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Image Segmentation Using Adaptive PDE based New Level Set Method

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Abstract: The most widely used image segmentation methods are Adaptive PDE-based and new level set algorithm typically depend on the uniform of the image intensities in the regions of interest, which often fail to provide accurate segmentation results due to the lack of homogeneity. This paper proposes a novel region-based method for image segmentation, which is able to deal with intensity inhomogeneities in the segmentation. First, based on the model of images with intensity lack of homogeneities, we derive a local intensity clustering property of the image intensities, and define a local clustering criterion function for the image intensities in a neighborhood of each point. This local clustering criterion function is then integrated with respect to the neighborhood center to give a global criterion of image segmentation. In an Adaptive PDE based new level set formulation, this criterion defines an energy in terms of the level set functions that represent a partition of the image domain and a bias field that accounts for the intensity inhomogeneity of the image. Therefore, by minimizing this energy, our method is able to simultaneously segment the image and estimate the bias field, and the estimated bias field can be used for intensity lack of homogeneity correction (or bias correction). This method has been validated on synthetic images and real images of various modalities, with desirable performance in the presence of intensity inhomogeneities. Experiments show that this method is more robust to initialization, faster and more accurate than the well-known piecewise smooth model.

Keywords: Adaptive Partial Differential Equations (PDE), Image segmentation, Inhomogeneity, Level set, MRI.

I. INTRODUCTION

Intensity inhomogeneity often occurs in real-world images due to various factors, such as spatial variations in illumination and imperfections of imaging devices, which complicates many problems in image processing and computer vision. In particular, image segmentation may be considerably difficult for images with intensity inhomogeneities due to the overlaps between the ranges of the intensities in the regions to segment. This makes it impossible to identify these regions based on the pixel intensity. Those widely used image segmentation algorithms [20], [21], [24], [25] usually rely on intensity homogeneity, and therefore are not applicable to images with intensity inhomogeneities. In general, intensity inhomogeneity has been a challenging difficulty in image segmentation. 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 [36].

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 [26],[27] 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],[6],[37]-[39]. An advantage of the new level set method is that numerical computations involving curves and surfaces can be performed on a fixed Cartesian grid without having to parameterize these objects. Moreover, the level set method is able to represent contours/surfaces with complex topology and change their topology in a natural way.

Existing level set methods for image segmentation [28] can be categorized into two major classes: region-based models [16], [19] and edge-based models. Region-based models aim to identify each region of interest by using a certain region descriptor to guide the motion of the active contour [2], [3], [7]. However, it is very difficult to define a region descriptor for images with intensity inhomogeneities. Most of region-based models [4], [16]–[18] are based on the assumption of intensity homogeneity. A typical example is piecewise constant (PC) models and level set methods are proposed based on a general piecewise smooth (PS) formulation originally proposed by Mumford and Shah. These methods do not assume homogeneity of image intensities, and therefore are able to segment images with intensity inhomogeneities.

However, these methods are computationally too expensive and are quite sensitive to the initialization of the contour [10], which greatly limits their utilities. Edge-based models use edge information for image segmentation. These models do not assume homogeneity of image intensities, and thus can be applied to images with intensity inhomogeneities. However, this type of methods are in general quite sensitive to the initial conditions and often suffer from serious boundary leakage problems in images with weak object boundaries. In this paper, we propose a novel region-based method [29]-[33] for image segmentation. From a generally accepted model

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of images with intensity inhomogeneities, we derive a local intensity clustering property, and therefore define a local clustering criterion function for the intensities in a neighborhood of each point. This local clustering criterion is integrated over the neighborhood center to define an energy functional, which is converted to a level set formulation. Minimization of this energy is achieved by an interleaved process of level set evolution and estimation of the bias field. As an important application, our method can be used for segmentation and bias correction of magnetic resonance (MR) images.

This paper is organized as follows. We first review two well-known region-based models for image segmentation in Section II. In Section III, we propose an energy minimization framework for image segmentation and estimation of bias field, which is then converted to a level set formulation in Section IV. Experimental results are given in Section V. This paper is summarized in Section VI.

II. BACKGROUND WORK

Let be the image domain, and be a gray level image. In [35], a segmentation of the image is achieved by finding a contour, which separates the image domain into disjoint regions, and a piecewise smooth function that approximates the image and is smooth inside each region. This can be formulated as a problem of minimizing the following Mumford-Shah functional.

$$F^{MS}(u,C) = \int_{\Omega}(I-u)^2 dx + \mu \int_{\Omega/C} |\nabla u|^2 dx + v|C| \qquad (1)$$

Where $|C|$ is the length of the contour C. In the right hand side of (1), the first term is the data term, which forces to be close to the image, and the second term is the smoothing term, which forces to be smooth within each of the regions separated by the contour [4]. The third term is introduced to regularize the contour [34].

In a variational level set formulation, Chan and Vese simplified the Mumford-Shah functional as the following energy:

$$F^{CV}(\phi, c_1, c_2) = \int_{\Omega} |I(x)-c_1|^2 H(\phi(x))dx + \int_{\Omega} |I(x)-c_2|^2 (1-H(\phi(x))dx + v \int_{\Omega/C} |\nabla H(\phi(x))| \; dx \qquad (2)$$

where H is the Heaviside function, and ϕ is a level set function, whose zero level contour partitions the image domain into two disjoint regions and .

III. VARIATIONAL FRAMEWORK FOR JOINT SEGMENTATION AND BIAS FIELD ESTIMATION

A. Image Model and Problem Formulation

In order to deal with intensity inhomogeneities in image segmentation, we formulate our method based on an image model that describes the composition of real-world images, in which intensity inhomogeneity is attributed to a component of an image [17].

In this paper, we consider the following multiplicative model of intensity inhomogeneity. From the physics of imaging in a variety of modalities (e.g. camera and MRI), an observed image can be modeled as

$$I = bJ + n \qquad (3)$$

Where J is the true image, b is the component that accounts for the intensity inhomogeneity, and n is additive noise. The component b is referred to as a bias field (or shading image). The true image J measures an intrinsic physical property of the objects being imaged, which is therefore assumed to be piecewise (approximately) constant. The bias field b is assumed to be slowly varying. The additive noise n can be assumed to be zero-mean Gaussian noise. In this paper, we consider the image as a function defined on a continuous domain. The assumptions about the true image and the bias field can be stated more specifically as follows:

- (A1) The bias field is slowly varying, which implies that can be well approximated by a constant in a neighborhood of each point in the image domain [22], [23].
- (A2) The true image approximately takes distinct constant values in disjoint regions, respectively, where forms a partition of the image domain, i.e. and for based on the model in (3) and the assumptions A1 and A2, we propose a method to estimate the regions, the constants, and the bias field. The obtained estimates of them are denoted by, the constants, and the bias field, respectively. The obtained bias field should be slowly varying and the regions should satisfy certain regularity property to avoid spurious segmentation results caused by image noise. We will define a criterion for seeking such estimates based on the above image model and assumptions A1 and A2. This criterion will be defined in terms of the regions, constants, and function, as an energy in a variational framework [5], [13] which is minimized for finding the optimal regions, constants, and bias field. As a result, image segmentation and bias field estimation are simultaneously accomplished.

B. Local Intensity Clustering Property

Region-based image segmentation methods typically relies on a specific region descriptor (e.g. intensity mean or a Gaussian distribution) 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. 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 of our method for image segmentation with simultaneous estimation of the bias field.

$$b(x) \approx b(y) \text{ for } x \in O_y \qquad (4)$$

$$b(x)J(x) \approx b(y)c_i \text{ for } x \in O_y \cap \Omega_i \qquad (5)$$

$$I(x) \approx b(y)c_i + n(x) \text{ for } x \in O_y \cap \Omega_i \qquad (6)$$

Where *n(x)* is additive zero-mean Gaussian noise.

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Therefore, the intensities in the set

$$I_y^i = \{I(x) : x \in O_y \cap \Omega_i \ \} \quad (7)$$

form a cluster with cluster center, which can be considered as samples drawn from a Gaussian distribution with mean. Obviously, the clusters, are well-separated, with distinct cluster centers, (because the constants are distinct and the variance of the Gaussian noise is assumed to be relatively small). This local intensity clustering property is used to formulate the proposed method for image segmentation and bias field estimation as follows.

C. Energy Formulation

The above described local intensity clustering property indicates that the intensities in the neighborhood can be classified into clusters, with centers, this allows us to apply the standard K-means clustering to classify these local intensities. Specifically, for the intensities in the neighborhood, the K-means algorithm is an iterative process to minimize the clustering criterion, which can be written in a continuous form as

$$F_y = \sum_{i=1}^{N} \int_{O_y} |I(x) - m_i|^2 u_i(x) dx \quad (8)$$

Since is the membership function of the region, we can rewrite as

$$F_y = \sum_{i=1}^{N} \int_{\Omega_i \cap O_y} |I(x) - m_i|^2 dx \quad (9)$$

In view of the clustering criterion in (8) and the approximation of the cluster center. We define a clustering criterion for classifying the intensities in as

$$\varepsilon_y = \sum_{i=1}^{N} \int_{\Omega_i \cap O_y} K\ (y-x)|I(x) - b(y)c_i|^2 dx \quad (10)$$

$$\varepsilon_y = \sum_{i=1}^{N} \int_{\Omega_i} K\ (y-x)|I(x) - b(y)c_i|^2 dx \quad (11)$$

$$\varepsilon_y \,\square \int \left(\sum_{i=1}^{N} \int_{\Omega_i} K(y-x)|I(x) - b(y)c_i|^2 dx \right) dy \quad (12)$$

$$K(u) = \begin{cases} \dfrac{e^{-|u|^2/2\sigma^2}}{a} & for\,|u| \le \rho \\ o & otherwise \end{cases} \quad (13)$$

IV. NEW LEVEL SET FORMULATION METHOD

Our proposed energy is expressed in terms of the regions. It is difficult to derive a solution to the energy minimization problem from the expression. In this section, the energy is converted to a level set formulation by representing the disjoint regions 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 [12]. In level set 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 into two disjoint regions and . Let be a level set function [8]-[11], [14], [15] then its signs define two disjoint regions [18].

$$\Omega_1 = \{x : \phi(x) \ge 0\} \text{ and } \Omega_2 = \{x : \phi(x) \le 0\} \quad (14)$$

A. Two-Phase Level Set Formulation

$$\varepsilon = \int \left(\sum_{i=1}^{N} \int K(y-x)|I(x) - b(y)c_i|^2 M_i(\phi(x))dx \right) dy \quad (15)$$

$$\varepsilon = \int \left(\sum_{i=1}^{N} \int K(y-x)|I(x) - b(y)c_i|^2 dy \right) M_i(\phi(x))dx \quad (16)$$

$$\varepsilon(\phi, c, b) = \int \sum_{i=1}^{N} e_i(x) M_i(\phi(x))dx \quad (17)$$

$$e_i(x) = \int K(y-x)|I(x) - b(y)c_i|^2 dy \quad (18)$$

$$e_i(x) = I^2 1_K - 2c_i I(b*K) + c_i^2(b^2 * K) \quad (19)$$

$$F(\phi, c, b) = \varepsilon(\phi, c, b) + vL(\phi) + \mu R_p(\phi) \quad (20)$$

$$L(\phi) = \int |\nabla H(\phi)| dx \quad (21)$$

$$R_p(\phi) = \int p |\nabla \phi| dx \quad (22)$$

$$\frac{\partial \phi}{\partial t} = -\frac{\partial F}{\partial \phi} \quad (23)$$

$$\frac{\partial \phi}{\partial t} = -\delta(\phi)(e_1 - e_2) + v\delta(\phi) div\left(\frac{\nabla \phi}{|\nabla \phi|}\right) + \mu div\left(d_p(|\nabla \phi|)\nabla \phi\right) \quad (24)$$

$$\hat{c}_i = \frac{\int (b*K) I u_i dy}{\int (b^2 * K) I u_i dy}, \quad i = 1, ..., N \quad (25)$$

With $u_i(y) = M_i(\phi(y))$ (26)

$$\hat{b} = \frac{(IJ^{(1)}) * K}{J^{(2)} * K} \quad (27)$$

Where $J^{(1)} = \sum_{i=1}^{N} c_i u_i$ and $J^{(2)} = \sum_{i=1}^{N} c_i^2 u_i$ (28)

B. Multiphase New Level Set Formulation

$$M_i(\phi_1(y), ..., \phi_k(y)) = \begin{cases} 1 & y \in \Omega_i \\ o & otherwise \end{cases} \quad (29)$$

$$M_1(\phi_1, \phi_2) = H(\phi_1)H(\phi_2), \quad (30)$$

$$M_2(\phi_1, \phi_2) = H(\phi_1)(1 - H(\phi_2)), \quad (31)$$

$$M_3(\phi_1, \phi_2) = (1 - H(\phi_1))H(\phi_2) \quad (32)$$

and $M_4(\phi_1, \phi_2) = (1 - H(\phi_1))(1 - H(\phi_2))$ (33)

$$\varepsilon(\phi, c, b) = \int \sum_{i=1}^{N} e_i(x) M_i(\phi(x))dx \quad (34)$$

$$F(\phi, b, c) \,\square\, \varepsilon(\phi, b, c) + R_p(\phi) \quad (35)$$

$$\frac{\partial \phi_1}{\partial t} = -\sum_{i=1}^{N} \frac{\partial M_i(\phi)}{\partial \phi_1} e_i + v\delta(\phi_1) div\left(\frac{\nabla \phi_1}{|\nabla \phi_1|}\right) + \mu div\left(d_p(|\nabla \phi_1|)\nabla \phi_1\right) \quad (36)$$

$$\frac{\partial \phi_k}{\partial t} = -\sum_{i=1}^{N} \frac{\partial M_i(\phi)}{\partial \phi_k} e_i + v\delta(\phi_k) div\left(\frac{\nabla \phi_k}{|\nabla \phi_k|}\right) + \mu div\left(d_p(|\nabla \phi_k|)\nabla \phi_k\right) \quad (37)$$

C. Numerical Implementation

$$H_\varepsilon(x) = \frac{1}{2}\left[1 + \frac{2}{\Pi} \arctan\left(\frac{x}{\in}\right)\right] \quad (38)$$

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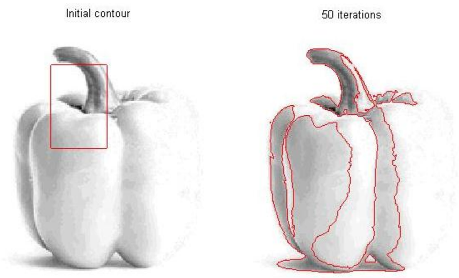
$$\delta_{\in}(x) = H_{\in}^{'}(x) = \frac{1}{\Pi}\frac{\in}{\in^2 + x^2} \qquad (39)$$

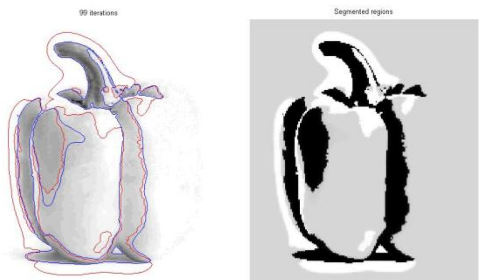
V. EXPERIMENTAL RESULTS

Figure. 1, 2, 3 and 4 shows the results for a camera image of capsicum, model, flower and lemon. The curve evolution processes are depicted by showing the initial contours. Our method is able to provide a desirable segmentation result for such images. The estimated bias field by our method can be used for intensity inhomogeneity correction (or bias correction). Given the estimated bias field, the bias corrected image is computed as the quotient. To demonstrate the effectiveness of our method in simultaneous segmentation and bias field estimation, we applied it to four images with intensity inhomogeneities. These results demonstrate desirable performance of our method in segmentation and bias correction. Therefore, we use the following contour- based metric for precise evaluation of the segmentation result. Let be a contour as a segmentation result, and be the true object boundary, which is also given as a contour. For each point, on the contour, we can compute the distance from the point to the ground truth contour. Then, we define the deviation from the contour to the ground truth by which is referred to as the mean error of the contour. This contour-based metric can be used to evaluate a sub pixel accuracy of a segmentation result given by a contour.

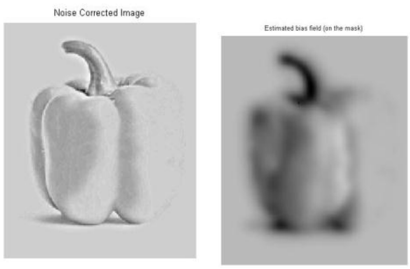
Capsicum



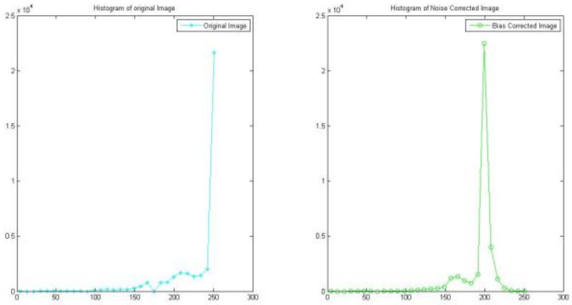
(a) (b)



(c) (d)



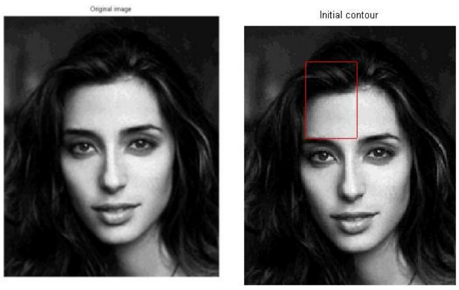
(e) (f)



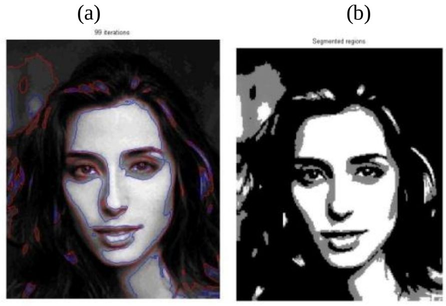
(g) (h)

Fig.1. (a) initial contour, (b) 50 iterations, (c) 99 iterations, (d) segmented regions, (e) Noise corrected image, (f) Bias field image, (g) Histogram of original image, (h) Histogram of Noise corrected image.

Model

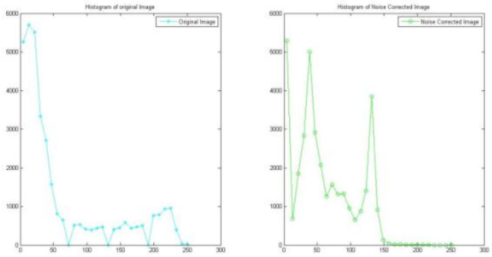


(a) (b)



(c) (d)

(e) (f)



(g) (h)

Fig.2. (a) original image, (b) initial contour, (c) 99 iterations, (d) segmented regions, (e) Noise corrected image, (f) Bias field image, (g) Histogram of original image, (h) Histogram of Noise corrected image

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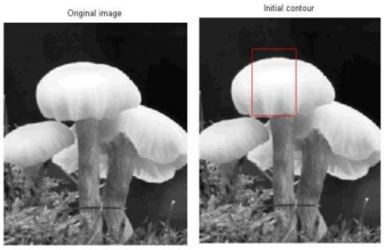
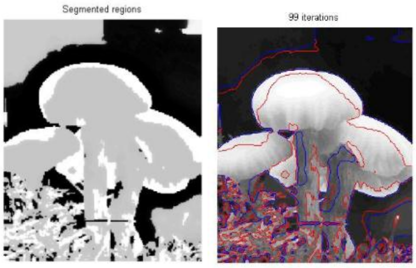
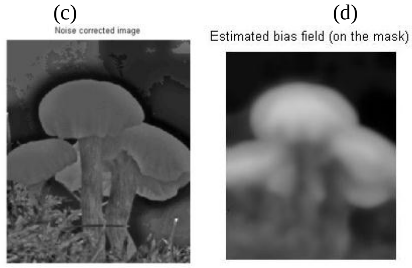
Flower



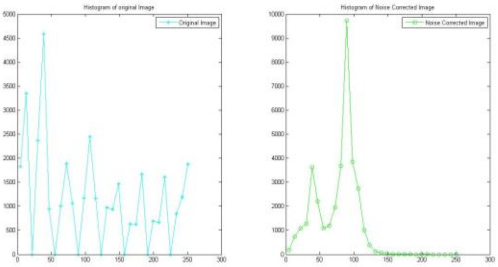
(a) (b)



(c) (d)



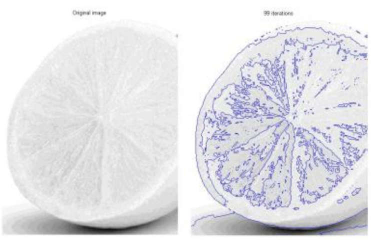
(e) (f)



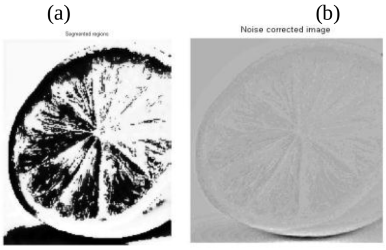
(g) (h)

Fig.3. (a) original image, (b) initial contours, (c) segmented regions, (d) 99 iterations, (e) Noise corrected image, (f) Bias field image, (g) Histogram of original image, (h) Histogram of Noise corrected image

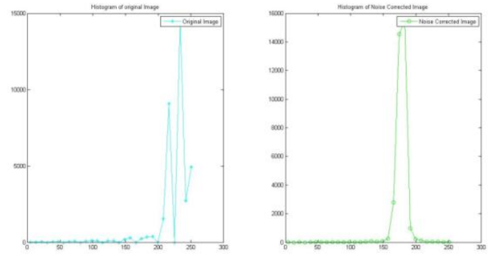
Lemon



(a) (b)



(c) (d)



(e) (f)

Fig.4. (a) original image, (b) 99 iterations, (c) segmented regions, (d) Noise corrected image, (e) Histogram of original image, (f) Histogram of Noise corrected image

VI. CONCLUSION

In this paper presented a variational level set framework for segmentation and bias correction of images with intensity inhomogeneities. Based on a generally accepted model of images with intensity inhomogeneities and a derived local intensity clustering property, we define an energy of the level set functions that represent a partition of the image domain and a bias field that accounts for the intensity inhomogeneity. Segmentation and bias field estimation are therefore jointly performed by minimizing the proposed energy functional. The slowly varying property of the bias field derived from the proposed energy is naturally ensured by the data term in our variational framework, without the need to impose an explicit smoothing term on the bias field. Our method is much more robust to initialization than the piecewise smooth model. Experimental results have demonstrated superior performance of our method in terms of accuracy, efficiency, and robustness.

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