A New Deformable Model Based on Level Sets for Medical Image Segmentation

D.Jayadevappa, S.Srinivas Kumar, and D.S.Murty

Abstract— **This paper presents a new deformable model based on level sets for medical image segmentation which plays a pivotal role in medical diagnosis. The current popular Image segmentation deformable models such as Snakes, Geometric Active Contours, Gradient Vector Flow, Level sets and Variational Level sets have a limitation that the convergence of the contour towards the object boundary is slow and hence not suitable for real time medical diagnosis. To counter this limitation we present an improved image segmentation algorithm which is computationally efficient and also the proximity of the contour towards the object is higher compared to existing algorithms. A new speed term is introduced in the evolution step of variational level set in order to speed up the convergence process. The variational level sets in images with intensity inhomogeneity, tend to be slower and prone to leakage of contour outside the object boundary. This is due to the selection of gradient information for the termination of convergence process. However, this limitation is overcome in the proposed algorithm by modifying the edge indicator function embedded with the speed term that optimizes the effective distance of the attractive force. Experimental results are provided using real time medical images. Comparative tables and graphs highlighting the performance of various deformable models are also presented**.

Keywords— **Deformable models, Medical image segmentation, Level sets and Variational level sets.**

I. INTRODUCTION

Medical image segmentation is the process of labeling each voxel in a medical image data set to indicate its tissue type and provide information about the anatomical structure. The various confrontations in medical image segmentation are poorly defined boundaries, blur or weak edges, intensity inhomogeneity, inconsistency in image quality while doing a scan and variable object shapes in medical images [1]. Snakes [5], Geometric Active Contours (GAC) [6], [7], Gradient Vector Flow (GVF) [8], Level sets [9]-[11], and Variational Level sets [12], [13], are the deformable models available in this literature. This work aims to review the various deformable models and the limitations of these models. Further, this work aims to modify the variational level sets to speed up the convergence for effective and fast segmentation.

This paper is organized as follows. Section II presents the review of various deformable models with necessary mathematics and limitations. Section III proposes and discusses the deformable model based on Variational level set. Experimental results comparing the performance of the proposed method with existing techniques in terms of number of iterations for convergence to segment the image, computation time and also the accuracy in capturing the region to be segmented are presented in section IV and the concluding remarks could be looked up in section V.

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II. REVIEW OF DEFORMABLE MODELS

A. Snakes

The classical energy based snake model has been initially proposed in [5], and was successful in dealing with a wide variety of computer vision applications. This framework matches a deformable model to an image by means of energy minimization and thereby exhibiting dynamic behavior.

Let us define a contour c parameterized by arc length s as

$$c(s) = \{c(s) = \{(x(s), y(s)) : 0 \le s \le L\} : \Re \to \Omega \qquad (1)$$

where, L denotes the length of the contour c and Ω denotes the entire domain of an image $I(x, y)$. An energy function $E(c)$ can be defined on the contour such as

$$E(c) = E_{\text{int}} + E_{ext} \qquad (2)$$

where, E_{int} and E_{ext} denote the internal and external energies respectively. The internal energy function determines the regularity, i.e., smooth shape, of the contour. A common choice for the internal energy is a quadratic function given by

$$E_{\text{int}} = \int_0^1 \alpha |c'(s)|^2 + \beta |c''(s)|^2 \, ds \qquad (3)$$

Here α controls the tension of the contour, and β controls the rigidity of the contour. The external energy term that determines the criteria of contour evolution depending on the image $I(x, y)$ can be defined as

$$E_{ext} = \int_0^1 E_{img}(c(s))ds \qquad (4)$$

$E_{img}(x,y)$, denotes a scalar function defined on the image plane, so that local minimum of E_{img} attracts the snakes to edges. A common example of the edge attraction function is a function of the image gradient given by

$$E_{img}(x,y) = \frac{1}{\lambda\left|\nabla G_\sigma * I(x,y)\right|} \tag{5}$$

where, G denotes a Gaussian smoothing filter with standard deviation σ, λ is the suitable constant chosen and '$*$' is the convolution operator. Solving the problem of snakes is to find the contour c that minimizes the total energy term E using Greedy algorithm [14] with the given set of weights α and β.

The limitations of snakes are as follows:

(i) The classic snakes provide an accurate location of the edges only if the initial contour is given sufficiently near the edges, since they rely on the local information along with the contour.

(ii) Estimating a proper position of initial contour without prior knowledge is a hindrance.

Classic snakes cannot detect more than one boundary simultaneously since the snakes maintain the same topology during the evolution stage, which implies that the snake cannot split to multiple boundaries or merge from multiple initial contours.

B. Geometric Active Contours (GAC)

The Geometric active contour model [15], can be viewed as an 'extension' of classical Snakes since it overcomes the limitations of Snakes. This model does not impose any rigidity constraints $(\beta = 0)$ and is given by

$$E(c) = \int_0^1 f(|\nabla \mathrm{I}(c(s))|)|c_s|\,ds \tag{6}$$

$$= \int_0^{L(c)} f\left(\left|\nabla I\left(c(s)\right)\right|\right)ds \tag{7}$$

where, the function f is the edge detecting function defined in equation (5), ds is the Euclidean element of length and $L(c)$ is the Euclidean length of the curve c defined by

$$L(c) = \int_0^1 |c_s|\,ds = \int_0^{L(c)} ds \tag{8}$$

Let us introduce an artificial time 't' and considering family of curves $c(s)$ such that the energy function

$$E(c) = \int_0^1 f\left(\left|\nabla I\left(c(s,t)\right)\right|\right)\left|c_s(s,t)\right|ds \tag{9}$$

The first variation of the energy $E(c)$ is then given as,

$$\frac{dE(c)}{dt} = \int_0^1 \left[\frac{\partial s}{\partial t}(\nabla f, N)\,N - KfN\right]|c_s|\,ds \tag{10}$$

Hence, the direction for which $E(c)$ decreases most rapidly provides us the following minimization flow

$$\frac{\partial s}{\partial t} = \left(Kf - \langle \nabla f, N\rangle\right)N \tag{11}$$

where, N is the unit normal to the curve c and K is its curvature. The 1st term on the right in (11) is the mean curvature motion also called curve shortening flow, weighted by the edge detection function f. The 2nd term attracts the curve towards the boundaries of objects by creating a valley centered on the edges. The limitation of GAC is that, this model relies on a non parameterized curve, and evolves an initial curve according to the boundary attraction term towards one direction (inwards/outwards). Thus, in order to be properly used it demands a specific initialization step, where the initial curve should be completely exterior or interior to the real object boundaries.

To overcome these short comings, efforts have been made by introducing some region based features which make the model independent from its initial conditions and more robust [16]-[18]. Although these approaches seem to have a reasonable behavior, they still suffer from the one direction flow imposed by the boundary term.

C. Geometric Vector Flow (GVF)

GVF was defined in [19] as an external force to push the snake into objects concavity and discussed the shortcomings of the original snake and GAC. It is a 2-D vector field $V(s) = \left[u(s), v(s)\right]$ that minimizes the following objective function

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

where, u_x, u_y, v_x, v_y are the spatial derivatives of the field, μ is the blending parameter, and ∇f is the gradient of the edge map which is defined as the negative external force i.e. $f = -E_{ext}$. The objective function is composed of two terms. They are the regularization term and the data driven term. The data driven term dominates this function in the object boundaries (i.e. $|\nabla f|$ is large), while the regularization term dictates the function in areas where the information is constant (i.e. $|\nabla f|$ tends to zero). The GVF is found by solving the following Euler equations by using calculus of variations and the normalized GVF is used as the static external force of the snake

$$\mu\nabla^2 u - (u - f_x)\left(f_x^2 + f_y^2\right) = 0 \tag{13a}$$

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

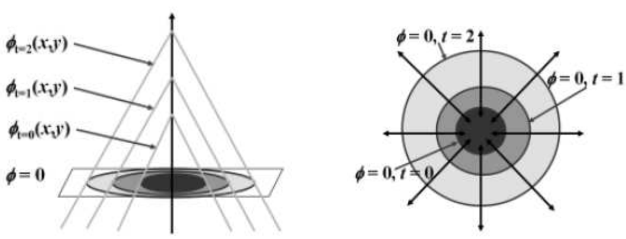
where, ∇^2 is the Laplacian operator. Limitations of Gradient Vector Flow are as follows:

(i) According to the definition of the objective function, the boundary information is not used directly (only its gradient affects the flow), which might be considered as a drawback. In other words strong edges as well as weak edges create a similar flow due to the diffusion of the flow information.
(ii) The generation of GVF is iterative and computationally intensive.

D. Level sets

Level set is a vital category of deformable models. Level set theory, a formulation to implement active contours was proposed by Osher and Sethian [20]. They represent a contour implicitly via two dimensional Lipchitz continuous function $\phi(x,y):\Omega \rightarrow \Re$, defined in the image plane. The function $\phi(x,y)$ is called level set function, and a particular level, usually the zero level of $\phi(x,y)$ is defined as the contour, such as

$$C=\{(x,y):\phi(x,y)=0\},\forall(x,y)\in\Omega \tag{14}$$



(a) (b)

Fig.1. Level set evolution and the corresponding contour propagation: (a) topological view of level set $\phi(x,y)$ evolution (b) the changes on the zero level set.

Fig.1 (a) shows the evolution of level set function $\phi(x,y)$ and Fig. 1(b) shows the propagation of the corresponding contour c. As the level set function $\phi(x,y)$ increases from its initial stage, the corresponding set of contours c, propagate towards outside. With this definition, the evolution of the contour is equivalent to the evolution of the level set function, i.e., $\frac{\partial c}{\partial t}=\frac{\partial \phi(x,y)}{\partial t}$, the advantage of using the zero level set is that a contour can be defined as the border between positive and negative areas, so the contours can be identified by just checking the sign of $\phi(x,y)$. The initial level set function $\phi_0(x,y):\ \Omega\rightarrow\Re$ may be provided by the signed distance from the initial contour such as

$$\begin{aligned}\phi_0(x,y) &= \{\phi(x,y):t=0\}\\ &= \pm D((x,y),N_{xy}(c_0))\end{aligned}$$

where, $\pm D(a,b)$ denotes a signed distance between a and b, and $N_{xy}(c_0)$ denotes the nearest neighboring pixel on initial contours $c_0=c(t=o)$ from (x,y) as a pixel (x,y) is located further inwards from the initial contours c_0. The initial level set function is zero at the initial contour points given by, $\phi_0(x,y)=0,\forall(x,y)\in 0$. The deformation of the contour is generally represented in a numerical form as a partial differential equation. A formulation of contour evolution using the magnitude of the gradient of $\phi(x,y)$ was initially proposed by Osher and Sethian [9] and is given by

$$\frac{\partial\phi(x,y)}{\partial t}=\left|\nabla\phi(x,y)\right|\left(\nu+\varepsilon k\left(\phi(x,y)\right)\right) \tag{15}$$

where, ν denotes a constant speed term to push or pull the contour, k denotes the mean curvature of the level set function $\phi(x,y)$, and ε controls the balance between the regularity and robustness of the contour evolution. Limitations of level sets are
(i) while implementing the traditional level set method, it is numerically necessary to keep the evolving level set function close to a signed distance function [21],[22].
(ii) Re-initialization, a technique for periodically re-initializing the level set function to a signed distance during the evolution, has been extensively used as a numerical remedy for maintaining stable curve evolution and ensuring reliable results. However, as pointed out by Gomes and Faugeras [23], re-initializing the level set function is obviously a disagreement between the theory of the level set method and its implementation.

E. Variational Level sets

In image segmentation, active contours are dynamic curves that move towards the object boundaries. To achieve this goal the external energy that can move the zero level curves towards object boundaries is defined. Let I be an image, and g be the edge indicator function defined by

$$g=\frac{1}{1+\left|\nabla G_\sigma * \mathrm{I}\right|^2} \tag{16}$$

where, G_σ is the Gaussian kernel with standard deviation σ. An external energy for a function $\phi(x,y)$ can be defined as

$$\xi_{g.\lambda.\nu}(\phi)=\lambda L_g(\phi)+\nu A_g(\phi) \tag{17}$$

where, λ and ν are constants, and the terms $L_g(\phi)$ and $A_g(\phi)$ are defined as

$$L_g(\phi)=\int_\Omega g\delta(\phi)\left|\nabla\phi\right|dxdy \tag{18}$$

$$A_g(\phi)=\int_\Omega gH(-\phi)dxdy \tag{19}$$

where, δ is the univariate Dirac function, and H is the Heaviside function which is defined as

$$H(\phi)=\begin{cases}0 & |\phi|\le-\rho,\\ \frac{1}{2}\left(\sin\left(\frac{\pi\phi}{2\rho}\right)+1\right) & -\rho<|\phi|<\varepsilon,\\ 1 & |\phi|\ge\rho,\end{cases} \tag{20}$$

Now the total energy functional

$$\xi(\phi) = \mu p(\phi) + \xi_{g,\lambda,v}(\phi) \quad (21)$$

The external energy $\xi_{g,\lambda,v}$ drives the zero level set towards the object boundaries, while the internal energy $\mu p(\phi)$ penalizes the deviation of (ϕ) from a signed distance function during its evolution. . By calculus of variations [24], Gateaux derivative (first variation) of the function ξ in (21) can be written as

$$\frac{\partial \xi}{\partial \phi} = -\mu\left[\nabla \phi - div\left(\frac{\nabla \phi}{|\nabla \phi|}\right)\right] - \lambda\delta(\phi) div\left(g\frac{\nabla \phi}{|\nabla \phi|}\right) - vg\delta(\phi) \quad (22)$$

(22) is the evolution equation of the level set used in [25].
Advantages of Variational Level sets are as follows:
(i)Significantly larger time step can be used for numerically solving the evolution of partial differential equation, and therefore speeds up the curve evolution.
(ii)The level set function can be initialized with general functions that are more efficient to construct and easier to use than widely used signed distance function.
(iii)The level set evolution in this method can be easily implemented by simple finite difference scheme and is computationally efficient. Limitations of Variational Level sets are:
(i) The gradient function in (22) give very small values at the boundary and makes the speed of the moving contour low.
(ii) In case of images with intensity inhomogeneity, the gradient based term can never stop the level set evolution completely even for ideal edges, making leakage often inevitable.

III. Modified Variational Level Set

To overcome the above mentioned drawbacks a modified variational level set method is proposed. This offers a long-range attraction generated by the object boundary and acting on the evolving contour for solving the segmentation problem. This frame work is generic and can be applied to images which are noisy, having weak and blurred edges along with intensity inhomogeneity. It is experimentally shown that this method is effective in detecting elongated and overlapped tissues structures.

In existing level set techniques, the gradient information is used as stopping criteria for curve evolution, and provides the attracting force to the zero level set from a target boundary. However, in case of images with intensity inhomogeneity, the gradient based term can never fully stop the level set evolution even for ideal edges, making leakage often inevitable.

In this work a novel frame work for level set evolution by introducing a new speed term, is proposed. This work explores a new edge indicator function embedded with a speed term, which optimizes the effective distance of the attracting force and also provides robust edge estimation. By using this term, the leakage problem is avoided effectively in most cases and also capture range is improved compared to traditional level set methods.

In this section a speed term q for interaction between object boundary and moving contour during the contour evolution is defined. Let ϕ be the level set function. The evolution is given as

$$\frac{\partial \phi}{\partial t} = q|\nabla \phi| \quad (23)$$

where, q represents the speed term, in which the values of speed are well defined in the whole space. We now define the speed term q of a two dimensional moving contour $c(s)$, as shown in Fig.2 represents the object boundary and another contour $\gamma(s)$ represents the moving contour. At any point p on the moving contour, the speed is derived based on the elastic interaction between line defects [26]-[28], the speed term q is defined as

$$q = -\int_{c(s)} \frac{l.n}{|l|} ds \quad (24)$$

where, l is a vector defined as $l = (x - x(s), y - y(s))$ between the point (x, y) and a point $(x(s), y(s))$ on $c(s)$ and $|l| = \sqrt{(x - x(s))^2 + (y - y(s))^2}$, and n represents the normal direction. Under this definition, the speed inside the object boundary and outside the object boundary differs in sign. We describe how the speed function defined above can be used for image segmentation problem. Let an image be $I(x, y)$ located in the $Z = 0$ plane.

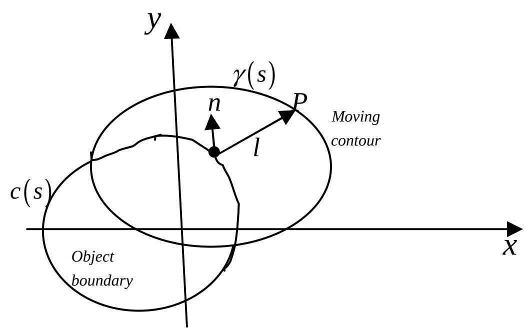


Fig.2. Interaction between object boundary and moving contour.

The speed term is set to depend on the intensity values in the image by replacing the normal direction n in (24) by the image gradient ∇I . However, the image based speed function is singular on the contour $c(s)$. The singularities can then be smeared out if the normal direction n is replaced with the gradient of the smoothed image $\nabla(G_\sigma * I)$, where G_σ represents a Gaussian smoothing filter with standard deviation σ . Therefore, the image based speed term' q ' is given as

$$q = \int_{\Omega} \frac{l \cdot \nabla(G_\sigma * I)}{|l|} \quad (25)$$

where, Ω denotes the image domain and $(x, y) \in \Omega$. Another important property of the speed term q is that it is a long range speed generated by the object boundary, and there is no need to place the initial contour entirely inside or outside the object. Also, the sign of the speed depends on the direction of the contour and the object boundary, so that the contour is not necessary to be placed entirely inside or near the object boundary.

In the above definition of speed function, the image noise also generates a speed term for the moving curve, resulting in spurious contours. The speed generated by the noise is relatively small as compared with that by the object boundary. We remove this contribution of the noise by adding the interaction within the moving contour, so that the relative weak interaction between the noise and the moving contour can be overcome. The speed term q is now defined as

$$q = -\int_{\Omega} \frac{l \cdot \nabla\left(G_\sigma * I + wH(\phi)\right)}{|l|} dxdy \tag{26}$$

where, w is the adjustable weight, $H(\phi)$ is the Heaviside function defined in (20) and ρ is constant. The value of speed term is calculated using the FFT algorithm. Now we can introduce a small curvature term associated with a small weight μ , along with the weighted length term and weighted area term then the new evolution equation becomes

$$\frac{\partial \phi}{\partial t} = \mu(\nabla\phi - k) + \lambda\delta(\phi)(g \cdot k) + q \cdot g\delta(\phi) \tag{27}$$

where, k is the mean curvature of the level set function given as

$$k(\phi(x, y)) = div\left(\frac{\nabla\phi}{\|\nabla\phi\|}\right) \tag{28}$$

$$= \frac{\phi_{xx}\phi_y^2 - 2\phi_x\phi_y\phi_{xy} + \phi_{yy}\phi_x^2}{\left(\phi_x^2 + \phi_y^2\right)^{3/2}} \tag{29}$$

where, ϕ_x , ϕ_{xx} , ϕ_y , and ϕ_{yy} denotes the first and second order partial derivatives of $\phi(x, y)$ with respect to x and y . In the proposed method, the Dirac function $\delta(x)$ in (27) is slightly modified to achieve additional control by introducing ς term and is given by

$$\delta_\varsigma(x) = \begin{cases} 0, & |x| > \varsigma, \\ \dfrac{1}{2\varsigma}\left(1 + \cos\left(\dfrac{\pi x}{\varsigma}\right)\right), & |x| \le \varsigma, \end{cases} \tag{30}$$

we use $\varsigma = 1.2$ and all the spatial partial derivative and temporal partial derivative are approximated by the central difference, and the backward difference scheme respectively. The right hand side in (27) by the difference scheme can be simply written as

$$\frac{\phi_{i,j}^{k+1} - \phi_{i,j}^{k}}{\tau} \tag{31}$$

The difference equation (31) can be expressed as the following iteration

$$\phi_{i,j}^{k+1} = \phi_{i,j}^{k} + \tau R\left(\phi_{i,j}^{k}\right) \tag{32}$$

where, τ is the time step, using larger time step can speed up the evolution, but may cause error in the boundary location if the time step chosen is too large.

A. Initialization of Level set Function

In this method not only the re-initialization procedure is completely eliminated, but also the level set function ϕ is no longer required to be initialized as a signed distance function. Here we propose the region based initialization of level set function, it is computationally efficient and allows for flexibility in some situations. The proposed initial level set functions are computed from an arbitrary region Ω_0 in the image domain Ω . For example, if the regions of interest can be roughly and automatically obtained in some way, such as thresholding, and then we can use these roughly obtained regions as the region Ω_0 to construct the initial level set function ϕ_0 . Then the initial level set function will evolve in an uniform fashion according to the evolution equation and level set curves converged to the region of interest.

B. Implementation

The implementation of the various deformable models starts with the identification of all adjustable parameters for each method. In this work, MATLAB 7.1 is used on dual core Pentium–IV processor with 1GB RAM in implementing various deformable models. The selected methods have all the following common simple characteristics: A Gaussian blurring filter is the pre-processing performed on the image and no post-processing is used; the gradient magnitude images or their thresholded results of the Gaussian blurred images are used as the edge maps; the initial contour is formed as a circle centered around the initial location, a selected image point defined by the user; no prior information of the object shape or texture pattern is available. The parameters, within each group of deformable contour methods, are very similar and are described in the next section.

C. Parameters for Deformable models

The Snake model, Geometric Active contour and Gradient Vector flow have six parameters in common: elasticity (α), rigidity (β), viscosity (γ), external force field (u, v) and deformation step (DS). The α and β parameters are associated with the internal force in the original snake model in (3). The γ and DS parameters are used in iteratively updating contour location (i.e., deformation), thus not explicitly included in the deformation equations. The combination of α and β parameters allows the contour to maintain smoothness during the deformation process. Decreasing α or β will result in corners and self intersections in the deforming contour, while increasing them will shrink the contour to a line or point. The γ parameter is a weight parameter to adjust the viscosity used in updating the contour position. Increasing γ will slow down the contour deformation process and make the deformation more stable. The external force field determines the strength of the effect of the image features that make up the external force. The GVF snake has two additional parameters, namely regularization μ and iterations N . The GVF regularization parameter, μ in (13a) and (13b), has a correlation with the noise level of the image. The image noise is directly proportional to μ .

The level set method has two common parameters and they are: iteration step (IS) and deformation step (DS). The iteration step is related to the discrete implementation of the level set contour deformation process. Decreasing iteration will result in a slow deformation process but a more stable deformation.

The component λ is used in the variational level set active contour, is a variable used to weight the area and length functionals, in (17). In the modified variational level set, the speed term q is used in (25) for the interaction between the object boundary and the moving contour to speed up the convergence process and the additional parameter ς to modify the Dirac delta function in (30).

D. *Parameter settings*

Once the parameters are identified, the next question is how to determine and adjust the parameter values to obtain good results with small errors compared with the expert contours. In practice, for a new set of images with similar characteristics some preliminary training and testing are normally required. In the experiments we used a course to fine scheme on the image test set to achieve the best parameter set based on both the qualitative and quantitative error measures. The following steps outline the process used to determine parameter settings and tuning of the deformable models under consideration.

(i) Except for the selected adjustable parameter and the deformation step parameter, fix all other parameters to their initial values or their acceptable ranges.

(ii) Adjust the selected parameters and run the program.

(iii) Determine the suitable range for the parameter in which the resultant contour converges to the object boundary.

Repeat the above steps for the other parameters with the assumptions that the parameters are independent, thus the order in choosing parameters does not matter. Intuitively, if the parameters were dependent on each other then the resultant contours would not converge or provide accurate results.

E. *Contour Initialization*

To broaden the scope of the deformable models test, the initial contour being formed as a circle around the user selected location, included two variations of initial contour locations and sizes, as illustrated in Fig.3. In general, initial contours for deformable models in medical image segmentation can be constructed by (a) placing a small contour within the object, (b) placing a large contour outside the desired boundary. The main experiments focused on the first condition because it requires the least user interaction for automated image segmentation. Fig. 3(b) shows the contour initialized around the object boundary. The differences in unit iteration times among the various images are functions of the initial contours as well as the type of image. For example, the number of iterations depends on how close the initial contour is placed to the region of interest.

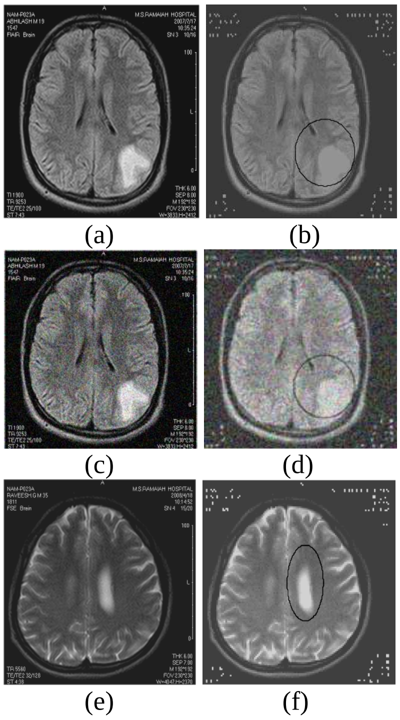


Fig. 3. Contour initialization. (a) Original image. (b) Contour position for original image. (C) Image with Gaussian noise ($\sigma = 0.02$). (d) Contour position for noisy image. (e) Image with weak object boundary. (f) Contour position for image with weak object boundary.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

The performance of the above mentioned deformable models have been tested and analyzed with three types of real image data sets of size 512 x 512 pixels. These images are the MRI slice of brain attained of tumors pathology, obtained from M S Ramaiah Medical College and Hospital, Bangalore.

Experimental results are obtained by implementing various deformable models [29]-[33]. In the following section, performance is tested considering the images with weak edges and also images affected by Gaussian noise.

The goal of the MRI brain image without noise experiment was to determine which method could segment an object that has diverse contrast in the region within the target boundary. In this test image, the Snake model, GAC, and GVF has almost same result, because there is no contour topology change, as shown in Fig. 7(a), (d) and (g). Level set and Variational level set also had poor results. All the results, except the proposed deformable model, Fig. 7(p), the contours could not reach or converge to the region of interest. From the visual observation of the radiologist, the proposed method gives the best segmentation result for MRI image without introducing noise.

In case of MRI brain image with Gaussian noise $\sigma = 0.02$ in Fig. 7 (b), the Snake model, GAC, GVF, are sensitive to noise and incapability of contour topology change and thus, unable to converge exact boundary as displayed in Fig.7 (b), (e) and (h). The Level set and variational level set were determined to provide the best qualitative results with small leakage in the contour near the object boundary as shown in Fig. 7(k) and 7(n). Therefore, the proposed method could yield acceptable result for the noisy image as displayed in Fig. 7(q).

In case of MRI brain image with weak edges, the segmentation problems result from the complex shape with inhomogeneous interior and gaps. Due to the proximity of the gaps, we observe that the contour leaks through the low contrast edges in Snake model, GAC, GVF, and Level set as shown in Fig. 7(c), (f), (i) and (l). Whereas the proposed method survives both weak and strong edge as shown in Fig. 7(r).

It is observed that the contour is converging towards the object boundary from iteration to iteration. However, the final result in terms of accuracy in converging to the object boundary is varying from one technique to another. It is also observed that, the method based on variational level sets is performing well for accurate boundary detection. However, it is computationally intensive and the performance is poor in the presence of noise. Hence, the modified variational level set with speed term, is used to speed up the segmentation process and also accurate convergence to the object boundary. Several visual results are presented. The computation time, and the number of iterations are reported in the following tables.

Table 1. Comparison of No. of Iterations and computation time for original image.

Parameters	Deformable models					
	Snake model	GAC	GVF	Level set	Variat. level set	Proposed method
Iterations	3400	2800	2600	760	850	510
Computation-time	220s.	180s	165s	123s.	111s.	62s.

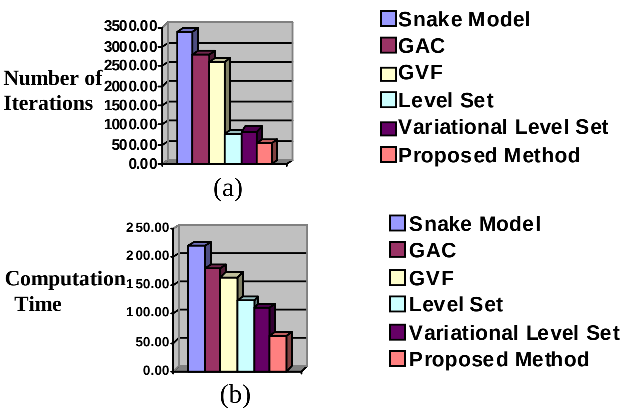


Fig. 4. Comparative performance of original image in terms of number of iterations and computation time for different Deformable models. (a) No. Iterations, (b) Computation time in sec.

Table 2. Comparison of No. of Iterations and Computation time for image corrupted by Gaussian noise ($\sigma = 0.02$).

Parameters	Deformable models					
	Snake model	GAC	GVF	Level set	Variat. level set	Proposed method
Iterations	3745	3200	2700	1100	1055	645
Comp. time	245s.	200s	175s	130s.	110s.	85s.

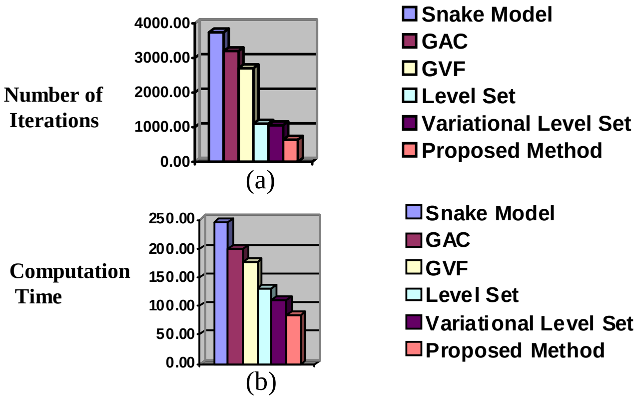
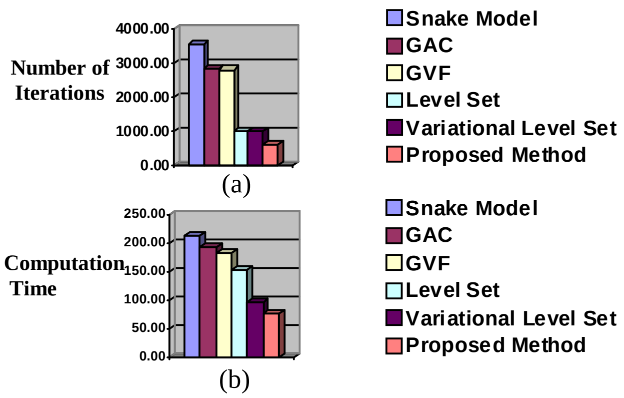


Fig. 5. Comparative performance of noisy image in terms of number of iterations and computation time for different Deformable models. (a) No. Iterations, (b) Computation time in sec.

Table 3. Comparison of No. of Iterations and Computation time for image with weak object boundary.

Parameters	Deformable models					
	Snake model	GAC	GVF	Level set	Variat. level set	Proposed method
Iterations	3555	2850	2800	1010	980	605
Computation-time	215s.	195s	185s	155s.	95s.	77s.



F ig. 6. Comparative performance of image with weak edges in terms of number of iterations and computation time for different Deformable models. (a)No. Iteration
(b) Computation time in sec.

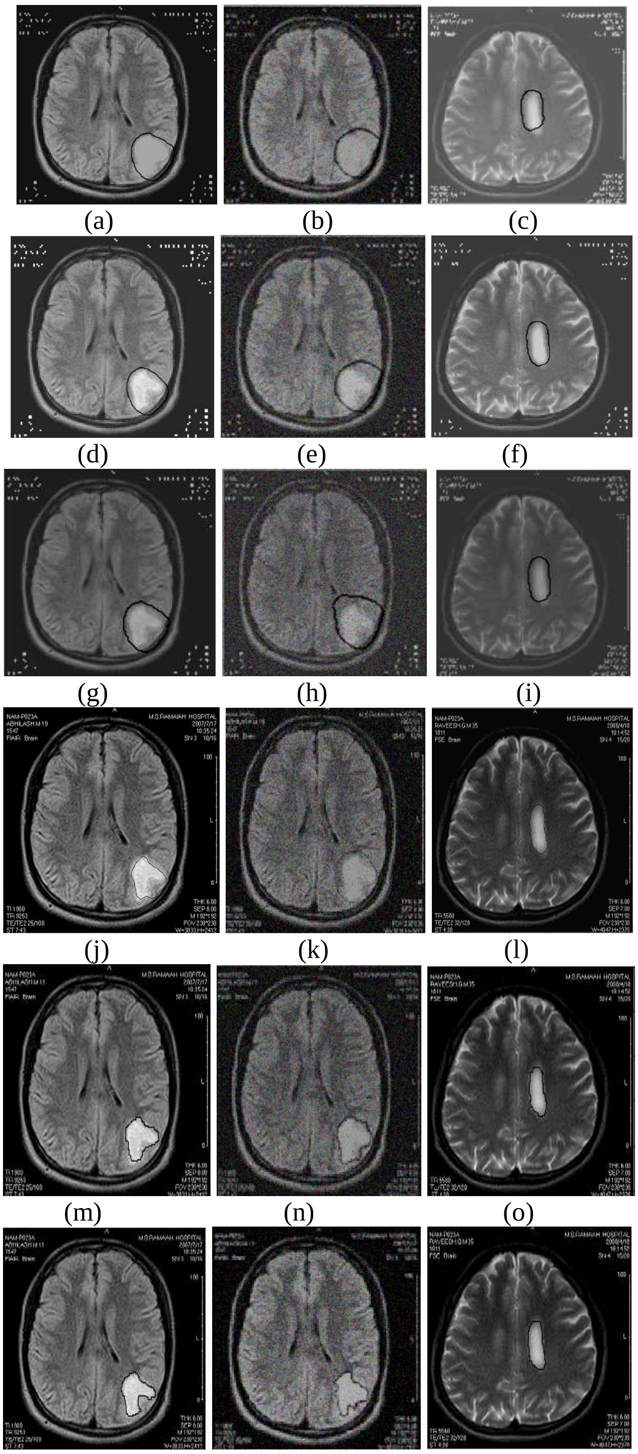


Fig. 7. Final segmentation results for original image, noisy image ($\sigma = 0.02$) and image with weak edges: (a) – (c) correspond to Snakes model, (d) – (f) correspond to GAC model, (g) – (i) correspond to GVF model, (j) – (l) correspond to Level set method, (m) – (o) correspond to Variational Level set method and (p) – (r) correspond to the proposed method.

It is also observed that, in the modified variational level set, the speed term q embedded with edge indicator function is adjusted. This in turn reduces the computation time compared to variational level set as shown in the tables, and the number of iterations are reduces from 1055 to 510. Further the performance is also tested in the presence of Gaussian noise with $\sigma = 0.02$, in both variational level set and also in modified variational level set. It is observed that the modified variational level is superior in terms of convergence to the object boundary compared to the variational level set. The experimental results are presented considering various deformable models shown in Fig. 7. The comparative result shows that, the proposed method survives both the image with weak edge and the strong edges (Fig. 7. (p) - (r), where as other methods, the contour leaks through the low contrast edges and noisy images (Fig. 7. (a) - (o). Level set method overcomes previous problems faced by Snakes, GAC, and GVF. Meanwhile, computation is intensive, so modified variational level set methods attempts to speed up the process. Comparative results shows that the proposed method is accurate in terms of locating the tumor in the image, and can be used for medical diagnosis to segment tumors automatically without much manual intervention.

V. Conclusion

The challenges of medical image segmentation are addressed by using deformable models and the effectiveness of the proposed technique in extracting features from noisy medical images has been demonstrated. The experimental results show that, for images with noise, the algorithm is able to speed up the process considerably while capturing the desired object boundary compared to other methods. Fine tuning the parameters in the associated equations might improve the performance of the algorithm. In the analysis and derivation of information in the image at different scales, removing unnecessary and irrelevant details, multi-resolution method can greatly improve the convergence and the computation speed. More emphasis should be placed on using adaptive edge detectors and smoothing operators on the image to eliminate noise and weak edge problems.

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