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Analysis of Image Segmentation and Edge Detection in Medical Images

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Abstract—Accurate Image segmentation and edge detection are fundamental for Medical diagnosis, Locate tumours and other pathologies, Measure tissue volumes, computer-guided imaginary, Treatment Planning and Study of anatomical structure. The proposed method for image segmentation is Active contour model. It uses parameterized representation of evolving curves to segment image images. It utilizes edge information of the image to lock the evolving curve on to the boundary of the objects in image. The second Geodesic Active contour method uses both edge and region information for segmentation. There are some Images whose boundaries are not well defined called "without edges" segmented through new region based active contour model. Recent Developments, reported in this paper, demonstrate that the proposed segmentation algorithms outperforms some well-known methods in both accuracy and processing speed**.**

Keywords: Active contour model, Edge Detection, Image processing, Image Segmentation, Region based active contour model.

I. Introduction

There are many techniques available for auto-segmentation of image like fuzzy based classifiers, Gradient Vector Field theory, tensor based segmentation etc. But most of them are suffering from problems like strucking at local minima, repeated initialization problems, and insufficient results in case of noisy images[5].

Most Image segmentation approaches proposed in the literature require highly complex-exhaustive search and learning of many modeling parameters and Characteristics, which prevents their effective real-time applications and makes the system highly sensitive to noise.

This paper presents a fast and efficient Image segmentation methodology to address relatively simple solutions to these problems. The proposed system uses three models, namely (1) Active Contour Model (2) Geodesic Active Contour Model (3) Region Based New Active Contour model. Computational difficulties of these Models for tackling changing topology of evolving curves were solved using Level set theory.

A curve [11]-[12] can be represented using explicitly or implicitly. It is found that implicit representation of curves using level set of a function is computationally suitable and traceable for image segmentation and edge detection problems [1]-[4].

In this paper Section 2 deals with Current image Segmentation Methods, We propose a new method for Image Segmentation and Edge Detection in section 3, Section 4 deals with our Recent Developments and finally section 5 Conclusions is presented.

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II. Current Methods in Image Segmentation

Segmentation is one of the most difficult tasks in medical image processing. Image Segmentation algorithm generally based on the two basic properties of intensity values. (1) Discontinuity (2) Similarity. The following are some of the Existing Image Segmentation Methods,

A. *Histogram Based Methods*

Histogram-based methods are very efficient when compared to other image segmentation methods because they typically require only one pass through the pixels.

In this technique, a histogram is computed from all of the pixels in the image, and the peaks and valleys in the histogram are used the clusters in the image. Color or intensity can be used as the measure.

B. *Edge Detection*

Edge detection is a well-developed field on its own within image processing. Region boundaries and edges are closely related, since there is often a sharp adjustment in intensity at the region boundaries.

C. *Region Growing Methods*

Region growing method was the seeded region growing method. This method takes a set of seeds as input along with the image. The seeds mark each of the objects to be segmented. The regions are iteratively grown by comparing all unallocated neighboring pixels to the regions.

The difference between a pixel's intensity value and the region's mean (δ) is used as a measure of similarity. The pixel with the smallest difference measured this way is allocated to the respective region. This process continues until all pixels are allocated to a region.

D. *Level set Methods*

Curve propagation is a popular technique in image analysis for object extraction, object tracking, stereo reconstruction, etc.

E. *Graph Partitioning Methods*

Graph Partitioning Methods can effectively be used for image segmentation. In these methods, the image is modeled

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as a weighted, undirected graph. Usually a pixel or a group of pixels are associated with nodes and edge weights define the dissimilarity between the neighborhood pixels.

The graph is then partitioned according to a criterion designed to model "good" clusters. Each partition of the nodes (Pixels) output from these algorithms are considered an object segment in the image. Some popular algorithms of this category are normalized cuts, random walker, minimum cuts, isoperimetric partitioning and minimum spanning tree based segmentation.

III. PROPOSED WORK

A. *Edge Based Image Segmentation*

To snap curve around the boundary of a given Image f, we add a term to the PDE above: $u_t = g(x, y)$.

K. $|\nabla u|$, where g(x, y) is a function designed to slow down the motion to $u_t = 0$, when the curve hits an edge in the image, Casselles et.al [4] suggest using

$$g(x, y) = \frac{1}{\left(1+|\nabla f|\right)^2} \qquad (1)$$

Note $g \approx 0$ when ∇f is large. Also note that this is a constant (since is derived from the image under consideration), it is not updated as the curve evolves That is g(x, y) is information taken from the image f and it does not change. The matrix g should be computed only once in the program, outside the loop.

Now we write a function that takes a gray scale image f and an initial level set function u as input. Then we evolve u so that the zero level set snaps around the objects in the image. At each iteration, we plot the zero level curves in red on top of the grayscale image f. After detecting Image gray scale image, you will have to first resize the image to the same size as the level set function u.

F = imresize (f, size (u)); (2)

Note that corresponding to a point in level set there is a point in image. Level set the theory is about evolving the level sets (first image) over time (iteration) according to the geometric properties of the level set (example a quantity representing curvature) and according to image (second image) properties (example magnitude of the gradient of the image) along the normal to the level set.

We visualize the process of evolution as 'local image properties act as force on the level set curves to change the level set values'. The net effect is that zero level set at time t = 0 moves to another location in its neighbourhood at time t = Δt. Needless to say that all other level set curves change its location over time.

Formulation of the problem of evolution is made such a way that zero level set function won't change (evolve) its location once it is aligned over object boundaries. That is, the zero level set lock on the boundary of the objects .During the curve evolution, the level set image u might become far from being a smooth distance function. In order to stabilize the algorithm, one needs to re-complete this distance function. It is a time consuming step. This is very essential if we are segmenting complex images.

1) *Problem of weak edge leakage*

It is found that the edge stopping is not robust and could not stop leaking of the boundaries. This means that if the level set front propagated and crossed the object boundary, then it could not come back, so caselles et.al and Kichensamy introduced a pullback term $(\nabla g, \nabla u)$, and the model is called Geodesic active contour. This term attracts the curve back to the boundary. However this method still suffers from boundary leaking for complex structures.

$$u_t = g(x, y).K.|\nabla u| + (\nabla g, \nabla u) = g(x,y).|\nabla u|.\mathrm{div}\left(\frac{\nabla u}{|\nabla u|}\right) + \langle \nabla g, \nabla u \rangle \qquad (3)$$

This is because ∇g becomes zero beyond the weak boundary. For redistancing 'u' we may use

u = [u > 0];

u = (1–u).*bwdist – u.*bwdist(1–u);

u = double (u);

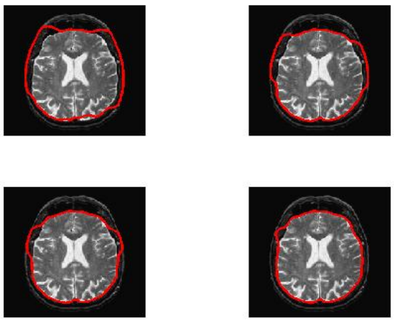

Fig 1:- Evolution of Level set in Geodesic Active contour Model

B. Formal theory behind edge based image segmentation

In this section we lists the fundamental properties of levelset curves and derive the curve evolution equation $\frac{\partial u}{\partial x} = F|\nabla u|$.

The geometric quantities of a curve C defined by a zero levelset function of u are

1. Unit normal to the curve in outward direction

$$\overrightarrow{\mathbf{N}} = \begin{pmatrix} \mathbf{N}_1 \\ \mathbf{N}_2 \end{pmatrix} = -\frac{\nabla \mathbf{u}}{|\nabla \mathbf{u}|} \qquad (4)$$

(Negative sign is because u is defined such that it is increasing inward. See figure 23.1 for more details)

2. Curvature at $(x, y) \in C$

$$K(x, y) = \frac{\partial}{\partial x}\left(\frac{u_x}{\nabla u}\right) + \frac{\partial}{\partial y}\left(\frac{u_y}{\nabla u}\right) \qquad (5)$$

This equation is similar to the EL equation for $\min_u \int_R |\nabla u| \, dxdy$

3. Heaviside function

$$H(u) = \begin{cases} 1, \text{if } u \ge 0 \\ 0, \text{if } u < 0 \end{cases} \quad (6)$$

Delta function, first derivative of Heaviside function is, $\delta(u) = H'(u)$.

4. Area enclosed by the curve C

$$A\{u \ge 0\} = \int H(u)\,dxdy \quad (7)$$

Inside the curve C, H has value 1 or otherwise 0.

5. Length of the curve

$$L\{C\} = \int |\nabla H(u)|\,dxdy \quad (8)$$

$|\nabla H(u)|$ has value only at the edge of the curve.

6. Mean value of a function (in our case an image)

$$\text{mean}(f)_{u\ge0} = \frac{\int f(x,y)H(u(x,y))dxdy}{\int H(u(x,y))dxdy} \quad (9)$$

This will give the mean value of f inside the curve.

$$\text{mean}(f)_{u<0} = \frac{\int f(x,y)(1-H(u(x,y)))\,dxdy}{\int (1-H(u(x,y)))\,dxdy} \quad (10)$$

It gives the mean value of f outside the curve.

1) PDE Formulation of Curve Evolution equation

Now, our aim is to evolve the curve over time $t \ge 0$. Let

$$C(t) = \{(x, y) \in \Omega : u(x, y, t) = 0\} \quad (11)$$

The curve C moves in the normal direction based on the equation

$$C'(t) = F\vec{N} \quad (12)$$

Where F is the speed function. This is derived as follows.

Differentiating $u(x, y, t) = 0$ with respect to time t in order to find the rate of change of $u(x, y)$, at zero level set.

$$\frac{d}{dt} u(x(t, s), t) = 0 \quad (13)$$

$$\frac{\partial u}{\partial t} + \frac{\partial u}{\partial x}\frac{\partial x}{\partial t} + \frac{\partial u}{\partial y}\frac{\partial y}{\partial t} = 0 \quad (14)$$

Where x (t, s), y (t, s) represent zero level set curve with s as the fictitious parameter [8]-[10]. That is, when s is changed from 0 to 1, x (t, s), y (t, s) traces the full curve.

We know that,

$$C'(t) = \left(\frac{\partial u}{\partial t}, \frac{\partial y}{\partial t}\right) \quad (15)$$

So,

$$\frac{\partial u}{\partial t} + \frac{\partial u}{\partial x} N_1F + \frac{\partial u}{\partial y} N_2F = 0 \quad (16)$$

Where N_1F and N_2F are the components of the velocity vector whose magnitude is F. Vector $\begin{pmatrix} N_1 \\ N_2 \end{pmatrix}$ form a unit normal to the curve at (x, y) on the curve C(t). So

$$C'(t) = \left(\frac{\partial x}{\partial t}, \frac{\partial y}{\partial t}\right) = F\begin{pmatrix} N_1 \\ N_2 \end{pmatrix} = F\vec{N} \quad (17)$$

(18) can now be written as

$$\frac{\partial u}{\partial t} + F\nabla u.\vec{N} = 0 \quad (18)$$

From equation (5)

$$\frac{\partial u}{\partial t} = F|\nabla u| \quad (19)$$

In the earlier section we used curvature K as the force function F driving the evolution of level set.

C. Region based models

There are some objects whose boundaries are not well defined through the gradient. For example, smeared boundaries and boundaries of large objects defined by grouping smaller ones

Chan and Vese introduced a new active contour model, called “without edges”. The main ideal is to consider the information inside the regions in addition to edge information. Chan and Vese define the following energy,

$$E(u, c_1, c_2) = \mu \int_\Omega \delta(u)|\nabla u| dxdy + \nu \int_\Omega H(u) dxdy + \lambda_1 \int_\Omega |f - c_1|^2 H(u) dxdy + \lambda_2 \int_\Omega |f - c_2|^2 (1 - H(u)) dxdy \quad (20)$$

Where f is the original image and c_1, c_2 are constants representing average pixel value inside and outside of curve C. H(u) is given by

$$H(u) = \begin{cases} 1, \text{if } u \ge 0 \\ 0, \text{if } u < 0 \end{cases} \quad (21)$$

This model looks for the best approximation of image f as a set of regions with only two different intensities (c_1 and c_2). One of the regions represents the objects to be detected (inside of C) and the other region corresponds to the background (outside of C). The snake C will be the boundary between these two regions.

In equation (24) the last two terms are fitting terms which guide the curve to the boundaries of the object.

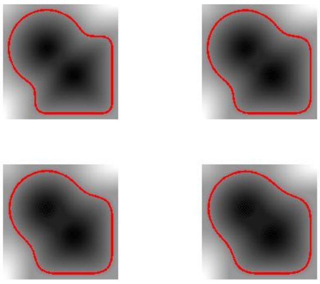

Fig:- 2 shows that fitting terms $E_1(C)$ and $E_2(C)$ are minimized only at the object boundary.

The first fitting term $E_1(C)$ gives the error resulting from approximating the original image inside C with c_1 and the second fitting term $E_2(C)$ gives the error resulting from approximating the original image outside C with c_2. The solution can be obtained by approximating H(u) and δ(u) and by solving the following three equations.

$$c_1 = \frac{\int_\Omega f(x,y)H(u)dxdy}{\int_\Omega H(u)dxdy}$$

$$c_2 = \frac{\int_\Omega f(x,y)\left(1-H(\phi)\right)dxdy}{\int_\Omega \left(1-H(\phi)\right)dxdy}$$

$$\frac{\partial u}{\partial t} = \delta(u)\left(\mu \, \mathrm{div}\left(\frac{\nabla u}{|\nabla u|}\right) - |f-c_1|^2 - |f-c_2|^2\right) \quad (22)$$

Where the last equation (23) is the Euler-Lagrange equations for (22).Chan Vese model is related in spirit to the Mumford-Shah functional , which can be given as

$$E_{MS}(C,u) = \mu \, \mathrm{length}(C) + \nu \, \mathrm{area}(\mathrm{inside}\ C) + \underbrace{\int_\Omega |u-f|^2 dxdy}_{\text{fitting term}} \quad (23)$$

Where u, the cartoon image approximating f is smooth except for jumps on the set C of boundary curves and the contour C segment the image into piecewise constant regions. The method in (23) is a simple approximation to (24) in that only two subregions are allowed in which u is piecewise constant. So u for (24) can be written as

$$u = c_1 H(u) + c_1\left(1-H(u)\right) \quad (24)$$

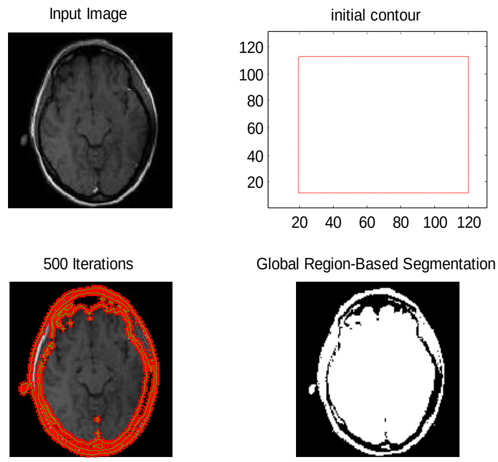

Fig:-3 Evolution of the curve evolution in Chan vase model

1) Mat lab implementation of Chan-vese model

For implementing (30) using level set theory, we replace δ(u) by |Δu|. So level set evolution becomes,

$$\frac{\partial u}{\partial t} = |\nabla u|\left(\mu \, \mathrm{div}\left(\frac{\nabla u}{|\nabla u|}\right) - |f-c_1|^2 - |f-c_2|^2\right) \quad (25)$$

Figure:-3 show that evolution of level set that finally locks on the boundary.

IV. Recent Developments

Optimization methods developed for compressed sensing is finding its way to many image processing applications. Most of the optimization methods in this category are convex optimization. Now segmentation problem can be formulated as a strict convex optimization problem. An active contour model was proposed which has global minimisers [7]. This Active contour is calculated by minimizing the following convex energy:

$$E[u] = \|\nabla u\|_1 + \mu \langle u, r \rangle \quad (26)$$

With $r = (m_f - f)^2 - (m_b - f)^2 \quad (27)$

Here, f represents the intensity values in the image, m_f and m_b are respectively images with mean intensity of the segment and the mean intensity of the background, i.e. every pixel not belonging to the segment. Note that this energy is convex, only if m_f and m_b are constant. This problem can be solved by iterating between the following two steps: first fix m_f and m_b and minimize equation (26), secondly update m_f and m_b.

In the convex energy function in (26) was generalized in order to incorporate edge information

$$E[u] = \|\nabla u\|_{1,g} + \mu \langle u, r \rangle \quad (28)$$

Where g is the result of the edge detector,

E.g $g = \frac{1}{1+|\nabla f|'}$

Here we define

$$\|\nabla u\|_{\alpha,g} = \sum_{x,y} (g(x,y)(|\nabla u(x,y)|^{\alpha}))^{1/\alpha}$$

So, $$\|\nabla u\|_{1,g} = \sum_{x,y} \frac{|\nabla f(x,y)|}{1+|\nabla f(x,y)|}$$

The active contour minimizing this energy function can be seen as a combination of edge based snake active contours[6] and the region based Chan-vase active contours[3]. Since this method only minimizes energy terms based on the image, it is highly influenced by the quality of the image. In the presence of noise and clutter the method will find false segments or distorted segment boundaries. In order to make the method more robust method was proposed to extend the energy function in (28) with an extra regulation term:

$$E[u] = \|\nabla u\|_1 + \gamma \|\nabla u\|_{1,g} + \mu < u, r > \qquad (29)$$

Where γ is a weighting parameter defining the influence of the extra regularization therm. This regularization term approximates the length of the segments boundary, thus penalizing small false segments and high curved boundaries due to noise.

V. Conclusions

Level set method can be a fast and accurate approach that can be used in segmentation and reduce human interaction as possible. The active contour without edges method provides a robust way of taking into account region information, including textures.Active contour uses image values and a target Geometry,level set method uses image values and a target geometry but in higer dimension with a different motion. Recent formulations combine region and edge information in a unified framework.

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