Semi Supervised Color Image Segmentation Using Region Based Method

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***Abstract*— We propose a novel region-based method for image segmentation, which is able to deal with intensity in homogeneities in the segmentation. First, based on the model of images with intensity in 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 a 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 inhomogeneity correction (or bias correction). Our 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 our method is more robust to initialization, faster and more accurate than the well-known piecewise smooth model. As an application, our method has been used for segmentation and bias correction of magnetic resonance (MR) images with promising results.**

***Keywords*— Region-based method, Edge-based method, Level-set method, Segmentation.**

I.INTRODUCTION

INTENSITY in homogeneity often occurs in real-world images due to various factors, such as spatial variations in illumination and imperfections of imaging devices, which com-plicates 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 segmented.

This makes it impossible to identify these regions based on the pixel intensity. Those widely used image segmentation.

algorithms 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. 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). An advantage of the 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 can be categorized into two major classes: *region-based models* 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.

II.EXISTING SYSTEM

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[1]. 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).

We propose a new model for active contours based on a geometric partial differential equation. Our model is intrinsic,stable (satisfies the maximum principle) and permits a rigorous mathematical analysis. It enables us to extract smooth shapes (we cannot retrieve angles) and it can be adapted to find several contours simultaneously. Moreover, as a consequence of the stability, we can design robust algorithms which can be engineed with no parameters in applications. Numerical experiments are presented[2].

Existing level set methods for image segmentation can be categorized into two major classes: region-based models 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. Edge-based models use edge information for image segmentation [3].

Disadvantage:

- It is very difficult to define a region descriptor for images with intensity in homogeneities in Region-based model.

- Existing methods are computationally too expensive and are quite sensitive to the initialization of the contour, which greatly limits their utilities.

- Edge based model do not assume homogeneity of image intensities, and thus can be applied to images with intensity in homogeneities.

A. Existing Algorithm

1) Edge based algorithm: The algorithm aims at performing two tasks: extraction of edge-end pixels and recognition of the associated directions. At the outset, the algorithm reads all the pixels in a 2-D image row by row by a speedy process. The search first identifies each pixel located at edge-ends by seeking the neighboring pixel values. If the target pixel is found it records the coordinates of the recognized pixel to complete the extraction. To perform the task of recognition, the numeric scheme is used to represent the eight 'directions' of the target pixel. Similar schemes have been used for image processing in the past. One method is the so-called Chain Coding , which traces a pixel-wide line, using the scheme. The direction of each of the detected pixels takes into account the known alignment of neighboring pixels.

2) Region based algorithm: Region-based segmentation Boundary estimation using edge detection. A group of connected pixels with similar properties. Important in interpreting an image because they may correspond to objects in a scene. For correct interpretation, image must be partitioned into regions that correspond to objects or parts of an object.

3) Disadvantages: The assumption does not hold true in all cases.

- To overcome this, group pixels using given principles and use domain-dependent knowledge.
- Match regions to object models.

III.PROPOSED SYSTEM

We propose a novel region-based method for image segmentation. From a generally accepted model of images with intensity in homogeneities, 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.

***Advantage*:**

- Our method can be used for segmentation and bias correction of magnetic resonance (MR) images.
- 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.

A. Proposed Algorithm

1) Level set method : A region-based image segmentation method 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 in homogeneities. Moreover, intensity in homogeneities often leads 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? Based on the image model and the assumptions A1 and A2, we are able to derive a useful property of local intensities, which is referred to as a local intensity clustering property as described and justified below. To be specific, we consider a circular neighborhood with a radius centered at each point, defined by. The partition of the entire domain induces a partition of the neighborhood, forms a partition of. For a slowly varying bias field, the values for all in the circular neighborhood are close to, Thus, the intensities in each sub region are close to the constant , Then, in view of the image model , we have for where is additive zero-mean Gaussian noise. Therefore, the intensities in the set 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.

B. Purpose of the system

Medical image segmentation is a complex and challenging task due to the intrinsically imprecise nature of the images. Magnetic resonance images (MRI) is of great importance for research and clinical study of much neurological pathology. The accurate segmentation of MR images into different tissue classes is important in research areas. We first review two well-known region-based models for image segmentation then, we propose an energy minimization framework for image segmentation and estimation of bias field, which is then converted to a level set formulation for energy minimization.

C. Scope of the system

Intensity in homogeneity often occurs in real-world images, which presents a considerable challenge in image segmentation. The most widely used image segmentation algorithms are region-based and typically rely on the homogeneity of the image intensities in the regions of interest, which often fail to provide accurate segmentation results due to the intensity in homogeneity. In particular, image segmentation may be considerably difficult for images with intensity in homogeneities 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.

D. Objectives and successive criteria

In particular, image segmentation may be considerably difficult for images with intensity in homogeneities 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 usually rely on intensity homogeneity, and therefore are not applicable to images with intensity in homogeneities. In general, intensity in homogeneity has been a challenging difficulty in image segmentation.

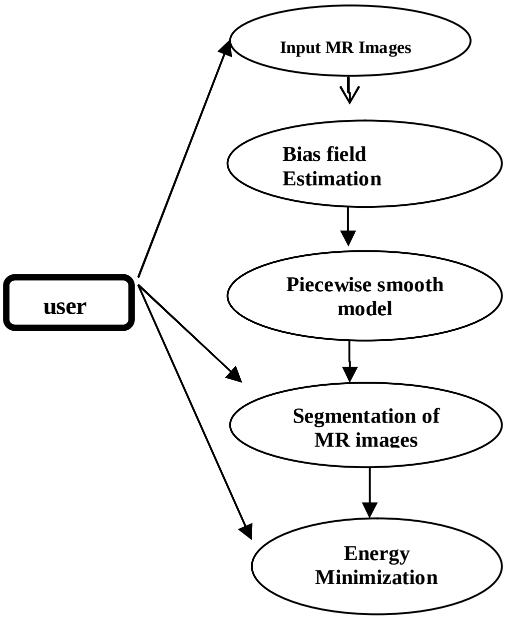


Fig. 1 **Use case Diagram**

E. Module Description

- Variational framework for joint segmentation and bias field estimation
- Level set formulation and energy minimization.

1) Variational framework for joint segmentation and bias field estimation:

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

$$I = bJ + n$$

where is J the true image, is the component that accounts for the intensity inhomogeneity, and ɳ is additive noise. The component 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 is assumed to be slowly varying. The additive noise ɳ can be assumed to be zero-mean Gaussian noise.

we consider the image *I* as a function *I* :Ω -> Ŕ defined on a continuous domain . The assumptions about the true image J and the bias field b can be stated more specifically as follows:

(A1) The bias field is slowly varying, which implies that b can be well approximated by a constant in a neighborhood of each point in the image domain.

(A2) The true image J approximately takes distinct constant values [c1,c2,,cn] in disjoint regions[Ω1,..Ωn], respectively, where $\{\Omega_i\}_{i=1}^{N}$ forms a *partition* of the image domain, i.e. and for based on the model in (3) and the assumptions A1 and A2.

The obtained bias field b should be slowly varying and the regions should satisfy certain regularity property to avoid spurious segmentation results caused by image noise.

1.2) ***Local Intensity Clustering Property:*** A region-based image segmentation method 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. This local intensity clustering property is used to formulate the proposed method for image segmentation and bias field estimation as follows

1.3) ***Energy Formulation:*** The above described local intensity clustering property indicates that the intensities in the neighborhood can be classified into N clusters, with centers $m_i \approx b(\mathbf{y})c_i, i = 1, \cdots, N$, . 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, which can be written in a continuous form as

$$F_{\mathrm{y}} = \sum_{i=1}^{N} \int_{O_{\mathrm{y}}} |I(\mathrm{x}) - m_i|^2 u_i(\mathrm{x}) d\mathrm{x}$$

Where mi is the cluster center of the i-th cluster, ui is the membership function of the region to be determined,

Therefore, we need to jointly minimize ε_y for all in Ω . This can be achieved by minimizing the integral of ε_y with respect to over the image domain Ω . Therefore, we define an energy

$$\mathcal{E} \triangleq \int \mathcal{E}_{\mathbf{y}} d\mathbf{y}, \text{ i.e.,}$$

$$\mathcal{E} \triangleq \int \left(\sum_{i=1}^{N} \int_{\Omega_i} K(\mathbf{y} - \mathbf{x}) \, |I(\mathbf{x}) - b(\mathbf{y})c_i|^2 \, d\mathbf{x} \right) d\mathbf{y}.$$

Image segmentation and bias field estimation can be performed by minimizing this energy with respect to the regions Ω , constants , and bias field b.

2) Level set formulation and energy minimization:

Our proposed energy ε in (3) is expressed in terms of the regions [Ω1,Ωn]. It is difficult to derive a solution to the energy minimization problem from this expression of ε. In this section, the energy ε is converted to a level set formulation by representing the disjoint regions [Ω1,Ωn], 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. 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 Ω1 and Ω2 . Let be a level set function, and then its signs define two disjoint regions.

$$\Omega_1 = \{\mathrm{x} : \phi(\mathrm{x}) > 0\}, \quad \text{and} \quad \Omega_2 = \{\mathrm{x} : \phi(\mathrm{x}) < 0\}$$

The above defined energy $\mathcal{E}(\phi, \mathbf{c}, b)$ is used as the data term in the energy of the proposed variational level set formulation, which is defined by

$$\mathcal{F}(\phi, \mathbf{c}, b) = \mathcal{E}(\phi, \mathbf{c}, b) + \nu\mathcal{L}(\phi) + \mu\mathcal{R}_p(\phi)$$

By minimizing this energy, we obtain the result of image segmentation given by the level set function ϕ and the estimation of the bias field b. The energy minimization is achieved by an iterative process: in each iteration, we minimize the energy with respect to each of its variables ϕ ,c , and b , given the other two updated in previous iteration.

F. Literature Review

1) MRI Images: Magnetic resonance imaging (MRI), nuclear magnetic resonance imaging (NMRI), or magnetic resonance tomography (MRT) is a medical imaging technique used in radiology to visualize detailed internal structures. MRI makes use of the property of nuclear magnetic resonance (NMR) to image nuclei of atoms inside the body.

Fig2: Example of MRI images

Fig 2 MRI uses a powerful magnetic field, radio frequency pulses and a computer to produce detailed pictures of organs, soft tissues, bone and virtually all other internal body structures. The images can then be examined on a computer monitor, transmitted electronically, printed or copied to a CD. MRI does not use ionizing radiation (x-rays).

G. Image Segmentation

In computer vision, segmentation refers to the process of partitioning a digital image into multiple segments (sets of pixels, also known as super pixels). The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze.[1] Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain visual characteristics.

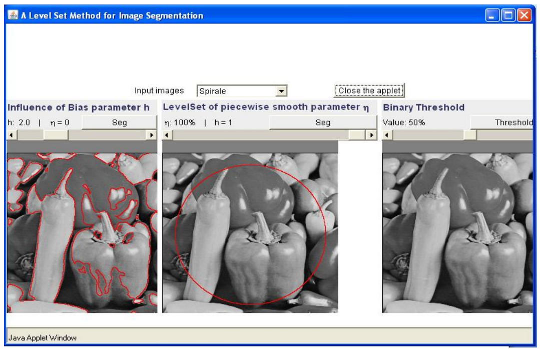
The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image (see edge detection). Each of the pixels in a region are similar with respect to some characteristic or computed property, such as color, intensity, or texture. Adjacent regions are significantly different with respect to the same characteristic(s).[1] When applied to a stack of images, typical in Medical imaging, the resulting contours after image segmentation can be used to create 3D reconstructions with the help of interpolation algorithms like Marching cubes.

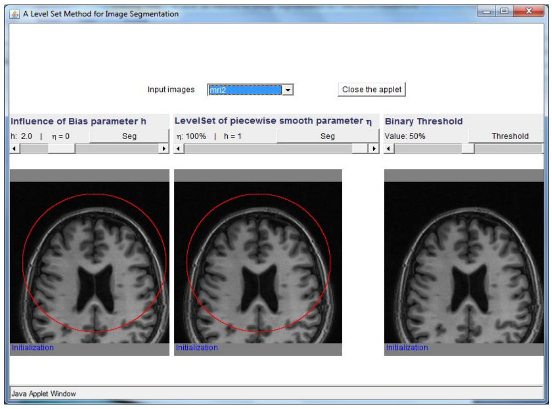
Image segmentation is the process that subdivides an image into its constituent parts or objects. The level to which this subdivision is carried out depends on the problem being solved, i.e., the segmentation should stop when the objects of interest in an application have been isolated e.g., in autonomous air-to-ground target acquisition, suppose our interest lies in identifying vehicles on a road, the first step is to segment the road from the image and then to segment the contents of the road down to potential vehicles. Image thresholding techniques are used for image segmentation.

1) Level set 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. 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).

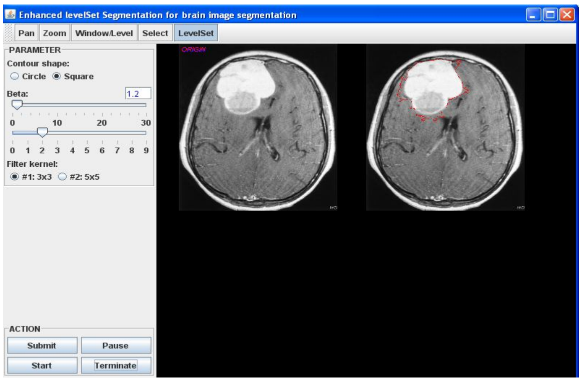
2) Results of Level Set Image Segmentation:





An advantage of the 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.

3) Results of Enhanced Level Set Image Segmentation:



Existing level set methods for image segmentation can be categorized into two major classes: region-based models 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. However, it is very difficult to define a region descriptor for images with intensity in homogeneities.

H. Process:

It provides a way to check the functionality of components, sub-assemblies, assemblies and/or a finished product. It is the process of exercising software with the intent of ensuring that the Software system meets its requirements and user expectations and does not fail in an unacceptable manner. There are various types of test. Each test type addresses a specific testing requirement.

1) Functional testing centered on the following items:

Valid Input :MR images of the users should be exact PNG type .
Invalid Input : if the PNG not present .
Functions :Check the images format.
Output : Valid MRI Brian images

2) Experimental Results: We first demonstrate our method in the two-phase case (i.e.). Unless otherwise specified, the parameter is set to 4 for the experiments.

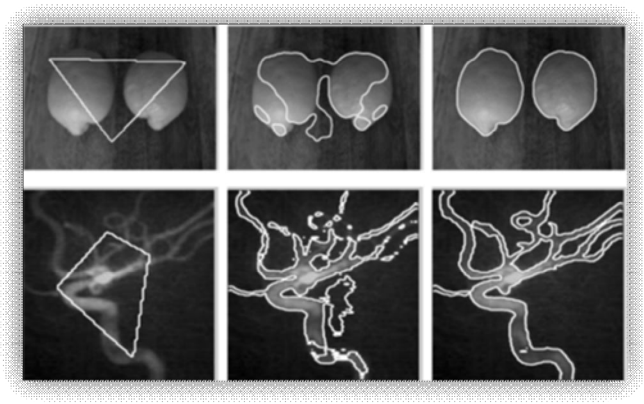


Fig 3: Initial contours, Intermediate contours, Final contours

Fig 3 shows the results for a camera image of Limon and a computed tomography angiography (CTA) image of blood vessel. The curve evolution processes are depicted by showing the initial contours (in the left column), intermediate contours (in the middle column), and the final contours (in the right column) on the images. Intensity inhomogeneities can be clearly seen in these two images.
Our method is able to provide a desirable segmentation result for such images.

IV. CONCLUSION

We have presented a variational level set framework for segmentation and bias correction of images with intensity in homogeneities.
Based on a generally accepted model of images with intensity in homogeneities 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 in homogeneity.
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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