Multi-Region Neural Representation: A novel model for decoding visual stimuli in human brains

Supplementary Materials

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1 Notations

Table 1: Variables

Variable	Description
$\sigma_G > 0$	The kernel parameter for smoothing the design matrix.
$\widehat{\mathbf{G}}$	The Gaussian kernel, which is used for smoothing the design matrix.
$\mathbf{T}_i$	Transform matrix for mapping the original images to the standard space.
NMI	Normalized Mutual Information
$\widehat{\beta}_i$	The estimated set of correlations for $i-th$ category in the original space.
$\mathbf{Ref}$	Anatomical reference image.
$\mathbf{W}_\ell$	Estimated weights for $\ell - th$ classifier.
C	The SVM parameter [1].
y_j	Class label for the $j - th$ stimulus.
$\mathbf{X}_{(j,\ell)}$	The neural features in the $j - th$ stimulus and $\ell - th$ anatomical region.
$\lVert.\rVert_1$	First norm
$\lceil . \rceil$	Ceiling function

(3.3)

$$\widehat{\mathbf{G}} = \left\{ \exp\left(\frac{-\widehat{\mathbf{g}}^2}{2\sigma_{\mathbf{G}}^2}\right) \middle| \, \widehat{\mathbf{g}} \in \mathbb{Z} \text{ and } -2\lceil\sigma_G\rceil \leq \widehat{\mathbf{g}} \leq 2\lceil\sigma_G\rceil \right\}$$

(3.11)
$$\mathbf{T}_i = \arg\min(NMI(\widehat{\beta}_i, \mathbf{Ref}))$$

(3.20)

$$\eta_\ell\text{:} \quad \min_{\mathbf{W}_\ell} \quad C\sum_{j=1}^{\tau} \max(0, 1 - y_j \mathbf{X}_{(j,\ell)} \mathbf{W}_{(j,\ell)}) + \lVert\mathbf{W}_\ell\rVert_1$$

2 Additional experimental results

This section provides more detailed empirical studies for the proposed method. Table 2 illustrates the technical information of the employed data sets in this paper.

2.1 Parameters Analysis In this section, the effect of different parameters on the performance of the proposed method will be analyzed. As the first parameter, σ_G in (3.3) is heuristically defined to change the level of smoothness in the design matrix. The general assumption here is the $0 < \sigma_G < 1$ can create design matrix, which is sensitive to small spikes. As a result, the detected local maximums and also the number of snapshots will be more than the real number. Moreover, $\sigma_G > 1$ can rapidly increase the level of smoothness, and also can remove some weak local maximums, especially in the event-related fMRI data sets. Figure 1.A illustrates the effect of different σ_G values on the number of wrong detected snapshots in the DS105, DS107, and DS117 data sets. As depicted in this figure, the level of error in the event-related fMRI data set (DS117) is more that other data sets. In addition, the level of error in DS105 is lower than the other data sets because this block design data set contains one stimulus on each column of the design matrix. This figure also shows that the $\sigma_G = 1$ generated better results in comparison with other values. This is the main reason that this paper uses σ_G=1 as the default value in the empirical studies.

The next parameter which can affect the performance of the proposed method is the distance metric in the objective function (3.11) for mapping functional snapshots to the standard space. Figure 1.B and C demonstrate two examples of the error of registration (normalization) in the detected snapshots. Here, gray parts show the anatomical atlas, the colored parts (yellow and blue) define the functional activities, and also the red rectangles illustrate the error areas after registration. Indeed, these errors can be formulated as the nonzero areas in the snapshots which are located in the zero area of the anatomical atlas (the area without region number). The performance of objective function

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Table 2: The data sets.

Title	ID	U	p	t	X	Y	Z	Scanner	TR	TE	FA
Visual Object Recognition	DS105	71	8	121	79	95	79	General Elect. 3 Tesla	2500	30	90
Word and Object Processing	DS107	98	4	164	53	63	52	Siemens 3 Tesla	2000	28	90
Multi-subject, multi-modal	DS117	171	2	210	64	61	33	Siemens 3 Tesla	2000	30	78

U is the number of subject; p denotes the number of visual stimuli categories; t is the number of scans in unites of TRs (Time of Repetition); X, Y, Z are the size of 3D images; TR is Time of Repetition in millisecond; TE denotes Echo Time in millisecond; FA is the flip angle. Please see *openfmri.org* for more information.

(3.11) on DS105, DS107, and DS117 data sets is analyzed in Figure 1.D by using different distance metrics, i.e. Woods function (W), Correlation Ratio (CR), Joint Entropy (JE), Mutual Information (MI), and Normalized Mutual Information (NMI) [2]. As depicted in this figure, the NMI generated better results in comparison with other metrics.

2.2 Regions of Interest (ROIs) Analysis The goal of fMRI studies is a better understanding of the brain's physiology. As mentioned before, the proposed method provides an opportunity for neuroscientists to ask this question: what is the effect of a stimulus on each of the anatomical regions rather than just study the fluctuation of voxels in the manually selected ROIs. This section introduces an approach to use the trained classifiers as a biomarker for visualizing and analyzing the effects of different visual stimuli on each of anatomical region. Since the proposed method used (3.20) to create a unique binary classifier for each anatomical region ($\mathbf{A}_\ell$), each binary classifier (η_ℓ) depicts the neural activities for an individual region. The whole of procedure for calculating the biomarker is so simple. Firstly, the weights ($\mathbf{W}_{(j,\ell)}$) belong to the region $\mathbf{A}_\ell$ and the category of visual stimuli β_i are selected, then the average of these weights are calculated, and finally this average will be normalized between 0 and 1 as the biomarker ($\mathbf{BIO}_{(i,\ell)}$) of the region $\mathbf{A}_\ell$ and the category β_i. The general assumption is that for each relevant stimulus the estimated biomarker must be near to 1, and also for each irrelevant stimulus the biomarker is near to 0. As depicted in Figure 2, these biomarkers are calculated for the ROIs, which are introduced in [3] for decoding visual stimuli. In this figure, the X-axis is the ROIs, i.e. Insular Cortex (IC), Triangular part of the Inferior Frontal Gyrus (tIFG), Inferior Parietal Cortex (IPC), Cerebrospinal Fluid (CSF), Cerebellum (CB), Middle Frontal Gyrus (MFG), Middle Occipital Gyrus (MOG), Medial Superior Frontal Gyrus (mSFG), Supramarginal Gyrus (SMG), Inferior Occipital Gyrus (IOG), Superior Occipital Gyrus (SOG), Superior Frontal Gyrus (SFG), Superior Parietal Cortex (SPC), Precuneus (PC), Middle Temporal Gyrus (MTG), Superior Temporal Gyrus (STG), Angular Gyrus (AG), and Middle Cingulate Gyrus (MCG). In addition, these results are generated by using one-versus-all strategy on combined version of all data sets, i.e. DS105, DS107, DS117. As depicted in this figure, the different categories generated distinctive patterns in these ROIs. These patterns can be used by neuroscientists to study the human brains.

References

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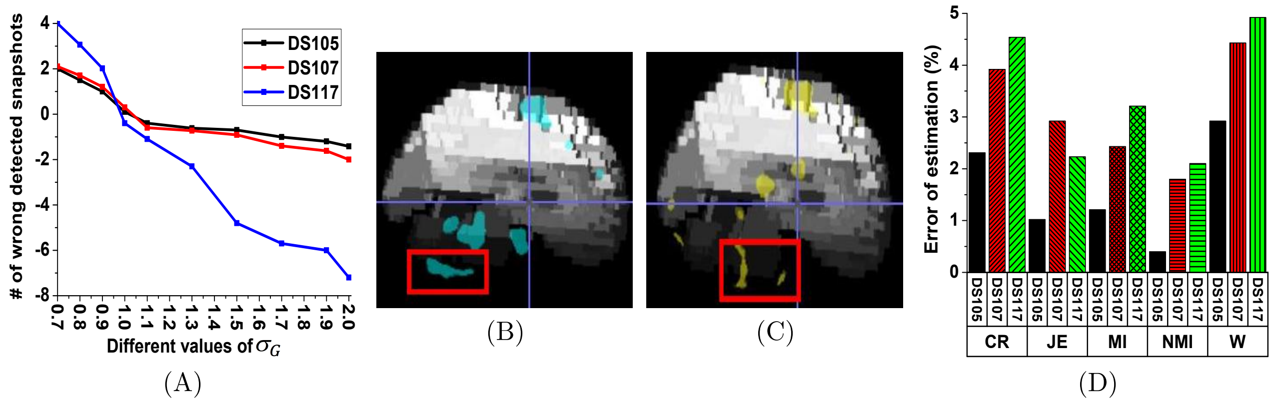

Figure 1: Parameters Analysis, (A) The effect of different σ_G values on the # of wrong detected snapshots, (B) and (C) two examples for the error of registration (normalization): the red rectangles illustrate the error areas after registration, (D) The effect of different objective functions in (3.11) on the error of registration.

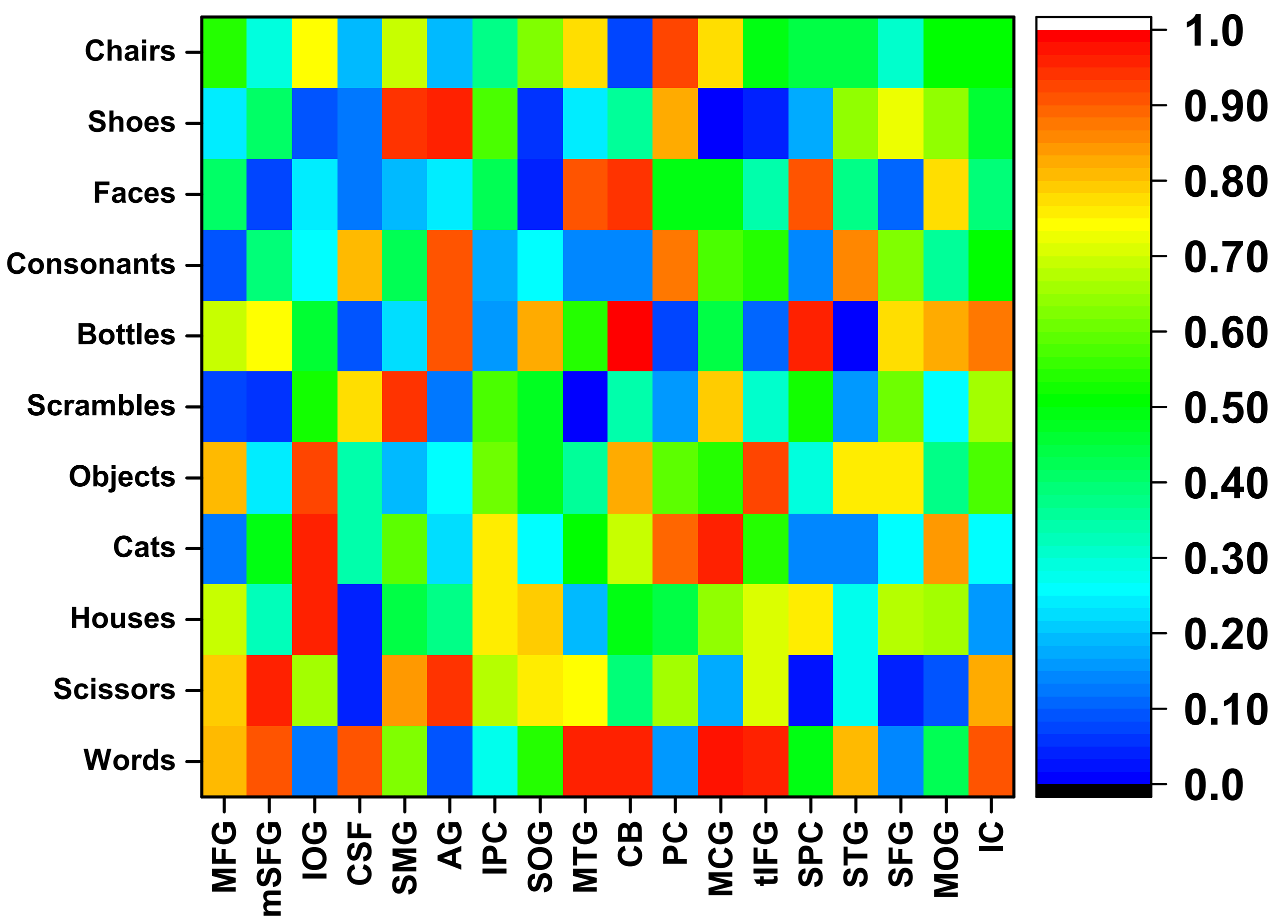

Figure 2: Comparing different categories of visual stimuli at the level of ROIs by using the biomarkers (the weights of the trained binary classifiers).