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Representation of Cognitive Processes Using the Minimum Spanning Tree of Local Meshes

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***Abstract*—A new graphical model called Cognitive Process Graph (CPG) is proposed, for classifying cognitive processes based on neural activation patterns which are acquired via functional Magnetic Resonance Imaging (fMRI) in brain. In the CPG, first local meshes are formed around each voxel. Second, the relationships between a voxel and its neighbors in a local mesh, which are estimated by using a linear regression model, are used to form the edges among the voxels (graph nodes) in the CPG. Then, a minimum spanning tree (MST) of the CPG which spans all the voxels in the region of interest is computed. The arc weights of the MST are used to represent the underlying cognitive processes. The proposed method reduces the curse of dimensionality problem that is caused by very large dimension of the feature space of the fMRI measurements, compared to number of instances. Finally, the arc weights computed over the path of the MST called MST-Features (MST-F) are used to train a statistical learning machine.**

The proposed method is tested on a recognition memory experiment, including data pertaining to encoding and retrieval of words belonging to ten different semantic categories. Two popular classifiers, namely k-Nearest Neighbor (k-NN) and Support Vector Machine (SVM), are trained in order to predict the semantic category of the item being retrieved, based on activation patterns during encoding. The classification performance of the proposed learning modelis superior to the classical multi-voxel pattern analysis (MVPA) methods for the underlying cognitive process.

I. Introduction

Several methods have been developed to understand how brain processes information. In particular, it is aimed to predict or decode the brain state associated with cognitive processes, based on distributed patterns of activation in the brain, acquired with functional Magnetic Resonance Imaging (fMRI) using various machine learning methods[1–8]. Massively coupled dynamic interactions of the brain at many scales cannot be fully understood by only employing the measurements recorded from the individual voxels. Therefore, there has been a growing interest in using brain connectivity and graph theoretical approaches. Graph theoretical analysis of functional and structural brain imaging data have become an efficient tool to characterize complex interactions taking place in the brain with an elegant formalization [9–19]. The main motivation of using graph theoretical framework for brain data analysis comes from the observation that the human brain exhibits a small-world property [20]. A small-world graph has a higher clustering coefficient and a lower characteristic path length, compared to random graphs, where clustering coefficient is used as a measure of cliquishness, and the edges are locally agglomerated [10],[19]. Therefore, appropriate graph measures help us quantify the topologies of brain networks that underlie their complex dynamics.

In this study, we examine potential applications of graph theoretic approaches to local activation patterns which span voxels in the entire region of interest to represent cognitive processes. We further employ classification methods to measure the accuracy of the representation for a multi-class classification task. Our method employs the following steps: A local mesh is formed around each voxel (called the seed voxel) by including the closest neighbors (called the surrounding voxels) in the mesh. The relationship between the seed voxel and its surrounding voxels are modeled by estimating the arc weights of the mesh in a linear regression model. The arc weights represent the relationship of each voxel to its closest neighbors in 3-dimensional physical space. In the proposed model, a graph called Cognitive Process Graph (CPG) is first formed by aggregating all the local meshes constructed around each voxel. Then, a minimum spanning tree of the graph is computed by the arc weights obtained at each time instance. Finally, the features called Minimum Spanning Tree Features (MST-F), which are extracted from the arc weights that reside on the selected path of the MST, are used to train a classifier which recognizes type of information and/or cognitive process. We particularly focused on classification of the type of information being encoded and retrieved during memory operations.

During the experiment, participants studied a list of words selected from one of ten pre-defined semantic categories, and made recognition memory judgments while neural activation was recorded using fMRI [21], [22]. Accordingly, we tested whether the proposed machine learning algorithm can successfully identify and differentiate the type of information (i.e. the semantic category to which the word belongs) represented in the brain at a given time.

We believe that the improvement in classification accuracy observed in comparison to standard MVPA approaches and efficiency-simplicity of the algorithm promotes the potential applicability of the proposed method to cognitive tasks.

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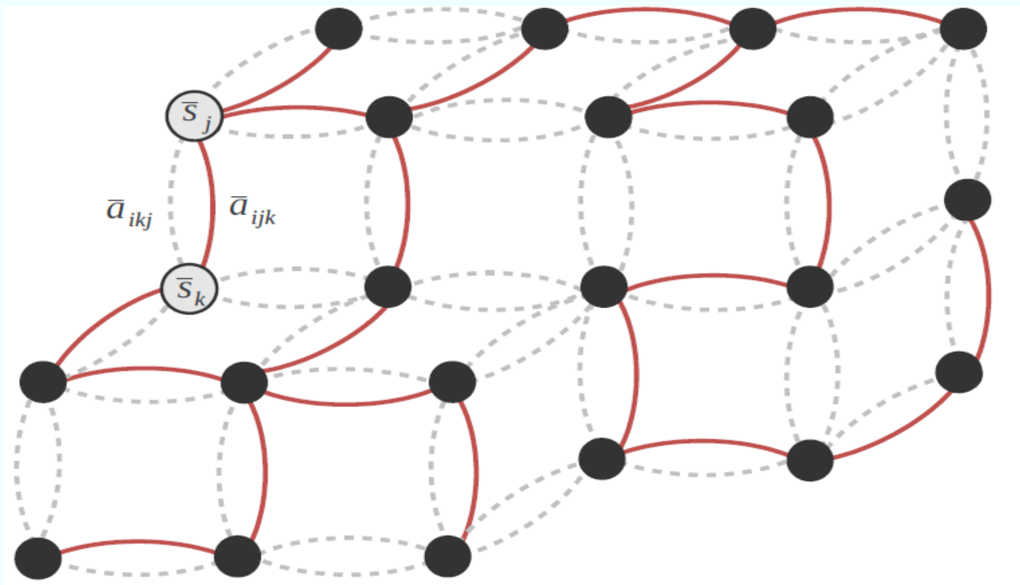

Fig. 1. A sampleMST computed in a BSG is given over 6-neighborhood system, voxels are represented by black dots and corresponding MST illustrated with red edges. Notice that edges in the MST have no cycles and span every node with optimal minimum weights over graph.

II. Materials and Methods

A. fMRI experiment and pre-processing

In the experiment, a participant is shown lists of words selected from a pre-defined semantic category, while being scanned using fMRI, see [21], [22]. After the presentation of each study list, the participant solves math problems and following this delay period, decides whether a probe word matches one of the members of the study list ("old" or "new"). Employing a delay period (about 14 sec during which the participant solved math problems) allows independent assessment of encoding related (i.e. study list period) brain activation from retrieval related (i.e. during the test probe) activity patterns. With this approach, one can test whether it is possible to identify and differentiate semantic categories of information that is represented in the brain at a given time based on distributed patterns of brain activity associated with each. A total of ten semantic categories were used in the study, namely *animals, colors*, *furniture*, *body parts*, *fruits*, *herbs*, *clothes*, *chemical elements*, *vegetables* and *tools*. We used the neural activation patterns that pertain to encoding and retrieval phases, to train and test the classifier.

The neuroimaging data underwent standard preprocessing stages before the pattern analysis step. Image processing and data analysis were performed using SPM5 (http://www.fil.ion.ucl.ac.uk/spm/). Following quality assurance procedures to assess outliers or artifacts in volume and slice-to-slice variance in the global signal, functional images were corrected for differences in slice acquisition timing by re-sampling all slices in time to match the first slice, followed by motion correction across all runs (using sinc interpolation). Functional data were then normalized based on MNI stereo-taxic space using a 12-parameter affine transformation along with a non-linear transformation using cosine basis functions. Images were re-sampled into 2-mm cubic voxels and then spatially smoothed with an 8-mm FWHM isotropic Gaussian kernel. Next, the functional data were detrended to account for baseline shifts across runs and for scanner drift across the entire session for the pattern analysis. Consistent with previous research, onsets were shifted forward by three points to account for the hemodynamic response lag [23].

B. Forming Local Meshes and Estimating Arc Weights

In this study, BOLD signals $v(t_i, \bar{s}_j)$ are measured at time instants t_i, $i = 1,2,3,\dots,N$, at voxel coordinates $\bar{s}_j$, $j = 1,2,3,\dots,M$, where N is the number of time samples, and M is the number of voxels.The data set $D = \{v(t_i, \bar{s}_j)\}$ consists of the voxels $v(t_i, \bar{s}_j)$, which are distributed in the brain in three dimensions. Therefore, the position $\bar{s}_j = (x_j, y_j, z_j)$ of a voxel $v(t_i, \bar{s}_j)$ at a time instant t_i can be represented as a 3-dimensional vector. At each time instant t_i, a participant is processing (either encoding or retrieving) a word belonging to a specific semantic category. Therefore, each sample $v(t_i, \bar{s}_j)$ has an object label at each time instance. The ten classes are modeled by making use of these local meshes for each individual voxel, called seed voxel $v(t_i, \bar{s}_j)$, which is defined in a neighborhood system η_p. In this mesh, a voxel $v(t_i, \bar{s}_j)$ is connected to p-nearest neighboring voxels $\{v(t_i, \bar{s}_k)\}_{k=1}^{p}$ by the arcs with weights $\{a_{i,j,k}\}_{k=1}^{p}$. Therefore, the relationship among the BOLD response measured at each voxel, are represented by the arc weights. p-nearest neighbors, η_p, are defined as the *spatially-nearest neighbors* to the seed voxel, where the distances between the voxels are computed using Euclidean distances between the spatial coordinates $\bar{s}_j$ of the voxels in brain (physical MNI coordinates obtained after preprocessing) [24]. The arc weights $a_{i,j,k}$ of the mesh are estimated by the following linear regression equation:

$$v(t_i, \bar{s}_j) = \sum_{\bar{s}_k \in \eta_p} a_{i,j,k}\, v(t_i, \bar{s}_k) + \varepsilon_{i,j}, \qquad (1)$$

where $\varepsilon_{i,j}$ indicates the error of voxel $v(t_i, \bar{s}_j)$ at time instant t_i, and $\eta_p(\bar{s}_j)$ is the set of p-nearest neighbors of the j^{th} voxel at $\bar{s}_j$. The arc weights $a_{i,j,k}$ are estimated by minimizing the squared error $\varepsilon_{i,j}{}^2$. This task is achieved by Levinson-Durbin recursion, given in [25]. The arc weights $a_{i,j,k}$, which are computed for each seed voxel at each time instant t_i, are used to form the mesh arc vector $\bar{a}_{i,j} = [a_{i,j,1} a_{i,j,2} \dots a_{i,j,p}]$. The arc vectors are employed for the construction of a Cognitive Process Graph (CPG) which is defined in the following section.

C. Forming the Cognitive Process Graph and Computing Minimum Spanning Trees

For an undirected weighted graph, a spanning tree is a connected sub-graph containing all of the nodes in the original graph with no cycles (see; Fig. 1). The spanning tree of a graph with the minimum total arc weights, is called Minimum Spanning Tree (MST). Thus, there is only one path connecting any two nodes of the MST and no two neighbors of a MST node can also be connected. Since human brain networks are shown to be cost effective [26], the MST can be considered as the backbone of the brain network under study. Secondly MST can be seen as a compact representation for the entire process resulting in a reduced dimension of feature vectors while preserving much of the network information. MSTs are widely used for assessing both in brain functional networks, resting-state default mode networks and disorder discovery in the literature [9], [10], [19], [27].

Cognitive state classification using fMRI data is a challenging task, due to the high dimensionality of the input feature space (between 8.000 and 80.000 dimensions) and small number of samples per class that are available. The problem gets even worse when the number of neighbors for a voxel (p) in the local mesh increases (e.g. 10 neighbors in a mesh for each voxel, with a total of 8.000 voxels results in an 80.000 dimensional feature vector). To overcome this problem, called the curse of dimensionality problem in the literature [28], the arc weights of local meshes are gathered under a graph called Cognitive Process Graph (CPG) to represent each class. Then, the MST of the CPG is extracted.

A CPG is an undirected graph, $G_i = (S, E_i)$, which represents a cognitive processat a time instant t_i, where the nodes of the graph, $\bar{s}_j \in S$, represent the voxel coordinates, and arc weights are defined as $\{a_{ijk}, a_{ikj}\} \in E_i$. The voxel positions do not change over time, thus, we dropped the time index i on the set of nodes S. Note that in this definition, there is a pair of arcs and their corresponding weights between two voxels, $\bar{s}_j \in \eta_p(\bar{s}_k)$ and $\bar{s}_k \in \eta_p(\bar{s}_j)$. The arc weights of the CPG are estimated for each local neighborhood of a seed voxel. Therefore, for a seed voxel at time instant t_i, p-number of nearest neighbors are used to estimate the arc weights $\bar{a}_{i,j} = \{a_{i,j,k}\}_{k=1}^{p}$, using (1).

The user defined neighborhood parameter (p) is bounded by adjacency of each voxel and can be taken as 6, 18 or 26. Note that in a regular grid over 3-dimensional space (suppose 1 unit of spacing), there exists 6 neighbors within 1 unit distance, 18 neighbors within ~1.5 unit distance and 26 neighbors within ~1.7 unit distance.

Computation of the MST of the CPG at each time instant t_i is straightforward after nodes and arc weights are defined. One minor detail is that, for each pair of adjacent voxels in a local neighborhood (e.g.at location $\bar{s}_j$ and $\bar{s}_k$) there are two arcs with different weights. One of them is defined between the seed voxel $\bar{s}_j$ and its surrounding voxel $\bar{s}_k$. The second one is defined between the seed voxel $\bar{s}_k$ and its surrounding voxel $\bar{s}_j$. The smaller arc weight is taken during the computation of MST, which approves the main intuition of the minimum spanning tree. We compute a set of MSTs $\{T_i\}_{i=1}^{N}$, for each time instant t_i, considering the arc weights $a_{i,j,k}$ estimated according to the number of adjacent voxels in the mesh with 6, 18 and 26 neighborhood. This procedure is conducted for both training and test feature sets. Resulting set of MSTs are then used to select final features for classification by only considering the arc weights which reside on the selected paths by MSTs. Fig. 1 shows a schematic illustration of the MST computed in a CPG over 6-neighborhood system.

III. Results

The goal of our MST-F model is to examine whether the MSTs employed on the CPGs could be used to accurately classify ten semantic categories, and compare it with classical MVPA methods [2] in which voxel intensity values are used as features in the classification.Our region of interest consists of the lateral temporal cortex of the brain. Results for the MST-F are generated using k-nearest neighbor (k-NN) and Support Vector Machine (SVM) methods. The k value of k-NN and kernel parameters of Gaussian Kernel in SVM classifier are selected using cross validation in training set. Cross validation ratio is selected as 20%-80% for *cross validation test* and *cross validation training* respectively by only using the training set. Classification accuracy is measured as the number of correctly predicted test samples over the number of total samples in the test set. MST of each CPG is computed by Kruskal's algorithm [29]. LIBSVM (http://www.csie.ntu.edu.tw/~cjlin/libsvm/) library is used for the implementation of SVM [30].

For assessing the power of MST-F in different size of neighborhoods, different sizes of meshes are formed and the arc weights are estimated accordingly. In other words, meshes are formed considering 6, 18 and 26 neighbors of a seed voxel, and then the corresponding MSTs are computed for each mesh.

TABLE I. Classification Accuracies for Each Method

Employed Method	***Number of Features***	**Classifier Accuracy**	
		k-NN	***SVM***
Classical MVPA Method*	8142	44.77%	39.75%
MST-F (6 neighbors)	8141	54.39%	58.16%
MST-F (18 neighbors)	8141	58.16%	59.83%
MST-F (26 neighbors)	8141	59.83%	61.09%

* Voxel intensities are directly fed to classifiers as features.

Classification performance using the proposed MST-F method and the MVPA method [2] are given in Table I. Classical MVPA method provides 45% and 40% classification accuracies in our 10-class classification task for k-NN and SVM, respectively. By employing MST along with CPG, we observe 10% and 18% improvement without increasing the dimension of feature space achieving classification accuracy up to 54% and 58% for k-NN and

SVM, respectively. We observe further performance gain as we increase the neighborhood size, since the region of voxels is expanded in order to obtain information from a larger number of voxels distributed in a wider region.

Moreover, it is well-known that SVM with Gaussian Kernel can perform classification in infinite dimensional spaces [30]. This property of SVM makes it less sensitive to the dimensionality problem than k-NN, resulting in a performance gain of greater magnitude than k-NN in the experiments in which MST-F is employed.

IV. Conclusions

In this study, we propose a graphical model called Cognitive Process Graph (CPG) which employs Minimum Spanning Trees (MST) in order to define local meshes to explore the relationships between the voxels and their p–nearest neighbors. In the current data set, the model has been tested during memory task and performed successfully.

In this study, we have only focused on modeling memory encoding and retrieval processes. Future research would bring additional insight into the generality of the success of the proposed algorithm for modeling cognitive processes. We hope to improve our algorithm by employing functional connectivity in the construction of the CPG and the computation of the MST.

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