SPM-based and ICA-based Approaches for
Functional Magnetic Resonance Imaging (fMRI)
Similarity Measures

Jinyan Guan
August, 2008
Abstract

I have been worked on two similarity measure techniques for fMRI images. One is SPM-based, which measure the similarity of Statistical Parametric Maps of the fMRI images, the other one is ICA-based, which measure the similarity of the voxels based on the Independent Component Analysis. In the SPM-based tool, I have implemented two image grouping techniques, graph-theory clustering and Replicator Dynamics, in order to group similar fMRI images. In ICA-based tool, I used bipartite graph matching to measure the similarity between fMRI images based on the similarities of the components.

1. Introduction

Functional Magnetic Resonance Imaging (fMRI) is a neuroimaging technique to monitor brain activities [1]. In an fMRI experiment, a subject is given different cognitive stimuli over different time periods. These different stimuli can produce different changes in the subject’s brain areas that response to the stimuli. The resulting fMRI signal is a ‘blood-level-oxygen-dependent’ (BLOD) signal that can detects the changes in the brain [1]. In principle, one can surf through each region in the brain to extract the time courses that look interesting in order to analysis fMRI data. However, this is not practical since there are thousands of voxels in each brain and the decision of whether a voxel is active or not is very subjective. Therefore, different statistical tools have been used to analyze fMRI images. In this paper, two popular fMRI analysis techniques, Statistical Parametric Mapping (SPM) and Independent Component Analysis (ICA), will be discussed on their applications on similarity measures of fMRI images. Specifically, SPM has been used to measure the similarity of the whole brain while ICA has been used to measure voxel similarity and investigate the functional networks of the brain.

1.1 Statistical Parametric Mapping (SPM)

Statistical Parameter Mapping is a voxel based neuroimage analysis technique using General Linear Model (GLM) and Gaussian Random field (GRF) to test hypotheses about regionally specific effects. It is the most prevalent approach to characterizing functional anatomy and disease-related changes in the brain. GLM can predict multiple dependent variables by allowing determination of multiple parameters. A design matrix, a parameter matrix and an error matrix are used in GLM. The design matrix contains the information about the designed aspects of the experiment which may explain the observed data. Minimizing the sum of differences between the modeled and observed data allows determination of the optimal parameters for the model. The parameters can be utilized to construct t- and t-tests to determine the significance of contrasts between experimental factors. The resulting statistical parametric maps (t-maps and f-maps) that contain thousands of voxels then be transformed to a GRF based on a null hypothesis no voxel is active for the experimental conditions. The GRF theory provides a way of adjusting the p-value based on the fact that neighbouring voxels are not independent by virtue of continuity in the original data. [2]

A similarity retrieval system using SPM was developed by Tungaraza [3]. Given a query fMRI image, this system tends to retrieve fMRI images that have similar activation patterns as the query image from the database. For each retrieved fMRI image, the system provides a numeric score to represent how similar the retrieved images to the query image. The goal of this system is to assist the brain researchers to analysis the brain activities of different people by retrieving similar fMRI images. For example, given an fMRI image of an abnormal brain, this system should retrieve fMRI images of the brains that have similar diseases as the query brain. In order to improve this system, I have worked on several tasks that related to the system. Firstly, in order to group similar fMRI images together, graph-theory clustering [4]
and Replicator Dynamic [5] are applied to the retrieval results. Secondly, Multidimensional Scaling (MDS) technique [6] is used to represent the similarity structures among the retrieved images. Furthermore, a visualization displaying of the feature properties of the query image and the retrieved images is created.

1.2 Independent Component Analysis (ICA)

Independent Component Analysis is a technique to extract spatially independent components of the observed data. It can be used to reliably separate fMRI data sets into meaningful constituent components, including task-related physiological changes, nontask-related physiological phenomena, and machine or movement artifacts. Each component consists of voxel values at fixed three-dimensional locations and a unique associated time course of activation. Unlike SPM technique, ICA doesn’t rely on priori hypothesis of the experimental context. Therefore, it can detect activations that could not be predicted in advance of the experiment. [7]

Based on the properties of ICA, Rolfe developed an ICA-based tool to explore the functional connections of the brain [8]. This tool is useful to analyze the fMRI scans from patients with autism since ICA is highly promising for investigating patients with pathological conditions that may alter the latencies, amplitudes, and brain distributions of their fMRI signals in unpredictable ways. This tool can allow the user to explore regions of similar activation within and across patients and to compare these with SMP generated statistically significant activations. It would be interesting to compare the ICA-based method with the SPM-based method on their performances of retrieving similar fMRI images. Since the ICA-based tool can only measure the similarity between the independent components, a way to measure the similarity between the fMRI images using the components similarity is needed. The bipartite graph matching technique has been used to fulfill this goal by finding the minimum-weighted matching between two fMRI images [10].

2. Methodology:

2.1 SPM-based Similarity Retrieval System:

In SPM-based approach, before applying statistical analysis for fMRI, the raw fMRI data need to go through a series of preprocessing, including motion correction, slice-time correction, coregistration, normalization, and smoothing [1]. The statistical maps (t-maps and f-maps) that generated from the experimental hypothesis are used in the SPM-based similarity retrieval system. To determine which voxels are active, a False Discovery Rate (FDR) threshold is applied to these statistical parameter maps to create spatial maps. Then six feature properties are extracted from each spatially distinct region (cluster) in each spatial map to form feature vectors:

1. The cluster centroid \((x, y, z)\).
2. The size of the cluster relatively to the brain.
3. The average of the activation values in the cluster.
4. The variance of the activation values in the cluster.
5. The average of the distances from each voxel to the cluster center.
6. The variance of the distance from each voxel to the cluster center.

Given a query fMRI image \(Q\), to find the similar fMRI images in the database, the similarity scores between \(Q\) and each image in the database is calculated using the Euclidean distance between the region
centers. For each feature vector \( v_i \) in \( Q \) there exists a minimum Euclidean distance \( \text{minDist}_{Q \rightarrow T} \) to the feature vectors in the target fMRI image \( T \). The similarity score is calculated using the following equation:

\[
\text{Score}_{QT} = \frac{\sum_{i=1}^{n} \text{minDist}_{Q \rightarrow T} + \sum_{i=1}^{m} \text{minDist}_{T \rightarrow Q}}{2}
\]

Figure 1 shows the steps in this SPM-based similarity retrieval system.

\[\text{Fig. 1 SPM-based approach for similarity measure between brains}\]

2.1.1 Grouping Similar fMRI Images

Most retrieval systems only retrieve the images that are close to query image because similar images are assumed to be close to each in the feature space. However, none of the existing feature extraction algorithms always map similar images to nearby locations in the feature space. [4] In order to increase the retrieve performance, graph-theory clustering and Replicator Dynamics techniques have been used to group similar fMRI images together [4] [5].

a. Graph-theory Clustering

The graphic-theory clustering has been used to increase the chance of retrieving similar images by adding a constraint that the retrieved images should be close to each other in the feature space [4]. The retrieval algorithm in [4] is described as following:

Step1: Use each image as a query to retrieve the best \( N \) matches from the database.

Step2: Construct a corresponding graph \( G \) by using every image in the database as the nodes. The edges can be drawn from each query image to each of its retrieved images. The similarity scores are assigned to the weights of the corresponding edges.

Each resulting cluster should contain images that are similar to each other in the feature space. Due to the complexity of the images content, some images may be grouped into multiple clusters. For each query, the clusters that contain the query image will be returned as the retrieval result. If more than one such cluster exists, the cluster that has the largest number of the nodes will be chosen. If more than one cluster has the largest number of nodes, the cluster with the minimum total weights will be returned as the result.

b. Replicator Dynamics

Replicator Dynamic has been used by Lohmann and Bohn as an approach to modeling and detecting functionally coherent networks in the human brain [5]. This approach is based on a well-known concept of theoretical biology called ‘replicator equations’. Replicator Dynamic describes the growth of population consisting of several species that interact with each other [14]. Each element in the detected network must be close to as many as other elements as possible. In other words, all members that belong to the same network are coherent with each other. In [5], the pairwise similarity between the time courses of any two voxels $i, j$ in the brain is used to create a similarity matrix $W = (w_{ij})$. This matrix is used to detect the coherent networks of voxels by iteratively applying the following dynamic equation:

$$x_i(t + 1) = x_i(t) \frac{(Wx(t))_i}{x(t)^T W x(t)}$$

The vector $x$ that maximizes $x^T W x$ contains the members in the detected coherent network with the constraint $x_i \in [0, 1]$ and $\|x\| = 1$. Initially, all values in $x$ are set to be $1/n$, where $n$ is the number of items in $x$. In order to use Replicator Dynamic to find coherent subgroups among different fMRI images, the similarity scores of different fMRI images has been used to create the similarity matrix $W$. Different from the graph-theory clustering approach, there is no overlapping between any two of the resulting networks, because once a network has been detected all the nodes in the detected networks will be removed from the system and another networks will be found by applying the replicator dynamics to the remaining nodes. For each query, the network that contains the query image will be returned as the retrieval result.

2.1.2 Exploring Similarity Structures among the Retrieval Images Using Multidimensional Scaling

Multidimensional Scaling (MDS) is a technique to transform the proximity structure of a set of objects to a low-dimensional space. For example, given a pair wise similarity matrix of a group of objects, MDS can create a two-dimensional spatial map, consisting geometric configuration of points. Each point corresponds to one of the subjects and geometric locations of the points can reflect ‘hidden structure’ of the subjects. The smaller the similarity between the subjects, the further apart they are placed on the map and vice versa. [6]

Currently, the system provides a numerical score for each retrieved image to represent how similar they are to the query image. The retrieved images are ranked from the most similar to the least similar based on these similarity scores. However, the users may be also interested in how similar the
retrieved images are to each other in order to find interesting fMRI images. Therefore, MDS can be used to represent the similarity structure among the retrieved images.

2.1.3 Displaying Feature Properties

As addressed at the beginning of this section, six feature properties are extracted from each spatially distinct region. In order to provide the details of the feature property to the user, the clusters that extracted from an fMRI image are plotted in a three dimensional space that represents the human brain. For comparison, the feature properties of two fMRI images are displayed side by side on the screen. The corresponding clusters are coded in the same color so that the users are able to see how the clusters match between the selected two brains.

2.2 ICA-based Brain Functional Connections Exploring System

In ICA-based approach, spatially independent components are extracted from the fMRI scans using fastICA [9]. The number of the components equals to the number of the scans. Each component is an independent voxel map that associates with a unique time-course. A threshold is applied to these independent voxel maps in order to find the spatially distinct regions (clusters). Voxels whose activation values are great enough are considered to be active and are assigned a value of one and the others are set to be zeros. Based on the assumption that an activated voxel is more likely to be signification when its neighbors are also activated, each activated voxel $x_i$ is weighted by the number of its activated neighboring voxels: $x_i = e^n$, where $n$ is the number of the neighboring voxels activated. After the clustering, the location of the activation clusters can be found by a modified k-means algorithm. In this modified k-means clustering, the contribution of each point to the mean to be used to find the new bin location is dependent on the weight $x_i$ at that location. Five feature properties are extracted from each activation cluster after the clusters are located:

1. Location of the bin center.
2. Number of activation locations in bin
3. Average distance from bin center
4. Average bin weight
5. Weighted variance of distances. This ensures that the locations with larger weights contribute more to the variance.

After the feature vectors extraction, in order to avoid the domination of any feature in the calculation of the difference, each feature is weighted by:

$$w_k = \frac{1}{F_k} \cdot \text{std} \left( \frac{F_k}{F_k} \right)$$

Where $w_k$ is the calculated weight for feature $k$, and $F_k$ is the set of all values for feature $k$. The similarity between two spatial maps is defined by the locations and characteristics of their activated voxel clusters. For each activation spatial map $i$ to a second activation map $j$, if the minimum distance between each cluster $k$ in activation map $i$ and each cluster $n$ in activation map $j$ is less than a threshold value, cluster $k$ is determined to have a match in activation map $j$. The total quality of this match is given by:
\[ m_{ij} = \text{abs}(n_i - n_j) \sum_k d_{ik} \times \frac{1}{\text{binsize}_k} \times \frac{1}{\text{averagebinweight}_k} \]

Where \( n_i \) is the number of clusters in activation map \( i \). The similarity score between spatial activation map \( i \) and spatial activation map \( j \) can be determined by:

\[ \text{Score}_{ij} = \frac{m_{ij} + m_{ji}}{2} \]

Where \( m_{ji} \) is calculated by the same method of calculating \( m_{ij} \). Figure 2 shows the steps in ICA-based approach.

![ICA-based approach for similarity measure between components](image)

2.2.1 Brain Similarity Measures using bipartite graph matching

Bipartite graph matching technique is used to measure the similarity between two fMRI images based on the similarity between their spatially independent components [10]. As Figure 3 (a) shows, given a bipartite graph \( \Gamma \) with two parts \( S_1 \) and \( S_2 \), weight \( c_{ij} \) is defined as the cost between a node \( i \) in \( S_1 \) and a node \( j \) in \( S_2 \). An optimal assignment between \( S_1 \) and \( S_2 \) is the matching that has the minimum total cost. Two fMRI images can form a bipartite graph and each component can be treated as the nodes. Then the minimum total cost of this bipartite graph is considered as the similarity score between these two fMRI images. Figure 3 (b) shows the basic scenario of applying bipartite graph matching to ICA components.
3 Implementation and results

3.1 SPM-based similarity retrieval system

The fMRI images used in the SPM-based image retrieval system is gathered from four cognitive experiments. Table 1 shows the description of the experiments. [3]

<table>
<thead>
<tr>
<th>Experiment</th>
<th>Cognitive Process</th>
</tr>
</thead>
<tbody>
<tr>
<td>Auditory Oddball (AOD) (15 subjects)</td>
<td>Recognize a new tone Vs. Recognize the same repeating tone</td>
</tr>
<tr>
<td>Sternberg Working Memeory (Sternberg) (15 subjects)</td>
<td>Recognize memorized alphabets Vs. Recognize non-memorized alphabets</td>
</tr>
<tr>
<td>Face Recognition (Checkerborad) (12 subjects)</td>
<td>Recognize human faces Vs. Recognize a black &amp; white checkerboard</td>
</tr>
<tr>
<td>Face Recognition (Central-Cross) (24 subjects)</td>
<td>Recognize human face Vs. Recognize a black cross at the center of a white background</td>
</tr>
</tbody>
</table>

Table 1 Description of Experiments

3.1.1 Grouping Similar fMRI Images

a. Graph-theory Clustering

After applying graph-theory clustering to our fMRI image database, images are grouped into different clusters based on some user-defined parameters. MDS is used to represent the similarity structures among the grouped images. Images that are in the same cluster are displayed in the same symbol using same color. Figure 4 (a) shows the similarity structures of the fMRI images from four different experiments. Figure 4 (b) shows the similarity structures of the grouped fMRI images. We can
see images that from the same experiment are grouped together. However, some images are not grouped into any clusters due to restraint of the dense regions [11].

![Fig. 4](image1.png)

(a) Similarity Structures of fMRI images from four experiments. (b) Subgroups of the fMRI images identified by the graph-theory clustering technique

b. Replicator Dynamics

After applying Replicator Dynamics to the fMRI database, several coherent networks are detected. From figure 5, we can see that images that are in the same coherent network are similar to each other in the feature space.

![Fig. 5](image2.png)

Fig. 5 Subgroups identified using the Replicator Dynamics.

3.1.2 Similarity Structures of the Retrieval images using MDS

Figure 6 is the interface of the retrieval results. The retrieval images are displayed on the left box based on the rankings of their similarity scores. The right part shows the configuration map of the
retrieved images using MDS technique. From this configuration map, the users can easily tell the similarities among the retrieval images. For this specific example, when an fMRI image from Sternberg experiment is used as a query image, images from three experiments (Sternberg Working Memory, Face Recognition and Auditory Oddball) are retrieved. On the configuration map, images that are in the same experiment are placed close to each other because their activation patterns are more similar.

![Similarity structures among the retrieved images are represented using MDS](image)

**Fig. 6** Similarity structures among the retrieved images are represented using MDS

### 3.1.3 Feature Property Display

Figure 7 shows the interface of the feature property displaying. The left part is a visualization displaying of the feature properties of the selected fMRI images. The cube represents the human brain and the dots represent the activated clusters. The matched clusters in these two fMRI images are coded in the same color while the unmatched clusters are displayed in black. For each cluster \( i \) on the left fMRI image, its matching cluster on the right fMRI is the one that has the minimum Euclidean distance to \( i \). We provide an option to switch the left and right images to view the new matching results. On the right part of this interface, the users can select a specific cluster and view the details of its feature properties.
3.2 Comparison between SPM-based and ICA-based Approach for Brain Similarity Measures

We used the fMRI images from the same experiment to compare the similarity measures of SPM-based approach and ICA-based approach. During the experiment, the subjects were assigned different visual stimuli at different time period. These visual stimuli are: human face, house, and a black cross on a white board background. SPM T-maps that contain two cognitive tasks, which are looking at human face and looking at a black cross, are used for the SPM-based similarity measure while ICA-based approach used the entire fMRI scans that have all three cognitive tasks. In these two approaches, each fMRI images are used as a query to get a similarity score between each other images in the database. The similarity matrix generated by SPM-based approach is $M_1$ while the similarity matrix generated by ICA-based approach is $M_2$. We compute the correlation coefficient between $M_1$ and $M_2$ and get the result of 0.5227, which is a large correlation. This is quite reasonable since the ‘house’, the cognitive stimulus that is not considered in the SPM T-maps, is very similar to the ‘face’ cognitive stimulus. Therefore, the fMRI images for looking at faces may have similar activation patterns as looking at houses. MDS is used again to explore the similarity structures that are defined by these two methods. From Figure 7, we can see that image 1 has the largest dissimilarity to the other images both in SPM-based approach and ICA-based approach. However, the similarities of other images are quite different in these two methods.
4. Conclusion and Future Work

Graph-theory clustering and Replicator Dynamics have been used to group similar images in SPM-based similarity measure for fMRI images. The results show that similar images can be grouped together; however, the retrieval results of using Graph-theory clustering and Replicator Dynamics are need to be evaluated in order to test whether they can increase the retrieval performance. In ICA-based approach, we have used bipartite graph matching technique to get a similarity score between two fMRI images using the similarities of their independent components. The similarity matrixes that generated from SPM-based approach and ICA-based approach have a high correlation of 0.5227; however, the similarities among individual fMRI images are quite different. In order to test whether bipartite graph matching is a solid method to measure the similarity between fMRI images in ICA-approach, we need to apply this method on a larger fMRI database, which comes from different experiment, to see whether it can retrieve fMRI images from the same experiment as the query image. Furthermore, other similarity measurement of the brain, such as clinical data, needs to be included in order to test the retrieval results.

5. Acknowledgement

I would like to thank Dr. Linda Shapiro for her support on this ten-week research project. I would also like to thank Rosalia Tungaraza, Sara Rolfe and Laura Finney for helping me understand the SPM-based tool and ICA-based tool. This research is supported by the Committee on the Status of Women in Computing Research’s Distributed Mentor Project.
Reference:


