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An Improved Method of Segmentation of Medical Images that Incorporates Bias Correction

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ABSTRACT: *The most widely used region-based image segmentation algorithms that typically rely on the homogeneity of the image intensities in the regions of interest often fail to provide accurate segmentation of medical images e.g., MRI images due to the presence of intensity inhomogeneity caused by the bias field in these images. This paper proposes a robust region-based method for image segmentation, which is able to deal with intensity inhomogeneities in the images. This method derives a local intensity clustering property of the image based on the model of images with intensity inhomogeneities, and then defines a local clustering criterion function in the neighborhood of each point. In a level set formulation, this criterion defines energy in terms of the level set function and a bias field. The level set functions represent a partition of the image domain whereas a bias field accounts for the intensity inhomogeneity of the image. The proposed method, by minimizing this energy, is able to simultaneously segment the image and estimate the bias field. The estimated bias field can be used for intensity inhomogeneity correction.*

KEYWORDS: *Active contour, Bias field, Contour evaluation, Energy minimization, Intensity inhomogeneity, Morphological erosion, Variational level set.*

I. INTRODUCTION

A major problem for automatic segmentation of images especially magnetic resonance images is the intensity inhomogeneity due to the bias field, which is caused by limitations in imaging devices and subject-induced susceptibility effect. A bias field is a low frequency smooth undesirable signal that corrupts MRI images because of the inhomogeneities in the magnetic fields of the MRI machine. The bias field introduces overlap of the intensity range of different tissues. As a result the pixels in different tissues are not separable based on their intensities. This causes serious misclassifications when intensity-based segmentation algorithms are used [1], [2]. Bias field, a low frequency signal, blurs or smoothes images and thus, reduces the high frequency contents of the image that sharpens the image such as edges and contours and changes the intensity values of image pixels so that the same tissue has different gray level distribution across the image [2]. A low level variation will not have huge impact on clinical diagnosis. However, it degrades the performances of image processing algorithms such as segmentation algorithms. In this research paper, an improved method of segmentation of medical images e.g., MRI images is proposed that incorporates bias correction method to solve the problem of intensity inhomogeneity.

II. LITERATURE REVIEW

Several general-purpose algorithms and techniques have been developed for image segmentation. Since there is no general solution to the image segmentation problem, these techniques often have to be combined with domain knowledge in order to effectively solve an image segmentation problem for a problem domain. The level set method, originally used as numerical technique for tracking interfaces and shapes, has been increasingly applied to image segmentation in the past decade. In the level set method, contours or surfaces are represented as the zero level set of a higher dimensional function, usually called a level set function. With the level set representation, the image segmentation problem can be formulated and solved in a principled way based on well-established mathematical theories, including calculus of variations and partial differential equations (PDE) [1], [3], [4]. An entirely popular approach to visual shape analysis is related to so called active contour models and snakes.

It is based on a curve respective surface evolution, starting from some initial curve or surface which is propagated to achieve a proper approximation of the segment boundary. Active contour models may incorporate a wide range of driving forces. Many of them are based on minimization of combined energy functionals controlling the fairness of the resulting curve on one hand and the attraction to areas of interest such as object boundaries on the other hand. Weighting parameters have to be carefully chosen to be a good balance between these terms. In early works explicit snakes with a standard parametric curve representation were used. The key disadvantage of this method is a topological constraint: the curve can not split to approximate boundaries of not simply connected segments. Such problems have been solved by introducing implicit snakes models [5], [6], in which the initial curve is interpreted as the zero level curve of a function. The evolution of these snakes is controlled by a PDE. An external term is considered to include information about the initial image. Although contours are able to split in this formulation, there remains the problem that the result of the segmentation relies significantly on a good initialization. Furthermore, many models have difficulties in progressing into boundary concavities. Addressing these particular problems a new class of external forces has been proposed by deriving from the original image a gradient vector in a variational framework. Sensitivity to initialization has been drastically reduced and contours have a more sensible behavior in the regions of concavities [7], [8].

III. PROPOSED METHOD

The proposed technique is based on combination of several existing methods. At first, use the Local Intensity Clustering Property. By using Local Intensity Clustering Property we consider a circular neighborhood pixel with a radius centered at each point. Finally, a new variational level set method is used to complete segmentation process. Instead of using traditional level set method, variational level set method is used to get better results. The main steps employed in the proposed method are shown in Fig. 1.

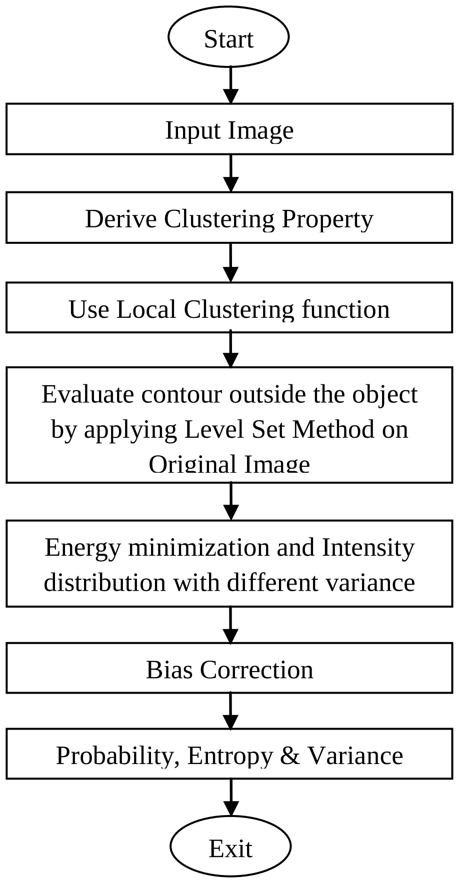


Fig. 1: Basic steps employed for analysis of medical images that incorporates bias correction.

Input Image: For experiments, an MRI image is used as input and converted to a gray scale image.

Local Intensity Clustering Property: Region-based image segmentation method typically relies on a specific region descriptor of the intensities in each region to be segmented. However, it is difficult to give such a region descriptor for images with intensity inhomogeneities. Moreover, intensity inhomogeneities often lead to overlap between the distributions of the intensities in the regions Ω_1. .Ω_N. Therefore, it is impossible to segment these regions directly based on the pixel intensities. Nevertheless, the property of local intensities is simple, which can be effectively exploited in the formulation for image segmentation with simultaneous estimation of the bias field. Based on the image model in and the assumptions A_1 and A_2, we are able to derive a useful property of local intensities, which is referred to as a local intensity clustering property. To be specific, we consider a circular neighborhood with a radius centered at each point. This local intensity clustering property is used to formulate the proposed method for image segmentation and bias field estimation. The local intensity clustering property indicates that the intensities in the neighborhood can be classified into N clusters. This allows us to apply the standard K-means clustering to classify these local intensities. Specifically, for the intensities I(x) in the neighborhood, the K-means algorithm is an iterative process to minimize the clustering criterion [9], [10].

Contour Evaluation: This is very crucial to implicit active contours in the placement of the initial contour. Since the contour moves either inward or outward, its initial placement will determine the segmentation that is obtained. For example, if there is a single object in an image, an initial contour placed outside the object and propagated inward will segment the outer boundary of the object. However, if the object has a hole in the middle, it will not be possible to obtain the boundary of this hole unless the initial contour is placed inside the hole and propagated outward. It should be noted that more than one closed curve can be used for initialization of the *zero*-th level set [11], [12].

Variational Level Set Method: The variational level set method is used to get better result. This process has some advantages, such as a significantly larger time step can be used for numerically solving the evaluation of partial differential equation and therefore, speed up the curve evaluation. Secondly, the level set function can be initialized with general functions that are more efficient to construct and easier to use in practice. In this method, the image after erosion and the original image are used. The image after erosion or the image after thresholding can be used demanding on the quality of the image [13]. If the image after applying morphological erosion is much complex or the image contains many small fragments in the thresholding technique, the variational technique is implemented using some steps. First, the image is smoothed using Gaussian Convolution. Then, edge indicator function is applied to the image after erosion or image after thresholding defending on the quality of the image. To achieve this goal, it explicitly defines an external energy that can move the zero level curve toward the object boundaries. Let I be an image, and g be the edge indicator function defined by [7], [14]:

$$g = \frac{1}{1+\left|\nabla G_\sigma * I\right|^2} \tag{1}$$

Then find coefficient of the internal (penalizing) energy term that help contour to outside the object boundary. It defines an external energy for a function Ø(x, y) as below:

$$\varepsilon_{g,\lambda,v}(\phi) = \lambda \ell_g(\varphi) + vA_g(\varphi) \tag{2}$$

where $\lambda > 0$ and ν are constants, and the terms $\ell_g(\varphi)$ and $A_g(\varphi)$ are defined by,

$$\ell_g(\varphi) = \int_\Omega g\delta(\varphi)\left|\nabla\varphi\right| dxdy \tag{3}$$

and

$$A_g(\varphi) = \int_\Omega gH(-\varphi)dxdy \tag{4}$$

Energy Minimization: Energy E is expressed in terms of the regions $\Omega_1, \ldots \Omega_N$. It is difficult to derive a solution to the energy minimization problem from this expression. The energy is converted to a level set formulation by representing the disjoint regions $\Omega_1, \ldots \Omega_N$ with a number of level set functions, with a regularization term on these level set functions. In the level set formulation, the energy minimization can be solved by using well-established variational 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 Ω into two disjoint regions Ω_1 and Ω_N. Here a level set function and its signs define two disjoint regions-

$$\Omega_1 = \{X:\acute{\phi}(x) > 0\} \qquad \Omega_1 = \{X:\acute{\phi}(x) < 0\} \tag{5}$$

which form a partition of the domain. For the case of N>2, two or more level set functions can be used to represent N regions $\Omega_1, \ldots \Omega_N$[14].

Bias Correction: Bias correction is used to remove intensity inhomogeinity. After completing all the iteration process and intensity distribution with different variance get energy minimization. Because it represents the disjoint region with number of level set function. This energy minimization changes the intensity of the pixel and that results image segmentation and bias field estimation [15], [16]. The proposed method segmentation technique based on variational level set method has been applied to a variety of synthetic and real images in different modalities.

Probability Analysis: Calculate Probability for Each Pixel and Weight Value. Each pixel in the image needs to be scanned for intensity values. The total number of pixels must be calculated along with the number of occurrences of each pixel intensity value.

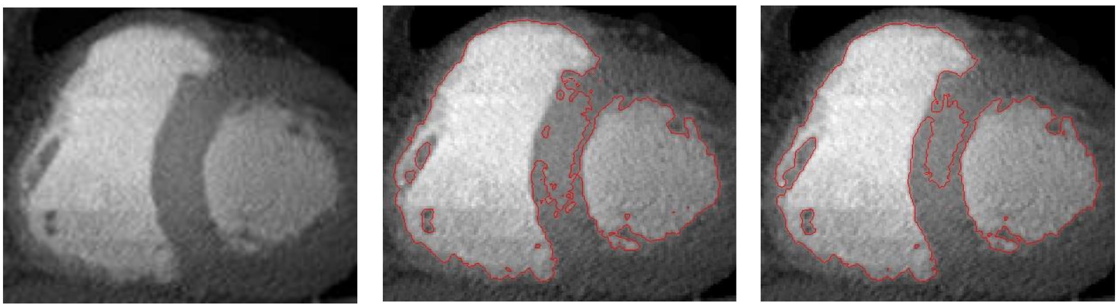
Entropy Analysis: Entropy means to consider the neighbourhood of the pixel of an image. Entropy is a measure of disorder, or more precisely unpredictability.

Variance Analysis: Variance is a measure of the dispersion of a set of data points around their mean value. It is a mathematical expectation of the average squared deviations from the mean [17], [18].

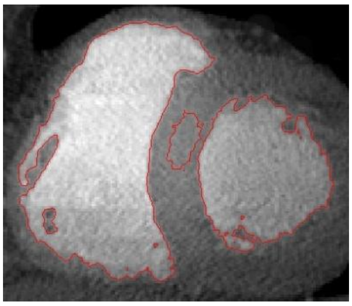
IV. IMPLEMENTATION AND RESULTS

The proposed approach has been implemented using MATLAB 7.1 on Intel(R) Core(TM) i5-3470 3.20 GHz Processor. Experiments show that the method is more robust to initialization, faster and more accurate than the well-known piecewise smooth model. As an application, the method has been used for segmentation and bias correction of magnetic resonance images. Fig. 2 shows an input MRI image. The segmentation results, computed bias fields, and bias corrected images are shown in the column respectively. It can be seen that the intensities within each tissue become quite homogeneous in the bias corrected images. The improvement of the image quality in terms of intensity homogeneity can be also demonstrated by comparing the histograms of the original images and the bias corrected images.

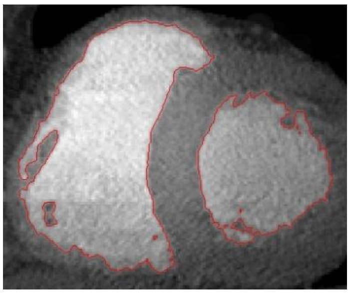
A. Output after Segmentation using Variational Level Set Method



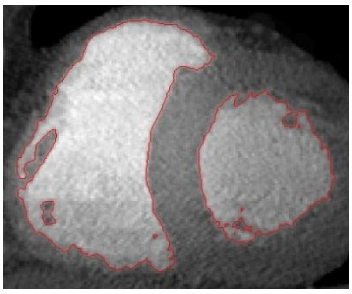
(a) Input Image (b) After 2 Iterations (c) After 6 Iterations



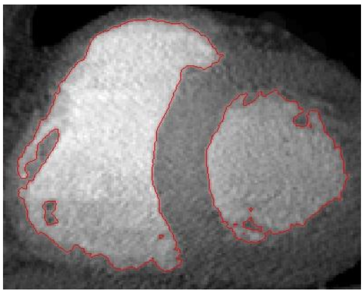
(d) After 10 Iterations



(e) After 16 Iterations



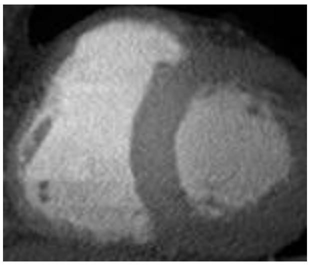
(f) After 25 Iterations



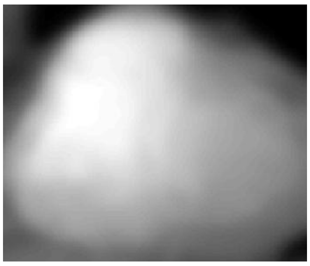
(g) Iterations Complete

Fig. 2: Contour Evaluation using Variational Level Set Method

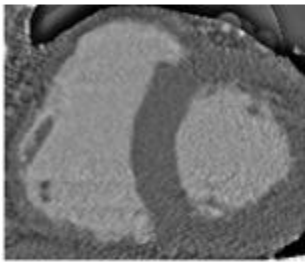
***B.* Output after Bias Correction**



(a) Original Image



(b) Computed Bias field



(c) Bias Corrected Image

Fig. 3: Output After Bias Corection

***C.* Probability Calculation:** Each pixel in the image needs to be scanned for intensity values. The total number of pixels must be calculated along with the number of occurrences of each pixel intensity value. The probability estimate of each pixel intensity value can then be calculated by dividing the occurrences over the number of pixels in the image. These values are then weighted by subtracting the resultant probability. The calculation for each pixel value for an image *M* is as follows:

$$P(\mathrm{n}) = 1 - (S \text{ occurrences of n in } M)/(S \text{ pixels in } M) \qquad (6)$$

The following figure shows the probability of the original image and that of the corrected image.

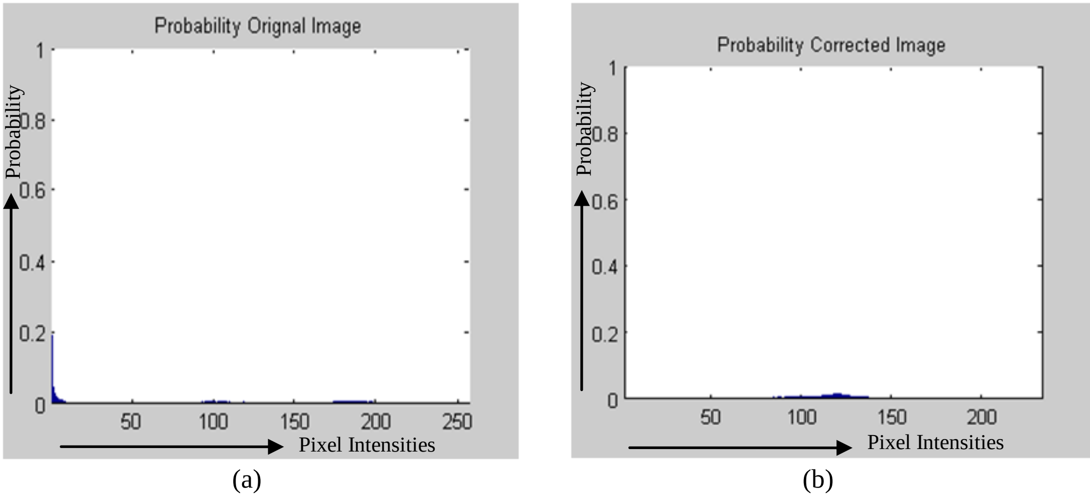


Fig. 4: (a) Probability of the original image and (b) Probability of the corrected image.

D. **Entropy Calculation:** Entropy is a measure of disorder, or more precisely unpredictability. The probability of an image intensity occurring at particular pixel in 'k', where 'k' is the set of all pixels in an image, is defined as $P\{n\}\log(P\{n\})$. The sum of all of this probability makes the entropy of, '*p*'. Thus,

$$G(K) = -\sum P\{n\}\log(P\{n\}) \tag{7}$$

Where n∈K, 'P{n}', is the probability mass function of particular pixel in 'k'. As its magnitude increases more uncertainty and thus, more information is associated with the source. If the source symbols are equally probable, the entropy or uncertainty of equation (7) is maximized and the source provides the greatest possible average information per source symbol. In this paper probability image is used as an input image to find entropy. Here it becomes necessary to select analyzing window size to find entropy for neighborhood of each pixel in the input image. For this paper, 3x3 window size is selected to find entropy. By moving analyzing window on complete image, calculating entropy for each window, new entropy image was formed by replacing the central pixel of the particular window by entropy and displayed as entropy image. The basic idea of the entropy-based registration uses the probability of occurrence of a pixel value at any point in the image to maximize the area of the images in which the pixel probabilities are shared. This can lead to error in images in which the background dominates or in which significant noise can alter pixel probability.

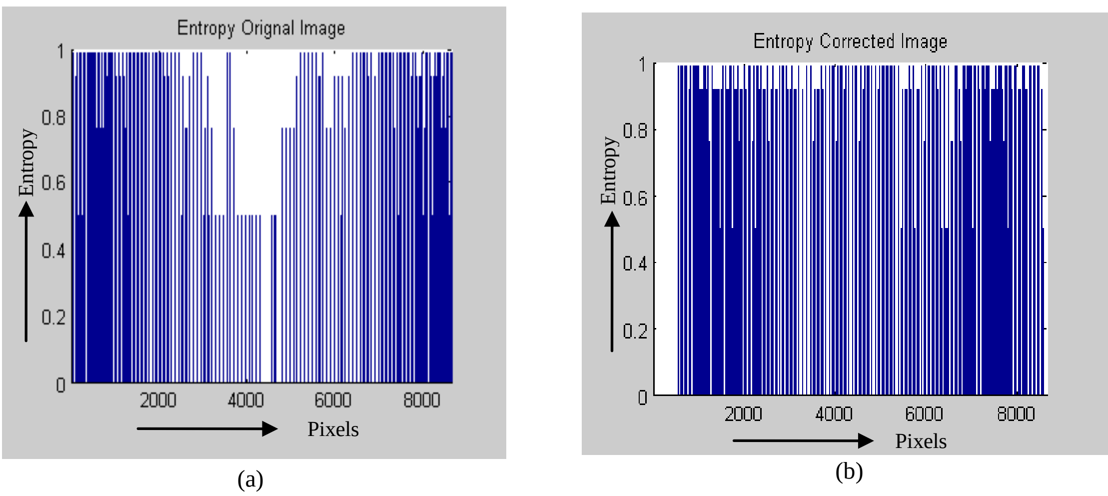
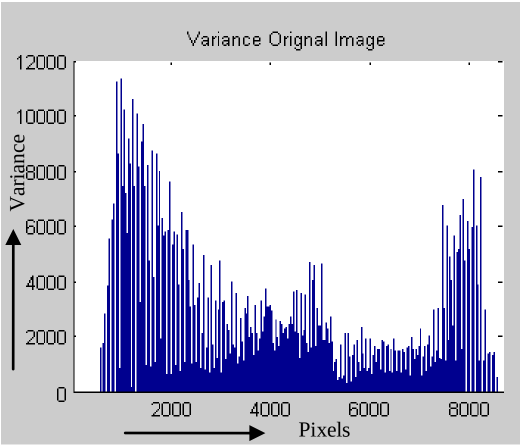


Fig. 5: (a) Entropy of the original image and (b) Entropy of the corrected image

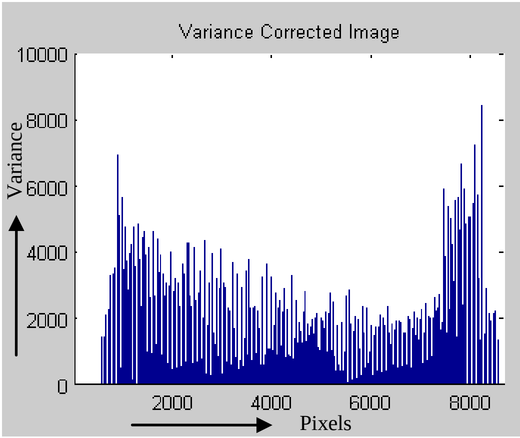
***E.* Variance Calculation:** Variance is a measure of the dispersion of a set of data points around their mean value. It is a mathematical expectation of the average squared deviations from the mean. The variance of a real-valued random variable is its second central moment and it also happens to be its second cumulant. The variance of random variable is the square of its standard deviation.

$$\text{Variance}(X) = E\,[(X - \mu)] \tag{8}$$

If $\mu = E(X)$, where $E(X)$ is the expected value (mean) of the random variable X. It can be expressed as "The average of the square of the distance of each data point from the mean". Initially, probability of image is calculated. Since the probability values are very small, equalized probability image is applied as an input image to find variance of probability image by using 3x3 window, as in case of entropy.



(a)



(b)

Fig. 6: (a) Variance of the original image and (b) Variance of the corrected image

V. PERFORMANCE ANALYSIS

Analysis of the processed image data is one of the hot topics in imaging field where segmentation plays vital role. Variational formulation based approaches like our proposed method produce significant output in the automatic and pixel based segmentation of MRI. Compared with pure PDE driven and traditional level set methods, the proposed method is more convenient and natural for incorporating additional information, such as region-based information and shape prior-information, into energy functions that are directly formulated in the level set domain, and therefore, produce more robust results. Besides this, the proposed method provides better output for large complex image, speeds up the curve evolution and easy to implement, easy to detect specific objects of image. Experimental results have demonstrated superior performance in terms of accuracy, efficiency, and robustness.

VI. CONCLUSION

MRI images have been studied to implement a better analytic system. Images are segmented first through variational level set method. Then bias correction operation is done to understand the image more precisely through denoising. The proposed method has been used for extraction more information from medical image. Segmentation and bias field estimation are jointly performed by minimizing the proposed energy function. It presents a more efficient way to analysis a medical image perfectly. Experimental results prove that the probability of image varies for both the images and is concentrated for certain pixel values, indicating refinement of the image. Entropy diversity of bias corrected image as compared to the original image is higher which indicates more information is available in the image which in turn helps in obtaining better image segmentation results. Lastly reduction in value of variance for individual pixel indicates less deviation of intensity value to that of mean value for the cluster of pixels in a given neighborhood.

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