International Journal of Applied Information Systems (IJAIS) – ISSN : 2249-0868
Foundation of Computer Science FCS, New York, USA
Volume 5– No.2, January 2013 – www.ijais.org

# Abnormality Detection of Brain MR Image Segmentation using Iterative Conditional Mode Algorithm

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## ABSTRACT

In medical image processing, Brain MR Image segmentation is a typical problem for researcher to extract information without loss of details with good resolution. In this paper, we propose a novel method of segmentation using Iterative Conditional Model (ICM) algorithm and Markov random field (MRF) model to detect the abnormality in MR images. The lowest energy label making is allowed by ICM and processed for all iterations. This method supports high compressed relation between label and boundary MRFs. The study of steadily takes will consider all conditions of a discontinues (single edge) existing in a 3 X 3 kernel also including problematical prior information about the interaction between label and boundary. The model is tested with 5 images and the segmentation evaluation is carry out by using objective evaluation criteria namely Jaccard Coefficient (JC) and Volumetric Similarity (VS), Variation of Information (VOI), Global Consistency Error (GCE) and Probabilistic Rand Index (PRI). The performance evaluation of segmented images is carried out by using image quality metrics. The simulated results proposed by using T1 weighted images are compared with the existing models.

**Keywords**: Brain MR, Iterative conditional mode, Markov Random field, Image segmentation, Kernel, Quality metrics.

## 1. INTRODUCTION

Image segmentation is play very vital role in various areas like biomedicine, remote sensing, control of quality and many others. The main aim of segmentation of image is to extract information from the images to make out different objects of significance. The Markov random Field method (MRF) is a dominant stochastic tool to model the joint probability distribution of the image pixels in terms of local spatial interactions[1][2][3]. MRF models can be used to extract texture features from image textures and also used to model the image segmentation problem, as from the viewpoint of the random field a segmentation result is a label distribution in the same lattice as the original image. In real scenes, neighboring pixels generally have similar intensities. In a probabilistic framework, such regularities are well expressed by Markov Random Fields.

Alternatively, the local behavior of MRF permits to develop highly parallel algorithms.

The first MRF theory was introduced into the ground of statistical image analysis in the mid-1980s, Geman and Geman[4] and Besag [5] functional MRFs to image restoration, which can be viewed as a generalization of segmentation. Similar to the work of Geman and Geman [4], Geiger and Girosi [6] also added a second MRF (line process) to the original MRF for surface reconstruction. Likewise, in the work of Jeng and Woods [7] and Molina *et al.* [8], line process (edge MRF) was incorporated into the intensity process (label MRF). In general, adopting two or more MRFs in one task is a way to solve two or more different problems. For example, Sun *et al.* [9] integrated three MRFs, disparity, line process and occlusion, for stereo problems because these three factors are all critical to stereo matching. Similarly, Arduini *et al.* [10] solved two problems, restoration of SAR images and extraction of intensity discontinuities, by using two distinct MRFs. Held *et al.* [11] used one added MRF, i.e., the bias field, to sweep the obstacle of MRI brain segmentation but they did not couple the two MRFs compactly because the two fields are assumed independent. In this paper, rather than using a single label MRF, we in corporate a new MRF(boundary MRF) to represent the boundary of a region and, thus, construct a compound MRF model like [4], [6]–[11]. This boundary MRF is dissimilar from the line process as we define the MRF not on the dual lattice between pixels but on the pixel site directly. Moreover, in our model, the two MRFs (label and boundary MRFs) interact in a more sophisticated way while the line process works implicitly [12] and is relatively simple.

This proposed method objective is to segment the medical images of various imaging technique by involving MRF in order to increase the segmentation accuracy. Complex interactions between labeling and boundary in a neighborhood process by combining a series of label patterns to reducing the effect of other factors with a basic assumption by true boundaries. It is identified that reasonably linked and matched with these label patterns while discontinuities caused by random noise are not. Using MRF models for image segmentation has a number of advantages. First, the spatial relationship can be effortlessly incorporated into a segmentation procedure. Second, the MRF based segmentation model can be conditional in the Bayesian framework which is able to utilize various kinds of image features. Third, the label distribution can be obtained when maximizing the probability of the MRF model. 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.

In this paper, the proposed method, Iterative conditional mode algorithm implemented on MR images data sets with different signal-to-noise ratios (SNR) are collected from Guntur Government Hospital, Radiology department. The object and performance evaluation is done by using the proposed model on the same data set and compared with existing models. The results show good accuracy of segmentation in detecting and preserving the segmented object boundaries.

## 2. EXISTING MODEL

The coupled MRF model is formulated in a probabilistic framework based on the Bayesian theory. The elements of the framework are given based on the details of the boundary

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model and coupling of two MRFs (label and boundary MRFs).

*MAP-MRF Framework*

Let us consider the image consisting of n pixels i.e S= {1,…….n}. X= {$x_i$|i$\epsilon s$} and D={$d_i$|i$\epsilon s$} are label and boundary tags of two MRF respectively. $X_i$ is assigned one of the labels in $L_1$={0,1,…..m-1} where m represents the number of possible classes,$d_i$ belong to one of the binary tags in L2 ={0,1}, where 0 and 1 represent non boundary and boundary sites, respectively .The observed field is denoted by y={yi/I *s*}, where yi is the known image intensity .Let $\Omega_{x} = L_1$ x….x $L_1 = L_1^n$ and $\Omega_D = L_2$ x ….x $L_2 = L_2^n$ be the configuration Spaces of the label MRF X and boundary MRF D, respectively. Advocated by Geman and Geman [4] and others, the maximum a posteriori (MAP) Approach is commonly used to estimate the optimal solution of MRF models .The MAP-MRF framework allows us to develop algorithms systematically based on the Bayesian decision and estimation theory .The posterior probability P(X,D/Y) in our model represents the joint probability of label and boundary MRFs, X and D, given the observed intensity field Y and can be estimated using the Bayes' theorem

$$P(X,D|Y) = \frac{P(Y|X,D)P(X,D)}{P(Y)} \quad (1)$$

Where P(Y\X,D) reflects the likelihood of the observed intensity values given the information of labels and boundaries in an image; P(X,D) embodies the joint prior knowledge of the label MRF X and boundary MRF D; and P(Y) is the likelihood of the observed intensity values. Since the observed intensity values are known and unchanged, P(Y) is thought to be constant so that (1) further leads to $(X,D|Y) \propto P(Y|X,D)P(X,D)$ . The Map estimation for the optimal solution is then estimated by

$$(\hat{X},\hat{D}) = arg \max_{X\in\Omega x, D\in\Omega D} P(Y\ X,D)P(X,D) \quad (2)$$

Where $\hat{x}$ is the final segmented image that target .By virtue of the Markovianity of MRF theory, interactions between sites in *S* are constrained in a neighborhood system N={$N_i$|i$\epsilon s$}

where $N_i$ denotes a set in the vicinity of site **i**. According to the Hammersley-Clifford theorem, *X* is an MRF with respect to *N*.A gibbs distribution of X is given by

$$P(X) = \frac{1}{Z} e^{-U(X)/T} \quad (3)$$

Where *T* is a temperature constant. Supposing that the likelihood function can be expressed in Gibbs distribution, the MAP estimation becomes

$$(\hat{X},\hat{D}) = arg \max_{X\in\Omega x, D\in\Omega D} \frac{1}{Z} e^{-\frac{U(Y\ X,D)+U(X,D)}{T}} \quad (4)$$

Where U(Y|X,D) and U(X,D) are the likelihood and prior energy functions, respectively. This further leads to an energy minimization problem i,e.,

$$(\hat{X},\hat{D}) = arg \max_{X\in\Omega x, D\in\Omega D} (U(Y\ X,D) + U(X,D)) \quad (5)$$

Where $\hat{x}$ is the solution to the segmentation problem. We assume that the intensity field *Y* and the boundary MRF D are independent of each other because observed image intensity is not affected whether the site on the region boundary or inside the region. Therefore, the likelihood energy becomes

$$U(Y\ X,D) = U(Y|X). \quad (6)$$

Assuming that each region is without texture and nearly homogenous before it is corrupted by a Gaussian noise with zero mean and standard deviation $\sigma$ we can formulate the likelihood energy as

$$U(Y\ X) = \sum_{i \in \vec{S}} \frac{(yi-\mu xi)^2}{2\sigma^2} \quad (7)$$

Where $u_j$ represents the mean intensity of region j Є ( j Є $L_1$ ).The standard deviation (***SD***) $\sigma$ can also be dependent on region class. In that case, only a small change is needed to make in (7), and we should use *M* different SDs, $\sigma j$ , j= 0,1,… *M-1* *for* each region j. The formulation of the prior energy function is introduced the next subsection.

*Combining label MRF With Boundary MRF*

The relationship between the label MRF X and boundary MRF D defined by the prior energy U(X,D). We systematically study the situations when a single edge passes through a 3X3 window to see what the likely configuarations of the two MRFs, X and D are. We select a number of preferable cases from all the possible combinations of X and D configuarations in N and penalize the other cases.

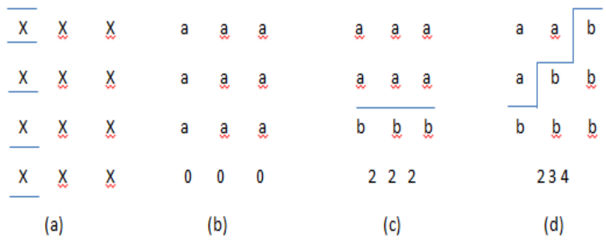


**Fig. 1. Subfigure (a) illustrates the numbering of edge positions along a column according to its height (4 and 1 represent top and bottom edges, respectively, and 0 represents no edge in the column). The rest [(b)–(d)] are examples of some edges passing through a 3x3 window and their corresponding numbers. For example, (b) shows no edges in three columns of the 3x3 windrow and, thus, gives the number: 000. The letters "a" and "b" represent two distinct region labels.**

The new prior energy formulation, which is given as

$$U(X,D)=\sum_{I\in S} \gamma . [\delta(d_i)T_1(i) + \delta(d_i - 1)T_2(i)], \gamma > 0 \quad (8)$$

$$T_1(i) = \sum_{j\in N_i} x_i \oplus x_j . \left( \left| \sum_{j\in N_i} x_i \oplus x_j - 1 \right| + \left| \sum_{j\in N_i} d_j - 4 \right| \right)$$

$$T_2(i) = \left( \left| \sum_{j\in N_i} x_i \oplus x_j - 1 \right| + \prod_{k=1}^{4} \left| \sum_{j\in N_i} d_j - k \right| \right)$$

$$\left( \left| \sum_{j\in N_i} x_i \oplus x_j - 2 \right| + \prod_{k=2}^{4} \left| \sum_{j\in N_i} d_j - k \right| \right)$$

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$$\left(\left|\sum_{j\in N_i} x_i \oplus x_j - 3\right| + \prod_{k=3}^{4}\left|\sum_{j\in N_i} d_j - k\right|\right)$$

Where⊕ represents the "exclusive or" operation and is $\gamma$ is the penalty. Terms and account for non boundary ( $d_i$ =0) and boundary ( $d_{i=1}$) situations, respectively. If the conditions of any row are satisfied, $T_1$or $T_2$ becomes zero and a low prior energy is obtained.

# 3. PROPOSED ALGORITHM

Iterative Conditional Mode (ICM) is a Gradient-based algorithm which is simple. Simultaneously, a novel method of segmentation is proposed using Iterative Conditional Model (ICM) algorithm and Markov random field (MRF) model to detect the abnormality in MR images. The lowest energy label making is allowed by ICM and processed for all iterations. This method supports high compressed relation between label and boundary MRFs. When no change of one site label can make the energy further decrease, the algorithm comes to convergence. The pseudo-code of the ICM algorithm for the proposed model is shown in Algorithm 1.Here it is replaced the prior energy function $U_{prior}$ with corresponding forms. $U_{likelihood}$ and $U_{prior}$ in (9) should include all the terms in the total energy that may change due to the change of $x_i$ and $d_i$ .

Where

$$\left(x_i^k, d_i^k\right) = \arg \min_{x_i^k \epsilon\{0,\ldots,m-1\}, d_i^k \epsilon\{0,1\}} \left(U_{likelihood}\left(y_i \middle| x_i^k\right) + U_{prior}\left(x_i^k, d_i^k\ x_{Ni}^{k-1}, d_{Ni}^{k-1}\right)\right) \quad (9)$$

In the experiments, is MaxItn set to 5.

**Algorithm 1.** The pseudo-code for the iterated conditional modes algorithm used for the proposed MRF model.

Step 1: Let be the iteration index and set k=1.

Step 2: Let be site index and set i=1.

Step 3: Compute (15), shown at the bottom of the page, where

$$U_{likelihood}\left(y_i \middle| x_i^k\right) = \left(y_i - \mu_{x_i^k}\right)^2 / 2\sigma^2$$

And

$$U_{prior}\left(x_i^k, d_i^k \mid x_{Ni}^{k-1}, d_{Ni}^{k-1}\right) = \gamma. \sum_{j\in N_i \cup\{i\}} [\delta(d_j)T_1(j) + \delta(d_j - 1)T_2(j)]$$

Where $T_1$ and $T_2$ are defined in (8)

Step 4: If i = n, then go to Step 5; else, i = i+1and go to Step 3. n is the total number of sites.

Step 5: If K = MaxItn or $x_i^k = x_i^{k-1}$ , $d_i^k = d_i^{k-1}$ , for every i $\epsilon\{1,\ldots,n\}$, then go to step 6; else, k= k+1, i=1 and go to step 3. MaxItn is the maximum number of iterations.

Step 6: Final estimate $\hat{x}_I = x_i^k$, i= 1, 2,….n

Where⊕ represents the "exclusive or" operation and is $\gamma$ is the penalty. Terms and account for non boundary ( $d_i$ =0) and boundary ( $d_{i=1}$) situations, respectively. $T_1$or $T_2$ becomes zero then a low prior energy is obtained.

From the ground truth of the synthetic images, it is convenient to quantify the performance of each segmentation method by calculating the error rate. The error rate of the segmentation is given by

$$\frac{\text{Number of misclassified pixels}}{\text{Total number of pixels in the image}} \times 100$$

# 4. EXPERIMENTAL RESULTS

In this section, The series of segmentation experiments on datasets have complex boundaries thus, it is challenging to get accurate segmentation the abnormality from the MR Images. The proposed model is performed with both binary and multiclass segmentations. This results are compared with existing Fuzzy and EM models [31] in the literature.

*Parameter Estimation*

There are a few parameters related to the proposed method needed to be estimated before we perform segmentation. These parameters are the mean intensity $\mu_j$ for every region j[in (7)], the standard deviation $\sigma$ of the noise [in (7)], the threshold for the gradient map and the weight, $\gamma$ , of the prior energy [in (8)].

In the current experiments, we set the initial value of $\gamma$ based on the mean intensity of all the regions from the datasets. The initial value of $\gamma$ is set based on a measure, ME=min $_{i,j}$ (|$\mu_i$ - $\mu_{j|)/\sigma(I,j)}$, refer to any two region numbers). This measure gives the ratio of the smallest absolute difference between the mean intensity in two regions. Note that the means and standard deviation have already been estimated. If ME is relatively low (i.e., lower than 2.5), it contains regions having relatively close intensity values. As such, we set the initial value of to 10 in order to attach more weight to the prior energy and impose more prior constrain. If ME is relatively high (i.e., not lower than 2.5), the image is relatively clean or the regions inside the image have relatively large intensity gaps. Therefore, we set the initial value of to 2 in order to give less weight associated with the prior energy and trust the likelihood energy more. We then perform searching around the initial value within a small integer range [initial -2, initial +2] and pick up the value that makes the model work best (i.e., with the lowest error rate).

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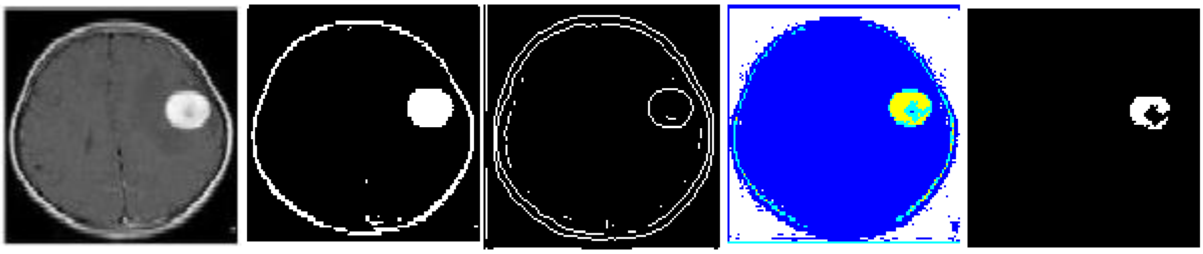


**Fig 1.1 Brain MR images: (a) is a original image and (b),(c),(d) and (e) are corresponding segmented images.**

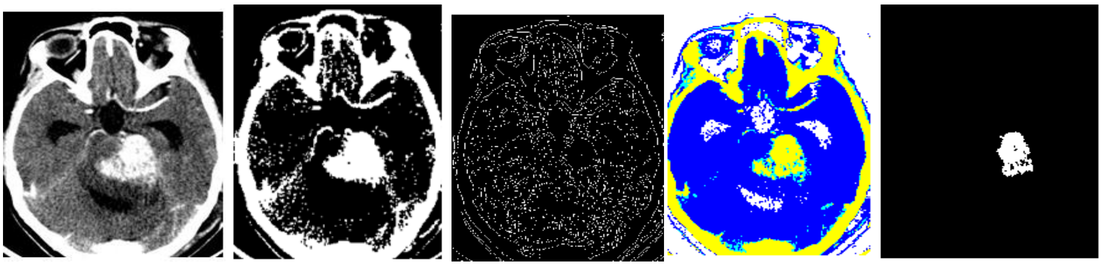
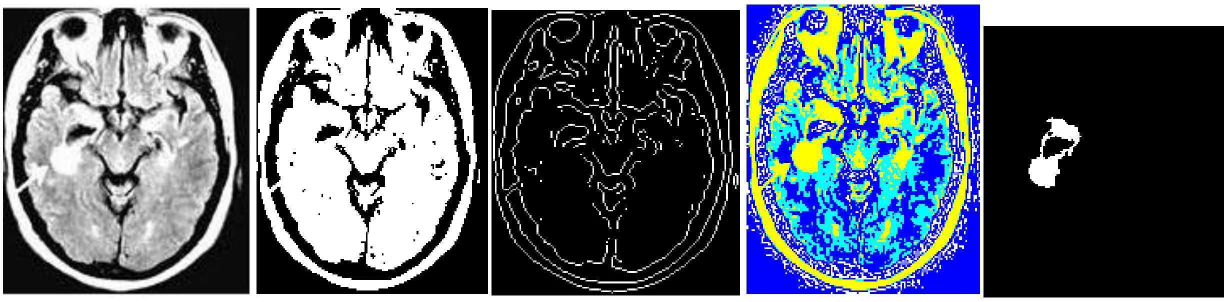


**Fig 1.2 Brain MR images: (a) is a original image and (b),(c),(d) and (e) are corresponding segmented images.**



**(Fig 1.3 Brain MR images: (a) is a original image and (b),(c),(d) and (e) are corresponding segmented images.**

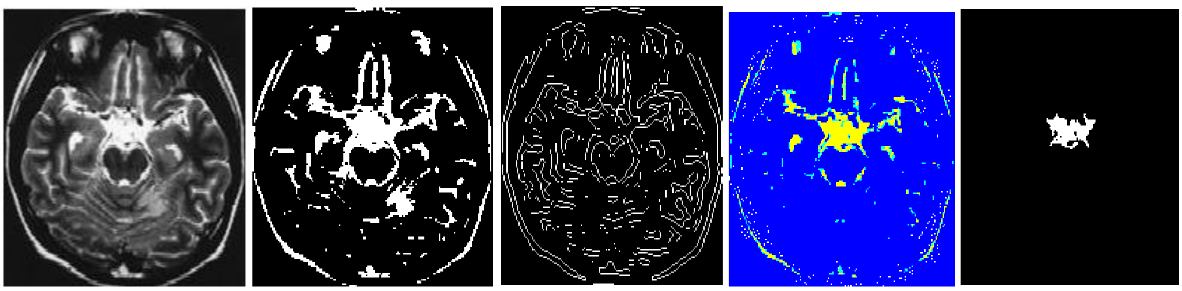


**Fig 1.4 Brain MR images: (a) is a original image and (b),(c),(d) and (e) are corresponding segmented images.**

The proposed model together with the existing control Fuzzy and EM models to a series of medical images. These brain images are obtained from Guntur Government hospital and the simulated brain database, Brain Web (available online [21]). The database contains a volume of brain magnetic resonance (MR) images with known anatomical labels to each voxel. We divide all brain image pixels into four classes, [Gray Matter (GM), White Matter (WM), cerebrospinal fluid (CSF), and others]. The datum on which we perform tissue classification is a T1-weighted MR image and has 181X 217 pixels. We assign zero intensity to those tissues belonging to "others" (e.g., fat, skin, skull, etc.) and focus on the segmentation of GM, WM, and CSF, because these three tissues occupy most of the brain volume and are characterized by complex structures. Since we know the true tissue label assigned to each pixel, it is easy to estimate the parameters in the likelihood energy function. Here, we set the mean intensities for "others," CSF, GM, and WM to 0, 72, 167, 210,

International Journal of Applied Information Systems (IJAIS) – ISSN : 2249-0868
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respectively. The segmentation results in terms of the error rate, object evaluation and quality metrics are listed in Table I, Table II and Table III. The proposed method achieves more accurate segmentation results with the advantage of 0.3 to 1.3 percentage points over the other existing models.

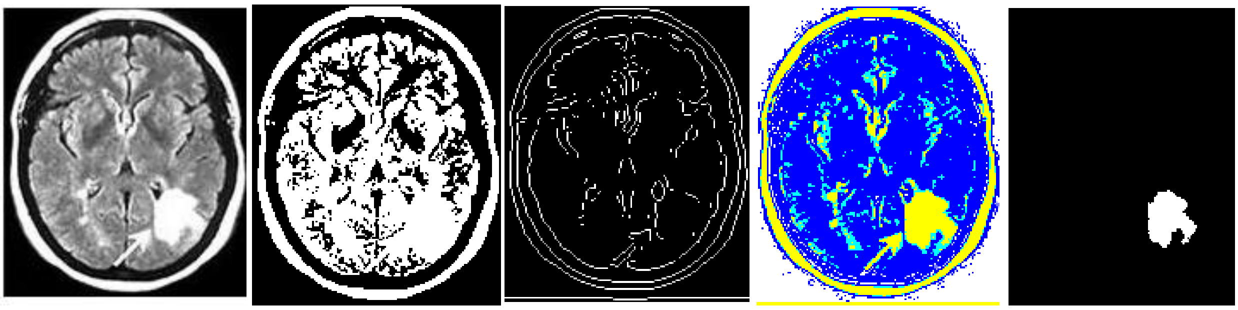

**Fig 1.5 Brain MR images: (a) is a original image and (b),(c),(d) and (e) are corresponding segmented images.**

**Table 1: Error rates of Fuzzy, EM and proposed model with different level of noises.**

| Error rates | | | |
|---|---|---|---|
| Noise levels | Fuzzy | EM | Our model |
| 3% | 2.98 | 1.68 | 0.89 |
| 5% | 3.72 | 2.54 | 1.45 |
| 7% | 4.18 | 3.22 | 1.78 |
| 9% | 5.37 | 4.46 | 2.01 |

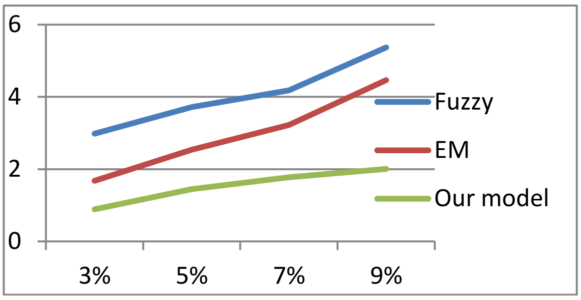


**Fig 2: Error rates of Fuzzy, EM and proposed model with different level of noises.**

The segmentation performance is evaluated by using objective segmentation evaluation criteria based on Jaccard Index and Volumetric similarity using formulas

.

$$JC=\frac{|X\cap Y|}{|X\cup Y|}=\frac{a}{a+b+c} \qquad (10)$$

$$VC= 1-\frac{||X|-|Y||}{|X|+|Y|} = 1-\frac{b-c}{za+b+c} \qquad (11)$$

Where $a=|X\cap Y|$, $b=\left|\frac{X}{Y}\right|$, $c=\left|\frac{Y}{X}\right|$, $d=\left|\overline{X\cup Y}\right|$

$$GCE(S,S') = \frac{1}{N}\min\{\sum LRE(S,S',x_i), \sum LRE(S', S, x_i)\} \qquad (12)$$

Where, $LRE=\frac{|C(S,x_i)\setminus C(S',x_i)|}{|C(S,x_i)|}$

S and S' are segment classes and $x_i$ is the pixel.

$$VOI(X,Y) = H(X) = H(Y) - 2I(X;Y) \qquad (13)$$

Where X and Y are two clusters

$$PRI(S_t, \{S\})= \frac{1}{\binom{N}{2}}\sum_{i,j,i<j}[I(l_i^{St} = l_j^{St})p_j + I(l_i^{St} \neq l_j^{St})(1-p_j)] \qquad (14)$$

Where, $p_j = P(l_i = l_j) = \frac{1}{K}\sum_{K=1}^{K} I(l_i^k = l_j^k)$ and the values range from 0 to 1. 1 denotes the segments are identical

**Table 2: Results for Segmentation Metrics**

| Image | Quality Metric | Fuzzy | EM | Our Model | Standard limit | Standard Criteria |
|---|---|---|---|---|---|---|
| Img1 | JC | 0.7815 | 0.8672 | 0.9812 | 0 to 1 | Close to 1 |
| | VS | 0.8123 | 0.8990 | 0.9911 | 0 to 1 | Close to 1 |
| | VOI | 2.8623 | 3.8771 | 5.9891 | -∞ to ∞ | Big Value |
| | GCE | 0.7912 | 0.9012 | 0.9976 | 0 to 1 | Close to 1 |
| | PRI | 0.8233 | 0.9001 | 0.9923 | 0 to 1 | Close to 1 |
| Img2 | JC | 0.7425 | 0.7632 | 0.9612 | 0 to 1 | Close to 1 |
| | VS | 0.7423 | 0.7992 | 0.9912 | 0 to 1 | Close to 1 |
| | VOI | 1.8323 | 3.8572 | 4.7431 | -∞ to ∞ | Big Value |
| | GCE | 0.8112 | 0.8903 | 0.9926 | 0 to 1 | Close to 1 |
| | PRI | 0.7833 | 0.7890 | 0.9394 | 0 to 1 | Close to 1 |
| Img3 | JC | 0.7813 | 0.8454 | *0.9624* | 0 to 1 | Close to 1 |
| | VS | 0.8525 | 0.7452 | *0.9935* | 0 to 1 | Close to 1 |
| | VOI | 2.8123 | 4.8932 | *6.7435* | -∞ to ∞ | Big Value |
| | GCE | 0.7412 | 0.7433 | *0.9706* | 0 to 1 | Close to 1 |
| | PRI | 0.7245 | 0.7760 | *0.9635* | 0 to 1 | Close to 1 |
| Img4 | JC | 0.8863 | 0.7489 | 0.9949 | 0 to 1 | Close to 1 |
| | VS | 0.7945 | 0.8558 | 0.9632 | 0 to 1 | Close to 1 |
| | VOI | 2.7943 | 4.9536 | 6.8949 | -∞ to ∞ | Big Value |
| | GCE | 0.7452 | 0.9432 | 0.9990 | 0 to 1 | Close to 1 |
| | PRI | 0.7838 | 0.7640 | 0.9654 | 0 to 1 | Close to 1 |
| Img5 | JC | 0.8944 | 0.8794 | 0.9847 | 0 to 1 | |
| | VS | 0.8245 | 0.7863 | 0.9928 | 0 to 1 | Close to 1 |
| | VOI | 2.7816 | 4.8953 | 6.7510 | -∞ to ∞ | Close to 1 |
| | GCE | 0.7928 | 0.7816 | 0.9423 | 0 to 1 | Big Value |
| | PRI | 0.8529 | 0.9634 | 0.9820 | 0 to 1 | Close to 1 |
| | | | | | | Close to 1 |

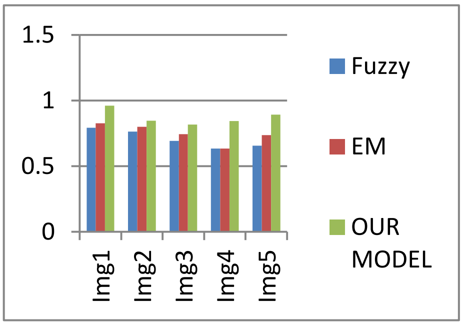


**Fig 3: Jaccard coefficient**

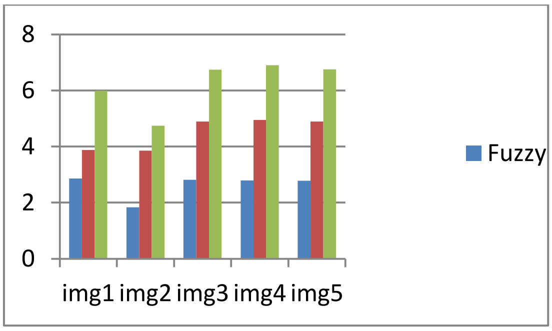


**Fig 5: Variation of Index**

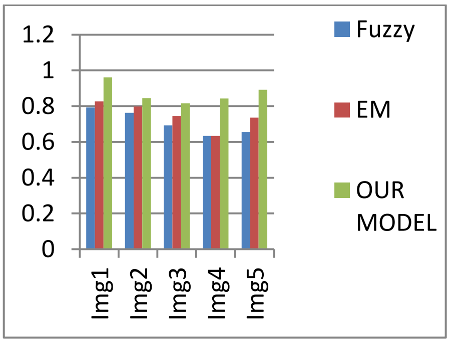


**Fig 4: Volumetric similarity**

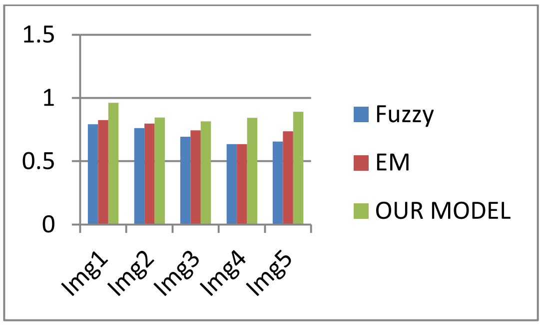


**Fig 6: Global consistency Error**

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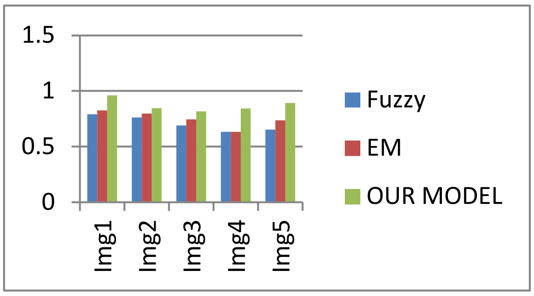


**Fig 7: Probability Random Index**

Using above segmentation metrics, it can be clearly seen that the model developed by using Iterative conditional mode algorithm shows better results with respect to the segmentation metrics. The model is compared the existing models based on Fuzzy and Expectation Maximization and the results are shown pictorially by the table-2 and the graphs are shown in figures 3-7. From the above graphs, it can be clearly seen that the model developed by using Iterative conditional mode algorithm performs better results compared to the existing models. This may be due to the fact that this model determines exact tumor mass effect in the brain MR images.

**Table- 3: Formulae for Evaluating Quality Metrics Used**

| **Quality metric** | **Formulae to Evaluate** |
|---|---|
| Average Difference | $\sum_{j=1}^{M}\sum_{k=1}^{N}[F(j,k)-\hat{F}(j,k)]/MN$ Where M,N are image matrix rows and columns |
| Maximum Distance | Max{\|F(j,k)-F(j,k)\|} |
| Image Fidelity | 1-[$\sum_{j=1}^{M}\sum_{k=1}^{N}[F(j,k)-\hat{F}(j,k)]^2 / \sum_{j=1}^{M}\sum_{k=1}^{N}[F(j,k)]^2$] Where M,N are image matrix rows and columns |
| Mean Squared error | $\frac{1}{MN}\sum_{j=1}^{M}\sum_{k=1}^{N}[O\{F(j,k)\} - O\{\hat{F}(j,k)\}]^2 / \sum_{j=1}^{M}\sum_{k=1}^{N}[O\{F(j,k)\}]^2$ Where M,N are image matrix rows and columns |
| Peak Signal to noise ratio | $10\log_{10}\left(\frac{MAX1}{\sqrt{MSE}}\right)$ Where $MAX_I$ is maximum possible pixel value of image, MSE is the Mean squared error. |

International Journal of Applied Information Systems (IJAIS) – ISSN : 2249-0868
Foundation of Computer Science FCS, New York, USA
Volume 5– No.2, January 2013 – www.ijais.org

**Table 4: Numerical Results for Quality metrics**

| Image | Quality Metric | Fuzzy | EM | Our Model | Standard Limits | Standard Criteria |
|---|---|---|---|---|---|---|
| Imag1 | Average Difference | 0.7923 | 0.8262 | 0.9612 | -1 to 1 | Close to 1 |
| | Maximum Distance | 0.7811 | 0.8591 | 0.9823 | -1 to 1 | Close to 1 |
| | Image Fedility | 0.7956 | 0.8611 | 0.9855 | 0 to 1 | Close to 1 |
| | Mean square error | 0.214 | 0.098 | 0.022 | 0 to 1 | Close to 1 |
| Imag2 | Average Difference | 0.7625 | 0.7982 | 0.9453 | -1 to 1 | Close to 1 |
| | Maximum Distance | 0.6814 | 0.7992 | 0.9562 | -1 to 1 | Close to 1 |
| | Image Fedility | 0.7658 | 0.8423 | 0.9435 | 0 to 1 | Close to 1 |
| | Mean square error | 0.145 | 0.085 | 0.045 | 0 to 1 | Close to 1 |
| Imag3 | Average Difference | 0.6923 | 0.7442 | 0.9662 | -1 to 1 | Close to 1 |
| | Maximum Distance | 0.6784 | 0.7363 | 0.9472 | -1 to 1 | Close to 1 |
| | Image Fedility | 0.7543 | 0.7933 | 0.9767 | 0 to 1 | Close to 1 |
| | Mean square error | 0.275 | 0.074 | 0.055 | 0 to 1 | Close to 1 |
| Imag4 | Average Difference | 0.6343 | 0.7343 | 0.9922 | -1 to 1 | Close to 1 |
| | Maximum Distance | 0.6911 | 0.7911 | 0.9812 | -1 to 1 | Close to 1 |
| | Image Fedility | 0.7634 | 0.8634 | 0.9228 | 0 to 1 | Close to 1 |
| | Mean square error | 0.255 | 0.0655 | 0.099 | 0 to 1 | Close to 1 |
| Imag5 | Average Difference | 0.6548 | 0.7356 | 0.9910 | -1 to 1 | Close to 1 |
| | Maximum Distance | 0.6944 | 0.74581 | 0.9578 | -1 to 1 | Close to 1 |
| | Image Fedility | 0.7344 | 0.7944 | 0.9868 | 0 to 1 | Close to 1 |
| | Mean square error | 0.158 | 0.072 | 0.025 | 0 to 1 | Close to 1 |

International Journal of Applied Information Systems (IJAIS) – ISSN : 2249-0868
Foundation of Computer Science FCS, New York, USA
Volume 5– No.2, January 2013 – www.ijais.org

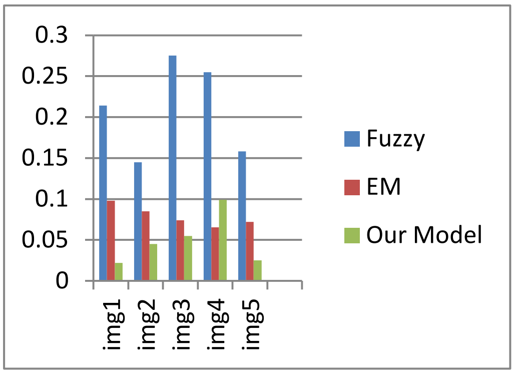


**Fig 8: Average Difference**

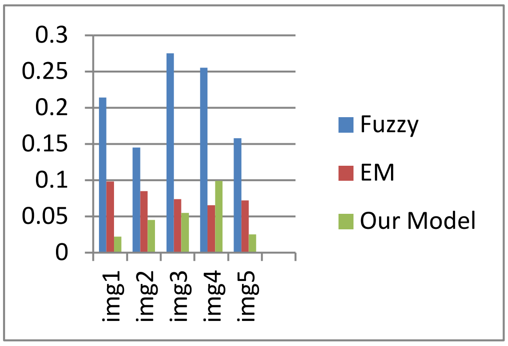


**Fig 9: Maximum Distance**

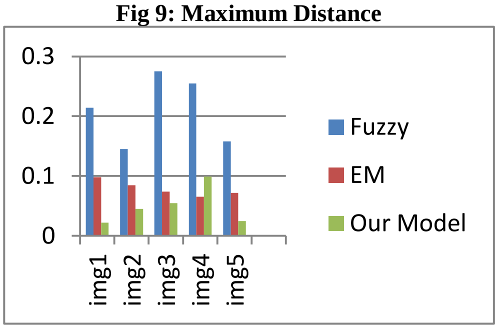


**Fig 10: Image Fedility**

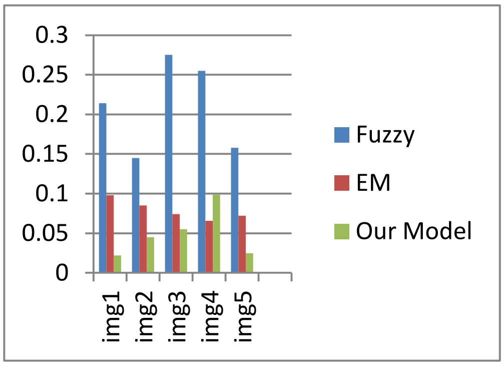


**Fig 11: Mean Square Error**

From the above Table – 4 and bar graphs – 3, it can be clearly seen that the model developed by using Iterative conditional mode algorithm shows better results with respect to the quality metrics. The model is compared the existing models based on Fuzzy and Expectation Maximization and the results are shown pictorially by the figures 8-11. From the above graphs, it can be clearly seen that the model developed by using Iterative conditional mode algorithm performs better results compared to the earlier models. This may be due to the fact that this model determine exact tumor mass effect in the brain MR images.

## 5. CONCLUSION:

In this paper, it is proposed a non texture segmentation model using Iterative conditional Mode algorithm based on a boundary model. The main target of this approach is to detect the abnormality in brain MR images and segmentation by emphasize the interactions between label and boundary MRFs. The comparisons with other existing models show that the proposed model can give more accurate segmentation results in both segmentation and evaluation metrics.

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