ISSN:0975-9646

Image Enhancement of Normal and Abnormal with Edema Segmentation of Brain MR Images Using Adaptive Wiener Filter

A.Ramaswamy Reddy[1], Dr. E.V.Prasad[2], Dr.L.S.S.Reddy [3]

[1] *Associate Professor, LBRCE, Mylavaram, A.P, India*
[2] Registrar, *JNTUK, Kakinada,A.P, India*
[3] *Director, LBRCE, Mylavaram, A.P, India*

Abstract-In this paper, we are present the efficient technique for the segmentation of normal, abnormal with tumor and edema tissues in the MR brain images. The normal brain tissues such as WM (White Matter), GM (Gray Matter) and CSF (Cerebrospinal Fluid) are segmented by using classical approach like gradient and binarization methods. In medical diagnosis it is very important to identify tissues which are infected and same equal importance to the tissues with are going to be damaged in due time like edema tissues. In this process of segmentation preprocessing is applied to eliminate non-cortical tissues using skull stripping with region growing method for a better focus on cortical tissues. The proposed method shows the best cortical tissue segmentation compare with the existing techniques. The same approached can also be used for efficient segment in noisy conditions using non-linear Adaptive Wiener filter. Performance of the proposed approach is compared against the Weiner filter and adaptive Weiner filter in terms of peak-signal-to-noise-ratio (PSNR) and Mean squared error (MSE) on real MR images collected from national brain research centre.

Key-words: Edema, MR brain images, WM,GM,CSF,PSNR,MSE.

1.INTRODUCTION

The segmentation of brain tumor from magnetic resonance (MR) images is a vital process for treatment planning and for studying the differences of healthy subjects and subjects with tumor. Brain MRI with tumor is difficult to segment due to a combination of the following factors: 1. The deformation of non-tumor structures due to tumor mass effect. 2. Infiltration of brain tissue by tumor and edema (swelling). Edema appears around the tumor mainly in white matter regions. 3. There is gradual transition from tumor to edema, often it is difficult to discern the boundary between the two structures.4. The standard MR modality used to identify tumor, T1w with contrast enhancement (typically using gadolinium), is not always ideal. Blood vessels and cortical cerebrospinal fluid (csf) tend to be highlighted along with tumor, while parts of tumor that are necrotic tissue do not appear enhanced at all. It is generally impossible to segment tumor by simply thresholding the contrast enhanced T1w image. It is one of the most vital reprocessing steps in several medical research and clinical applications, such as quantification of tissue volume, visualization and analysis of anatomical structures, multimodality fusion and registration, functional brain mapping, identification of pathology, surgical planning, surgical navigation, and brain substructure segmentation [1]. Segmentation at preliminary stage is important and necessary for the analysis of medical images for computer-aided diagnosis and treatment. As the images are inherent in nature, medical image segmentation is a difficult and challenging task [2] [14] [15]. Magnetic resonance imaging (MRI) is a significant diagnostic imaging method, which is employed for the early detection of abnormal changes in tissues and organs [3] [16] as well as it is a non-invasive imaging technique, so it allows a radiologist to create an image of the inner aspects of living tissue [12]. Normally the structure of brain is complex and its accurate segmentation is very crucial for finding the tumors, edema and necrotic tissues in order to specify proper therapy [4]. The brain matters are mainly categorized as white matter, gray matter, cerebrospinal fluid (CSF) or vasculature. Mostly the brain structures are clearly described by the boundaries of the tissue classes, so a technique to segment tissues based on these categories is a major step in quantitative morphology of brain [6]. Apart from other diagnostic methods, Magnetic resonance imaging (MRI) systems can generate many images and each image indicates a different essential parameter of inner anatomical structures in the same body section with multiple differences, based on the local variations of spin–spin relaxation time (T2), spin–lattice relaxation time (T1), and proton density (PD) [5]. The presence of noise, errors in the scanners, and the structural variations of the imaging objects are the major obstruction to the segmentation of MR images, such obstructions are categorized into four types: thermal/electronic noise, magnetic field inhomogeneities, biological tissue variations, and incomplete volume effects [7]. Moreover, recognition and analysis of the lesions manually Moreover, recognition and analysis of the lesions manually from MR brain images are generally time consuming, expensive and can produce unacceptably high intra observer and inter observer variability [8]. The segmented MR images used in the medical diagnostic process depends on a combination of two, often conflicting, requirements, that is, the removal of the unnecessary information present in the original MR images and the maintenance of the significant details in the resulting segmented images [13] [17]. MR-image segmentation methods are usually evaluated based on their ability to

differentiate i) between cerebro-spinal fluid (CSF), white matter, and gray matter and ii) between normal tissues and abnormalities [9]. Many techniques proposed in the recent years, which are used for the segmentation of brain tissues from MR image, are classical pattern recognition methods, rule-based systems, image analysis methods, crisp and fuzzy clustering procedures, feed-forward neural networks, fuzzy reasoning, geometric models to determine lesion boundaries, connected component analysis, deterministic annealing, atlas based methods and contouring approaches [10] [11]. Lots of researches have been performed for the segmentation of normal and abnormal tissues in MRI brain images. We are proposed a new enhanced technique for the segmentation of normal, abnormal with tumor and edema tissues in brain MR images.

2 METHODOLOGY

Segmentation process is performed in both normal and abnormal images. In normal images, the normal tissues such as WM, GM and CSF are segmented and in abnormal images, the edema and tumor tissues are segmented. Two steps involved in the segmentation process those are

(i) Preprocessing

(ii) Tissue Segmentation

2.1 Preprocessing

Various preprocessing methods have been proposed to deal with the MRI brain images used for segmentation. Among all preprocessing methods, Skull stripping is used for the segmentation of brain tissues.

Skull stripping: This is pre processing step which is required to produce better results. Skull is outer part of the brain surrounding it i.e. the removal of its non-cerebral tissues. The main problem in skull-stripping is the segmentation of the non-cerebral and the intracranial tissues due to their homogeneity intensities. So it may affect the result of seed point selection. Some observations are required to find the range of gray value of skull portion. Following of the steps which are involved in skull removal process:

(1)First of all find the size of the image and store the no of rows and columns in separate variables.

(2) Perform iteration for half of the columns and all rows

(3) Process half of image to convert white pixels into the black pixels by setting their gray value to zero.

(4) Same steps is repeated for the remaining column and row.

The brain cortex can be visualized as a distinct dark ring surrounding the brain tissues in the MRI images. The distinct dark ring surrounding the brain tissues are removed by skull stripping method. In skull stripping, initially the given MRI brain image is converted into gray scale image and then a morphological operation [25] is performed in the gray scale image. Then the brain cortex in the gray scale image is stripped by using region based binary mask extraction. The preprocessing process is performed in the classified normal images, not abnormal images. Because preprocessing process helps to improve the normal tissue CSF is lightly placed in the cortex surrounding area. The normal is image obtained after skull stripping is denoted as . $I_{s.}$

2.2 Tissue Segmentation

After skull stripping, the brain MRI images are involved in the tissue segmentation process. Different methods are used to segment the WM, GM, CSF, edema and tumor tissues.

2.2.1 Normal Tissue Segmentation

Segmentation of Normal tissues such as WM, GM and CSF are performed from the normal images. Here, segmentation process is performed in two ways namely,

(i) WM and GM segmentation

(ii) CSF segmentation

WM and GM segmentation

The skull stripped image I_s is given as input to the WM and GM segmentation process. Here, the major step is to segment the WM and GM tissues from the image I_s by utilizing Gradient Method. The smoothing process is performed in the input image I_G by applying Gaussian convolution filter. Smoothed image obtained from the Gaussian convolution filter is I_G . After that, gradient operation is applied to the image I_G . The gradient of two variables *x* and *y* is defined as follows,

$$\nabla I_G(x,y) = \frac{\partial I_G}{\partial x}\hat{i} + \frac{\partial I_G}{\partial y}\hat{j} \qquad (1)$$

Using the gradient values, the current edges in the image are marked using the Equ. (2) and (3)

$$G = x_{(i)}^{2} + y_{(j)}^{2} \qquad (2)$$

$$E_m = \frac{1}{1+G} \qquad (3)$$

Then, the binarization process is performed in the edge marked image . In binarization process, the gray level value of each pixel in the image E_m is observed by using global threshold T_g and the resultant binarized image is L_b .Then the binarized image L_b is subjected to morphological opening and closing operation. Opening and closing operation is utilized to remove small objects and small holes from the image L_b . Finally, MRI brain image WM and GM tissues are segmented based on their intensity values.

$$I_{wg} = \begin{cases} WM; \text{ if } I_{b_i} = 1 \\ GM; \text{if } I_{b_i} = 0 \end{cases} \qquad (4)$$

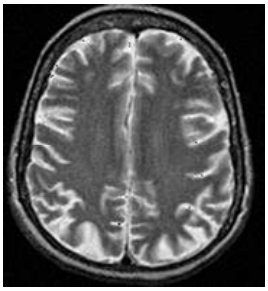
CSF segmentation

To segment the cerebrospinal fluid from the brain MRI image, an Orthogonal Polynomial transform (OPT) is applied to the skull stripped imageI_s. In orthogonal polynomial transformation, image I_s is computed using the following formula,

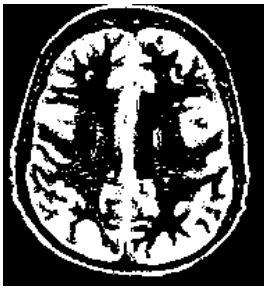
$$I_{cf} = Sin\left(\frac{I_{s(i)}{}^{3}}{100}\right)^{2} + (0.05 * rand(|I_s|)) \quad (5)$$

After the polynomial transform, the corresponding CSF region is segmented in the resultant image $I_{cf.}$

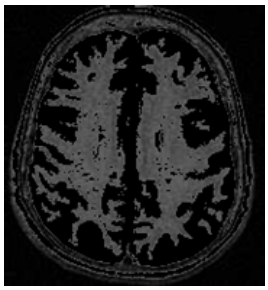
The segmentation process is performed on the classified images. The normal images are segmented into three normal tissues such as WM, GM and CSF



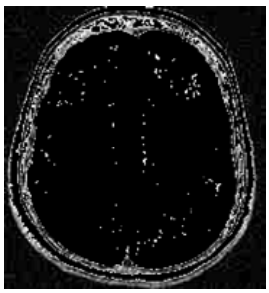
a)



b)



c)



d)

Figure-1:Results of normal image:

Segmentation outputs of normal image (a) Original image (b) WM segmentation (c) GM segmentation (d) CSF segmentation

2.2.2 Pathological Tissue Segmentation

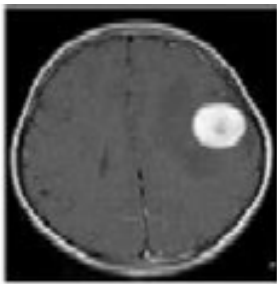
Pathological tissues such as edema and tumor are segmented from the classified abnormal images and these tissues are segmented by two different methods:

(i) Tumor segmentation

(ii) Edema segmentation

Tumor Segmentation

The tumor tissue segmentation is performed in the abnormal brain MRI images. The main objective is to segment the tumor tissue in the abnormal image I_a. Here we utilize the Region Growing Method (RGM) to segment the tumor tissue. Region growing method is a region based image segmentation method; it selects the initial seed points from the input image I_a . The RGM observes the neighbor pixel values with the initial seed points, that is it checks whether the neighbor pixels are included in this region or not [24]. The tumor segmentation result is represented as $I_{T.}$



(a)Original image

b)SegmentedTumor

Figure-2:Results of abnormal image:

Edema Segmentation

Edema tissue is segmented from the abnormal image I_a . Before the edema segmentation process, histogram equalization process is executed over the image I_a . The quality of image I_a is enhanced by the histogram equalization and it is denoted as I_a^1.Then the enhanced I_a^1 image is converted into indexed image by using multilevel thresholding function. Gray-slice function converts the grayscale I_a^1 image into indexed image using multilevel threshold and the result image is I_a^{11}. After that, the image I_a^{11} is converted into HSV (Hue, Saturation and Value) color model and it is represented as I_a^{111} . Next, the threshold process is performed in the image I_a^{111}. We define separate threshold value for Hue, Saturation, and Value. Each pixel in the image is compared with these threshold values to select the pixels

$$H \rightarrow t_3, S \rightarrow t_4, V \rightarrow t_5$$

$$X - \begin{cases} p_u ; p_u \le t_3, t_5 \& \ge t_4 \\ 0; otherwise \end{cases} \quad (6)$$

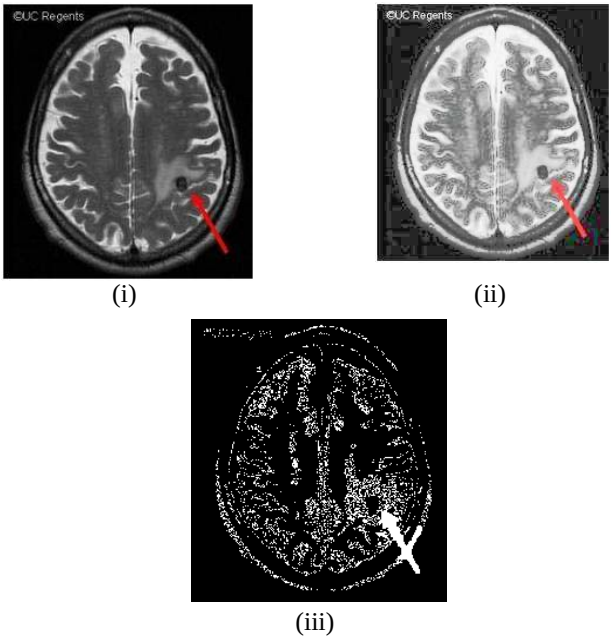
In the above eq(1), X is the pixel values that satisfy the above conditions. Morphological closing operation is applied on the mask X and the resultant image is denoted as X_c . Now, the image X_c contains *z* number of regions and then we compute the centroid value for each region, which is represented as $X_c^{(h)}(x,y)$,h=1,2,……z. Subsequently, the distance is determined between the coordinates of center pixels of the regions in as $X_c^{(h)}$ (x,y) and the tumor centroid coordinate t(x,y).

$$\mathbf{O_h\,(x,y) = X_c^{(h)}\,(x,y) - t(x,y)} \quad (7)$$

The resultant O_h (x,y) is then verified with threshold value t_6 and an edema region coordinate values are obtained

$$I_e = \begin{cases} O_h(x,y) \ge t_6 \\ 0; otherwise \end{cases} \quad (8)$$

Then the morphological dilation and closing operations are performed in the image. I_e.



(i) (ii)

(iii)

(iv) (v)

Figure-3:The intermediary result of the edema segmentation

Images obtained from (i) Original image (ii) Histogram Equalized Image ((iii) Image obtained from HSV Thresholding Process iii) HSV color model Image result (v) Edema region result.

3. WAVELET TRANSFORM ADAPTIVE WIENER FILTER

In this paper, we are proposed an enhanced adaptive wiener filter based on fast lifting wavelet transform by applying the thresholding. First step is to convert the noisy image into the wavelet domain with the use of Fast Lifting Wavelet Transform. Then the thresholding is applied in wavelet domain using VisuShrink and BayesShrink thresholding[27]. After that, Lifting-based adaptive Wiener filter is applied to all the sub-band images. Finally, these sub-band images are inversely transformed to reconstruct the final improved image.

By transforming the experimented noisy image y(i,j) into wavelet domain, four sub-images are acquired as $A_{y(I,j)}$, $W_{dy(i,j)}$ (d=1, 2,3) which represents the approximation coefficients and three sets of feature coefficients, correspondingly. Each sub-band can be presumed as a band restricted spatial signal and the noise in all sub-band can be presumed as white noise [26]. Wiener filtering can be implemented to all sub band to smoothen the resultant white noise. The wavelet domain wiener filter can be built as follows

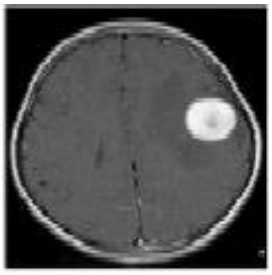
$$\hat{m}_{W_{dy(i,j)}} = \frac{1}{(2m+1)(2n+1)} \sum_{k=i-m}^{i+m} \sum_{l=j-n}^{j+n} W_{dy(k,l)}.$$

$$\hat{\sigma}^2_{W_{dy(i,j)}} = \frac{1}{(2m+1)(2n+1)} \sum_{k=i-m}^{i+m} \sum_{l=j-n}^{j+n} \left[W_{dy(k,l)} - \hat{m}_{W_{dy(i,j)}} \right]^2.$$

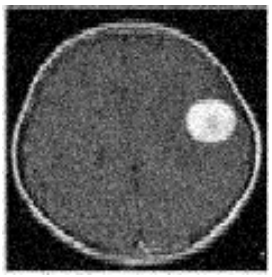
$$\hat{\sigma}^2_{W_{dx(i,j)}} = \max\left\{0, \sigma^2_{W_{dy(i,j)}} - \sigma_n^2\right\}.$$

$$W_{d\hat{x}(i,j)} = \hat{m}_{W_{dy(i,j)}} + \frac{\hat{\sigma}^2_{W_{dx(i,j)}}}{\hat{\sigma}^2_{W_{dx(i,j)}} + \sigma_n^2} \left(W_{dy(i,j)} - \hat{m}_{W_{dy(i,j)}} \right). \quad \textbf{(9)}$$

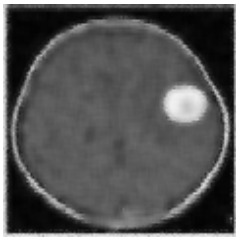
$\hat{m}_{W_{dy(i,j)}}$ **and** $\hat{\sigma}^2_{W_{dy(i,j)}}$ represents the local statistics restructured at every pixel in each sub band of the real image to reconstruct the image, but they can be computed from all sub band of the experimented image.



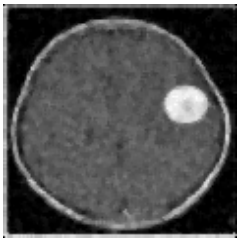
(a)Original MR image



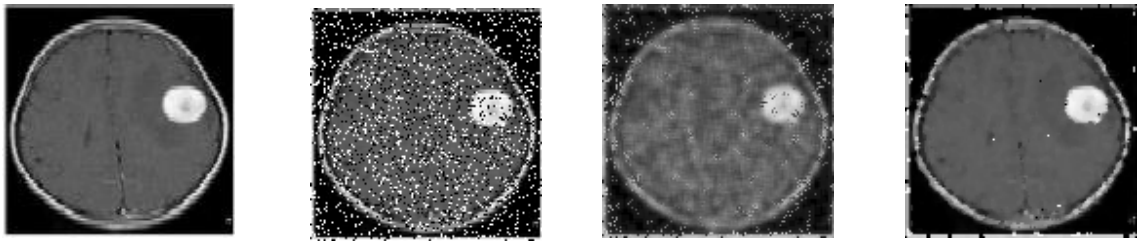
(b)Noise MR image



(c)Enhanced MR image Using Wiener Guassian



(d)Enhanced MR image using Adaptive Wiener



(i)Original image (ii)Noise image (iii)Enhanced MR image Using Wiener (iv)Enhanced MR image using Adaptive Wiener

Figure-4: Result of image Enhanced.

4. EXPERIMENTAL RESULTS

This paper implemented in MAT LAB 7.0.1 have been performed on a grey-scale normal and abnormal with edema images of size 256×256 . To evaluate the performance of the proposed image enhancement method, it is compared with the image enhancement methods such as Mean Filter, Gaussian Filter and Wiener Filter and Adaptive Wiener Filter based on the peak signal-to-noise ratio (PSNR), Mean Squared Error (MSE).

4.1. Peak Signal-to-Noise Ratio (PSNR)

For natural images contaminated with noise, the PSNR is tested. The definition of PSNR is:

$$PSNR = -20 \log_{10} \frac{\sqrt{x(m,n) - \hat{x}(m,n)^2}}{M \times N}. \quad \textbf{(10)}$$

where m =1, 2,…,M, n =1, 2,…., N are positive integers. $x(m, n)$ is the original image, $x\hat{}(m,n)$ is the reconstruction image or noised image. PSNR value of the degraded image and enhanced image using Wiener Filter, Adaptive Wiener Filter, Adaptive Wiener Filter with VisuShrink Threshold and Adaptive Wiener Filter with BayesShrink Threshold is calculated and its values are given in Table I.

Image Enhancement method	*PSNR value*	
	Degraded Image	**Enhanced Image**
Mean filter	4.3548	7.2651
Gaussian filter	7.6682	9.8262
Wiener filter	9.2689	10.7893
Adaptive Wiener filter	11.7002	21.0752

Table 1: PSNR Value for Mean filter, Gaussian filter, Wiener Filter, Adaptive Wiener Filter.

It is observed from the table that the proposed adaptive wiener filter with threshold provides very high PSNR value for both the degraded image and enhanced image.

4.2. Mean Squared Error (MSE)

Mean Square Error (MSE) can be calculated using the following formula

$$MSE = \sum_{m=1}^{M} \sum_{n=1}^{N} (\hat{x}(m,n) - x(m,n))^2. \quad \textbf{(11)}$$

MSE value of Wiener Filter, Adaptive Wiener Filter, Adaptive Wiener Filter with VisuShrink Threshold and Adaptive Wiener Filter with BayesShrink Threshold based image enhancement technique for the degraded image and enhanced image is tabulated in Table II.

Image Enhanced method	*MSE value*	
	Degraded Image	**Enhanced Image**
Mean filter	36.23	31.258
Gaussian filter	34.118	28.149
Wiener filter	31.326	24.154
Adaptive Wiener filter	29.267	19.527

Table II: MSE Value for Mean filter, Gaussian filter, Wiener Filter, Adaptive Wiener Filter.

From the table, it is very clear that the proposed adaptive wiener filter with BayesShrink threshold provides very low MSE value for both the degraded image and enhanced image.

CONCLUSION

In this paper, an efficient segmentation was developed to segment the normal and abnormal with edema tissues from the MRI brain images. The normal brain tissues such as WM (White Matter), GM (Gray Matter) and CSF (Cerebrospinal Fluid) are segmented by using classical approach like gradient and binarization methods. In binarization process, the gray level value of each pixel in the image is observed by using global threshold value and get the resultant binarized image. The performance of the proposed segmentation was analyzed using defined set of MRI normal and abnormal images. The proposed method shows the best cortical tissue segmentation compare with the existing techniques. Adaptive Wiener filter used for efficient segment in noisy conditions. Hence the performance of the method was understood from the experimental results and analysis.

REFERENCES

[1] Chaozhe Zhu and Tianzi Jiang, "Multicontext Fuzzy Clustering for Separation of Brain Tissues in Magnetic Resonance Images", NeuroImage, Vol.18, No. 3, pp. 685-696, 2003

[2] Shan Shen, William Sandham, Malcolm Granat and Annette Sterr, "MRI Fuzzy Segmentation of Brain Tissue Using Neighborhood Attraction With Neural-Network Optimization", IEEE Transactions On Information Technology In Biomedicine, Vol. 9, No. 3, pp. 459-467, September 2005

[3] Senthilkumaran and Rajesh, "Brain Image Segmentation using Granular Rough Sets", International Journal of Arts and Sciences, Vol. 3, No. 1, pp. 69 - 78, 2009

[4] Pradipta Maji, Malay K. Kundu and Bhabatosh Chanda, "Second Order Fuzzy Measure and Weighted Co-Occurrence Matrix for Segmentation of Brain MR Images", Journal of Fundamenta Informaticae, Vol. 88, No. 1-2, pp. 161-176, 2008

[5] Jzau-Sheng Lin, Kuo-Sheng Cheng, and Chi-Wu Mao, "Segmentation of Multispectral Magnetic Resonance Image Using Penalized Fuzzy Competitive Learning Network", Journal of Computers and Biomedical Research, Vol. 29, No. 4, pp. 314–326, 1996

[6] Mostafa G. Mostafa, Mohammed F. Tolba, Tarek F. Gharib and Mohammed A-Megeed, "A Gaussian Multiresolution Algorithm For Medical Image Segmentation", In Proceedings of IEEE International Conference On Intelligent Engineering Systems, Assiut-Luxor, Egypt, 2003

[7] Jagath C. Rajapakse, Jay N. Giedd and Judith L. Rapoport, "Statistical Approach to Segmentation of Single-Channel Cerebral MR Images", IEEE Transactions on Medical Imaging, Vol. 16, No. 2, pp. 176-186, April 1997

[8] W.Wells, W.Grimson, R. Kikinis, F.A. Jolesz, "Adaptive Segmentation of MRI Data", IEEE Transaction on Medical Imaging ,Vol.15, No. 4, pp. 429-442, August 1992

[9] Nicolaos B. Karayiannis and Pin-I Pai, "Segmentation of Magnetic Resonance Images Using Fuzzy Algorithms for Learning Vector Quantization", IEEE Transactions on Medical Imaging, Vol. 18, No. 2, pp. 172-180, February 1999

[10] Fitsum Admasua, Stephan Al-Zubia, Klaus Toenniesa, Nils Bodammerb and Hermann Hinrichsb, "Segmentation of Multiple Sclerosis Lesions from MR Brain Images Using the Principles of Fuzzy-Connectedness and Artificial Neuron Networks", In Proceedings of International Conference on Image Processing, Barcelona, Spain, Vol. 3, 2003

[11] N. K. Subbanna, M. Shah, S. J. Francis, S. Narayanan, D. L. Collins, D. L. Arnold and T. Arbel, "MS Lesion Segmentation using Markov Random Fields", In Proceedings of International Conference on Medical Image Computing and Computer Assisted Intervention, London, UK, September 2009

[12] Kenneth Revett and Aurangzeb Khan, "An On-Line (Real-Time) Automated MRI Based Pathology Detection System Using Selforganised Maps", In Proceedings of Virtual Multi Conference on Computer Science and Information Systems, pp. 213-216, 2005

[13] Nahla Ibraheem Jabbar and Monica Mehrotra, "Application of Fuzzy Neural Network for Image Tumor Description", World Academy of Science, Engineering and Technology, Vol. 44, pp. 575-577, 2008 .

14] Manisha Sutar and Janwe, "A Swarm-based Approach to Medical Image Analysis", Global Journal of Computer Science and Technology, Vol. 11, No. 3, pp. 23-26, March 2011

[15] Pradipta Maji, Malay K. Kundu and Bhabotosh Chanda, "Segmentation of Brain MR Images Using Fuzzy Sets and Modified Co-Occurrence Matrix", In Proceedings of IET International Conference on Visual Information Engineering, Bangalore, India, pp. 327-332, 2006

[16] Forghani, Forouzanfar and Forouzanfar, Tehran "MRI Fuzzy Segmentation of Brain Tissue Using IFCM Algorithm with Particle Swarm Optimization", In Proceedings of International Symposium on Computer and Information Sciences, Ankara, pp. 1-4, 2007

[17] Nicolaos B. Karayiannis, "A Methodology for Constructing Fuzzy Algorithms for Learning Vector Quantization", IEEE Transactions on Neural Networks, Vol. 8, No. 3, pp. 505-518, May 1997

[18] Zhiqiang Lao, Dinggang Shen, Dengfeng Liu, Abbas F. Jawad, Elias R. Melhem, Lenore J. Launer, R. Nick Bryan and Christos Davatzikos, "Computer-Assisted Segmentation of White Matter Lesions in 3D MR Images Using Support Vector Machine", Academic Radiology, Vol. 15, No. 3, pp. 300-313, March 2008

[19] Zhang, Wang, and Wu, "A Novel Method for Magnetic Resonance Brain Image Classification Based On Adaptive Chaotic PSO", Progress In Electromagnetics Research, Vol. 109, pp. 325-343, 2010

[20] Mina Rafi Nazari and Emad Fatemizadeh, "A CBIR System for Human Brain Magnetic Resonance Image Indexing", International Journal of Computer Applications, Vol. 7, No.14, pp. 33-37, October 2010

[21] Shafaf Ibrahim, Noor Elaiza Abdul Khalid and Mazani Manaf, "Seed-Based Region Growing (SBRG) vs Adaptive Network-Based Inference System (ANFIS) vs Fuzzy c-Means (FCM): Brain Abnormalities Segmentation", International Journal of Electrical and Computer Engineering, Vol. 5, No. 2, pp. 94-104, 2010

[22] Nandita Pradhan and Sinha, "Development of a Composite Feature Vector for the Detection of Pathological and Healthy Tissues in FLAIR MR Images of Brain", Journal of ICGST-BIME , Vol. 10, No. 1, pp. 1-11, December 2010

[23] Jayashri Joshi and Phadke, "Feature Extraction and Texture Classification in MRI", In Proceedings of International Conference on Computer Technology, Vol. 2, No. 2, 3, 4, pp. 130-136, 2010

[24] Frank Y. Shih and Shouxian Cheng, "Automatic seeded region growing for color image segmentation", Journal of Image and Vision Computing, Vol. 23, pp. 877–886, 2005

[25] Soumya Maitra, "Morphological Edge Detection Using Bit-Plane Decomposition in Gray

[26] J. Kim, and J.W. Woods, "Image Identification and Restoration in the Subband Domain", *IEEETrans. Image Process*, vol. 3, no. 3, pp.312–314

[27] G. M. Rajathi and G. M. Rajathi ," EfficientAdaptive Wiener Filter with thresholding for Better Image Enhancement**"** European Journal of Scientific Research ISSN 1450-216X Vol.69 No.1 (2012), pp.143-153

A. Ramaswamy Reddy Assoc.prof, LBRCE, Mylavaram. He has 14 years of experience in teaching and has 7 International journals. His research interests Image processing, Data mining and Queuing theory and attended 5 conferences , 10 workshops. He has taught over 8 courses in CSE &IT and 6 courses in various branches.

Dr. E. V. Prasad Registrar, JNTU Kakinada, Professor of CSE, joined in JNTU service in March, 1979. His research interests include Parallel Computing, Data Mining, Image processing and Information Security. He has taught over 15 courses in CSE and supervised 4 PhD students. He held different positions in his carrier like Head of the Department, Vice Principal, Principal, Director and BOS Chairman. He is the Co author of four books and published more than five dozen papers in national and International journals and conferences **.**

Dr. L.S.S Reddy, Director, LBRCE, Mylavaram. He has taught over 15 courses in CSE and supervised 4 PhD students. He held different positions in his carrier like Head of the Department, Principal and President. He has published more than 40 journals in national and international. His research interests include Parallel Computing, Data Mining and Image processing.