Level Set Approach for Segmentation of Intensity Inhomogeneity Image with Application to MRI

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Abstract— **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. This paper proposes a region-based method for image segmentation, which is able to deal with intensity inhomogeneities in the segmentation. An interactive modulation of the front speed, depending on various boundary and regularization criteria ensures this goal. Here, level set method is used to capture interfaces. Energy minimizing splines called snakes are also used which are guided by external and internal constraints and are influenced by image forces that pull them towards features like lines and edges. Therefore, by minimizing this energy, our method is able to simultaneously segment the image and estimate the bias field which can be used for intensity inhomogeneity correction. Our method is validated on synthetic images and real images of various modalities, with desirable performance in the presence of intensity inhomogeneities.**

Keywords— Image segmentation, level set, snake algorithm, MRI,intensity inhomogeneity.

I. INTRODUCTION

Diagnostic imaging is an invaluable tool in medicine today. Magnetic resonance imaging (MRI), computed tomography (CT), digital mammography and other imaging modalities provide an effective means for noninvasively mapping the anatomy of a subject. These technologies have greatly increased knowledge of normal and diseased anatomy for medical research and are a critical component in diagnosis and treatment planning. With the increasing size and number of medical images, the use of computers in facilitating their processing and analysis has become necessary. In particular, computer algorithms for the delineation of anatomical structures and other regions of interest are a key component in assisting and automating specific radiological tasks. These algorithms, called image segmentation algorithms, play a vital role in numerous biomedical imaging applications.

II. SEGMENTATION OF IMAGE

An image is a collection of measurements in two-dimensional (2-D) or three-dimensional (3-D) space. In medical images, these measurements or image intensities can be radiation absorption in X-ray imaging, acoustic pressure in ultrasound or RF signal amplitude in MRI. Images may be acquired in the continuous domain such as on X-ray film or in discrete space as in MRI. In 2-D discrete images, the location of each measurement is called a pixel and in 3-D images, it is called a voxel.

Image segmentation is defined as the partitioning of an image into non-overlapping, constituent regions which are homogeneous with respect to some characteristic such as intensity or texture. Classically, image segmentation is the process of separating or grouping an image into different parts. These parts normally correspond to something that humans can easily separate and view as individual objects. Computers have no means of intelligently recognising objects, and so many different methods have been developed in order to segment images. The segmentation process in based on various features found in the image. This might be colour information that is used to create histograms, or information about the pixels that indicate edges or boundaries or texture information.

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. Some of the segmentation methods are thresholding, live-wire boundaries and watershed transforms.

III. MAGNETIC RESONANCE IMAGING (MRI)

In practice, images obtained from MRI acquisition systems, exhibit intensity inhomogeneities which appear for different reasons. One source of error is spatial variations in the magnetic fields during the measurement. Another is the regional differences in the magnetic properties of the biological materials. They can cause the effective magnetic field to become non-uniform. Next to such technical reasons, intensity inhomogeneities are also introduced through unavoidable movement of the person during the scanning procedure.

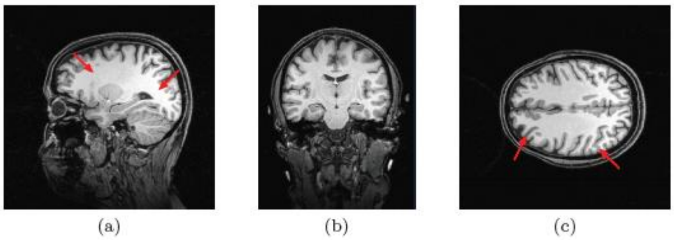


Fig.1. a) sagittal b) coronal c) axial orientations of MR image of brain.

Fig.1. indicates the visual impact of intensity inhomogeneity. The two arrows point in areas of different mean intensity values within the white matter.

IV. PROPOSED SYSTEM

A. Level Set Method

The level set method has been used to capture interfaces rather than tracking. Since the method is stable, the equations are not unnecessarily stiff, geometric quantities such as curvature become easy to compute and three dimensional problems present no difficulties, this technique has been used in a wide collection of problems involving moving interfaces. They embed the initial position of the moving interface as the zero level set of a higher dimensional function and link the evolution of the new function to the evolution of the interface itself through a time-dependent initial value problem. At each time, the contour is given by the zero level set of higher dimensional function.

It is possible to restrain the computation domain to a band of cells around the zero-level set for the decrease of the computational cost. Classical approaches are referred to as narrow-band methods. The level set method requires specifying initial curves and can only provide good results if these curves are placed near symmetrically with respect to the object boundary. When using the level set method in image segmentation, an initial front should be chosen appropriately and let it propagate with a speed function that stops the motion when the boundary is reached. So the initial front and the speed function are important ones to decide the accuracy of the final segmentation. Thus, level set segmentation is not sufficient for the segmentation of complex medical images. They must be combined with powerful initialization techniques in order to produce successful segmentation.

B. Snakes/Energy Minimizing Splines

Snakes are energy minimizing splines that are guided by external constraints and internal constraints and are influenced by image forces that pull them towards features like lines and edges. Snakes are so called due to the wriggling motion they undergo while minimizing their energy functions. They are designed to be interactive, in that the user must give some clues as to where about the boundaries are and then snakes are used to minimize the energy and so trace the contour or boundary. Snakes work on the assumption that edges are found not only by looking at the local gradient but also at the long range distribution of the gradient. This is done by using curvature constraints as well as continuity constraints. Snakes have an internal energy function which determines their elasticity and rigidity, and an external energy function based on image information and user interaction.

C. Combination of Snake and Level Set Method

In the initial step, the noise corrupting the image is reduced by noise reduction technique. This noise suppression allows a more accurate calculation of the image gradient and reduction of the number of the detected false edges. Except for the pre-processing stage, our segmentation strategy uses snake transform as a pre-segmentation tool and then refine the segmentation result with the level set method. This approach combines the advantages of both methods: the snake transform pre-segmentation which is rough but quick and the level set, that needs only a few iterations to produce the final, fast and smooth segmentation.

The decision of choosing the snake segmentation as the initialization of the level set method is according to the following reasons. The first reason is, if the real boundaries of interested objects are overlapped, then with the result of snake transform, the blindness of segmentation is reduced and the accuracy of segmentation is improved. The second reason is for improving the computation speed. There is no need to compute arriving time of the inside point of sub-regions, hence the whole computation cost will be reduced.

The snake algorithm is applied to the gradient magnitude of the original image data set. The output of the snake algorithm is a partitioning of the input data in volume regions of which the interior does not contain any sharp gray value transitions. Since all the crest lines of the data set are detected, the algorithm leads inevitably to an over segmentation of the data. Therefore, noise filtering pre-processing is needed to be applied to the image data first. After the initial segmentation based on snake transform, the final segmentation is accomplished based on level set method. By combining snake transform and level sets, highly accurate segmentations of topologically and geometrically complex structures are produced in less time.

In level set framework, the interface is implicitly moved. This is mathematically described by Partial Differential Equations and the framework defines three different kinds of motion. These are motion in an externally generated velocity field, motion in normal direction and motion involving mean curvature. The most general form for propagation of fronts using level set method which involves all the kinds of motion is described by

$$\varphi_t + \vec{V} \cdot \nabla\varphi + V_n|\nabla\varphi| + b_k|\nabla\varphi| = 0 \qquad (1)$$

where φ_t is partial derivative in time t, ∇ is divergence and $\vec{V}$ is external velocity field. The solution to this equation is approximated by scheme based on finite differences.

V. NUMERICAL IMPLEMENTATION

In numerical implementation, Kernel function is chosen as Gaussian function K given by

$$K(u) = \begin{cases} e^{-|u^2|/2\sigma^2}, & for|u| \le \rho \\ 0, \ otherwise \end{cases} \qquad (2)$$

The Heaviside function is replaced by a smooth function called the smoothed Heaviside function, which is defined by

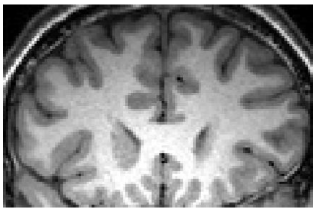
$$H(x) = \frac{1}{2}[1 + \frac{2}{\pi} + \arctan\left(\frac{x}{\epsilon}\right)] \qquad (3)$$

Accordingly, the dirac delta function, which is the derivative of the Heaviside function , is replaced by

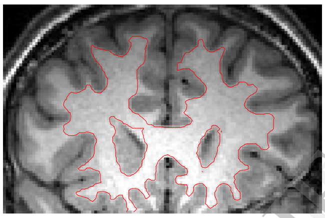
$$\delta(x) = \frac{1}{\pi}[\frac{\epsilon}{\epsilon^2 + x^2}] \qquad (4)$$

The parameters such as μ and time step Δt can be fixed. The parameter ν is usually set to $0.001 x 255^2$ as a default value for most of digital images with intensity range in [0, 255]. The parameter σ and the size of the neighborhood (specified by its radius ρ) should be relatively smaller for images with more localized intensity inhomogeneities. The convolution kernel K is constructed as a *w* x *w* mask, with *w* being the smallest odd number such that $w \ge 4\sigma + 1$.

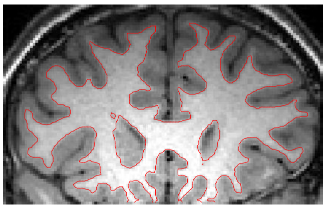
VI. RESULT



a) Initial Contour



b) Intermediate Contour



c) Final Contour

Fig. 2. Image Segmentation results.

VII. CONCLUSION

Level set method is a numerical technique used for tracking moving interfaces. In the level set framework interfaces are represented by the implicit function and all points having the same value in this implicir functon form level sets. Movement is computed and represented by changes in implicit function. Implicit active contours are the models that apply level set methods to image segmentation. Their main task is the extraction of meaningful regions. The fundamental principle is the transformation of image or model information into velocity fields that drive the interface towards the required boundaries. Early approaches just incorporated edge-based information. Gradients were used to stop the propagation at the objects boundary. However gradients usually vary in their magnitude and can only be sufficiently applied if they are an important property of the object. As a result of this drawback, models including region-based information have been developed. Level set method show many advantages in the field of image segmentation. They immanently allow for topological changes, maintain a constant resolution of the interface and preserve smooth surfaces.

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