Predicting Individual Differences from Brain Responses to Music using Functional Network Centrality

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Abstract

Individual differences are known to modulate brain responses to music. Recent neuroscience research suggests that each individual has unique and fundamentally stable functional brain connections irrespective of the task they perform. 77 participants' functional Magnetic Resonance Imaging (fMRI) responses were measured while continuously listening to music. Using a graph-theory-based approach, we modeled whole-brain functional connectivity. We then calculate voxel-wise eigenvector centrality and subsequently use it to classify gender and musical expertise using binary Support Vector Machine (SVM). We achieved a cross-validated classification accuracy of 97% and 96% for gender and musical expertise, respectively. We also identify regions that contribute most to this classification. Thus, this study demonstrates that individual differences can be decoded from brain responses to music using a graph-based method with near-perfect precision.

Keywords: Individual differences; fMRI; Naturalistic paradigm; Functional connectivity; Centrality; Classification

Introduction

Individual differences such as gender and musical expertise are known to modulate responses to music both behaviorally and neurologically (North, 2010; Alluri et al., 2017) and are critical in determining how individuals perceive and process music and, hence, their preferences (North, Hargreaves, & O'Neill, 2000; Alluri et al., 2015, 2017). Only one study to date has aimed at predicting an individual's musicianship class from brain responses to continuous music listening (Saari, Burunat, Brattico, & Toiviainen, 2018). However, they used a segregated approach, presuming that each region processes music independently and achieved a classification accuracy of 77%. Gratton et al. (2018) concluded that each individual has unique functional connectivity patterns independent of tasks they perform, and it can then be used to identify individual differences. Mohanty et al. (2020) compared various measures that characterize the brain's functional connections for age-based classification and prediction of behavioral data. However, it has to be shown whether these functional patterns can be used to identify individual differences using brain responses while participants perform a continuous music listening task.

Our study examines global functional connectivity to identify gender and musical expertise, using fMRI responses measured during a continuous music listening task. Eigenvector centrality (EC; (Bonacich, 2007)), a graph-theory-based measure, has been previously used to investigate functional networks during music listening and the modulatory effect of musical training(Alluri et al., 2017) and empathy(Moorthigari, Carlson, Toiviainen, Brattico, & Alluri, 2020) thereof. EC helps identify nodes central to coordinating whole-brain network functioning. In addition to its parameter-free nature, it does not rely on thresholding, making it the appropriate choice for the current study. Subsequently, we use a machine learning-based approach to classify distinct population groups such as males-females, musicians-nonmusicians, and combined population groups.

Methods

Participants

77 Participants' (43 Females, age = 29.6 $\pm$ 8.9 years) functional Magnetic Resonance Imaging (fMRI) responses were measured while listening to an 8-minute instrumental piece Adios Nonino by Astor Piazzolla. The participant pool consisted of 26 musically trained and 51 untrained participants. The two groups were comparable in gender, age distribution, cognitive measures, and socioeconomic status. Participants were also asked to rate the liking of the musical piece on a discrete 5-point scale. This data in its entirety and parts has already been used in previous studies, and extensive details can be found in (Toiviainen, Burunat, Brattico, Vuust, & Alluri, 2020; Moorthigari et al., 2020).

Preprocessing

In previous studies that used the same data, identical preprocessing steps were taken. Participants' brain responses were acquired while listening to the music delivered via MR-compatible insert earphones while keeping their eyes open. Thirty-three oblique slices (FoV: 192mm x 192 mm, 64 x 64 matrix, interslice skip = 0mm) were acquired every 2 sec, with echo time = 32ms and voxel size = 2 x 2 x 2 mm^3 using a single-shot gradient echo-planar imaging (EPI) sequence, providing whole-brain coverage for each participant. fMRI scans were preprocessed in Matlab using SPM8 and VBM5. Normalization to MNI segmented tissue template was carried out. Head movement-related components were regressed, followed by spline interpolation and temporal smoothing.

Graph-based Functional Connectivity

For each participant, the functional connectivity matrix was generated by computing the Pearson correlation of the fMRI time series between every pair of voxels. This matrix was then made non-negative by incrementing each entry by 1. A power-iteration method(Mises & Pollaczek-Geiringer, 1929) was used to compute the first eigenvector for each participant's FC matrix. The result was a voxel-wise EC map for each participant (Refer to Eq. 1)(Fig. 1).

$$x_i = \frac{1}{\lambda} \sum_k FC_{k,i} x_k, \tag{1}$$

where, x_i is centrality of ith node and k denotes all voxels, $FC_{k,i}$ denotes the FC matrix value between nodes k and i.

Feature Selection and Classification

From the resultant EC maps, features(voxels) were selected using a Random Forest Regressor (RFR)(Breiman, 2001; Geurts, Ernst, & Wehenkel, 2006) which is an ensemble of individual decision trees. It also provides feature importance

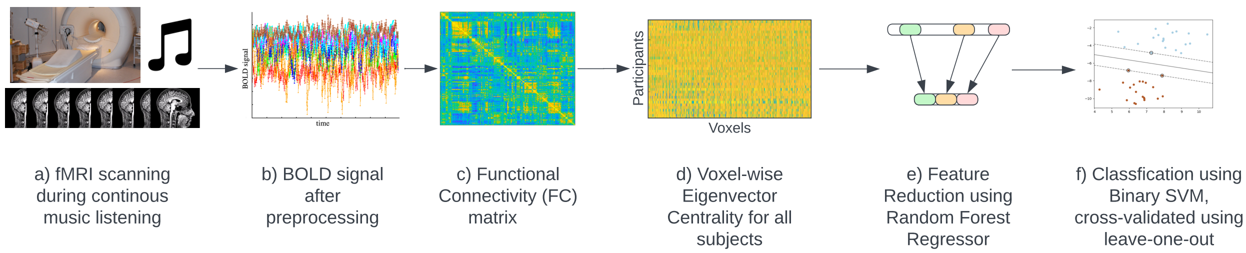

Figure 1: An overview of our study.

in terms of weights that can be used to find crucial regions contributing to identifying individual differences. RFR was performed with the default number of trees in the forest, implemented using python's scikit-learn toolbox(Pedregosa et al., 2011). A meta-transformer was followed, selecting features based on feature importance weights. Mean weight was used as the threshold value for feature selection. Then, we used a binary SVM classifier, the accuracy of which was tested using the leave-one-out cross-validation strategy to maximize the size of the training dataset. The average accuracy was calculated across all the left-out subjects. We also performed a 4-class classification on combined groups of males-females and musicians-nonmusicians.

Results

To examine differences in liking ratings specific to gender and musical expertise, we performed a non-parametric alternative to a two-way ANOVA called the permuted Wald-type statistic (WTP)(Friedrich, Brunner, & Pauly, 2017). It revealed a significant main effect of musical expertise($F=15.73$, $p < 0.01$) and gender($F=13.51$, $p < 0.01$) on liking ratings. As seen in Figure 2, there was also a significant interaction between gender and musical expertise ($F=10.48$, $p < 0.01$) on liking ratings. This finding supports the aforementioned previous work highlighting the role of gender and musical expertise on musical preferences.

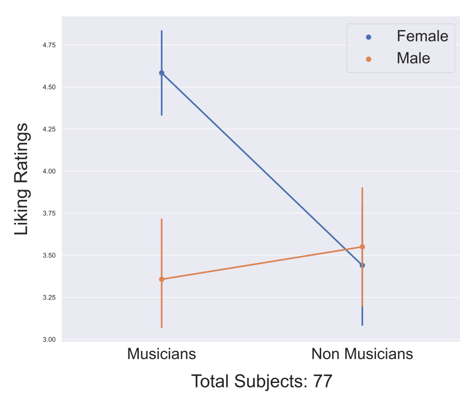

Figure 2: Liking Ratings Grouped by Musical Expertise and Gender.

The SVM model demonstrated a near-perfect accuracy of 96% and 97% for classifying musicians from non-musicians and males from females, respectively. Feature importance via RFR revealed the highest contribution of voxels belonging to the left middle and superior occipital Gyrus and right middle and superior frontal gyrus in musical expertise classification. On the other hand, voxels of the left precuneus, median, and paracingulate gyrus, right pre- and post-central gyrus, and middle and superior frontal gyrus possessed the highest feature importance for the gender classification task. An accuracy of 75.32% was achieved for 4-class classification on combined groups of males-females and musicians-nonmusicians.

To conclude, this is the first study to use the graph-based FC measure measured during continuous music listening to classify gender and musical expertise. The classification model thus built outperforms the non-FC-based approach done on the same dataset in Saari et al. (2018). This can be extended in the future to accommodate more musical stimuli and participants.

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