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Image Segmentation Using Level Set Method For Images With Intensity Inhomoginities

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Abstract

The active contour method is one of the most successful image segmentation techniques. It has received a tremendous amount of attention in medical image processing. The segmentation operation can be carried out manually or automatically. A manual segmentation requires a skilled operator trained to use a digital tool to mark the contours of the desired structures. In this project the three-phase formulation of the level set evolution (LSE) and bias field estimation and a Level Set Method for Image Segmentation in the Presence of Intensity is done. The three-phase formulation is used to segment an image into three regions. Intensity inhomogeneity 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 inhomogeneity. Matlab code is used for the three phase formation and bias field estimation.

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Keywords: *Level Set Methods, MATLAB, IMAGE SEGMENTATION.*

1. Introduction

The goal of image segmentation is to cluster the pixels into salient image regions i.e., regions corresponding to individual surfaces, objects, or natural parts of objects. Segmentation is an important technique used in image processing to identify the objects in the image .Segmentation techniques that can be applied in a robust and efficient way to both image and mesh data. Mesh data is frequently unstructured; this precludes the direct application of techniques that were originally developed for the more structured image data. The idea behind active contours, or deformable models, for image segmentation is quite simple. The user specifies an initial guess for the contour, which is then moved by image driven forces to the boundaries of the desired objects. In such models, two types of forces are considered - the internal forces, defined within the curve, are designed to keep the model smooth during the deformation process, while the external forces, which are computed from the underlying image data, are defined to move the model toward an object boundary or other desired features within the image.

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2. Present Work and Proposed Work

In this project, we developed a new model for image segmentation with intensity inhomogeneity and bias field estimation. We firstly defined a local intensity clustering criterion function by considering the local difference between the measured image and estimated image. Then, the energy is minimized by a level set evolution process. A regularization is used in the level set process to ensure that the active contours are smooth and eliminate the re-initialization of level set function in the evolution of the active contours. We further extend our model into a multi-phase one to segment multi-phase images

. Intensity inhomogeneity 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 inhomogeneity. First, based on the model of images with intensity inhomogeneities, 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).

Imagine that you are given an image, say a medical (MRI or CT) scan. Suppose you want to extract the important feature within the image; in this case, the outline of the artery. One idea is to look for places where there is a big jump in intensity between neighboring pixels. However, it is hard to pick a good value for the jump; too small and you get extra boundaries; too large and you miss the whole show. Another problem is that you can get fooled by large spikes of noise. An Evolving Interface Approach to Active Contours .A different approach comes from initializing a small circle inside the region of interest, and allowing it to grow outwards until it reaches the desired boundary.

The level set approach allows the evolving front to change topology, break, and merge, which means that the evolving front can extract the boundaries of particularly intricate contours. In addition, the method works in three dimensions with almost no change, so three dimensional surfaces can be extracted as well.

Present Method:

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.

In order to deal with intensity inhomogeneities in image segmentation, we formulate a 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 present method, 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

$$I = b\,J + n$$

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

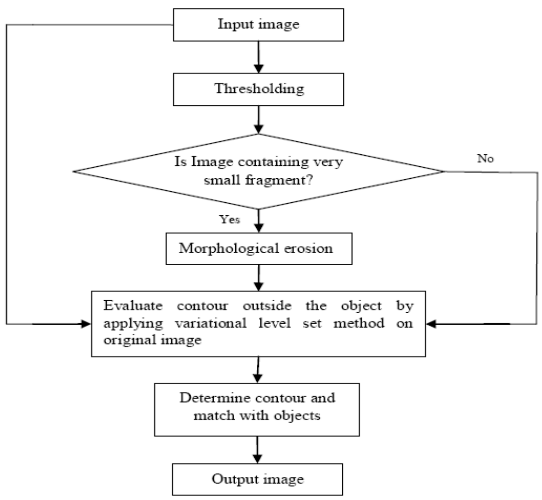


Fig 1 .Basic steps employed for new medical image segmentation technique based on level set method

Proposed Work:

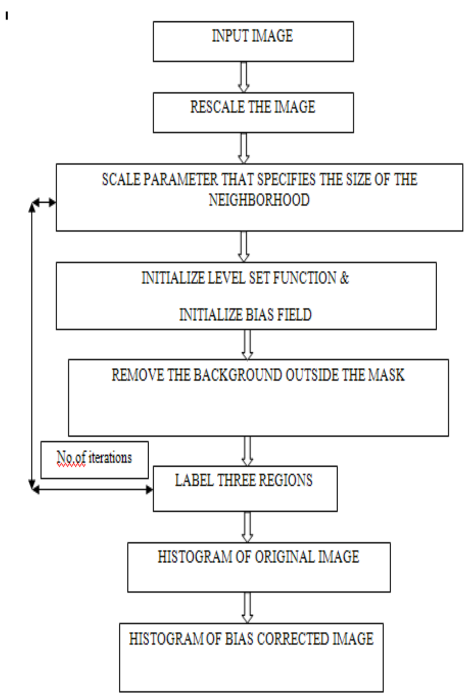


Fig 2 Steps employed for Image segmentation of Intensity Homogeneity based on level set method

3. Results:

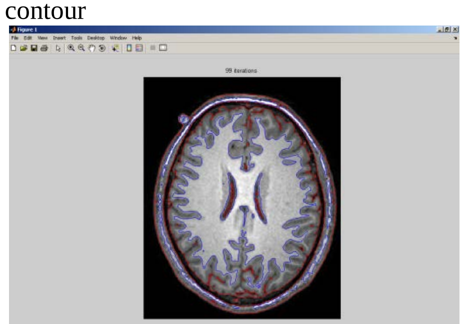
As a level set method, our method provides a contour as the segmentation result. Therefore, we use the following contour-based metric for precise evaluation of the segmentation result.

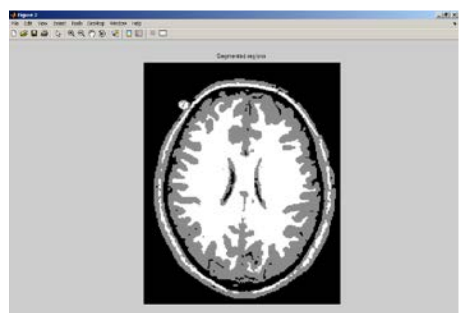
Let C be a contour as a segmentation result, and S be the true object boundary, which is also given as a contour. For each point Pi; i=1,2,3,…..N. on the contour , we can compute the distance from the point Pi to the ground truth contour , denoted by dist(Pi,S). Then, we define the deviation from the contour C to the ground truth S by

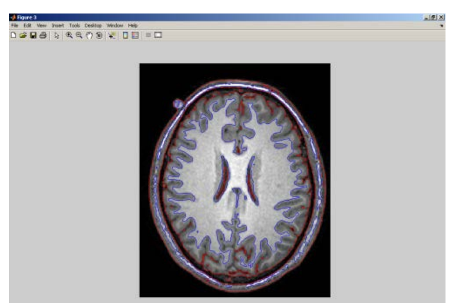
$$e_{\mathrm{mean}}(C) = \frac{1}{N}\sum_{n=1}^{N} \mathrm{dist}(P_i, S)$$

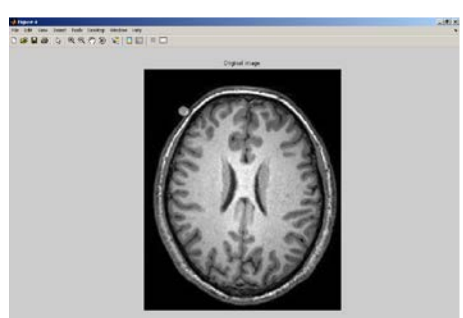
which is referred to as the mean error of the contour C.

This contour-based metric can be used to evaluate a subpixel accuracy of a segmentation result given by a contour









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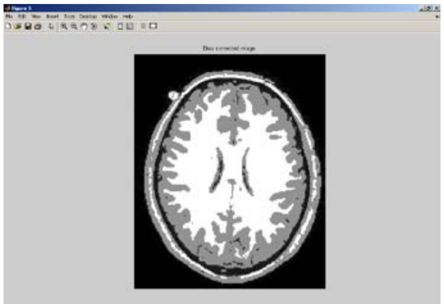

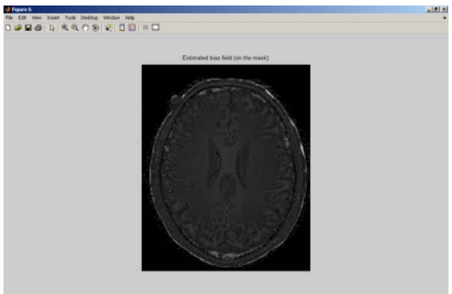

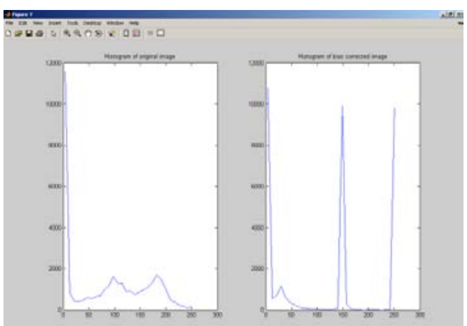

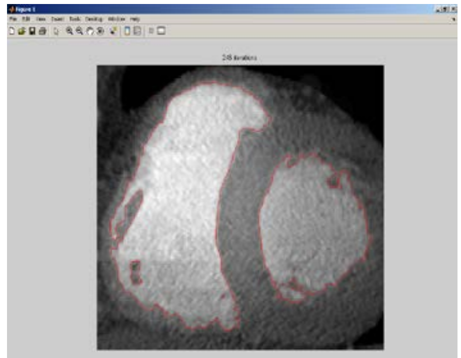

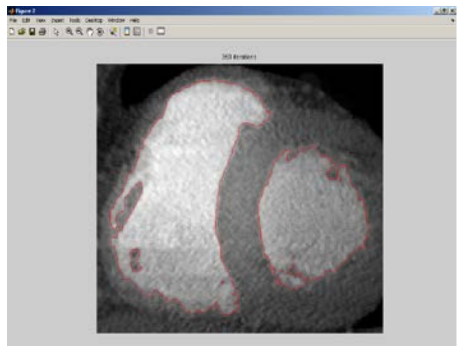

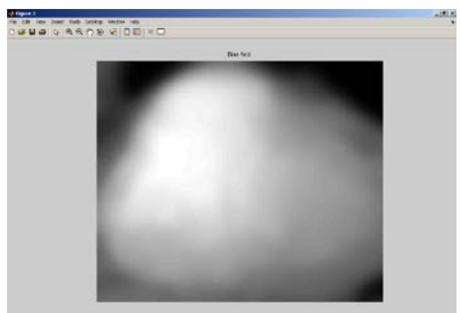

4. Conclusions

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. The histograms of the original images (left) and the bias corrected images (right) are plotted. 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.

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