An Improved Fuzzy C-Means Algorithm for Brain MRI Image Segmentation

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***Abstract*—Segmentation of brain magnetic resonance imaging (MRI) data plays an important role in the computer-aided diagnosis and neuroscience research. Fuzzy c-means (FCM) clustering algorithm is one of the most usually used techniques for brain MRI image segmentation because of its fuzzy nature. However, the conventional FCM method fails to carry out segmentation well enough due to intensity inhomogeneity in MRI data. To overcome this issue, we propose an improved algorithm based on FCM clustering for segmentation of brain MRI data. Specifically, we modify the conventional FCM algorithm to allow for intensity inhomogeneity by introducing the regularization of the neighborhood influence and bias field. Results show that our proposed algorithm obtains reasonable segmentation of white matter (WM), gray matter (GM), and cerebrospinal fluid (CSF) from MRI data, which is superior to the expectation-maximization (EM) and conventional FCM methods.**

Keywords—image segmentation ; fuzzy c-means (FCM) clustering; brain magnetic resonance imaging(MRI)

I. INTRODUCTION

Image segmentation is a challenging task in image analysis and understanding, which has drawn significant attention. The goal of image segmentation is to divide an image into different areas and extract the region of interest (ROI). Study of brain structure and function requires segmentation of cerebro spinal fluid (CSF), gray matter (GM) and white matter (WM) from magnetic resonance imaging (MRI) data [1]. In fact, manual segmentation by medical experts has been often adopted in clinical application. However, manual segmentation is time-consuming and prone to bias.

In the past decade, a large number of automated methods have been proposed for segmentation of brain MRI images, such as level set [3,4], clustering[4-9], EM[10-12], graph cut[13-15], and so on. Among clustering methods, fuzzy c-means (FCM) method is a useful tool used widely and commonly. However, the main weakness of the conventional FCM algorithm is that it fails to perform well enough in the presence of intensity inhomogeneity in MRI data and meanwhile it is sensitive to noise because it does not take local spatial information into account [16]. Since medical images always include considerable uncertainty and unknown noise, this generally leads to degradation in segmentation quality.

Many algorithms have been proposed to overcome the problem. For instance, Ahmed et al presented a modified FCM algorithm in which bias field was corrected. Dubey et al [17] presented a rough set based intuitionistic fuzzy c-means (RIFCM) clustering algorithm to allow for intensity inhomogeneity. Kesemen et al [18] utilized angular difference as the similarity measure to form a distribution-free approach which was successfully applied to directional data. Recently, Sarker et al [19] presented a hybrid clustering technique based on rough set theory, statistical approach and fuzzy set theory to deal with vagueness and outlier problem.

In this study, we present an improved FCM algorithm for automated segmentation of WM, GM and CSF in brain MRI images. Different from the existing methods, our algorithm modify the traditional FCM formulation to compensate for intensity inhomogeneity by considering the regularization of the neighborhood influence and bias field.

The rest of this paper is organized as follows. Section II introduces image preprocessing, the conventional FCM method and our improved FCM algorithm as well as its implementation. The experimental results are shown and discussed in Section III. The conclusions are given in Section V.

II. METHODS

In this study, the brain MRI image is segmented using a fuzzy C-means (FCM) clustering based scheme which consists of two main steps: image preprocessing and FCM segmentation.

A. Image preprocessing

In image preprocessing, the skull stripping is carried out using 3D SLICER software, which provides the brain parenchyma based on atlas. The extracted brain parenchyma is used for the following segmentation of WM, GM, and CSF. After skull stripping, a nonlocal filtering and a bottom hat filtering are then used to reduce noise and enhance image contrast. Figure 1 shows an example of the image preprocessing result.

B. FCM segmentation

The FCM clustering method was initially proposed by Dunn [20] and improved by Bezdek [21]. The FCM algorithm assumes that each point belongs to more than one cluster with

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different membership values.

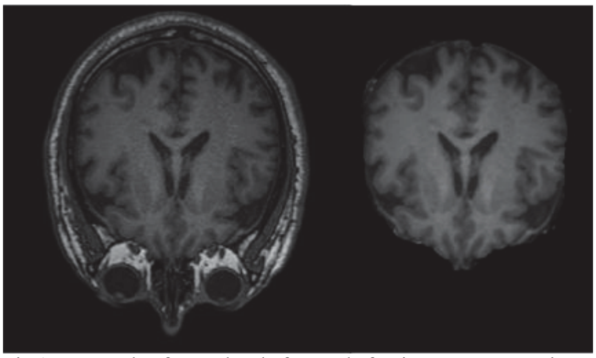


Fig.1. a example of MRI data before and after image preprocessing .

Given a dataset $X=\{x_1,x_2,x_3,...,x_N\}$, Clustering aims to separate the data set into different subsets each with a cluster center. The traditional FCM algorithm assigns fuzzy memberships u_{ij} for pixels x_j $(j=1,2,..,N)$ in each category c by minimizing the following cost function:

$$J=\sum_{j=1}^{N}\sum_{i=1}^{c}u_{ij}^{m}\left\|x_j-v_i\right\|^2 \tag{1}$$

where m is the weighting fuzziness parameter and usually set as 2. v_i represents the ith cluster center. $\|.\|$ denotes the Euclidean distance. u_{ij} means a partition matrix that is subject to $u_{ij}\in[0,1]$ and $\sum_{i=1}^{c}u_{ij}=1$.

By using the Lagranian method, the partition matrix and cluster centers are calculated as follows.

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

$$v_i=\frac{\sum_{j=1}^{N}u_{ij}^{m}x_j}{\sum_{j=1}^{N}u_{ij}^{m}} \tag{3}$$

In this study, considering the MRI image is often with spatial inhomogeneity due to the imperfection in the magnetic field, the intensity x_j is modeled by $x_j=y_j-\gamma_j$. Here, y_j and γ_j mean the measured intensity and the corresponding bias field. We propose a novel algorithm as an extension of the traditional FCM clustering by modifying the cost function in Eq. (1) as:

$$J=\sum_{j=1}^{N}\sum_{i=1}^{c}u_{ij}^{m}\left\|x_j-v_i\right\|^2+\alpha S+\beta R \tag{4}$$

where S is a regularizer indicating the neighborhood influence during segmentation, which is used to compensates for noise. R is the regularization term on bias field. α and β are constants that control the effect of the two regularization terms respectively. Specifically, S and R are defined as:

$$S=\sum_{j=1}^{N}\sum_{i=1}^{c}u_{ij}^{m}\left(\frac{1}{N_\varepsilon}\sum_{x\in N_\varepsilon}\left\|x-v_i\right\|^2\right) \text{ and } R=\sum_{j=1}^{N}\sum_{i=1}^{c}u_{ij}^{m}\left(\left\|\gamma_j\right\|^2\right),$$

where N_ε represent neighborhood centering at x_j.

Similarly to the traditional FCM clustering method, by differentiating the cost function respect to u_{ij}, v_i and γ_j respectively and setting the result to zero, we can obtain the updating u_{ij}^{*}, v_i^{*} and γ_j^{*} as:

$$u_{ij}^{*}=\frac{1}{\sum_{k=1}^{c}\left(\frac{\left\|x_j-v_i\right\|^2+\alpha\cdot\frac{1}{N_\varepsilon}\sum_{x\in N_\varepsilon}\left\|x-v_i\right\|^2+\beta\cdot\gamma_j}{\left\|x_j-v_k\right\|^2+\alpha\cdot\frac{1}{N_\varepsilon}\sum_{x\in N_\varepsilon}\left\|x-v_k\right\|^2+\beta\cdot\gamma_j}\right)^{1/(m-1)}} \tag{5}$$

$$v_i^{*}=\frac{\sum_{j=1}^{N}u_{ij}^{m}\left(x_j+\alpha\cdot\frac{1}{N_\varepsilon}\sum_{x\in N_\varepsilon}(x-v_i)\right)}{(1+\alpha)\sum_{j=1}^{N}u_{ij}^{m}} \tag{6}$$

$$\gamma_j^{*}=y_j-\frac{\sum_{i=1}^{c}u_{ij}^{m}v_i}{(1+\beta)\sum_{i=1}^{c}u_{ij}^{m}} \tag{7}$$

C. Algorithm implementation

The proposed FCM clustering algorithm is performed on the brain MRI data and described as the following steps.

Step 1: Input the MRI image and perform image preprocessing.

Step 2: Initialize the bias field as 0. Set the parameters m=2, α=1 and β=1. Here, the parameter m is a weighing exponent on each membership, which determines the level of cluster fuzziness. A large m results in smaller memberships and leads to fuzzier clusters. Without domain knowledge, m is commonly set to 2 [18]. We set α and β with the same value considering the tradeoff effect between the neighbors term and the regularization term on bias field.

Step 3: Set each cluster centers of the WM, GM and CSF. In this study, intensity information is used as the spatial feature for pixels. Considering the gray scale histogram is an approximation of the probabilistic distribution of intensity, it is possible to decide the values of intensity for the initial centers corresponding to the WM, GM and CSF. Specifically, the centers are coarsely initialized by the three peaks of the gray scale histogram.

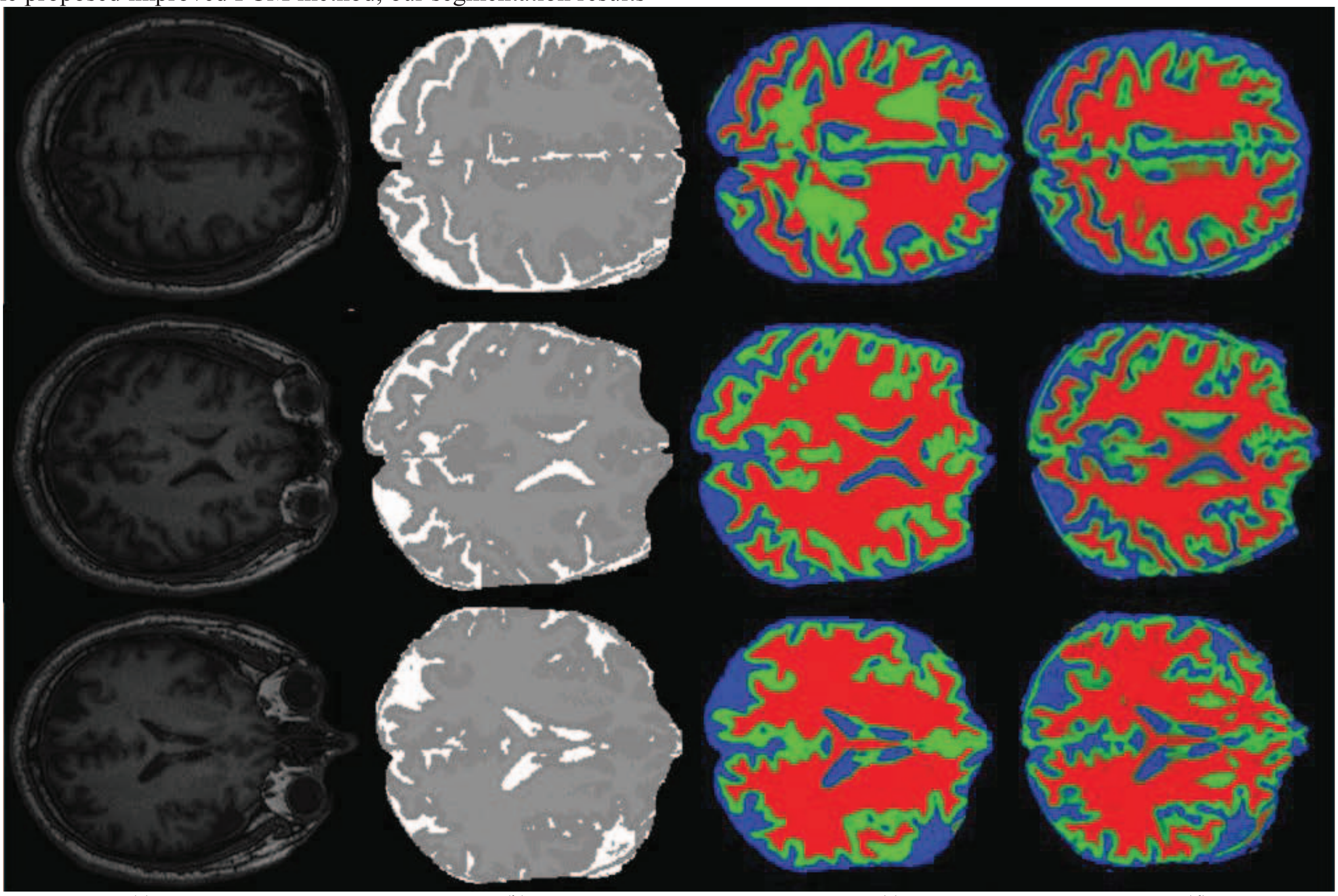
Step 4: Compute the partition matrix, the new cluster center and the bias field using Eq. (5), (6) and (7) respectively.

Step 5: Repeat step 4 until the change between the current and previous cluster center is less than a predefined threshold. Output the partition matrix to obtain the segmentation results of WM, GM and CSF.

III. RESULTS

The MRI data used in this study was provided by the Third Military Medical University and the image matrix was 512 pixels × 512 pixels. In order to evaluate the performance of the proposed improved FCM method, our segmentation results are compared with those produced using the EM method and the conventional FCM algorithms. Fig.2 illustrates the comparison of segmented WM, GM and CSF produced by different methods for representative slice images. The images in the first column show the original brain MRI images. Images in the second column are the results produced by EM algorithm. Images in the third and fourth columns are the results produced by the conventional and improved FCM methods respectively.

Generally, using the EM method, the WM is extracted reasonably, however, some CSF is obviously partitioned into GM at the boundaries of brain parenchyma in Fig.2 (b) which does not occur when using the improved FCM method. Compared with segmentation results in Fig.2(c) produced by the conventional FCM method, the improved FCM approach achieves more accurate results in Fig.2(d).



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

Fig.2. Comparison of segmented WM, GM and CSF produced by different methods for representative slice images: (a) original images, and segmentation results produced by (b) the software SLICER , (c) the conventional FCM method, and (d) the proposed FCM method..

For quantitative analysis, medical experts' manual segmentation results are used as the gold standard. We calculate dice similarity coefficient (DSC), false-positive dice (FPD), and false-negative dice (FND). DSC measures the overlap extent between segmentation results and the gold standard. Usually, segmentation results with DSC values greater than 0.7 are considered to be in excellent agreement with the gold standard. FPD is used to measure over-segmentation, whereas FND is used to measure under-segmentation.

Table 1 shows the mean (standard derivation) values of

DSC, FPD, and FND for the segmentation results of WM, GM and CSF using the EM, conventional and improved FCM methods. Compared with the EM and conventional FCM method, our proposed FCM method achieves highest values of DSC, which indicates that results produced by the proposed method agree best with the gold standard. In addition, the proposed method obtains lowest FPD and FND values for WM, GM and CSF segmentation, which reveals that the segmentation produced by our method is not prone to over-segmentation or under- segmentation.

Table 1. Quantitative evaluation results

Method	ROI	Mean DSC	Mean FPD	Mean FND
EM	WM	0.86(0.04)	0.15(0.03)	0.17(0.03)
	GM	0.82(0.07)	0.19(0.05)	0.22(0.05)
	CSF	0.75(0.10)	0.14(0.05)	0.36(0.04)
Conventional FCM	WM	0.83(0.07)	0.24(0.05)	0.27(0.04)
	GM	0.73(0.10)	0.20(0.04)	0.34(0.06)
	CSF	0.64(0.11)	0.37(0.05)	0.39(0.04)
Improved FCM	WM	0.90(0.04)	0.09(0.02)	0.13(0.03)
	GM	0.88(0.05)	0.12(0.03)	0.14(0.04)
	CSF	0.79(0.05)	0.07(0.04)	0.34(0.03)

IV. CONCLUSIONS

In this study, we have presented an improved FCM algorithm for brain MRI image segmentation. The proposed method takes intensity inhomogeneity into consideration and makes full use of the local neighbor influence with bias field constraints to form regularization terms. Applying the proposed algorithm to brain MRI images and comparing it with the EM and conventional FCM methods, results indicate that the improved FCM method produces more accurate and reasonable segmentation of WM, GM and CSF from MRI data.

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