A MR Brain Classification Method Based on Multiscale and Multiblock Fuzzy C-means

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***ABSTRACT*—A fully automatic, multiscale and multiblock fuzzy C-means (MsbFCM) classification method with intensity correction for MR images is presented in this paper. We use a bilateral filter to process MR images and to build a multiscale image series by increasing the standard deviation of spatial function and reducing the standard deviation of range function. We separate every scale image into multiple blocks and for every block a multiscale fuzzy C-means classification method is applied along the scales from the coarse to fine levels to overcome the effect of intensity inhomogeneity. The method is robust for noise MR images with intensity inhomogeneity because of its multiscale and multiblock bilateral filtering scheme. Our method was compared with the conventional FCM, a modified FCM (MFCM) and multiscale FCM (MsFCM) method on synthesized images, simulated brain MR images, and real MR images. The MsbFCM method achieved an overlap ratio of greater than 91% as validated by the ground truth even if original images have 9% noise and 40% intensity inhomogeneity. Experimental results using real MR images demonstrate the effectiveness of the proposed method. Our MsbFCM classification method is accurate and robust for various MR images.**

Keywords; Magnetic Resonance images (MRI), image classification, fuzzy C-means (FCM), bilateral filter, multiscale, multiblock.

I. INTRODUCTION

Many clinical and research applications using magnetic resonance imaging (MRI) require image classification. Unfortunately, classification of MR images can be challenging because MR images are affected by multiple factors such as noise, intensity inhomogeneity and partial volume effects.

A variety of fuzzy classification methods were reported. Fuzzy C-means (FCM) is an unsupervised algorithm and allows soft classification of each pixel which possibly consists of several different tissue types [1]. Although the conventional FCM algorithm works well on most noise-free images, it does not incorporate spatial correlation information thus it can be sensitive to noise and MR inhomogeneity. Different modified FCMs have been proposed to compensate for field inhomogeneity and to incorporate the spatial information. Recently, some approaches directly added regularization terms to the objective function and showed increased robustness in the classification of intensity inhomogeneity images [2]. A multiscale fuzzy C-means classification method for MR images was presented in our lab [3, 4]. This method used a diffusion filter to process MR images and to construct a multiscale image series. A multiscale fuzzy C-means classification method is applied along the scales from the coarse to fine levels. In our study, we propose a new, fully automatic, multiscale and multiblock fuzzy C-means (MsbFCM) classification method for MR images. We construct multiscale, bilateral-filtered images by increasing the standard deviation of spatial function and reducing the standard deviation of range function. We separate every scale image into multiblock, and a fuzzy C-means classification method is applied in every block from the coarse to fine levels. Our MsbFCM method is described in the following section.

II. METHOD

Since image classification algorithms can be sensitive to noise, image filtering can improve the performance of classification. Linear filters can reduce noise variance and thus increase signal-to-noise ratio (SNR). However they smoothed images and results in the degradation of image contrast and details. Bilateral filtering can overcome this drawback by introducing a partial edge detection step into the filtering so as to encourage intra-region smoothing and preserve the inter-region edge.

MR bias field is seen as a smoothly varying multiplicative field [4]. Although for the whole image bias field affects the absolute intensity of different tissue, for a small region we can reasonably assume that the bias field is the same and that the bias field does not affect the relative intensity of different tissue [5]. So we divide the whole image into multiblock and perform a multiscale classification in the small region. This can overcome the disadvantage of image classification algorithms that are sensitive to intensity inhomogeneity. A schematic flow chart of our proposed algorithm for the multiscale and multiblock FCM method is shown in Fig. 1.

A. Bilateral filtering

Bilateral filtering is a non-linear filtering technique introduced by [6]. This filter is a weighted average of local neighborhood samples, where the weights are computed based on temporal (or spatial in case of images) and radiometric distance between the center sample and the neighboring samples. It smoothes images while preserving edges by means of a nonlinear combination of nearby image values. Bilateral filtering can be described as follows:

$$h(x)=\lambda^{-1}(x)\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} I(\xi)W_{\sigma_s}(\xi-x)W_{\sigma_r}(I(\xi)-I(x))d\xi \quad (1)$$

$$\lambda(x)=\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} W_{\sigma_s}(\xi-x)W_{\sigma_r}(I(\xi)-I(x))d\xi \quad (2)$$

Where $I(x)$ and $h(x)$ denote input images and output images, respectively. W_{σ_s} measures the geometric closeness between the neighborhood center x and a nearby point ξ; and W_{σ_r} measures the photometric similarity between the pixel at the neighborhood center x and that of a nearby point ξ. $\lambda(x)$ is the normalization factor. Many kernels can be used in bilateral filtering. A simple and important case of bilateral filtering is shift-invariant Gaussian filtering [7].

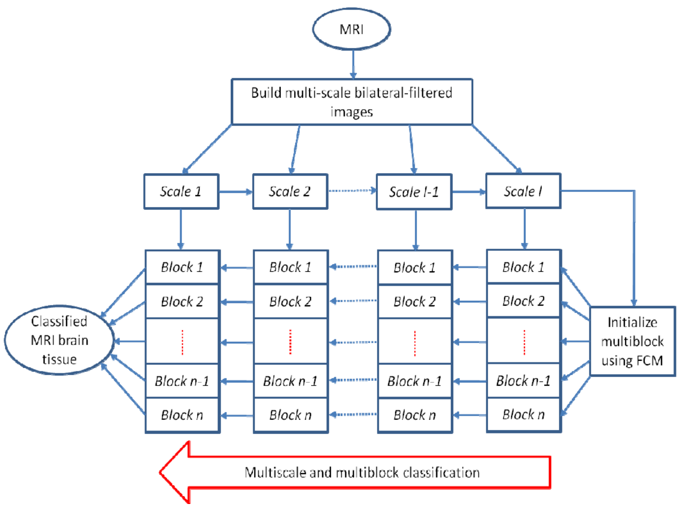

Fig. 1. Schematic flow chart of the proposed MsbFCM method.

B. Multiscale and multiblock Fuzzy C-means (MsbFCM) method

A scale space was generated by increasing the standard deviation of spatial function, by reducing the standard deviation of range function in the bilateral filter, and by keeping the general structure information in the images at a coarser scale. After bilateral filtering processing, the MsbFCM algorithm performs classification from the coarsest to the finest scale, i.e. the original image. During the classification processing at the level *l+1*, the pixels with the highest membership above a threshold are identified and assigned to the corresponding class. These pixels are labeled as training data for the next level *l*. The objective function of the MsbFCM at the level *l* and block *n* is

$$J^{nl}_{MsbFCM}=\sum_{k=1}^{{}^{n}c}\sum_{i=1}^{{}^{n}N}{}^{n}u_{ik}^{p}\left\|{}^{n}x_i-{}^{n}v_k\right\|^2+$$
$$\frac{\alpha}{N_R}\sum_{k=1}^{{}^{n}c}\sum_{i=1}^{{}^{n}N}{}^{n}u_{ik}^{p}\Big(\sum_{{}^{n}x_i\in N_i}\left\|{}^{n}x_i-{}^{n}v_k\right\|^2\Big)+$$
$$\beta\sum_{k=1}^{{}^{n}c}\sum_{i=1}^{{}^{n}N}({}^{n}u_{ik}-{}^{n}\hat{u}_{ik})^{p}\left\|{}^{n}x_i-{}^{n}v_k\right\|^2 \quad (3)$$

Similarly, the parameter p is a weighting exponent on each fuzzy membership and is set as 2. ${}^{n}u_{ik}$ stands for the membership of the pixel i belonging to the class k in block n and ${}^{n}v_k$ is the vector of the center of the class k in block n. ${}^{n}x_i$ represents the feature vectors in block n from multi-weighted MR images, and N_i stands for the neighboring pixels of the pixel i. N_R is the total number of neighboring pixels. ${}^{n}c$ is the number of underlying tissue types in n^{th} block and ${}^{n}N$ is the total voxels in n^{th} block. The objective function is the sum of three terms where α and β are scaling factors that define the effect of each factor term. The first term is the object function used by the conventional FCM method which assigns a high membership to the voxel whose intensity is close to the center of the class. The second term allows the membership in neighborhood pixels to regulate the classification toward piecewise-homogeneous labeling. The third term is to incorporate the supervision information from the classification of the previous scale with ${}^{n}\hat{u}_{ik}$ becoming the membership obtained from the classification in the previous scale.

III. CLASSIFICATION EXPERIMENT AND RESULTS

Our MsbFCM classification method has been evaluated by synthetic images, simulated brain MR database and real MR images. We compared the performance of these four fuzzy classification methods. To evaluate the classification methods we used Dice overlap ratios [8] between the classified results and the ground truth. For synthesized images we set $\alpha=\beta=0.85$ and $N_i=8$ for MFCM, MsFCM and MsbFCM methods, and set the scale level as 5 for MsFCM and MsbFCM. The bilateral filter was performed when $\sigma_s=1.2$, $\sigma_r=25$. Four blocks were used in our MsbFCM. For simulated brain data and real data, we selected 16 blocks for our MsbFCM, and the other parameters are the same as those used in the synthesized images.

A. Synthesized images

In order to test the algorithm on images with low contrast, we synthesized the images with three tissue types (labeled as Class 1, 2, 3). We defined the relative intensity difference between one class and its surroundings as Image Contrast (IC). Gaussian noise with a mean of 0 is added to the images and the standard deviation of the added noise is 10% of the intensity of Class 1. Meanwhile, in order to simulate intensity inhomogeneity, we added a 35% bias field into the synthetic image. Here 35% indicates the difference between the maximum and minimum of multiplied bias field. The five different intensities (50, 80, 100, 120, and 150) were given to Class 2, and five different IC (10%, 20%, 30%, 40%, and 50%) were used to calculate the intensity of Class 1 and 3. A total of 25 images were synthesized to test the classification methods.

Fig. 2 illustrates the visual assessment of the classification results on synthesized images with 35% intensity inhomogeneity and different image contrasts. For the images with 40% contrast the MFCM and MsFCM methods have better results than the FCM approach. Our classification methods can successfully restore the class distribution. Our MsbFCM achieved acceptable results even for images with 20% contrast where the other three methods failed. When IC is higher than 40%, all four methods achieve accurate classification. As the contrast decreases, the performance of the FCM, MFCM and MsFCM decreases, especially when the contrast is less than 30%. However, the MsbFCM method can still achieve over overlap ratios of 50% for Class 2, even with a contrast of 10%. It shows that our MsbFCM method is robust for noise and intensity inhomogeneity.

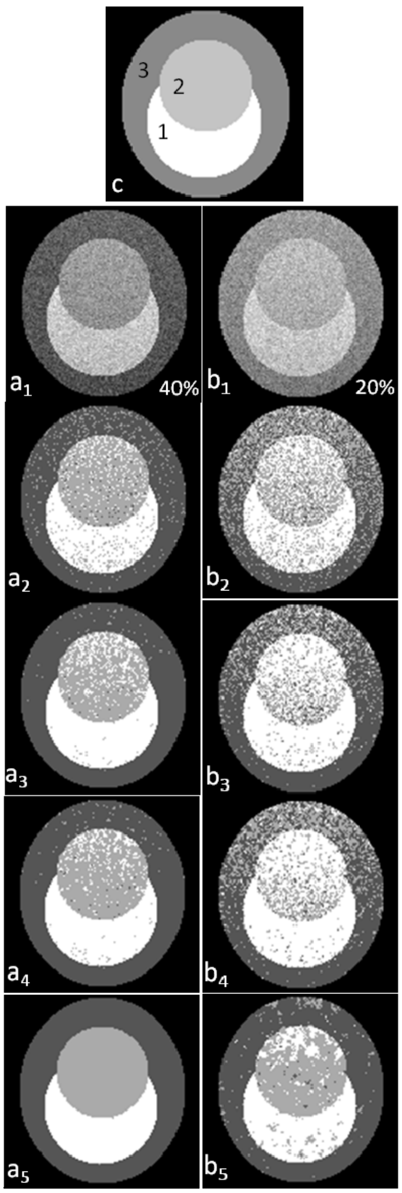

Fig. 2. Comparison of the classification results using the four methods for synthesized images. Top: Image c is original synthesized image. a1 and b1 have 40% and 20% IC and 35% intensity inhomogeneity, respectively. a_2 and b_2, a_3 and b_3, a_4 and b_4, a_5 and b_5 are the classification results using the FCM, MFCM, MsFCM and MsbFCM methods, respectively.

B. Simulated MR images

From the McGill phantom brain database [9, 10] we obtained T1-weighted MR volumes with an isotropic voxel size of 1 mm, 20% intensity inhomogeneity and with different noise levels. Prior to the classification, the extracranial tissues had been removed manually so that the MR images for classification consisted of only three types of tissue, i.e. gray matter (GM), white matter (WM), and cerebrospinal fluid (CSF). We selected ten 2D transverse slices of the volumes with different noise levels for the classification evaluation.

Fig. 3 demonstrates the classification results on T1-weighted brain MR images with noise of 9% and intensity inhomogeneity of 20%. Compared to the ground truth, our MsbFCM method performed better than FCM, MFCM, and MsFCM. Fig. 4 shows the comparison results of the four methods for images at different noise levels. Although the four methods have good results for images with a low noise level, as the noise level increases the Dice overlap ratios of the other three methods decreased remarkably. However, our MsbFCM achieved the Dice overlap ratios of 83% ± 1% for the gray matter at a noise level of 15%. Our method is not sensitive to noise and intensity homogeneity.

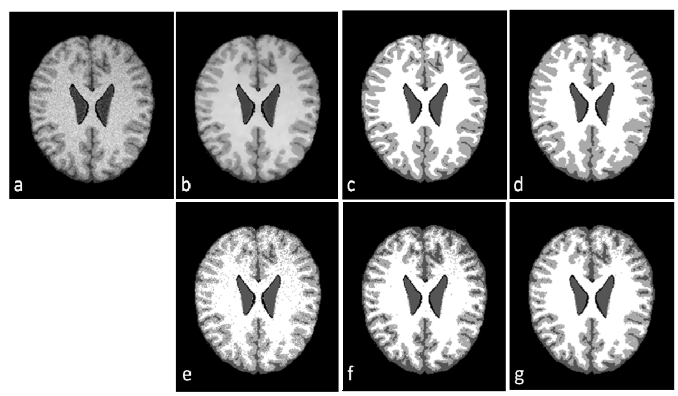

Fig. 3. Classification results of brain MR images. The original MR image (a) with 9% noise and 20% intensity inhomogeneity is smoothed after the bilateral filter processing (b). c is the ground truth of the classification from database. d, e, f and g are the classification results using the MsbFCM, FCM, MFCM, and MsFCM methods, respectively.

C. Real MR images

The four classification methods were applied to real T1-weighted MR images of a human brain. The MR images were acquired with a 4.0 Tesla MedSpec MRI scanner on a Siemens Syngo platform. T1-weighted magnetization-prepared rapid gradient-echo sequence (MPRAGE) (TR = 2500 ms and TE = 3.73 ms) was used for the image acquisition. The volume has 256×256×176 voxels covering the whole brain yielding 1.0 mm isotropic resolution. First, non-brain structures such as the skull were removed manually. Finally, manual segmentation of brain structures was performed to evaluate the classification. MsbFCM, FCM, MFCM and MsFCM were performed on defferent slices. The experiments show that FCM, MFCM and MsFCM cannot classify these three tissue types correctly because of intensity inhomogeneity, but our MsbFCM performs well. The Dice overlap ratios are 92±2% for CSF, 84±1% for gray matter and 94±0% for white matter.

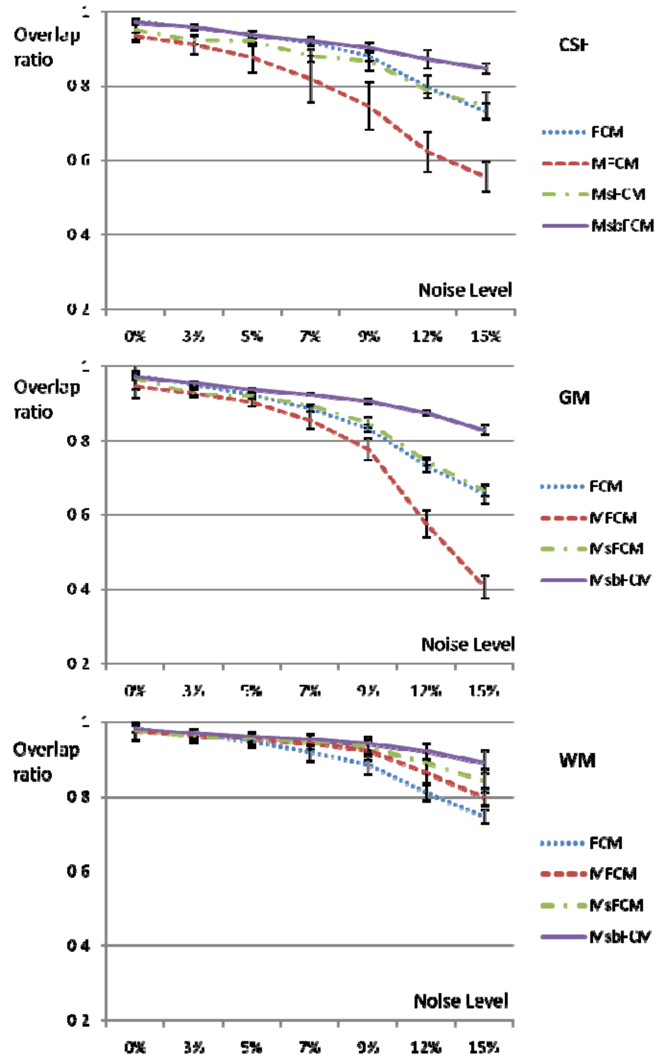

Fig. 4. Dice overlap ratios of the classification results of the four methods, i.e. FCM, MFCM, MsFCM and MsbFCM. The images were obtained from the brain database with different noise (as shown in this figure) and 20% intensity inhomogeneity.

IV. Discussion and Conclusions

We developed and evaluated a multiscale and multi-block fuzzy C-means classification method for MR images. We used a bilateral filter to effectively attenuate the noise within the images while preserving the edges between different tissue types. A scale space was generated by increasing the standard deviation of spatial function, by reducing the standard deviation of range function in the bilateral filter, and by keeping the general structure information in the images at a coarser scale. In order to reduce the effect of intensity inhomogeneity we divide every image into multiple blocks and for every block the classification was advanced along the scale space to include local information in the next fine scale. The result from a coarser scale provides the initial parameter for the classification in the next scale. Our method was evaluated with synthesized images, a brain MR database, and real MR images. It is accurate and robust for noisy images with intensity inhomogeneity. The multiscale classification for every block can be performed using a parallel framework to speed up the algorithm for real-time classification. The automatic classification method can provide a useful quantification tool in neuroimaging and other applications.

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