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Fast FCM Algorithm for brain MR Image Segmentation

Abbas Biniaz[1], Ataollah Abbasi [2,*], Mosa Shamsi[3]
[1,2] Computational Neuroscience Laboratory, Sahand University of Technology, Tabriz, Iran
[3] Department of Electrical Engineering, Sahand University of Technology, Tabriz, Iran
Email: CNLab@sut.ac.ir

Abstract

In medical applications it is very important for a physician to be informed of patient situation as soon as possible especially in emergency circumstances. Therefore all efficient agents in patient health must be fast even medical algorithms such as clustering ones. Among clustering methods Fuzzy C-Means (FCM) clustering has been frequently used for segmentation of medical images. In this paper an optimized method is presented to decrease execution time of standard FCM. Applying the new method simultaneously decreases convergence time and iteration numbers of FCM. Experimental results show that the proposed Fast FCM (FFCM) spend moderately half time of standard FCM and number of its iterations is decreased significantly; Quantitative assessment using conventional fuzzy validation functions shows similar performances of FCM and FFCM.

Keywords: Segmentation, MRI, Fast FCM.

1. Introduction

Image segmentation is a technique to label pixels/voxels and categorizes the image into separate sections, each section with uniformity in gray levels. Medical image segmentation extracts tissue borders in medical images. Magnetic resonance imaging (MRI) is a medical imaging modality and an important tool in the evaluation of brain diseases. Segmentation of MR images has many applications in medicine such as [1-6]:

- Identification of tissue anatomy
- Pre-and-post surgical Evaluation
- Detection of abnormal tissues such as tumors and pathological lesions
- Investigation of nervous system diseases such as MS and Alzheimer
- Evaluation of arteriosclerosis disease
- Detection of left and right ventricles
- Breast cancer detection
- Diagnosis of seizures
- Diagnosis of immune system weakness

MR image segmentation methods are commonly based on statistical or structural properties of medical images [7]. In statistical based methods, the statistical features are extracted from different models and functions such as the probability distribution function of the image intensities. Statistical methods segment an image by estimation of intensity distribution and assign the class labels to their corresponding pixels. They can either be

[1] M.Sc student, Biomedical Engineering, medical image processing
[2*] Corresponding author: Assistant Professor, Biomedical Engineering, medical image processing
[3] Assistant Professor, Biomedical Engineering, medical image processing

parametric or nonparametric. Both are widely used in segmentation of brain MR images such as Markov random model (MRF) and Bayesian network classifiers [8, 9]. In structural based methods the spatial characteristics of the image like edge and region are applied. Segmentation with structural characteristics includes several groups: Pixel based methods, for instance thresholding, k-means or fuzzy c-means clustering [10, 11]; Edge based methods, such as active contours or common edge detections like prewitt, sobel & canny[1, 7]; Region-based methods, such as region growing techniques[1, 7]. Segmentation using fuzzy techniques, especially FCM has been widely used in medical images [12, 13]. FCM is capable to reserve more information about the original image compared with other approaches because of its fuzziness[14]. However, in medical image processing specifically in emergency situations doesn't have requisite convergence speed so patient health encounter with danger. In this paper a fast FCM algorithm is presented with a novel rule to update cluster centers in each iteration step. FFCM decreases computation time and iteration number of FCM. However, significantly preserves its quality.

The rest of this paper is as follows: In Section 2.1 the conventional FCM is reviewed. Section 2.2 presents Fast FCM algorithm. Fuzzy validation functions are expressed in section 3. Results and discussion are presented in Section 4 and conclusions of this paper are summarized in Section 5.

2. Method

2.1. Standard FCM

The c-means families are well developed group of batch clustering types because they are "least square" models. Each cluster consists of one or more common characteristics depending on the dimension of input data. FCM assigns fuzzy memberships to each element of dataset instead of hard membership, developed in 1970s [15]. Therefore in FCM each data point is belongs to multiple clusters with different membership values. Let $X=\{x_1,x_2,...,x_n\}$ denote an input vector with *n* pixels which should be partitioned into *c* clusters ($2\leq c\leq n$) and x_j is feature value. FCM is an iterative optimization procedure which minimizes the following cost function [16]:

$$J_m(U,V)=\sum_{i=1}^{c}\sum_{j=1}^{n}u_{ij}^{m}\left\|x_j-v_i\right\|^2 \qquad (1)$$

Where n is data point numbers, m is the fuzzy fitness grade, u_{ij} is the membership of pixel x_j in the i-th cluster, v_i is the centroid of i-th cluster, and $\|.\|$ is Euclidean norm. Membership function u_{ij} satisfies the following constraints:

$$0\leq u_{ij}\leq 1 \text{ for } 1\leq i\leq c,\ 1\leq j\leq n,$$

$$0<\sum_{k=1}^{N}u_{ij}<n \text{ ,for } 1\leq i\leq c,$$

$$\sum_{i=1}^{c}u_{ij}=1, \text{ for } 0\leq j\leq n.$$

Since the cost function must be minimized, pixels which are close to their clusters center should have high membership values and low membership values are assigned to pixels which are far from cluster center. In the other hand, the maximum distance between the cluster centroids leads to the optimum clustering. Membership function and cluster centers are updated by the following equations:

$$u_{ij}=\frac{1}{\sum_{k=1}^{c}\left(\frac{\left\|x_j-v_i\right\|}{\left\|x_j-v_k\right\|}\right)^{2/(m-1)}} \qquad (3)$$

$$v_i=\frac{\sum_{j=1}^{n}u_{ij}^{m}x_j}{\sum_{j=1}^{n}u_{ij}^{m}} \qquad (4)$$

Starting with an initial value for each cluster center, the FCM will be converged to a solution for v_i that representing the local minima or a saddle point of the cost function[16]. Convergence rate can be determined by comparing the differences between the membership function or cluster centers in two successive iterations.

2.2. Fast FCM: FFCM

As mentioned above in medical applications it is necessary to use high speed algorithms such as clustering ones. FCM assigns c membership grades to every pixel. However, updating membership matrix with $c \times n$ member is a time consuming procedure. In FCM, centroids are updated by fuzzy memberships which need much time. To reduce time and amount of computations in FCM, a hard membership can be assigned to pixels for updating cluster centers in each iteration step. However, segmentation will be a fuzzy procedure. By applying hard membership the new algorithm to update centroids is proposed as following:

Step1: For p-dimensional input data, rearrange u_{ij} to $d_1 \times d_2$ matrix; where d_1, d_2 are input dimensions.

Step2: Set new fuzzy membership as u^*_{ij} and label matrix as $L = \{L^1, L^2, \ldots L^c\}$; where L^k is label matrix of k-th cluster in current iteration.

Step3: Set all data points which are correspond to L^k label matrix as I^k.

Step4: Define $I^k = I_1^k, I_2^k, \ldots, I_{nc_k}^k$ for k-th cluster, where nc_k is the number of data points in k-th cluster.

Step5: Update centroid of k-th cluster by equation 5:

$$v_k^* = \frac{\sum_{j=1}^{nc_k} I_j^k}{nc_k} \tag{5}$$

The new fuzzy membership and cost function can be calculated by the following equations:

$$u^*_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{\| x_j - v_i^* \|}{\| x_j - v_k^* \|} \right)^{2/(m-1)}} \tag{6}$$

$$J^*_m(U^*, V^*) = \sum_{i=1}^{c} \sum_{j=1}^{n} (u_{ij}^*)^m \| x_j - v_i^* \|^2 \tag{7}$$

The proposed FFCM algorithm can be summarized as following:

Step 1: Select the number of clusters(c) and fuzziness value (m=2), initialize $V^{*(0)}$ by small values.

Step 2: Update the new membership matrix U^* by Eq.(6).

Step 3: Update cluster center matrix V^* by Eq.(5).

Step 4: Repeat steps 2–3 until $\left\| v_i^{(t+1)} - v_i^{(t)} \right\| < \varepsilon$, where ε is a small positive constant.

3. Validity Functions

Mostly two types of validity functions are used to evaluate the performance of clustering: fuzzy partition and geometric structure. Partition coefficient V_{pc} and partition entropy V_{pe} are fuzzy partition functions and defined as following [17, 18]:

$$V_{PC} = \frac{\sum_{j=1}^{n} \sum_{i=1}^{C} {u_{ij}}^2}{N} \tag{8}$$

$$V_{pe} = (-1) \times \frac{\sum_{j=1}^{n} \sum_{i=1}^{c} u_{ij} log(u_{ij})}{n} \quad (9)$$

The best clustering is achieved when the V_{pc} is close to maximum value (one) or V_{pe} is close to minimum value (zero). However, fuzzy partition functions can only measure the fuzzy partition and don't have a direct access to feature vector. In validity functions based on the geometric structure samples within one partition should be compact and samples between different clusters should be separate for an improved optimization[19]. To quantify the ratio of total variation within clusters, V_{fs} and V_{xb} are proposed and defined as following [17-19]:

$$V_{fs} = \sum_{j=1}^{n} \sum_{i=1}^{C} u_{ij}^{m} \left(\left\| x_j - v_i \right\|^2 - \| v_i - \bar{v} \|^2 \right) \quad (10)$$

$$V_{xb} = \frac{\sum_{j=1}^{n} \sum_{i=1}^{c} {u_{ij}}^{m} \left(\left\| x_j - v_i \right\|^2 \right)}{n * \left(min_{i,k} \{ \| v_k - v_i \|^2 \} \right)} \quad (11)$$

And $v_i \neq v_k$

Minimized V_{fs} or V_{xb} lead to optimal clustering.

4. Result and discussion

To verify the effectiveness of the proposed FFCM in comparison with FCM they are evaluated on both synthetic and real clinical MR images. In the simulations images were corrupted by additive Gaussian noise therefore they segmented by FCM and FFCM algorithms. Fuzzy and hard clustering results of segmented MR images by FCM and FFCM are represented in continue. An important point is that time consumed by FFCM is less than FCM in various real and synthetic images. On the other hand number of iterations has been significantly decreased by the proposed FFCM technique.

Since T1 weighted MR images use the longitudinal component of magnetic resonance imaging, they have high contrast and resolution therefore, they are proper for image segmentation. Fig. 1(a) is a synthetic T1 weighted image[16], which is corrupted by additive Gaussian noise ($\sigma = 0.002$) in Fig. 1(b). The gray levels are 50 (UL), 100 (UR), 150 (LL), and 200 (LR) in the T1 weighted image. Each gray level represents a living tissue on MR images and at the end of the simulations must be specified as separate clusters. As seen in Fig. 1(c)-(d), FCM and FFCM algorithms lead to similar results in the presence of noise.

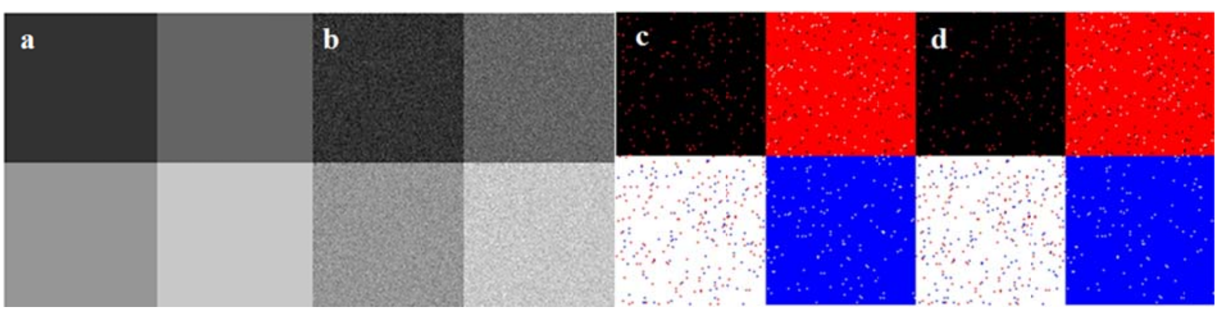

Fig. 1: (a) Simulated T1 image, (b) corrupted by Gaussian noise; segmentation results by (c) FCM and (d) FFCM.

Fig. 2 (a) shows a simulated T1 weighted brain MR image corrupted by Gaussian noise (m=0, $\sigma = 0.0001$). Segmentation results using FCM and FFCM are shown in Fig. 2 (b) and (c) respectively. Image background (BGND) and brain tissues, including white matter (WM), gray matter (GM), and the cerebrospinal fluid (CSF) were segmented with relatively similar accuracy.

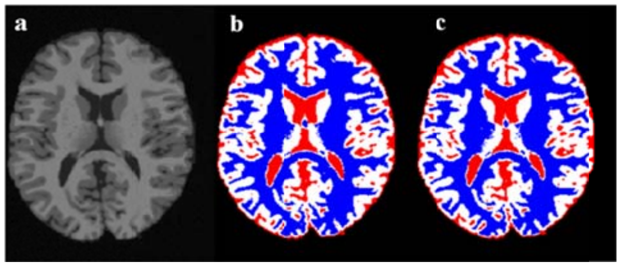

Fig. 2: (a) simulated brain MR image corrupted by Gaussian noise; segmentation results by (b) FCM, (c) FFCM.

In Fig. 3 results of hard clustering by FCM and FFCM are depicted and in Fig. 4 fuzzy membership functions for four clusters BGND, WM, GM and CSF are portrayed.

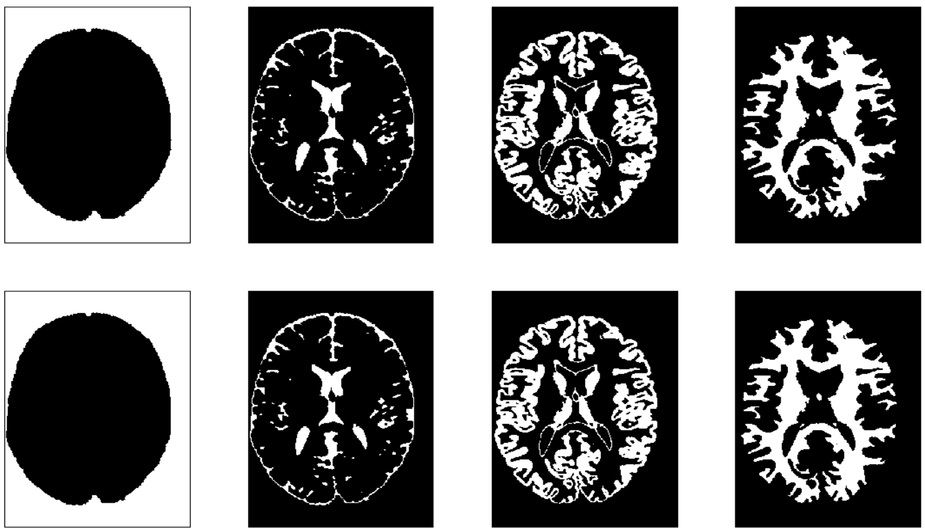

Fig. 3: Hard clustering on simulated MR image; 1st and 2nd rows are result of FCM and FFCM respectively; Columns from left to right are BGND, CSF, GM and WM.

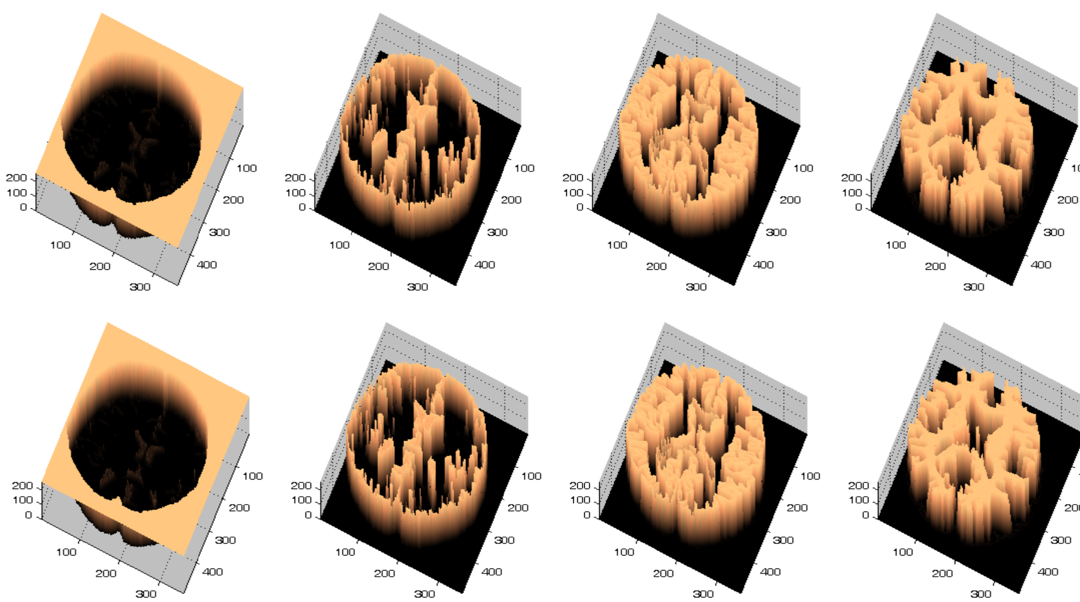

Fig. 4: Fuzzy membership functions for simulated T1 weighted MR image; 1st and 2nd rows are result of FCM and FFCM respectively; columns from left to right are BGND, CSF, GM and WM.

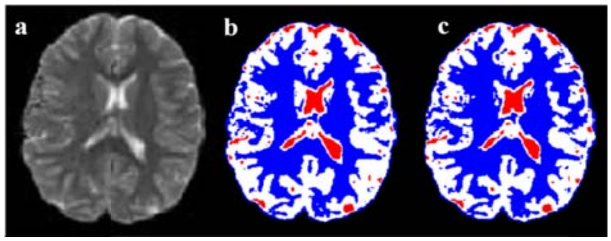

Fig. 5: (a) Real T1 weighted MR image, segmented image resulted from (b) FCM, (c) FFCM.

Performances of FCM and FFCM on real brain MR images are depicted in Fig.5. To scrutinize in Fig. 6 results of hard clustering by FCM and FFCM are depicted; and in Fig. 7 fuzzy membership functions for four clusters BGND, WM, GM and CSF are portrayed.

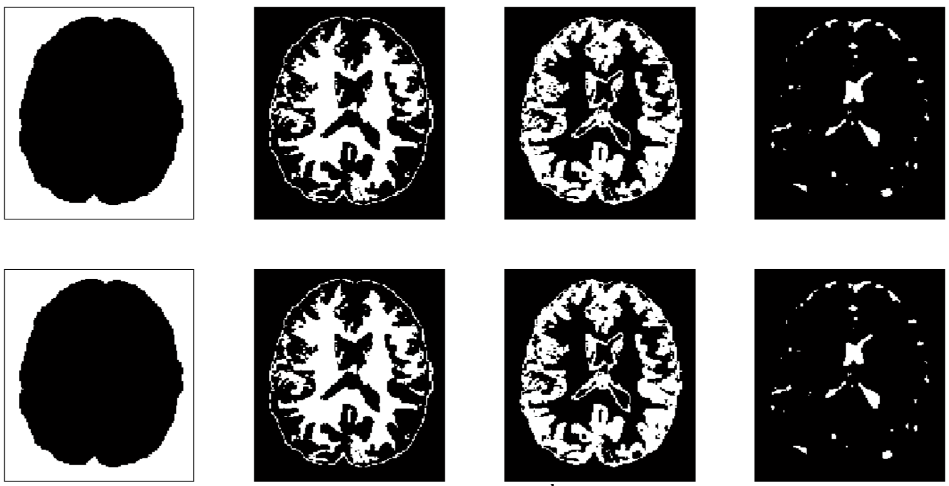

Fig. 6: Hard clustering for real T1 weighted MR image; 1st and 2nd rows are results of FCM and FFCM respectively; Columns from left to right are BGND, WM, GM and CSF respectively.

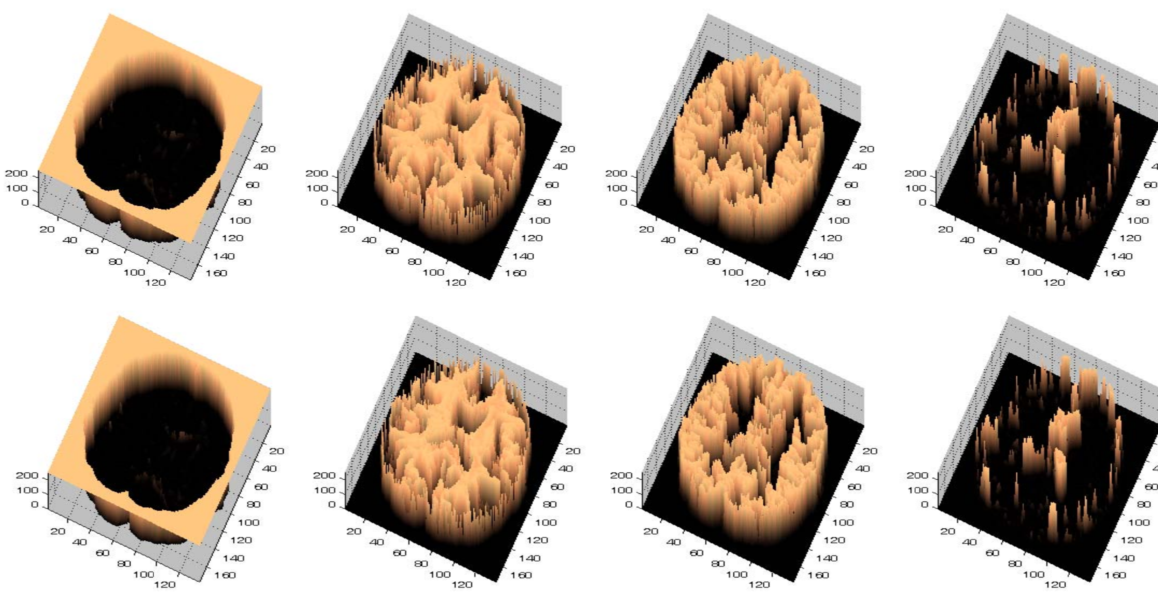

Fig. 7: Fuzzy membership functions for real T1 weighted MR image; 1st and 2nd rows are result of FCM and FFCM respectively; columns from left to right BGND, WM, GM and CSF are shown.

Qualitative comparison between FCM and FFCM from Fig.1to Fig.7 confirm that both algorithms FCM and FFCM segment brain MR images with similar accuracy. Furthermore Table 1 represents quantitative comparison of FCM and FFCM by the fuzzy validity functions. In most cases, the validity functions based on the fuzzy partition have high similarity in the FCM and FFCM algorithms and differences between two techniques are insignificant.

Table 1: Clustering results of three images using FCM and FFCM techniques.

validator	Images	FCM	FFCM
V_{pc}	simulated 4 level MRI (σ=0.002)	0.858	0.858
	Simulated brain MRI (σ=0.0001)	0.905	0.904
	Real MRI	0.867	0.863
V_{pe}	simulated 4 level MRI (σ=0.002)	0.126	0.126
	Simulated brain MRI (σ=0.0001)	0.083	0.084
	Real MRI	0.109	0.115
V_{xb}	simulated 4 level MRI (σ=0.002)	0.037	0.039
	simulated MRI (σ=0.0001)	0.027	0.028
	Real MRI(0.001)	0.069	0.073
$V_{fs \times(-10^{6})}$	simulated 4 level MRI (σ=0.002)	169	162
	Simulated brain MRI (σ=0.001)	140	138
	Real MRI	195	189

Nevertheless execution time and number of iterations in FCM and FFCM are different. For both FCM and FFCM techniques simulations repeated ten times on each image, with same initial cluster centers +selected randomly. In all simulations FCM spent more time than FFCM also iteration numbers of FFCM were less than FCM. In Fig.8 simulation time and number of iteration steps are shown.

Fig. 8: Simulation time and number of iterations to convergence of FCM and FFCM for various MR images

5. Conclusion

Segmentation of medical images using fuzzy clustering has many applications. FCM is a common unsupervised clustering method to segmentation of medical images. FCM is not fast enough in medical applications particularly in emergency situations. This paper presented a Fast FCM technique with a new rule to update cluster centers in each iteration step. Proposed FFCM reduced the computational amount of FCM and segmented brain MR images relatively with the same quality of the FCM. FFCM reduced execution time and iteration number in comparison with FCM. Quantitative assessment of FCM and FFCM techniques was evaluated by common fuzzy validation functions.

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