Active contours in Brain tumor segmentation

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Abstract: Image segmentation plays a central role in biomedical imageprocessing. Tumor segmentation from MRI data is an important but time consuming task performed manually by medical experts. Automating this process is challenging due to the high diversity in appearance of tumor tissue, among different patients and in many cases, similarity between tumor and normal tissue.Parametric active contour method is one of many segmentation approaches. In this paper we used four type of parametric active contour (snake) for Brain tumor segmentation.

[Ali Elyasi, Mehdi Hosseini, Marzieh Esfanyari. Active contours in Brain tumor segmentation**.** Journal of American Science 2011;7(7):519-524]. (ISSN: 1545-1003). http://www.americanscience.org.

Keywords: Image segmentation; Brain tumor; snake; GVF.

Introduction:

Medical imaging allows scientist and physicians to decide about life saving information regard to the human physiological activities. It plays an important role in the diagnosis, therapy and treatment of various organs, tumors and other abnormalities.There are more than 120 types of brain tumors; Brain tumors contain all tumors inside the cranium or in the central spinal canal. They are produced by an abnormal and uncontrolled cell division, normally either in the brain itself (neurons, glial cells (astrocytes, oligodendrocytes, ependymal cells, myelin-producing Schwann cells), lymphatic tissue, blood vessels), in the cranial nerves, in the brain envelopes (meninges), skull, pituitary and pineal gland, or spread from cancers primarily located in other organs (metastatic tumors). Any brain tumor is naturally serious and dangerous because of its invasive and infiltrative character in the limited space of the intracranial cavity. However, brain tumors (even malignant ones) are not invariably fatal. Brain tumors or intracranial neoplasms can be cancerous (malignant) or non-cancerous (benign); however, the definitions of malignant or benign neoplasms differs from those commonly used in other types of cancerous or non-cancerous neoplasms in the body. Its threat level depends on the combination of factors like the type of tumor, its location, its size and its state of development. Because the brain is well protected by the skull, the early detection of a brain tumor only occurs when diagnostic tools are directed at the intracranial cavity. Usually detection occurs in advanced stages when the presence of the tumor has caused unexplained symptoms. Image segmentation is typically used to locate objects and boundaries in images and should stop when the object of interest in an application have been isolated .It is used to calculate the geometric shape and size of tumors and abnormal growth of any tissue. There are many techniques available for auto-segmentation of images like Active contours [1], Fuzzy based classifiers, Gradient Vector Field theory, Tensor based segmentation, Level set [2], etc. But many of them are suffering from problems like optimization, initialization and insufficient results in noisy images. Active contour can be roughly classified in to two types: parametric and geometric active contours .The parametric active contours are explicitly represented as parameterized curves in Lagrange formulation .They are sensitive to the initial contour and cannot naturally handle topological changes. While the geometrical active contours are represented implicitly and evolve according to the Euler formulation based on the theory of surface evolution and geometric flows.

Parametric Active contours:

Parametric active contours were originally developed by Kass, Witkin et al [3]. The method is considered parametric because the snake evolution in the Euclidean space is controlled by a temporal function (i.e., the functions are parameterized in time). The function, or more accurately the functional, is formulated as an energy minimization problem. Thus, given an initial contour, the snake deforms to the global optimum of an objective function.

It is often the case in object recognition problems that constraints of the object boundary (like continuity, smoothness, etc.) are not imposed a priorion the problem; rather, they are expected to evolve from the solution to the problem. However, parametric active contours impose a prioriknowledge of the object (or expected attributes) on the problem domain via an internal energy function that imposes such traits on the contour.

Parametric snakes are described by an objective function that consists of three parts the internal energy of the snake, the image energy and external energies. One approach is to formulate the internal energy of the snake by using the (weighted) first and second derivatives of the curve. The first derivative term is indicative of the "elasticity" of the snake, in that it penalizes points that move away from each other. The second derivative term is a measure of the stiffness of the snake, viz., how strongly it resists bending. It is also possible to pick more complex shape constraints like rectilinearity, parallelism [4] and radial symmetry [5].

The image energy term determine what features of the image the snake seeks, e.g., edges, lines and terminations. The image energy term is chosen so that it minimizes the energy at the features where the snake is expected to converge. For example, in a binary edge image, the pixel intensity can be a good term for the image energy. This term can also factor in the area enclosed, as proposed in [6].External forces are extremely important since they determine behavior of the snake imposed by a higher level algorithm. For example, the external force can be used to force a snake to expand, knowing that the snake has been initialized inside the contour to be determined.

Original Snake:

A snake is an energy minimizing parametric curve, *C*, represented by the vector v(s) = (x(s), y(s)), where *x* and *y* are coordinate functions of *s*, the normalized arc length. *s*[0, 1] is the parametric domain. in this paper we will be dealing exclusively with closed curves so *C* (0) = *C* (1). To conform to the boundary of an object it is placed in proximity to, a snake works by minimizing an associated energy functional. The energy functional associated with the snake can be viewed as the representation of the energy of the snake and the final snake corresponds to the minimum of this energy [7]. A snake conforms to the boundary of an object by deforming its shape and moving through the spatial domain of the image until it reaches a location (theoretically the object's boundary) where its energy functional is at a minimum. The energy functional is defined as follows:

$$E_{snake} = \int_0^1 E_{snake}\left(v(s)\right)ds \qquad (1)$$

$$E_{snake} = \int_0^1 E_{int}\left(v(s)\right) + E_{ext}\left(v(s)\right)ds \qquad (2)$$

$$E_{ext} = E_{image}\left(v(s)\right) + E_{con}\left(v(s)\right) \qquad (3)$$

$$E_{snake} = \int_0^1 E_{int}\left(v(s)\right) + E_{image}\left(v(s)\right) + E_{con}\left(v(s)\right)ds \qquad (4)$$

Where E_{int}, E_{ext}, E_{image} and E_{con} respectively denote internal energy, external energy, external image energy and external constraint energy [3]. The internal energy, E_{int}, is calculated based on the shape and location of the snake and serves to preserve the continuity and smoothness of the snake. The external energy term, E_{ext}, is composed of two terms: the external image energy term and the external constraint energy term. The external image energy, E_{image}, is calculated using image information, typically the negative magnitude of the gradient of the image, and is used to drive the snake towards image features like lines, edge and subjective contours [3]. The external constraint energy, E_{con}, is an optional term that is responsible for forcing the snake away or towards any particular feature in the image. This optional term is defined by a user or some other higher level process. The expanded general form of the energy functional without the optional constraint energy term is:

$$E_{snake} = \int_0^1 \frac{1}{2}\alpha(s)\left|\frac{dv}{ds}\right|^2 + \frac{1}{2}\beta(s)\left|\frac{d^2v}{d^2s}\right|^2 + E_{ext}\left(v(s)\right)ds \qquad (5)$$

Where α(s) and β(s) are non-negative weighting parameters that control the snake's tension (elasticity) and rigidity (inability to bend). In most applications and for this paper they are treated as constants. From calculus of variations, the snake that minimizes the energy functional must satisfy the following Euler equation:

$$-\frac{\partial}{\partial s}\left(\alpha(s)\frac{\partial v(s)}{\partial s}\right) + \frac{\partial^2}{\partial s^2}\left(\beta(s)\frac{\partial^2 v(s)}{\partial s^2}\right) + \nabla E_{ext} = 0 \qquad (6)$$

In compact form:

$$\alpha(s)v''(s) - \beta(s)v''''(s) - \nabla E_{ext} = 0 \qquad (7)$$

The above equation can be viewed as a force balance equation:

$$F_{int} + F_{ext} = 0 \qquad (8)$$

Where $F_{int} = \alpha(s)v''(s) - \beta(s)v''''(s)$ and $F_{ext} = -\nabla E_{ext}$. F_{int} and F_{ext} denote internal force and external force respectively. The internal force discourages stretching and bending while the external force pulls the snake towards the desired image edges [8]. Using these force terms, the deformation process of the snake can be viewed as an interaction of forces. The deformation process stops when the forces balance each other out $F_{int} = -F_{ext}$.

In order to find the solution to (7), the snake is treated as a function of time *t* as well as *s* i.e. v(*s, t*) [10]. The partial derivative of v with respect to *t* is then set equal to the left hand side of (7):

$$v_t(s,t) = \alpha v''(s,t) - \beta v''''(s,t) - \nabla E_{ext} \quad (9)$$

When the solution v(s, t) stabilizes, the term v_t (s, t) goes to zero and we obtain the solution v(s, t_{final}) to equation (7).

Balloon Snake:

The internal constraint to minimize the length of the snake causes the snake to shrink to nothing when placed on a uniform gray scale. Pressure forces were introduced by Cohen in [8] to counter the effect of the shrinking energy term. The method allowed for the inclusion of information from a good local edge detector. Internal pressure forces were introduced that allowed the snake to expand, allowing it to find the edges even when initialized within the Region of Interest (ROT). In addition to the above properties, the balloon force also allows the snake to pass through weak edges and actively seek the desired edge. The modified force equation thus becomes

$$F(v) = k_1\vec{N} - k\frac{\nabla p}{|\nabla p|} \quad (10)$$

Where$\vec{N}$ is the normal unit vector with magnitude k_1(inflation force), and k is the external force weight.

Distance snake:

Cohen and Cohen [9] used a finite element method to implement a deformation strategy called the distance snake. Compared with the original snake, the external force field on the image is constructed also as the negative of the external energy gradient, which is the distance from each point to its closest edge points in the image. The new external energy enables a large magnitude for the external force everywhere in the image. Thus, the distance snake has a large capture range, i.e., the initial contour can be located far away from the desired boundary if there are no spurious edges along the way. By using a finite element method, the deformable contour is represented as a continuous curve in the form of weighted sum of local polynomial basis functions. The result has good stability and convergence in the energy minimization process. The distance snake uses the external force function

$$F = -\nabla Q(v) \quad (11)$$

In Equation Q (v) = d (v) and d (v) is the smallest normalized Euclidean distance from v to an edge point withthe edge point identified by a threshold gradient.

Gradient Vector Flow (GVF) Snake:

This approach is external force model for active contours and deformable surfaces, which is called the gradient vector flow (GVF) field [10]. The field is calculated as a diffusion of the gradient vectors of a gray level or binary edge map. It allows for flexible initialization of the snake or deformable surface and encourages convergence to boundary concavities. We define the gradient vector flows field to be the vector field $V(x,y) = [u(x,y), v(x,y)]$ that minimizes the energy functional:

$$E = \iint \mu\left(u_x^2 + u_y^2 + v_x^2 + v_y^2\right) + |\nabla f|^2 |V - \nabla f|^2 dxdy \quad (12)$$

This variation formulation follows a standard principle that of making the result smooth when there is no data. In particular, we see that when $|\nabla f|$ is small; the energy is dominated by sum of the squares of the partial derivatives of the vector field, yielding as lowly varying field. On the other hand, when$|\nabla f|$ is large, the second term dominates the integrand, and is minimized by setting V= ∇f.This produces the desired effect of keeping V nearly equal to the gradient of the edge map when it is large, but forcing the field to be slowly varying in homogeneous regions. The parameter μ is a regularization parameter governing the tradeoff between the first term and the second term in the integrand. This parameter should be set according to the amount of noise present in the image (more noise, increase μ).We note that the smoothing term the first term within the integrand of(1) is the same term used by Horn and Schunck in their classical formulation of optical flows [11]. It has recently been shown that this term corresponds to an equal penalty on the divergence and curl of the vector field [11]. Therefore, the vector field resulting from this minimization can be expected to be neither entirely irrational nor entirely solenoidal. Using the calculus of variations it can be shown that the GVF field can be found by solving the following Euler equations.

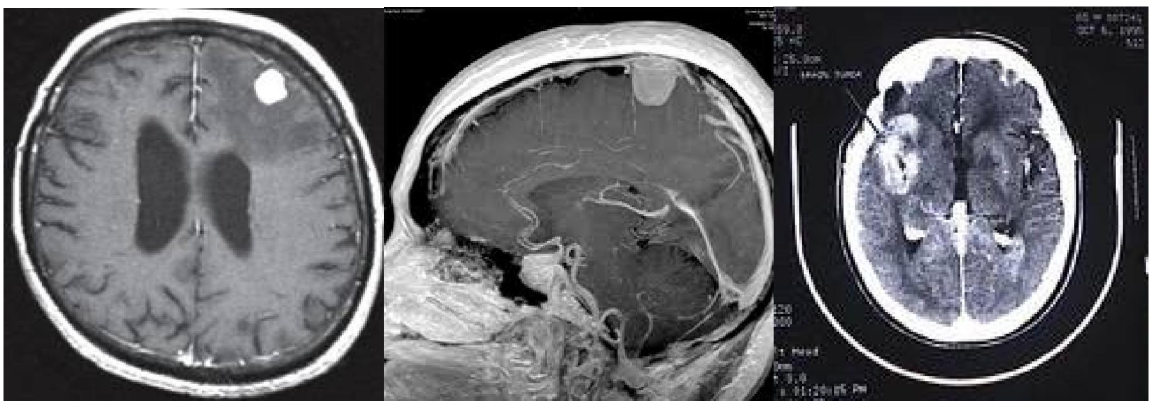
$$\mu\nabla^2 u - (u - f_x)(f_x^2 + f_y^2) = 0 \quad (13a)$$

$$\mu \nabla^2 v - (v - f_y)(f_x^2 + f_y^2) = 0 \tag{13b}$$

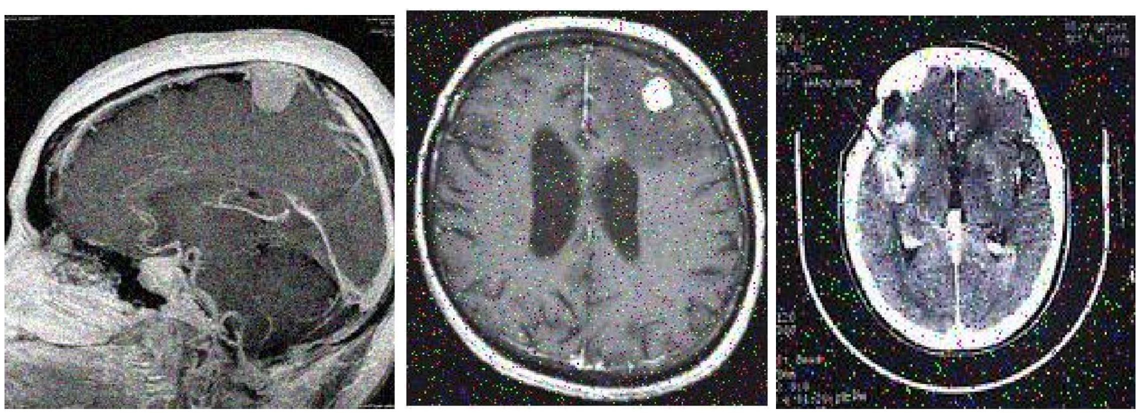
Where $\nabla^2$is the Laplacian operator. These equations provide further intuition behind the GVF formulation. We note that in a homogeneous region [where I(x, y) is constant], the second term in each equation is zero because the gradient of f(x, y) is zero. Therefore, within such a region, u and v are each determined by Laplace's equation, and the resulting GVF field is interpolated from the region's boundary, reflecting a kind of competition among the boundary vectors. This explains why GVF yields vectors that point in to boundary concavities. Clearly, the capture range of traditional snake is very small and GVF snake has a much larger capture range than traditional snake.

Experimental results:

The goal of the Brain tumor image (fig. 1) was to determine which method could better segment tumor. The test images are at different sizes and resolutions. Included are also images with added noises (Gaussian, salt and pepper) corrupting the overall quality of the images Fig.1. Although these types of noise are normally modality dependent or not present due to the high quality of today's imaging devices, it is still interesting to show the performance of the methods in the presence of different types of noise.



(a) (b) (c)



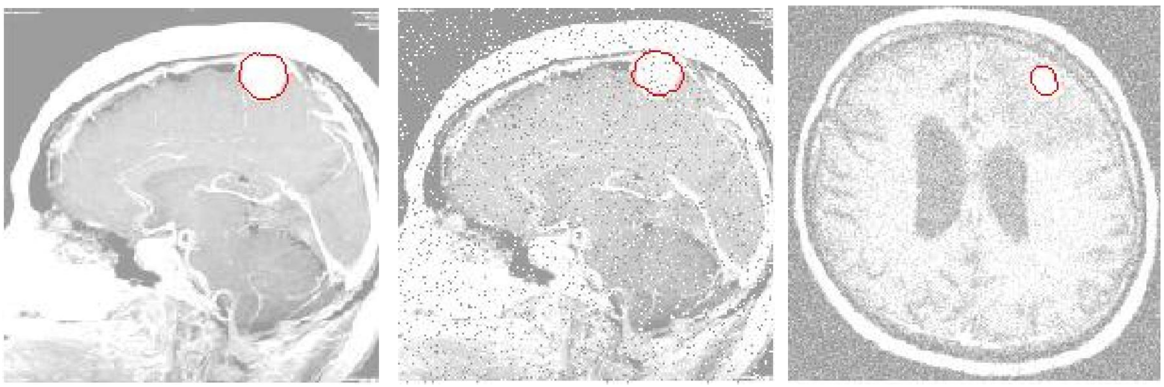
(d) (e) (f)

Figure 1: (a),(b),(c) Brain tumor (c),(d),(e) images with noise (Gaussian and Salt & pepper)

We add noise to images with Matlab program and noise density in salt & pepper is 0.05, the balloon snake is more insensitive to initial contour locations than the methods do not have pressure forces like the distance snake and GVF snake. This is due to the shape and edge strength of the desired boundary. The best results for the distance snake and the original snake occurred with the upper middle initial location and are shown in fig.4, fig. 3, respectively.Distance snake required a bigger initial contour (e.g., double and triple the initial contour radius) than others in order to catch the attraction forces from the edge points in all directions.

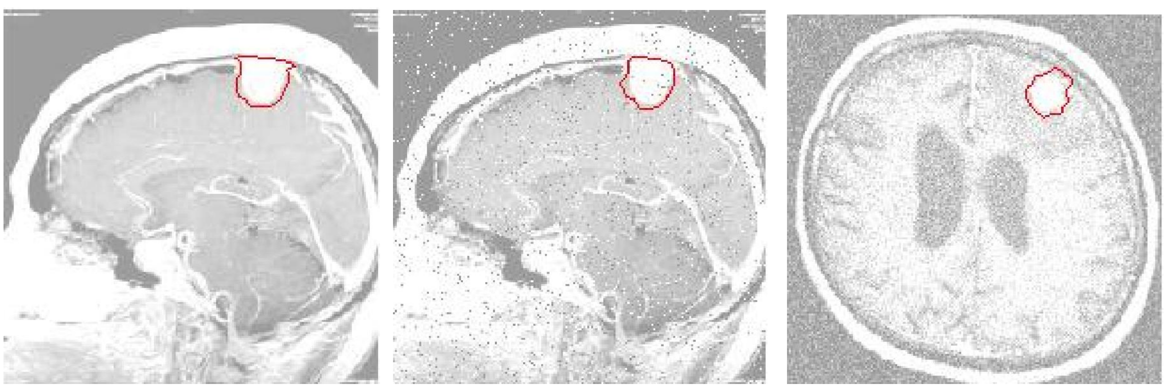
When we add noise (Gaussian and salt & pepper), these methods cannot segment like in original image. Balloon snake in image that add Gaussian noise have some wrong part but with salt & pepper noise it can segment interest part of image as shown in fig.2. Distance snake and original snake work better than other methods when noise (Gaussian and salt & pepper) is added in images (fig.3 (b),(c)),(fig.4(b),(c)).

GVF snake cannot segment images with and without noise of course when salt & pepper noise is added this method cannot work (fig.5).



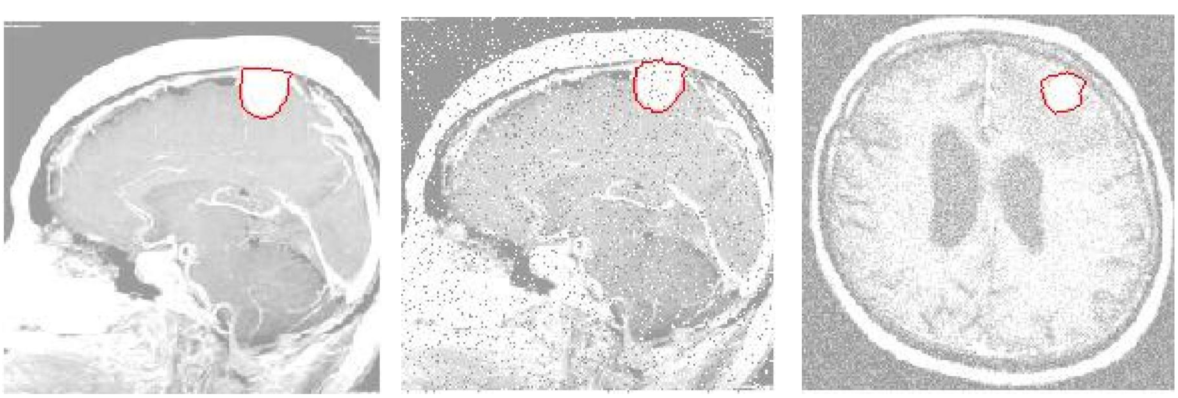
(a) (b) (c)

Fig.2(a) segmentation of original image with balloon snake (b), (c)balloon snake segmentation in image with salt &pepper and Gaussian noise



(a) (b) (c)

Fig. 3. (a)segmentation of original image with original snake(b),(c)original snake segmentation in image with salt & pepper and Gaussian noise



(a) (b) (c)

Fig. 4(a) segmentation of original image with distance snake (b), (c) distance snake segmentation in image with salt &pepper and Gaussian noise

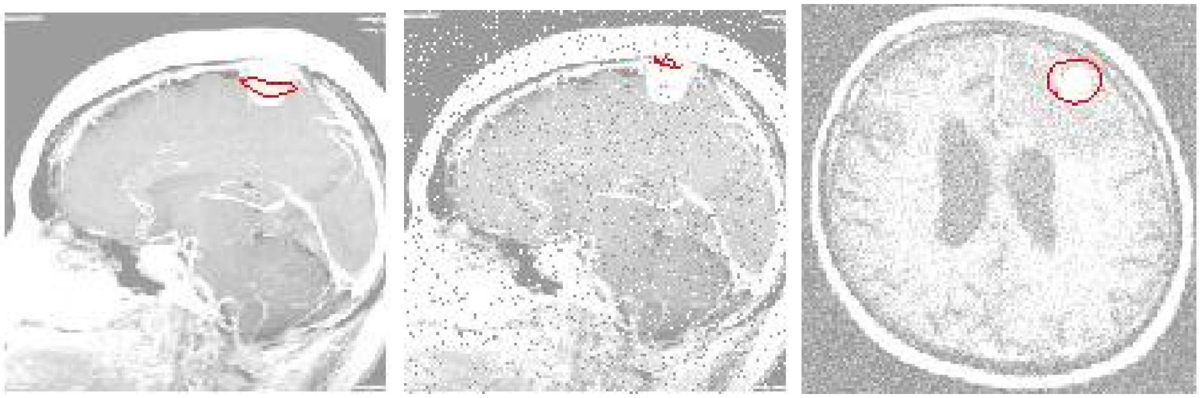


Fig. 5 (a) segmentation of original image with GVF snake (b), (c) GVF snake segmentation in image with salt & pepper and Gaussian noise

Discussion:

This paper presents a study of four deformable contour methods applied to segmentation of Brain tumor imagery. These methods can be used for image segmentation but original and distance snake have better segmentation result. Even in images that are added noise in them, distance and original snake have good result in compare of other methods of course balloon snake have good result in noisy image in compare of original image.

References:

[1]Li, C., Kao, C., Gore, J., Ding, Z. Implicit active contours driven by local binary fitting energy. In the Proceedings of the IEEE Conference Computer Vision and Pattern Recognition. . 2007

[2]Elyasi, A., Ganjdanesh, Y., Kangarloo, K., Hosseini, M., Esfandyari, M. Level set segmentation method in cancer's cells images. Journal of American scienc. 2011. 7(2). (196-204).

[3] Kass, M., A. Witkin, D. Terzopoulos,. Snakes: active contour models, Int. J. Comput. Vis.1988. 1(4): 321–331.

[4]Fua P., and Y. G. Leclerc,. Model driven edge detection, Machine Vision and Applications, 1990.vol. 3: 45-56.

[5]Terzopoulos, D., A. Witkin, and M. Kass,. Constraints on deformable models: Recovering 3D shape and no rigid, Artificial Intelligence. 1988 36(1): 91-123.

[6]Fua, p.,. Object Delineation as an optimization ,A Connection Machine implementation, presented at the Proceeding of the Fourth International conference on supercomputing, Santa Clara, CA. 1989.

[7] McInerney, T., D. Terzopoulos, Deformable models in medical image analysis: A survey, Medical Image Analysis. 1996. 1(2): 91-108.

[8] Cohen, L. On active contour models and balloons, CVGIP Image Understand. 1991. 52 (2):211–218.

[9] Cohen, L., I. Cohen,. Finite element methods for active contour models and balloons for 2-D and 3-D images, IEEE Trans. Pattern Anal. Machine Intell. 1993. 15 (11): 1131–1147.

[10] Xu, C., J. Prince, Snakes, shapes, and gradient vector flow. IEEE Trans. Image Process. 1998. 7(3): 359–369

[11]Gupta, S.N., J.L. Prince, Stochastic models for DIV-CURL optical flow methods. IEEE signal Processing Lett. 1996. Vol. 3: 32–35.

22/6/2011