Spatial Fuzzy Clustering of fMRI SPMs Using MRF's

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INTRODUCTION

The most widely used method for analysis of an fMRI statistical parameter map (SPM) is either voxel-wise thresholding or context-free clustering. However, the low SNR of the data greatly challenges these conventional methods. In order to be more robust to noise, we present a spatial fuzzy clustering algorithm (SFC) via Markov Random Fields (MRF's) [1]for detecting activation regions in fMRI SPMs. SFC is a generalized version of the spatial-spectral fuzzy c-means method, which was first implemented in [2] to produce thematic maps from remotely sensed multispectral imagery. In the paper, we consider an fMRI SPM as an MRF and a fuzzy neighborhood energy function is defined to describe the interaction between neighboring voxels; the final result is determined by a joint fuzzy membership. Validation experiments are conducted based on both synthetic and real fMRI data. The results show that SFC outperforms both voxel-wise thresholding and general fuzzy clustering in reducing false positives, localizing the activations and preserving extremely small size activation regions.

THEORY AND METHODS

Let $I = i_1, i_2, \ldots, i_N$ be the set of voxels in an SPM map, and s_i, $i \in I$ be the corresponding statistical value. The aim of SFC is to detect different activation regions in SPM, say ω_j, $j = 1, \ldots, m$. Denote the representative parameter of the ω_j as θ_j, the dissimilarity between θ_j and s_i as $d(s_i, \theta_j)$, and P, P_{spat} and P^* as a non-spatial, spatial and joint membership matrix, respectively. The (i,j) element of each matrix is $P(\omega_j \mid s_i)$, $P_{spat}(\omega_j \mid s_i)$ and P_{ij}^*, respectively. In a general fuzzy algorithm, P is defined as $p(\omega_j \mid s_i) = (1/d(s_i, \theta_j))^{1/(q-1)} / \sum_{k=1:m} (1/d(s_i, \theta_j))^{1/(q-1)}$, where q is called the *fuzzifier* The local spatial interactions between neighboring voxels are described via MRF's. The fuzzy energy function is defined as: $U(\omega_j \mid s_i) = \sum_{si' \in \eta si} [1 - p(\omega_j \mid s_i)]$ where η_{si} is the neighborhood of s_i and then the spatial membership is $p_{spat}(\omega_j \mid s_i) = \exp(-\beta U(\omega_j \mid s_i)) / Z$ and $\sum_{j=1:m} p_{spat}(\omega_j \mid s_i) = 1$, where Z is a scale parameter and β is a positive value to weight the influence of the spatial context. Finally, the joint statistical-spatial membership is defined as $P_{ij}^* = p(\omega_j \mid s_i) \cdot p_{spat}(\omega_j \mid s_i) / \sum_{j'=1:m} p(\omega_{j'} \mid s_i) \cdot p_{spat}(\omega_{j'} \mid s_i)$ and $\sum_{j=1:m} p_{ij}^* = 1$.

The generalized spatial fuzzy clustering scheme can be implemented as follows: 1) choose $\theta_j^{(0)}$ and compute $p^{(0)}(\omega_j \mid s_i)$; 2) set $l = 1$; 3) Repeat: compute $p_{spat}^{(l)}(\omega_j \mid s_i)$ and $p^{(l)}(\omega_j \mid s_i)$ based on $p^{(l-1)}(\omega_j \mid s_i)$ and $\theta_j^{(l-1)}$, respectively; compute $p_{ij}^{(l)*}$; update $p^{(l)}(\omega_j \mid s_i)$ by assigning $p_{ij}^{(l)*}$ to it; update $\theta_j^{(l)}$); increment l by 1, until termination criterion is met. Obviously, the definition of $d(s_i, \theta_j) = \| s_i - \theta_j \|^2$ will lead general SFC to a spatial fuzzy c-means approach, where θ_j is the cluster center. Note that an alternative way to obtain initial $p^{(0)}(\omega_j \mid s_i)$ is to run any known fuzzy clustering method completely at very first step. In this way, local optimum clustering without spatial regularization has been achieved, and then the spatial component is used for fine tuning the result. Since we expect highly compact clusters in fMRI SPMs, we utilized either Expectation Maximization (EM) or fuzzy c-means algorithms to obtain the initial clustering in the paper. In fact, after local optimum clustering was obtained, each primary cluster could reasonably be represented by a point parameter, which could simply be the mean of the cluster. Eight nearest neighbors were used for computing local energy.

RESULTS AND DISCUSSIONS

We define the contrast-to-noise ratio (CNR) as the ratio of mean interclass contrast to the standard deviation of the noise. The improvement of SFC over EM algorithm is shown in Fig.1. We find that the non-spatial EM algorithm fails in the images with very low quality - CNRs of 1.0 and 1.25. The noise dominates the whole images such that the objects (activated regions) are almost lost in the noise; although the objects are detected in the image with CNR 3.33, they are not smoothed and contain many holes (false nonactivates). On the contrary, the SFC clustering successfully detected the objects. It is not as sensitive to noise as non-spatial EM. In addition, the real fMRI data were used for the verification as shown in Fig.2. Imaging was performed on a 3T whole-body scanner Trio (Siemens Medical Systems) using an echo-planar (EPI) sequence. From Fig.2, we observe that the SFC clearly and focally detected bilateral activations in both the optical gyrus and the motor cortex, which corresponded to the visual stimulus and motor task presented to and performed by subjects. In comparison with the conventional non-spatial fuzzy c-means and voxel-wise thresholding with p-value of 0.05, SFC effectively reduced false positive rate and was robust to noise; while in comparison with the voxel-wise thresholding with p-value of 0.01, SFC detected more realistic activity patterns by adding the spatial regularization and successfully retained extremely small area activations. In summary, we extend the idea from [2] to a general SFC framework and implemented it in detecting brain activation regions in fMRI SPMs. Theoretically, any conventional fuzzy clustering method could be embedded into the framework, at least for obtaining initial clustering. The experimental results indicate that the SFC is superior to either voxel-wise thresholding or context-free fuzzy clustering. The incorporated spatial information improved the performance of the clustering in reducing the false positives and localizing the activations and preserving extremely small size activation regions.

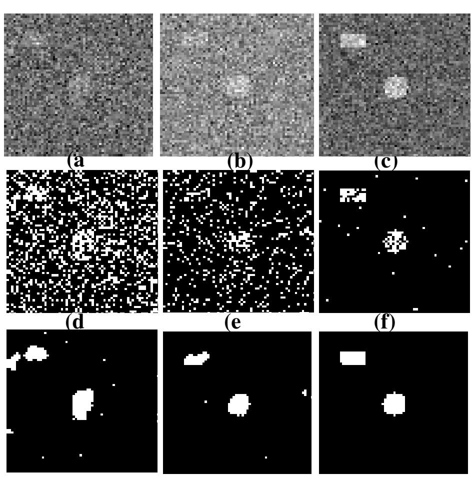

Fig1. Clustering results of EM and SFC**.** Gaussian noises with zero mean and different standard deviations were added to a binary to generate images (a),(b) and (c), with CNR of 1.0,1.25 and 3.33, respectively; (d)-(f) are the results of EM clustering of (a)-(c); and (g)-(i) are the results of SFC, correspondingly.

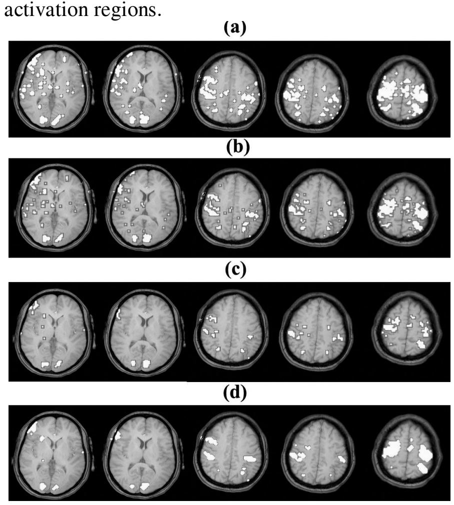

Fig.2. Brain activation regions detected by (a) non-spatial fuzzy c-means; (b) voxel-wise thresholding with p-value of 0.05; (c)voxel-wise thresholding with p-value of 0.01; (d) SFC.

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