Analytical study of fuzzy C-means clustering algorithm and LVQ ANN

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ABSTRACT
Image segmentation is a significant process in the visualization of human tissues, particularly during clinical analysis of magnetic resonance (MR) images. The Whole brain consists of several tissues precisely white matter (WM), gray matter (GM) and cerebrospinal fluid (CSF). It is hard to differentiate these tissue regions exclusively because these areas are not properly defined by boundaries. MRI brain images are extensively used in medical field for diagnosis, treatment, surgical planning, and research.

In this paper, we have implemented the different version of fuzzy C-Means clustering algorithm and Learning Vector Quantization (LVQ) ANN on MR brain image to extract WM, GM, and CSF. These algorithms have been commonly used and provide a flexible method to automated image segmentation, particularly in the area of brain segmentation. The performance of FCM and LVQ is appraised on Brain Web Database where T1, T2, and ρ weighted images are chosen, whose thickness is 5mm with different noise and intensity non uniformity (RF). Experimental results show the supremacy of segmentation accuracy even on the noisy MRI brain image. The accuracy, sensitivity, and specificity are improved with better segmentation.

Keywords *- cerebrospinal fluid, Fuzzy C-means, gray matter, LVQ, MRI, segmentation, white matter.*

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I. INTRODUCTION

Several imaging techniques are implemented by the doctors namely magnetic resonance imaging (MRI), computed tomography CT, mammography, X-ray, Single photon emission computed tomography SPECT. Magnetic resonance imaging is a very versatile in case of whole body imaging, like brain, heart, abdomen, knee etc. [1]. Radio waves and strong magnetic field are used in MRI scan to produce pictures of tissues, organs and other structures inside our body which is displayed on a computer. Magnetic resonance imaging (MRI) offers comprehensive images of living tissues. Data acquired from MR images is used for identifying tissue abnormalities such as injuries and cancers; MR is also used comprehensively in studies of brain pathology, where regions of interest (ROI's) are frequently examined in detail, for example in multiple sclerosis (MS) studies [2]. Magnetic resonance images (MRI) is commonly used in the study of brain function, pathology, and anatomy. MRI is a non-invasive technique to present high resolution images which provide high intensity contrast between different soft tissues. It plays a significant role in brain tissue visualization. Tissue segmentation for assessing the brain abnormalities, brain development and evaluation of the progress of treatment can be done by using automatic segmentation, where WM, GM, CSF are main tissues in a normal brain [3].

Dividing an image into a number of non-overlapping meaningful regions is called image segmentation. Segmentation is hard to be performed usually because of region inhomogeneity, blurred region boundaries, and noise [4]. Image segmentation is a key technique to analysis, understand and describe medical images for diagnosing various diseases [5]. It is one of the basic problems in image analysis. In the investigation of medical images for computer-aided diagnosis and therapy, segmentation is often required at an initial stage. It is a challenging and complex task because of the inherent nature of the images. The brain has a very complex structure and its accurate segmentation is vital for detecting necrotic tissues, tumors, and edema for prescribing appropriate therapy. MRI is a vital diagnostic imaging method for the initial finding of abnormal changes in organs and tissues [6].

The processing operation in which an area of the image with specific characteristics is labeled is known as Brain MRI segmentation (BMS). It is the main processing step in many medical researches and clinical applications where decision making is critical. As brain MRI is a set of images with large volume information. Manual segmentation is a time consuming task so an automatic segmentation method with adequate speed, high accuracy, and generalization capability is needed [7].

Many researchers have proposed different segmentation methods for brain MRI segmentation. These image segmentation algorithms are broadly classified into four groups: thresholding, edge detection, region based and clustering [8]. Thresholding methods isolate the original image into foreground and background by setting up a threshold. Edge detection algorithms locate the boundaries of the objects in the image by analyzing the unexpected changes in the intensities of the image pixels. Region based approaches make segmentation by utilizing region features and finally in clustering algorithms it divides the objects or patterns into different groups in a way that the samples in a group are more similar to each other than the samples of other groups [9]. Because of the complexity for classification of tissue intensities in brain images threshold determination becomes very difficult. Due to this thresholding methods are normally restrictive and always combined with other methods [10]. In region growing it extends thresholding by combining it with region homogeneity criteria or connectivity conditions. Any methods become Successful if they collect accurate anatomical information to locate single or multiple seed pixels for each region along with their associated homogeneity [11]–[13]. Clustering is a very popular technique for medical image segmentation. There are Different clustering algorithms, such as K-Means, EM (the Expectation Maximization algorithm), SOM (self-organizing map), the mean shift algorithm and fuzzy c-means (FCM) clustering [15].

Clustering is an unsupervised learning problem in which meaningful and useful objects were accumulated together based on some similarity measure. The most used algorithm for image segmentation in the last decade is Fuzzy c- Means clustering (FCM) [15]. Fuzzy c-means was first proposed by Dunn and it was used as the general FCM clustering algorithm by Bezdak. This algorithm splits the image pixels into different clusters depends on the degree of the membership in other words each pixel can belong to multiple regions based on the membership value. FCM has been broadly implemented in several medical applications because of its good performance [9]. Unfortunately, over-sensitivity to noise is the greatest limitation of FCM. The original FCM algorithm delivers better results for segmenting noise free images but it cannot properly segment images that are corrupted by noise, outliners and other imaging objects. The FCM algorithm is modified to improve the partition of the meaningful regions [16].

Learning Vector quantization (LVQ) ANN is supervised learning algorithm used for classification of MR Images. It used codebook vectors for training purpose, where the correctness of classification and segmentation for MR images depends upon codebook.

II. RELATED WORK

Medical image segmentation is a very significant issue in medical imaging. Many segmentation techniques have appeared in literature out of which some are discussed here.

Clustering algorithm segments an image by grouping homogeneous data points in the feature space into the same cluster. The main motive of this algorithm is to partition the image into clusters of similar data points by iteratively minimizing a cost function in accordance with a distance metric, which depends upon the distance between the pixels and the cluster centers in the feature space. However, the FCM algorithm only considers the intensity information and does not consider the spatial information present in the image into consideration, therefore, has a drawback of having high sensitivity to noise and other image artifacts. Ahmed et a1. [9] proposed an alteration in FCM algorithm with spatial constraints named FCM_S by combining a neighbor regularization term into the objective function of the FCM algorithm. This algorithm improves the noise sensitivity on account of heavy computational time. Chen and Zhang [18] proposed two alternatives of the FCM named FCM_SI and FCM _ S2. In which they use the mean filtered and median filtered image respectively to change the neighborhood term in the FCM_S, and these filtered images are calculated in advance, therefore, decreasing the computational time. Szilgyi et al [10] proposed the enhanced EnFCM, in which they use the grey level histogram to perform clustering, because the numbers of grey levels are generally less in comparison with the number of pixels in the image, thus reducing the time complexity. To further reduce the computational time Cai et al.[11] proposed a fast generalized FCM(FGFCM) which integrates both the local spatial and the local grey level relationship into the FCM algorithm, which further decreases the noise sensitivity as well as reduces the time complexity. All these clustering methods use the local information of the pixel for image segmentation. In the case of MRI images corrupted by high intensity of noise, the result of all these algorithms decreases; it is the major drawbacks of all these methods. Zexuan et.al [16] proposed a method known as weighted image patch based FCM algorithm

(WIPFCM), which uses the image patches instead of pixels in FCM algorithm to increase the robustness. Motivated by patch based methods Zaixin et.al [17] proposed a neighborhood weighted FCM algorithm (NWFCM) which uses both the patch difference and local statistics to show a new similarity measure into the objective function of the FCM algorithm, making it compete better with the other algorithms.

Dzung L. Pham et al. [2] develops an algorithm in which they altering the objective function in the Fuzzy C Means algorithm to include a multiplier field. But if there is extreme noise, it may perform poorly. Ardizzone et al. [3] modified the FCM segmentation of MRl by using Gullied filter for pre-processing to remove inhomogeneity in the images. Bianrgi, P.M. et al [4] proposed an MRI segmentation using neural network based FCM clustering algorithm. The method applied on one channel MR data, but MR images are multi-spectral and give additional information. Because of noise and inhomogeneity, this algorithm fails to work. Wang et al. [5] proposed the Modified Fuzzy C- Means (MFCM) algorithm. It changes original FCM by using local and nonlocal information, and distance metric was replaced by dissimilarity index. K. Sikka et al. [6] develops a fully automated algorithm for Modified FCM framework. Neelum Noreen et al. [8] proposed MRl segmentation using wavelet and Fuzzy c means to remove inhomogeneity but it does not enhance edge detail. Iraky khalifa et al. [9] proposed Fuzzy C Means (FCM) Clustering in which they use wavelet Decomposition for feature extraction and feature vector treat as input to FCM. This gives better segmentation than Fuzzy C Means. Anil A Patil et al, [10] proposed Image denoising by applying curvelet transform with Bayes Shrink Soft Thresholding to improve smoothness and edge preservation. Priti Naik et al. [11] develops denoising method using curvelet transform with two thresholding techniques which are hard thresholding and partial reconstruction. For further accurate segmentation, M. Arfan Jaffar et al. [13] proposed a Spatial Fuzzy method with wrapping based curvelet transform for denoising. This method uses spatial relationship for c1ustering. Hamed shamsi et al. [14] proposed new fuzzy algorithrn. In which the initial membership matrix for clusters obtained by initial cluster center using spatial information to improve the strength of the clusters.

Javad Alirezaie, M. E. Jernigan, and C. Nahmias introduce a study exploring the potential of artificial neural networks (ANN's) for the segmentation and classification of MR images of the human brain. In this study, they introduce the application of a learning vector quantization (LVQ) ANN for the multispectral supervised classification of MR images. They have improved the LVQ for superior and more precise classification. They have analyzed the results using LVQ ANN versus back-propagation ANN. This comparison demonstrates that there technique is impervious to the gray-level variation of MR images between different slices. It presents that tissue segmentation using LVQ ANN performs better and faster than that using back-propagation ANN.

III. Fuzzy C - Means Clustering algorithm (FCM)

The standard FCM algorithm is worldwide accepted for image segmentation method. It is unsupervised learning algorithm which was presented by Dunn and later on extended by Bezdek. This algorithm is a slight variation of k-means algorithm. FCM algorithm is the application of image segmentation of MRI brain images which extracting into three clusters specifically white matter (WM), gray matter (GM) and cerebrospinal fluid (CSF) [28]. FCM algorithm produces the better performance compared to Kmeans algorithm. In FCM clustering it allows data to be divided into a number of clusters. It depends on minimizing an objective function, with respect to fuzzy membership, and set of cluster centroids V.

$$J_m(U,V)=\sum_{j=1}^{N}\sum_{i=1}^{C}u_{ij}^{m}d^2(x_j,v_i) \qquad (1)$$

In the above equation, $X=\{x_1,x_2,...x_j,...x_N\}$ is data matrix where p denotes the dimension of each Xj, "feature" vector, and N denotes the number of feature vectors. C represents the number of clusters. The m is weighting exponent on each fuzzy membership and control the degree of "fuzziness" of the resulting classification. U is a fuzzy matrix. $d\left\|x_j-v_i\right\|$ is the Euclidean norm. The membership function is represented as follows:

$$u_{ij}=\frac{1}{\sum_{k=1}^{C}\left(\frac{d\left(X_j,V_i\right)}{d\left(X_j,V_k\right)}\right)^{2/(m-1)}} \qquad (2)$$

$V=\left\{v_1,v_2,...v_i,...v_c\right\}$, which is a $p\times C$ matrix and represents the cluster feature center

$$v_i=\frac{\sum_{j=1}^{N}(u_{ij})^m x_j}{\sum_{j=1}^{N}(u_{ij})^m}(i=1,2,...C) \qquad (3)$$

$m \in (1,\infty)$ is a weighting exponent on each fuzzy membership, which controls the degree of fuzziness. $d^2(x_j, v_i)$ is a measurement of similarity between x_j and v_i

$$d^2(x_j, v_i) = \|x_j - v_i\|^2 \quad (4)$$

$\|.\|$ is defined as a straightforward Euclidean distance or its generalization such as the Mahalanobis distance. The feature vector X in MR images represents the pixel intensities, so $p=1$. The FCM algorithm iteratively optimizes $J_m(U,V)$ with the continuous update of U and V, until $U^{(l+1)} - U^{(l)} \le \varepsilon$, where is the number of iterations.

There are some limitations of FCM for image segmentation. First, equation-1 shows that the objective function of FCM doesn't take into consideration any spatial dependence among X, but deals with images the same as separate points. Secondly, the membership function U in equation-2 is typically decided by $d^2(x_j, v_i)$, which measures the similarity between the pixel intensity and the cluster center. Higher membership depends on closer intensity values to the cluster center so it increases the sensitivity of the membership function to noise. If an image comprises noise or is affected by objects, it will change the pixel intensities, which results in an incorrect membership and improper segmentation. These problems must be properly resolved to improve the robustness of the FCM algorithm.

IV. Learning vector quantization (LVQ)

Learning Vector Quantization ANN is a classification network developed by Kohonen in 1988. It consists of two layers which classifies patterns by using the finest set of reference vectors or codewords. A codeword is a set of connection weights from input to output nodes as shown in Figure [29]. The set of vectors $w_1, w_2, ..., w_k$ is called a codebook in which each vector w_i is a codeword for Vector Quantization. If numerous codewords are allocated to each class, and everyone is labeled with the corresponding class symbol, the class region in the x space (input) are well-defined by simple nearest-neighbor comparison of x with the codewords w_i; the label of the closest w_i defines the classification of x.

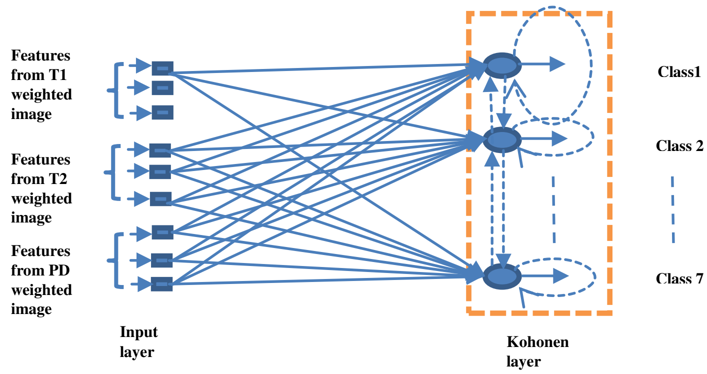


Fig.1 Topology of LVQ ANN

To define the optimum placement of w_i in an iterative learning process, initial values must be set. In next step, we have determined the labels of the codewords, by presenting a number of input vectors with known classification, and assigning the codewords to different classes by majority voting, according to the frequency with which each w_i is closest to the calibration vectors of a particular class x.

The classification accuracy improves if the w_i are modified as per the algorithm described below. The idea is to pull codewords away from the decision surface to mark the class borders more accurately. In the following algorithm assume w_i is the nearest codeword to the input vector x (1) in the Euclidean metric; then, also defines the classification of x:

$$\|x - w_i\| MIN_{j=1}^{k} \|x - w_i\| \quad 1$$

Where the Euclidean distance between any two vectors X and Y is defined as

$$\|X - Y\| = \left[\sum_{i=1}^{n} (x_i - y_i)^2\right]^{\frac{1}{2}}$$

The following algorithm shows how the codewords will be updated:

$$w_i(t+1) = w_i(t) + \alpha(t)[x - w_i(t)] \quad 2$$

if x is classified properly means if the label agreed with codeword assignment

$$w_i(t+1) = w_i(t) - \alpha(t)[x - w_i(t)] \quad 3$$

if the classification is incorrect (if the label does not agree with the codeword assignment), and

$$w_i(t+1) = w_j(t), i \ne j \quad 4$$

(the other codewords are not modified).

Here $\alpha(t)$ is a learning rate such that $0 < \alpha(t) < 1$ and is decreasing monotonically in time. We chose

$$\alpha(t) = 0.2\left(1 - \frac{t}{10000}\right)$$

After enough iteration, the codebook normally converges and the training is terminated.

V. Experiment and results

In this section, we present the results from two approaches for segmentation of MR brain images i.e. LVQ and FCM. In LVQ methods we use pixel intensity values and spatial information of neighboring pixels as features. The number of input nodes in the network is equal to the number of features, and the number of output nodes is equal to the number of target tissue classes. In FCM we compare the segmentation performance of FCM, KFCM, and SFCM.

In each of the cases, the images are segmented into three classes: CSF, white matter, gray matter.

5.1 Results of the LVQ ANN Approach

Codebook Initialization: To initialize the codebook vectors a set of vectors is chosen from the training data, one at a time. All the entries used for initialization must fall within the borders of the corresponding classes, which are checked by the K-nearest neighbor (K-nn) algorithm. In this step, the placement of all codebook vectors is first determined without considering their classification. Then for initialization codebook vector is selects based on the desired number of codewords. For our segmentation problem, different sets of codebooks including 60 to 120 codewords for each set have been tested.

The precision of classification may depend on the number of codebook entries allocated to each class. There is not any simple rule to find out the best distribution of the codebook vectors. We used the method of iteratively balancing the medians of the shortest distances in all classes. Our program first computes the medians of the shortest distances for each class and corrects the distribution of codewords in a way that the classes in which the distance is greater than the average, codewords are added; and for those classes in which the distance is smaller than the average, some codewords are deleted from the initialized codebook vector [29].

Finally, when the codebook has been initialized properly, training is started. Training vectors are selected by manual segmentation of Multi-spectral MR images (Tl, T2, and p-weighted images) of the brain.

Fig. 2 shows results obtained using this approach. The original T1 weighted image is shown in Fig. 2(a). CSF, white matter and gray matter are shown separated in Fig. 2(b)–(d).

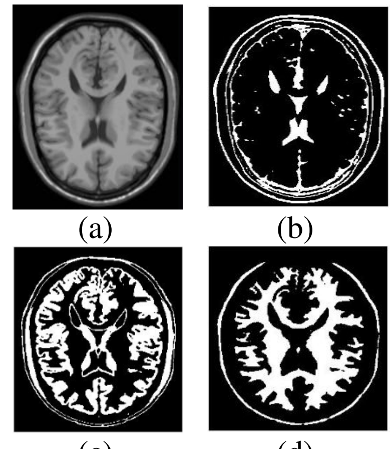


Fig.2. Result of LVQ (a) original T1 weighted image (b) CSF (c) gray matter (d) white matter

5.2 Results of the FCM Approach

Fig. 3 shows results obtained using FCM approach. The original T1 weighted image is shown in Fig. 3(a). CSF, white matter and gray matter are shown separated in Fig. 3(b)–(d).

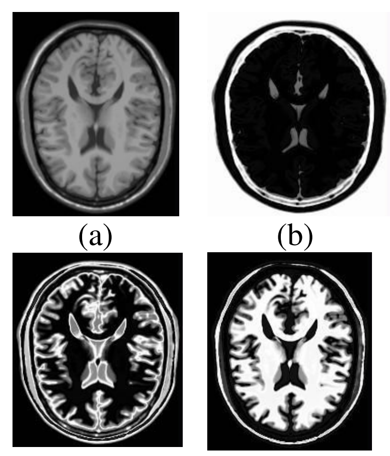
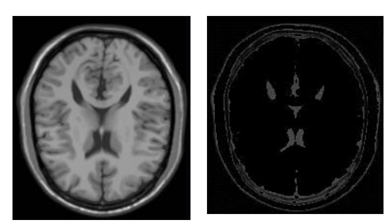
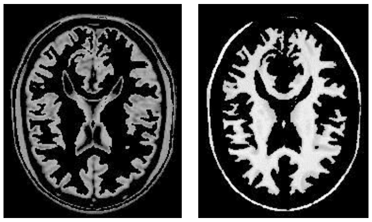


Fig.3. Result of FCM (a) original T1 weighted image (b) CSF (c) gray matter (d) white matter

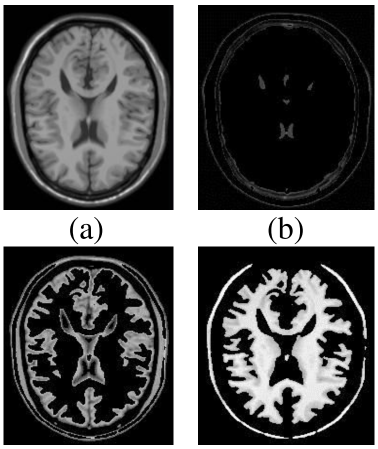


(a) (b)



(c) (d)

Fig.4. Result of KFCM (a) original T1 weighted image (b) CSF (c) gray matter (d) white matter



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

Fig.5. Result of SFCM (a) original T1 weighted image (b) CSF (c) gray matter (d) white matter

Table I: Evaluations of LVQ and different FCM methods

Segmented Image	Segmentatiion Technique	Validation Function	
		Vpc	*Vpe*
Noice 9% HH 40%	FCM	0.802	0.381
	KFCM	0.891	0.178
	SFCM	0.876	0.052
	LVQ	0.985	0.030
Noice 9% HH 20%	FCM	0.801	0.379
	KFCM	0.893	0.180
	SFCM	0.881	0.050
	LVQ	0.984	0.030
Noice 7% HH 40%	FCM	0.821	0.347
	KFCM	0.910	0.157
	SFCM	0.883	0.052
	LVQ	0.983	0.029
Noice 7% HH 20%	FCM	0.823	0.343
	KFCM	0.889	0.157
	SFCM	0.882	0.056
	LVQ	0.986	0.027

In above table, we have described the comparative study of LVQ and different variations of FCM. The T1 weighted brain MRI image is taken from the freely available Brain Web dataset [30]. Different combination (noise percentage and intensity inhomogeneity percentage) of T1 weighted simulated brain MRI image have been chosen.

The quantitative results of a T1-weighted simulated brain MRI images are shown in Table I. The performance of all the method has been tested for the different level of noise and inhomogeneity for the T1 weighted simulated brain MRI images, which are freely available in the Brain Web database [30] and found that the LVQ method is significantly improved over the FCM, KFCM, and SFCM.

Table II. Appraisal of segmentation techniques on T1 weighted MR image

class	Evaluation Prameters	FCM	KFCM	SFCM	LVQ
CSF	Uns(%)	0.5	0	0.47	0.21
	OvS(%)	7.98	100	7.98	6.8
	InC(%)	0.76	34	0.73	0.51
White matter	Uns(%)	1.35	0	1.11	0.93
	OvS(%)	11.08	100	10.92	7.11
	InC(%)	2.33	10.16	2.11	1.2
Gray matter	Uns(%)	0.75	15.86	0.76	0.51
	OvS(%)	7.23	0	5.72	2.61
	InC(%)	1.68	13.57	1.47	0.93
Average	Uns(%)	0.87	5.29	0.78	0.51
	OvS(%)	8.76	66.67	8.21	5.5
	InC(%)	1.59	19.24	1.44	1.05

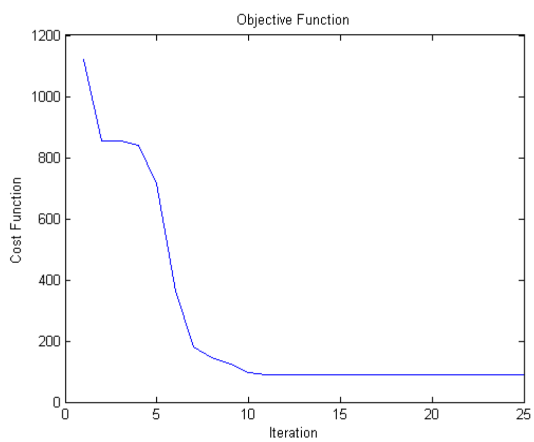


Fig.6. Objective function

VI. CONCLUSION

Medical images usually contain unknown noise and substantial uncertainty, and therefore clinically acceptable segmentation performance is difficult to achieve. MRI brain image segmentation is useful for further investigation by the radiologists and is suitable to measure the content of tissue regions under any abnormality developed in the human brain. Here we have evaluated the segmentation technique on MRI images where Vpc and Vpe are validated according to increasing of noise level with 7% and 9% of noise.

In this paper, we have also compared different methods for tissue segmentation of MRI brain images like gray matter, white matter, and Cerebrospinal Fluid. The appraisals of segmentation technique of T1 weighted are shown in table 2. The implementation of LVQ, FCM, KFCM, and SFCM algorithms have been tested on brainweb images, with different noise levels. Experimental results show that the LVQ method is robust for tissue segmentation.

REFERENCES

[1] Pankhuri Agarwal et al, "A combination of bias-field corrected fuzzy cmeans and level set approach for brain MRI image segmentation", IEEE sponsored Second International Conference on Soft Computing and Machine Intelligence, 978-1-4673-9819-0/15

[2] M. S. atkins and B. T. Machkiewich, "Fully Automatic Segmentation of the Brain in MRI", IEEE transactions on medical imaging, vol. 17, no. 1, February 1998.

[3] Zhang Shi, She Lihuang, Lu Li, Zhong Hua, "A Modified Fuzzy C-Means for Bias Field Estimation and Segmentation of Brain MR Image", 25th Chinese Control and Decision Conference (CCDC), 978-1-4673-5534-6/13/$31.00 2013 IEEE.

[4] Pratibha Singh et al, "Automatic Brain MRI Image Segmentationusing FCM and LSM", 978-1-4799-6896-1/14/$31.00 ©2014 IEEE.

[5] Jianwei Liu, Lei Guo, "A New Brain MRI Image Segmentation Strategy Based on Wavelet Transform and K-means Clustering", ICSPCC2015, 978-1-4799-8920-1/15/$31.00 ©2015 IEEE

[6] Shan Shen et al, "MRI Fuzzy Segmentation of Brain Tissue Using Neighborhood Attraction With Neural-Network Optimization", IEEE transactions on information technology in biomedicine, vol. 9, no. 3, sep. 2005, 1089-7771/$20.00 © 2005 IEEE.

[7] Jamal Ghasemi, Mohamad R. Karami, Reza Ghaderi, Ali Hojjatoleslami, "Brain Tissue Segmentation by FCM and Dempster-Shafer Theory", 978-1-4577-1535-8/11/$26.00 ©2011 IEEE.

[8] Pal, N.R. et al, "A Review on Image Segmentation Techniques", 1993. 26(9): p. 1277-1294.

[9] Iman Omidvar Tehrani, Subariah Ibrahim, "An Enhanced Fuzzy c-means Medical Segmentation Algorithm", 2014 International Symposium on Biometrics and Security Technologies (ISBAST), 978-1-4799-6444-4/14/$31.00 ©2014 IEEE.

[10] L. Lemieux, G. Hagemann, K. Krakow, and F. G. Woermann, "Fast, accurate, and reproducible automatic segmentation of the brain in T1-weighted volume MRI data," Magn. Reson. Med., vol. 42, pp. 127–135, 1999.

[11] A. R. Robb, Biomedical Imaging, Visualization, and Analysis. New York: Wiley, 2000.

[12] R. Pohle and K. D. Toennies, "Segmentation of medical images using adaptive region growing," Proc. SPIE— Med. Imag., vol. 4322, pp. 1337–1346, 2001.

[13] T. Y. Law and P. A. Heng, "Automated extraction of bronchus from 3D CT images of lung based on genetic algorithm and 3D region growing," Proc. SPIE— Med. Imag., vol. 3979, pp. 906–916, 2000.

[14] Lahouaoui Lalaouia, Tayeb. Mohamadib, and Abdelhak Djaalabb, "New Method for Image Segmentation," Lahouaoui Lalaoui et al. / Procedia - Social and Behavioral Sciences 195 (2015) 1971 – 1980.

[15] Benson. C. C, Deepa V, Lajish V. L and Kumar Rajamani, "Brain Tumor Segmentation from MR Brain Images using Improved Fuzzy c-Means Clustering and Watershed Algorithm," 2016 Intl. Conference on Advances in Computing, Communications, and Informatics (ICACCI), Sept. 21-24, 2016, Jaipur, India, 978-1-5090-2029-4/16/$31.00 @2016 IEEE.

[16] Ayuni Fateeha Muda, Norhashimah Mohd Saad, Nazreen Waeleh, Abdul Rahim Abdullah, Low Yin Fen, "Integration of Fuzzy C-Means with Correlation Template and Active Contour for Brain Lesion Segmentation in Diffusion-Weighted MRI", 2015 Third International Conference on Artificial Intelligence, Modelling and Simulation, 978-1-4673-8675-3/15 $31.00 © 2015 IEEE, DOI 10.1109/AIMS.2015.88

[17] M. Ahmed, S. Yamany, N. Mohamed, A. Farag, T. Moriarty, "A modified fuzzy C-means algorithm for bias field estimation and segmentation of MRI data," IEEE Trans. Med. Imaging., vol. 21, pp. 193-199, 2002.

[18] S. Chen and D. Zhang, "Robust image segmentation using FCM with spatial constraints based on new kernel-induced distance measure," IEEE Trans. Syst., Man, Cybern., B, Cybern., vol. 34, no. 4, pp. 1907- 1916, Aug. 2004.

[19] L. Szilagyi, Z. Benyo, S. Szilagyii, H. Adam, "MR brain image segmentation using an enhanced fuzzy C-means algorithm," in Proc. 25th Annu. Int. Conf. IEEE EMBS, pp. 17-21,2003.

[20] W. Cai, S. Chen, D. Zhang, "Fast and robust fuzzy c-means clustering algorithms incorporating local information for image segmentation," Pattern Recognit., vol. 40, no. 3, pp. 825-838, Mar. 2007.

[21] Zexuan. Ji, Y. Xia, Q. Chen, Q. Sun, D. Xia, D. Feng, " Fuzzy c-means clustering with weighted image patch for image segmentation," Applied Soft Computing, 12(2012), 1659-1667. 2012.

[22] Z. Zaixin, C.Lizhi, C. Guangquan, "Neighbourhood weighted fuzzy c means clustering algorithm for image

segmentation ", IET Image processing, Vol. 8, Iss. 3, pp. 150-161,2014.

[23] Dzung.L. paum, Jerry.L. Prince, "An adaptive fuzzy c-means algorithm for image segmentation in the presence of intensity inhomogeneities," Pattern Recognition letters, 1998.

[24] Ardizzone.E, Pirrone.R, and Orazio.O.G, "Fuzzy C-Means Segmentation on Brain MR Slices Corrupted by RF-Inhomogeneity," In Proc. The 7th international workshop on Fuzzy Logic and Applications: Applications of Fuzzy Sets Theory, WILF '07, Springer-Verlag, pp: 378-384,2007.

[25] Bianrgi.P.M, Ashtiyani.M, and Asadi.S, "MRI Segmentation Using Fuzzy C-means Clustering Aigorithm Basis Neural NetworK," In Proc. ICTT A 3rdInternationai Conference on Information and Communication Technologies: From Theory to Applications, pp: 1-5, 2008.

[26] Wang.J, Kong.J, Yinghua.L, "A modified FCM algorithm for MRI brain image segmentation using both local and non-Iocal spatial constraints," Computerized Medical Imaging and Graphics, vol. 32, pp. 685-698, 2008.

[27] Sikka.K, Sinha.N, Singh.P.K, and "A fully automated algorithm under modified FCM framework for improved brain MR image segmentation," Magn. Reson. Imag., vol. 27, pp. 994--1004, Jul. 2009.

[28] S.Jansi, P.Subashini, "Modified FCM using Genetic Algorithm for Segmentation of MRI Brain Images", 2014 IEEE International Conference on Computational Intelligence and Computing Research, 978-1-4799-3975-6/14/$31.00 ©2014 IEEE.

[29] Javad Alirezaie, M. E. Jernigan, and C. Nahmias, "Neural Network-Based Segmentation of Magnetic Resonance Images of the Brain", IEEE TRANSACTIONS ON NUCLEAR SCIENCE, VOL. 44, NO. 2, APRIL 1997.

[30] http://www.bic.mni.mcgill.ca/brainweb/