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A REVIEW ON THE IMPLEMENTATION OF SNAKE ALGORITHM IN SEGMENTATION OF TUMORS

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ABSTRACT
Tumor is an abnormal mass of tissue in which some cells grow and multiply uncontrollably,apparently unregulated by the mechanisms that control normal cells. So detection of the tumor is very important in earlier stages. Various techniques were developed for detection of tumor in brain, lungs, blood and skin. This paper focuses on survey of well-known snake segmentation algorithm , that have been proposed so far to detect the location of the tumor. The Snake algorithm applied to various tumor detection is discussed in this paper.
Keywords: *Snake, Image segmentation, tumor, Blood cancer, Skin , lungs tumor*

I. INTRODUCTION

Snake is an energy minimizing, deformable spline influenced by constraint and image forces that pull it towards object contours. Snakes may be understood as a special case of general technique of matching a deformable model to an image by means of energy minimization.[1] Snake is an “active” model as it always minimizes its energy functional and therefore exhibits dynamic behavior.

A simple elastic snake is thus defined by

- a set of n points
- an internal elastic energy term
- an external edge based energy term

One may visualize the snake as a rubber band of arbitrary shape that is deforming with time trying to get as close as possible to the object contour. When Snake is placed near the object contour, it will dynamically move towards object contour by minimizing its energy iteratively.

A. Energy function

In Snakes, we use the technique of matching a deformable model to an image by means of energy minimization. A snake initialized near the target gets refined iteratively and is attracted towards the salient contour. A snake in the image can be represented as a set of n points.

$$\mathbf{v}_i = (x_i, y_i) \quad \text{where } i = 0 \ldots n-1$$

We can write its energy function as

$$E^*_{snake} = \int_0^1 E_{snake}(\mathbf{v}(s))\,ds = \int_0^1 \left(E_{internal}(\mathbf{v}(s)) + E_{image}(\mathbf{v}(s)) + E_{con}(\mathbf{v}(s))\right) ds$$

$$E_{external} = E_{image} + E_{con}$$

The combination of E_{image} and E_{con} can be represented as $E_{external}$, that denote the external energy acting on the spline.

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B. Internal energy

Internal Energy of the snake is $E_{internal} = E_{cont} + E_{curv}$ where E_{cont} denotes the energy of the snake contour and E_{curv} denotes the energy of the spline curvature.

$$E_{internal} = (\alpha(s)\left|\mathbf{v}_s(s)\right|^2 + \beta(s)\left|\mathbf{v}_{ss}(s)\right|^2)/2$$
$$= \left(\alpha(s)\left\|\frac{d\bar{v}}{ds}(s)\right\|^2 + \beta(s)\left\|\frac{d^2\bar{v}}{ds^2}(s)\right\|^2\right)/2$$

The first-order term makes the snake act like a membrane and second-order term makes it act like a thin plate. Large values of $\alpha(s)$ will increase the internal energy of the snake as it stretches more and more, whereas small values of $\alpha(s)$ will make the energy function insensitive to the amount of stretch. Similarly, large values of $\beta(s)$ will increase the internal energy of the snake as it develops more curves, whereas small values of $\beta(s)$ will make the energy function insensitive to curves in the snake. Smaller values of both $\alpha(s)$ and $\beta(s)$ will place fewer constraints on the size and shape of the snake.

C. Image forces

Further, E_{image} has three components:

- Lines
- Edges
- Terminations

The energies can be represented as follows:

$$E_{image} = w_{line}E_{line} + w_{edge}E_{edge} + w_{term}E_{term}$$

Adjusting the weights in the image will determine salient features in the image which will be considered by the snake.

Line functional

A line functional is nothing but the intensity of the image, which can be represented as

$$E_{line} = I(x,y)$$

Depending on the sign of w_{line}, the line will be attracted to either dark lines or light lines.

Edge functional

Image gradient

Edges in the image can be found by the following energy function which will make the snake attract towards contours with large image gradients.

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Scale space

It is rather common that a snake started far from the object converges to the desired object contour. If a part of the snake finds a low energy feature, it pulls the other parts of the snake to continue to the contour. Scale Space continuation can be used in order to achieve desired results. One can allow the snake to come to equilibrium on a blurry energy edge functional and reduce the blurring as the calculation progresses. The energy functional is

$$E_{edge} = -\left|G_\sigma * \nabla^2 I\right|^2$$

Where $G_\sigma$is a Gaussian standard deviation σminima of this functional lie on zero-crossings of $G_\sigma \nabla^2 I$ which define edges in Marr-Hildreth Theory. Thus the snake gets attracted towards zero-crossing constrained by its own smoothness.

Termination functional

Curvature of level lines in a slightly smoothed image is used to detect corners and terminations in an image. Let $C(x,y) = G_\sigma * I(x,y)$be a slightly smoothed version of the image.Let $\theta = \arctan(\frac{C_y}{C_x})$ be the gradient angle.

And let $\mathbf{n} = (\cos\theta, \sin\theta)$and $\mathbf{n}_\perp = (-\sin\theta, \cos\theta)$be unit vectors along and perpendicular to the gradient direction. The termination functional of energy can be represented as

$$E_{term} = \frac{\partial\theta}{\partial n_\perp} = \frac{\partial^2 C/\partial^2 n_\perp}{\partial C/\partial n} = \frac{C_{yy}C_x^2 - 2C_{xy}C_xC_y + C_{xx}C_y^2}{(C_x^2 + C_y^2)^{3/2}}$$

D. Constraint energy

Some systems, including the original snakes implementation, allowed for user interaction to guide the snakes, not only in initial placement but also in their energy terms. Such constraint energy E_{con}can be used to interactively guide the snakes towards or away from particular features.

E. Implementation

We can approximate the energy function of the snake by using the discrete points on the snake.

$$E^*_{snake} \approx \sum_1^n E_{snake}(\bar{v}_i)$$

The derivative of above sum is nothing but the sum of derivatives.

$$\nabla E^*_{snake} \approx \sum_1^n \nabla E_{snake}(\bar{v}_i)$$

Now we should iteratively adjust the points vector $\mathbf{v}_i$by using gradient descent minimization.

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Applying the derivative to energy function gives

$$\nabla E_{snake}(\bar{v}_i) = w_{internal} \nabla E_{internal}(\bar{v}_i) + w_{external} \nabla E_{external}(\bar{v}_i)$$

Derivative of internal Energy of the image can be solved as

$$\nabla E_{internal}(s) = \nabla \left[(\alpha(s) \left\| \mathbf{v}_s(s) \right\|^2 + \beta(s) \left\| \mathbf{v}_{ss}(s) \right\|^2)/2 \right]$$

$$\nabla E_{internal}(s) = \left[\left(\alpha(s) \nabla \left\| \frac{d\bar{v}}{ds}(s) \right\|^2 + \beta(s) \nabla \left\| \frac{d^2\bar{v}}{ds^2}(s) \right\|^2 \right) /2 \right]$$
$$= \alpha \frac{\partial^2 \bar{v}}{\partial s^2} + \beta \frac{\partial^4 \bar{v}}{\partial s^4}$$

These can be approximated using finite differences—the second derivative w.r.t. s can be calculated using three adjacent points on the snake, and the fourth derivative w.r.t. s can be calculated using five adjacent points. It also helps to separate the x and y components.

Final equations are

$$\bar{v}_i = \leftarrow \bar{v}_i - \gamma \left\{ w_{internal} \left[\alpha \frac{\partial^2 \bar{v}}{\partial s^2}(\bar{v}_i) + \beta \frac{\partial^4 \bar{v}}{\partial s^4}(\bar{v}_i) \right] + \nabla E_{ext}(\bar{v}_i) \right\}$$

$$\bar{x}_i = \leftarrow x_i - \gamma \left\{ w_{internal} \left[\alpha \frac{\partial^2 x}{\partial s^2}(\bar{v}_i) + \beta \frac{\partial^4 x}{\partial s^4}(\bar{v}_i) \right] + \frac{\partial}{\partial x} E_{ext}(\bar{v}_i) \right\}$$

$$\bar{y}_i = \leftarrow y_i - \gamma \left\{ w_{internal} \left[\alpha \frac{\partial^2 y}{\partial s^2}(\bar{v}_i) + \beta \frac{\partial^4 y}{\partial s^4}(\bar{v}_i) \right] + \frac{\partial}{\partial y} E_{ext}(\bar{v}_i) \right\}$$

Where

$$E_{external} = E_{image} + E_{con}$$

F. Other implementations of snakes

GVF active contours

The snake is developed based on new type of external field, called Gradient Vector Flow, or GVF. This computation causes diffuse forces to exist far from the object, and crisp force vectors near the edges. Combining these forces with the usual internal forces yields a powerful computational object: the GVF snake (2D), or the GVF deformable model (N-D). Even though this snake is started far from the object, it still gets attracted towards the object.Especially, GVF active contours can handle broken object edges and subjective contours.

Balloon snake

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In this case, the snake behaves like a balloon which is blown up. When it passes by edges, it is stopped if the contour is strong,or passes through if the contour is too weak. Thus, the initial snake need not be too close to the solution(object) to converge. This approach modifies the definition external forces (derived from gradient of the image) presented in traditional snake . A new pressure force is introduced which makes the curve behave like a balloon.

Diffusion snakes

The diffusion snake is a modification of the Mumford-Shah functional for spline contours. A modification of the Mumford-Shah functional and its cartoon limit is used to incorporate statistical prior on the shape of the segmenting contour. By minimizing a single energy functional, we obtain a segmentation process which maximizes both the Grey value homogeneity in the separated regions and the similarity of the contour with respect to a set of training shapes.

Geometric Active Contours

This class of snake models employs ideas from Euclidean curve shortening evolution which defines the gradient direction in which the Euclidean perimeter is shrinking as fast as possible. One therefore notes that new active contour models may be derived by multiplying the Euclidean arc-length by a conformal factor tailored to the features of interest that one wants to capture, then writing down the resulting gradient evolution equations. The latter becomes a curve shortening equation with respect to the new conformally Euclidean metric. These models may be implemented using level sets, and have been extensively employed in medical image computing. They have been called geodesic snakes and conformal active contours.Statistical models combining local and global features have been formulated in.

II. SNAKE ALGORITHM IN BRAIN TUMOR DETECTION

In [1], a novel and rapid approach for the detection of brain tumors and deformity boundaries in medical images using a genetic algorithm with wavelet based preprocessing is presented. The contour detection problem is formulated as an optimization process that seeks the contour of the object in a manner of minimizing an energy function based on an active contour model. The brain tumor segmentation contour, however, cannot be detected in case that a higher gradient intensity exists other than the interested brain tumor and deformities. Our method for discerning brain tumors and deformities from unwanted adjacent tissues is proposed. The proposed method can be used in medical image analysis because the exact contour of the brain tumor and deformities is followed by precise diagnosis of the deformities.

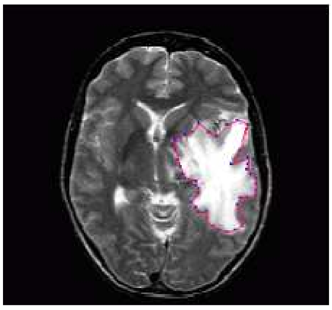

Figure 1: Brain Tumor detection using Wavelet based processing

In [2], two methods have been suggested for the detection of the brain tumor . (which is defined as the abnormal growth of cells), The first method is using the snake algorithm and the second Fuzzy C-mean . Initial image has been processed that converts the image to gray then a Median filtering method is used to remove noise and other false features while maintaining the quality of public image. The methods are applied on a number of brain image with different angles. The results have to been presented of both methods and compared. The result show that snake method with a high speed in detecting the tumor.

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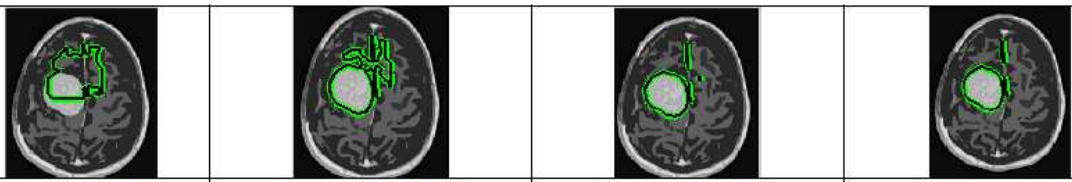

(a) Initial contour	(b) After 100 interaction	(c) After 160 interaction	(d) After 360 interaction

Figure 2 : Using Snake Algorithm in brain tumor detection

original image	fuzzy method

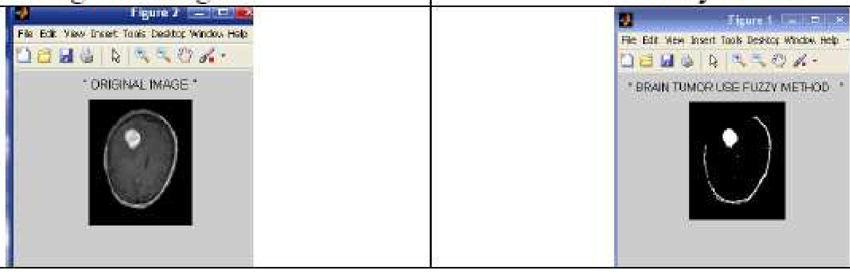

Figure 3: Using Fuzzy logic to detect brain tumor

A. Comparison of time with both the methods:

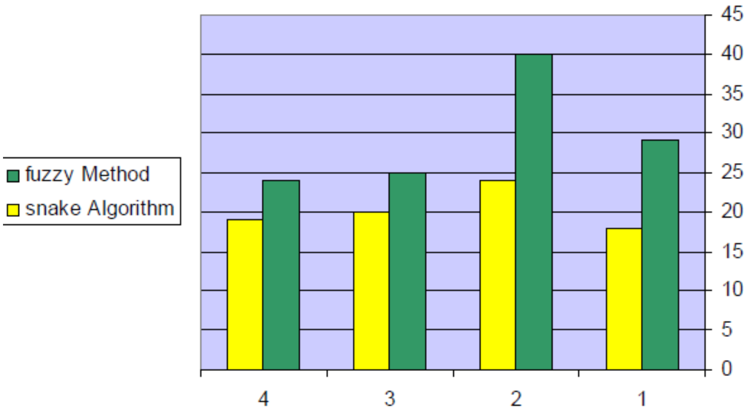

Figure 4: Comparison of time between the 2 methods

III. SNAKE ALGORITHM IN LUNG TUMOR DETECTION

Paper [3] concentrates on project which is used to improve the efficiency of CAD system and to detect the growth of tumor in efficient manner. This system is carried out by two processes. First, the image is pre-processed for the easier analysis and, second is the segmentation process, where the hybrid segmentation algorithm is used to detect the edge and create the database then the ROI are extracted from database. Finally the assessment of tumor growth is carried out using a nearest neighbor rule. This experimental result can help radiologist to improve the diagnosis efficiency by calculating the tumor growth in each stage accurately. CAD is the software program that recognizes certain pattern and brings its attention to the radiologists.

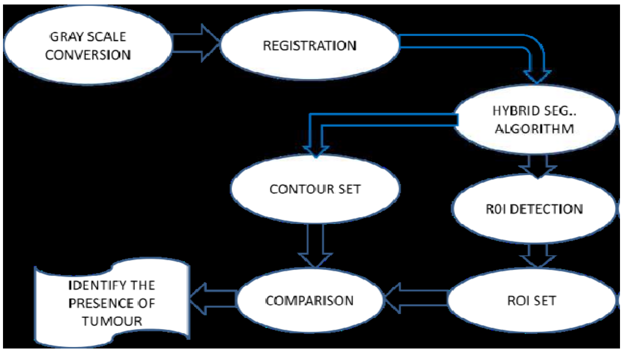

Figure 5: Block diagram of the steps followed

In paper [4], the lung segmentation problem is addressed in pulmonary magnetic resonance imaging and propose an automated method based on a robust region aided geometric snake with a modified diffused region force into the standard geometric model definition. The proposed method has been successful in segmenting the lungs in every slice of 30 magnetic resonance images with 80 consecutive slices in each image. Results are compared with manually segmented lung cavities provided by the radiologist.

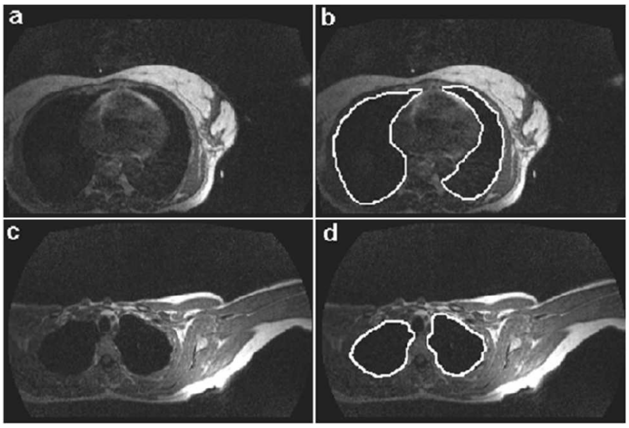

Figure 6: Manual Segmentation: (a) middle lung region slice (b) manually segmented lung outlines (c) an upper lung region slice (d) manually segmented lung outlines

IV. SNAKE ALGORITHM IN SKIN SEGMENTATION

In [5], an unsupervised approach to border detection in dermoscopy images based on the Statistical Region Merging (SRM) algorithm is presented. The SRM algorithm is adapted to this problem due to its simplicity, computational efficiency, and excellent performance on a variety of image domains.

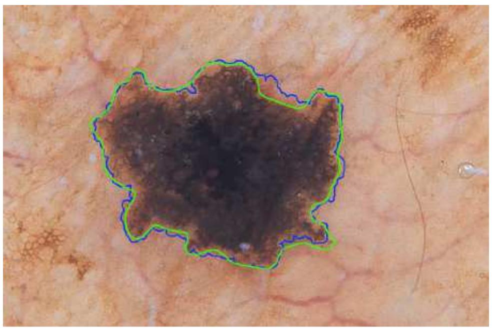

Figure 7: Skin Segmentation (green: manual border, blue :automatic border)

In [6], paper a novel method called automatic segmentation of skin lesion in conventional macroscopic images. Many approaches have been proposed to determine the skin cancer. An extensive literature survey is done to study the state-of-art techniques for skin cancer recognition; level set active contours (LSAC), skin lesion segmentation (SLS) and multidirectional gradient vector flow (MGVF) have given considerable results. A technique based on stochastic region merging (SRM) and region adjacency graph (RAG) is adopted in the proposed method. Segmenting the skin lesion from macroscopic images is a very challenging problem due to some factor such as, illumination variation, presence of hair, irregular skin color variation and multiple unhealthy skin regions. To solve all these factors they have introduced a new approach called novel iterative stochastic region merging likelihood for segmenting the skin lesion from macroscopic images based on the discrete wavelet transformation (DWT).

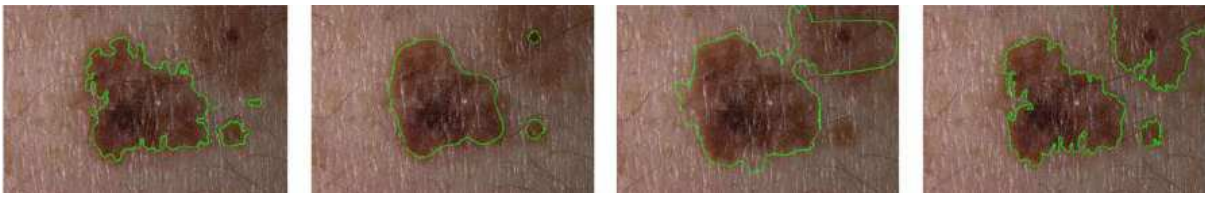

Figure 8: Segmentation using SLS, LSAC, MGVF and proposed algorithm using DWT

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