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A modified fuzzy c-means algorithm brain MR images segmentation with bias field compensation

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Abstract. Segmentation of brain magnetic resonance (MR) images is always required as a preprocessing stage in many brain analysis tasks. Nevertheless, the bias field (BF, also called intensity in-homogeneities) and noise in the MRI images always make the accurate segmentation difficult. In this paper, we present a modified FCM algorithm for bias field estimation and segmentation of brain MRI. Our method is formulated by modifying the objective function of the standard FCM algorithm. It aims to compensate for bias field and incorporate both the local and non-local information into the distance function to restrain the noise of the image. We have conducted extensive experimental and have compared our method with different types of FCM extension methods using simulated MRI images. The results show that our proposed method can deal with the bias field and noise effectively and outperforms other methods.

Introduction

Medical image segmentation is a complex and challenging task in many medical image analysis problems, especially for the human brain image analysis [1]. Segmentation results of 2D or 3D brain tissues play an important role in the diagnosis and analysis of the brain disease [2,3]. It can be used to deal with the quantification of tissue volume visualization and analysis of anatomical structures, multimodality fusion and registration, functional brain mapping, detection of pathology, surgical planning, and surgical navigation, etc. In recent years, although many researchers have proposed various methods for MR image segmentation, the accurate segmentation of brain MR image is still challenging due to the complicated structure of the brain and the influence of bias field and noise. Therefore, the research of brain MR image segmentation algorithm is still the hot spot of the current medical image processing and analysis.

MR brain image segmentation generally aims at dividing the tissue into three classes: white matter (WM), gray matter (GM) and cerebrospinal fluid (CSF). Because most brain structures are anatomically defined by boundaries of these tissue classes, accurate segmentation of brain tissues into one of these categories is an important step in quantitative morphological study of the brain. There are a lot of methods available for brain image automatic segmentation: classification-based methods (such as statistical classification [4], cluster algorithm [5]), region-based methods (such as region growing [6], watershed [7]), dynamic model methods (such as snake [8], level set [9]), mixed methods (such as atlas-guided approaches [10], artificial neural networks [11]), etc. Compared with other technologies, the classification methods are more widely used in brain MR image segmentation. Classification methods dealing with brain MRI data can be divided into two groups: hard and soft segmentation method. Due to the partial volume effect, bias field and noise, it is difficult and inaccurate for the hard segmentation method to divide the image pixel only into a certain kind of tissue types in the segmentation process. Therefore, in order to overcome the disadvantages of the hard segmentation method, the soft segmentation method was proposed. The soft segmentation method divide each pixel into several tissue types by different memberships, then divide each pixel only into a certain tissue according to a rule of optimization, and get the final segmentation results. The fuzzy c-means (FCM) algorithm is a well-known soft segmentation method.

The FCM clustering algorithm was first proposed by Dunn[12] and promoted as the general FCM clustering algorithm by Bezdek [13]. Though the FCM algorithm has been applied to some image segmentation tasks successfully, since the brain MR images are inevitable disturbed by different levels of noise in the imaging process, the standard FCM algorithm cannot get satisfactory segmentation results. In order to overcome this shortage, many modified FCM algorithms have been proposed [14-18]. However, in some of these algorithms, the bias field artifacts are not taken into consideration. Thus, they may suffer from the high-amplitude bias field artifacts in the brain MR images which makes the intensities of different tissues types overlap. In order to solve this problem, we present a modified FCM algorithm for bias field estimation and segmentation of MRI in this paper. Our method is formulated by modifying the objective function of the standard FCM algorithm. It aims to compensate for such bias field and incorporating both the local and non-local information into the distance function to restrain the noise of the image. The proposed method can deal with the bias field and Gaussian noise effectively.

The rest of the report is organized as follows: In Section 2, we present the bias field model, the standard FCM clustering algorithm. Our proposed modified method is described in Section 3. Experimental results and comparisons are presented and discussed in Section 4. And we conclude this paper in Section 5.

Background

Bias field. The observed MRI signal is modeled as a product of the true signal generated by the underlying anatomy, and a spatially varying factor called the bias field

$$Y_k = X_k G_k \qquad \forall k \in \{1,2,\ldots,N\} \tag{1}$$

where X_k and Y_k are the true and observed intensities at the kth voxel, respectively, G_k is the bias field at the kth voxel, and N is the total number of voxels in the MRI image.

After applying a logarithmic transformation to Equation (1), the bias field artifact in the MR image can be modeled as [4]

$$y_k = x_k + b_k \qquad \forall k \in \{1,2,\ldots,N\} \tag{2}$$

where x_k and y_k are the true and observed log-transformed intensities at the kth voxel, respectively, and b_k is the log-transformed bias field at the kth voxel.

Standard Fuzzy C-Means. The standard FCM [12] objective function minimized the following objective function to partition $\{x_j\}_{j=1}^{n}$ into c clusters.

$$J_{FCM}(U,V) = \sum_{i=1}^{c}\sum_{j=1}^{n} u_{ij}^{m} d^2(x_j, v_i) \tag{3}$$

where $\{v_i\}_{i=1}^{c}$ are the fuzzy cluster centroids and the array $\{u_{ij}\} = U$ represents a membership function, which are defined as follows:

$$u_{ij} = \left(\sum_{k=1}^{c} \left(\frac{d(x_j, v_i)}{d(x_j, v_k)} \right)^{2/(m-1)} \right)^{-1} \tag{4}$$

and

$$v_i = \frac{\sum_{j=1}^{n} u_{ij}^{m} x_j}{\sum_{j=1}^{n} u_{ij}^{m}} \tag{5}$$

the membership function are constrained to satisfy $\sum_{i=1}^{c} u_{ij} = 1$.

The parameter *m* (generally set to 2) is a weighting exponent on each fuzzy membership that controls the degree of "fuzziness" in the resulting membership functions. And the distance matric measures the vector distance of a feature vector from a cluster centroid v_i in the feature space by using Euclidean norm.

The objective function can be easily minimized using an iterative algorithm which alternatively computes the cluster centroid and the membership u_{ij} using Equation (4) and (5).

Proposed Modified FCM

In this section, we present a modified FCM algorithm for bias field estimation and segmentation of MRI. Our method is formulated by modifying the objective function of the standard FCM algorithm. It aims to compensate for such bias field and incorporating both the local and non-local information into the distance function to restrain the noise of the image. The proposed method can deal with the bias field and noise effectively.

Objective function. Let *I* denotes the brain MR image, x_j is the observed log-transformed intensities at the *j*th pixel and v_i is the log-transformed fuzzy cluster centroids of the *i*th cluster. The objective function of the modified FCM proposed in our paper can be written as

$$J(U,V)=\sum_{i=1}^{c}\sum_{j=1}^{n}u_{ij}^{m}\left(\left(1-\lambda_j\right)d_{bl}^{2}\left(x_j,v_i\right)+\lambda_j d_{bnl}^{2}\left(x_j,v_i\right)\right) \tag{6}$$

where $\{v_i\}_{i=1}^{c}$ are the fuzzy cluster centroids and the array $\{u_{ij}\}=U$ represents a membership function. d_{bl} stands for the distance measurement influenced by local information and bias field estimation, and d_{bnl} stands for the distance measurement influenced by non-local information and bias field estimation. The parameter λ_j is the weighting factor controlling the tradeoff between them.

In the following subsection, we will discuss the distance function, bias field and the objective function minimization.

Distance function. Wang proposed a novel modified FCM (NFCM)[16], which incorporated both the local and non-local information into standard FCM clustering.

In our method, the distance function is influenced not only by local and non-local information but also by the bias field estimation. The distance measurement influenced by local information and bias field estimation is defined as follows:

$$d_{bl}^{2}\left(x_j,v_i\right)=\frac{\sum_{x_k\in N_j}w_l\left(x_k,x_j\right)d_b^{2}\left(x_k,v_i\right)}{\sum_{x_k\in N_j}w_l\left(x_k,x_j\right)} \tag{7}$$

where N_j denotes a local neighborhood of x_j, $d_b^2(x_k,v_i)$ is the distance measurement influenced by the bias field estimation (Section 3.3), $w_l\left(x_k,x_j\right)$ is the weight of each pixel in N_j and defined as

$$w_l\left(x_k,x_j\right)=e^{-\frac{\left|x_k-x_j\right|^2}{\sigma^2}} \tag{8}$$

where σ^2 is the variance of N_j. It specifies the steepness of the sigmoid curve.

The distance measurement influenced by non-local information and bias field estimation is defined as follows:

$$d_{bnl}^{2}\left(x_j,v_i\right)=\sum_{x_{k\in I}}w_{nl}\left(x_k,x_j\right)d_b^{2}\left(x_k,v_i\right) \tag{9}$$

where the weight $w_{nl}(x_k,x_j)$ depends on the similarity between the pixel x_k and x_j. The similarity between two pixel x_k and x_j depends on the similarity of the intensity gray level vector $v(N_k)$ and $v(N_j)$, where N_k denotes a square neighborhood of fixed size and centered at a pixel x_k. This similarity is measured as a decreasing function of the weighted Euclidean distance $\left\|v(N_k)-v(N_j)\right\|_{2,a}^{2}$, where a>0 is the standard deviation of the Gaussian kernel. This weight is defined as

$$w_{nl}(x_k, x_j) = \frac{1}{Z(x_j)} U(x_k, x_j) \tag{10}$$

where $U(x_k, x_j)$ is the exponential form of the similarity, and $Z(x_j)$ is the normalizing constant:

$$U(x_k, x_j) = e^{-\frac{\|v(N_k) - v(N_j)\|_{2,a}^2}{h^2}} \tag{11}$$

$$Z(x_j) = \sum_{x \in I} e^{-\frac{\|v(N_k) - v(N_j)\|_{2,a}^2}{h^2}} \tag{12}$$

The parameter h acts as a degree of filtering. It controls the decay of the exponential function and therefore the decay of the weights as a function of the Euclidean distance.

Bias field. As we mentioned before, the bias field manifests itself as a slow varying multiplicative artifact. Hence, we accommodate that into the clustering algorithm by making the cluster prototype adaptive to the spatial position. Specifically, we defined the distance measurement influenced by the bias field estimation as

$$d_b^2(x_k, v_i) = \|x_k - G(b_k) - v_i\|^2 \tag{13}$$

where b_k is the bias field estimation at the kth pixel

$$b_k = x_k - \frac{\sum_{i=1}^{c} u_{ik}^m v_i}{\sum_{i=1}^{c} u_{ik}^m} \tag{14}$$

$G(b_k)$ denotes a Gaussian filtering step after having computed the bias field. The bias field artifact varies slowly in the image. In order to smoothen the estimated field and thus eliminate the high frequency components that mainly correspond to tissue details, this filtering step is necessary in each computation cycle.

The objective function minimization. The objective function of our method can be minimized in a similar way to the standard FCM algorithm. The u_{ij} and v_i can be updated by the following equations

$$u_{ij} = \left(\sum_{k=1}^{c} \left(\frac{(1-\lambda_j) d_{bl}^2(x_j, v_i) + \lambda_j d_{bnl}^2(x_j, v_i)}{(1-\lambda_j) d_{bl}^2(x_j, v_k) + \lambda_j d_{bnl}^2(x_j, v_k)} \right)^{2/(m-1)} \right)^{-1} \tag{15}$$

$$v_i = \frac{\sum_{j=1}^{n} u_{ij}^m (x_j - G(b_k))}{\sum_{j=1}^{n} u_{ij}^m} \tag{16}$$

Flow of the algorithm. The proposed modified FCM algorithm can be summarized as follows:

Step1: Initialize the number of clusters c, the max iterative steps and the cluster centroids V. Set initial bias field b_k to equal a very small values.

Step2: Calculate the modified distance measurement.

Step3: Update the membership function U with Eq. (15).

Step4: Update cluster centroids V with Eq. (16).

Step5: Update the bias field with Eq. (14).

Step6: Smooth the estimated bias field.

Step7: Repeat Steps 2-6 until termination.

Results and Discussion

In this section, we test the proposed modified FCM algorithm on the simulated MRI images obtained from the BrainWeb Simulated Brain Database. We compared our method with different types of FCM extension methods, they are NFCM [16] which incorporated the local and non-local information to the distance measurement, and BFCM [19] which modified the objective function of the standard FCM and used a special spread method to obtain a smooth and slowly varying bias field.

Quantitative evaluation. In order to evaluate the segmentation performance quantitatively, we employ two indices (the Kappa Index (*KI*) overlap measure [18] and the misclassification rate (*MCR*) [17]) in our experiment. They are computed respectively as follows:

$$KI = \frac{2*TP}{2*TP + FP + FN} \tag{17}$$

$$MCR = \frac{number\ of\ pixels\ misclassified}{total\ number\ of\ pixels} \tag{18}$$

where *TP* is the similarity index, *FP* is false positive ratio, and *FN* is the false negative ratio [16]. For a given image, suppose that A_i and B_i represent the sets of pixels belong to class *i* in "ground truth" and in segmentation result. $|A_i|$ denotes the number of pixels in A_i . The three indices are defined respectively as

$$TP = \frac{2|A_i - B_i|}{|A_i| + |B_i|} \tag{19}$$

$$FP = \frac{|B_i| - |A_i| \cap |B_i|}{|A_i|} \tag{20}$$

$$FN = \frac{|A_i| - |A_i| \cap |B_i|}{|A_i|} \tag{21}$$

Results on Brainweb images. BrainWeb is a database, providing simulated brain MRI data for several acquisition modalities (T1, T2, etc.) and acquisition parameters. Each image is provided with anatomical ground truth and tissue class label for each intracranial voxel. In our experiments, the considered BrainWeb data have been chosen with classical acquisition parameters, namely by considering T1-weighting, with 1 mm resolution, and a size of $181 \times 217 \times 181$ voxels. The tissue is segmented into three classes, namely GM, WM and CSF. Background pixels are ignored in our experiment.

The brain image in Fig. 3a is a slice of the simulated volume corrupted by bias field. The segmentation results of the standard FCM, NFCM, BFCM and Bias field estimations using BFCM are shown in Fig. 3b-e, respectively. The segmentation result and the estimation of the Bias field using our method are shown in Fig. 3f and g. The " ground truth" of Fig. 3a is shown in Fig. 3h. The Kappa Index (*KI*) of segmentation results in Fig. 3 are shown in Table 1. From Fig. 3 and Table 1 we can see that standard FCM and NFCM are influenced by the bias field seriously. The BFCM exhibits good performance, but our proposed method gets better results.

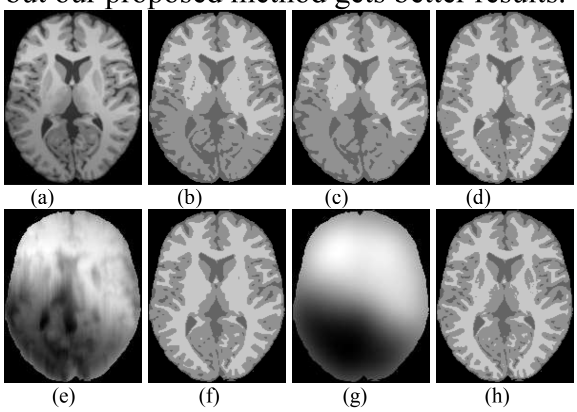

Figure 1. Segmentation results of image corrupted by bias field. (a) Original image corrupted by bias field; (b) Standard FCM; (c) NFCM; (d) BFCM (e) Bias field estimations using BFCM; (f) Our proposed method; (g) Bias field estimation using our proposed method; (h) ground truth.

TABLE I. The Kappa Index (KI) of segmentation results in Fig. 3.

	GM	WM	CSF
FCM	71.08	79.89	70.49
NFCM	72.18	77.42	76.22
BFCM	90.06	92.30	91.48
Our proposed method	92.45	94.15	93.94

In order to test the performance of our method, experiments are carried out on images corrupted not only by bias field, but also by noise. Fig. 4a and Fig. 5a are simulated MRI images corrupted by the bias field, and with noise levels 5% and 9%, respectively. The corresponding segmentation results of the standard FCM, NFCM, BFCM and Bias field estimations using BFCM are shown in Fig. 4b-e and Fig. 5b-e, respectively. The segmentation result and the estimation of the bias field using our proposed method are shown in Fig. 4f-g and Fig. 5f-g. The "ground truth" images are shown in Fig. 4h and Fig 5h. Visual inspection shows that our segmentation results are closer to the ground through compared to other algorithms.

We also apply standard FCM, NFCM, BFCM and our proposed method to simulated MRI brain volumes corrupted by bias field and different noise levels for comparison. The Kappa Index (*KI*) and the misclassification rate (*MCR*) are shown in Fig. 6 and Fig. 7, respectively. We can see that our proposed method is more accurate and stable for different noise levels.

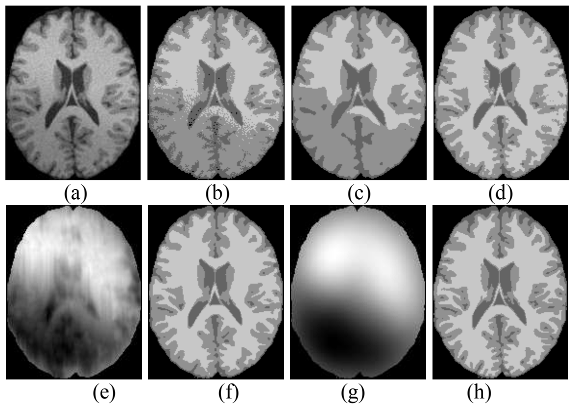

Figure 2. Segmentation results of image corrupted by bias field and 5% noise. (a) Original image corrupted by bias field and 5% noise; (b) Standard FCM; (c) NFCM; (d) BFCM (e) Bias field estimations using BFCM; (f) Our proposed method; (g) Bias field estimations using our proposed method; (h) Ground truth.

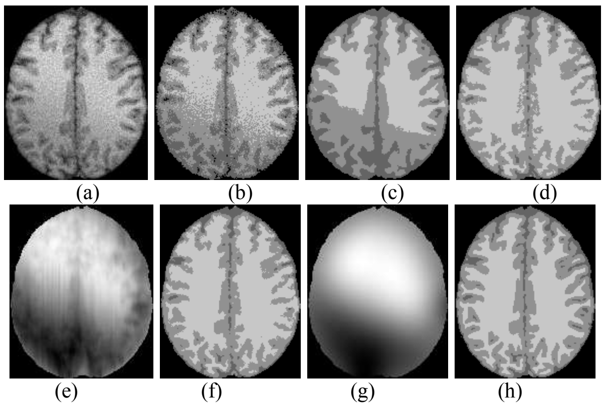

Figure 3. Segmentation results of image corrupted by bias field and 9% noise. (a) Original image corrupted by bias field and 9% noise; (b) Standard FCM; (c) NFCM; (d) BFCM (e) Bias field estimations using BFCM; (f) Our proposed method; (g) Bias field estimations using our proposed method; (h) Ground truth.

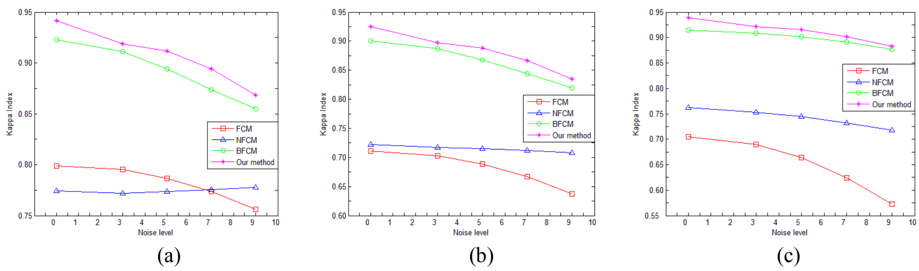

Figure 4. Validation results for bias filed estimation and different noise levels: (a) White matter; (b) Gray matter; (c) Cerebrospinal fluid.

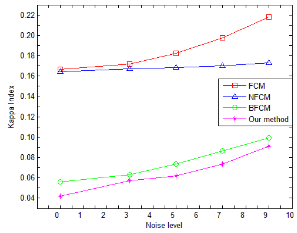

Figure 5. The misclassification rate (MCR) for bias field estimation and different noise levels.

Conclusions

In this paper, we present a modified FCM algorithm for bias field estimation and segmentation of MRI. Our method is formulated by modifying the objective function of the standard FCM algorithm. It aims to compensate for such bias field and incorporating both the local and non-local information into the distance function to restrain the noise of the image. We have conducted extensive experiments and have compared our method with different types of FCM extension methods using simulated MRI images. The results show that our proposed method can deal with the bias field and noise effectively and performed better than other methods.

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