

Neural Processing of Emotional Auditory Stimuli

Group Members: Tristán Fonquerne Torres, Nicolás Reátegui Rodríguez,
Emanuele Rimoldi, Imane Jennane

1 Introduction

In this mini-project, we investigate the neural data of emotionally provocative auditory stimuli. Using fMRI data from the OpenNeuro dataset [1], we aim to identify and compare regions activated by positive and negative musical stimuli to understand the auditory processing of emotional content.

2 Dataset

The dataset consists of both anatomical and fMRI scans from control subjects listening to blocks of positive and negative music, interspersed with neutral tones. We focus only on the first subject and on musical experiments. We begin by performing the following preprocessing steps on the fMRI samples:

3 Preprocessing

- a) **Treatment of anatomical imaging:** We start by using robust BET for skull stripping the anatomical volume of the subject, and then apply `flirt` for co-registration to the MNI152 reference template. The transformation matrix and the tissue segmentation data were saved for co-registration of our functional data which will be done later in the preprocessing pipeline. The tissue segmentation will be used for computing ICA.
- b) **Volume correction:** We continue with the functional data where we observe on volume 17 a white line on the outside of the brain, producing a large spike on the average voxel value. We correct it by replacing the corrupted plane with the corresponding one from the previous volume as this does not seem to have a significant effect on the brain.
- c) **Standardization & Concatenation:** We continue by normalizing the different runs, we explored both min-max normalization and standardization and decided to keep the latter as it allows us to have centered data. After standardizing each run we concatenated them into a single image.
- d) **Motion Correction:** Then, we use `mcfliirt` with 6 DOF to apply rigid body transformation to it. We save the transformation matrices for later use.
- e) **Additional preprocessing:** In order to overlay our ATLAS to our fMRI we perform co-registration to the anatomical T1 image. We use the provided `epi_reg` command with the middle volume as `epi_target`. To have an efficient pipeline we concatenate both the linear transformations from `flirt` and `epi_reg` to a single warp field. Due to computational limitations, we split our concatenated fMRI into single volumes using `fslibsplitt` and use `applywarp`, with the `mcfliirt` matrix as `premat`, to co-register and align each of split fMRI images. Once all transformations have been applied and the fMRI is co-registered to the reference MNI template, we apply 6mm smoothing to improve the signal-to-noise ratio. Finally, we merge the resulting smoothed fMRI volumes back to a single image using an HPC given the extensive RAM requirements.

4 GLM Analysis

4.1 Design matrix

The design matrix of our GLM models the event-related information (obtained from the participants .tsv file) as well as additional factors to account for undesired variability. The basic regressors in our GLM include positive and negative music stimuli, participant response as well as constant tone. We introduce a polynomial drift component, up to degree 3, for each of the participant's runs to account for the mean value drift observed during the preprocessing. Furthermore, we introduce a one-hot encoding regressor for each of the participant's runs to absorb any run-related noise as well as motion outliers (accounting for both the translational and rotational motion). Our final GLM matrix is depicted in Figure 3. We used a standard HRF response over our regressors and fitted it to the entire participant fMRI data.

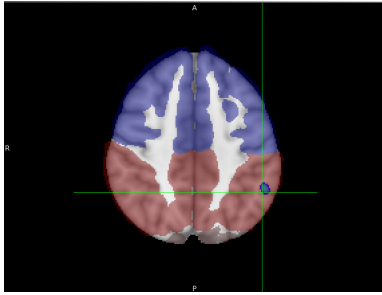


Figure 1: Axial view

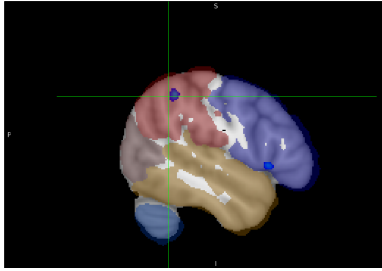


Figure 2: Sagittal view

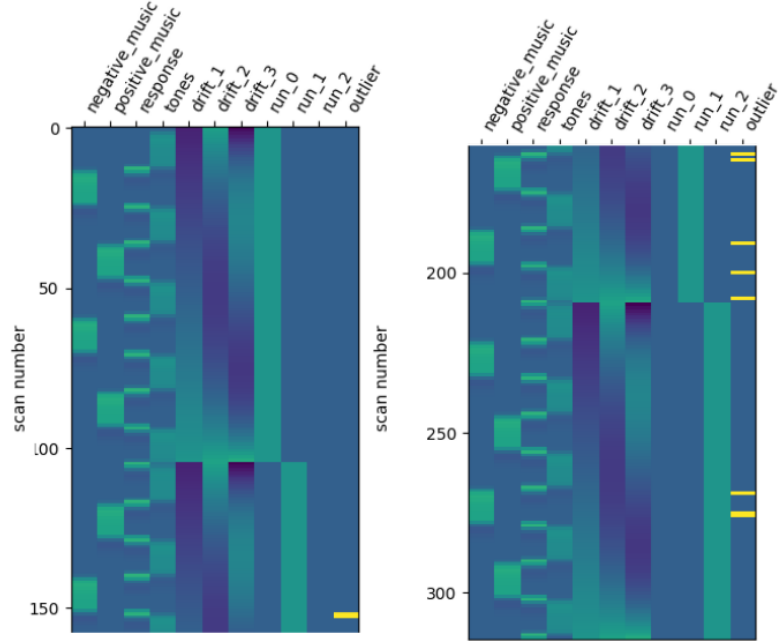


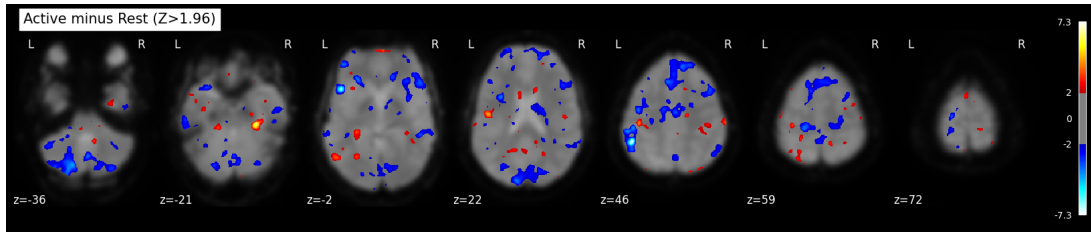
Figure 3: GLM matrix

5 GLM results

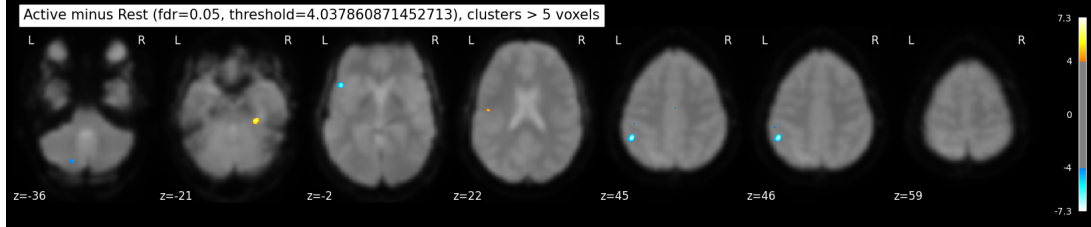
After fitting the GLM and applying our contrast vector, we obtain beta maps highlighting brain areas activated during positive or negative music. As shown in Figure 4b, both the frontal and parietal cortex are differentially sensitive to these stimuli. Furthermore, we observe a positive activation in the temporal lobe.

6 ICA analysis

We run the `FastIca` command over the concatenated runs with a grey matter mask from our tissue segmentation to isolate CSF noise and constrain the component detection to areas likely leading to a differential activation. To uncover the clearest structures and functional networks we run multiple ICA iterations with different numbers of independent components basing ourselves on our knowledge and literature (3, 4, 7, 17 & 22). While sweeping close to literature values 7 & 17 [3] we identified functional networks with 22 components, 2 of which are shown in Figure 5.

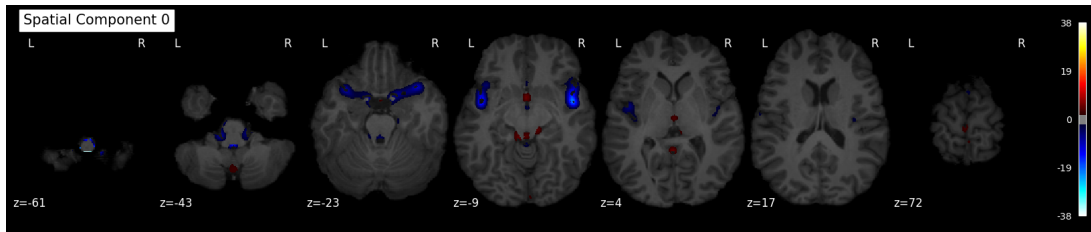


(a) Beta map using the design matrix from Figure 3 with threshold: 1.96

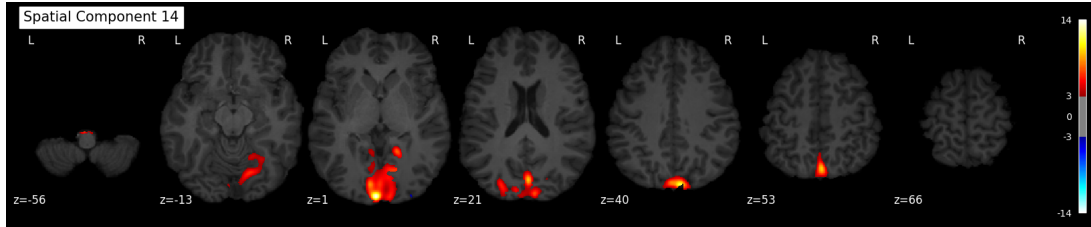


(b) Beta map with FDR correction (q: 0.05, cluster size: 5) resulting in an effective threshold of 4.14

Figure 4: Beta maps using the design matrix from Figure 3 and the contrast from positive minus negative music stimuli



(a) Auditory system



(b) Visual system

Figure 5: Spatial components from ICA obtained using FastICA with 22 components

7 Theoretical Analysis

7.1.1 Can We Conduct a Second-Level Analysis?

Yes, a second-level analysis is feasible with this dataset as it includes multiple subjects. This analysis would aggregate the first-level results (individual beta estimates) to examine consistent brain activation patterns across the control group.

7.1.2 Contrast for Second-Level Analysis

For the second-level analysis, the contrast between positive and negative music could reveal differential activation in emotional processing areas, such as the amygdala and prefrontal cortex, answering our question on how positive and negative auditory stimuli are processed differently. One of the ways of obtaining this is to use n-sample t-tests with contrast between positive and negative music, with regressors to take

into account inter-subject variability. This could help us obtain more relevant results. There are many other possibilities to use various subject comparisons such as ANOVA that incorporate additional components, e.g. the interaction between subjects and music. This could help assess the potential impact of depression on brain regions involved in processing auditory emotional responses.

7.2.1 Functional brain networks

Researchers have used both 7 and 17 ICA components [3] as these were closely related to the number of functional networks previously discovered. As shown in Figure 5, we were able to uncover both the auditory and visual systems which show a clearer structure amongst the 22 ICA components.

7.2.2 Denoising ICA

In order to identify components that do not relate to relevant networks we can start by using a grey matter mask (obtained with the `fast` tool from `fs1`) to isolate changes in the CSF. Furthermore, there are other sources of structured noise such as head motion artifacts which can pollute the extracted components. These additional noise sources can be identified with a classifier using a small and predefined set of features including maximum RP correlation, edge fraction, CSF fraction, and high-frequency content [2].

7.2.3 Comparison GLM

When comparing our ICA components to the GLM results we cannot correctly identify a similar network activated in those components. We believe using the data from a single participant makes finding relevant components harder. Furthermore, GLM is preferable when aiming at finding regions that are differentially sensitive to a given stimulus, i.e. when working with a contrast vector. ICA aims to extract independent components (by maximization of non-gaussianity) which allows us to identify different functional networks. As in this study, we want to find zones that differentially activate between positive and negative music stimuli, GLM is better suited for this task even though ICA can provide interesting insights.

8 Conclusion

Our analysis suggests distinct activation patterns for positive and negative musical stimuli, indicating the brain's differential processing of emotionally charged auditory inputs. This project provides insights into neural responses to positive versus negative music, with potential implications for understanding emotional processing in clinical populations.

References

- [1] Rebecca J. Lepping, Ruth A. Atchley, Evangelia Chrysikou, and et al. Neural processing of emotional musical and nonmusical stimuli in depression. *PLOS ONE*, 11(6):e0156859, 2016.
- [2] Raimon H.R. Pruim, Maarten Mennes, Daan van Rooij, Alberto Llera, Jan K. Buitelaar, and Christian F. Beckmann. Ica-aroma: A robust ica-based strategy for removing motion artifacts from fmri data. *NeuroImage*, 112:267–277, 2015.
- [3] B. T. Thomas Yeo, Fenna M. Krienen, Jorge Sepulcre, Mert R. Sabuncu, Danial Lashkari, Marisa Hollinshead, Joshua L. Roffman, Jordan W. Smoller, Lilla Zöllei, Jonathan R. Polimeni, Bruce Fischl, Hesheng Liu, and Randy L. Buckner. The organization of the human cerebral cortex estimated by intrinsic functional connectivity. *Journal of Neurophysiology*, 106(3):1125–1165, 2011. PMID: 21653723.