Gain Field Correction Fast Fuzzy c-Means Algorithm for Segmenting Magnetic Resonance Images

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Abstract. In this paper, we present a new and fast algorithm of fuzzy segmentation for MR image, which is corrupted by the intensity inhomogeneity. The algorithm is formulated by modifying the FFCM algorithm to incorporate a gain field, which compensate for such inhomogeneities. In each iteration, we allow the gain field transforming to a gain field image and filter it using an iterative low-pass filter, and then revert the gain field image to gain field term again for the next iteration. We also use c-means algorithm initializing the centroids to further accelerate our algorithm. Our method reduces lots of executive time and will obtain a high-quality result. The efficiency of the algorithm is demonstrated on different magnetic resonance images.

1 Introduction

Magnetic resonance (MR) images are often corrupted by intensity inhomogeneities in MR imaging[1][10]. It is prone to producing errors by using traditional intensity based segmentation method. Many methods have been proposed to solve this problem[1][2][6][7][10]. In Pham and Prince's AFCM algorithm [6][10], a multiplier field term is incorporated into the FCM objective function to model the brightness variation caused by the inhomogeneity. Besides, the authors add first and second order regularization term into the objective function to ensure that the estimated field is smooth and varies slowly. Without these terms, a multiplier field could always be found to set the objective function to zero[10]. However, AFCM algorithm is sensitive to noise and converge slowly. In Ahmed at al's BCFCM[1], the authors improve the algorithm by including immediate neighborhood as a regularization term in the objective function of FCM. BCFCM algorithm is insensitive to noise, but the computational load is heavy. He et al propose an adaptive FCM algorithm[2]. This algorithm is used to segment three-dimensional multi-spectral MR images. For medical image segmentation, the existing algorithms often take much time in computing, and may be inconvenient for clinical applications.

In this paper, we propose a gain field correction fast fuzzy c-means (GCFFCM) algorithm. A gain filed term is appended to the objective function of fast fuzzy c-means(FFCM) to cut down the influence of intensity inhomogeneity. In each

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iteration, we transform the gain field term to gain field image and filter it using an iterative low-pass filter, and then revert the gain field image to gain field term again for the next iteration. We use c-means algorithm initializing the centroids to accelerate our algorithm. The efficacy of our algorithm is demonstrated in section 3.

2 Discussion About Algorithms

2.1 Standard FCM Algorithm

Suppose a voxel at position i is modeled as a product of the "true" signal intensity multiplied by a slowly varying factor g called gain field [7], namely,

$$y_i = g_i x_i + noise(i) \ \forall i \in \{1,2,...,N\} \tag{1}$$

where y_i and x_i are the observed and the true intensity values at the ith voxel, respectively, $noise(i)$ is the independent white Gaussian distributed noise at voxel i. N is the total number of voxels. The objective function of conventional FCM to classify x_i (i =1, 2,…, N) into c clusters can be expressed as[11]:

$$J_{FCM} = \sum_{k=1}^{c}\sum_{i=1}^{N} u_{ik}^{p} \left\| x_i - v_k \right\|^2 \ , \ \sum_{k=1}^{c} u_{ik} = 1 \ , \ \forall i \ , \ \forall i,k \ \ 0 \le u_{ik} \le 1 \ , \ \forall i,k \tag{2}$$

u_{ik} is the grade of the ith voxel belonging to class k, and p is a weighting exponent which determines the amount of "fuzziness" of a classified result. The norm operator $\|\cdot\|$ represents the standard Euclidean distance. v_k is the centroid of class k.

2.2 GCFFCM Algorithm

We could find that if two voxels have same intensity value, they will belong to the same class. Suppose there are q intensity levels, MR data can be transformed to X={ $x_1, x_2, \ldots, x_l, \ldots, x_q$ }, where h_l (l=1, 2, …, q) denotes the number of voxels with value x_l. It is similar to the histogram. So the objective function can be written as:

$$J_{FFCM} = \sum_{k=1}^{c}\sum_{l=1}^{q} h_l u_{lk}^{p} \left\| x_l - v_k \right\|^2 \quad \Big(\sum_{l=1}^{q} h_l = N\Big). \tag{3}$$

Since q is much smaller than N, FFCM algorithm is much faster than FCM.

Proper initial centroids will improve the accuracy and reduce the number of iterations. If the initial centroids are very far from the real centroids, the segmentation may fail. Thus selecting good initial centroids is a very important step. Considering the fast convergence of the c-means algorithm, we can use this algorithm first, and then treat the results as the initial centroids of our GCFFCM algorithm.

In order to reduce the influence of non-homogeneity, and to incorporate the gain field into the FFCM mechanism, we combine (1) and (3) to yield:

$$J_M = \sum_{k=1}^{c}\sum_{l=1}^{q} h_l u_{lk}^{p} \left\| y_l - g_l v_k \right\|^2 . \tag{4}$$

To minimize J_M , we take the first derivatives of J_M with respect to u_{lk} , v_k and g_l , then make them to be zero. We gain three conditions below:

$$u_{lk} = \sum_{j=1}^{c} \left(\frac{y_l - g_l v_k}{y_l - g_l v_j}\right)^{\frac{-2}{p-1}} . \tag{5}$$

$$v_k = \sum_{l=1}^{q} h_l u_{lk}^p g_l y_l \Big/ \sum_{l=1}^{q} h_l u_{lk}^p g_l^2 . \tag{6}$$

$$g_l = \sum_{k=1}^{c} h_l u_{lk}^p v_k y_l \Big/ \sum_{k=1}^{c} h_l u_{lk}^p v_k^2 . \tag{7}$$

It is seemed that J_M can be minimized directly using formula (5), (6) and (7). However, there are two aspects we should consider. Firstly, estimated field should vary slowly and smoothly. AFCM[10] contains first and second order regularization term in the objective function. BCFCM[1] includes a term that considers immediate neighborhood. It is to ensure that the estimated field is smooth and varies slowly. We use another method to solve this problem. An iterative low-pass filter is used to filter the estimated gain field by using (7). The strategy is based on that the gain field is of lower frequency and other parts are of higher frequency. However, g_l can not be directly filtered, because g_l loses two-dimensional space information. We should transform g_l to a two-dimensional gain field image firstly. We can notice that if a voxel has the intensity *l*, the value in the two-dimensional gain field image should be g_l. According to this relation, we can easily get the gain field image, then use the low-pass filter on it. Finally, we should transform the gain field image to g_l again for the next iteration. Our algorithm can be described as the following:

(1)Use the results of c-means algorithm as the initial centroids, and initialize g_l with 1.

(2)Update u_{lk} using (5).

(3)Update centroids v_k using (6).

(4)Update gain field g_l using (7).

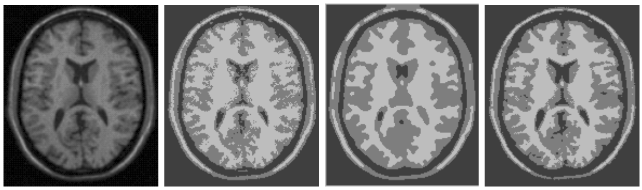
(5)Transform g_l to gain field image, filter the gain field image using an iterative low-pass filter, and revert gain field image to g_l .

(6)Return step (2) until $\|V_{new} - V_{old}\| < \varepsilon$, where ε is an error threshold .

3 Experiments

In this section, we describe the application of our GCFFCM algorithm on MR images. We set fuzzy index p=2, the termination criterion ε =0.01, and use an iterative mean filter to smooth the gain field image.

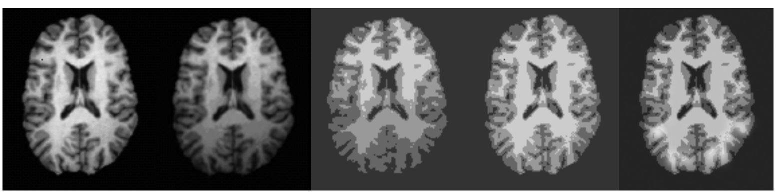
Fig.1 shows the results from FCM, BCFCM and GCFFCM on a T1-weighted MR phantom corrupted with 5% Gaussian noise and 20% intensity non-homogeneity. We can see that FCM algorithm provides an inaccurate segmentation. There is lots of noise and the contour of white matter is fuzzy. Since considering neighborhood, the BCFCM result is smooth and loses some details in Fig.1(c). Fig.1(d), nevertheless, the GCFFCM provides a better result than the other two algorithm.



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

Fig. 1. FCM, BCFCM and GCFFCM segmentation on a noisy MR image. (a) Original image. (b) FCM segmentation. (c) BCFCM segmentation. (d)GCFFCM segmentation.

Fig.2 shows the results of using the FCM, BCFCM and our algorithm to segment a simulated MR image into 4 classes. The MR image is corrupted by 5% noise and 20% intensity inhomogeneities. Both results using BCFCM and GCFFCM should be acceptable. We use accuracy ratio (ACR: 100%×number of correctly segmented voxels / total number of voxels) to measure the segmentation. The ACR of BCFCM and GCFFCM are 90.4% and 92.1%, so our algorithm is better than BCFCM.



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

Fig. 2. Comparison of segmentation results on a noisy simulated MR image. (a) Original image. (b) FCM segmentation. (c) BCFCM segmentation. (d) GCFFCM segmentation.

Besides, we consider the computational complexities of our algorithm. From table 1, we can easily see that if the number of iteration is fixed, the execution time of GCFFCM is much shorter than AFCM and BCFCM. Firstly, AFCM and BCFCM algorithm act on all voxels in a MR image data. However, the number of intensity levels is definite. For 8 bit resolution, there are only 256 intensity levels for each voxel. Hence, the GCFFCM cluster is on a very smaller data space than AFCM and BCFCM algorithm. Secondly, the results of BCFCM may be misclassified if the initial centroids are not appropriate. GCFFCM uses c-means clustering algorithm initializing good centroids. Thirdly, AFCM uses a multigrid algorithm to estimate the multiplier field, and BCFCM uses a regularization term to optimize the bias field. Both of these algorithms are with heavier computational load than GCFFCM.

Table 1. Performance time of different algorithm segmenting a 256×256 image into 4classas

Performance time	Number of iteration		
	50	100	200
BCFCM	207sed	450sed	818sed
GCFFCM	6sed	13sed	26sed

4 Conclusions

In this paper, we propose an effective GCFFCM algorithm for MR image corrupted by intensity inhomogeneity. The experimental results show that our algorithm is much better than FCM, and the computing speed of GCFFCM is much faster than AFCM and BCFCM. In the next, we plan to integrate a neighborhood regularization term into our algorithm to improve the immunity to noise.

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