ISSN: 0976-9102 (ONLINE)
DOI: 10.21917/ijivp.2021.0347

EXTENDING BENEFIT BASED SEGMENTATION TECHNIQUES PERFORMANCE ANALYSIS OVER INTENSITY NON UNIFORMED BRAIN MR IMAGES

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Abstract

The bias field is an undesirable image foible that formulate during the process of image procurement. Segmentation is the procedure of segregating a digital image into constituent component or substantial segments which help in extracting quality amount of information from the region of interest. There is several bias correction strategies have been recommended till date, all these algorithms helps in reducing bias but none of them perfectly removes bias. When incorporating computer aided diagnosing in treatment planning, the leftover bias cause to inaccurate segmentation which leads to faulty diagnosis of the diseases. This paper scrutinizes the segmentation algorithms over bias corrupted brain MR Images and analyzes which segmentation algorithm efficiently segments the image components even though it is corrupted by bias field. The bench mark brain MR Images with different bias spectrum is employed for the research. Quantitative metrics are adopted to conclude the result. The outcome of this paper tends to provide accuracy in computer aided diagnosing and to elect appropriate segmentation technique while developing bias correction based segmentation algorithm.

Keywords:

Bias Field, Chan Vese, Expectation Maximization, Fuzzy Level Set, Distance Regularized Level Set Evaluation

1. INTRODUCTION

Image processing is defined by the functions that carried over a digital image. These functional activities incorporates refinement, filtration, restoration, compression, segmentation, object detection, recognition etc. Image components comprises substantial amount of information. Segmentation plays an essential role in extracting this quality amount of cognitive data in the interested region. The endeavor of segmentation is to segregate the strongly correlated pixels of an object in an image. There are several approaches of segmentation techniques exist, that are model based, atlas based, layer based and block based segmentations [1] [2]. Based upon the requirements various segmentation techniques have been recommended till date, such as threshold based segmentation, region growing, region split and merge, fuzzy logic, normalized cuts, genetic algorithm and neural network based segmentation techniques, etc. Segmentation plays a vital role in analyzing the medical images, which helps physician’s to procure insight about the human anatomy, devastating diseases and assist doctors in treatment planning.

Bias is an image glitch that constructs a smog effect over the images. Bias less than 40% in the medical images are unable to witness by the beholder. Bias field can also be termed by the phrases Intensity in Homogeneity (IIH), Intensity Non Uniformity (INU) and shading. The sources of bias are imperfection in the scanner device, patient position and transition during the scanning procedure [3]-[8]. The correction strategies are branched under two categories prospective and retrospective. Prospective techniques used to fix scanner associated shortcomings and retrospective techniques used to fix anatomy or patient associated defects. Bias constructed by scanner can be corrected using the following techniques, phantom based calibration, shimming techniques and arrangement of Radio Frequency coils by building new numerical model [9]-[12]. Filtering, histogram, segmentation, surface based methodologies are utilized to correct bias constructed by patients [13] [14]. There are several bias correction and bias correction based segmentation algorithm have been proposed present day. Nonparametric Non uniform intensity Normalization (N3) [15] and N4ITK [16] is proposed for bias correction. N3 make use of B spline strategy whereas N4ITK replaces the B spline strategy by applying modified iterative hierarchical optimization scheme to eradicate bias presents in lung and hippocampus brain image data. N4ITK provides enhanced performance in the escalation of noise and mesh level. A Non Iterative Multi-Scale (NIMS) approach is recommended for Intensity. In Homogeneity correction using Log Gabor and S-Golay filter [17]. A novel surface fitting method incorporating Non Local Means (NLM) and pattern matching is proposed, to correct bias present in brain images [18]. Local entropy minimization with bi cubic spline model is proposed to correct Intensity. In Homogeneity in atherosclerosis images, in which bicubic spline model is used for entropy optimization [19]. All these techniques are proposed for fixing image intensities only by eradicating bias, doesn’t concentrate over segmentation. The essential post processing technique need to be performed after bias removal is segmentation.

There is several simultaneous segmentation and bias correction techniques are also proposed. Each technique builds unique strategy in eradicating bias and uses different segmentation algorithm to segment the images. Three steps iterative expectation maximization functions is used in IIH correction and segmentation of MR Images [20].

A novel region based level set method [21] and Correntropy based level set method [22] is proposed to correct bias and segment the image using local intensity clustering and local fitted image model. Gradient based algorithm is recommended to correct bias, in which image components extracted using region growing algorithm and polynomial surface fitting is used to fit the bias in extracted image regions [23]. Fuzzy C Means algorithm is customized to perform simultaneous segmentation and bias correction. Fuzzy membership mask and Fuzzy C Means algorithm fused to correct IIH and segment the liver MR Images using local, global, and spatial intensities [24]. A novel Chan-Vese model is built for concurrent IIH correction and segmentation, but efficiency of this algorithm is high only for bi model images [25]. An adaptive fuzzy level set method is proposed for simultaneous segmentation and bias correction by introducing weighting scheme using spatial intensities and third order polynomial function [26].

None of these proposed bias correction and bias correction based segmentation algorithms completely eradicates the bias. After applying the bias correction strategy also, there is some amount of bias still present in the image. The leftover bias which is hardly visible, but can affect the segmentation quality which leads to faulty results in computer aided investigation of medical images. This paper scrutinizes the state of art algorithm, Expectation Maximization (EM) [28], Chan Vese (CV) [29], Distance Regularized Level Set Evaluation (DRLSE) [30] and Fuzzy Level Set (FLS) segmentation algorithms to check which efficiently segments the image when it is affected by Intensity. In Homogeneity. Performance Metrics are adopted to measure the efficiency of the algorithm. The outcome of this paper tends to provide an unflawed result in computer assistance diagnosing, and to elect the efficient segmentation technique while constructing simultaneous bias correction based segmentation algorithms.

2. METHODOLOGY

2.1 EXPECTATION MAXIMIZATION

It is dyadic iterative and an unsupervised segmentation algorithm. It is a consolidation of expectation and maximization step. It employs the cluster technique in segmenting the image pixels. In expectation procedure each pixel x in image I are appointed to distinct clusters with certain probability (P), mean (μ) and variance (σ) rather than considering it as a whole. The Gaussian probability function (P) for each pixel x is computed as follows,

$$P(x)=\frac{1}{\sqrt{2\pi\sigma^2}}e^{-\frac{(x-\mu)^2}{2\sigma^2}} \tag{1}$$

After initial assignment the mean, variance, and probability distribution is re-determined in maximization procedure. The outcome nominates the cluster where the pixel may belong ($x\in C_k$, where k is a number of clusters). The procedure will continue until the criterion condition fulfilled and each image pixel is appointed to the clusters with maximum probability.

2.2 CHAN VESE SEGMENTATION

It is an unsupervised energy minimization based image segmentation algorithm. It is built over the concept of Mumford Shah model. It adopts active contour in the process of detecting object boundaries. Along with this, the contour property length and area are used as a regularization term. Then the energy minimization function is defined by,

$$\begin{aligned} F(c_1,c_2,C) &= \mu\cdot Length(c)+v\cdot Area(inside(C)) \\ &+\lambda_1\int_{inside(c)}\left|\mu_0(x,y)-c_1\right|^2 dxdy \\ &+\lambda_2\int_{outside(c)}\left|\mu_0(x,y)-c_2\right|^2 dxdy \end{aligned} \tag{2}$$

where, C is a curve or contour. Average pixel intensities inside the contour C is represented by c_1 and average pixel intensities outside the contour C is represented by c_2. $\mu\geq 0$, $v\geq 0$, λ_1, $\lambda_2 > 0$ are constants. $\mu_0(x,y)$ is an image to be segmented. For better segmentation process the constant μ and v is set to zero 0, λ_1 and λ_2 should be set to one.

2.3 DISTANCE REGULARIZED LEVEL SET EVALUATION

This technique is the improvement of level set algorithm. Regularization property, energy and potential terms are used in building the DRLSE technique. External energy helps in moving the contour at zero level to the expected desired position. Let φ be the Level Set Function defined over the domain Ω. Energy function $E(\phi)$ is represented by,

$$E(\phi)=\mu R_P(\varphi)+E_{ext}(\varphi) \tag{3}$$

where $R_P(\varphi)$ is the distance regularization term, μ is a constant, $E_{ext}(\varphi)$ is the external energy over the curve and P is the potential function $[P(0:\infty)\rightarrow R]$.

Distance regularization term combined with potential function helps in preserving the frame of level set function by deriving the diffusion strategies.

$$R_p(\varphi)\triangleq\int_\Omega P(|\nabla\varphi|)dx \tag{4}$$

Double well potential function P is defined by,

$$P_2(S)=\begin{cases}\frac{1}{(2\pi)^2}\left(1-\cos(2\pi S)\right) & if\ S\leq 1\\ \frac{1}{2}(S-1)^2 & if\ S>1\end{cases} \tag{5}$$

where, S is a minimal point.

To achieve fine smoothing effect, the minimal point will be set to zero and one. Rather than traditional level set method, DRLSE helps in stabilizing the evaluation of level set, improve the accuracy and reduced the computation time by eliminating the process of re initialization.

2.4 FUZZY LEVEL SET SEGMENTATION

It is fusion of fuzzy theory and level set segmentation. Fuzzy technique is adopted to escalate the efficiency of the level set algorithm. The segmentation algorithm commence with fuzzy clustering which uses the pixel intensity information in the process of finding image boundaries of interested regions approximately. All the dominant parameters such as penalty variable, smoothing term, length and property functions which drive the initiation and evolution of level set curve are derived from fuzzy clustering technique. Based upon the outcome of dominant parameters, the level set segmentation performed its execution. If the region of interest is adequate then the promptness of curve evolution is also high.

3. RESULT AND DISCUSSION

The examination procedure carried over the wide amount of benchmark dataset imported from brain web [27] repository. It is a collection of T1 and T2 weighted magnetic resonance images of brain organ. Each category consists of one hundred and eighty one images. The properties are one mille meter thickness, twenty and forty proportion of comprised bias and 100% noise free images. The performance assessment is carried over using the metrics Accuracy (Acc), Sensitivity (Sen) or Recall, Specificity (Spe), Precision (Prec), F Score (FS), Border Error (BE) and Jaccard Distance (JD).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (6)$$

$$Sensitivity = \frac{TP}{TP + FN} \quad (7)$$

$$Specificity = \frac{TN}{TN + FP} \quad (8)$$

$$Precision = \frac{TP}{TP + FP} \quad (9)$$

$$F - Score = 2 * \frac{(Recall * Precision)}{(Recall + Precision)} \quad (10)$$

$$\text{Border Error} = \frac{FP + FN}{TP + FN} \quad (11)$$

$$J(S_1, S_2) = 1 - \frac{S_1 \cap S_2}{S_1 \cup S_2} \quad (12)$$

The Fig.1 shows the four types of input images and its appropriate segmented images using the segmentation algorithms expectation maximization, chan vese segmentation, distance regularized level set evaluation and fuzzy level set. From the perspective view expectation maximization algorithm, provide equal segmentation result for both T1 and T2 weighted images. Chan vese technique provides poor segmentation for T1 weighted images and little efficient segmentation result for T2 weighted images, in the same manner fuzzy level set provides satisfactory segmentation for T1 weighted images than T2 weighted images. Eye balls and brain matter clearly confesses that, distance regularized level set evaluation segments both T1 and T2 weighted brain MR Images corrupted with twenty and 40% bias. From the qualitative aspect, the result from Fig.1 can be concluded as good segmentation result supplied by distance regularized level set evaluation. The Table.1-Table.4 displays the performance evaluation of four segmentation algorithms on T1 and T2 weighted MRI with twenty and 40%age INU, using the quantitative metrics accuracy, sensitivity, specificity, precision and F Score. Results are presented in percentage form. Sensitivity, specificity and precision are individually represents how accurate the image region or background region is segmented and discarded during the segmentation procedure. But accuracy and F Score yields result by incorporating how accurate image region is included and background region is excluded during the process of segmentation.

So, accuracy and F Score are given preference over sensitivity, specificity and precision. Maximum results of these parameters depict the good segmentation. Based on that, the outcomes are derived. The Table.1 and Table.2 concludes that, expectation maximization shows higher efficiency because its accuracy (±98.86) and F Score (±98.76) range is high. After EM, accuracy and F Score values are descended in the following order DRLSE (accuracy (±98.30), F Score (±98.14)), FLS (accuracy (±94.98), F Score (±94.81)) and CV (accuracy (±90.70), F Score (±90.79)) segmentation algorithm. The Table.3 and Table.4 states that, DRLSE shows higher efficiency because its accuracy (±97.46) and F Score (±96.61) range is high. After DRLSE, accuracy and F Score values are descended in the following order EM (accuracy (±96.29), F Score (±96.24)), FLS (accuracy (±95.98), F Score (±94.27) and CV (accuracy (±78.60), F Score (±78.54)).

The Table.5-Table.8 displays the performance evaluation of four segmentation algorithms on T1 and T2 weighted MRI with 20% and 40% bias, using the quantitative metrics border error and Jaccard distance. Lesser of these values indicates the best performance. From Table.5 and Table.6, the performance indicator border error and Jaccard distance ranks the algorithm in the following sequence, EM (border error (±0.0113), Jaccard distance (±0.0236), DRLSE (border error ±0.0169), Jaccard distance (±0.0335), FLS (border error ±0.0501), Jaccard distance (±0.1075) and CV (border error (±0.0919), Jaccard distance (±0.1793). From Table.7 and Table.8, the performance indicator border error rank the algorithms efficiency as follows DRLSE (±0.0253), EM (±0.0370), FLS (±0.0401) and CV (±0.2139). Jaccard distance ranks the algorithms efficiency as, good performance provided by DRLSE (±0.0404), unsatisfactory result from CV (±0.3452) and moderate result shared by FLS (±0.0616) and EM (±0.0621) because values share the same range scale.

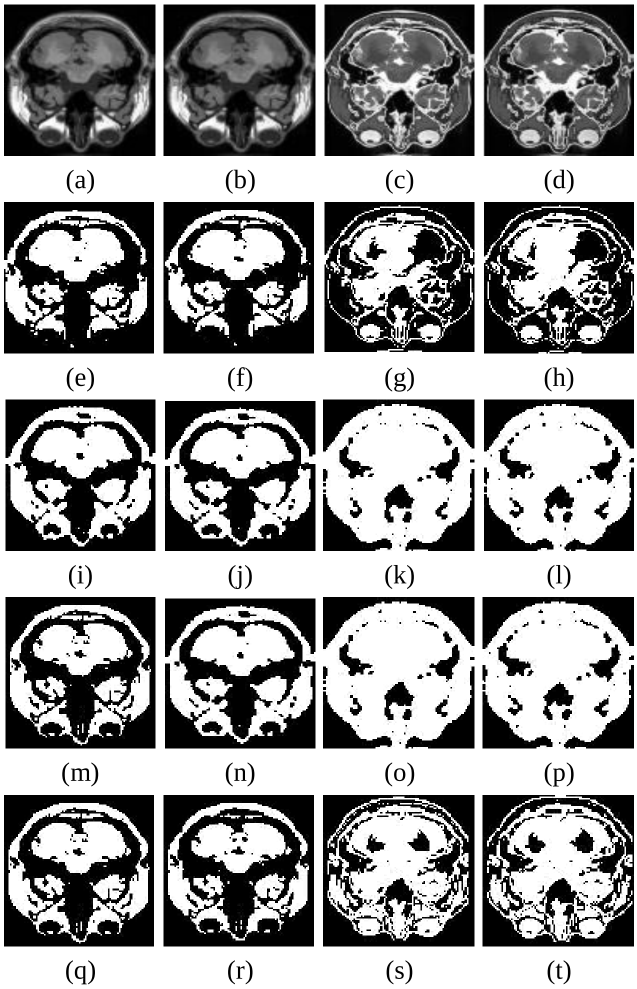

Fig.1. (a)-(d) Input Images, (a) T1 Weighted Images with 20% INU, (b) T1 Weighted Images with 40% INU, (c) T2 Weighted Images with 20% INU, (d) T2 Weighted Images with 40% INU, (e)-(h) input images corrected with Expectation Maximization segmentation algorithm, (i)-(l) input images corrected with Chan Vese segmentation algorithm, (m)-(p) input images corrected with Fuzzy Level Set segmentation algorithm, (q)-(t) input images corrected with Distance Regularized Level Set Evaluation

Table.1. Performance on T1 weighted images with 20% INU

Methods	Acc	Sen	Spe	Prec	F score
EM	98.80	98.78	98.72	98.64	98.70
CV	90.60	99.90	82.14	83.43	90.69
DRLSE	98.29	98.73	97.82	97.52	98.12
FLS	94.88	92.88	97.20	96.95	94.64

Table.2. Performance on T1 weighted images with 40% INU

Methods	Acc	Sen	Spe	Prec	F score
EM	98.92	98.77	98.92	98.91	98.84
CV	90.81	99.91	82.44	83.80	90.91
DRLSE	98.33	98.77	97.86	97.59	98.17
FLS	95.09	93.70	97.12	96.75	94.99

Table.3. Performance on T2 weighted images with 20% INU

Methods	Acc	Sen	Spe	Prec	F score
EM	96.34	98.65	94.71	95.01	96.29
CV	78.13	99.99	65.04	65.48	77.97
DRLSE	97.52	98.13	97.15	95.23	96.64
FLS	96.26	91.74	98.95	98.01	94.62

Table.4. Performance on T2 weighted images with 40% INU

Methods	Acc	Sen	Spe	Prec	F score
EM	96.25	98.46	94.58	94.93	96.21
CV	79.08	99.99	65.95	66.90	79.12
DRLSE	97.42	97.95	97.06	95.32	96.60
FLS	95.71	90.50	98.94	98.03	93.93

Table.5. BE and JD on T1 weighted images with 20% INU

Methods	BE	JD
EM	0.0120	0.0246
CV	0.0940	0.1809
DRLSE	0.0171	0.0339
FLS	0.0512	0.1083

Table.6. BE and JD on T1 weighted images with 40% INU

Methods	BE	JD
EM	0.0108	0.0226
CV	0.0919	0.1777
DRLSE	0.0167	0.0332
FLS	0.0491	0.1067

Table.7. BE and JD on T2 weighted images with 20% INU

Methods	BE	JD
EM	0.0366	0.0607
CV	0.2187	0.3498
DRLSE	0.0248	0.0392
FLS	0.0374	0.0574

Table.8. BE and JD on T2 weighted images with 40% INU

Methods	BE	JD
EM	0.0375	0.0635
CV	0.2092	0.3407
DRLSE	0.0258	0.0416
FLS	0.0429	0.0659

The result concluded from this section based on performance metrics accuracy, F Score, border error and Jaccard distance are, the algorithms which efficiently segments T1 weighted images with any bias can be ranked as follows EM, DRLSE, FLS and CV. Likewise for T2 weighted images with any bias the algorithms are ranked in the following sequence DRLSE, EM FLS and CV. Accuracy, F Score values of DRLSE and EM algorithm over T1 MRI images, falls under a same scale range. Concurrently Jaccard distance of EM and FLS algorithms also share the same range scale. This ambiguity can change the algorithms ranking. To abolish this confusion and determine the accurate outcome, overall performance of four segmentation algorithms need to be calculated.

Table.9. Overall performance on different performance metrics

Methods	Acc	Sen	Spe	Prec	F score	BE	JD
EM	97.58	98.67	96.74	96.87	97.31	0.0242	0.0429
CV	84.66	99.95	73.89	74.90	84.67	0.1534	0.2623
DRLSE	**97.89**	98.40	97.47	96.42	**97.38**	**0.0211**	**0.0370**
FLS	95.48	92.20	98.05	97.44	94.55	0.0452	0.0846

The comprehensive performance of four segmentation algorithms over T1 and T2 weighted images with twenty and 40% bias, for the metrics accuracy, sensitivity, specificity, precison, F Score border error and Jaccard distance are show in in Table.9. The combination of sensitivity specificity and precision should be high to indicate good result. By considering this and other performance metrics accuracy, F Score, border error and Jaccard distance the results were concluded. The overall performance clearly states the outcome that, DRLSE algorithm segments the bias corrupted images precisely, After DRLSE, EM do the better segmentation. Third place taken by FLS algorithm and finally the unsatisfactory result provided by CV segmentation algorithm because its accuracy, F score values, combination of sensitivity, specificity, precision is low and border error and Jaccard distance is high. The performance fluctuation between DRLSE and EM is very microscopic. From qualitative aspect EM algorithms efficiency is not much satisfactory based on figure 1 which leads the algorithm to take the second position. By considering all these, the algorithms are ranked in the following order DRLSE, EM, FLS and CV.

4. CONCLUSION

This paper scrutinizes the segmentation algorithms Expectation Maximization, Chan Vese, Distance Regularized Level Set Evaluation and Fuzzy Level Set over T1 and T2 weighted with twenty and 40% added bias, in brain MR Images. The primary quantitative metrics accuracy, sensitivity, specificity, precision, F Score and secondary quantitative metrics border error and Jaccard distance are used in disclosing the conclusion. To indicate the better segmentation, the primary performance metrics value should be superlative and secondary performance metrics value should be merest. Initially Algorithms performance is evaluated on each data type. There are totally seven metrics used in evaluation, among those accuracy, F Score, border error and Jaccard distance are prioritized. Based on that algorithms are ranked. The algorithms which efficiently segment the T1 weighted images with twenty and 40% bias is ranked as EM, DRLSE, FLS and CV. Similarly for T2 weighted images with twenty and 40% bias the algorithms are ranked as follows, DRLSE, EM, FLS and CV. The accuracy, F Score values of DRLSE, EM algorithm over T1 weighted images and Jaccard distance of EM and FLS algorithms over T2 weighted images are approximately same, which may change the algorithms ranking. For arriving accurate conclusion, comprehensive performance is calculated by incorporating all input images. All metrics are used in disclosing the conclusion. The comprehensive performance clearly states that DRLSE provides good segmentation after DRLSE, accuracy, F Score, border error and Jaccard distance values are descended in the following order: EM, FLS and CV. Hence the result can be concluded as DRLSE algorithm segment the images more precisely even though it is corrupted by Intensity Non Uniformity which is hardly visible to the beholder. It helps to provide the accurate outcome in computer aided diagnosing of diseases, treatment planning and 3D reconstruction etc.

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