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Performance Evaluation Study of Active Contour Models in Medical Imaging

Sugandhi Midha,
Lecturer, CMRIMS, Bangalore
mailmetech@gmail.com

Abstract

Over the past years image segmentation has played an important role in medical imaging. Segmented images are used for a number of applications such as computer aided surgery, treatment planning, diagnosis, study of anatomical structures and many more. Deformable models provide a general method of performing non-rigid object segmentation. They offer an attractive approach to overcome the limitations of traditional low level segmentation approaches. A snake is a flexible deformable model which can be matched to an image contour by energy minimisation. Snakes are a powerful technique in segmenting formless shapes when little or no prior knowledge about the shape is available. Rather than handcrafting a prior knowledge into the model, the shape variation is extracted from a training set by applying PCA to PDM. In this paper some familiar Active Contour models such as Snakes by Kass et al, Balloon model, Greedy snakes method, Gradient Vector Flow Snakes are compared on the basis of qualitative and quantitative measures. The GVF Snakes have the ability to move into boundary concavities whereas the Greedy Snakes, Original Snakes have problems trying to locate the contour of an object which has a boundary concavity.

Keywords: Concavity, Convergence, Gaussian Noise, Energy, Elastic Energy, Bending Energy, External Forces, Error Measures.

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1. Introduction

Imaging plays a vital role in the diagnosis of diseases present in the medical images. Medical images are hard to segment due to presence of inherent complexity in the images. The theme of current study is a group of high level segmentation models, the so called active contour models for detecting linear characteristics. No doubt various models before the advent of active contour exist but fail to give accurate results. The earlier methods do not use any prior information and also are not effective in the presence of noise and sampling artifacts. Hough and Template Matching techniques tried to detect shapes by defining the prior information, but the prior required are very high for these methods. Active Contour Models use less amount of prior and is best to detect any shape in the image that is smooth and forms a closed contour.

An Active Contour is widely called dynamically evolving parametric curve, which in its effort to minimize its energy, gets attracted towards the object edges. Active contour models, also known as snakes, are used broadly in image processing applications; including edge detection, shape modeling, medical image-analysis, to identify object boundaries. Snakes are curves defined in the image domain that can move under the influence of internal forces within the curve itself and external forces derived from the image data. The internal and external forces are defined so that the snake will eventually conform to an object boundary or some other desired image feature.

The common steps used in Active Contour Model are given as:-

a) User gives a Shape Model of the Object to be searched.

b) An image exist which contains the object.

c) The parameters for the shape model are determined by varying the parameters so as to best fit the model image.

The paper is organized as follows: Section (2) gives the study of various Active Contour Models. Section (3) presents the performance evaluation criteria of these Snakes Models. Section (4) presents experimental results of various Snakes Models and finally, Section (5) gives a conclusion of the comparative study.

2. Active Contour Models

Active Contours have received wide popularity due to its effectiveness and efficiency in finding dynamic objects of any shape. These are widely used in number of areas such as medical visualization, object tracking, feature extraction, animation and many others. Active Contour Models can be classified into following categories:-

2.1 Snakes – The Kass Model

The snakes were first introduced by Kass et al in 1987. It represents the object boundary as a parametric curve. An energy function E is associated with the curve. The objective is to minimize the energy to lock the object boundary with the object. A parametric curve is defined as an equation:-

$$v(s) = (x(s), y(s))$$

An Energy Function E is defined as:

$$E_{total} = \int E_{internal} + E_{external} + E_{constraint}$$

$$E_{total} = \int (E_{elastic} + E_{bending}) + Eexternal + Econstraint$$

Where,

$$Eelastic = \frac{1}{2}\int_C \alpha(s)\,|v_s|^2 ds$$

$$E_{bending} = \frac{1}{2}\int_C \beta(s)\,|v_{ss}|^2 ds$$

$$E_{external} = -|\nabla I(v(s))|^2$$

$$E_{constraint} = \int_C E_{internal} + E_{external}$$

With c defines scaling and rotation ranges.

$$v_s = \frac{dv(s)}{ds}$$

$$v_{ss} = \frac{d^2 v(s)}{ds^2}$$

α, β are scaling parameters

Energy formulations are minimized using two independent Euler Equations:-

$$A_x + f_x(x, y) = 0$$

$$Ay + f_y(x, y) = 0$$

where,

A is a matrix consisting of $\alpha(s)$ and $\beta(s)$

x,y are new snake coordinates.

$$f_x(x,y) = \frac{\delta E_{external}}{\delta x}$$

$$f_y(x,y) = \frac{\delta E_{external}}{\delta y}$$

2.2 An Active Contour Balloon Model – Cohen's Approach

The snakes model introduced by Kass was revised by Lauren D. Cohen and named the new model as Ballon model. The Kass model based on the principle that the parametric curve would shrink when not under the influence of image forces, where as the Cohen Snake expands. The expansion of snake resembles the shape of balloon i.e. why the model named to Balloon Snake.

Cohen alters the values of $f_x(x,y)$ and $f_y(x,y)$.

$$f_x(x,y) = K_1 n(s) - k \frac{\nabla P_x}{\|\nabla P_x\|}$$

$$f_y(x,y) = K_1 n(s) - k \frac{\nabla Py}{\|\nabla Py\|}$$

where,

n(s) is unit principal normal vector.

K_1 is the amplitude of these forces.

$$\nabla Px = \partial E_{external} / \partial x$$

$$\nabla Py = \partial E_{external} / \partial y$$

2.3 The Gradient Vector Flow Snake (GVF) Snake – Xu and Prince Approach

The basic model is identical to that proposed by Kass. However, GVF Snake is associated with a new kind of external field that is a vector force field. So the difference in algorithm is only in the way this external field is calculated.

The gradient vector flow is defined as, v(x,y) = (u(x,y), v(x,y)) that minimizes the energy function.

Now the Euler equations will take the forms.

$$\alpha v_{ss} - \beta v_{ssss} - F_{external}$$

$$E = \iint (u_x^2 + u_y^2 + v_x^2 + v_y^2) + |\nabla I|^2 |F - \nabla I|^2 \; \partial x \partial y$$

3. Performance Evaluation

The aim of performance evaluation is to give route to the selection and modification of the Active Contour Model parameters alpha and beta or to increase the number of iterations, so as to improve the quality of snakes.

It may also be noted that most of the evaluation would be more qualitative rather than quantitative. The primary goal is to obtain a good lock on the object whose confirmation can be obtained by visual inspection.

3.1 Subjective Criteria

The subjective criteria based on visual perception. These are qualitative in nature. Following points can be visually perceived by looking at the images:

Multiple Contours

Gap or blurry Edges

Complex Shapes with Large Curvature Variation

Circular Shape

Elongated Shape

Noise Interiors

Initial Contour Outside or Contour Boundary

3.2 Objective Criteria

These measures allow you to differentiate between different models quantitatively. Two error measures are being used to evaluate the models.

3.2.1 Error Measure 1

Error 1 quantifies the overlap of the EC and the TC and it equals to zero if the two contours are identical (complete overlap). Error 1 provides an indicator of the overall goodness of the result, thus a global evaluation measure.

$$\varepsilon_1 = 1 - \frac{|TP \cap EP|}{|TP \cup EP|}$$

TC denotes the set of pixels belonging to the true boundary

EC denotes the set of pixels belonging to the extracted boundary

TP denotes the set of pixels inside the TC

EP denotes the set of pixels inside the EC

3.2.2 Error Measure 2

Error 2 measures the maximum Euclidean distance between the EC and the TC. It is a local measure, which is useful in determining if the high curvature portions of the contour are extracted.

$$\varepsilon_2 = \max_{X \in TC} \min_{Y \in EC} \mathrm{dist}(X, Y).$$

TC denotes the set of pixels belonging to the true boundary

EC denotes the set of pixels belonging to the extracted boundary

The dist(X,Y) function in e2 represents the Euclidean distance between the integer coordinates of the pixels X and Y.

4. Experimental Results

This section compares the result of several Active Contour Models based on the qualitative and quantitative measures.

Table 1: Comparison Table Deformable Contour Method Selection

Method	Multiple Contours	Gap or Blurry Edges	Complex Shapes with long curvature variation	Circular Shape	Elongated Shape	Noise Interior	Initial Contour Outside or Cross Boundary
Balloon		√		√		√	√
Original Snake		√		√		√	
GVF		√	√	√	√	√	√

Error Measures: the bolded values represent the best quantitative result and the values marked by asterisk represent the qualitative result

Table 2: Comparison Table Error Measure 1

Measure	Medical Image	Balloon	Original Snake	GVF
Error 1	Knee	0.20*	0.21*	0.17*
	Cell	0.13	0.10*	0.09*
	Brain (sulci)	0.51	0.97	0.91
	Brain (Corpus callosum)	0.71	0.72	0.85
	Heart	0.16	0.17	0.12
	Kidney (SP)	0.17*	0.75	0.89
	Kidney (G)	0.57	0.80	0.87

Table 3: Comparison Table Error Measure 2

Measure	Medical Image	Balloon	Original Snake	GVF
Error 2	Knee	5.0*	5.0*	3.0*
	Cell	6.1	3.0*	3.6
	Brain (sulci)	12.8	76.7	72.0
	Brain (Corpus callosum)	42.2	59.3	57.1
	Heart	11.7	16.3	8.6
	Kidney (SP)	6.0*	48.4	51.0
	Kidney (G)	35.2	47.0	48.3

Table 4: Comparison Table Time Complexity for Knee

Snake	Running Time For 50 iteration
Kass	0.897623 seconds
Balloon	1.563412 seconds
GVF	2.129876 seconds

Figure 1: Knee Image

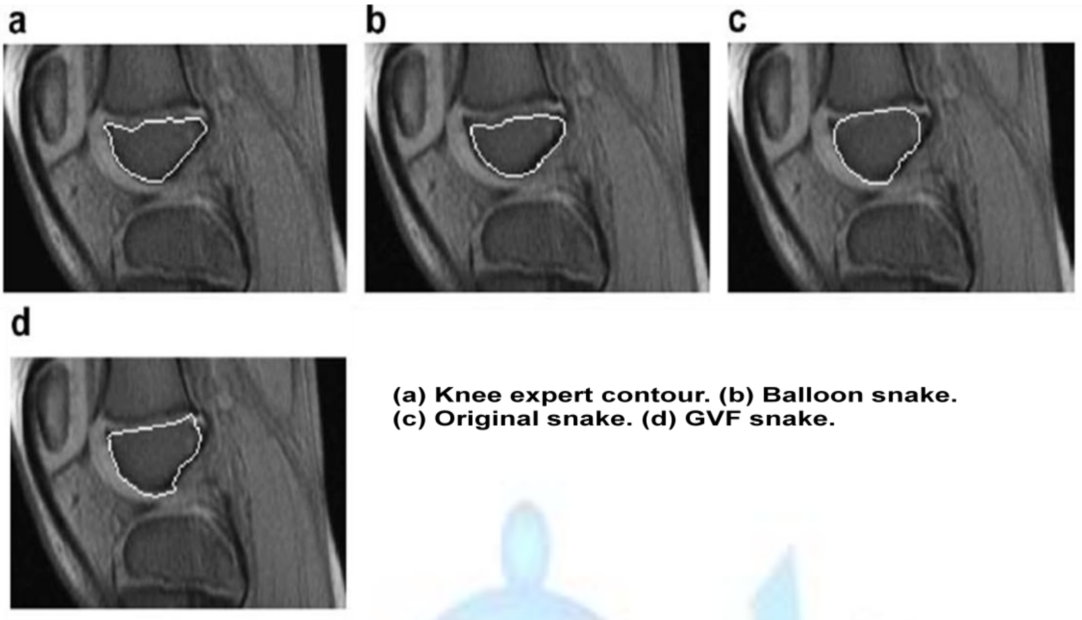
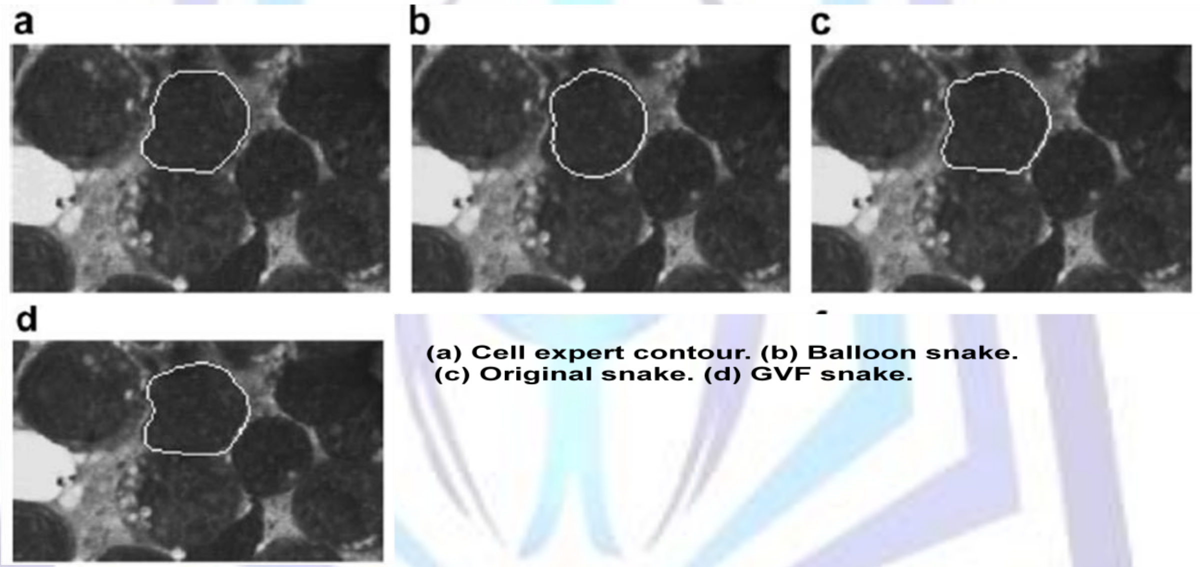


Figure 2: Cell Image



5. Conclusion

When images are not too noisy and objects do not overlap, snakes have a high degree of accuracy, as it was shown in this work. As far as the implementation of the snake evolution equation is concerned, the Fourier spectral method has the best spatial accuracy. Problems arise when the object of interest overlaps with another object. Alternatively it may have a “tail”, as in the case of corpus calossum segmentation, which is a part of the object but we do not want to include it in the result. Since the shape space snake contours is not limited, the snake follows the potential function derived from the image. This problem can be controlled to some extent by adjusting the parameters.

Kass Snakes take less time as compared to balloon and GVF Snake. GVF Snakes are best suited to concave boundaries. Concave boundaries are not detected by balloon or Kass snake. For MRI images, all the 3 methods Kass, balloon and GVF gives best result. For CT scan images, all the 3 methods Kass, balloon and GVF gives best result. For ultra sound images, GVF is the best technique. Anyhow, no method is mutually exclusive.