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Brain MR Image Segmentation using Coherent Local Intensity Clustering Phenomena

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Abstract — *Bias field estimation and classification is one of the important task in medical image analysis. In this paper a new unified Magnetic Resonance Image (MRI) Segmentation algorithm present which simultaneously segments, estimates the bias field and removes the noise in MRI with the same Energy model. The total invariant term introduced to the coherent local intensity clustering phenomena function for solving the nonconvex problem with membership function. The quantitative comparison and evolution is done with Fuzzy C Means (FCM), Modified Fuzzy C Means (MFCM) and Multiplicative Intrinsic Component Optimization (MICO). The performance evolution is done inters of Jccard Similarity Index (JSI) and Timing analysis. The proposed method shows better time response.*

Keywords- *MRI, Image Segmentation, Intensity inhomogeneity, Energy minimization, Bias field estimation.*

I. INTRODUCTION

The intensity inhomogeneity occurs in real-time MRI images, which presents a huge challenge in image segmentation. The most widely used region-based image segmentation typically depends on the homogeneity of the image intensities variations in the regions of interest, which cannot provide accurate segmentation results because the intensity inhomogeneity.

Magnetic resonance imaging is a universal and powerful medical imaging technique [1], which provides comprehensive images with the high distinction between different soft tissues; MR Image thus has compiling advantages over other medical imaging techniques, making it very useful for neurological, cardiovascular, musculoskeletal, and oncological imaging. However, there are commonly considerable artifacts in real magnetic resonance images, such as image no uniformities caused by inhomogeneities in the B1 or B0 fields, especially in high field magnetic resonance images. The intensity inhomogeneity will be severely challenging in quantitative image analysis methods, such as those used for image segmentation and image registration. Intensity [2] inhomogeneities are particularly serious in MRI at ultra-high field strengths and frequently make it difficult even for expert human viewer to view the images. The volumetric and spatial analysis of the normal tissues, like, gray matter, white matter and cerebrospinal fluid, is very important to characterize morphological distinction between subjects.

Among the various segmentation methods developed in last decade, FCM [3] has been used widely for MRI segmentation. The removal of spatial intensity inhomogeneity is very difficult because these artifacts vary from slice to slice, patient to patient and changes with different MRI acquisition parameter.

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Any MRI signal can be modeled as a product of the true signal and a spatial varying factor (also called as gain field)

$$Y_K = X_K G_K \tag{1}$$

Where $K = 1,2, \dots \dots \dots N$ by apply a logarithmic transform the artifact can be modeled as an additive bias field

$$y_k = x_k + \beta_k \tag{2}$$

Here $k = 1,2, \dots N$ and β_k is bias field. If bias field is known, then tissue class will be estimated by applying a conventional intensity based segmentation methods (like Edge based, Phantom based, Surface fitting, Homomorphic filtering and fuzzy approach). If tissue class is known bias field is estimated but if both parameters are not know, then both need to be estimated

However, the automatic segmentation is still a challenge because of the intensity inhomogeneity and noise due to Radio Frequencies coils in MR images. Typically, corrupted images are segmented using either a two-step approach or a joint segmentation algorithm. In the two-step method, segmentations are usually performed assuming no inhomogeneity is present, with a preprocessing is used to remove the intensity inhomogeneity.

This paper is organized as follows: Section II presents the brief summary of related work, In Section III proposed method with necessary equations. In Section IV, we show the experimental results, which are applied to, head and brain MRI. The results of each image segmentation technique are compared using Jaccard Similarity Index time response. Section IV gives the concluding remarks of this paper.

II. Related work

Wells et al [4] used Bayesians approach to estimate the bias field that represents the gain artifacts. Applied on log transformed MR image data with Expectation Maximization (EM) approach

$$P(y_k/\gamma_i,\beta_k)=G_k(y_k-\mu_k-\beta_k)$$

$$G_k(y_k-\mu_i-\beta_k)=\frac{1}{\sigma^2}e^{\frac{(y_k-\mu_i-\beta_k)}{2\sigma^2}} \tag{3}$$

The bias field has different value for every pixel and it is modelled by N-dimensional Gaussian prior probability density.

A. Expectation maximization (EM)

Wells used EM Algorithm to obtain an iterative solution for segmentation and bias correction (i.e By using Maximum a posterior (MAP) approach which is similar to Maximum likely hood probability)

$$\hat{\beta}=\arg\max_{\beta} p(\beta/y)$$

Assuming statistical independence of pixel intensities the probability density of entire image is

$$P(y,\beta)=\prod_k P(y_k/\beta_K)$$

By using definition of conditional probability and the joint probability Where

$$P(y_k/\beta_K)=\sum_{\gamma_i}P(y_k,\gamma_i/\beta_K)=\sum_{\gamma_i}P(y_k/\gamma_i,\beta_K)P(\gamma_i)$$

The necessary condition is $\left[\frac{\partial \ln p(\beta/y)}{\partial\beta_k}\right]_{\beta=\hat{\beta}}=0$, for all k

After simplification we get E Step: Adaption of weight, M Step: To estimate bias field, By this we can segment and estimate the bias field simultaneously The EM works well if classes fallow a Gaussian distribution. It is computationally intensive. Requires good initial estimates of bias field Sensitive to noise

B. Fuzzy C-Means (FCM)

It clusters data by iteratively computing a fuzzy membership function and mean value of each class. Membership function reflects the degree of similarity between data value and centroid of the class

$$\boldsymbol{J_m}=\sum_{i=1}^{c}\sum_{j=1}^{n}\boldsymbol{u_{ij}^m d_{ij}^2}$$

$$=\sum_{i=1}^{c}\sum_{j=1}^{n}\boldsymbol{u_{ij}^m}\left\|\mathbf{x}_j-\mathbf{v}_i\right\|^2 \tag{4}$$

In the FCM algorithm the data items are assigned to more than one cluster with membership values between 0 and 1. The center is initialized and the count t, for the number of iterations is initialized to zero. Then the membership function is found using the equation “1”. Then the value of t is incremented by 1 and new centers are found using “(2)”. Till convergence the second and third steps are run.

The Main limitations of FCM are it is a point operation and high sensitive to noise.

C. Modified FCM

It gives equal importance to particular pixel and its neighboring pixels [5].

$$J_m=\sum_{i=1}^{c}\sum_{j=1}^{N}u_{ij}^p\left\|y_j-\beta_j-\mathbf{v}_i\right\|^2+\frac{\alpha}{N_R}\sum_{i=1}^{c}\sum_{j=1}^{N}u_{ij}^p\left(\sum_{y_r\in N_k}\left\|y_j-\beta_j-\mathbf{v}_i\right\|^2\right) \tag{5}$$

p is weighted exponent on each fuzzy membership

N_K is set of neighbors that exist in window around x and N_R (N_R is the cardinality of N_K)

The function J_m can be minimized by taking first derivative of it with respect to ,

D. Multiplicative intrinsic component optimization (MICO)

In this section, we present the foundation of multiplicative intrinsic component expansion for tissue segmentation and bias field [6, 18] estimation based on the decomposition of a magnetic resonance image into two multiplicative components. We propose energy minimization method to optimize these multiplicative components, which leads to an algorithm for both tissue segmentation and bias field estimation.

Consider the following model of magnetic resonance image formation with additive noise and multiplicative bias

$$I(x) = b(x)J(x) + n(x) \tag{6}$$

Where *I(x)* is the image intensity at voxel x, *J(x)* is true image need to be restored, *b(x)* is unknown bias field that accounts for intensity inhomogeneity, and *n(x)* is additive noise

The aim of bias correction is to predict the bias field *b(x)* from the measured image intensity *I(x)*. This is an underdetermined problem, as neither J(x) nor b(x) is known. To make the problem controllable, it is necessary to make a prediction on the unknown's *b(x)* and *J(x)*. The generally accepted assumption on the bias field is that it is slowly varying. Ideally, the intensity *J(x)* in each tissue should take a specific value c_i of the physical characteristic being measured. This property, in coincidence with the spatially consistent nature of each tissue's distribution [10], implies that the true image *J(x)* is approximately a piecewise constant map. In addition, the additive noise *n(x)* can be considered as zero-mean Gaussian noise.

$$b(x) = W^T G(x)$$

Where $G(x) = (g_1(x)........ g_M(x))^T$ is the basis function in terms of vector representation, $w = (w_1...... w_M)^T$ is the Colum vector coefficient .The energy Function interns of there variables is given by

$$F(u,c,w) = \int_{\Omega_i} \sum_{i=1}^{N} \left| I(x) - W^T G(x) C_i \right|^2 U_i(x) dx \tag{7}$$

This expression of the energy F used to derive the minimization scheme of effective energy. As a result, the energy minimization F(u, c, w), can be obtained the by optimum membership function [7, 14] $\hat{u} = (\hat{u}_1 ... \hat{u}_N)^T$ as a result of segmentation and the vector optimum $\hat{w}$ from where the bias field is estimated is given by $b(x) = \hat{w}^T G(x)$ ..

To implement Fuzzy segmentation, the energy function F can be modified by introducing fuzzifier [8, 9, 10] $q \geq 1$ and modified energy function is

$$F_q(u,c,w) = \int_{\Omega} \sum_{i=1}^{N} \left| I(x) - W^T G(x) C_i \right|^2 U_i^q(x) dx \tag{8}$$

The energy function $F_q(u,c,w)$ will have a unique minimum point in each of its variables

III. PROPOSED METHOD

A Magnetic Resonance Image model is best described by equation (6) where the basis function in terms of vector representation is $G(x) = (g_1(x)........ g_M(x))^T$ and the Colum vector coefficient is represented as $w = (w_1...... w_M)^T$

$$b(x) = W^T G(x)$$

Consider the image domain as Ω, the neighbor of every point $x \in \Omega$, defined by $\phi_x \triangleq \{y: |y - x| \leq \rho\}$, where the ρ is radius of neighborhood. By considering true signal with piecewise liner constant the intensities in each sub region is represented by

$$I(y) = w^T G(x) C_i + n(y) \text{ For } y \in \phi_x \cap \Omega_i \tag{9}$$

The minimization of energy is done through clustering criterion and the neighborhood [6] intensities ϕ_x. This is represented as

$$\xi_x^{Loc} = \int_{\phi_x} \sum_{i=1}^{N} u_i(y) |I(y) - m_i|^2 dy \tag{10}$$

Here u_i is the membership function whose value lies between0and 1. Where as m_i is cluster center with N clusters. The truncated modal of Gaussian kernel is added to above equation (10) for controlling the influence of local intensities on function of clustering criterion [11, 12, and 14], it is defined as

$$\xi_x^{Loc}(U,c,w) = \sum_{i=1}^{N} \int_{\phi_x} u_i(y) K(x-y) |I(y) - w^T G(x) c_i|^2 dy \tag{11}$$

In the above equation $K(x-y)$ is Gaussian Kernel weight [13] of intensity$I(y)$.

To perform bias correction, tissue segmentation and noise reduction an energy function defined in terns of nonconvex regularization. The membership regularization is done by varying membership function [15]. Then the clustering criterion function[16, 17] is defined as

$$E(U,c,w) = \int \sum_{i=1}^{N} \int k\,(x-y) |I(y) - w^T G(x) c_i|^2 u_i(y) dy dx + \lambda \sum_{i=1}^{N} \int_{\Omega} |\nabla u_i| dy \quad \text{i=1......N} \tag{12}$$

The first term in the above equation represents measurement of fidelity and the second term is smoothing term. The λ is greater then 0 for regularization of weightes. The energy minimization of $E(U,c,w)$ is done by keeping two variables constant at a time. The resultant energy is nonconvex with membership function U, thefore to solve this nonconvex problem we used the Chambolles fast dual projection algorithm [18].

However, the optimization of membership function U is difficult from equation (12) so a new auxiliary variable $V = (v_1 \dots \dots v_N)$ is introduced

$$E(U,c,w,V) = \int \sum_{i=1}^{N} d_i(I(y))u_i(y)dy + \lambda \sum_{i=1}^{N} \int_{\Omega} |\nabla u_i| dy$$

$$+ \frac{1}{2\theta} \sum_{i=1}^{N} \int_{\Omega} (v_i - u_i)^2 \qquad (13)$$

In the above equation $d_i(I(y)) \triangleq \int k(x-y)|I(y) - w^T G(x)c_i|^2 dx$ The θ value should be chosen such that V_i and u_i are almost same in tens of L^2 norm.

IV. RESULTS AND DISCUSSION

The proposed simulations are based on an anatomical Magnetic Resonance Image model of normal brain from BrainWeb[19] custom MRI simulations interface. It can serve as the ground truth for any analysis procedure. In this simulated brain database (SBD), the pre-computed parameter settings are fixed to 3 modalities (T1, T2, PD), 5 slice thicknesses, 3 levels of intensity non-uniformity, and 6 levels of noise. The voxel values in each image are magnitude values. This paper illustrates a framework whereby bias correction, tissue classification and noise reduction are integrated within the same modified energy model. The nonconvex problem is solved with Chambolle's fast dual projection methode which is varied by the spatial regularization term for noise reduction in the MR image. In this, we first show experimental results of our method for brain MR images, including some images with large intensity inhomogeneities. We also present the results of quantitative comparisons with the level set method in terms of time. The amount of similarity is measured with the help of

$$\text{Jaccard Similarity Index(JSI)} = J(S_1, S_2) = \frac{|S_1 \cap S_2|}{|S_1 \cup S_2|}$$

Where $|.|$ Represents area of a region, S_1 reference or Ground truth image and S_2 segmented image of proposed Algorithm. The JSI value is 1 if both images are same or more accurate segmentation, 0 if both image not similar. To illustrate advantage of our method we compared with the Multiplicative Intrinsic Component Optimization (MICO). The comparisons of segmentation results for synthetic images are shown in figure1; First image in the figure is input image, second is bias estimated image, third is bias corrected image and fourth is segmented image

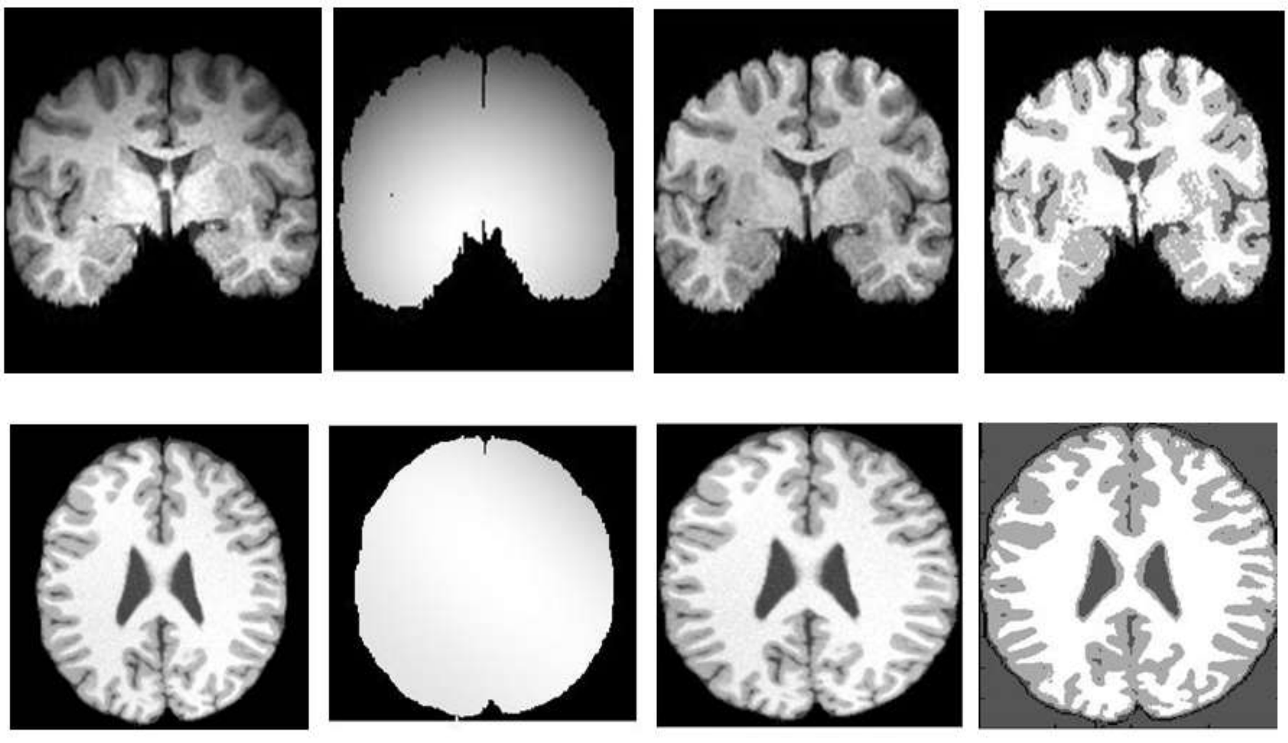

Fig. 1. a) Original Image b) Bias Field c) Bias corrected image d) Segmented image

TABLE I. OMPARISON OF TIME RESPONSE

Method	Time Response(In seconds)	
	Brain Image1	Brain Image2
MICO	59.29	130.2
Proposed Method	20.23	16.64
Image dimension 512x512		

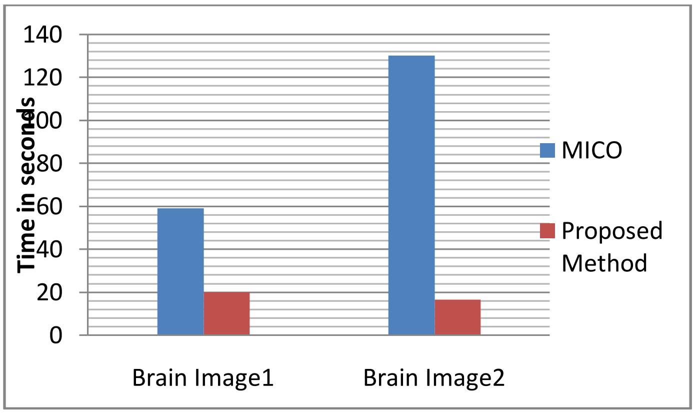

Fig. 1. Comparison of MICO and Proposed Method inters of Timing analysis

TABLE II. COMPARISON OF JCCARD SIMILARITY INDEX

Method	Jaccard Similarity Index	
	Brain Image1	Brain Image2
MICO	0.9625	0.9692
Proposed Method	0.9825	0.9884
Image dimension 512x512		

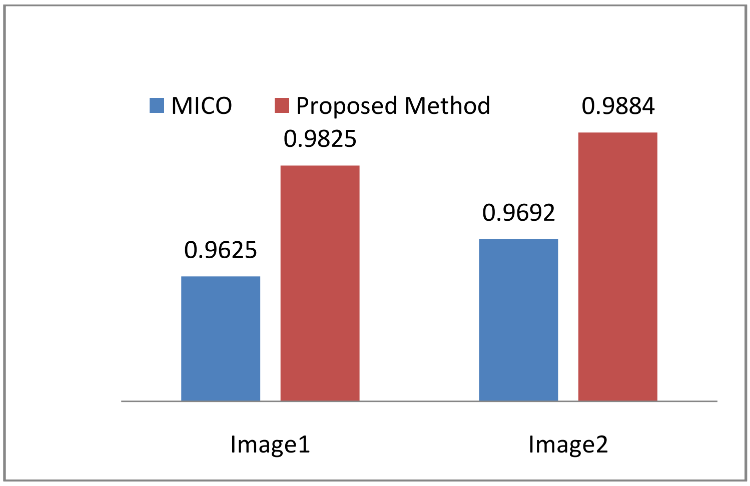

Fig. 2. Comparison of MICO and Proposed Method inters of Jccard Similarity Index

The proposed coherent local intensity clustering phenomena algorithm shows better performance over multiplicative intrinsic component optimization (MICO) [18]. A Novel Bias Field Estimation Analysis and Classification of MR Images is developed using MATLAB 2014a software.

V. Conclusion

In this paper, we have proposed a method, called A Novel Bias Field Estimation Analysis and Classification of MR Images, for segmentation and bias field estimation of MR images by a new coherent local intensity clustering phenomena. The method has been applied successfully to 1.5 T and 3 T MR Images. The shown Experimental results have well in terms of time response in comparison with FCM, MFCM and MICO Methods, We conclude that the use of our modified energy functional model can achieve a pretty good performance on either tissue classification or bias correction, the coherent local intensity clustering phenomena can be extended to 3D segmentation.

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