# Edge-preserving Clustering Algorithms and Their Application for MRI Image Segmentation

M.A. Balafar, A. R. Ramli and S. Mashohor

*Abstract*— **our lately defined edge-preserving neighborhood is used to improve an already exist extension for Fuzzy C-Mean (FCM). In the defined neighborhood, a window is centered on the pixel. Then, each sample, in the window, is considered the neighbor of the pixel if there is not any edge between the sample and the pixel. Moreover two extensions for Expectation Maximizing (EM) are introduced to have better clustering results in presence of noise. Promising experimental results of our proposed extensions in compare to two state-of-art extensions for FCM demonstrate the potential of proposed modifications.**

*Index Terms*—**Neighborhood information, Brain segmentation.**

## I. Introduction

The application of image processing techniques has rapidly increased in recent years. Medical images almost are stored and represented digitally [1]. Medical imaging types mostly are ultrasound images, X-ray computed tomography, digital mammography, magnetic resonance image (MRI), and so on [2]. MRI images have good contrast in compare to computerized tomography (CT). Therefore, most of researches in medical image processing use MRI images. Magnetic resonance imaging (MRI) is an important imaging technique for detecting abnormal changes in different parts of brain in early stage. MRI imaging is popular to obtain image of brain with high contrast. MRI acquisition parameters can be adjusted to give different grey level for different tissues and various types of neuropathology [3].

The brain images segmentation is a complicated and challenging task. However, accurate segmentation of these images is very important for detecting tumors, edema, and necrotic tissues. Moreover, accurate detecting of these tissues is very important in diagnosis systems.

Data acquisition, processing and visualization techniques facilitate diagnosis. Medical image segmentation has very important rule in many computer aided diagnostic tools. These tools could save clinicians time by simplifying the time consuming process [4]. Main part of these tools is to design an efficient segmentation algorithm. Medical images mostly contain unknown noise, in-homogeneity and complicated structure. Therefore, segmentation of medical images is a challenging and complex task. Medical image segmentation has been an active research area for a long time. There are many segmentation algorithms [5-14] but there is not a generic algorithm for totally successful segmentation of medical images. Fuzzy Clustering is most popular unsupervised learning. Expectation-maximization (EM) and fuzzy c-mean (FCM) are the most popular fuzzy clustering algorithms. EM algorithm is used for segmentation of brain MR [15]. EM algorithm models intensity distribution as normal distribution of image, which is untrue, especially for noisy images [15]. FCM just consider intensity of image and in noisy images, intensity is not trustful. Therefore, this algorithm has not good result in low contrast, in-homogeneity and noisy images. Many algorithms introduced to make FCM robust against noise but nevertheless most of them were and are flawless to some extent [16-19].

Sometimes, due to in-homogeneity, low contrast, noise and inequality of content with semantic, automatic methods fail to segment image correctly. Therefore, for these images, it is necessary to use user help to correct method’s error. However, robust semi-automatic methods can be developed in which user help is minimized. When user help is necessary, Segmentation would be supervised. Supervised methods need training data consist of data with known class. The reducing clustering error is the advantage of supervised methods and the need for user help is the disadvantage of these methods. In this paper, new extension based clustering is proposed.

M. A. Balafar is with Department of Computer & Communication Systems, Faculty of Engineering, University Putra Malaysia, 43400 Serdang, Selangor, Malaysia (phone: +60173754148; e-mail: gs19162@mutiara.upm.edu.my).

A. R. Ramli is Department of Computer & Communication Systems, Faculty of Engineering, University Putra Malaysia, 43400 Serdang, Selangor, Malaysia (e-mail: arr@putra.upm.edu.my).

S. Mashohor is with Department of Computer & Communication Systems, Faculty of Engineering, University Putra Malaysia, 43400 Serdang, Selangor, Malaysia (e-mail: syamsiah@eng.upm.edu.my).

## II. Methods

### A. FCM

FCM is a clustering algorithm introduced by Bezdek based on minimizing an object function as follow [20]

$$J_q = \sum_{i=1}^{n} \sum_{j=1}^{m} u_{ij}^{q} d(x_i, \theta_j) \cdot \tag{1}$$

Where d is distance between data $x_i$ and centre of the cluster *j*, $\theta_j$ and U is the fuzzy membership of data $x_i$ to cluster with centre $\theta_j$

$$u_{ij} \in [0,1], \sum_{j=1}^{n} u_{ij} = 1 \ \& \ 0 < \sum_{j=1}^{n} u_{ij} < n \cdot \tag{2}$$

The membership function and the centre of each cluster obtained as follow

$$U_{ij} = 1 / \sum_{k=1}^{m} \left( d(x_i, \theta_j) / d(x_i, \theta_k) \right)^{(2/1-1)} . \qquad (3)$$

$$\theta_j = \sum_{i=1}^{N} U_{ij}^{q} x_i / \sum_{i=1}^{N} U_{ij}^{q} . \qquad (4)$$

Where $q$ specifies the degree of fuzziness in clustering.

FCM optimizes object function by continuously updating membership function and centers of clusters until optimization between iteration is less than a threshold.

### B. FCM_EN

In order to speed up the clustering process for input image, Szilágyi [21] introduced a new extension named FCM_EN. In this extension, instead of using neighborhood information in iteration process, a linearly-weighted sum image from the original image and its average image is used as input image for clustering. That is:

$$S_i = \frac{1}{1+\alpha}(X_i + \alpha \overline{X}_i) \qquad (5)$$

The $\alpha$ has the same role as before. The grey-level histogram of the sum image $S$ is used as input for clustering.

### C. The Edge-preserving mean

A pixel is considered to define its postulated neighborhood [22]. A rectangular window is centered with size $n*n$ on considered pixel. A sample in the window is a postulated neighbor of pixel if there is not any edge between that sample and pixel.

The edge-preserving mean of pixel *i is considered as* the average value of samples in the postulated neighborhood of $i$ as follow:

$$\overline{X}_i^e = \sum_{j \in I} e_{ij} X_j \qquad (6)$$

Where $e_{ij}$ specifies whether sample $j$ is in the postulated neighborhood of pixel or not. The value of $e_{ij}$ is one if sample $j$ is the postulated neighbor of pixel $i$ otherwise it is zero. Sometimes there is not any sample in postulated neighborhood of a pixel in this case; median of the neighborhood distance is considered as edge-preserving average:

$$\overline{X}_i^e = \overline{X}_i^e + (\sum_{j \in I} e_{ij} == 0) * med(X_i) \qquad (7)$$

### D. New extension for FCM

In FCM_EN, average image $\overline{x}$ is replaced with edge-preserving average image $\overline{x}^e$. The extension is named FCM_ENE.

Incorporating neighborhood distance improves the performance of clustering methods in high level of noise but due to blurring effect; degrade the performance of them in low noise level. In other hand, the experiment show that in low level of noise result of FGFCM is better than ordinary FCM. As result, the variance of noise is used as a threshold to automatically trade between use of new method and FGFCM as follow:

$$FCM\_ENE = (\delta^2 <= .5) * FGFCM + (\delta^2 > .5) * FCM\_ENE \qquad (8)$$

### E. New extensions for Expectation Maximizing (EM)

Two new extensions for EM are introduced. In first extension, in order to make EM more roust against noise, neighborhood information is incorporated in clustering process.

In second extension, mean filter is applied to input image. Moreover, histogram of input image is used as clustering data.

## III. Experiments and Results

Our introduced algorithm, FCMEN [22] and FGFCM [23] are simulated in MATLAB and tested on the MRI rain image from BrainWeb [24]. The results of mentioned algorithms are compared quantitatively to investigate their effectiveness.

Three main tissue classes are considered: GM (gray matter), WM (white matter) and cerebral spinal fluid (CSF). The similarity index [25] is used to evaluate the algorithms quantitatively. The similarity index is the degree of matching pixels between ground truth and segmentation result. It is defined as

$$\rho = \frac{2|X_i + Y_i|}{|X_i| + |Y_i|} . \qquad (9)$$

Where $X_i$ represents class i in ground truth and $Y_i$ represents the same class in the segmentation result.

It is difficult to evaluate the segmentation of real MRI brain image quantitatively due to unavailability of ground-truth images. There are simulated brain database along with ground-truth of them in Brainweb which enable researcher to evaluate the performance of different image segmentation qualitatively. In this section, we used a simulated MRI brain 3D image with T1-weighted sequence from Brainweb, slice thickness of 1 mm, volume size of 217×181×181.

The effect of different noise levels on performance of mentioned algorithms are investigated when they are applied to 3D simulated MRI brain volumes. The experiments shows that introduced methods have higher similarity indices, and with increasing the noise level, its similarity indices decreases more slowly than other methods.

## IV. Conclusion

Researchers widely use clustering methods for medical image segmentation. FCM and EM are most popular clustering methods. Traditional clustering methods just consider intensity information and have not good results in presence of noise. Using spatial information is one solution to overcome this problem. In this paper, extensions for FCM and EM are introduced. In introduced algorithms, neighborhood information is incorporated in clustering process.

Our algorithms are applied on simulated MRI images, with different noise levels. The performance of FCM-EN, FCM-FG and introduced algorithms are compared qualitatively. The similarity parameter is exploited and measured the segmentation results. Experiments demonstrate the effectiveness of introduced algorithm in compare to FCM-EN and FCM-FG.

In this research, we worked on improvement of neighborhood algorithms. In future, we consider doing

ISBN: 978-988-17012-8-2
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

research for improvement of other kinds of clustering methods. Also, we investigate the effect of different clustering algorithms in segmentation of medical images for diagnosis abnormal or different important matters in medical images.

## REFERENCES


[1] Ping-Lin, Chang., Wei-Guang Teng: Exploiting the Self-Organizing Map for Medical Image Segmentation. CBMS. (2007) 281-288

[2] Jan, J.: Medical Image Processing Reconstruction and Restoration Concepts and Methods. Taylor & Francis. CRC (2005).

[3] Tian, Dan., Fan, Linan. : A Brain MR Images Segmentation Method Based on SOM Neural Network. ICBBE. (2007) 686-689.

[4] Jiang, Y., Meng, J., Babyn, P.: X-ray Image Segmentation Using Active Contour Model with Global Constraints. (2007) 240 - 245

[5] Pohle, R., Toennies, L.D.: Segmentation of Medical Images using Adaptive Region Growing . Proc,SPIE, Medical Imaging, vol. 4322. (2001)

[6] M. A. Balafar, A. R. Ramli, M. I. Saripan, S. Mashohor, Review of brain MRI image segmentation methods, Artif Intell Rev, DOI 10.1007/s10462-010-9155-0, 2010.

[7] Balafar MA (2008) Medical image segmentation using fuzzy C-mean (FCM) and dominant grey levels of image. In: Visual information engineering conference , pp 314–317

[8] Balafar M et al (2008a) Medical image segmentation using fuzzy C-mean (FCM), Bayesian method and user interaction. In: International conference on wavelet analysis and pattern recognition , pp 68-73

[9] Balafar MA et al (2008b) New multi-scale medical image segmentation based on fuzzy c-mean (FCM). In: IEEE conference on innovative technologies in intelligent systems and industrial applications, pp 66–70

[10] Balafar MA et al (2008c) Medical image segmentation using anisotropic filter, user interaction and fuzzy C-mean (FCM). In: Advanced intelligent computing theories and applications with aspects of contemporary intelligent computing techniques: 4th international conference on intelligent computing, Springer, pp 169-176

[11] Balafar MA et al (2008d) Medical image segmentation using fuzzy C-mean (FCM), learning vector quantization (LVQ) and user interaction. In: Advanced intelligent computing theories and applications with aspects of contemporary intelligent computing techniques: 4th international conference on intelligent computing, Springer, p 177-184

[12] Balafar MA et al (2008e) MRI segmentation of medical images using FCM with initialized class centers via genetic algorithm. In: International symposium on information technology , pp 1-4.

[13] M.A. Balafar, ABD. Rahman ramli, M.Iqbal saripan, Syamsiah mashohor, Rozi Mahmud, MEDICAL IMAGE SEGMENTATION USING FUZZY C-MEAN (FCM) AND USER SPECIFIED DATA, Journal of Circuits, Systems, and Computers, 2010. DOI: 10.1142/S0218126610005913.

[14] M.A. Balafar, ABD. Rahman ramli, M.Iqbal saripan, Syamsiah mashohor, Rozi Mahmud, IMPROVED FAST FUZZY C-MEAN AND ITS APPLICATION IN MEDICAL IMAGE SEGMENTATION, Journal of Circuits, Systems, and Computers, 2010. DOI: 10.1142/S0218126610006001.

[15] Shen, S., Sandham, W., Granat, M., Sterr, A.: MRI Fuzzy Segmentation of Brain Tissue Using Neighbourhood Attraction with Neural-Network Optimization. IEEE Trans. Inform. Tech. Biomedicine. Vol. 9, no. 3. (2005) 459 – 467

[16] Hall, L. O., Bensaid, A. M., Clarke, L. P., Velthuizen, R. P., Silbiger, M. S., Bezdek, J. C.: A Comparison of Neural Network and Fuzzy Clustering Techniques in Segmenting Magnetic Resonance Images of The Brain. IEEE Trans. Neural Netw., vol. 3, no. 5. (1992) 672–682

[17] Acton, S. T., Mukherjee, D. P.: Scale Space Classification Using Area Morphology. IEEE Trans. Image Process., vol. 9, no. 4. (2000) 623–635

[18] Zhang, D. Q., Chen, S. C.: A Novel Kernelized Fuzzy C-means Algorithm With Application in Medical Image Segmentation. Artif. Intell.Med., vol. 32. (2004) 37–52

[19] Dave, R. N. R. N.: Characterization and Detection of Noise in Clustering. Pattern Recognit. Lett., vol. 12. (1991) 657–664

[20] J. C. Bezek, Pattern Recognition with Fuzzy Object Function Algorithms. New York: Plenum, 1981.

[21] L. Szilágyi, Z. Benyó, S.M. Szilágyii, H.S. Adam, MR brain image segmentation using an enhanced fuzzy *c*-means algorithm, in: 25$^{th}$ Annual International Conference of IEEE EMBS, 2003, pp. 17–21.

[22] M.A. Balafar et. al., A New Edge-Preserving Neighbourhood Filter for MRI Image Enhancement, submitted to IET image processing.

[23] Weiling Cai, Songcan Chen, Daoqiang Zhang, Fast and robust fuzzy c-means clustering algorithms incorporating local information for image segmentation, Pattern Recognition 40 (2007) 825 – 838

[24] BrainWeb [Online]. Available: www.bic.mni.mcgill.ca/brainweb/

[25] Zijdenbos, A., Dawant, B..: Brain segmentation and white matter lesion detection in MR images. Critical Reviews in Biomedical Engineering 1994; 22(5–6):401–65.



ISBN: 978-988-17012-8-2
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)