ISSN No. 0976-5697

Volume 1, No. 4, Nov-Dec 2010

International Journal of Advanced Research in Computer Science

RESEARCH PAPER

Available Online at www.ijarcs.info

A Novel Clustering Based Segmentation of Multispectral Magnetic Resonance Images

D.Janaki Sathya*
Research Scholar, Department of EEE,
Karpagam University, Coimbatore, India
janu_sathya@rediffmail.com

Dr. K. Geetha
HOD, Department of EEE,
Karpagam Institute of Technology, Coimbatore, India
geetha.arulmani@gmail.com

Abstract: The application of image processing techniques has rapidly increased in recent years. Medical images almost are stored and represented digitally [26]. 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 [27]. 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. Image segmentation is an established necessity for an improved analysis of Magnetic Resonance (MR) images. Segmentation from MR images may aid in tumor treatment by tracking the progress of tumor growth and shrinkage. The advantages of Magnetic Resonance Imaging are that the spatial resolution is high and provides detailed images. Functional Magnetic Resonance Imaging data are a major challenge to any image processing software because of the huge amount of image voxels [8]. Magnetic Resonance Imaging has proved to provide high quality medical images and is widely used especially for brain [9]. The various MR image slices of the brain are recorded depending on the tasks the patient is performing. The MR feature images used for the segmentation consist of three weighted images namely T1, T2 and Proton Density (PD) for each axial slice through the head. In this paper, a novel algorithm is presented for unsupervised segmentation of multi-spectral images, based on the research, through neural network techniques, of an optimized space in which to perform clustering. Tests performed on both real and simulated MR images shows good result, encouraging the application to different medical targets and further investigation.

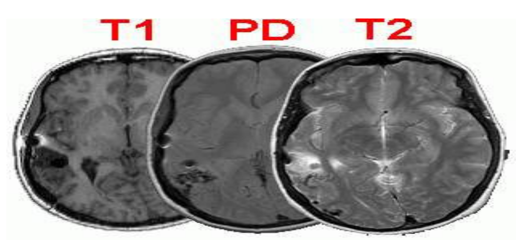
Keywords: Image Voxels, Neural Networks, Image Segmentation, Self-Organizing maps, clustering

I. INTRODUCTION

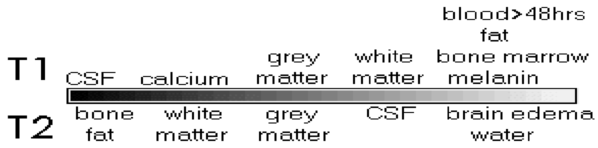
Segmentation of medical images is a challenging and complex task. Medical image segmentation has been an active research area for a long time. There are many segmentation algorithms [28], [29], [30] but there is not a generic algorithm for totally successful segmentation of medical images. The Segmentation of images holds an important position in the area of image processing. It becomes more important while typically dealing with medical images where pre-surgery and post-surgery decisions are required for the purpose of initiating and speeding up the recovery process. Computer aided detection of abnormal growth of tissues is primarily motivated by the necessity of achieving maximum possible accuracy. Manual segmentation of these abnormal tissues cannot be compared with modern day's high speed computing machines which enable us to visually observe the volume and location of unwanted tissues.

A. *Medical Imaging*

The medical research has been quite receptive of image processing in applications like X-ray, Computer Aided Tomography, Ultrasound and Magnetic Resonance. The output of these techniques, an image of the patient's body, allows the physician to examine and diagnose without the need of surgery. The introduction of advanced medical imaging techniques has dramatically improved the quality of brain pathology diagnosis and treatment. In particular, Magnetic Resonance Imaging (MRI) allows the acquisition of three-dimensional, high resolution and highly detailed images of brain anatomy, with unparalleled soft tissue contrast with respect to other medical imaging modalities [4]. The MR images are widely used not only for detecting tissue deformities such as cancers and injuries, but also for studying brain pathology [14]. In any magnetic resonance image there exists many different types of tissues each with characteristic T1, T2 decay times and proton densities is shown in Fig. 1. For instance, the T1 images give anatomical details, but tend to be noisy due to the short acquisition time (< 1000 ms for one slice). T2 images possess bigger contrast between the tissues but take longer to acquire (3000 - 4000 ms). The PD images (typical acquisition time: 2000 ms) generally manifest the smallest contrast between the tissues. Hence PD images present the greatest challenges for anatomical segmentation. The complexity of tissue boundaries causes many voxels to be composed of at least two or more tissues. On the other hand, the constitution of a brain cannot be restricted to only three pure tissues (GM, WM and CSF). If these parameters of tissues can be calculated from the regular magnetic resonance images, the type of tissue could also be determined on any MR image independent of MR hardware characteristics. One such important hardware limitation is the varying sensitivity of an imaging coil spanally. Segmentation algorithms cannot distinguish between an intensity variation caused by the imaging coil sensitivity or a variation by tissue change. Calculated T1, T2 and PD images provide consistent pixel intensity corresponding to the same tissue and therefore are easier to utilize in conventional segmentation algorithms.



(a)



(b)

Figure 1. (a): T1, proton density and T2 weighted slices from the same patient. The 'pathological' T2 scan is useful for locating the lesioned region in the brain. The 'anatomical' T1 scans usually have the best scan resolution and are useful for localizing anatomical structures. The PD scan shows overall hydrogen density per cubic mm. (b) gray scale intensities of the various matters present in the brain slice.

B. *Image Processing tools*

Segmentation is a fundamental tool which aids in identification and quantitative evaluation. It conditions the quality of analysis. Computer based segmentation has reminded largely an experimental work many efforts have exploited MRI's multi-dimensional data capability through multi-spectral analysis. Segmentation as defined by Kapur [8] is a labeling problem in which the goal is to assign to each voxel in an input gray-level image, a unique label that represents an anatomical structure". Many approaches to MRI segmentation both supervised and unsupervised have been proposed in literature [1], [9], [12], [13], [19]. Among the unsupervised segmentation techniques, the K-means algorithm is applied. Self organizing feature maps (SOM) in a hierarchical manner is developed, with this approach using a certain degree of supervision. An acceptable classification is obtained when applied to test images.

In particular, Neural Networks try to simulate a structure similar to the one that is believed the human brain has. Two dimensional layers of cellular modules that are densely interconnected between them model most neural networks in the brain, especially in the cortex [18]. This area of the brain is organized into several sensory modalities such as speech or hearing. The engineering approach of neural networks develops hardware or software inspired by the brain's structure [17].

Neural network attracted more and more researchers for its abilities of parallel operation, self learning, fault tolerance, associative memory, multifactorial optimization and extensibility [15]. Neural network based clustering has yielded good results [2] [3], yet the possibility of transforming the input space in order to facilitate segmentation has been largely unexplored [25]. This paper proposes a new unsupervised algorithm for multi-spectral MR image segmentation is implemented. In this method, classical Kohonen map-based clustering is enhanced through the search of an optimized space in which to operate the clustering [22], [23]. It allows for the ability to make the clustering methods able to retain more information from the original image than the crisp or hard segmentation methods [21].The paper is organized as follows: Section II, system architecture is described; while results are reported in Section III. Conclusions and possible further developments are illustrated in Section IV.

II. IMPLEMENTATION

The framework of the present work is the development of a novel algorithm acting as a support to the diagnosis process for those affections that require medical imaging. Such tools present to the clinician both a qualitative and a quantitative description of the disease. In this proposed algorithm each input is a slice of the image dataset, which undergoes a number of sequential processing steps: preprocessing, clustering, error back propagation, and classification as shown in Fig. 2. Magnetic resonance imaging is a tomography technique, i.e. each image comprises of a number of slices, each corresponding to a given slice of tissue; following the pulse repetition period (TR) and parameters related to the applied radio-frequency magnetic field. It is possible to obtain images with different contrast, each reflecting a different parameter regulating the relaxation of the excited tissues. Multispectral datasets comprising three images (also referred to as channels) weighted by spin-lattice time constant T1, spin-spin time constant T2 and proton density (PD) is considered. After the clustering process, each cluster is manually interpreted and assigned to a proper tissue class.

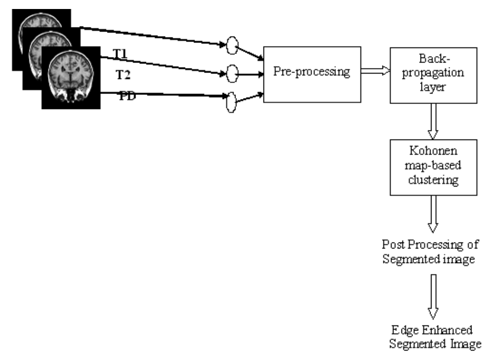


Figure 2. Segmentation Process

A. *Preprocessing*

In segmenting MRI data, three main difficulties are considered namely: noise, partial volume effects (where more than one tissue is inside a pixel volume) and intensity in-homogeneity [20]. The majority of intensity in-homogeneities are caused by the irregularities of the scanner magnetic fields–static (B0), radio-frequency (B1) and gradient fields, which produce spatial changes in tissue static. Partial volume effects occur where multiple tissues contribute to a single voxel, making the distinction between tissues along boundaries more difficult. Noise in MR images can induce segmentation regions to become disconnection.

An important part of any image processing system is represented by the pre-processing phase. This phase could imply contrast enhancement techniques or methods for removing the noise. Preprocessing aims at improving the quality of each input image and reducing the computational burden for subsequent analysis steps. Specifically, since skull and other extrameningeal tissues are usually of scarce clinical interest in most MRI studies, they were discarded, along with the background, as described by the preprocessing technique proposed in [4]. Subsequently, each voxel in the input image is assigned a six-dimensional feature vector, which comprises the gray level intensities of the corresponding pixel in the three channels, as well as the mean intensities calculated in a 3x3 neighborhood of the pixel in each This aims at compensating the effects of random noise, while minimizing the loss of resolution.

All feature vectors are normalized prior to segmentation by subtracting the mean and dividing by the standard deviation, where the mean and standard deviation are estimated independently for each slice.

B. Clustering

Clustering is a technique for finding similarity groups in data, called clusters. i.e., it groups data instances that are similar to (near) each other in one cluster and data instances that are very different (far away) from each other into different clusters. Clustering is often called an unsupervised learning task as no class values denoting an apriori grouping of the data instances are given, which is the case in supervised learning [11]. Unsupervised methods, on the other hand, do not require any human interference and can segment the brain with high precision. For this reason, unsupervised methods are preferred over conventional methods. Many unsupervised methods such as Fuzzy c-means, Self-Organizing map, etc. exist but Kohonen's Competitive Learning Algorithms yields good results [22], [24].

The proposed network architecture consists of two fully interconnected layers; the first layer, composed of computing elements of order zero with linear activation function, followed by a second layer of computing elements of order two, with gaussian activation function. Let **X** be the input pattern, **H** the output of the hidden layer and **Y** the output of the network. **W** and **Z** are the weight vectors of the first and second layer, respectively. In order to jointly optimize both layers, training is carried out in two steps. In the first step, the second layer is trained using the standard Kohonen rule for unsupervised learning at each iteration, the winning neuron's centers are adjusted according to (1)

$$\Delta Z_{ji} = \eta_z.(H_i - Z_{ji}) \tag{1}$$

Where

ΔZ_{ji} = Change in weight vector

η_z = learning rate of the Kohonen layer

H_i = Out put of the ith neuron of the hidden layer

Z_{ji} = The weight vector of the Winning neuron

The weights of the neighboring neurons are updated according to (2).

$$\Delta Z_{ji} = \eta_z.f_{neigh}(H_i - Z_{ji}) \tag{2}$$

Where

f_{neigh} = Gaussian activation function

Contrarily to the second layer, the first layer is trained using Enhanced version of error back-propagation with the linear activation function, search of feature space. In supervised learning schemes, the error is given by.

$$E = \sum_p \left\| Y^p - T^p \right\|^2 \tag{3}$$

Where $\mathbf{T^P}$ is the user-supplied target associated to the $\mathbf{P^{th}}$ training pattern. Here the target is determined by associating each input pattern with the winning neuron. Intuitively, this corresponds to searching a linear transformation of the feature space, requiring that input patterns be as close as possible to the associated centroids. the hidden layer is then trained using the classical delta rule for training and is derived from (3).

$$\frac{\partial E}{\partial W_{1i}} = \sum_p \eta_p \sum_j (\delta_j^{lp} . x_i^p) \tag{4}$$

Where p denotes the pth input pattern and

$$\delta_j^{lp} = y_j^p - t_j^p$$

The weights of the first layer are then updated according to (5).

$$\Delta W_{ij}(t+1) = -\eta_w \cdot \frac{\partial E}{\partial W_{ij}} + \mu \Delta W_{ij}(t) \tag{5}$$

$$\Delta W_{ij}(t) = \eta_w \delta_p H_j$$

Where

μ = momentum factor

η_w = learning rate of the Back propagation layer

The momentum term introduces the old weight change as a parameter for the computation of the new weight change. This avoids oscillation problems common with the regular back propagation algorithm when the error surface has a very narrow minimum area. Momentum allows the net to make reasonably large weight adjustments as long as the corrections are in the same general direction for several patterns. Using smaller learning rate prevents a large response to the error from any training pattern.

The first layer consists of 4 computing elements with linear activation function. Thus, not only the hidden layer performs a linear transformation of the input space, but it also reduces the dimensionality of the feature space. This allows obtaining, in average, better experimental results than when all features are retained in the clustering step. The second layer has 4 computing elements. Four clusters are sufficient to discriminate between the three tissue classes (white matter, gray matter and cerebrospinal fluid) that can be found in normal brain parenchyma (i.e. after the removal of extrameningeal tissues).

The network is separately trained for each slice to account for inhomogeneities in intensity across different slices by randomly selecting 16641 pixels per slice as the training set. A Gaussian neighborhood function f_{neigh} is used for unsupervised training. An adaptive learning coefficient is initially selected for the first layer as η_w and for the second one as η_z. If the error increases, η is decreased and weight values are set to those of the previous iteration, whereas if the error decreases below a predefined threshold, η is increased. Finally, training is stopped when a predetermined level of error is reached.

C. Edge Enhancement

Digital image enhancement techniques are concerned with improving the quality of the digital image. The principal objective of enhancement techniques is to produce an image which is better and more suitable than the original image for a specific application. This process detects boundaries between objects and background in the image.

Many characteristics are used to segment an image into regions e.g. colour, brightness, texture and edge detection. Usually, the obtained edges need some additional improvement for the satisfactory segmentation. Linear filters have been used to solve many image enhancement problems. The unsharp filter is a simple sharpening operator which derives its name from the fact that it enhances edges (and other high frequency components in an image) via a procedure which subtracts an unsharp, or smoothed, version of an image from the original image. The unsharp filtering technique is commonly used in the photographic and printing industries for crispening edges.

Unsharp masking produces an edge image $g(x, y)$ from an input image $f(x, y)$ via

$$g(x, y) = f(x, y) - f_{smooth}(x, y) \qquad (6)$$

where $f_{smooth}(x, y)$ is a smoothed version of $f(x, y)$ as illustrated in Fig. 3

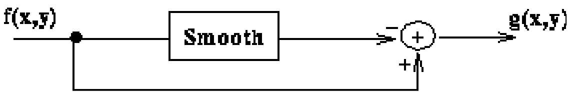


Figure 3 Unsharp filter

The unsharp filter can be implemented using an appropriately defined lowpass filter to produce the smoothed version of an image which is then pixel subtracted from the original image in order to produce a description of image edges, i.e. a high passed image.

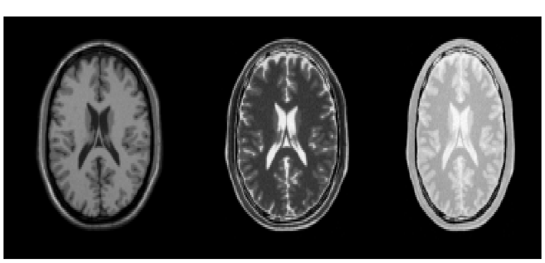
III. RESULTS

In this section, the results obtained using real and simulated MR images are illustrated.

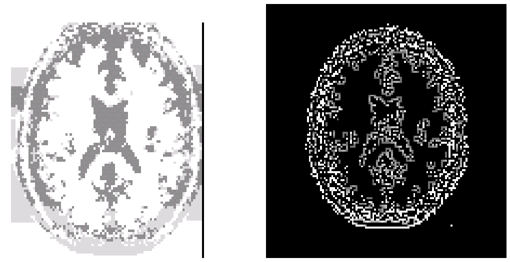
A. *Testing on Real and Simulated MR images*

The use of simulated images simplifies the task of validating a segmentation method as a reproducible. Moreover, it allows to separately test the proposed segmentation method stability against intensity inhomogeneities and random noise [6]. The simulated datasets are obtained from the Brain web institution [7]. All multichannel datasets comprise of 129x129, 8- bit gray level ,T1- weighted, T2-weighted and PD-weighted images with 1.0 mm slice thickness. Three reference slices were selected. With each cluster is associated with the most probable tissue class using maximum likelihood estimation.

A representative slice is shown in Fig. 4. To evaluate the results, trainings for each reference slice were performed with different random initial conditions for the centers of the neurons in the second layer. It is well-known that the training speed depends on the choice of the learning rate. If the learning rate is small, the learning process is stable but at the expense of computation time [15]. If the learning rate is too large, the estimation of the weights may diverge. Because of fast convergence in using SOM with adaptive learning rate, it can be applied in online applications. The lower learning rate provides better convergence and better quality than higher learning rates. This has been proved with the test results shown in Fig. 5. The Fig. 6 shows the result for image with lesion.

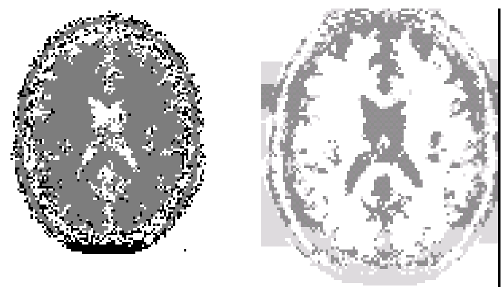


(a) (b) (c)



(d) (e)

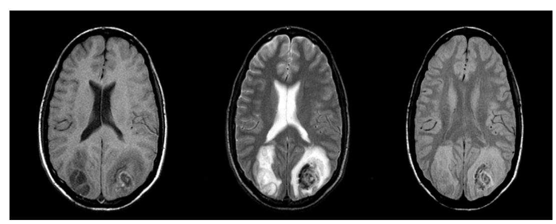
Figure 4. A representative slice from the simulated datasets and the corresponding segmentation. (a) T1-weighted image, (b) T2-weighted image, (c) PD-weighted image, (d) result of the clustering procedure (e) Edge Enhanced output



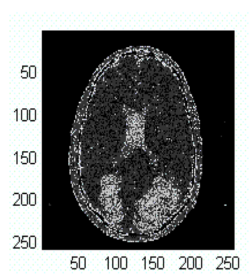
(a) (b)

Figure 5. The segmented image with different learning rates

(a) learning rate of 0.03 (b) learning rate of 0.001



(a) (b) (c)



(d)

Figure 6. A representative slice with lesion and the corresponding segmentation.

(a)T1-weighted image (b) T2-weighted image,

(c) PD-weighted image (d) result of the clustering Procedure

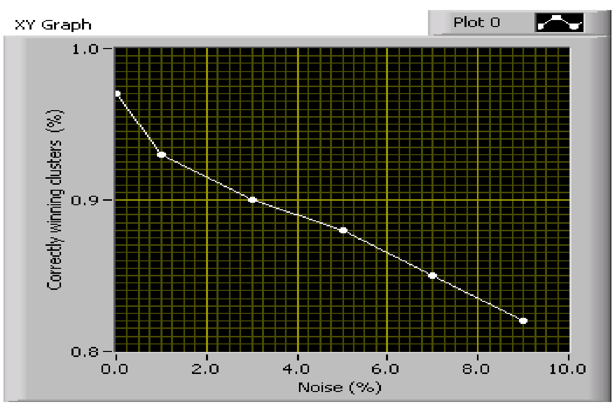
B. *Segmented Image with Various Noise Levels*

The simulated MR images with various percentage of noise such as 0%, 3%, 5%, 7% and 9% are taken from the database and its performance is evaluated for correctly winning clusters. As the percentage of noise increases, the percentage of correctly winning cluster declines but it gives better results even for noisy images. It is the major advantage of the segmentation algorithm. The effect of noise over the segmented image is illustrated in the performance evaluation graph Fig. 7(b)

C. Performance evaluation of the algorithm

An objective method is needed to evaluate the performance of the new proposed image segmentation algorithm. The most important performance criterion is accuracy that is the degree to which an algorithm's segmentation matches some reference standard segmentation [16]. A number of similarity coefficients are used to specify how well a given segmentation matches a reference illustrated in figure 7(a). The Table I shows the comparison of classification rate between the previous works and the proposed method.

(a)



(b)

Figure 7. Clustering results with varying levels of

a) learning rate b) noise

Table I Quantitative comparison of various segmentation algorithms classification rates

Performance measure / *Segmentation technique*	*Tissue Types*		
	GM	*CSF*	*WM*
SOM	87.934	90.120	85.955
FCM	90.970	92.532	87.970
Neuro-fuzzy system	93.120	95.03	90.943
KCL	94	98.5	92.5
Novel clustering algorithm	**96**	**98.5**	**98**

IV. CONCLUSION

The accurate and effective algorithm for segmenting image is very useful in many fields, especially in medical image. The training set originally had large dimension of data matrix, so the program used to reduce the dimension of training set and the new algorithm method is applied to show the ability of the method. A Self-Organizing Map network was programmed to receive images, as input signal regions. For this work, medical images were used and different segmentations were obtained. In this paper, a novel approach to the segmentation of multispectral cerebral MR images is proposed, which enhances the unsupervised clustering capabilities of a Kohonen self-organizing map with a linear transformation of the input space. The proposed technique was evaluated on real and simulated MR images, showing promising performances from a qualitative point of view. Noisy images were generated by adding white gaussian noise with different strengths. These noisy images are used to compare the percentage of segmentation error of this proposed algorithm at different noise levels. From the given graph it is clear that the noise introduced will not affect the output of segmentation, which proves the ability of this proposed algorithm to segment images with noise Furthermore, being the proposed technique fully unsupervised, and the results substantially independent of the initial network conditions, Future efforts will be devoted to the further testing of the proposed technique, both from a qualitative and quantitative point of view, and to its application to the study of brain pathologies, in particular to brain tumor diagnosis and follow-up.

V. REFERENCES

[1] L. P. Clarke, R. P. Velthuizen, M. A. Chamaco, J. J. Heine, M. Vaidyanathan, L.O. Hall et al.: MRI Segmentation: methods and applications. Magnetic Resonance Imaging, 13,343-368 1995.

[2] L. Morra, F. Lamberti, C. Demartini: A neural network approach to unsupervised segmentation of single-channel MR images. Proc. of the 1st IEEE/EMBS Conference on Neural Engineering, 1, 515-518 2003.

[3] W.E. Reddick, J. O. Glass, E. N. Cook, T. D. Elkin, R. J. Deaton: Automated segmentation and classification of multispectral magnetic resonance images of brain using artificial neural networks. IEEE Trans. on Medical Imaging, 16, 911-918 1997.

[4] M. S. Atkins, B. T. Mackiewich: Fully automatic segmentation of the brain in MRI. IEEE Transaction on Medical Imaging,17, 98-107 1998.

[5] L.M. Reyneri: Unification of neural and wavelet networks and fuzzy systems, IEEE Transaction on Neural Networks, 10, 801-814 1995.

[6] R.K-S. Kwan, A.C. Evans, G.B. Pike: MRI simulation-based evaluation of image processing and classification methods. IEEE Transaction on Medical Imaging, 18, 1085-1097 1999.

[7] C.A. Cocosco, V. Kollokian, R.K.-S. Kwan, A.C. Evans: BrainWeb: Online Interface to a 3D MRI Simulated Brain Database, Proc. of 3rd Intern. Conference.

[8] T Kapur. Model based three dimensional Medical Image Segmentation, Ph.D. Thesis, Artificial IntelligenceLaboratory, Massachusetts Institute of Technology, 1999.

[9] Constantino Carlos Reyes-Aldasoro, "Image Segmentation with Kohonen Neural Network Self-

Organising Maps" International Conference on Telecommunications ICT 2000 May 2000.

[10] Rafael C.Gonzalez & Richard E.Woods, Prentice – Hall, "Digital Image Processing", Second edition, 2005.

[11] Clustering,http://www2.cs.uregina.ca/hamilton/courses/ 831/ notes/ clustering/ clustering.html.

[12] Erhan Gokcay, A New Clustering Algorithm For Segmentation Of Magnetic Resonance Images, Thesis for Doctor of Philosophy, University of Florida, 2000.

[13] M. C. Clark., L.O. Hall., D. B. Goldof., L. P. Clarke., R. P. Velthuizen., M.S. Silbiger., "MRI segmentation using fuzzy clustering techniques", IEEE Engineering in Medicine and Biology, pp. 730/742, November 1994.

[14] C. A. Cocosco., A. P. Zijdenbos., A. C. Evans., "A fully automatic and robust brain MRI tissue classification method". Medical Image Analysis 7, 513–527. 2003.

[15] Laurene Fausett, Prentice – Hall, Inc "Fundamentals of Neural Networks"1994.

[16] Petrou Maria, John Wiley, "Image Processing: The Fundamentals"1999.

[17] Mohamad H Hassoun, MIT press, "Fundamentals of Artificial Neural Networks" 1995.

[18] J. G. Taylor and Mannion C.L.T, Springer, "Theory and applications of Neural Networks"s 1992.

[19] S. Datta, B. R. Sajja, and P. A. Narayana, " Generalized fuzzy clustering for segmentation of multi-spectral magnetic resonance images ", Computerized Medical Imaging and Graphics , vol. 32, pp: 353–366. 2008.

[20] W. M. Wells, W. E. L. Grimson, and R. Kikins, "Adaptive segmentation of MRI data", IEEE Trans. Medical Imaging, vol. 15, pp: 429-442, 1996.

[21] D. L. Pham., C. Y. Xu, and J. L. Prince, "A survey of current methods in medical image segmentation", Annual Review of Biomedical Engineering, vol. 2, pp. 315-337, 2000.

[22] Kong, W. Lu, J. Wang, N. Che, and Y. Lu, " A Modified Fuzzy Kohonen's Competitive Learning Algorithms Incorporating Local Information for MR Image Segmentation", IEEE International Conference on Bioinformatics and Bioengineering , pp: 647-653, Oct. 2007.

[23] 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.

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

[25] 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

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

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

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

[29] 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.

[30] Balafar MA (2008) "Medical image segmentation using fuzzy Cmean (FCM) and dominant grey levels of image". Visual information engineering conference , pp 314–317.

