*Materials and Methods*

**Experimental Design**

**Participant**

The only participant willing to volunteer for our study is a 43 year old healthy right-handed male (n=1). He was recruited from Florida International University (FIU) and has corrected-to-normal vision. The rationale behind running only one participant is that we only have access to that one participant’s data. Thus, this is a within-subject fMRI study. Study procedures were approved by the local IRB and the participant gave informed consent to take part in the study. The study lasted one session and involved both T1-weighted structural and T2\*-weighted functional scans. The experiment consisted of two tasks, the ‘localizer’ task and the ‘study’ task.

**Localizer Task**

The localizer task is a block design experiment with three categories of visual stimuli: faces, scenes and math. Between each block, there is a short time interval where a white fixation cross is displayed on the screen. During scenes, the task is to press a button if there was water. During faces, the task was to determine if the face was male or female and press the corresponding button. The math block acted as the ‘resting’ block since math was not a regressor of interest. There were two scans in the localizer experiment. The goal is to separate the neural responses to different kinds of stimuli; in this case, faces versus scenes. To prevent the BOLD response from responding in a similar pattern for one event type, the blocks were arranged for both scans, with no two consecutive blocks the same, in the order of: ‘face’, ‘math’, ‘scene’, ‘math’ and repeating until the experiment was over. Each stimulus within the block lasted for 500ms, with 20 stimuli per block for faces and scenes, and 10 stimuli per block for the math category. The total number of stimuli for each scan was 420, with 14 blocks dedicated for math, 7 blocks for faces and 7 blocks for scenes. Therefore, each category had 140 stimuli for each scan. The ISI for the localizer tasks is fixed between trials and is approximately 0.748 seconds or 748 milliseconds.

**Study Task**

The study task is an event-related design experiment with two scene conditions, two face conditions, a baseline condition and a ‘COND’ condition. In the study, participants were instructed to associate the shape that appeared with the appropriate object for the first four images. The first and third image represents ‘face 1’ and ‘face 2’ respectively. The second and fourth image represents ‘scene 1’ and ‘scene 2’ respectively. The fifth image acted as the ‘COND’ condition and gave choices between a face or a scene; the correct answer depended on what image shape came before it. For example, if shapes one and three came before, the correct answer was the face. If shapes two and four came before, the correct answer was the scene. The baseline condition displayed two grey noise static images. Participants were tasked with identifying which of the two images were brighter. The trials were randomized and there were a total of 180 trials per scan. There were four scans in the study experiment.

**Purpose**

Although we provided a brief description of the study task, we are primarily interested in the localizer task since we want to identify correlated activity for the brain regions in our ROI (see below). We plan on running analyses with the study task experiments at a later time, but for the purpose of this paper, we report on the localizer tasks only.

**Image Acquisition**

**ROI**

In order to achieve systematic accuracy, we defined the ROIs anatomically and a priori with 3D masks coregistered from FreeSurfer labels. Our study concerned areas of the brain related to face and scene processing, as well as object processing in the study task. Since the fusiform gyrus majorly involves processing faces and objects (McCarthy et al., 1997), and the retrosplenial cortex (RSC) involves processing scenes (Shine et al., 2016), we defined our ROIs with these structures on FreeSurfer. Since we are using anatomical markers and are only concerned with the localizer task for the analysis, we decided to not define specifically the fusiform face area and just focus on the physical structure.

**MRI Parameters**

Data was collected using the 3T Siemens MAGNETOM Prisma scanner with a 32-channel head coil at the Center for Imaging Science at FIU. A T2\*-weighted EPI sequence was collected (TR=1760ms, TE=35ms, flip angle=52 degrees, FOV=1800mm, slice acceleration=3, voxel size= 2mm isotropic). There were 304 whole brain volumes per localizer file. With two localizers, that brings the collective total to 608 whole brain volumes. A T1-weighted structural scan was also collected (MPRAGE: TR=2500ms, TE=2.9ms, flip angle=8 degrees, FOV=256mm, voxel size= 1mm isotropic). There were 176 whole brain volumes.

**Preprocessing**

**Data Organization**

First, data was arranged in DICOM format. For standardization with open science databases, we converted the subsequent DICOM files into the highly adopted BIDS format (NIFTI files). This was accomplished by using a heuristic file and calling a function that converted the file format. After reorganizing the data, we were able to begin preprocessing. Using a custom scripted neuroimaging in python pipeline (Nipype version 0.12.1; Gorgolewski et al., 2011), we used multiple softwares depending on the goal in mind: Analysis of Functional Neuroimages (AFNI version 20.0.19; Cox, 1996), FMRIB Software Library (FSL version 5.0.11; Smith et al., 2004) and FreeSurfer (version 7.1.0; Fischl, 2012).

**Motion Correction**

The first preprocessing step we instilled is motion correction. It has been recommended to apply motion correction first, even before slice timing correction, because the effects of motion are so large, it can skew voxel intensities and lead to the wrong conclusions (Poldrack et al., 2011). We used AFNI’s Volreg command (Cox, 1996) to execute this step with a two-pass fourier interpolation and zeropad argument set to 4. To determine motion outliers, we used AFNI’s outlier count function (Cox, 1996). The base input volume to compare with the other volumes for motion correction was selected from the outputs from this function. First, we took the outlier count output and selected the volume with the least number of outliers. Then, we used FSL’s extract ROI function (Smith et al., 2004) to extract the earliest volume with the fewest outliers of the first run, setting that volume as the reference. Volreg used this reference to register the motion correction.

**Slice Timing Correction**

AFNI’s TShifter function (Cox, 1996) was used for slice-timing correction (TR=1.76 seconds). We used the output file from Volreg and applied the slice timing correction to it.

**Coregistration & Normalization**

Since there was only one participant in our sample, we did not normalize the structural scans before coregistering.

Data was coregistered to the structural scan through FreeSurfer’s BBRegister command (Fischl, 2012). The low-resolution functional scan was aligned to the high-resolution structural scan. This command was initialized with FSL’s FLIRT (Smith et al., 2004). A brain mask was subsequently created and binarized, then transformed into the EPI space. Finally, the functional runs were masked with the extracted mask with FSL’s ImageMaths function (Smith et al., 2004).

**Smoothing**

To reduce high-frequency noise and increase the signal-to-noise ratio, spatial smoothing was implemented. We used AFNI’s BlurToFWHM function (Cox, 1996) with an automask. A kernel with a width of 4mm was chosen to satisfy GLM assumptions used in the analysis section. 4mm was chosen since a common choice in the field is somewhere between one and three voxel widths (Ashby, 2019). Picking the middle at two voxel widths, since our voxel size was 2mm, 2\*2= 4mm for the kernel.

Temporal smoothing was not executed in this study since we are focusing on the localizer task which is a block design. Temporal smoothing can be dangerous in block designs because it can remove much of the signal (Ashby, 2019) and since our TR is relatively short (1760ms), we felt temporal smoothing was not necessary.

**Statistical Analysis**

**Outliers**

Outliers were detected using motion and intensity parameters with the RapidArt ArtifactDetect function (Gorgolewski et al., 2011). We used a global mask (spm\_global), threshold value of 1 (norm\_threshold; >1mm displacement) and z-intensity threshold of 3 (>3SD mean intensity).

**Clustering**

We used the AFNI program 3dFWHMx (Cox, 1996) to calculate the average acf, then used the output in 3dClustSim (Cox, 1996) to identify the minimum voxel cluster size needed for a corrected p-value of 0.001, or an uncorrected p-value of 0.005. The new version that we used of 3dFWHMx is more accurate, as it does not assume a Gaussian function and uses the autocorrelation function to better control for false positives. Clusters were defined as voxel groups above the threshold whose faces only touched (NN1).

**Deconvolution**

The functional neuroimaging data was analyzed using a general linear model (GLM) approach. We concatenated the motion related regressor files in order to use AFNI’s 3dDeconvolve (Cox, 1996) to calculate the deconvolution of the dataset. In this case, a 2-Gamma hrf model was assumed since it includes the late negative dip (overshoot), a major signifier of the BOLD response (Ashby, 2019).

**Regressors**

The regressors of interest for our localizer task are brain activity for faces and brain activity for scenes. Our regressors of no interest include motion (x, y, z translations; pitch, roll, yaw rotation), the first and second derivatives of the motion parameters, normalized motion, first through third order Lagrange polynomials to account for low frequency changes in the signal, and a regressor for each outlier time-point that exceeded our defined outlier thresholds. A GLM was fit to the time series of each cluster and a regression analysis was performed on each pre-defined ROI.

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