Spatially Adaptive Kernels for Adaptive Spatial Filtering of fMRI Data

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***Abstract*— Making use of neighborhood time series is an effective way of noise reduction in fMRI data. However the conventional averaging methods blur activated areas. In this paper, a filter with adaptive kernel is designed such that its kernel size and direction are defined at each voxel. First, for finding the optimum size of kernel, a linear combination of some isotropic Gaussian filters with different variances is used, and optimum value of variance is specified. Then, the appropriate kernel direction is determined by a linear combination of some anisotropic basic filters with various directions. The weights of these linear combinations can be calculated by using the restricted canonical correlation method. The proposed method is compared with a similar method based on the steerable filters ([7]) and the results show that the proposed method improves the ROC curve and prohibits false spread of the activation areas.**

***Index Terms*— fMRI- Averaging models- isotropic filters- ROC- steerable filters.**

I. Introduction

Functional Magnetic Resonance Imaging uses the BOLD (Blood Oxygenation Level-Dependent) effect for localizing activated brain areas.

To reach this end, some statistical analysis must be performed on MRI images acquired during a cognitive task. T-test and cross-correlation analysis are two conventional detection methods [1]. In T-test, while the noise is assumed to be white and Gaussian it may not be white and Gaussian generally [2]. Moreover, these methods use each voxel's signal separately and ignore spatial correlation of data. Several researches were reported in which spatial information of data were taken into account.

Friman *et al.* [3] proposed a method based on canonical correlation that maximizes the cross-correlation between a linear combination of time series of a neighborhood and a linear combination of a signal subspace bases.

Freeman *et al.* proposed a method for designing arbitrary orientation filters from linear combinations of some basic filters. These basic filters are made by rotating a main filter to different angles. In this manner, they made a *steerable* filter [4].

Sole *et al.* proposed a method which progressively enhances the temporal signal by means of adaptive anisotropic spatial averaging. This averaging is based on a new metric for measuring the similarity of signals corresponding to various voxels [5].

Hossein-Zadeh *et al.* proposed a method that maximizes a test statistic, designed to indicate the presence of activation. This statistic is the ratio of the filtered time series energy in a *signal subspace* to the energy of the residuals. This approach equates the spatial filter coefficients to the elements of an eigenvector corresponding to the largest eigenvalue of a specific matrix, while the largest eigenvalue itself becomes the maximum energy ratio. The distribution of this statistic under the null hypothesis is derived by a nonparametric permutation technique in the wavelet domain [6].

Also Friman *et al.* used the linear combination of an isotropic Gaussian filter and three anisotropic Gaussian filters to produce an optimum spatial filter. To make the designed filter steerable, two of the anisotropic filters are rotated 60 and 120 degrees, respectively. The variance of the initial Gaussian filter is assumed to be constant for all voxels. Also, a linear combination of signal subspace bases is used as the reference signal for activation detection. Finally the cross-correlation between these two linear combinations is maximized by restricted canonical correlation method [7]. A limitation of this method is its assumption for the variance of main Gaussian filter. Because the variance is assumed to be constant for all voxels, the size of the filter can not change according to each voxel's signal. This may cause false spread of the active regions to the surrounding inactive voxels.

In this paper, we are going to design a filter with adaptive size and direction, for each voxel to produce maximum correlation between a linear combination of the filtered signals of the neighbor voxels and the stimulation pattern of activation. This increases the signal content and reduces the noise at each voxel. Therefore, the signal to noise and the performance of activation detection will be improved without false spread of the activation area.

In our proposed method, first the optimum variance for the initial Gaussian filter in [7] was determined automatically. So, the mentioned limitation in [7] will be

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avoided. Then the Taylor expansion was used to make the filter steerable. In this manner, the spatial filter will be able to change in size and direction according to the size of the activation area and also the active voxel's signal can not affect the neighboring inactive voxels.

II. THEORY

As mentioned previously, the goal of this paper is to design a filter that its size and direction can be changed according to the spatial contents of data, and with the aim of enhancing the performance of activation detection.

A 2D isotropic Gaussian filter and some 2D anisotropic Gaussian filters are considered. The different anisotropic filters are made by rotating a specific anisotropic filter to different angles, via;

$$\begin{cases} x_p = x.Cos(\alpha) - y.Sin(\alpha) \\ y_p = x.Sin(\alpha) + y.Cos(\alpha) \end{cases} \tag{1}$$

$$f_{aniso}(x, y; \sigma_x, \sigma_y, \alpha) = \frac{e^{-\frac{1}{2}.(\frac{x_p^2}{\sigma_x^2} + \frac{y_p^2}{\sigma_y^2})}}{\sqrt{2\pi.\sigma_x^2.\sigma_y^2}} \tag{2}$$

$$f_{iso}(x, y; \sigma) = \frac{e^{-\frac{1}{2}.(\frac{x^2 + y^2}{\sigma^2})}}{\sqrt{2\pi}.\sigma^2} \tag{3}$$

Where $f_{aniso}(x, y; \sigma_x, \sigma_y, \alpha)$ defines the anisotropic filter and $f_{iso}(x, y; \sigma)$ defines the isotropic filter, also α is the rotation angle.

Now a linear combination of one isotropic filter and N-1 anisotropic filters is made as the following:

$$f(x, y) = w_1 f_{iso}(x, y; \sigma) + \sum_{i=2}^{N} w_i f_{aniso}(x, y; \sigma_x^i, \sigma_y^i, \alpha_i) \tag{4}$$

The observed data can be filtered by this filter via:

$$f(x, y) ** I(x, y, t) = w_1 (f_{iso}(x, y; \sigma) ** I(x, y; t)) + \sum_{i=2}^{N} w_i (f_{aniso}(x, y; \sigma_x^i, \sigma_y^i, \alpha_i) ** I(x, y; t)) = W_x.X \tag{5}$$

Where I(x, y, t) is the observed signal and X defines a matrix containing the filtered signals.

According to the recent equation, the data can first be filtered using each base filter (isotropic and anisotropic filters) and then the desired linear combination can be made using these filtered signals. Optimum values of weights w_i will be derived later by CCA.

Suppose that a set of temporal bases for fMRI signal (signal subspace) are put in the rows of matrix Y. Friman *et al.* in [7] proposed a method based on PCA for deriving these bases. Now the unknown weight vectors W_x and W_y must be derived such that they are positive and the linear combination of the filtered signals has maximum correlation with a linear combination of temporal bases in Y.

The correlation coefficient between $W_x X$ and $W_y Y$ is calculated as the following:

$$\rho = \frac{W_x.C_{xy}.W_y^T}{\sqrt{W_x.C_{xx}.W_x^T W_y.C_{yy}.W_y^T}} \tag{6}$$

Also to ensure that the unknown weight vectors W_x and W_y are positive, restricted canonical correlation method must be used [8]. Thus, for each voxel we are going to find unknown parameters $\sigma, \sigma_x^i, \sigma_y^i, \alpha_i$, which maximize ρ :

$$\underset{\sigma, \sigma_x^i, \sigma_y^i, \alpha_i}{Max} \quad \rho(\sigma, \sigma_x^i, \sigma_y^i, \alpha_i) \tag{7}$$

As can be inferred, the parameters (isotropic filter's variance and the variances and orientations of the anisotropic filters) must be adjusted in such a way that is able to maximize the correlation coefficient.

Regarding many parameters in the above problem, the numerical optimization will be very time consuming. To overcome this, we first find the optimum variance (σ), and then we find the rest of remaining parameters in another procedure.

A. Deriving the optimum values for σ_i 's

In the first step, the kernels of M different Gaussian spatial filters with M different variances are built as the following:

$$f_{iso}(x, y; \sigma_i) = \frac{e^{-\frac{1}{2}.(\frac{x^2 + y^2}{\sigma_i^2})}}{\sqrt{2\pi}.\sigma_i^2} \tag{8}$$

$$i = 1, \ldots, M; \sigma_1^2 = 0.1; \sigma_2^2 = 1; \ldots; \sigma_M^2 = M - 1$$

The linear combination of the filtered data can be obtained as the following:

$$f(x,y)=\sum_{i=1}^{M} w_i f_{iso}(x,y;\sigma_i)$$
$$f(x,y)**I(x,y)=$$
$$\sum_{i=1}^{M} w_i.(f_{iso}(x,y;\sigma_i)**I(x,y,t))=W_x X \qquad (9)$$

Now the maximum correlation coefficient between $W_x X$ and $W_y Y$, and also W_x and W_y are calculated using the restricted canonical correlation method. Then the filter that has the largest coefficient in W_x is selected as the initial isotropic filter and its variance is considered as σ^2 (in Eq. (7)). This isotropic Gaussian filter is known as *the initial filter*.

B. Definition of the anisotropic filters

The second step, based on the method proposed in [7], makes the filter steerable. First, three weight filters are built from the initial isotropic filter, an isotropic $h_{iso}(x,y)$ and two anisotropic $h_i(x,y), i=1,2$. These weight filters are used to build the final isotropic and anisotropic filters by multiplying them with the initial isotropic filter (Eq. (12)).

$h_{iso}(x,y)$ has a similar shape to the initial filter and its variance is:

$$\sigma^2_{h_{iso}}=K.\sigma^2_{f_M} \quad ; \ 0<K<1 \qquad (10)$$

Where f_M denotes the initial isotropic filter and K is the magnitude coefficient. The effect of choosing K on activation detection will be discussed later. To compensate the changes in the variance around its initial value, the Taylor expansion of $h_{iso}(x,y)$ around this initial variance is constructed.

To reduce the number of parameters in Eq. (7), two oriented filters are used, and their orientation is considered to be fixed. In this article two anisotropic filters are rotated 45 and 135 degrees with respect to X axis. So, these two anisotropic filters can be defined as:

$$x_p=x.Cos(\alpha)-y.Sin(\alpha); y_p=x.Sin(\alpha)+y.Cos(\alpha);$$
$$\alpha=45^\circ,135^\circ;$$
$$h_i(x,y;\sigma^2)=(x_p+y_p)^2.\frac{\partial h_{iso}(x_p,y_p;\sigma^2)}{\partial\sigma^2} \qquad (11)$$

Finally the basic spatial filters can be defined as the following,

$$f_{iso}(x,y)=h_{iso}(x,y;\sigma^2).f_M(x,y)$$
$$f_i(x,y)=h_i(x,y;\sigma^2).f_M(x,y), \ i=1,2 \qquad (12)$$

Where $f_i(x,y)$ defines the anisotropic filter. Now the linear combination of these three basic filters can make a spatial filter that is steerable and can change around the optimum variance.

To accelerate the activation detection algorithm, some preprocessing operations must be performed to reduce the number of voxels that must be processed. Intracerebral voxels are separated using a mask. Then correlation coefficient between each voxel and the stimulation pattern is calculated separately and then the voxels with the correlation coefficients higher than a predefined threshold are selected. The threshold must be such that all active voxels determined as active. In other words, this threshold must be considered relatively low. In our experiments this threshold is equaled to 0.1.

C. Experimental and simulated data

Simulated data are used for evaluating the proposed method including two kinds of block design and event related data. To reach this goal, a series of fMRI data are acquired from a subject using a 1.5-Tesla scanner in resting-state. Data corresponding to a slice (with FOV=64×64) in 252 different times are extracted and the simulated activation signal is added to the predefined locations as shown in Fig.1. The stimulation pattern was selected as a boxcar function with five 150 s periods. Each period consisted of 60 s of ON condition followed by 90 s of OFF or baseline condition.

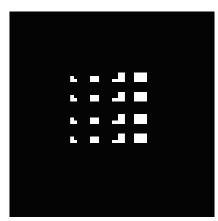

Fig.1. Spatial pattern of activation in the simulated dataset.

In the other set of data, the activation signals are simulated for an event-related pattern activation including 44 stimulation pulse which lies between scans 0 and 252 randomly.
Experimental fMRI data analyzed in this article are acquired from a healthy volunteer using a 1.5-tesla scanner. Two different kinds of pictures are shown to the subject. The subject must click the mouse button for specific kind of pictures. These data include 16 slices of size 64×64 and are gathered for 124 different times (with TR=2.68s).

III. RESULTS

The proposed method is applied to the block design and event related simulated data and the results are compared with that of steerable filters method in [7]. Since in the simulated data, spatial pattern of activation is known, the numbers of false detections and true detections can be determined after thresholding, thus an ROC curve is plotted for each method. Fig.2 shows two ROC curves resulted from two methods:

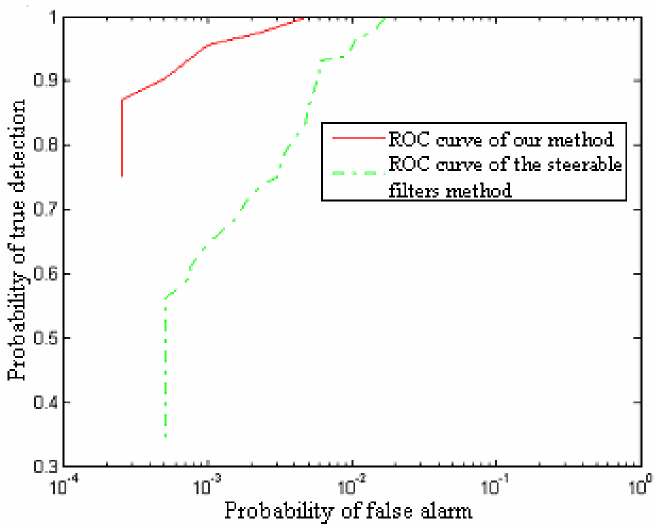

Fig.2. The ROC curves for two methods applied to block design data with k = 0.5. It can be seen that our proposed method (solid line) has better result. The initial variance for isotropic filter is assumed to be 1

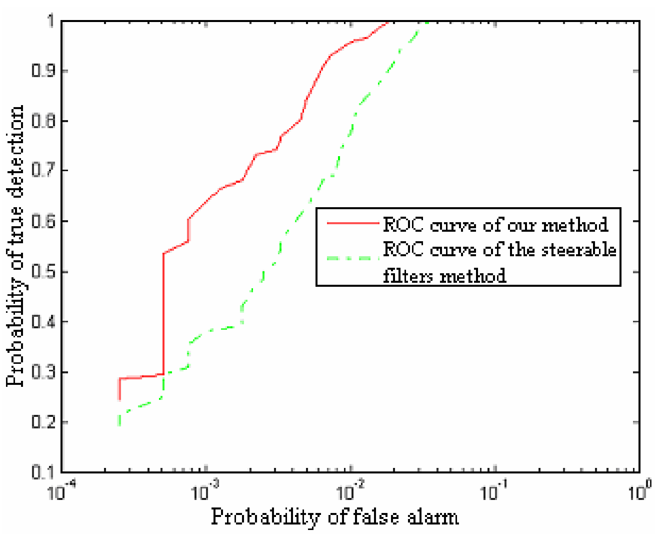

Fig.3. The ROC curves for two methods applied to event related data with k = 0.5. It can be seen that our proposed method (solid line) has better result. The initial variance for isotropic filter is assumed to be 1

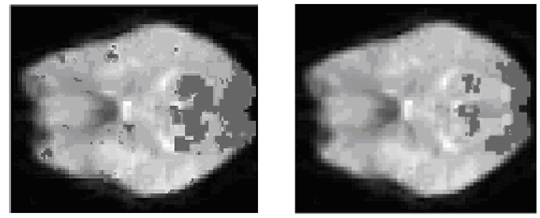

Fig.4. The results of our proposed method applied to experimental data with K = 0.5 and threshold = 0.25 (right) and the results of the method proposed in [7], applied to experimental data with K = 0.5 and threshold = 0.28 (left). The initial variance for isotropic filter is assumed to be 1.

Two methods are applied to the experimental data. The results of activation detection areas for two methods are shown in Fig.4. As mentioned, our experimental data are visual stimulation data, so, it is rational that the posterior part of the brain becomes active.

According to the ROC curves, for two methods, the result of our proposed method is considerably better than the results of the steerable filters method in [7].

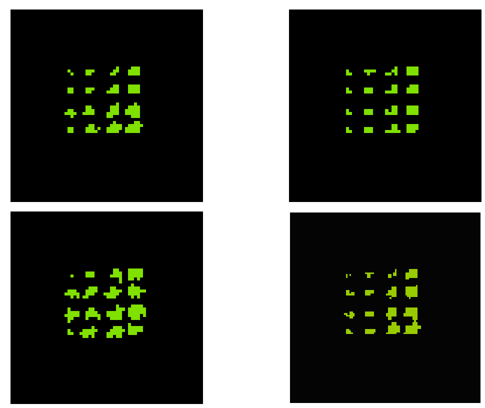

Fig.5. The results of our proposed method applied to block design (top row) and event related (bottom row) data with K = 0.5 and threshold = 0.25 (right column) and the results of the proposed method in [7], applied to block design and event related data with K = 0.5 and threshold = 0.3 (left column), the initial variance for isotropic filter is assumed to be 1.

In Fig.5 detected activation areas are demonstrated for block design and event related data for two methods. It can be seen that our proposed method shows better results compared to the results of the other methods, for both block design and event related data.

A. Sensitivity

As defined in the previous section, choosing appropriate value for the coefficient K defined in Eq. (10), can affect the final results of our method. In this section, the effects of this parameter on ROC curve will be examined for various values and then this effect will be compared with the method proposed in [7].

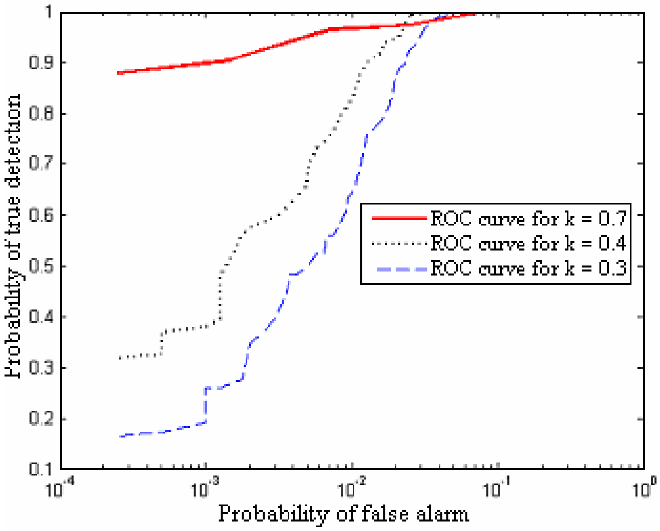

Fig.6. ROC curves of the proposed method in [7] for various values of K. Solid line k = 0.7, Dot line k = 0.4, Dash line k = 0.3.

In the method proposed in [7], an isotropic filter with predefined variance is used to make a steerable filter. This constant variance increases the sensitivity of this method to different values of K. This problem is examined by assigning various values to K and measuring changes in the obtained ROC curves. Fig.6 shows ROC curves for various values of K.

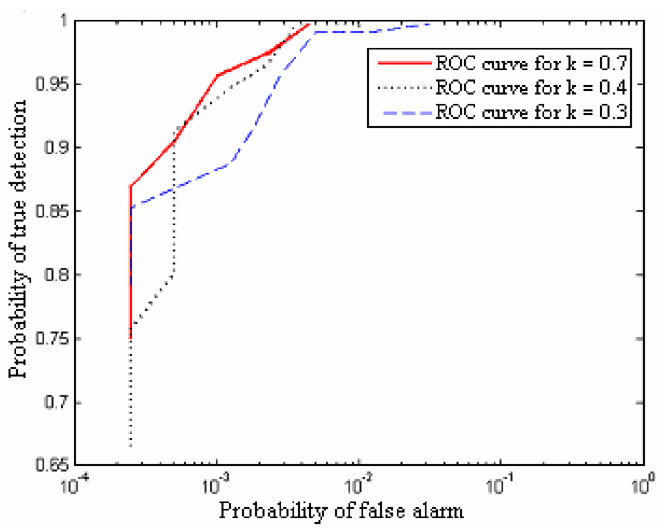

Fig.7. ROC curves of our proposed method for various values of K. Solid line k = 0.7, Dot line k = 0.4, Dash line k = 0.3.

For measuring our proposed method's sensitivity, various values are assigned to K and then ROC curves are obtained for each value. These ROC curves are demonstrated in Fig.7. If two sets of curves in Fig.6 and Fig.7 are compared to each other, it can be seen that the deviation of ROC curves in Fig.7 is less than that of ROC curves in Fig.6. So, our method is less sensitive to the changes in K than the proposed method in [7].

IV. Conclusion

In the proposed method, the filter size can change adaptively in addition to its orientation. This makes the designed filter more compatible with various spatial pattern of activation. Therefore more kinds of spatial pattern of activation can be detected correctly. In the previous method, based on steerable filters, it is difficult to find an optimum filter size that affects the final results and activation detection area. But in this method this optimum filter size is determined automatically according to the observed signals. In addition, the results of the experiments show that the proposed method is less sensitive to the changes in K parameter defined in Eq. (10). On the other hand, this method is only performed on some voxels placed in the candidate-active regions. Therefore, the time needed for detecting specific pattern activation is trivial.

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