



Segmentation and Classification of MRI Brain Tumor using FLGMM Segmentation and Neuro-Fuzzy Classifier

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Abstract: Segmentation and Detection of Brain tumor is very vital because it provides anatomical information of tissues which helps in treatment of patient. There are number of techniques for image segmentation. Efficient segmentation methods lead to accurate diagnosis. For early diagnosis it will make sense to combine segmentation, feature extraction and classification process into one model. Taking into account this, we are proposing an approach for brain tumor identification based on Fuzzy Local Gaussian Mixture Model segmentation method by assuming local data within pixels neighborhood satisfy Gaussian Mixture Model and grey level co-occurrence is used for feature extraction. Gray Level Co-occurrence Matrix (GLCM) characteristics features are used with the MR image for training of neural network then tumor is detected using neuro fuzzy classifier. Experimental results show promising results in terms of classification and segmentation accuracy.

Index Terms: Magnetic Resonance Imaging (MRI), Brain Tumor Segmentation, GLCM, Neuro-Fuzzy Classifier, Brain Tumor Detection

I. Introduction

Brain MR Image segmentation is one of the most important parts of clinical diagnostic tools and challenging task. For early detection of abnormalities in brain parts, MRI imaging is the most efficient imaging technique. Brain images mostly contain noise, inhomogeneity and Bias field. Therefore, accurate segmentation of brain images is a very difficult task. However, the process of accurate segmentation of these images is very important for a correct diagnosis by clinical tools. A lot of research efforts have been directed in the field of Medical Image Analysis with the aim to assist in diagnosis and clinical studies. Computer-aided analysis of medical involves four basic steps: a) image filtering or pre-processing, b) image segmentation, c) feature extraction, and d) classification or analysis of extracted features by classifier or pattern recognition system. Image Segmentation is an important step in image analysis. Segmentation is a process of dividing an image into regions having similar properties or characteristics. There are different techniques to segment an image into regions that are unique in nature. Not all the techniques are suitable for medical image analysis because of inaccuracy and complexity. There is no standard image segmentation technique that can give satisfactory results for all imaging applications. Brain tumor is a severe type of disease that occurs when there is an uncontrolled growth of cancer cells in the brain. According to the World Health Organization (WHO), brain tumor can be classified into some of following groups: Class I (Astrocytoma), Class II (Meningioma), Class III (Metastatic bronchogenic carcinoma), and Class IV (Sarcoma). MRI is efficient in the application of brain tumor detection and identification as compared to all other imaging techniques, due to the high contrast of soft tissues, high spatial resolution and since it does not produce any harmful radiation. Computer Aided Diagnosis is gaining major importance in the usual life. Medical image analysis is an important biomedical application which is very computational in nature and requires the assist of the automated systems. These analysis techniques are repeatedly used to detect the abnormalities in the human bodies through scan images. Automated brain disorder diagnosis with MR images is one of the particular medical image analysis methodologies.

II. Literature Survey

Objective of this review section is to present literature survey .Most of the key features of methods are mentioned in Table I with respective limitations and benefits.

Table I. Compare table

Author	Title	Proposed Technique	Algorithm Used	Benefits	Identified Problems
Zhang (2001)	Segmentation of Brain MR Images through a Hidden Markov Random Field Model and the Expectation-Maximization Algorithm[1]	Segmentation	Expectation Maximization	Technique possesses ability to encode both spatial and statistical properties of an image.	The method requires estimating threshold and does not produce accurate results most of the time.
Ahmed (2002)	A modified fuzzy c-means algorithm for bias field estimation and segmentation of MRI data[2]	Bias field estimation	Modified fuzzy C-means	Faster to generate results	Technique is limited to a single feature input.
Tolba (2003)	MR-Brain Image Segmentation Using Gaussian Multi resolution Analysis and the EM Algorithm[3]	Gaussian Multi resolution Analysis	Expectation Maximization	Less sensitive to noise	Rarely preserve edges.
Sing (2005)	Segmentation of MR Images of the Human brain using Fuzzy Adaptive Radial Basis function Neural Network[4]	Neural network	Fuzzy adaptive radial basis function	It preserves sharpness of image.	Able to do only one task related to fusion
Yu (2008)	Three-level Image Segmentation Based on Maximum Fuzzy Partition Entropy of 2-D Histogram and Quantum Genetic Algorithm [5]	Fuzzy partition entropy of 2D histogram and genetic algorithm	QGA	QGA is selected for optimal combination of parameters.	Practically impossible
Kumar (2011)	A Texture based Tumor detection and automatic Segmentation using Seeded Region Growing Method[6]	Texture based Tumor detection and automatic segmentation	Seeded Region growing	This is region growing segmentation method for segmentation of brain tumor in MRI, in which it is possible to determine abnormality is present in the image or not.	It takes more time.
Roy (2012)	Detection and Quantification of Brain Tumor from MRI of Brain and it's Symmetric Analysis[7]	Modular approach to solve MRI segmentation	Symmetry analysis	The proposed approach can be able to find the status of increase in the disease using quantitative analysis	Time consuming.

III. Proposed system

A. Architecture

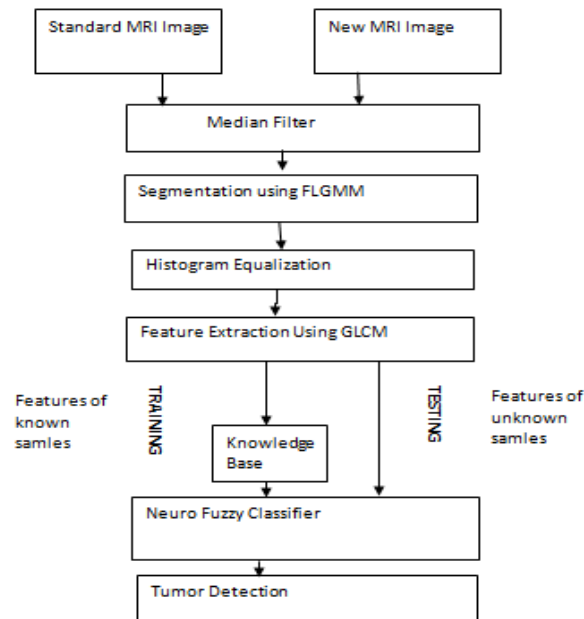


Figure 1: Architecture

B. Proposed Work

(i) Noise removal

Median filter technique used to remove the noise from input MRI image. Image filters can be classified as linear or nonlinear. Median filtering is a nonlinear method used to remove noise from images. It is widely used as it is

very effective at removing noise while preserving edges. It is particularly effective at removing salt and pepper type noise. The median filter works by moving through the image pixel by pixel, replacing each value with the median value of neighbouring pixels. The pattern of neighbours is called the "window", which slides, pixel by pixel over the entire image. The median is calculated by sorting all the pixel values from the window into numerical order, and then replacing the pixel being considered with the middle (median) pixel value.

(ii) *Image segmentation and Enhancement*

This is achieved by using Fuzzy Local Gaussian Mixture Model algorithm [1]. This approach propose the fuzzy local Gaussian mixture model (FLGMM) algorithm for automated brain MR image segmentation by assuming local image data within each voxels neighbourhood satisfy the Gaussian mixture model (GMM). This algorithm estimates the segmentation result that maximizes the posterior probability by minimizing an objective energy function, in which a truncated Gaussian kernel function is used to impose the spatial constraint and fuzzy memberships are employed to balance the contribution of each GMM. This algorithm improves the accuracy of brain MR image segmentation [10]. Histogram equalization technique is used to enhance the segmented image.

(iii) *Features Extraction*

Gray Level Co occurrence Matrix (GLCM) features are used to distinguish between normal and abnormal brain tumours. Five co-occurrence matrices are constructed in four orientations horizontal, right diagonal, vertical and left diagonal i.e. 0, 45, 90, and 135. A GLCM is a matrix where the number of rows and columns is equal to the number of gray levels, G , in the image. The matrix element $P(i, j | \Delta x, \Delta y)$ is the relative frequency separated by a pixel distance $(\Delta x, \Delta y)$. Matrix element also represented as $P(i, j | d, \theta)$ which contains the second order probability values for changes between gray level i and j at distance d a particular angle θ . Various features are extracted from GLCM, G is the number of gray levels used and μ is the mean value of P μ_x, μ_y, σ_x and σ_y are the means and standard deviations of P_x and P_y . $P_x(i)$ is the i_{th} entry obtained by summing the rows of $P(i, j)$:

Homogeneity (Angular Second Moment)

$G-1 \ G-1$

$$ASM = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \{P(i, j)\}^2$$

Contrast

$G-1$

$$Contrast = \sum_{n=0}^{G-1} n^2 \left\{ \sum_{i=1}^G \sum_{j=1}^G P(i, j) \right\}, |i-j|=n$$

Inverse Difference Moment

$G-1 \ G-1$

$$IDM = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \frac{1}{1 + (i-j)^2} P(i, j)$$

Entropy

$G-1 \ G-1$

$$Entropy = - \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} P(i, j) \times \log(P(i, j))$$

Correlation

$$Correlation = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \frac{\{i \times j\} \times P(i, j) - \{\mu_x \times \mu_y\}}{\sigma_x \times \sigma_y}$$

(iv) *Classification*

A neuro-fuzzy Classifier is used to detect tumor. Artificial neural network is a network of interconnected computational units, called nodes. The input of a node is the weighted sum of the output of all the nodes to which it is connected. The output of a node is a non-linear function (referred to as the activation function) of its input value. The multiplicative weighing factor between the input of node a and the output of node b is called the weight w_{ab} [11]. This mapping is done by adjusting the value of the weight w_{ab} using a learning algorithm, the most popular of is the generalized delta rule. After the weights are adjusted on the training set, their value is fixed and the ANN's are used to classify unknown input images. After the training phase parameters are fixed and the system is deployed to solve the problem (Testing phase). Back-propagation ANN's used; it consist of one input layer, one or two hidden layers, and one output layer. With back-propagation, the input data (Extracted Features) is repeatedly presented to the Artificial Neural Network, with each presentation the output of the neural network is compared to the desired output (Grade of Tumor) and an error is computed. This error is

then fed back (back-propagated) to the system [11].

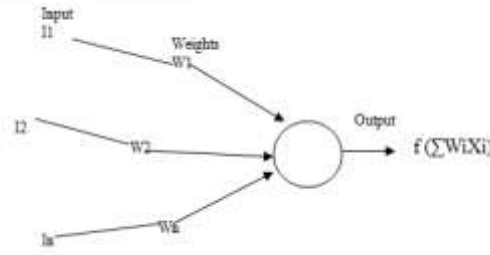


Figure 2: Illustration of classification model

IV. FLGMM ALGORITHM

A. Fuzzy C-Mean

Let $I = \{ I(k) \in R^d; 1 \leq k \leq n; 1 \leq c \leq n \}$ be a set of d -dimensional image features. The FCM partitions this feature set into c clusters based on minimizing the sum of distances from each feature to every cluster centroid weighted by its corresponding membership. Let the membership function be $U = \{ u_i(k) \} \in R^{c \times n}$, where $u_i(k) \in [0, 1]$ is the degree of feature $I(k)$ belonging to cluster i and follows the constraint $\sum_{i=1}^c u_i(k) = 1$. The quadratic objective function to be minimized is

$$J_{FCM} = \sum_{i=1}^c \int u_i(k)^m |I(k) - v_i|^2 dk$$

Where v_i is the centroid of cluster i , and $m \in (1, \infty)$ is the fuzzy coefficient [10a].

B. Gaussian Mixture Model

The GMM is a weighted sum of c Gaussian density distributions. With the GMM, the likelihood of the observed data $I(k)$ is as follows:

$$P(I(K)|\Theta_i) = \sum_{i=1}^c p_i N(I(k)|\mu_i, \Sigma_i)$$

where $\Theta_i = \{p_i, \mu_i, \Sigma_i\}$ is the assembly of parameters, and p_i is the mixing coefficient of i th Gaussian component $N(I(k)|\mu_i, \Sigma_i)$ and follows the constraint $\sum_{i=1}^c p_i = 1$. The parameters involved in the GMM are denoted by $\Theta = \{\Theta_i, i = 1, \dots, c\}$ [10].

C. Implementation details of FLGMM algorithm

Image segmentation aims to partition image domain Ω into c disjoint regions, in such a way, $\Omega = (\Omega_i)^c; i = 1 \dots c$. $\forall$ Voxel x , if its neighborhood region is denoted by O_x , $(\Omega \cap O_x)^c; i = 1 \dots c$ forms a partition of O_x . Local image data within O_x satisfy the GMM.

Let $p(y \in \Omega_i \cap O_x | I(y))$ be the posterior probability of voxel y belonging to the subregion $\Omega_i \cap O_x$ on condition that it has the intensity value $I(y)$. According to the Bayes rule,

$$p(y \in \Omega_i \cap O_x | I(y)) = \frac{p(I(y)|y \in \Omega_i \cap O_x) p(y \in \Omega_i \cap O_x)}{p(I(y))}$$

where $p(I(y)|y \in \Omega_i \cap O_x)$ is the probability distribution within the sub region $\Omega_i \cap O_x$, $p(y \in \Omega_i \cap O_x)$ is the prior probability of voxel y belonging to $\Omega_i \cap O_x$, and $p(I(y))$ is the probability of observing the intensity $I(y)$. To minimize the GMM energy (E_{FLGMM}) over every voxel x in the image domain, objective function for FLGMM algorithm [11]:

$$J_{FLGMM} = \int \sum_{i=1}^c u_i(y)^m di(I(y)) dy$$

Where,

$$di(I(y)) = \int K(x - y) \times (-\ln((p_i(x)/((2\pi)^{d/2} |\Sigma_i(x)|^{1/2})) \exp((-1/2)(I(y) - b(x)v_i)^T \Sigma_i(x)^{-1}(I(y) - b(x)v_i)))) dx$$

Constraints: $\sum_{i=1}^c u_i(x) = 1$, and $\sum_{i=1}^c p_i(x) = 1$.

This can be achieved analogously to the traditional FCM algorithm using the Lagrange multiplier method which is iterative as explained follows.

Step 1: Initialization.

Initialize the number of clusters, standard deviation, and neighborhood radius of the truncated Gaussian kernel, cluster centroids, and bias field at each voxel.

Step 2: Updating parameters.

Step2.1: Updating membership function

$$u_i(y) = \left(\sum_{j=1}^c \left(\frac{d_i(I(y))}{d_j(I(y))} \right)^{1/m-1} \right)^{-1}$$

Step 2.2: Updating covariance matrix

$$\Sigma_i(x) = \frac{\int u_i(y)^m K(x-y)((I(y) - b(x)v_i)(I(y) - b(x)v_i)^T) dy}{\int u_i(y)^m K(x-y) dy}$$

Step 2.3: Updating bias field.

$$b(x) = \frac{\sum_{i=1}^c \int K(x-y) u_i(y)^m (I(y)^T \Sigma_i(x)^{-1} v_i) dy}{\sum_{i=1}^c \int K(x-y) u_i(y)^m (v_i^T \Sigma_i(x)^{-1} v_i) dy}$$

Step 2.4: Updating mixture weight

$$p_i = \frac{K * u_i^m}{\sum_{j=1}^c K * u_j^m}$$

Step 2.5: Updating centroid.

$$v_i = \left(\iint u_i(y)^m K(x-y) b(x)^2 (\Sigma_i(x)^{-1}) dx dy \right)^{-1} \times \left(\iint u_i(y)^m K(x-y) b(x) (\Sigma_i(x)^{-1} I(y)) dx dy \right)$$

Step 3: Checking the termination condition.

If the distance between the newly obtained cluster centers and old ones is less than a user-specified small threshold ϵ , stop the iteration; otherwise, go to step 2[10].

V. Result and Discussion

Following figures are showing results for practical work done. Figure shows the main screen showing filtered image. For comparison purpose we also compared our result with Gaussian filter. Figure 3 shows the filtered image obtained by applying median filter method.



Figure 3: a) Input Image b) Gaussian Filter Image c) Median Filter Image

We are using dataset from Brain web [12], Whole Brain Atlas. We empirically set the parameters used, the fuzzy factor $m = 2$, standard deviation of the kernel function $\sigma = 4$, and neighbourhood radius of the kernel function $\rho = 10$. The segmentation accuracy was measured by the Jaccard similarity (JS), the value of JS ranges from 0 to 1, and a higher JS represents more accurate segmentation. Figure 4 shows the segmentation result after applying FLGMM algorithm.



Figure 4: (a) Input brain MR images (b) its region of interest (c) segmentation result

Graph of js values shown in figure in Figure 5. JS value for segmented image is WM 0.911 and GM 0.8520 which is very much nearer to 1.

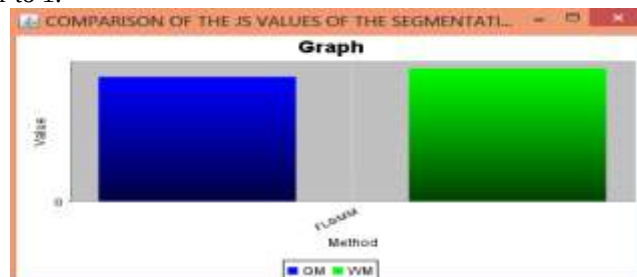


Figure 5: JS values of (left) GM segmentation and (right) WM segmentation

GLCM feature extraction result is depicted in Figure 6 and classification result is shown in Figure 7. Applying all procedures on different images classifier performance is calculated. Classifier performance in terms of Accuracy is depicted in Table II.

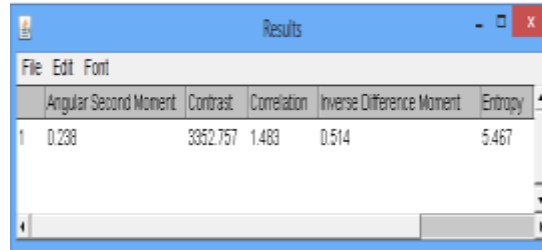


Figure 6: GLCM Result

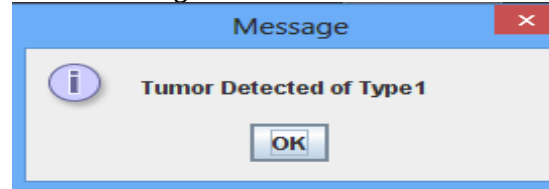


Figure 7: Classification Result

Classes	Total no. of Images	No. of classified Images	No. of misclassified Images	Accuracy (%)
Class-I	10	9	1	90
Class-II	10	10	0	100
Class-III	10	8	2	80
Class-IV	10	9	1	90

Table II. Classifier performance

VI. Conclusion

Thus, proposed approach provides an efficient method for Brain MR Image segmentation and brain tumor detection. This approach is about combining various preprocessing procedures into a single generative model will produce accurate and timely brain disease identification. Result shows that it produces more accurate segmentation results compared to other methods and timely brain tumor identification.

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