]])$p.value
    ks_pv_matrix_within[i,t] <-
ks.test(anova_list_split[[i]][[t]]$values,rnorm(length(anova_list_spli
t[[i]][[t]]$values),mean(anova_list_split[[i]][[t]]$values)))$p.value
    bp_pv_matrix_within[i,t] <-
bptest(anova_list_split[[i]][[t]]$values~anova_list_split[[i]][[t]]$in
d)$p.value
    }

}
write.csv(anova_pv_matrix_within, file = 'anova_within_subjects.csv')
write.csv(welch_pv_matrix_within, file =
'welch_within_subjects_vas_f.csv')
write.csv(ks_pv_matrix_within, file = 'ks_within_subjects.csv')
write.csv(bp_pv_matrix_within, file = 'bp_within_subjects.csv')


remove_outliers <- function(x, na.rm = TRUE, ...) { #function for remo
ve outliers
  qnt <- quantile(x, probs=c(.25, .75), na.rm = na.rm, ...)
  H <- 1.5 * IQR(x, na.rm = na.rm)
  y <- x
  y[x < (qnt[1] - H)] <- mean(x)
  y[x > (qnt[2] + H)] <- mean(x)
```

```
  y
}

anova_list_split_outliers <- rep(list(list()),4)
anova_matrix_outliers <- matrix(ncol=6)
colnames(anova_matrix_outliers) <- c('values','ind','subject','vas','v
as_f','audio_type')
anova_list_outliers <- rep(list(anova_matrix_outliers),4)



#create anova matrixes for between and within subject analysis removin
g outliers
for (i in c(1:length(data_sampled))){
  for (t in c(1:length(data_sampled[[1]]))){
    C1 <- remove_outliers(data_sampled[[i]][[t]][[2]][1:880] - mean(da
ta_sampled[[i]][[t]][[1]][3:length(data_sampled[[i]][[t]][[1]])]))
    P1 <- remove_outliers(data_sampled[[i]][[t]][[5]][1:880]- mean(dat
a_sampled[[i]][[t]][[4]]))
    W1 <- remove_outliers(data_sampled[[i]][[t]][[8]][1:880]- mean(dat
a_sampled[[i]][[t]][[7]]))
    P2 <- remove_outliers(data_sampled[[i]][[t]][[11]][1:880]- mean(da
ta_sampled[[i]][[t]][[10]]))
    W2 <- remove_outliers(data_sampled[[i]][[t]][[14]][1:880]- mean(da
ta_sampled[[i]][[t]][[13]]))
    C2 <- remove_outliers(data_sampled[[i]][[t]][[17]][1:880]- mean(da
ta_sampled[[i]][[t]][[16]]))
    P3 <- remove_outliers(data_sampled[[i]][[t]][[20]][1:880]- mean(da
ta_sampled[[i]][[t]][[19]]))
    subject_1 <- cbind.data.frame(C1,P1,W1,P2,W2,C2,P3)
    stacked_subject <- cbind.data.frame(stack(subject_1),subject = as.
vector(rep(subjects_names[t],6160))) #add subject name
    stacked_vas <- cbind.data.frame(stacked_subject,vas = as.vector(va
s_list_columns[[t]])) #add vas score
    stacked_vas_f <- cbind.data.frame(stacked_vas,vas_f = as.vector(va
s_list_columns_f[[t]])) #add vas score factorized
    stacked_type <- cbind.data.frame(stacked_vas_f, audio_type = as.ve
ctor(audio_type_vector))
    anova_list_split_outliers[[i]][[t]] <- stacked_type
    anova_list_outliers[[i]] <- rbind.data.frame(anova_list_outliers
[[i]],stacked_type)


    anova_list_outliers[[i]]$ind <- factor(anova_list_outliers[[i]]$in
d)
    anova_list_outliers[[i]]$subject <- factor(anova_list_outliers
[[i]]$subject)
    anova_list_outliers[[i]]$vas_f <- factor(anova_list_outliers[[i]]
$vas_f)
    anova_list_outliers[[i]]$audio_type <- factor(anova_list_outliers
[[i]]$audio_type)
```

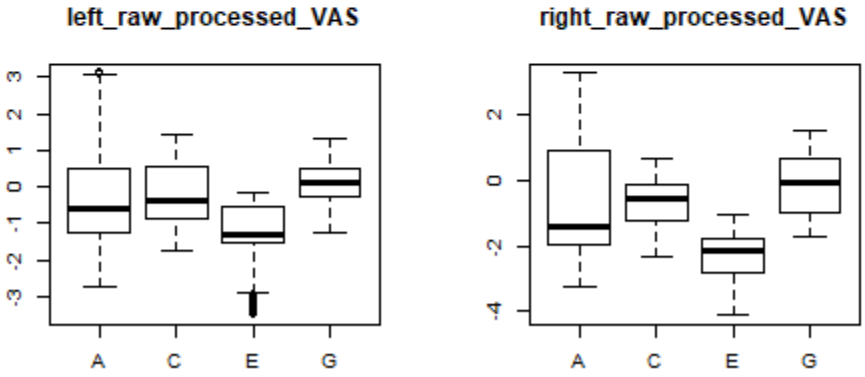
```
    anova_list_outliers[[i]] <- anova_list_outliers[[i]][complete.case
s(anova_list_outliers[[i]]),]
  }
}

#NO OUTLIERS: Between subjects: obtain pv matrix and csv's for anova a
nd welch's anova, kolmogorov and breusch pagan tests
anova_pv_matrix_between_outliers <- matrix(nrow =4,ncol=2)
colnames(anova_pv_matrix_between_outliers) <- c('ind','subject')
ks_pv_matrix_between_outliers <- matrix(nrow =4)
bp_pv_matrix_between_outliers <- matrix(nrow=4,ncol=2)
colnames(bp_pv_matrix_between_outliers) <- c('ind','subject')
welch_pv_matrix_between_outliers <- matrix(nrow=4,ncol=2)
colnames(welch_pv_matrix_between_outliers) <- c('ind','subject')
for (i in c(1:length(anova_list_outliers))){
  anova_pv_matrix_between_outliers[i,1] <- summary(aov(anova_list_outl
iers[[i]]$values~anova_list_outliers[[i]]$vas_f))[[1]][["Pr(>F)"]][1]
  anova_pv_matrix_between_outliers[i,2] <- summary(aov(anova_list_outl
iers[[i]]$values~anova_list_outliers[[i]]$subject))[[1]][["Pr(>F)"]]
[1]
  welch_pv_matrix_between_outliers[i,1] <- welch.test(values~vas_f,ano
va_list_outliers[[i]])$p.value
  welch_pv_matrix_between_outliers[i,2] <- welch.test(values~subject,a
nova_list_outliers[[i]])$p.value
  ks_pv_matrix_between_outliers[i,1] <- ks.test(anova_list_outliers
[[i]]$values,rnorm(length(anova_list_outliers[[i]]$values),mean(anova_
list_outliers[[i]][complete.cases(anova_list_outliers[[i]]),]$value
s)))$p.value
  bp_pv_matrix_between_outliers[i,2] <- bptest(anova_list_outliers
[[i]]$values~anova_list_outliers[[i]]$subject)$p.value
}
write.csv(anova_pv_matrix_between_outliers, file = 'anova_between_subj
ects_outliers.csv')
write.csv(welch_pv_matrix_between_outliers, file = 'welch_between_subj
ects_outliers.csv')
write.csv(ks_pv_matrix_between_outliers, file = 'ks_between_subjects_o
utliers.csv')
write.csv(bp_pv_matrix_between_outliers, file = 'bp_between_subjects_o
utliers.csv')

#NO OUTLIERS: anova & bp between subjects for subject and genre with v
as score
vas_pv_matrix_between_outliers <- matrix(nrow=2,ncol=2)
colnames(vas_pv_matrix_between_outliers) <- c('vas_f','subject')
rownames(vas_pv_matrix_between_outliers) <- c('anova','bptest')
vas_pv_matrix_between_outliers[1,1] <- summary(aov(anova_list_outliers
[[1]]$values~anova_list_outliers[[1]]$vas_f))[[1]][["Pr(>F)"]][1]
vas_pv_matrix_between_outliers[1,2] <- summary(aov(anova_list_outliers
[[1]]$values~anova_list_outliers[[1]]$subject))[[1]][["Pr(>F)"]][1]
vas_pv_matrix_between_outliers[2,1] <- bptest(anova_list_outliers[[1]]
$values~anova_list_outliers[[1]]$vas_vas_f)$p.value
```

```
vas_pv_matrix_between_outliers[2,2] <- bptest(anova_list_outliers[[1]]
$values~anova_list_outliers[[1]]$vas_f)$p.value
write.csv(vas_pv_matrix_between_outliers, file = 'anova&bp_vas_f_betwe
en_subjects_outliers.csv')

#NO OUTLIERS: Within subjects: obtain pv matrix and csv's for anova an
d welch's anova, kolmogorov and breusch pagan tests
anova_pv_matrix_within_outliers <- matrix(ncol = length(data_sampled
[[1]]),nrow =4)
ks_pv_matrix_within_outliers <- matrix(ncol = length(data_sampled
[[1]]),nrow=4)
bp_pv_matrix_within_outliers <- matrix(ncol=length(data_sampled[[1]]),
nrow=4)
welch_pv_matrix_within_outliers <- matrix(ncol=length(data_sampled
[[1]]),nrow=4)
for (i in c(1:length(anova_list_split_outliers))){
  for (t in c(1:length(anova_list_split_outliers[[1]]))){
    anova_pv_matrix_within_outliers[i,t] <- summary(aov(anova_list_spl
it_outliers[[i]][[t]]$values~anova_list_split_outliers[[i]][[t]]$vas_
f))[[1]][["Pr(>F)"]][1]
    welch_pv_matrix_within_outliers[i,t] <- welch.test(values~vas_f,an
ova_list_split_outliers[[i]][[t]])$p.value
    ks_pv_matrix_within_outliers[i,t] <- ks.test(anova_list_split_outl
iers[[i]][[t]]$values,rnorm(length(anova_list_split_outliers[[i]][[t]]
$values),mean(anova_list_split_outliers[[i]][[t]]$values)))$p.value
    bp_pv_matrix_within_outliers[i,t] <- bptest(anova_list_split_outli
ers[[i]][[t]]$values~anova_list_split_outliers[[i]][[t]]$vas_f)$p.valu
e
  }

}
write.csv(anova_pv_matrix_within_outliers, file = 'anova_within_subjec
ts_outliers.csv')
write.csv(welch_pv_matrix_within_outliers, file = 'welch_within_subjec
ts_outliers.csv')
write.csv(ks_pv_matrix_within_outliers, file = 'ks_within_subjects_out
liers.csv')
write.csv(bp_pv_matrix_within_outliers, file = 'bp_within_subjects_out
liers.csv')

library(userfriendlyscience) #games-howell
for (i in c(1:2)){ #between subjects for VAS factorized
  table <- posthocTGH(anova_list[[i]]$values,anova_list[[i]]$vas_f, me
thod="games-howell",conf.level = 0.95, digits=9)
  write.csv(table$output$games.howell,file = paste(toString(i),sep = '
_','games-howell.csv'))
}

for (i in c(1:2)){ #between subjects for VAS factorized
  table <- posthocTGH(anova_list[[i]]$values,anova_list[[i]]$audio_typ
e, method="games-howell",conf.level = 0.95, digits=9)
```

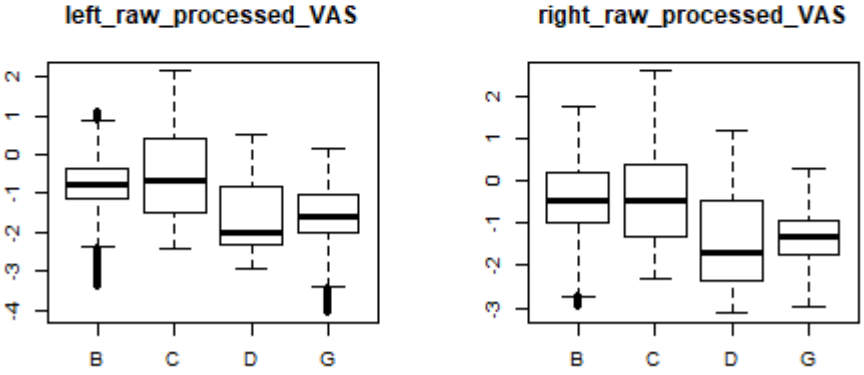
```
  write.csv(table$output$games.howell,file = paste(toString(i),sep = '
_','games-howell_audio_type.csv'))
}

for (i in c(1:length(anova_list_split[[1]]))){#within subjects for VAS
 factorized left channel
  table <- posthocTGH(anova_list_split[[1]][[i]]$values,anova_list_spl
it[[1]][[i]]$vas_f, method="games-howell",conf.level = 0.95, digits=9)
  write.csv(table$output$games.howell,file = paste(toString(i),sep = '
_','games-howell_left.csv'))
}

for (i in c(1:length(anova_list_split[[2]]))){#within subjects for VAS
 factorized right channel
  table <- posthocTGH(anova_list_split[[2]][[i]]$values,anova_list_spl
it[[2]][[i]]$vas_f, method="games-howell",conf.level = 0.95, digits=9)
  write.csv(table$output$games.howell,file = paste(toString(i),sep = '
_','games-howell_right.csv'))
}

for (i in c(1:length(anova_list_split[[1]]))){#within subjects for aud
io type left channel
  table <- posthocTGH(anova_list_split[[1]][[i]]$values,anova_list_spl
it[[1]][[i]]$audio_type, method="games-howell",conf.level = 0.95, digi
ts=9)
  write.csv(table$output$games.howell,file = paste(toString(i),sep = '
_','games-howell_left_audio_type.csv'))
}

for (i in c(1:length(anova_list_split[[2]]))){#within subjects for aud
io type right channel
  table <- posthocTGH(anova_list_split[[2]][[i]]$values,anova_list_spl
it[[2]][[i]]$audio_type, method="games-howell",conf.level = 0.95, digi
ts=9)
  write.csv(table$output$games.howell,file = paste(toString(i),sep = '
_','games-howell_right_audio_type.csv'))
}
```

8.2. Boxplots from all the subjects categorized by VAS evaluation factorized

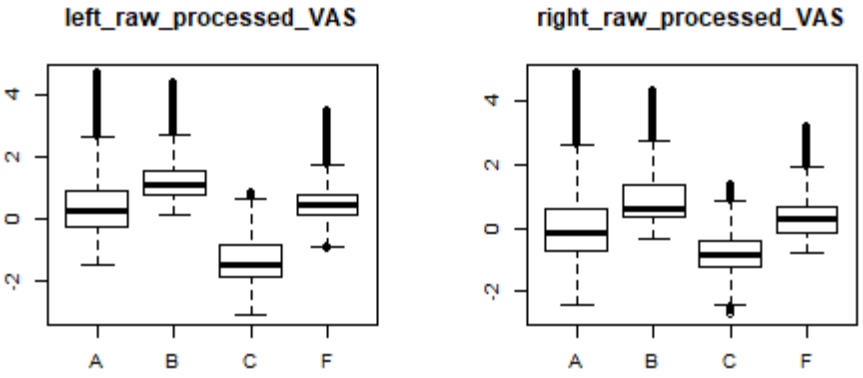
Subject 1



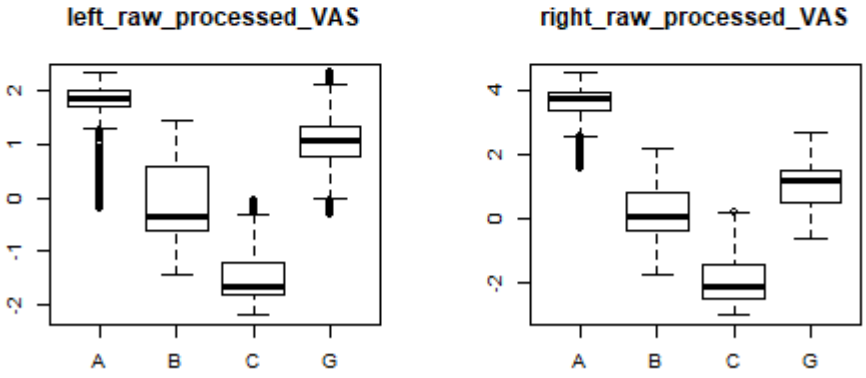
Subject 2



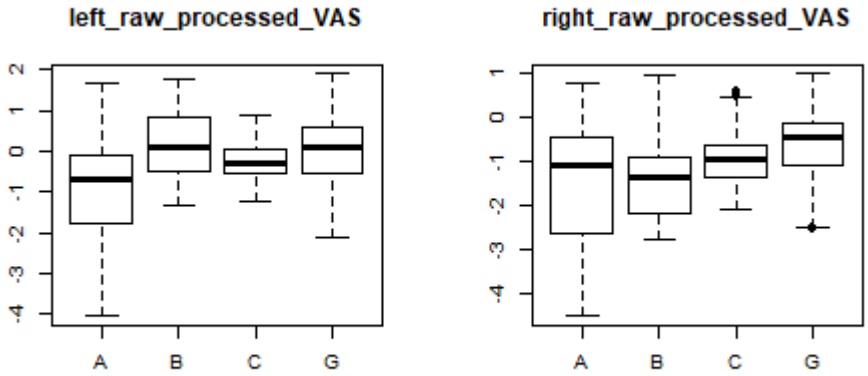
Subject 3



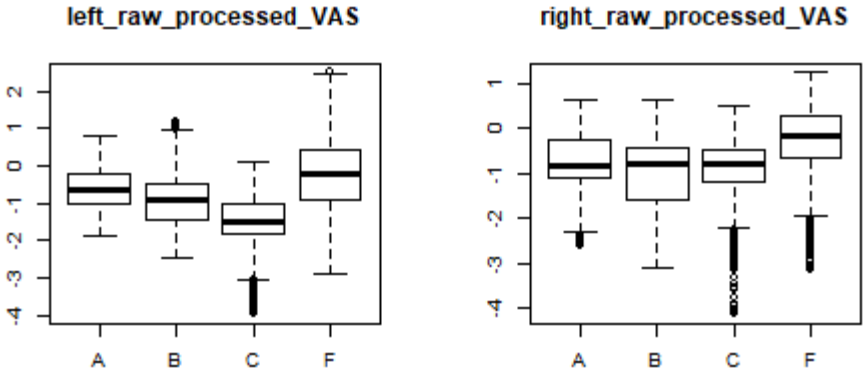
Subject 4



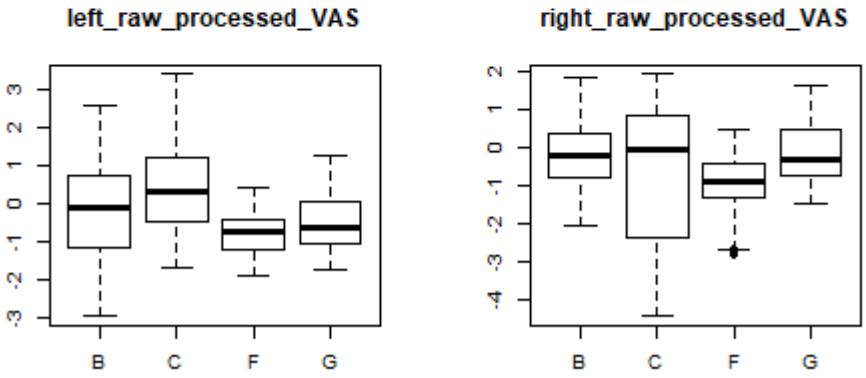
Subject 5



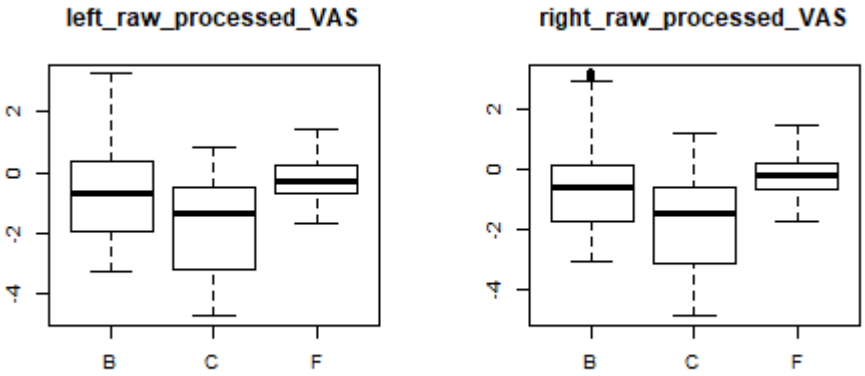
Subject 6



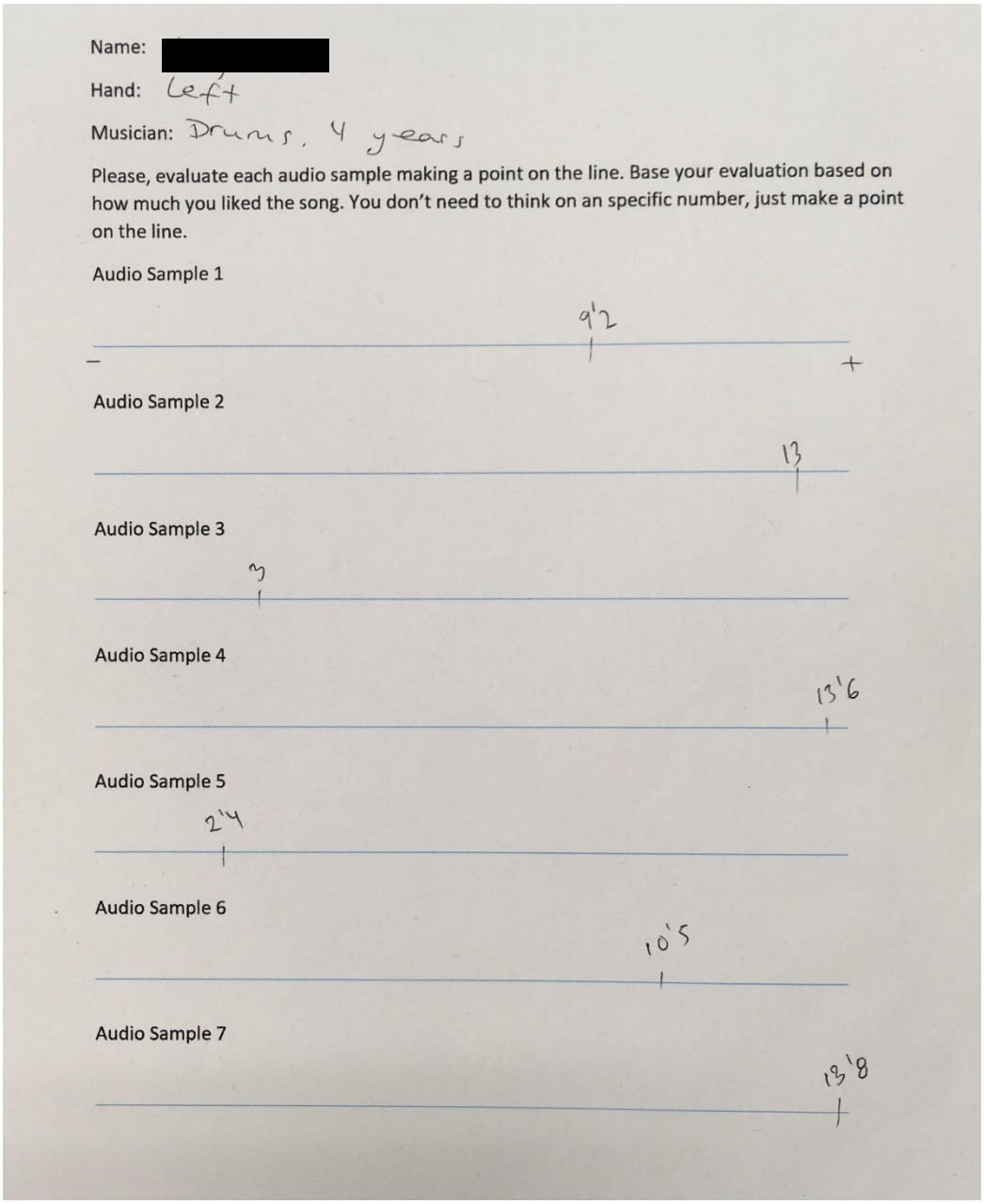
Subject 7



Subject 8



8.3. Example of VAS evaluation



Name: [redacted]

Hand: Left

Musician: Drums, 4 years

Please, evaluate each audio sample making a point on the line. Base your evaluation based on how much you liked the song. You don't need to think on an specific number, just make a point on the line.

Audio Sample 1

9'2

– +

Audio Sample 2

13

Audio Sample 3

3

Audio Sample 4

13'6

Audio Sample 5

2'4

Audio Sample 6

10'5

Audio Sample 7

13'8

8.4. HOT-1000 device info

HOT-1000

Human oriented technology

A compact and lightweight (125 grams) real-time brain activity measurement headset that is easy to operate with reduced user-fatigue. Fast and easy smartphone and tablet connectivity!

Principle of Measurement

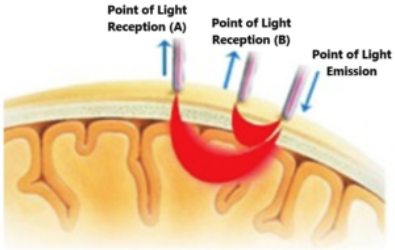
- **Brain activity and changes in blood flow:**

For brain function measurements, participants' brain activities are observed while fulfilling experimental tasks. Based on the results, we analyse potential relationships between experimental tasks and brain functions, where changes in the brain's activities cause changes in the brain's hemodynamics (detected by blood flow increases to areas where the brain is activated).

- **Observation of changes in blood flow with light:**

The HOT-1000 uses light with a wavelength of around about 800 nm that is easily absorbed by the hemoglobin in the blood. Light scattered from above the scalp will diffuse and return to the detector. In the case where there is a good amount of hemoglobin in the region, much of the diffused light is absorbed.

The headset's detector position is around 3 cm from the light irradiation point. When the part of the brain that corresponds to the path of the light is activated, blood flow and light absorption increases, and the amount of light returning to the detector decreases. The rate that the light decreases when returning to the detector is the principle behind how the HOT-1000 measures brain activity.



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