



e-ISSN: 2319-8753 | p-ISSN: 2347-6710

# IJIRSET

International Journal of Innovative Research in  
**SCIENCE | ENGINEERING | TECHNOLOGY**

# INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

Volume 13, Issue 4, April 2024

**ISSN** INTERNATIONAL  
STANDARD  
SERIAL  
NUMBER  
INDIA

Impact Factor: 8.423

9940 572 462

6381 907 438

[ijirset@gmail.com](mailto:ijirset@gmail.com)

[www.ijirset.com](http://www.ijirset.com)

# Automated Segmentation of Brain Tumor by MRI Images Using Deep Learning

S.CHANDRASEKAR, POSAM ANUHYA, SHAIK JASMINE, SOMAPALLI ANUSHA

Assistant Professor, Department of CSE, Muthayammal Engineering College (Autonomous), Rasipuram, Tamil Nadu, India

Department of CSE, Muthayammal Engineering College (Autonomous), Rasipuram, Tamil Nadu, India

Department of CSE, Muthayammal Engineering College (Autonomous), Rasipuram, Tamil Nadu, India

Department of CSE, Muthayammal Engineering College (Autonomous), Rasipuram, Tamil Nadu, India

**ABSTRACT:** A combination of Graph cut technique and k-means clustering with multi threshold for medical image segmentation is presented. The main objective of medical image segmentation is to extract the anatomic structures and its characteristics with respect to some input features. There exist various methodologies for medical image segmentation but struggles with missing features due to the noise presence in the medical images. We propose a new technique to increase the resolution of the medical images to identify the features and edges of the medical images. The medical image is preprocessed to reduce the noise, and then multilevel histogram is generated in the first phase of the process. In the second stage, with the initial segmentation obtained with gray level contours, and we generate the histogram then we construct the pixel adjacency graph in which each nodes represents the set of pixels of the image and edges links the neighbor pixels. We calculate the similarity of neighboring pixels; based on the distance value we cluster the similar pixels to a class. We use k-means clustering to group similar pixels and we used Euclidean distance measure to calculate the similarity between pixels. The proposed method is carried out iteratively until the user gets satisfied. The method will be carried out repeatedly with the user defined threshold value. The threshold is used to group pixels with in the distance. With the proposed technique the features are maintained and the resolution of the image enhanced. The time complexity of the process is reduced.

**KEYWORDS:** K-means clustering, User Interacted Medical image Segmentation, Threshold based segmentation, Weight Map, histogram, edge detection.

## 1. INTRODUCTION

Intensity inhomogeneity often occurs in real-world images due to various factors, such as spatial variations in illumination and imperfections of imaging devices, which complicates many problems in image processing and computer vision. In particular, image segmentation may be considerably difficult for images with intensity inhomogeneities due to the overlaps between the ranges of the intensities in the regions to segment. This makes it impossible to identify these regions based on the pixel intensity. The goal of the image processing for earth science application is to enhance geographical data in digital format, so as to make it more meaningful to a user to extract quantitative information for problem solving. Image processing is a broad time describing with most operation that you can apply to image data may be in the form of 2D, 3D and 4D waves. The intensity inhomogeneity in an MR image can be modeled as a multiplicative component of an observed image described by

$$I(x) = \tilde{b}(x)\tilde{J}(x) + n(x) \quad (1)$$

where  $I(x)$  is the measured image intensity at location (voxel)  $x$ ,  $\tilde{J}$  is the true signal to be restored, the energy  $F(U, \mathbf{c}, \mathbf{w})$  is convex in each of its variables[1].

GMM parameters are assumed to be stochastic variables governed by “hyper parameters,” which, together with the latent voxel labels, can be estimated in a variational extension of the EM technique, GMM parameters  $\Theta$  are assumed to be stochastic variables[2]. The level set method was introduced independently by *Caselles et al.* in the context of active contour (or snake) models for image segmentation [3]. Our method is based on an observation that intensities in a relatively small local region are separable, despite of the inseparability of the intensities in the whole image caused by the intensity inhomogeneity. due to the intensity inhomogeneity caused by the bias field, the measured intensities are not separable by using traditional intensity based classification methods. We first consider the case of  $N = 2$ . In this case, the

image domain is partitioned into two regions  $\{\Omega_i\}_{i=1}^2$ . These two regions can be represented by the regions separated by the zero level contour of a function  $\phi$ . Using Heaviside function  $H$ , the energy  $E$  in Eq.

$$\mathcal{E}(\phi, b, c) = \int \left( \sum_{i=1}^2 \int K(x-y) |I(y) - b(x)c_i|^2 M_i(\phi(y)) dy \right) dx \quad (2)$$

Where  $M_1(\phi(x)) = H(\phi(x))$  and  $M_2(\phi(x)) = 1 - H(\phi(x))$ , a unified framework of bias correction and segmentation [4]. Existing level set methods for image segmentation can be categorized and edge-based models. Region-based models aim to identify each region of interest by using a certain region descriptor to guide the motion of the active contour [5].

In this paper, we propose a novel region-based method for image segmentation. From a generally accepted model of images with intensity inhomogeneities, we derive a local intensity clustering property, and therefore define a local clustering criterion function for the intensities in a neighborhood of each point. An efficient hybrid level set (HLS) model is proposed for segmenting the images with intensity inhomogeneity, which is a difficult problem for traditional region-based level set methods. The total energy functional for the proposed model consists of three terms, i.e., global term, local term and regularization term. By incorporating the local image information into the proposed model, the images with intensity inhomogeneity can be efficiently segmented.

In addition, the time-consuming re-initialization step widely adopted in traditional level set methods can be avoided by introducing a penalizing energy. Finally, experiments on some synthetic and real images have demonstrated the efficiency and robustness of the MRI. Another important factor in radiation therapy concerns the treatment margins around the GTV that form the clinical target volume (CTV). The prescribed margin is used to accommodate uncertainties in the position of the target volumes, and the uncertainty can be high due to the large movement of the bladder, uterus and rectum. Therefore, the clinical motivations to shrink the margin, to place accurate dosage and to adapt the treatment plan call for a robust method that can achieve precise organ segmentation, tumor detection, and non rigid registration.

## II. EXISTING METHOD

### 2.1 Segmentation Module

#### 2.1.1 Shape Model

In the last decade, level set distribution model (LSDM) was widely used to represent the organs, and principal component analysis (PCA) was then performed on a set of signed distance functions embedding a set of sample shapes. LSDM was first introduced by Leventon, and it gave birth to a lot of related approaches. However, the use of PCA to model level set based shape distributions has some unsolved mathematical limitations: the space of signed distance functions is not a linear space, i.e. arbitrary linear combinations of signed distance functions will in general not correspond to a valid signed distance function. In addition, the evolution and re-initialization of level set surface usually takes long time. In order to achieve a fast and accurate segmentation, instead of using the level set distribution model, we use a point distribution model (PDM). The initial model for the organ is built from a set of training images. The statistical shape model is widely used in deformable object segmentation to enforce shape constraints and make the system more robust. The shape of an object is represented by a dense collection of landmark points on its boundary. The most important requirement here is that all chosen landmark points must be situated at corresponding locations on all training images. There are some literatures on building a statistical 3D shapemodel automatically using pair-wise or group-wise registration based approaches, or by consistently resampling the 2D intersection of 3D meshes. Here, we employ the Procrustes Analysis to Perform the shape alignment. A mean shape is then produced by averaging all training shapes. Based on this mean shape model, a deformable model is constructed as a triangulated mesh  $M$  with vertex set  $V$  and edge set  $E$ , which has exactly the same topology as the the statistical shape model. For each vertex in  $V$ , there is a corresponding point on the original model. A constructed mesh for the prostate is shown in Figure 1.

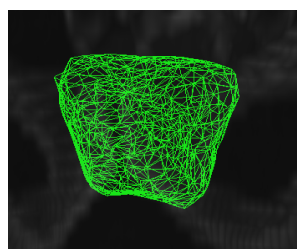


Fig.1. Constructed mesh for the prostate



**2.1.2 Non rigid Mesh Deformation**

After constructing the statistical shape model, we project the mean shape into the test image, and then deform the mean shape to fit the object boundary. Active shape models (ASM) are widely used to deform an initial estimate of a non rigid shape under the guidance of the image evidence and the shape prior. The generic boundary detector in the original ASM does not work in our application due to the complex background and weak edges. Here, we impose a modified model from the ASM by incorporating the constraints from the point-based shape registration.

The best fitted mesh can then be found by finding a feasible surface  $S$  minimizing the energy:

$$E(S) = EASM(S) + ERegistration(S) \quad (3)$$

The registration-constraint energy term serves as an external force, which drives the mesh towards the best fit to the image data.

**2.2 Registration Module**

**2.2.1 Robust Point Matching**

The Robust Point Matching methodology that was first introduced by Chui *et al.* The registration procedure consists of two alternative steps:

(i) The correspondence estimation step and (ii) the transformation estimation step. In the following discussion we will label the point set in reference image as  $X$  and the point set in source image as  $Y$ . Note that  $X$  is the control point set that we are trying to estimate in the segmentation module.

The goal of the registration is to estimate the transformation  $T : Y \rightarrow X$ . We will label  $T_k$  the estimate of  $T$  at the end of iteration  $k$ .  $T^0$  is the starting transformation which can be the identity transformation.

**2.3 MAP framework**

The appearance of an object is always dependent on the gray level variation in an image. Segmentation can be made easier if suitable models containing such relationship priors and likelihoods are available. Meanwhile, registration can be achieved more precisely by incorporating both intensity matching and segmented organ matching constraints.

A probabilistic formulation is a powerful approach to realize these two aims. Deformable models can be fit to the image data by finding the model shape parameters that maximize the posterior probability. Follow a Bayesian line of thinking, assuming  $S_d$  is independent from  $I_0, S_0$ , we have:

$$\begin{aligned} \widehat{S}_d, \widehat{T}_{0d} &= \arg \max_{S_d, T_{0d}} [p(S_d, T_{0d} | I_0, I_d, S_0)] \\ &= \arg \max_{S_d, T_{0d}} [p(I_d | S_d) \cdot p(S_0, T_{0d} | S_d) \cdot p(S_d) \cdot p(I_0, I_d | T_{0d}) \cdot p(T_{0d})] \end{aligned} \quad (4)$$

This multi parameter MAP estimation problem in general is difficult to solve, however, we reformulate this problem such that it can be solved in two basic iterative computational stages using an iterative conditional mode (ICM) strategy. This reformulation then reduces to a framework where we simultaneously maximize over a range of possible segmentations (using a trial registration to pass initialization information) in one stage, and perform a nonrigid registration in a second stage (using a fixed segmentation in the reference image and the current segmentation estimate in the second image as key constraints). With  $k$  indexing each iterative step, we have:

$$\begin{aligned} \widehat{S}_d^k &= \arg \max_{S_d^k} [p(S_d^k | T_{0d}^k(S_0), I_d)] \\ \widehat{T}_{0d}^{k+1} &= \arg \max_{T_{0d}^{k+1}} [p(T_{0d}^{k+1} | S_d^k, S_0, I_d, I_0)] \end{aligned} \quad (5)$$

These two equations represent the key problems we are addressing:  $\widehat{S}_d^k$  represents the estimation of the segmentation of the important day  $d$  structure  $S_d^k$  and (ii)  $T_{0d}^{k+1}$  represents the estimation at the next iterative step of the mapping  $T^{k+1}_{0d}$  between the day 0 and day  $d$  spaces.

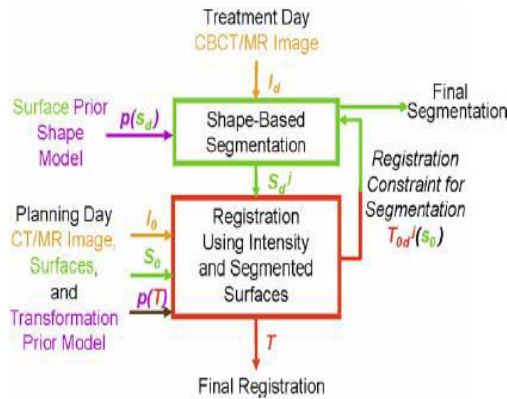


Fig.2. Flowchart of the integrated segmentation and registration algorithm.

### 2.3.1 Segmentation module

We first apply Bayes rule,

$$\begin{aligned} \hat{S}_d^k &= \arg \max_{S_d^k} [p(S_d^k | T_{0d}^k(S_0), I_d)] \\ &= \arg \max_{S_d^k} [p(I_d | S_d^k) \cdot p(T_{0d}^k(S_0) | S_d^k) \cdot p(S_d)] \end{aligned} \quad (6)$$

### Results:

Evaluation of segmentation of bladder.

|                  | MAD (mm)    | HD (mm)     | PTP (%)      |
|------------------|-------------|-------------|--------------|
| Without prior    | 7.61 ± 2.69 | 8.63 ± 3.18 | 43.18 ± 7.92 |
| With shape prior | 3.91 ± 1.73 | 4.54 ± 2.04 | 72.47 ± 4.91 |
| Proposed method  | 1.06 ± 0.12 | 1.29 ± 0.33 | 86.53 ± 2.18 |

Evaluation of the segmentation module.

| Method   | MAD (mm)         | HD (mm)      | PTP (%)      |               |
|----------|------------------|--------------|--------------|---------------|
| Prostate | Without prior    | 12.76 ± 4.33 | 15.42 ± 4.56 | 47.92 ± 8.15  |
|          | With shape prior | 8.02 ± 2.43  | 8.73 ± 2.90  | 60.13 ± 5.53  |
|          | Proposed method  | 1.96 ± 0.48  | 2.83 ± 0.76  | 85.32 ± 2.83  |
| Bladder  | Without prior    | 18.54 ± 5.39 | 20.13 ± 6.16 | 38.25 ± 10.28 |
|          | With shape prior | 11.69 ± 4.72 | 13.18 ± 5.31 | 65.20 ± 4.01  |
|          | Proposed method  | 2.96 ± 0.81  | 4.31 ± 1.24  | 90.33 ± 3.28  |
| Rectum   | Without prior    | 18.21 ± 4.81 | 19.87 ± 5.30 | 32.43 ± 8.92  |
|          | With shape prior | 9.91 ± 4.04  | 12.25 ± 5.36 | 54.71 ± 9.43  |
|          | Proposed method  | 2.85 ± 0.47  | 3.69 ± 1.20  | 84.72 ± 2.83  |

## III. OUR CONTRIBUTIONS

Since a standard approach based on MR image intensity matching only may not be sufficient to overcome these limiting factors, in this paper, we present a novel probability based technique as an extension to our previous work in, for the motivations mentioned above. This module deal with intensity inhomogeneities in image segmentation, we formulate our method based on an image model that describes the composition of real-world images, in which intensity inhomogeneity is attributed to a component of an image. Local Intensity Clustering Property and Energy Formulation are other two models in this module. This part of the code in the application uses the approach to handle the elements like level set spline.

The minimum energy level is calculated by estimating the time taken to initialize the images, applying bias formation to filter the images and the storage time and tracing of similar intensity pixel elements.

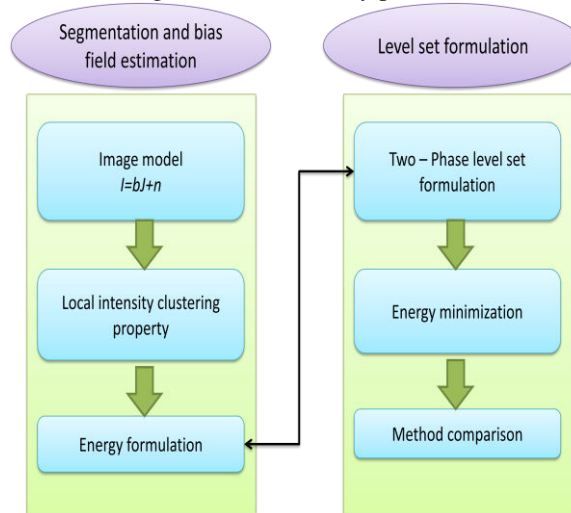


Fig. 3 Diagram of the proposed method

#### IV. VARIATIONAL FRAMEWORK FOR JOINT SEGMENTATION AND BIAS FIELD ESTIMATION

##### 4.1 Image Model and Problem Formulation:

In order to deal with intensity inhomogeneities in image segmentation, we formulate our method based on an image model that describes the composition of real-world images, in which intensity inhomogeneity is attributed to a component of an image. an observed image can be modeled as

$$I = bJ + n \quad (7)$$

Where  $J$  is the true image, is the component that accounts for the intensity inhomogeneity, and  $n$  is additive noise. The bias field is assumed to be slowly varying. The additive noise can be assumed to be zero-mean Gaussian noise.

##### 4.2. Local Intensity Clustering Property:

Clustering is process for classifying the objects or patterns in such a way that samples of the same group are more similar to one another than samples belonging to different groups. Many clustering strategies have been used, such as the hard clustering scheme and the fuzzy clustering scheme, each of its own special characteristics. The Region-based image segmentation methods typically rely on a specific region descriptor (e.g. intensity mean or a Gaussian distribution) of the intensities in each region to be segmented. However, it is difficult to give such a region descriptor for images with intensity inhomogeneities. The intensity inhomogeneities often lead to overlap between the distributions of the intensities in the regions.

$$b(x) \approx b(y) \text{ for } x \in O_y, \quad (8)$$

Where  $N(x)$  is additive zero-mean Gaussian noise. Therefore, the intensities in the set.

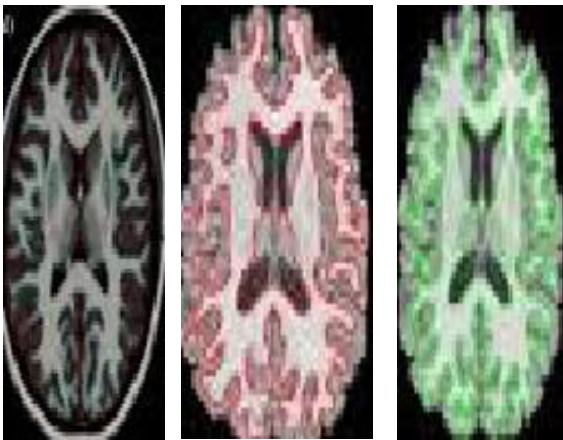


Fig. 2 Applications of our method to an MR image of Clustering Property.

### 4.3. Energy Formulation:

The above described local intensity clustering property indicates that the intensities in the neighborhood can be classified into clusters, with centers. This allows us to apply the standard K-means clustering to classify these local intensities. The K-means algorithm is an iterative process to minimize the clustering criterion, which can be written in a continuous form as

$$F_y = \sum_{i=1}^N \int_{O_y} |I(x) - m_i|^2 u_i(x) dx \quad (9)$$

where  $m_i$  : cluster center of the  $i$ -th cluster,  $u_i$  : membership function of the region  $\Omega_i$  i.e. to be determined,  $u_i(x)=1$ , for  $x \in \Omega_i$  and  $u_i(x)=0$ , for  $x \notin \Omega_i$  In view of the clustering criterion in (2) and the approximation of the cluster center by  $m_i = b(y) c_i$ , a clustering criterion for classifying the intensities in  $O_y$  is defined as

$$\epsilon_y = \sum_{i=1}^N \int_{\Omega_i \cap O_y} K(y-x) |I(x) - b(y) c_i|^2 dx \quad (10)$$

Where  $K(y-x)$  is introduced as a nonnegative window function, also called kernel function, such that for  $K(y-x) = 0$  for  $x \notin \Omega_i$ , with the window function, the clustering criterion function  $\epsilon_y$  can be rewritten as

$$\epsilon_y = \sum_{i=1}^N \int_{\Omega_i} K(y-x) |I(x) - b(y) c_i|^2 dx \quad (11)$$

### 4.4 Level Set Formulation and Energy Minimization:

Our proposed energy is expressed in terms of the regions  $\Omega_1, \Omega_2, \dots, \Omega_n$ . It is difficult to derive a solution to the energy minimization problem from this expression of the energy is converted to a level set formulation by representing the disjoint regions  $\Omega_1, \Omega_2, \dots, \Omega_n$  with a number of level set functions. In level set methods, a level set function is a function that take positive and negative signs, which can be used to represent a partition of the domain  $\Omega$  into two disjoint regions  $\Omega_1$  and  $\Omega_2$ . Let  $\varphi : \Omega \rightarrow \mathbb{R}$  be a level set function, and then its signs define two disjoint regions

$$\Omega_1 = \{x: \varphi(x) > 0\} \quad \text{And} \quad \Omega_2 = \{x: \varphi(x) < 0\} \quad (12)$$

Which form a partition of the domain  $\Omega$ . For the case of  $N > 2$ , two or more level set functions can be used to represent  $N$  regions  $\Omega_1 \dots \Omega_N$ .

A local clustering criterion function for the intensities in a neighborhood of each point is established based on the local intensity clustering property, from a generally accepted model of images with intensity inhomogeneities. Therefore, the intensities  $b(y) J(y)$  in each sub region  $O_x \cap \Omega_i$  is approximately the constant  $b(x) c_i$ .  $b(y) J(y) \approx b(x) c_i$  for  $y \in O_x \cap \Omega_i$ .

Now after the Bias correction the next step Fig.3 is shown to obtain values of statistical parameters of the Brain MR images like probability, entropy and variance.

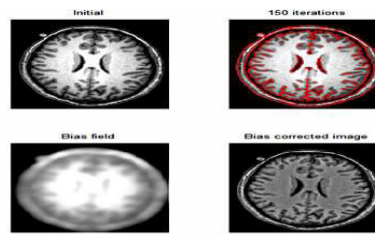


Fig.3 Level Set Segmentation

#### 4.5 Statistical Properties Using Histogram:

The Fig.4 variance of random variable is the square of its standard deviation.

$$\text{Variance}(X) = E[(X - \mu)^2] \quad (13)$$

If  $\mu = E(X)$ , where  $E(X)$  is the expected value (mean) of the random variable  $X$ .

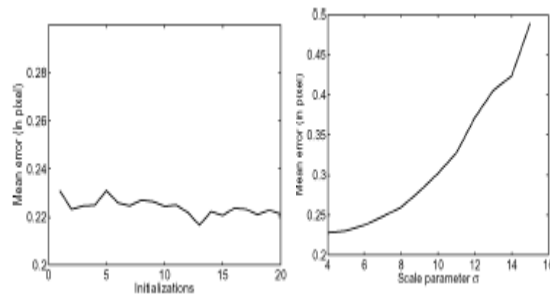


Fig.4 Segmentation accuracy of our method for different initializations and different scale parameters.

If the source symbols are equally probable, the entropy or uncertainty of Equation 14 is maximized and the source provides the greatest possible average information per source symbol.

$$G(K) = - \sum P\{n\} \log(P\{n\}) \quad (14)$$

If the source symbols are equally probable, the entropy or uncertainty of Equation 13 is maximized and the source provides the greatest possible average information per source symbol.

#### 4.6 Robustness to Contour Initialization:

The contour pixels are generally a small subset of the total number of pixels representing a pattern. Therefore, the amount of computation is greatly reduced when we run feature extracting algorithms on the contour instead of on the whole pattern. It's different characteristics will be examined and used as features which will later on be used in pattern classification. Therefore, Fig 5 correct extraction of the contour will produce more accurate features which will increase the chances of correctly classifying a given pattern.



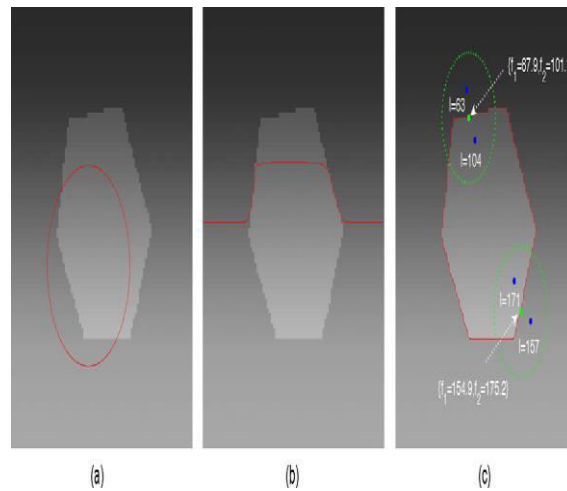


Fig.5 Synthetic image with intensity inhomogeneity

#### 4.7 MR Image Segmentation and Bias Correction:

The improvement of the Fig. 6 image quality in terms of intensity homogeneity can be also demonstrated by comparing the histograms of the original images and the bias corrected images. The histograms of the original images (left) and the bias corrected images (right) are plotted in the fifth column. There are three well-defined and well-separated peaks in the histograms of the bias corrected image, each corresponding to a tissue or the background in the image.

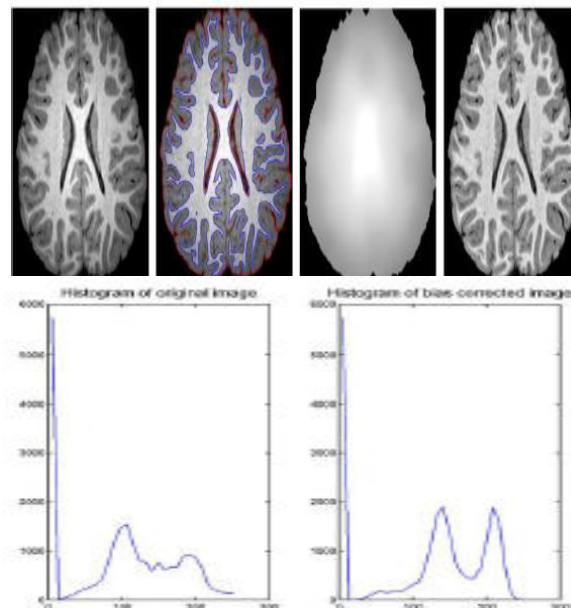


Fig. 6 Applications of our method to 3T MR images.

The histograms of the original images do not have such well-separated peaks due to the mixture of the intensity distribution caused by the bias.

## VI. RESULTS

This paper proposes a novel region-based method for image segmentation, which is able to deal with intensity inhomogeneities in the segmentation.

In a level set formulation, this criterion defines an energy in terms of the level set functions that represent a partition of the image domain and a bias field that accounts for the intensity inhomogeneity of the image using MATLAB 8.1.0 v.

### 6.1 Bias Corrected & Bias Field Image:

The first model involves resetting the image to a hypothetical Ideal. And An integration of this metric defines an energy on a bias field, membership functions of the tissues, and the parameters that approximate the true signal from the corresponding tissues.

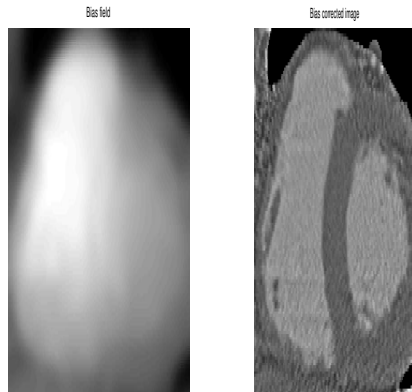


Fig.7 Simulation Result for Bias Corrected & Field Image

### 6.1 Initial Contour & Iterations:

In the level set method, Fig 8 contours or surfaces are represented as the zero level set of a higher dimensional function, usually called a level set function. And Iteration is the act of repeating a process with the aim of approaching a desired goal, target or result. Each repetition of the process is also

called "iteration" and the results of one iteration are used as the starting point for the next iteration.

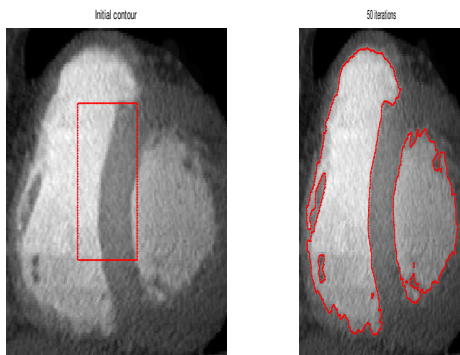


Fig.8 Simulation Result for Initial Contour & Iterations.

## VII. CONCLUSION

Based on a generally accepted model of images with intensity inhomogeneities and a derived local intensity clustering property, we define an energy of the level set functions that represent a partition of the image domain and a bias field that accounts for the intensity inhomogeneity. We have presented a variational level set framework for segmentation and bias correction of images with intensity inhomogeneities. Segmentation and bias field estimation are therefore jointly performed by minimizing the proposed energy functional. The slowly varying property of the bias field derived from the proposed energy is naturally ensured by the data term in our variational framework, without the need to impose an explicit smoothing term on the bias field. Our method is much more robust to initialization than the piecewise smooth model. Experimental results have demonstrated superior performance of our method in terms of accuracy, efficiency, and robustness. As an application, our method has been applied to MR image segmentation and bias correction with promising results.



## VIII. FUTURE WORK

With the presence of intensity inhomogeneities of image segmentation based on two-phase level set formulation is done. Future work of this project is image segmentation in the presence of intensity inhomogeneities based on multiphase level set formulation.

## REFERENCES

- [1] Chunming Li 1, Chris Gatenby 1, Li Wang 2, John C. Gore 1, “A Robust Parametric Method for Bias Field Estimation and Segmentation of MR Images”,(2009 IEEE).
- [2] GuangJian Tian, Yong Xia, *Member*, “Hybrid Genetic and Variational Expectation-Maximization Algorithm for Gaussian-Mixture-Model-Based Brain MR Image Segmentation”. IEEE Transactions On Information Technology In Biomedicine, Vol. 15, No. 3, May 2011.
- [3] Chunming Li, Chenyang Xu, “Distance Regularized Level Set Evolution and Its Application to Image Segmentation”, IEEE Transactions On Image Processing, Vol. 19, No. 12, December 2010.
- [4] Chunming Li1,\_, RuiHuang2, Zhaohua Ding1, Chris Gatenby1, Dimitris Metaxas2, “A Variational Level Set Approach to Segmentation and Bias Correction of Images with Intensity Inhomogeneity”,( 2008).
- [5] Chunming Li, Rui Huang, Zhaohua Ding, J. Chris Gatenby, Dimitris N. Metaxas, “A Level Set Method for Image Segmentation in the Presence of Intensity Inhomogeneities With Application to MRI”, IEEE Transactions On Image Processing, Vol. 20, No. 7, July 2011.
- [6] How many women get cancer of the cervix. Atlanta, GA, Am. Cancer Soc., 2010 [Online]. Available:<http://www.cancer.org/Cancer/CervicalCancer/DetailedGuide>.



INTERNATIONAL  
STANDARD  
SERIAL  
NUMBER  
INDIA



# INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

 9940 572 462  6381 907 438  [ijirset@gmail.com](mailto:ijirset@gmail.com)



[www.ijirset.com](http://www.ijirset.com)

Scan to save the contact details