International Journal of Advances in Electronics Engineering
Vol:1 Issue:1 ISSN 2278 - 215X

Magnetic Resonance Image Segmentation based on FGM of Snake Model

G. Ramesh
M.Tech(E.S)
Sree chaitanya college of Engineering,
ramesh.gajelli@gmail.com

G. Narsimhulu
Associate Professor (ECE)
Sree chaitanya college of Engineering
narsiroopa@gmail.com

***Abstract*— Image segmentation is one of the most important steps in image analysis and has been a key problem in computer vision. The main aim of this process is to separate an image to several regions or parts which correlate strongly the interested objects. Snakes, or active contours, have been widely used to locate boundaries of image segmentation and computer vision. Problem associated with the existence of the local minima in the active contour energy function makes snakes have poor convergence in segmentation process; therefore, the poor convergence has limited applications. In this work, a fast minimization of snake model is used for an MRI knee image segmentation. This method provides a satisfied result. As a result, it is a good candidate for MRI image segmentation approach. In other words an improper initial contour can give inaccurate result. The problem with the initial contour relates to the non-convexity of the energy function, *EGAC* , to be minimized and then the existence of the local minimum**.

I.INTRODUCTION

In computer vision, segmentation refers to the process of partitioning a digital image into multiple segments (sets of pixels, also known as superpixels). The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain visual characteristics.

The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image (see edge detection). Each of the pixels in a region are similar with respect to some characteristic or computed property, such as color, intensity, or texture. Adjacent regions are significantly different with respect to the same characteristics.

In automated medical image processing, image segmentation plays an important role. It is very useful for doctor's diagnoses, because the segmented area gives useful information so that doctor can make decision easier and quicker. Accordingly, medical image segmentation has been obtained much attention.

Active contours, or "snakes", which were originally introduced by Kass *e t a l* in 1988 , are used extensively in computer vision and image processing application, particular to locating object boundaries . Snakes are energy-minimizing curves that deform under the influence of internal forces within curve itself and external force derived from the image to minimize the energy function. They are general techniques of marching a deform model to an image using energy minimization. Traditional snakes often converge to the *l o c a l m i n i m u m* of the energy function of active contour. It is sensitive to the initialization and has difficult in the progressing into boundary concavities. The classical snakes have some

To overcome above drawbacks, in this paper the fast global minimization of snake model is used to segment the MRI Image. The successful implementation of this paper shows the advantages of the proposed method. It can be considered as a good candidate for MRI image segmentation.

II. ACTIVE CONTOUR MODELS: SNAKES

1. Classical snakes

A drawback such as the segmentation result does not converge to the actual objects, especially with the objects in MRI image.

The concept of active contours was introduced in 1988 and has been developed by the many researchers. A classical snake is a curve $C(s) = [x(s), y(s)]$, $s \sim [0,1]$ that moves thought the spatial domain of an image $I(x, y)$ to minimize energy functional:

$$E_{snake} = \int E_{snake}(C(s)ds$$

$$\int E_{\text{int}}(C(s) + E_{image}(C(s)) + E_{cont}(C(s)ds$$

Where:

Eint $(C(s))$: represents the internal energy of the spline due to bending

Eimage $(C(s))$: represents the image forces

Econ $(C(s))$: represents the external constraint force

*Internal Energy E*int

The internal energy can be written as:

$$E_{\text{int}} = (\alpha(s)\left|C_s(s)\right|^2 + \beta(s)\left|C_{ss}(s)\right|^2) / 2$$

In this equation, the first-order term makes the snake act like a membrane and the second-order term makes it act like a thin plate

The internal energy is composed of first-order and second-order terms. The first-order term, which controlled by $\alpha(s)$ adjusts the elasticity (tension) of the snake. The second-order term, which controlled by $\beta(s)$ adjusts the stiffness of the snake

External energy E_{ext}

The external energy can be written as:

$$E_{ext}(v(s)) = E_{image}(C(s)) + E_{con}(C(s))$$

Snake drives this energy from the image so that external forces deform snake toward the object's borders. For example: when given a gray-level image $I(x, y)$ typical external energies are designed to lead snake as

$$E^1_{ext}(x, y) = -\left|\nabla I(x,y)\right|^2$$

$$E^2_{ext}(x, y) = -\left|\nabla (G_\sigma(x,y) * I(x,y))\right|^2$$

Where $G_\sigma(x, y)$ is a two dimensional Gaussian function with standard deviation σ and ∇ is the gradient operator

II. New version of snake model – Geometric Active Contour (GAC)

Based on the classical snakes, Caselles *et al* in and Kichenassy et *al* in proposed a new model of snake-Geometric Active Contour (GAC). The model is defined by the following minimization problem

$$\min_c\{E_{GAC}(C) = \int_0^{L(c)} g(\left|\nabla I(C(s))\right|)ds\}$$

Where *ds* is the length of the Euclidean element and *L(C)* is the length of the curve C defined:

$$L(C) = \int_0^{L(C)} dl$$

So, the energy function in is actually a new length *dl* obtained by -Euclidean element of length and function *g* which contains information concerning the boundaries of object .The function *g* is an edge indicator function. It has values close to zero in the regions where the gradient of image is high. For example

$$g = \frac{1}{1+\left|\nabla \hat{I}\right|^2}$$

Where $\hat{I}$ is a smoothed version of image I

Although it has many good properties when using GAC model in segmentation but the snake/GAC model is highly sensitive to the initial of contour. In other words an improper initial contour can give inaccurate result. The problem with the initial contour relates to the non-convexity of the energy function, E_{GAC} , to be minimized and then the existence of the local minimum. It prevents the segmentation of the objects (parts) lying in images. So, choosing an image segmentation model, which gives correct results but is independent of initial contour, is necessary. Such method is to find a global minimum of the energy function of GAC model.

III GLOBAL MINIZATION OF THE GAC MODEL

In this section a new segmentation method based on the Chan–Vese (C-V) model to determine the global minization of standard GAC will be considered. The Active contours without edges model proposed by Chan-Vese [4] is an important segmentation model based on Mumford-Shah method and level set approach. This model is not based on the image gradient such as classical snake model detecting the boundaries of the object, but on the homogeneous regions The model of Chan-Vese (C-V model) is as follow:

$$E(c1,c2,C) = \mu length(C) + v.area(inside(C)) + \lambda_1 \int_{inside(C)} \left|I(x,y)-c_1\right|^2 dxdy + \lambda_2 \int_{outside(C)} \left|I(x,y)-c_2\right|^2 dxdy$$

Where $\mu \geq 0$, $v \geq 0$, $\lambda_1, \lambda_2 > 0$ are fixed parameter. In Chan–Vese had most numerical calculations with $\lambda_1 = \lambda_2 = \lambda$ and v=0. *I(x, y)* is the given image, constants c_1 and c_2 are averages of image *I(x, y)* inside and outside *C* respectively.

Define the curve *C* as the boundary of an open subset Ωc of Ω. Denote the region Ωc by inside *(C)* and the region Ω/Ω*c* by outside (C), let

$$Per(\Omega_c) = \mu length(\Omega_c)$$

And

$$E(c1,c2,C) = Per(\Omega_c) + \lambda_1 \int_{\Omega_c} \left|I(x,y)-c_1\right|^2 dxdy + \lambda_2 \int_{\Omega/\Omega_c} \left|I(x,y)-c_2\right|^2 dxdy$$

By using Heaviside function with the regions and Ω / Ω_c the energy function E can can be Written according to level set function φ , as follow

$$E_e(c1,c2,C) = \int_{\Omega} \left|\nabla H_e(\varphi)\right| dxdy + \int_{\Omega} (H_e(\phi)(I(x,y)) - c_1)^2 + (1 - H_e(\phi)(I(x,y)-c_2))^2) dxdy$$

where Ω is image domain and He is a slightly regularization of Heaviside function H.
The gradient decent flow of the energy function

$$E^1(\phi, c_{1,} c_{2,} \lambda) = \int_{\Omega} \left|\nabla \phi\right| dxdy + \lambda \int_{\Omega} r(x,y,c_1,c_2)\phi dxdy$$

To carry out the global minimization of the segmentation task in, authors propose the energy function:

$$E_2(u, c_{1,} c_{2,} \lambda) = TV_g(u) + \lambda \int_{\Omega} r(x,y,c_1,c_2) dxdy$$

Above equation is based on the weighted total

variation energy $TV_g(u)$ which is the function of u with a weight function g above equation gives a link between C-V model and Snake model..
The energy equation is a case of characteristic functions and is expressed as bellow

$$E_2(u, c_{1,} c_{2,} \lambda) = TV_g(u) + \lambda \int_\Omega r_1(x, y, c_1, c_2) u dxdy$$

$$= \int_c g ds + \lambda \int_\Omega ((c_1 - I(x,y))^2) - (c_2 - I(x,y))^2) u dxdy$$

So minimizing E_2 is equivalent to minimizing $\int_c g ds = G_{GAC}(C)$ While approximating *I(x,y)* by two regions: Ω_c and Ω / Ω_c with c_1 and c_2

Note that: $\int_c g ds = G_{GAC}(C)$ is the snake energy equation

Energy function E_2 also provides a global minimum for the active contour model. It has a stationary solution if u satisfies the condition $0 \le u \le 1$ Minimization problem with E_2 for $0 \le u \le 1$ has the same set of minimizers as minimization of problem with E_3 where

$$E_3(u, c_{1,} c_{2,} \lambda, \alpha) = TV_g(u) + \lambda \int_\Omega r_1(x, y, c_1, c_2) + \alpha v(u) dxdy$$

E_3 is not strictly convex that means any minimizer of E_3 is the global minimizer. We can use standard Euler-Lagrange
equation technique and explicit gradient descent based algorithm to compute a global minimizer of E_3.But this way takes much computation since the regularization of the TV-norm.

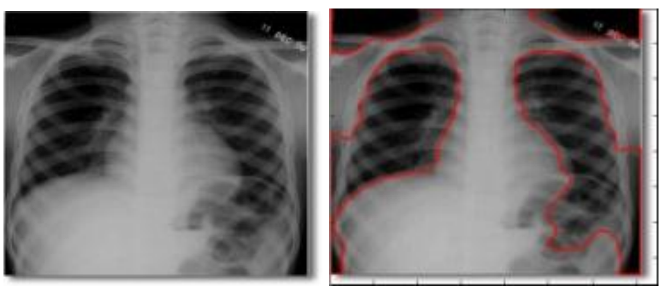
Consider the variational model:

$$\min\{E_3(u, c1, c2, \lambda, \alpha) = TV_g(u) + \lambda \int_\Omega r_1(x, y, c_1, c_2) + \alpha v(u) dxdy\}$$

This is a new numerical model that defines a fast segmentation algorithm. And the following will give an application in MRI image segmentation of this model.

IV. MEDICAL IMAGE SEGMENTATION BASED ON FAST GLOBAL MINIMIZATION OF SNAKE MODEL

This section will show the possible application of the segmentation, based on fast global minimization of snake model, to an MRI image. The method was implemented in Matlab program package. The successful segmentation result given by Fig.1 shows the possibility in MRI image segmentation**.**



a) b)

Fig 1: Segmentation of a MR image

(a) The original image (b) the results after 10 iterations

V. CONCLUSION

we have demonstrated the applicability of global minimization of the snake model, for medical image segmentation. This approach has some advantages over the standard snake approach

- Overcoming the existence local minimum in energy function

- Increase the converge of the segmentation process
- Reducing time need to converge to solution
- Improved signal to noise ratio
- Better detection specially in noise conditions

REFERENCES

1. G.Narsimhulu and G.Ramesh,"Magnetic Resonance Image Segmentation based on FGM of Snake Model" on Image Processing, 2010-11

2. Tony F.Chan and L.Vese "Active contours without edges", IEEE Transaction on Image Processing, vol 10(2), 266-277 2001

3. Chan, T., Golub, G., Mulet, P. "A nonlinear primal-dual method for total variation-based image restoration. SIAM" J. Sci. Comput. 20(6), 1964–1977 (1999)

4. Chambolle, A." An algorithm for total variation minimization and applications." J. Math. Imaging Vis. 20(1–2), 89–97 (2004) [9]. Aujol, J.-F., Chambolle, A. "Dual norms and image decomposition models". Int. J. Comput. Vis. 63(1), 85–104 (2005)

5. X. Bresson and J. Thiran Image "Segmentation Model Using Active contour and Image Decomposition", IEEE, International Conference on Processing, Atlanta, USA, 2006

6. V.Caselles. F. Catté, T.Coll and F.Dibos, "A geometric model for active contour in image processing," Nummer.Math., Vol 66, pp 1-31, 1993.

RAMESH.GAJELLI, received B.Tech degree in E.C.E from JNTU, Hyderabad. Pursing M.TECH in EMBEDDED SYSTEMS (E.S) from SREECHAITANYA COLLEGE OF ENGINEERING,KARIMNAGAR, ANDRAPRADESH

G.NARSIMHULU, received B.Tech degree in E.C.E from JNTU, Hyderabad, M.Tech Degree in Digital System and Computer Electronics (DSCE) from JNTU, Hyderabad. Presently working as ASSOCIATE PROFESSOR in SREECHAITANYA COLLEGE OF ENGINEERING, KARIMNAGAR, ANDHRAPRADESH