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A Modified Fuzzy C-Means Algorithm for Segmentation of Magnetic Resonance Images

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Abstract. This paper presented a new approach for robust segmentation of Magnetic Resonance images that have been corrupted by intensity inhomogeneities and noise. The algorithm is formulated by modifying the objective function of the standard fuzzy C-means (FCM) method to compensate for intensity inhomogeneities. A additional term is injected into the objective function to constrain the behavior of membership functions with the neighborhood effect. And an adaptive K-means clustering algorithm that initializes the centroids is described. The efficacy of the algorithm is demonstrated on both simulated and real Magnetic Resonance images.

1 Introduction

Many clinical and research applications using Magnetic Resonance images require a segmentation into different intensity classes which are regarded as the best available representations for biological tissues. Unfortunately, segmentation methods for performing tissue classification are hindered by multiple imaging artifacts such as noise, intensity inhomogeneities, and partial volume effects. The majority of intensity inhomogeneities are caused by the irregularities of the scanner magnetic fields–static (B_0), radio-frequency (B_1) and gradient fields, which produce spatial changes in tissue statics. Partial volume effects occur where multiple tissues contribute to a single voxel, making the distinction between tissues along boundaries more difficult. Noise in MR images can induce segmentation regions to become disconnection. Therefore, it is important to take advantage of useful date while at the same time overcoming potential difficulties.

Numerous approaches have been proposed for Magnetic Resonance images segmentation[1][3][4][10][11]. There has been an increasing interest in soft segmentation algorithms where a pixel may be classified partially into multiple classes. The membership thus gives an indication of where partial volume effects have occurred in the image. The fuzzy C-means clustering algorithm (FCM) is soft segmentation method that has been used extensively for segmentation of MR images[2]. Standard fuzzy C-means, however, can not effectively compensate for intensity inhomogeneities. Pham and Prince[1][3] used first- and second-order regularization terms to estimated bias field and produce a soft segmentation

while simultaneously adaptive to intensity inhomogeneities. While this method has been shown to be effective in correcting for inhomogeneities, it doesn't place any contextual constraints on the membership functions. Its main disadvantages are that the performance degrades significantly with increased noise and its computational complexity.

To solve the problem above, we propose a new approach for fast fuzzy segmentation of MRI dates in the present of intensity inhomogeneities and noise. We first obtain the initial estimates of the centroids through the K-means clustering methods, which is faster than fuzzy C-means, then modify the objective function of the standard fuzzy C-means (FCM) method to compensate for intensity inhomogeneities. A additional term is injected into the objective function to constrain the behavior of membership functions with the neighborhood effect, which make it robust to both intensity inhomogeneity artifacts as well as noise and other artifacts.

2 Methods

2.1 Background

We all know that models of intensity inhomogeneities are the basis of retrospective correction methods. An approach to model it has been proposed in lectures[1][4][11]. In these papers, intensity inhomogeneities are modelled as a continuous, slowly varying multiplicative field g over the image domain with constant true intensity $\mathbf{v}_k$ for each tissue class K.

$$y_i = g_i x_i + n_i \qquad x_i \in (v_1, v_2, \cdots, v_c) \tag{1}$$

where y_i and x_i are the observed and true intensity at the ith pixel, respectively. n_i is the measurement noise of independent white Gaussian distribution at pixel i. c is the desired number of pixel in a MR image.

FCM has been used with some success in the soft segmentation of MR images and for the estimation of partial volumes. It is formulated as the minimization of the following objective function with respect to the membership function u and the centroids $\mathbf{v}$:

$$J_{FCM} = \sum_{j \in \Omega} \sum_{k=1}^{C} u_{jk}^{q} \|\mathbf{y}_j - \mathbf{v}_k\|^2 \tag{2}$$

Where Ω is the set of voxel locations in the image domain. The parameter $q(q > 1)$ is a weighting exponent on each fuzzy membership and determines the amount of "fuzziness" of the resulting classification. u_{jk} and $\mathbf{y}_j$ are the membership value and the observed image intensity at voxel location j. $\mathbf{v}_k$ is the centroid of class k. FCM, however, assumes that the centroids of the image are spatially invariant, which is not true of the image that has been corrupted by intensity inhomogeneities and noise. Pham and Prince[1][3] incorporated a gain field term into the objective function of standard FCM methods, and placed

constraints on the gain field to ensure the estimated field smooth and slowly varying. The objective function of the AFCM algorithm is:

$$J_{AFCM} = \sum_{j\in\Omega}\sum_{k=1}^{C} u_{jk}^{q}\|\mathbf{y}_j - g_j\mathbf{v}_k\|^2 + \lambda_1 \sum_{j\in\Omega}\sum_{r=1}^{R}(D_r * g)_j^2 + \lambda_2 \sum_{j\in\Omega}\sum_{r=1}^{R}\sum_{s=1}^{R}(D_r * D_s * g)_j^2 \quad (3)$$

Here g_j is an unknown gain field, D_r is a finite difference operator along the rth dimension of image. Although results based on the AFCM algorithm show great promise, it does not place any contextual constraints on the membership functions, which made it sensitive to the present of extreme noise.

2.2 Objective Function

In this section, in order to solve the problem of noise sensitivity and computational complexity, and preserve the advantage of these former methods, we proposed a modification to (2)(3)by introducing a new term that constrains the behavior of membership functions to be influent not only by the date at that pixel, but also by the neighboring membership values. We call the new algorithm Fast Adaptive Fuzzy C-means method (FAFCM). The objective function is given by:

$$J_{FAFCM} = \sum_{j\in\Omega}\sum_{k=1}^{C} u_{jk}^{q}\|\mathbf{y}_j - g_j\mathbf{v}_k\|^2 + \sum_{j\in\Omega}\sum_{k=1}^{C} u_{jk}^{q}\sum_{r\in N_j}\left(\frac{\alpha}{N_R}\|\mathbf{y}_r - g_r\mathbf{v}_k\|^2 + \frac{\beta}{N_R}\sum_{m\neq k} u_{rm}^{q}\right) \quad (4)$$

Here N_j is the set of first order neighbors of pixel j. N_R is the cardinality of N_j. The parameter α and β control the effect of the neighbors term. The additional term forces the membership values at each pixel to be dependent on its neighbors. The objective function J_{FAFCM} can be minimized in a fashion similar to the standard FCM algorithm.

In practice, we have found in MR data that the scalar gain field assumption provides nearly identical results to that of the vector gain field. Furthermore, it is also faster and requires fewer computations. The algorithm derived from the scalar case is more easily explained. Therefore we focus mainly on the scalar MR data. In the following subsections, we will give the details of the algorithm steps.

2.3 Initial Centroids

FAFCM requires an initial estimate of centroid values. Proper selection will generally improve accuracy and reduce the number of iterations as well as increase

the speed. Although clustering algorithms (such as K-means, Fuzzy C-means and EM) do not directly incorporate spatial modeling and can therefore be sensitive to noise and intensity inhomogeneities, this lack of spatial modeling, however, can provide significant advantage for fast computation. Furthermore, K-means has demonstrated less sensitivity to initialization than the EM algorithm.

So we plan to use the K-means method to do initial segmentation, whose results are used as the initial centroids of our method. The K-means method is an iterative procedure, which identifies compact tissue cluster. The algorithm iteratively minimizes the object function:

$$J = \sum_{j \in c_k} \sum_{k=1}^{K} \|\mathbf{y}_j - \mathbf{v}_k\|^2 \tag{5}$$

Here $\mathbf{v}_k = \frac{1}{n_k} \sum_{x \in c_k} y_j$. K is the number of tissue classes. Thus the results server as a suboptional solution and later are refined as the number of FAFCM iterations increased.

2.4 Algorithm Steps

The proposed FAFCM algorithm can be summarized in the following five steps:

1. Obtain the initial values for centroids $\mathbf{v}_k$ $(k = 1, 2, \cdots, c)$ through the K-means clustering methods
2. Computer membership functions as follows:

$$u_{jk}^{u} = \frac{1}{\sum_{l=1}^{C} \left(\frac{\delta_{jk} + \gamma_k}{\delta_{jl} + \gamma_l} \right)^{\frac{1}{q-1}}} \tag{6}$$

where the δ_{jk} and γ_k are given by:

$$\delta_{jk} = \|\mathbf{y}_j - g_j \mathbf{v}_k\|^2 \tag{7}$$

$$\gamma_k = \sum_{r \in N_j} \left(\frac{\alpha}{N_R} \|\mathbf{y}_r - g_r \mathbf{v}_k\|^2 + \frac{\beta}{N_R} \sum_{m \neq k} u_{rm}^q \right) \tag{8}$$

3. Updating the centroids as follows:

$$\mathbf{v}_k = \frac{\sum_{j \in \Omega} u_{jk}^q \left(\mathbf{y}_j g_j + \sum_{r \in N_j} \frac{\alpha}{N_R} \mathbf{y}_r g_r \right)}{\sum_{j \in \Omega} u_{jk}^q \left(g_j^2 + g_r^2 \right)} \tag{9}$$

4. Estimate a new gain field given by:

$$g_j = \frac{\sum_{k=1}^{C} u_{jk}^q \mathbf{y}_j \mathbf{v}_k}{\sum_{k=1}^{C} u_{jk}^q \mathbf{v}_k^2} \tag{10}$$

5. Return to step 2 and repeat it from 2 to 4 until convergence.

$$\|V_{new} - V_{old}\| < \varepsilon \tag{11}$$

Here $\|\cdot\|$ is the Euclidean norm, $\mathbf{V}$ is a vector of cluster centers, ε is the convergence threshold. Usually $\varepsilon = 0.01$

3 Results

Our FAFCM algorithm was implemented in MATLAB on a PC with Intel Pentium 4 1.7GHz processor and 512M RAM. The real and simulated MR images were gained from the McConell Brain Imaging Center at the Montreal Neurological Institute, McGill University[8]. In this section, we present the methods on 2-D brain images and the extracranial tissues such as skull, meninges and blood vessels have been removed from all images prior to applying any segmentation algorithm.

We first evaluate the visual performance on MR data. Fig.1 shows the results from FAFCM and FCM on a real image corrupted by intensity inhomogeneities. We can see that FCM was unable to correctly classify the image while FAFCM yielded a much better result by performing fuzzy clustering in a local way.

Fig.2 demonstrate the comparison of the result between FCM and our proposed algorithm. Fig.2(b) is the simulated image corrupted by 5% noise and 20% intensity inhomogeneities. The result Fig.2(d) of our method is similar to the true tissue classification Fig.2(a). FCM, however, show the misclassification and specking in the present of noise in Fig.2(c).

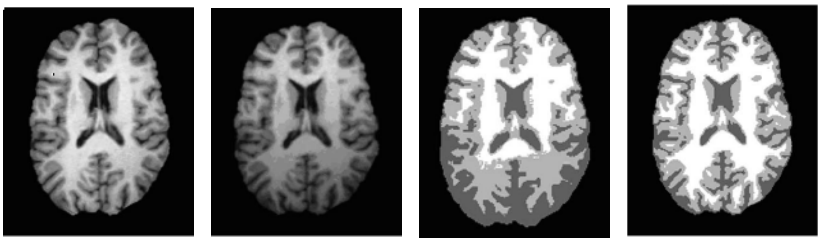
To measure the segmentation accuracy, we also apply the quantitative evaluation of performance by defining the misclassification ratio (MCR), which is given by:

$$MCR = \frac{\text{number of misclassfied pixels}}{\text{total number of pixels}}$$

The MCR columns show that as the percentage of noise is increased, the errors for all methods also increase. Our method, however, are much more robust to increased inhomogeneity and noise than the other two methods.

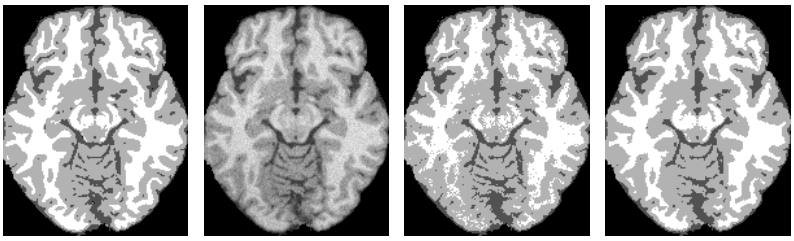
Method	MCR		
	3%N, 20%I	5%N, 20%I	7%N, 20%I
FCM	5.632%	7.833%	11.424%
AFCM	4.837%	6.936%	10.758%
FAFCM	4.367%	5.032%	6.365%

Table 1. Misclassification ratio (MCR) for simulated MR results



(a) (b) (c) (d)

Fig. 1. FAFCM and FCM segmentation in the case of intensity inhomogeneities: (a) Original image. (b) Corrupted image of (a). (c) FCM segmentation. (d) FAFCM segmentation.



(a) (b) (c) (d)

Fig. 2. Simulated MR phantom results: (a) True tissue classification. (b) Simulated MR image corrupted by 5% noise and 20% intensity inhomogeneities. (c) Result of FCM segmentation. (d) Result of our proposed method (FAFCM).

4 Conclusions

In this paper, we proposed a simple and effective algorithm for automatic tissue classification. This method has been applied to the segmentation of MR brain structures with intensity inhomogeneities and noise. The experimental results are promising and outperform the standard fuzzy C-means.

We acknowledge that the results is preliminary and more research are required in the future. Further validation studies are required for better evaluation of the results. and future works will focus on the preservation of useful details while removing the intensity inhomogeneities and noise.

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