Role of Active contour Models in Image Segmentation

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Abstract:

Due to rapid development in medical imaging technology, amount of information generated is increasing rapidly. To handle this large amount of information, automation is desperately needed. Also, manual segmentation techniques are time-consuming and require intensive human effort. It is also subjected to high variations from one expert to another. Medical images possess intensity inhomogenity. They are corrupted with noise, and often have blur boundaries so segmentation is challenging. For segmenting medical images, we may employ techniques such as region growing, watershed segmentation, global thresholding, artificial intelligence etc. Our driving application, in this paper, is the extraction of contour from the ultrasound images.

I. Introduction

The curves or surfaces that deform under the influence of internal and external forces to delineate object boundary are deformable models. The internal forces preserve the shape smoothness and the external forces drive the model toward the desired region boundaries.

Deformable models are classified as parametric and geometric deformable model. The parametric model uses explicit representation based on Lagrange formulation.

An active contour is a top-down approach, which was introduced by Kass in 1988. It is widely used in regional tracking, edge detection, object classification, and motion tracking. It reduces human intervention in the task of segmentation. Energy functional F which is associated with closed contour curve is minimized to evolve curve toward the object boundary. An energy function F has two components. First is external component which is used for pulling the contour towards desired image features. Second component is internal energy component which helps in smoothing the boundaries. Energy functional F is minimal at object boundary. In order to locate the boundary of region of interest, active contour model integrates the boundary and region information with curve theory and optimization methods [6].

II. Active Contour Model

An early implementation of active contours, called Snakes. It is parametric deformable models. The active contour models are visually represented as closed contours (like an irregular balloon or bubble). In active contour model energy is dependent upon contours shape and location within an image. Local energy minima represent the corresponding image properties. Snakes depend on initial shape and location which is near to object of interest. We may have open (like a length of string) or closed (more like balloons) snakes [5].

Snake model shows improved reliability and accuracy of contour extraction compared to conventional moving target detection algorithm. It uses local and global information to achieve the objectives of the exact location of the border.

A traditional parametric active contour (or snake) is a curve $P(s) = [x(s), y(s), s \in [0,1]$, which moves through the spatial domain of an image to minimize the energy functional [2].

The energy function of snakes is:

$$E'_{snake}=\int_0^1 E_{snake}(v'_s)ds= \int_0^1 E_{int}(p'_s) + + E_{ext}(p'_s)\, ds \qquad (1)$$

Internal energy is expressed as:

$$E_{int}=\frac{1}{2}(\alpha_s\,|p'(s)|^2 + \beta|p''(s)|^2 \qquad (2)$$

$p'(s)$ an d$p''(s)$ express the first and second derivatives about $p_{s;}$ α,β respectively express the elastic force and bending forces weights, they determine degree of extension and bending.

III. Level set

It is a geometric deformable model, proposed independently by Caselles and Malladi which depend on a definition of speed function for curve evolution. The speed and direction of the propagation is determined using image gradient and curvature. Curve evolution is independent of parameterization. Level set uses implicit representation to handle topological changes.

Three different geometric active contour models are as follows: (1) Geodesic Active Contour Model; (2) Chan and Vese Model; (3) Localizing Region-Based Active Contour Model.

A. GAC Model

Suppose a curve drawn around any object be represented by $\gamma(t)$ and curve is moving toward the boundary of that object. Let t represents the iteration number and a signed distance function is denoted byΨ. Thus, distance of point (x,y) to the curve $\gamma(t)$ is $\Psi(x,y)$.When (x,y) is on the curve then $\Psi(x,y) = 0$. When (x,y) is inside the curve, $\Psi(x,y)<0$ and it is greater than zero for point outside the curve.

Image I(x,y) and Ψ have same diamension. Level-set function of Ψ is curve $\gamma(t)$. $\Psi=0$ represents 0^{th} level set,$\Psi=1$ represents 1^{st} level set and so on. $\gamma(t)$ is represented implicitly by Ψ. Ψ undergoes evolution under the influence of image gradients and regions characteristics when the curve $\gamma(t)$ approaches the boundary of the object. Ψ is evolved rather than evolution of the parametric curve $\gamma(t)$.

The 0^{th} level set of Ψ be curve $\gamma(t)$ be. This implies that,

$$\frac{\partial\Psi}{dt} = 0$$

Using chain rule

$$\frac{\partial\Psi}{\partial t} = \frac{\partial\Psi}{\partial x}\frac{\partial x}{\partial\Psi} + \frac{\partial\Psi}{\partial y}\frac{\partial y}{\partial\Psi} + \frac{\partial\Psi}{\partial t}$$

i.e.,

$$\frac{\partial\Psi}{\partial t} = -\nabla\Psi.\gamma'(t)$$

Let the normal component be (N(t)) and tangential component be (T(t)) of the $\gamma'(t)$

$$\frac{\partial\Psi}{\delta t} = -\nabla\Psi.(v_N(N(t) \ + v_T(T(t)$$

$\nabla\Psi$ is perpendicular to tangent to $\gamma(t)$,

$$\frac{\partial\Psi}{\delta t} = -\nabla\Psi.(v_N(N(t)) \qquad (2)$$

The normal component is given by

$$N=\frac{\nabla\Psi}{||\nabla\Psi||}$$

So equation (2) is

$$\frac{\partial\Psi}{\delta t}=-\left(div\left(K\frac{\nabla\Psi}{||\nabla\Psi||}\right)+cK\right)||\nabla\Psi||$$

Thus the evolution equation for Ψ_t is given by (3) when $\gamma(t)$ remains at 0^{th} level set,

$$\Psi_t = -K(c+\varepsilon k)\,||\nabla\Psi|| + \nabla\Psi\,.\,\nabla K \qquad (3)$$

Where K represents the stopping term used to decelerate the evolution near the boundaries, velocity of the evolution, degree of smoothness, curvature of the level set are represented by c,ε and k respectively.

$$\boldsymbol{k}=\frac{-\varphi_{xx}\,.\varphi_y^{\,2}\;-2\varphi_x\,.\varphi_y\,\varphi_{xy}+\varphi_{yy}\;\varphi_x^{\,2}}{(\varphi_y^{\,2}+\varphi_x^{\,2})^{3/2}}$$

where φ_x is the gradient of the image in the *x* direction, φ_y is the gradient of the image in the *y* direction, $\varphi_{xx}$is the second-order gradient in the *x* direction, $\varphi_{yy}$is the second order gradient in the *y* direction and φ_{xy} is the second-order gradient first in the *x* direction, then in *y* direction. Exp. (3) is the level-set representation of the GAC model. This means that the level-set C of Ψ is evolving according to,

$$C_t = -K(c+\varepsilon k)\,N - (\nabla K\,N\,).N \qquad (4)$$

where normal to the curve is represented using N. The total curvature of the level sets is reduced using first term. The pushing of the curve outward towards the object boundary is done using second term. The stopping function slows down the evolution at the boundaries. However, the evolution of the curve will terminate only when K=0, i.e., near an ideal edge. In most images, the gradient values will be different along the edge, thus, necessitating different K values. In order to circumvent this issue, the third geodesic term ($\nabla K\,N$) is necessary so that the curve is attracted towards the boundaries (∇K points towards the middle of the boundary).This term makes it possible to terminate the evolution process even if (a) the stopping function has different values along the edges, and (b) gaps are present in the stopping function.

The stopping term used for evolution of level sets is given by

$$K(x,y)=\frac{1}{1+\frac{||\nabla G(x,y)*I(x,y)||^{\alpha}}{k}} \qquad (5)$$

B. Chan-Vese Model

Chan-Vese Model is based on homogeneity criteria of both the object to be segmented and background. For image I in domainΩ, level set function ϕ : R->ϕ , the Chan-Vese energy function ε(ϕ) is as follows:

$$E^{cv}(c_1,c_2,C) = \mu.Length\,(C) + \lambda_1\int_{inside(C)}|I(x,y)-c_1|^2dxdy + \lambda_2\int_{outside(C)}|I(x,y)-c_2|^2dxdy$$

where μ ,λ_1,λ_2 >0 are fixed parameters. λ_1,λ_2=1. The average of grey level intensities inside and outside *C* is c_1 and c_2.

In order to minimize the above function, the Euler–Lagrange equation is considered and gradient descent method is used to update the level set function:

$$\frac{\delta\phi}{\delta t}=\delta(\phi)[\mu\,div\,(\frac{\nabla\phi}{|\nabla\phi|}) - \lambda_1(I-c_{1)}{}^2 + \lambda_2(I-c_{2)}{}^2]$$

C. Localizing Region-Based Active Contour Model

A contour is evolved based on local image statistics in this approach rather than global. Objects with heterogeneous feature profiles can be segmented using Localized contours.

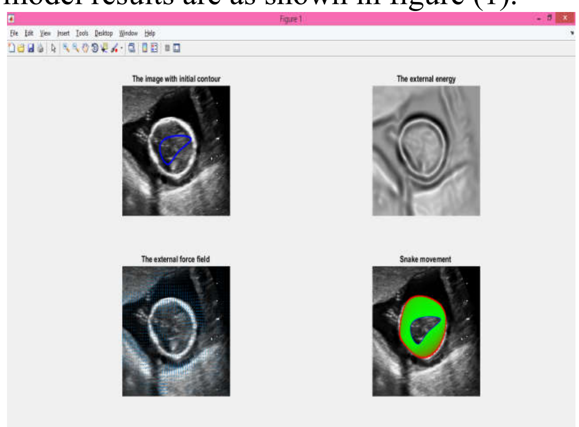
The localized region energy is given by

$$\epsilon(\phi) = \int_{\Omega_x} \delta\phi(x) \int_{\Omega_y} B(x,y)[H(\phi(y))\,(I(y) - u_x)^2 + (1\text{-}H(\phi(y)))(I(y) - v_x)^2]\, dy\, dx$$

where B (x,y) represents local mask and Hϕ(y) represents Heaviside function.

IV. Result

For experimentation, we used MATLAB R2014a. The DICOM images used in experimentation are taken from authorized sonographic center. After applying the parametric deformable model results are as shown in figure (1).



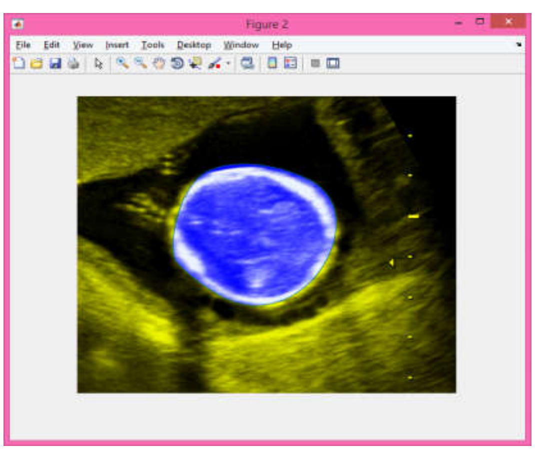


Fig.1 (a) before snake application
Original image

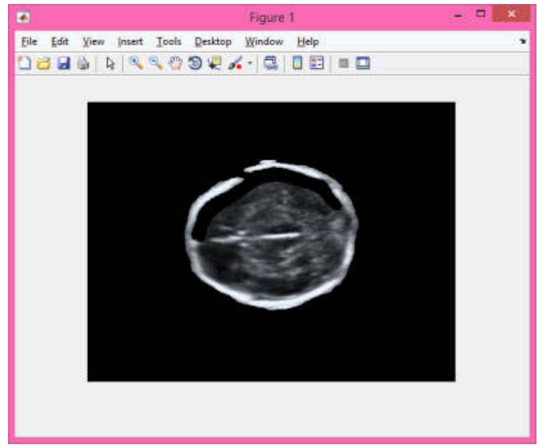


Fig. 1(b) after snake application

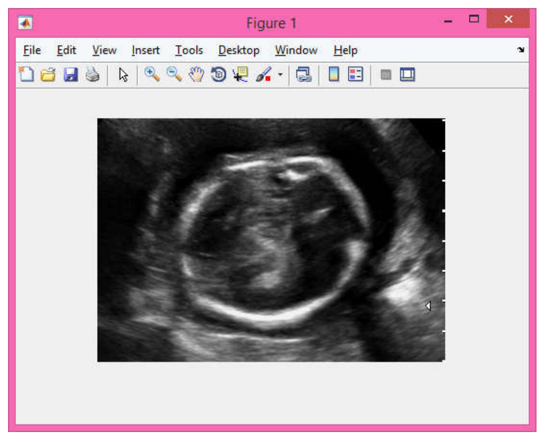


Fig. 2 Result of level set.

V. Conclusion

After experimentation with ultrasound images it is observed that in snake, before the curve evolution can begin, initial contour need to be specified. Result depends on initial selection. In addition, the evolving snake contour is sensitive to noise [7].

We set the number of iterations equal to 2500 for both methods. It is observed that level set method is independent from the shape and location of initial contour, while segmentation by the active contour depends on the location of the initial contour.

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