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Modified Fuzzy C-means Algorithm and Its Application

D. SUGANTHI

Arulmigu Meenakshi Amman College of Engineering (AMACE),
Namandi Post, Thiruvannamalai (India).
*Corresponding author: E-mail: dr.suganthi23@rediffmail.com

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ABSTRACT

The accurate and effective algorithm for segmenting image is very useful in many fields, especially in medical image. In this paper we introduced a novel method that focus on segmenting the brain MR Image that is important for neural diseases. Because of many noises embedded in the acquiring procedure, such as eddy currents, susceptibility artifacts, rigid body motion, and intensity inhomogeneity, segmenting the brain MR image is a difficult work. In this algorithm, we overcame the inhomogeneity shortage, by modifying the objective function with compensating its immediate neighborhood effect using Gaussian smooth method for decreasing the influence of the inhomogeneity and increasing the segmenting accuracy. With simulate image and the clinical MRI data, the experiments shown that our proposed algorithm is effective.

Key words: FCM Cluster, Brain MRI, Image segmentation, Whiter matter.

INTRODUCTION

Recently the anatomy image is fusing with those images from diffusion tensor imaging, and using the white matter to lead the fibre tack[1-2], the accuracy of segmenting white matter is key problem. In spite of many algorithms for segmenting MRI of data[4-8], such as watershed algorithm, eSneke algorithm, generic algorithm. In addition, those algorithms are based on the homogeneity of image. In fact, intensity inhomogeneity is impact on every image and we have to solve the problem with new method.

Wells[9] developed a new statistical approach based on the expectation-maximization (EM) algorithm, but the results are too dependent on the initial values, extremely consuming the time and just looking for local maximum point. Modifying the objective function of the standard FCM algorithm to compensate for such inhomogeneities. The method is outperformed, but because the average of immediate neighborhood is influenced localized measurements, and it is no good for accuracy segmentation of WM.

In this paper, modified the objective function of FCM employed the Gaussian smoothing to compensate immediate neighborhood influence, estimated the inhomogeneities.

METHODS

Model of fuzzy c-mean method(FCM)

The standard FCM is an iterative, unsupervised clustering algorithm, initially developed by FCM algorithm ,introduced by Bezdek[11]. The following model of FCM is described by Ahmed[10].

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 gain field

$$Y_k = X_k G_k \qquad \text{...(1)}$$

groups the values , Y_k and G_k are the true intensity, observed intensity and the gain field at the *k*th voxel, respectively. N is the total number of pixels in the MRI volume.

The application of a logarithmic transformation to the intensities allows the artifact to be modeled as an additive bias field

$$y_k = x_k + \beta_k \qquad \text{...(2)}$$

where and y_k are the true and observed log-transformed intensities at the *k*th voxel, respectively, and β_k is the bias field at the *k*th voxel. If the gain field is known, then it is relatively easy to estimate the tissue class by applying a conventional intensity-based segmentation to the corrected data. The following discussion is based the model of (2) and estimation of the gain field β_k.

Modified FCM algorithm(M-FCM)

In the followings, we will introduce some modifications to this algorithm. The evaluation of the method for localized measurements, such as the impact on tumor boundary or volume determinations also needs further work.

$$J_m = \sum_{i=1}^{c} \sum_{k=1}^{N} u_{ik}^p \, \| y_k - \beta_k - v_i \|^2 + \sum_{i=1}^{c} \sum_{k=1}^{N} u_{ik}^p \Big(\sum_{y_r \in N_k} w(y_k, y_r) \| y_r - \beta_r - v_i \|^2 \Big) \qquad \text{...(3)}$$

Where $w(y_k, y_r)$ is a weighting function, satisfied the following conditions

$$\sum_{y_r \in N_k} w(y_k, y_r) = \alpha$$

especially, when , the J_m is BCFCM objective function(3) proposed by Ahmed[10].

Formally, the optimization problem is estimated those parameters in the form

$$\min_{u_{i,k}, v_i, \beta_k} J_m \qquad \text{...(4)}$$

The objective function can be calculated as the BCFCM algorithm. Taking the first derivatives of j_m with respect to u_{ik} , v_i , β_k, and setting them to zero results in three necessary but not sufficient conditions forto be at a local maximum. In the following sections, we derive these estimating results and propose the algorithm..

Membership Evaluation

$$\forall k \in \{1, 2, \ldots, N\} \quad w(y_k, y_r) = \frac{\alpha}{N_R} \quad v_i = \frac{\sum_{k=1}^{N} u_{ki}^p \left((y_k - \beta_k) + \sum_{y_r \in N_k} w(y_k, y_r)(y_r - \beta_r) \right)}{\sum_{k=1}^{N} u_{ki}^p \left(1 + \sum_{y_r \in N_k} w(y_k, y_r)\right)}$$

$$u_{ik} = \frac{1}{\sum_{j=1}^{c} \left(\frac{D_{ik} + \gamma_{ik}}{D_{ij} + \gamma_{ij}} \right)^{1/(p-1)}} \qquad \text{...(5)}$$

where $D_{ik} = \| y_k - \beta_k - v_i \|^2$, and

$$\gamma_{ik} = \sum_{y_r \in N_k} w(y_k, y_r) \| y_r - \beta_r - v_i \|^2$$

Cluster Prototype Updating

...(6)

Bias-Field Estimation

$$\beta_k^* = y_k - \frac{\sum_{i=1}^{c} v_i \left(u_{ik}^p + \sum_{y_r \in N_k} w(y_k, y_r) u_{ir}^p \right)}{\sum_{i=1}^{c} \left(u_{ik}^p + \sum_{y_r \in N_k} w(y_k, y_r) u_{ir}^p \right)} \qquad \text{...(7)}$$

The discuss of the convergence

Theory: if $w(y_k, y_r) \geq 0$ and

, ,

and is a 4 or 8 – connective neighborhood.

Then objective functionis J_m is convergence.

M-FCM Algorithm

The M-FCM algorithm for correcting the bias field and segmenting the image into different clusters can be summarized in the following steps.

Step 1: Select the Weighting function, in general,

$$w(y_k - y_r) = \alpha e^{-\frac{\|y_k - y_r\|^2}{\sigma^2}} \qquad ...(8)$$

Step 2: Select initial class prototypes $\{v_i\}_{i=1}^{c}$, for example $\left\{v_i = \log(255 * {(2i-1)}/{2c})\right\}_{i=1}^{c}$

Set $\{\beta_k\}_{k=1}^{N}$ to equal and very small values

Step 3

Update the partition matrix using (5).

Step 4

The prototypes of the clusters are obtained in the form of weighted averages of the patterns using (6).

Step 5

Estimate the bias term using (7).

Repeat Steps 3)–5) till termination. The termination criterion is as follows:

$$\|V_{new} - V_{old}\| < \varepsilon \qquad ...(9)$$

where II´II is the Euclidean norm, V is a vector of cluster centers, andis a small number that can be set by the user (e.g., 0.01).

RESULTS

In this section, we describe the application of the M-FCM segmentation on synthetic images corrupted with multiplicative gain and real T1 brain MR images. For compared with the BCFCM algorithm, we created the simulating image used by Ahmed[10]. Simulating image is a T1-weighted phantom with in-plane high resolution, Gaussian noise with 6.0, and three-dimensional linear shading 7% in each direction[2]. There are many advantages for using digital phantoms rather than real image including in prior knowledge of the true tissue types and control over image parameters such as mean intensity values, noise and intensity inhomogeneities. We also employed the fast algorithm[12] for improving calculational effect , because its consumed time is 1/4 of the traditional algorithm.

For compare our new method with BCFCM [10] with low SNR images, according to the reference, the parameters (the neighbors effect) for BCFCM are 0.85, 2, 9 (a 3 X 3 window centered around each pixel) and 0.01. Fig. 1 display the simulating image (a) and the segmentation results. It is difficult to correct using standard FCM approaches in Fig. 1(b). while the BCFCM and M-FCM algorithms have succeeded in correcting and classifying WM from the image as shown in Fig. 1(c) and (d) (α = 0.09, σ = 1.25). The both estimated the bias fields and received the similar results, but M-FCM outperformed beyond the BCFCM. We employed the true ratio (TR) to evaluate the differences.

$$TR(A) = \frac{number\{x \mid x \in A \subset WM\}}{number\{x \subset WM\}} \times 100\% \qquad ...(10)$$

Where the TR is the percent of divided segmentation umbers of WM pixels by number of original all the WM pixels. Table 1 display TR that can explain the performance of those algorithms with different noise level.

The none column is without noise. The FCM, BCFCM and M-FCM are 89.24%, 96.76% and 98.20% respectively. In addition, the M-FCM is more robust for noise, In table 1, other columns except none can explain this point.

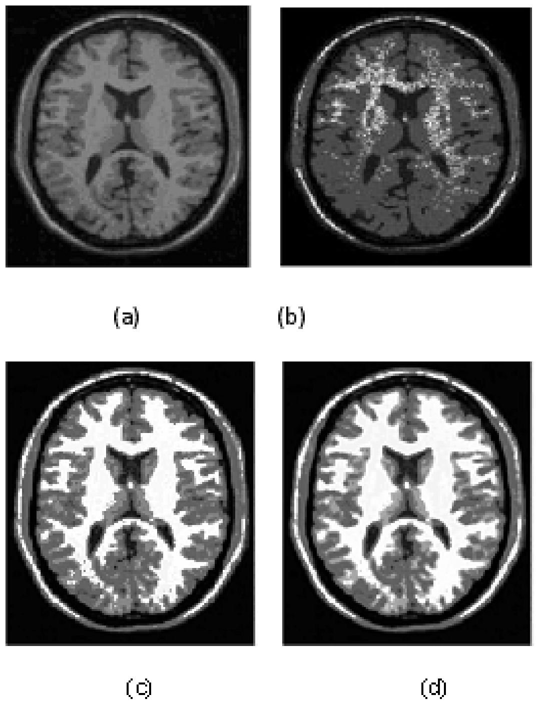
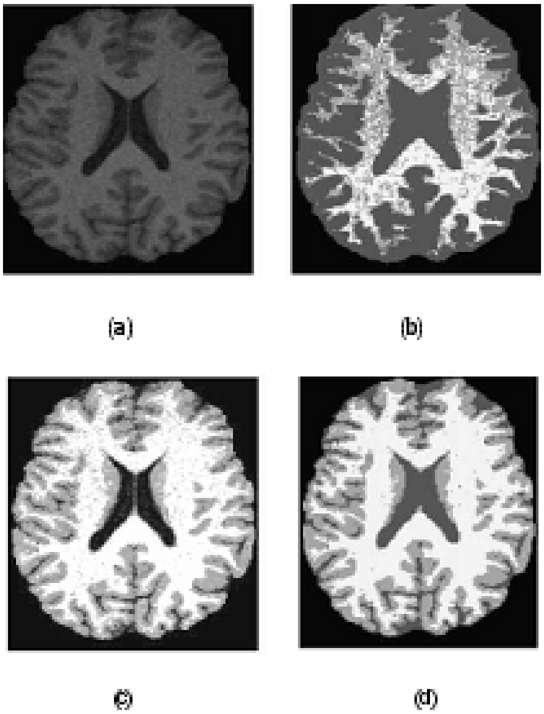


Fig. 1: Comparison of segmentation results on simulated T1 MR image



(a) Original image, (b) FCM, (c) BCFCM, and (d) M- FCM.

Fig. 2: Comparison of segmentation results on real brain MRI, T1 weighted image

The real MRI image is T1-weighted MR images of human brains in the axial plane on a GE 1.5T scanner in the Navy General Hospital of PLA with image matrix size of 256 X 256 pixels, FOV of 20 cm, TR of 400 ms, and TE of 25 ms. Fig. 2 shown the clinical T1 MR Imaging , because of the space limit, we just show one image with segmentation results. The standard FCM is no good algorithm, both BCFCM and M-FCM are acceptable. But BCFCM is sensitive to noise and the result is also accompany with more noises. In the leaves of particular branches, the M-FCM is better. In addition, we segmented 32 T1 brain MR images using BCFCM and M-FCM respectively, then we invited the experts to select better one from every image. There are twenty nine images from thirty two better images are our results of M-FCM algorithm. Although the conclusion is personality, M-FCM is better algorithm.

CONCLUSION

In this paper, we have described an unsupervised fuzzy segmentation method, based on new objective function, which seems well adapted and efficient for functional MRI data segmentation. When the real data are fuzzy, such as functional MRI brain data, the use of M-FCM segmentation is always more effective than the use of the other one.

The results presented in this paper are preliminary and further clinical evaluation is required. There are also need new methods for preprocessing the original image, including denoising and enhancing to increase the SNR. How to combine segmenting with preprocessing procedure is our work in future.

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