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Medical Application of Image Segmentation with Intensity Inhomogeneities

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Abstract: ***Most image segmentation techniques are based on the intensity homogeneity. Intensity inhomogeneity frequently occurs in real word image like MRI, ultrasound, satellite images etc. This type of images fails to provide accurate segmentation result; this is challenging issue. In this paper propose a novel region based method for image segmentation, which is help to deal with intensity inhomogeneity images. First based on a 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 images intensities in a neighborhood of each point. This local clustering criterion is then integrated with respect to the neighborhood center to give global criterion of image segmentation. In a level set formulation, this criterion defines an energy in terms of level set function that represent a partition of the image domain and 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 he bias field, and the estimated bias field can be used for intensity inhomogeneity correction (or bias correction).***

Keywords: Intensity Inhomogeneity, Level set methods, Local Intensity clustering Property
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1. Introduction

The influence and impact of digital images on modern society is tremendous, and image processing is now a critical component in science and technology. The rapid progress in computerized medical image reconstruction, and the associated developments in analysis methods and computer-aided diagnosis, has propelled medical imaging into one of the most important sub-fields in scientific imaging. Many clinical and research applications using magnetic resonance (MR) images require a segmentation into different intensity classes which are regarded as the best available representations for biological tissues. Segmentation of MR Head scans is a prerequisite for three-dimensional visualization of brain surface and structures, surgery planning and guidance, detection of anatomical structures in brain morphometry, defining targets in radioactive therapy treatment and planning and derivation of brain anatomical Atlases. Manual segmentation of MR scans is both time-consuming and inconsistent and affected by operator Bias. A major obstacle to any automated method of segmentation of MR images is the presences of spatial intensity inhomogeneities.We refer to intensity inhomogeneities as no uniformities of intensities over the same class of tissues or structures, which are not caused by random noise.

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.

We propose a novel region-based method for image segmentation. From a generally accepted model 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.

2. The Level Set Method

The level set method was initially proposed to track moving interfaces by Osher and Sethian in 1988 and has spread across various imaging domains in the late nineties. It can be used to efficiently address the problem of curve/surface/etc. propagation in an implicit manner. The central idea is to represent the evolving contour using a signed function, where its zero level corresponds to the actual contour. Then, according to the motion equation of the contour, one can easily derive a similar flow for the implicit surface that when applied to the zero-level will reflect the propagation of the contour. The level set method encodes numerous advantages: it is implicit, parameter free, provides a direct way to estimate the geometric properties of the evolving structure, can change the topology and is intrinsic. Furthermore, they can be used to define an optimization framework as proposed by Zhao, Merriman and Osher in 1996. Therefore, one can conclude that it is a very convenient framework to address numerous applications of computer vision and medical image analysis. Furthermore, research into various level set data structures has led to very efficient implementations of this method.

3. Implementation

Let Ω be the image domain. Convert Ω to R(gray level), We can get image I.A segmentation of I is achieved by finding the contour C, In segmentation , the image seperates Ω1, Ω2,….., Ωn and piecewise smooth function μ that approximates the image I and this smooth inside each region Ωi.This can be formulated as a problem of minimizing the following Mumford -sha –functional equation(1)

$$\mathcal{F}^{MS}(u,C)=\int_{\Omega}(I-u)^2 d\mathbf{x}+\mu\int_{\Omega\setminus C}|\nabla u|^2 d\mathbf{x}+\nu|C| \quad (1)$$

Where |C| is the length of contour

In RHS, first term is data term, which forces μ to be close to the image I. Second term is smoothing term, which forces to be smooth within each of the region separates by the contour C.Third term is introduced by regularize the contour C.

Piecewise Smooth (PS) Model:

Let Ω be separated by contour and get Ω1, Ω2… Ωn regions;

$$\Omega\setminus C=\cup_{i=1}^{N}\Omega_i.$$

Then C can be expressed as the union of boundaries of the regions; ie C1, C2, C3,…..,Cn

$$C=\cup_{i=1}^{N}C_i.$$

Therefore, the above energy can be equivalently written as

$$\mathcal{F}^{MS}(u_1,\cdots,u_N,\Omega_1,\cdots,\Omega_N)=\sum_{i=1}^{N}\left(\int_{\Omega_i}(I-u_i)^2 d\mathbf{x}+\mu\int_{\Omega_i}|\nabla u_i|^2 d\mathbf{x}+\nu|C_i|\right)$$

Where, μi is a smooth function defined on the region Ωi. The methods aiming to minimize this energy are called *piecewise smooth (PS)* models. In level set methods were proposed as PS models for image segmentation.

To minimize this energy , N Partial derivative equations for solving the function μ1, μ2… μN associated with the corresponding smoothing terms are introduced and solved each time step in the evolution of contour C or the regions Ω1, Ω2, Ω3,…. ΩN. This procedure is too expensive. Another difficulty is sensitive initialize contour C or regions Ω1, Ω2, Ω3… ΩN.

$$\mathcal{F}^{MS}(u_1,\cdots,u_N,\Omega_1,\cdots,\Omega_N)=\sum_{i=1}^{N}\left(\int_{\Omega_i}(I-u_i)^2 d\mathbf{x}+\mu\int_{\Omega_i}|\nabla u_i|^2 d\mathbf{x}+\nu|C_i|\right)$$

Piecewise constant (PC) model:

Chan and vese simplified the Mumford Shah functional as the following energy,

$$\mathcal{F}^{CV}(\phi,c_1,c_2)=\int_{\Omega}|I(\mathbf{x})-c_1|^2 H(\phi(\mathbf{x}))\,d\mathbf{x}+\int_{\Omega}|I(\mathbf{x})-c_2|^2(1-H(\phi(\mathbf{x})))\,d\mathbf{x}+\nu\int_{\Omega}|\nabla H(\phi(\mathbf{x}))|\,d\mathbf{x} \quad (2)$$

Where, H is the Heaviside and ϕ is a level set function, whose zero level contour

$C=\{\mathbf{x}:\phi(\mathbf{x})=0\}$ Partitions the image domain into two disjoint regions;

$\Omega_1=\{\mathbf{x}:\phi(\mathbf{x})>0\}$;

$\Omega_2=\{\mathbf{x}:\phi(\mathbf{x})<0\}$.

The first two term are data fitting terms and third term, with a weight v regularizes the zero level contour. In PC model, image segmentation is achieved by find the level set function ϕ and the constants c1,c2 that minimize the energy $\mathcal{F}^{CV}$. This model is called pc model, as it assumes that image I can be approximated by constants c1 and c2 in the regions Ω1and Ω2.

4. Image Model and Problem Formulation

In this section explains how to get image, i.e. we can model the image from camera image or MRI image and problem formulation.

I = b J + n………….(3)

In equation (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 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 can be assumed to be zero-mean Gaussian noise

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. 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 energy in a variational framework, which is minimized for finding the optimal regions, constants and bias field. As a result, image segmentation and bias field estimation are simultaneously accomplished. Based on a 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 images intensities in a neighborhood of each point. This local clustering criterion is then integrated with respect to the neighborhood center to give global criterion of image segmentation.

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5. Local Intensity Clustering Property

Region based segmentation methods typically based on a region descriptor (for e.g.; intensity mean or Gaussian distribution) of the intensities in each region to be segmented. But it is difficult to give such a region descriptor for images with intensity in homogeneities so therefore impossible to segment directly based on the pixel intensities. Here we can based on the image modal and assumption A1 and A2, we are able to derive a useful property of local intensities, which is referred to as a local intensity clustering property.

To be short, we consider a circular neighborhood with radius ρ centered at each point y € Ω, defined by,

$$\mathcal{O}_{\mathbf{y}} \triangleq \{\mathbf{x} : |\mathbf{x}-\mathbf{y}| \leq \rho\}. \quad \text{....(3)}$$

The partition of entire domain { Ωi}i=1 to N; induced a partition of the neighborhood Ơy, ie ;{ Ơy∩ Ωi}i=1to N forms a partions of Ơy; For slowly varying bias field b,the values b(x) for all x in the circular neighborhood Ơy; are close to b(y),ie

$$b(\mathbf{x}) \approx b(\mathbf{y}) \quad \text{for} \quad \mathbf{x} \in \mathcal{O}_{\mathbf{y}}.$$

.... (4)

Then the intensities b(x)J(x) in each sub region Ơy∩ Ωi are close to through constant .Form a cluster with center m(i)=b(y)ci which can be considered as samples drawn from a Gaussian distribution with mean m(i).

Generally N clusters are separated by distinct cluster centers. This local intensity clustering property is used to formulate the proposed method for image segmentation and bias field estimation as follows. The above defined clustering property separated N clusters. This allows us to apply t he standard K mean clustering classify these local intensities.

The local clustering criterion is used to minimize the energy .We can proposed the energy €y. We can use level set method for minimizing energy .It is very difficult €y is convert to Ω1 to ΩN. we can use level set functions Here two phase level set function is used. This function used for minimizing energy. By minimizing energy we can obtain the image segmentation and bias field estimation.

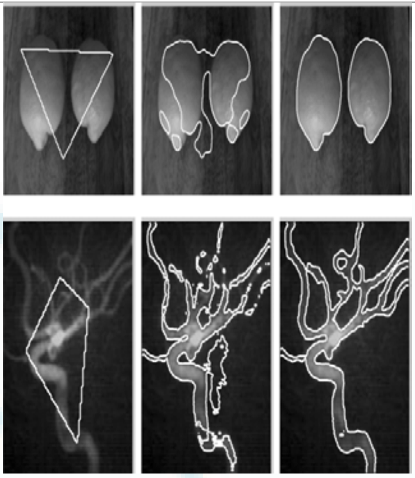

Figure 1: Segmentation for an image of Limon (upper row) and a CT image of vessel (lower row)

The left, middle, and right columns show the initial contours (a triangle for the limon image and a quadrangle for the vessel image), the intermediate contours, and the final contours, respectively.

6. Conclusion

In this project we propose a novel region-based method for image segmentation. From a generally accepted model of images with intensity inhomogeneities, a local intensity clustering property is being derived, and therefore defines 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.

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. Experimental results are followed by a discussion of the relationship between our model and the piecewise smooth Mumford–Shah and piecewise constant Chan–Vese models.

This Project involves following problem statements.

Given MR Image(s), find (in an automated way):

- The borders between different head compartments (segmentation).
- An appropriate map of the normal directions, in particular of the brain surface (classification).
- A representation useful for further finite element modelling.

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Need for Segmentation:

- To discriminate noise and textures (small scale structures).
- To incorporate prior knowledge
- To be flexible with respect to complicated shapes (or even topology).

These are issues before segmentation . First two issues treated via regularization,third via level set methods.

Regularization is a process, most often used in digital image processing that has applications in noise removal. It is based on the principle that signals with excessive and possibly spurious detail have high total variation, that is, the integral of the absolute gradient of the signal is high. According to this principle, reducing the total variation of the signal subject to it being a close match to the original signal, removes unwanted detail whilst preserving important details such as edges. This noise removal technique has advantages over simple techniques such as linear smoothing or median filtering which reduce noise but at the same time smooth away edges to a greater or lesser degree. By contrast, total variation denoising is remarkably effective at simultaneously preserving edges whilst smoothing away noise in flat regions, even at low signal-to –noise ratio.

To formulate the level set method to be applied for segmentation and its implementation. First we read heart MRI image. Then we can find segmentation in automated way. We can use region growing algorithm for segmentation. The region is iteratively grown by comparing all unallocated neighboring pixels to the region. The difference between a pixel's intensity value and the region's mean is used as a measure of similarity. The pixel with the smallest difference measured this way is allocated to the respective region This process stops when the intensity difference between region mean and new pixel become larger than a certain threshold . After segmentation we have face some issues .One is noise and texture. This issue solved by regularization method. Then we will formulate the level set method.

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