Precise Foreground Extraction, Bias Correction and Segmentation of Intensity Non Uniformed Brain MR Images

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Abstract - *Medical images are frequently ruined by intensity non uniformity which degrade the nature of the images and provide incorrect outcomes during the image processing approaches. This paper proposes a novel algorithm which perfectly cut out the present bias and accurately segments the image components. The bench mark dataset are imported from Brain Web repository. The performance metrics are used in proving the statement. The proposed algorithm is compared with the state of art Bias Corrected Fuzzy C Means (BCFCM) and Multiplicative Intrinsic Component Optimization (MICO).*

Key Words: Bias Field, Brain MR Images, MICO and BCFCM.

1.INTRODUCTION

Medical image acquisition devices, processing techniques have been developed throughout the years. Magnetic Resonance Imaging is widely used imaging modality to investigate the brain organs because of its non intrusive nature and excellent portrait for soft tissues. The medical images are corrupted by artefacts, noise, contrast sensitivity etc. Bias filed is a shading effect developed in the medical images. The causes are old MRI machines and anatomy related shortcomings [1-6]. The bias removal strategies are categorized into following types, prospective and retrospective. A prospective technique depends upon machine related correction strategies and retrospective techniques process bias removal in developed medical images. The prospective techniques uses phantom based calibration and multicoil imaging to correct the bias. The retrospective techniques used filtering based correction such as homomorphic filtering, homomorphic unsharp masking, surface fitting based methods, intensity based, gradient based, segmentation based, fuzzy c means based, histogram based, intensity distribution based bias correction techniques [7]. This phenomenon also termed as Intensity Non Uniformity, Intensity in Homogeneity and shading. Intensity Non Uniformity can affect any type of image capturing techniques such as Computed Tomography, Ultrasound etc. Bias hardly perceives but still causes fallacious outcomes in medical image processing techniques. Bias correction is important step need to perform before proceeding with successive operations. Image segmentation is the procedure of isolating image components; it may be automatic, manual or semi automatic and it may be of any type model based, atlas based, edge based, region based and level set based segmentation algorithms. There are several IIH correction strategies and simultaneous segmentation algorithms are also proposed.

Intensity in homogeneity correction is performed in SD - OCT data, which uses macular flat space to convert the image property then applied N3 algorithm for bias rectification [8] Combination of threshold, morphology technique is implemented for MRI image Intensity Non Uniformity correction and reclaiming the partial volume. Fuzzy C Means algorithm is enforced for segmenting the image components [9]. Gaussian based sliding window protocol with maximum likelihood algorithm is recommended to remove the bias [10]. Bias correction embedded fuzzy c means algorithm is proposed to remove the bias, but this algorithm needs prior information regarding the number of classes [11]. Non parametric Non uniform intensity Normalization [12] is recommended to eliminate bias in brain MR Images. And N4 [13] is the up gradation of N3 algorithm which makes use of B Spline strategy in bias correction. N4 algorithm efficiency is higher when bias and noise level is high. A variation of level set method is proposed for bias correction and segmentation but its efficiency is limited because of inaccurate foreground extraction [14]. Bias correction strategy is implemented using modified possiblistic fuzzy c means algorithm which uses local and global intensity information, but it inappropriately removes the lesser intensity information in the natural image [15]. Modified intensity clustering is prescribed for IIH correction, proficiency of this technique is relies upon the initialization of the cluster center [16]. In paper [17] the author has recommended INU correction technique constructed over the level set method. This methods outcome becomes erroneous when image foreground and background share the same image intensity. This paper is an expansion of author's preceding work, in which existing bias correction algorithms are scrutinized to find out the efficient bias correction algorithm [18], then shortcomings present in that efficient algorithm is neglected by proposing new algorithm [19], To annex a segmentation algorithm, bias correction based segmentation algorithms are compared [20]. Presently this paper proposing a complete bias correction based segmentation technique which uses preceding bias correction algorithm to discards an INU at initial stage and Distance Regularized Level Set Technique (DRLSE) [21] is applied to segment the image components accurately. The recommended algorithm is scrutinized with MICO [22] and BCFCM [23]. The remaining paper is formulated as, section 2 handle the technical background of intensity non uniformity, section 3 consists the detailed description about the proposed algorithm, section 4 enclose the result & discussion and section 5 summarizes the outcome.

2. BIAS FIELD MODEL

The basic logic behind bias correction is restoring the image intensities accurately. The bias can be addressed as a lower frequent, smoothly oscillating multiplicative or additive field. The intensity non uniformity in image signals can be represented as,

$$Z(x,y) = I(x,y)\,B(x,y) + N(x.y) \qquad (1)$$

Z(x,y) is bias corruped image, I(x,y) is a original image, B(x,y) is a an added bias, it is smoothly differentiating multiplicative field. N(x,y) is noise variable which is zero mean additive or Gaussian noise. The noise term is mostly neglected in bias correction techniques. If bias field is known then the initial image signals can be effortlessly retrieved.

$$I(x,y) = Z(x,y) \,/\, B(x,y) \qquad (2)$$

3. METHODOLOGY

3.1 Proposed Method

The bias correction algorithm integrates the following operations. Foreground of brain MR Images need to be extracted, this must be erroneous due to intensity non uniformity. Mask need to be constructed by filling the holes and removing the artefacts present near extracted foreground. Simultaneously directional modulations of intensities are evaluated using the gradient operation. Once bias is estimated, elimination of intensity non uniformity is performed by augmenting the bias removed image with the constructed kernel. The important procedure need to be performed after evaluation is segmentation. The Distance Regularized Level Set Evaluation is needed to be performed to accurately segment the images. This is an advancement of classical level set algorithm. Entropy or Energy, potential term, Regularization field is adopted to build the algorithm. Curve starts at the zero level and evolved passing through the desired location. The energy or entropy term helps in this process. Let φ be the level set function and Ω be the domain. Then energy $E(\phi)$ is defined by,

$$E(\phi) = \mu R_P(\varphi) + E_{ext}(\varphi)$$

Where P is the potential function, μ is a constant, $R_P(\phi)$ is the distance regularization term and $E_{ext}(\varphi)$ is the external energy over the curve.

3.2 Bias Corrected Fuzzy C Means (BCFCM):

A classical fuzzy C Means clustering technique is updated by adding homogeneous labelling property, convergence matrix and class models are utilized to deal with the INU present in the medical images. Bias field is approximated by the following expression.

$$\beta_k^* = y_k - \frac{\sum_{i=1}^{c} u_{ik}^{p} v_i}{\sum_{i=1}^{c} u_{ik}^{p}}$$

β* is bias term, yk is an kth pixel, in a perceived image y. vi is the cluster prototype, c is the cluster number, p is any real number. Iteration will get terminated once convergence criterion met.

3.3 Multiplicative Intrinsic Component Optimization (MICO):

An energy reduction method is recommended to remove the intensity non uniformity. The image is split up into two components true image intensity and bias field. A piecewise approximate technique is used here. The energy function is derived by the succeeding equation,

$$F(b,J) = F(u,c,w) = \int_{\Omega} \left| I(x) - w^T G(x) \sum_{i=1}^{N} c_i u_i(x) \right|^2 dx$$

I(x) is an percieved image. w, G(x) is optimal coefficient and bias function. (.)T is the transpose operator. ci, ui is ith pixel constant and membership function. N is number of pixel types accessible in the picture space Ω. In every emphasis the range of u, c, and b will be optimized to meet the convergence criterion.

4. RESULT AND DISCUSSION

The investigation method extended over the wide measure of benchmark dataset imported from brain web [24] data base repository. It is a combination of T1 & T2 weighted MRI of brain organ. Each classification comprises of one hundred and eighty one images. The properties are one mille meter thickness, 20% and 40% comprised bias and one hundred percent noise free images. The performance assessment is carried over using the metrics Accuracy, Sensitivity or Recall, Specificity, Precision, False Positive Rate , F Score, Border Error and Jaccard Distance.

$$Accuracy = \frac{\#(TP) + \#(TN)}{\#(TP) + \#(TN) + \#(FP) + \#(FN)}$$

$$Specificity = \frac{\#(TN)}{\#(TN) + \#(FP)}$$

$$Sensitivity = \frac{\#(TP)}{\#(TP) + \#(FN)}$$

$$Precision = \frac{\#(TP)}{\#(TP) + \#(FP)}$$

$$False\ Positive\ Rate = \frac{\#(FP)}{\#(FP) + \#(TN)}$$

$$F\ Score = 2 * \frac{\#(Recall * Precision)}{\#(Recall + Precision)}$$

$$Border\ Error = \frac{\#(FP) + \#(FN)}{\#(TP) + \#(FN)}$$

$$Jaccard\ Distance\ JD(S1, S2) = 1 - \frac{S1 \cap S2}{S1 \cup S2}$$

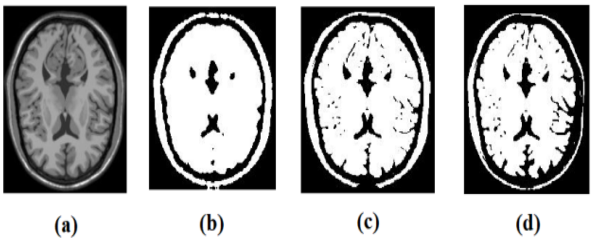

Fig.1: (a) T1 Weighted with 20% Intensity In Homogeneity, (b)Input Image corrected with BCFCM Bias Correction Algorithm, (c) Input Image corrected with MICO Bias Correction Algorithm, (d) Input Image corrected with Proposed Bias Correction Algorithm.

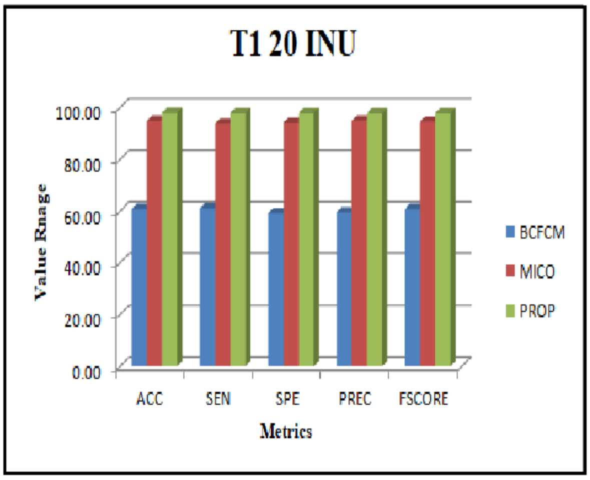

Fig.2 Accuracy, Sensitivity, Specificity, precision and F Score performance of three segmentation algorithm on T1 weighted images with 20% INU

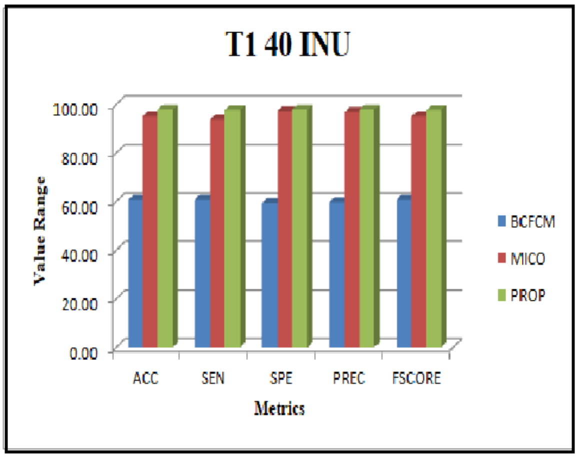

Fig.3 Accuracy, Sensitivity, Specificity, precision and F Score performance of three segmentation algorithm on T1 weighted images with 40% INU

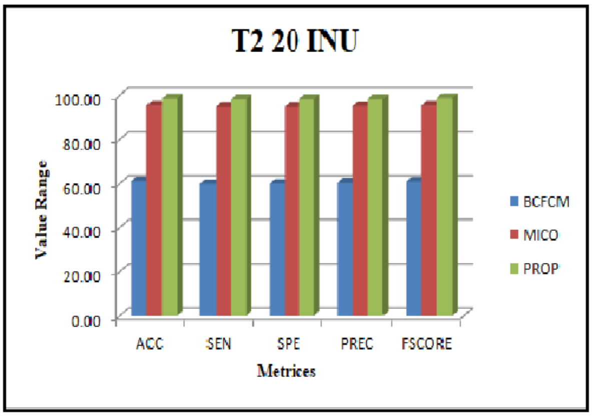

Fig.4 Accuracy, Sensitivity, Specificity, precision and F Score performance of three segmentation algorithm on T2 weighted images with 20% INU

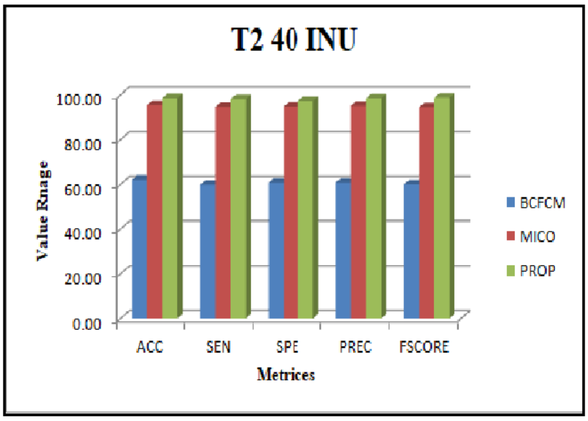

Fig.5 Accuracy, Sensitivity, Specificity, Precision and F Score performance of three segmentation algorithm on T2 weighted images with 40% INU

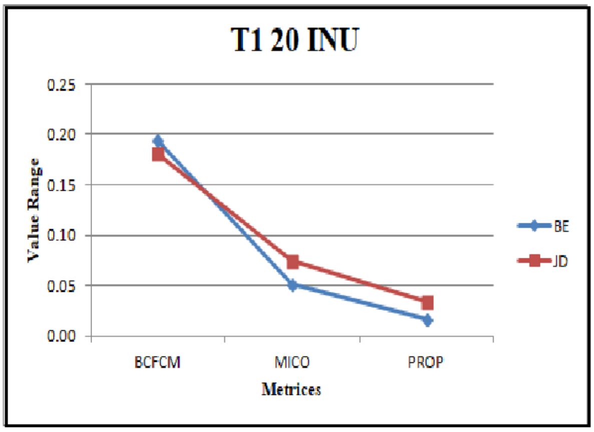

Fig.6 Border Error and Jaccard Distance performance of three segmentation algorithm on T1 weighted images with 20% INU

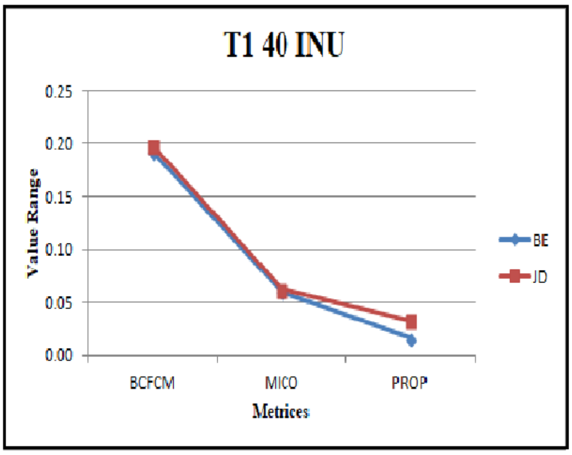

Fig.7 Border Error and Jaccard Distance performance of three segmentation algorithm on T1 weighted images with 40% INU

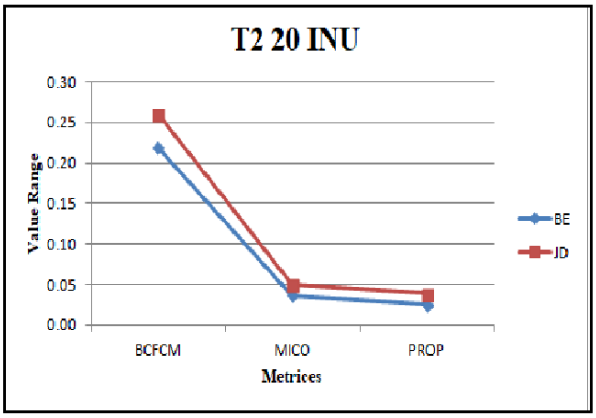

Fig.8 Border Error and Jaccard Distance performance of three segmentation algorithm on T2 weighted images with 20% INU

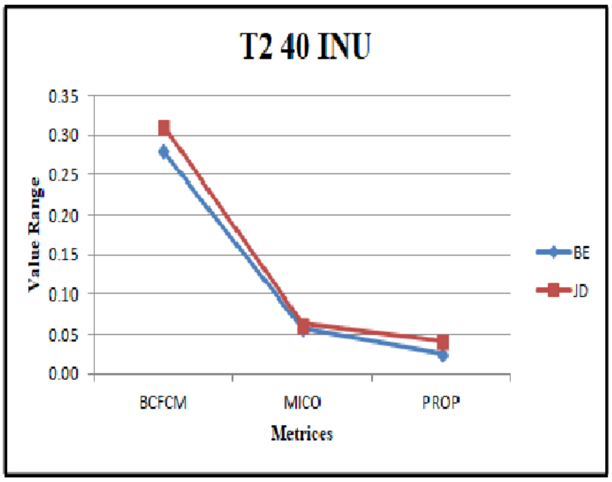

Fig.9 Border Error and Jaccard Distance performance of three segmentation algorithm on T2 weighted images with 40% INU

To stipulate the better performance the performance metrics accuracy, sensitivity, specificity, precision and F Score range should hold the higher value and the border error and jaccard distance should hold the merest value. Figure 2, 3, 4 and 5 indicates the performance assessment of the BCFCM, MICO and proposed bias correction algorithm over the metrics accuracy, sensitivity, specificity, precision and Fscore on T1 and T2 Weighted images with 20 and 40 percentage influenced bias brain MR Images. Accuracy and FScore given preference over the other images based on that the results were analyzed. From the figures we can conclude that the proposed algorithm shows the higher performance because its performance metrics value is higher than the other algorithms. Figure 6, 7, 8 and 9 indicates the performance assessment of the BCFCM, MICO and proposed bias correction algorithm over the

Table -1: Comprehensive performance of all algorithms

	ACC	SEN	SPE	PREC	FS	BE	JD
BCFCM	61.10	60.39	59.84	60.10	60.61	0.22	0.23
MICO	95.20	94.23	95.21	95.47	94.84	0.05	0.06
PROP	**98.23**	**97.97**	**97.78**	**98.09**	**98.26**	**0.02**	**0.03**

metrics border error and jaccard distance on T1 and T2 Weighted images with 20 and 40 percentage influenced bias brain MR Images. From the figures we can state that the recommended algorithm shows the higher performance because its performance metrics value is lower than the other algorithms. Table 1 lists the comprehensive performance of three algorithms over all input images. The output clearly states that the proposed algorithm efficiently removes the bias and segments the images in a precise manner.

5. Conclusion:

This paper recommends an algorithm to exterminate the bias and segment the brain MR Images. Bias eradication involves the following phases, foreground extraction, mask construction, bias estimation and bias correction. The DRLSE algorithm is utilized to segment the images. The proposed algorithm is compared with the state of the art BCFCM and MICO. The performance metrics are used in determining the result. The metrics states that the proposed algorithm efficiently eliminate the bias present in the brain MR Images and segment the images accurately, because its accuracy, sensitivity, specificity, precision, recall, Fscore is high and border error and jaccard distance is low than the other algorithm.

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