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Bias Field Correction and Image Segmentation in MRI

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Abstract. Segmentation of brain MR images into types of tissues is an important job for automatic image analysis technique**.** In medical images the Bias field estimation and classification is an important task for image processing and analysis. In this paper a new incorporated classification and bias field analysis of Magnetic Resonance Image (MRI) of brain is present, which simultaneously segments and estimates the bias field and removes the noise in MRI with the same Energy model. The Rough Set Theory defines total coherent local intensity clustering phenomena function for solving the problem with membership function. The proposed method defines with 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 in terms of Jccard Similarity Index (JSI) and Timing taken analysis. The proposed method shows better time taken compare with existing algorithms**.**

Keywords: Segmentation, MRI, bias field, rough set theory and applications, expectation-maximization

I. Introduction

SEGMENTATION is an important preprocessing step for the analysis of medical images. It is particularly useful for medical diagnostic and clinical analysis of brain images. The main success of an image analysis system depends on the quality of image segmentation. MRI is an important diagnostic imaging technique for the early detection of abnormal changes in tissues and organs, also majority of research in medical imaging concerns on MR images. One of the important advantages of using MRI for brain diagnosis is that the brain MR images are piecewise stable with small number of tissue classes, which makes the automated segmentation procedure much easier and reliable than other medical imaging modalities. However, this does not occur in real time due to the presence of some degrading artifacts in MR images. This artifact is commonly known as intensity inhomogeneity or bias field and creates a shading effect in MR images, which results in reduction of mean increase in overall variation of each tissue class. Some of the properties of MRI method such as static field inhomogeneity, bandwidth filtering of the data. Transmission and reception inhomogeneity shading effect [4]. However, bias field can arise from shape, position, and orientation of imaged object. Although this inhomogeneity artifact is hardly visible by human eyes, it is enough to degrade the performance of any image segmentation technique. Several inhomogeneity correction methods exist, which are capable of removing both MR scanner and patient induced inhomogeneity. The polynomial or spline [5], template [7], and histogram [5]–[6] based methods are among them. While some histogram based methods such as N3 [4] estimate the bias field by maximizing high frequency information of the tissue intensity distribution, others try to estimate it by minimizing image entropy [6]. There also exist some simplest and computationally economical methods, which estimate bias field by low-pass filtering the image. In general, bias field correction is often required as a necessary preprocessing step, which enables MR image segmentation, whereas accurate segmentation makes bias field correction rather than minor. So, bias field correction and segmentation can be viewed upon as two together procedures. In segmentation based bias field correction methods, these two procedures are merged so that they benefit from each other, simultaneously yielding better segmentation and inhomogeneity correction. Also, one of the main problems in brain MR image segmentation is uncertainty and vagueness. Some of the sources of this uncertainty include imprecision in computations and vagueness in class definitions. The possibility concept introduced by the theory of probability, fuzzy set, and rough set theory has gained popularity in modeling and propagate uncertainty. They provide mathematical frameworks to detain uncertainties and vagueness associated with human cognition process.

Ahmed et al. [7] proposed adaptive fuzzy *c*-means approach for simultaneous segmentation and bias field correction. Additional spatial constraints on fuzzy c-means are provided in [7]–[8] for robust brain MR image segmentation. The theory of rough set theory has been successfully used for bias field estimation [11] and MR image segmentation [11]–[5]. However, the most popular structure to model brain tissue classes for segmentation is probabilistic model. Ashburner and Friston [6] used a probabilistic framework to enable image registration, tissue classification, and bias correction to be combined within the same generative model. The expectation-maximization (EM) algorithm is used for simultaneous segmentation and bias field correction. A new algorithm is proposed for simultaneous segmentation and bias field correction in brain MR images, integrating the concepts of probability distribution, Rough sets, and hidden Markov random field model. The proposed method assumes that each tissue class consists of two regions, namely, lower approximation, upper 2approximation and a probabilistic boundary region. The lower approximation influences the overlapping characteristics of the final tissue class. Integration with rough sets and probability distribution deals with uncertainty, vagueness, and incompleteness in tissue class.

II. RELATED WORK

In this related work Wells et al [19] 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 used 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)

$$\partial = argmax\, p\left(\frac{\partial}{y}\right) \qquad (1)$$

Assuming statistical independence of each pixel intensity. To estimate bias field, in 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 calculating a fuzzy membership value and mean value of each and every class. Membership function value reflects the amount of similarity among data value and centroid of a class. 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 value of t is incremented by 1. 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. *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.

$$I(x) = a(x)j(x) + m(x) \qquad (2)$$

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

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), u it can be obtained the by optimum membership function. W as a result of segmentation and the vector optimum from where the bias field is estimated is given w.

III. PROPOSED METHOD

A.DEFINATIONS AND CONCEPTS

The Rough Set Theory (RST) was anticipated by Z. Pawlak in 1982 for alternative to Fuzzy set theory [1]. Amit Satish Unde proposed Active contour based variational energy minimization frame work for edge detection and tumor segmentation[2], James F. Peters, RST induces notion of approximation space [3], RST has access to look at subset of object as one unit instead of dealing with individuals.

Rough Sets provide a unique approach for approximation of sets using granular information. It provides distinction between overlapping boundary, in a given domain data. Rough set methods have been applied as a component of hybrid solutions in machine learning and data mining and also artificial neural network [9]. The rough sets have been found to be particularly useful for rule induction and feature selection. Rough sets concept can be distinct quite generally by means of topological operations, interior and closure, called approximations [10].

Given a set of objects $\underline{U}$ called the universe and an indispensability relation $R \subseteq U \times U$ representing our require knowledge about elements of U. the basic concepts of rough set theory given below.

- The lower approximation of a set X with respect to R is the set of all objects, which can be for certain classified as X with respect to R (are certainly X with respect to R).
- The upper approximation of a set X with respect to R is the set of all objects which can be possibly classified as X with respect to R (are possibly X in view of R).
- The boundary region of a set X with respect to R is the set of all objects, which can be classified neither as X nor as $not - X$ with respect to$R$.

Candiditions:

- Set X is crisp (exact with respect to R), if the boundary region of X is empty.
- Set X is rough (inexact with respect to$R$), if the boundary region of X is nonempty.

Formal definitions of approximations and the boundary region are as follows:

I. Lower approximation of X

$$\underline{R}(x) = \bigcup_{x\in U} r(x) : r(x) \subseteq X \qquad (3)$$

II.Upper approximation of X

$$\bar{R}(x) = \cup_{x\in S} r(x) \cap X \neq \emptyset \qquad (4)$$

Image granules with upper and lower approximation of an object as conceptualized in Rough Set Theory

- boundary region of X

$$Br(X) = \underline{R}(x) - \overline{R}(x) \qquad (5)$$

1.Indiscernibility relation

In the RST data are stored in a tabular format, being a pair $S = (U, A)$called information system, where U is non empty set of Universe and A is finite set of conditional attributes.

Given an system $S = (U, A)$ it is possible to define an equivalence relation $IND_A(B)$ for any sub set of attributes as follows

$$IND_A(B) = \{(x, x' \in U) \forall a \in B, a(x) \neq a(x')\} \qquad (7)$$

The equivalence relation is called B-indiscernibility relation.

2. Reducts

In RST, the size of the dataset can be reduced either by representing a whole class given by an indiscernibility relation or by eliminatingsuperfluous attributes that do not contribute to the classification.

The RST based approach, with the help of granules, provides partitions in the image to create lower and upper approximations of the objects. Note that, lower approximation set will be contained completely in upper approximation set. The difference of both approximations provides a possible edge region for a particular object or class present in the image. Here, in this work, we considered four major class/objects namely, CSF, White matter, Gray matter and Background in the brain MR images.

B. ROUGH SETS FOR BIAS FIELD CORRECTION

The bias field is a shading effect that reduces the intensity values of the pixels. According to the multiplicative model of the HUM, the bias field is a component that is multiplied with the intensity value of a specific pixel and reduces its intensity value. In general, it is assumed that the bias field component of the pixel . If a fixed amount of bias field is applied to two different pixels, then the pixel with higher intensity value will suffer the effect of bias field much more than the pixel with lower intensity value. Hence, the pixel with higher intensity value should be given more priority than the pixel with lower intensity value while estimating the bias field.

Incorporating both the concept of the CHM, and lower and upper approximations of rough sets into the HUM algorithm, next a new bias field correction method is described. CHM enables efficient computation of bias field of RST. with uncertainty, vagueness, and incompleteness in filter structure definition. The proposed approach provides better restoration as it is free from the effect of outliers, which is an obvious problem in any moment measure based method. In general, all pixels within the filtered area do not contribute equally in estimating the bias field component of the center pixel. The pixels with higher intensity value carry higher weight than the pixels with lower intensity value. Also, the pixels with similar intensity value with respect to the center pixel are expected to contribute more in estimating the bias field as they lie in same or similar cluster. Hence, all pixels in the filtered area should not be given equal priority in estimating the bias field component of the center pixel.

IV. RESULTS AND DISCUSSION

The proposed simulation are based on an anatomical Magnetic Resonance Image model of normal brain from BrainWeb[18] custom MRI simulations interface. It can help 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, and PD), 5 slice thicknesses, 3 levels of intensity non-uniformity, and 6 levels of noise. The voxel values in each image are magnitude values.

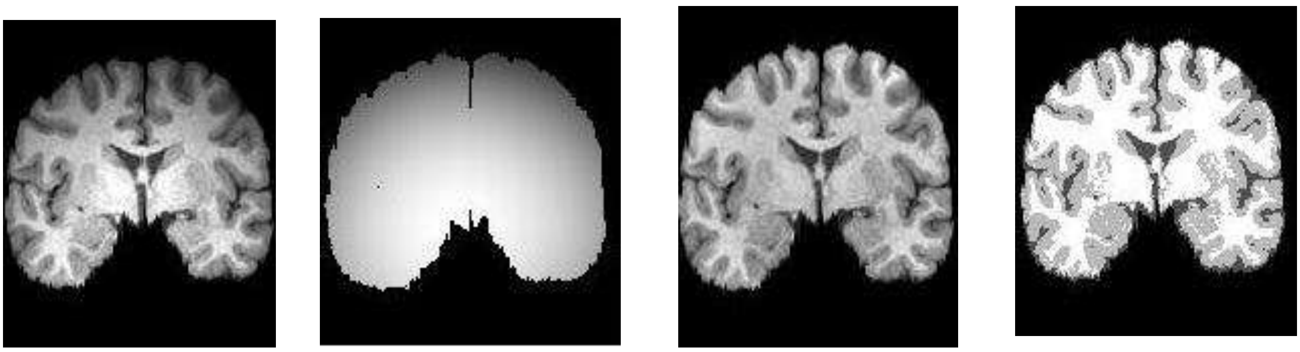
This research work describes a framework whereby bias correction, brain tissue classification and noise reduction are done within the same modified energy model. The non convex problem is solved with Chambolle's fast dual projection method which is varied by the spatial regularization term for noise reduction in the MR image. In the result, we first illustrated experimental results of A Novel Bias Field Analysis and Classification of MR Images using RST method, with some images with large intensity in homogeneities. We also represented the results with quantitative comparisons with the jaccard similarity index and in terms of time.

The amount of similarity is measured with the help of

$$\textit{Jaccard Similarity Index (JSI)} = \frac{|A \cap B|}{|A \cup B|} \qquad (6)$$

where A and B are two segments generated by proposed method and ground truth images. It measures the overlap between the segmented image and ground image .If JSI=0 ,it implies no overlap with ground image and the value of JSI=1,implies that perfect segmentation. 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.

Figure 1:



A.original image B.Bias Field C.Bias Field corrected D.Segmented Image

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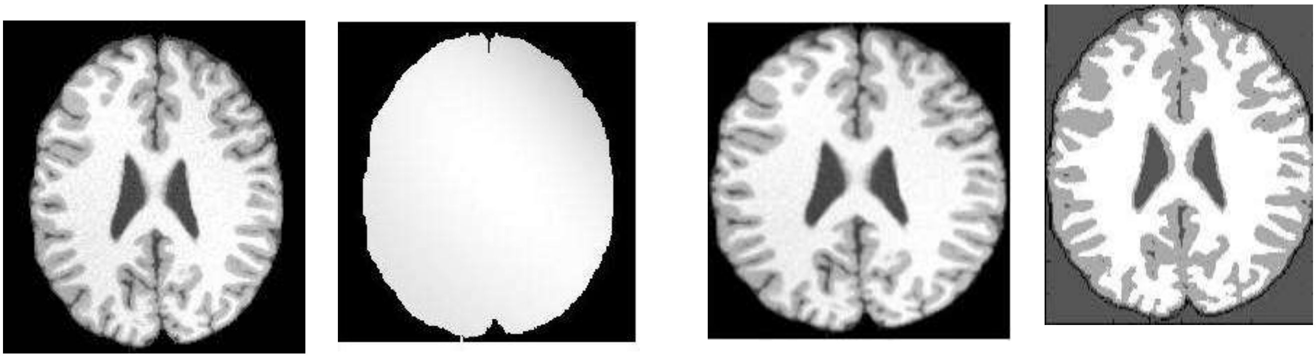
Figure 2:



A.original image B.Bias Field C.Bias Field corrected D.Segmented Image

TABLE.1. COMPARISON OF TIME TAKEN

methods	Time taken(in seconds)	
	Image 1	Image 2
MICO	59.29	130.2
Existing	20.23	16.89
Proposed	16.98	12.56
Image dimensions(512×512)		

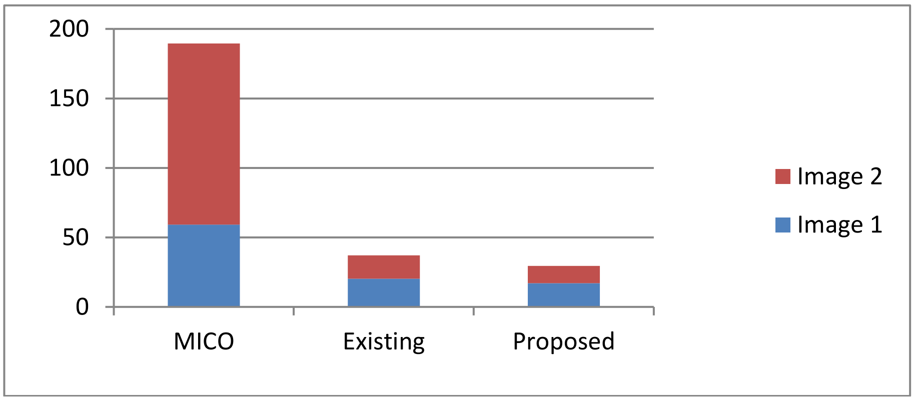


Figure 3.Comparison of MICO, Existing and Proposed Method inters of JSI

TABLE.2. COMPARISON OF JCCARD SIMILARITY INDEX

Method	JCCARD SIMILARITY INDEX	
	Image 1	Image 2
MICO	0.962	0.969

Existing method	0.982	0.988
Proposed	0.992	0.995
Image dimensions 512×512		

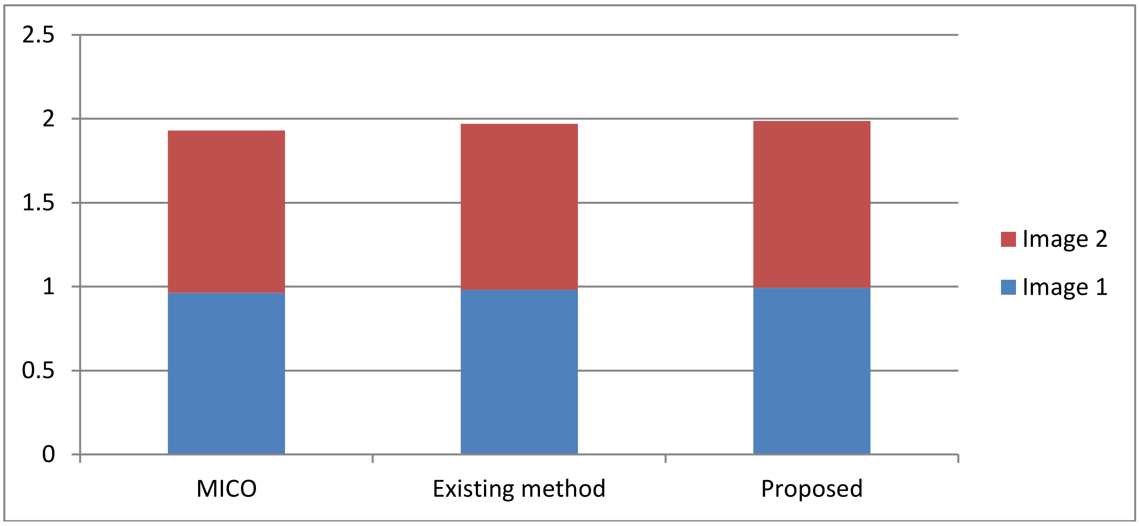


Figure 4.Comparison of MICO, Existing and Proposed Method inters of JSI

The proposed coherent local intensity clustering (RST) 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, A Novel Bias Field Estimation Analysis and Classification of MR Images is defined, for segmentation and bias field estimation of MR images by a new local intensity clustering method. 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, Existing and MICO Methods. We conclude that the use of our modified energy functional model can achieve a 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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