A New robust Level Set image segmentation method based Signed Pressure Force function : Application to Medical Images

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***Abstract*— Segmentation is an extremely active field of research since it is an important step in the treatment and the interpretation of the medical images. It represents one of the most difficult step for relevant parameters extraction from images. In this paper, we study A New robust Level Set image segmentation method is developed by formulating Signed Pressure Force Function (SPF). The advantages of this method are Firstly, the Function of Signed Pressure can efficiently stop the contours at weak or blurred edges, Second, exterior and interior boundaries can be detected no matter where the initial contour starts. We compare this method with Chan Vese (C-V) model and Geodesic Active Contours (GAC). The performance of each method can be evaluated either visually, or from similarity measurements between a reference and the results of the segmentation. We have applied each method for different medical images. Through simulated results, we have demonstrated that the best results are achieved by the proposed method.**

Keywords*— *Image Segmentation, Geodesic Active Contours (GAC), Level Set, Chan Vese (C-V) model Active Contours, Medical Images, Function of Signed Pressure (SPF).

I. INTRODUCTION

Accurate image segmentation is a testing research point of expanding interest, particularly in the most recent decade. It has been, and still, a vital errand in the fields including PC vision, restorative images, and image investigation. The segmentation approaches vary starting with one methodology of medical images [1], then onto the next. In other words, the procedure for segmentation ought to be done, as indicated by a methodology of obtaining (scanners, radiography, Magnetic Resonance Images).Different methods have been proposed for image segmentation including the Active Contour Models (ACM).[2-5] The fundamental idea of ACM is to evolve a curve under some constraints from a given image to reach the boundaries of the desired objects, by minimizing energy functional. According to the energy, ACM are classified into two main categories: edge-based models [5-8] and region-based models. Edge-based models rely on the image gradient information to stop the evolving curve on the desired object boundaries [9-14]. Geodesic Active Contour (GAC) is one of the well-known models in this category. Although GAC has been successfully applied for images with high variation in gradient at the object's boundaries, it meets difficulty when dealing with the objects having blurred or discrete boundaries and it hardly detects the object corrupted by noise. Unlike to edge-based models, the region-based models do not utilize the image gradient; they utilize image statistics inside and outside the curve to control the evolution with better performance including weak edges and noise. One of the famous region-based models is the Chan and Vese (C-V) model which is a simplified Mumford-Shah model. The C-V model utilizes the global information of homogeneous regions. Thus, it has good segmentation result for the objects with weak or discrete boundaries but often has erroneous segmentation for images with intensity inhomogeneity.

To ameliorate the robustness to contour initialization, we proposed a hybrid model combining the local and global intensity information, which utilizes a region-based Signed Pressure Force (SPF) function to update curve evolution to regularize the Level set function. This technique named Selective Binary and Gaussian Filtering Regularized Level Set (SBGFRLS) method [17], is based on Chan Vese (C-V) model [8] and Geodesic Active Contours (GAC) [6], [7]. Both these models are based on active contour model. The SBGFRLS model is able to overcome the problems of the GAC and the C-V model but still it is not good for medical images. It is not able to detect all boundaries. So here in the proposed model a new SPF function (SPFn) is developed to overcome this problem. Proposed model also takes less time to converge.

The paper is structured as follows: In Section 2, we describe two distinguished classes of segmentation approaches the classic GAC and C–V models. Section 3 describes the formulation of our proposed methods. In particular we show how Gaussian smoothing kernel is used to regularize a level set function. Result discuss of implementation issues of the considered methods is presented in Section 4. We evaluate the behavior of the methods using biomedical images. The main conclusion of this work is given in Section 5.

II. METHODS OF SEGMENTATION

The level set method is a numerical technique for capturing moving fronts, and was introduced by Osher and Sethian [15] in 1987. The formulation of moving fronts (contours C) in level set method, the fronts are represented by the zero level set:

$$C = \{(x,y): \phi(x,y) = 0\}, \forall (x,y) \in \Omega \tag{1}$$

Where:

$\phi(x,y): \Omega \to IR$ level set function **LSF** .

Ω : plan of the image.

The level set evolution equation can be written in the following general form (partial differential equation **PDE**):

$$\frac{\partial \phi}{dt} = F|\nabla \phi| \tag{2}$$

F :Speed function (depend on the LSF and image data)

∇ : is the gradient operator.

The advantage of the level set method is that numerical computations involving curves and surfaces on a fixed Cartesian grid without having to parameterize the points on a contour as in parametric active contour models. Another advantage of level set methods is that they can represent contours of complex topology and are able to handle topological changes, such as splitting and merging, in a natural and efficient way, which is not allowed in parametric active contour models [9], unless extra indirect procedures are introduced in the implementations.

A. Geodesic Active Contours

Geodesic Active Contours (GAC here) is a model that theoretically combines explicit Active Contour Models (Snakes) with the Implicit Active Contour Models (Level Sets).It was simultaneously introduced by Kichenassamy et al [16] and Caselles & Kimmel [6] . The model starts from the Snakes formulation and shows that it is equivalent to finding a geodesic curve in a Riemannian space with a metric based on the image content. Level set formulation for GAC model is given by:

$$\frac{\partial \phi}{\partial t} = g(|\nabla \phi|)\left(div\left(\frac{\nabla \phi}{|\nabla \phi|}\right) + \alpha\right) + \nabla g.\nabla \phi \tag{3}$$

Where ϕ is the level set function, ∇ is the gradient operator, α is real constant called the balloon force which controls the curve evolution and g is the edge based function and defined as in eq. (4)

$$g(|\nabla I|) = \frac{I}{I + |\nabla G_\sigma * I|^2} \tag{4}$$

Where G_σ is a Gaussian Kernel with standard deviation σ.

Because GAC model is based on gradient information so it is not suitable for images with weak edges. In some cases balloon force, which is very difficult to design has been used. The other weak balloon force doesn't allow the contour to pass through narrow part of the object and in case of the large balloon force, contour will pass through the weak edges. When contour is far from the object boundary then also it is difficult to find interior or exterior boundaries of the object.

B. Chan & Vese Method

It is a new model for image segmentation based on Mumford-Shah functional and level sets [9], and is used widely in the medical imaging field. This model doesn't depend on the gradient of the image as stopping term. Therefore it can be used in images with ambiguous boundaries. This algorithm is a region-based method. It tends to separate the image into two homogeneous region. $\phi(x,y)$ is implemented as a signed distance function and is reinitialized at each iteration. The evolution equation is as follows [10]:

$$\frac{\partial \phi}{dt}(x) = \delta(\phi(x))((I(x)-v)^2 - (I(x)-u))^2 + \lambda\, \delta(\phi(x))\, k \tag{5}$$

The Energy criterion:

$$E(\phi) = \int_\Omega F(I(x), \phi(x))\, dx + \lambda \int_\Omega \delta(\phi(x)) \|\nabla \phi(x)\|\, dx \tag{6}$$

$$F(I(x), \phi(x)) = H(\phi(x))\left(I(x)-v\right)^2 + (1 - H(\phi(x)))\left(I(x)-u\right)^2 \tag{7}$$

Where:

δ: the Dirac function.

H: the Heaviside function.

$$u = \frac{\int_\Omega (1 - H(\phi(x))).I(x)\, dx}{\int_\Omega 1 - H(\phi(x)) dx} \tag{8}$$

$$v = \frac{\int_\Omega H(\phi(x)).I(x)\, dx}{\int_\Omega H(\phi(x))\, dx} \tag{9}$$

u and v are two parameters updated at each iteration.

The C-V model has good performance when segmenting images with weak edges and noise. Thus, the use of global information of the image leads to inaccurate segmentation results for images with intensity Inhomogeneity.

III. THE PROPOSED METHOD

This method utilizes the advantages of both GAC and C-V model. In the substitution of Edge Stooping Function (ESF), a region based Singed Pressure Force function has been (SPF) developed. This SPF function controls the direction of evolution. Opposite signs (range of SPF function is [-1 1]) around the boundaries of the object in this function make the contour to able to expand when it is inside the boundary and to shrinks when it is outside the boundary.

SPF function proposed in this model is as in eq. (10):

$$spf\left(I(x,y)\right)=\frac{(u+v)*\left(I(x,y)-\frac{u+v}{2}\right)}{\max\left((u+v)*\left|I(x,y)-\frac{u+v}{2}\right|\right)},x,y\in\Omega \qquad (10)$$

Where:

u and v are two parameters updated at each iteration, in eq. (8) and eq. (9) respectively.

On the substitution of SPF function in eq. (3), the level set formulation takes the form as in eq. (11)

$$\frac{\partial\phi}{\partial t}=spf\left(I(x,y)\right).\left(div\left(\frac{\nabla\phi}{|\nabla\phi|}\right)+\alpha\right)|\nabla\phi|+\nabla spf\left(I(x,y)\right).\nabla\phi,x,y\in\Omega \qquad (11)$$

The regular terms $div\left(\frac{\nabla\phi}{|\nabla\phi|}\right)|\phi|$ and $\nabla spf\,.\nabla\phi$ can be removed because the method utilizes the statistical in formation of the regions. Thus the final level set model is given as in eq. (12)

$$\frac{\partial\phi}{\partial t}=spf\left(I(x,y)\right).\alpha|\nabla\phi|,x,y\in\Omega \qquad (12)$$

Concrete Steps of *proposed* Method

Input: Image of size $n_l \times n_c$.

Image I : $\Re \rightarrow \Omega$: where:

$\Omega \in R^n$ is the domain of the image.

Step 1 Initialize the level set function ϕ as:

$$\phi\,(x,t=0)=\begin{cases}-\rho & x\in\Omega_0-\partial\Omega_0\\ 0 & x\in\partial\Omega_0\\ \rho & x\in\Omega-\Omega_0\end{cases} \qquad (13)$$

ρ=constant >0

$\Omega_0 \in \Omega$: subset in the image domain .

$\partial\Omega_0$: the boundary of Ω_0 .

Step 2 Compute the coefficients u and v are defined in eq. (8) and (9) respectively.

Step 3 Evolve the level set function according to Eq. (12)

Step 4 Let $\phi=1$ if $\phi>1$, otherwise $\phi=-1$

Step 5 Regularize the level set function with a Gaussian filter, i.e $\phi=\phi*G_\sigma$

Step 6 Check whether the evolution of the level set function has converged. If not, return to step 2.

(end of procedure).

The algorithm flow diagram is as follows :

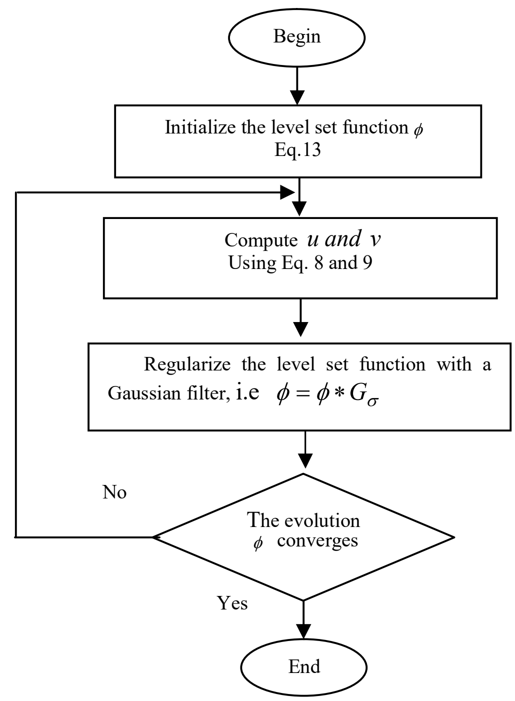

Fig 1. Fundamental steps employed for the proposed method

A. *Segmentation Quality, in the Context of Computational Performance*

To quantitatively evaluate the performance of the developed segmentation algorithm, we have computed four similarity criteria, in addition to the visual criterion which compares between the result contours of each selected algorithm and the reference image. The calculated criteria are Dice criterion, Peak Signal-to-Noise Ratio PSNR, Hausdorff Distance (HD), and the Mean Sum of Square Distance

(MSSD). The considered criteria Dice coefficient, PSNR, HD and MSSD measure the closeness between the reference segmentation and the segmentation provided by each selected algorithm. The larger the PSNR, the more efficient our LSM method. While, the smallest HD and MSSD, the more efficient our LSM method. Dice coefficient should be between 0 and 1. When Dice coefficient reaches 1, the segmentation is perfect.

1) Dice Criterion

Dice criterion is defined by:

$$Dice = \frac{2(A \cap B)}{A+B} \tag{14}$$

A and B are the reference mask region and the result mask region of the LSM algorithm.

2) PSNR

$$PSNR = 10\log_{10}\left(\frac{d}{MSE(A,B)}\right) \tag{15}$$

d : The maximum possible value of the picture.
$MSE(A,B)$: Mean Square Error.

$$MSE(A,B) = \frac{1}{MN}\sum_{m=1}^{M}\sum_{n=1}^{N}\left\|A(m,n) - B(m,n)\right\|^2 \tag{16}$$

3) Hausdorff distance

$$Hausdorff = \max\left(D_1(A,B), D_1(B,A)\right) \tag{17}$$

Where:

- A : The reference contour.
- B : The final contour of the LSM algorithm.
- $D_1(A,B) = \max_{x\in A}(\min_{y\in B}(\|x-y\|))$

4) Mean Sum of Square Distance (MSSD)

$$MSSD = \frac{1}{N}\sum_{n=1}^{N} D_2^2(A, B(x_n)) \tag{17}$$

Where:

- A : The reference contour.
- B : The final contour of the LSM algorithm.
- N : Is the size of the final contour.
- $D_2(A, B(x_n)) = \min_{y\in A}(\|y-x\|)$.

IV. Experimental Results

In this part, we discuss the performances of our proposed segmentation scheme. A quantitative comparative study is also established to highlight the superiority of our method. The proposed method has been applied to medical images with different modalities. The comparison is carried out in term of the Dice, PSNR, HD, and MSSD coefficients. All the numerical experiments were run on a PC with 3.40GHz Core i5 CPU, 8GB RAM and Matlab (R2016b). We use four examples of medical images, namely the Brain image, the chest image, Arms_XRay and Vessel_CTA1 respectively.

Example1

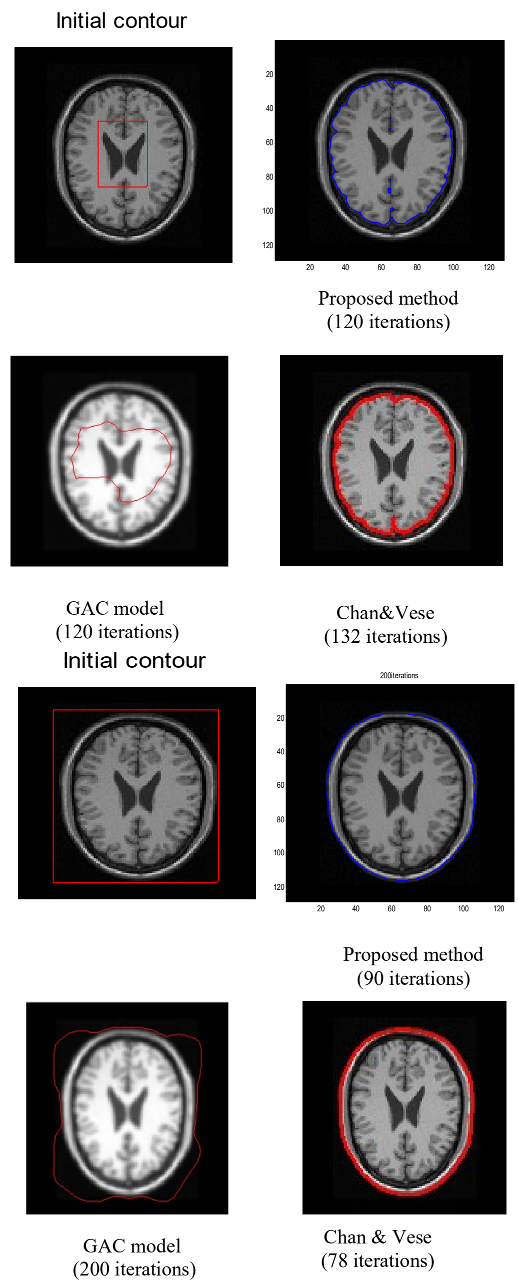

Fig. 2 Segmentation of Brain image.

Example2

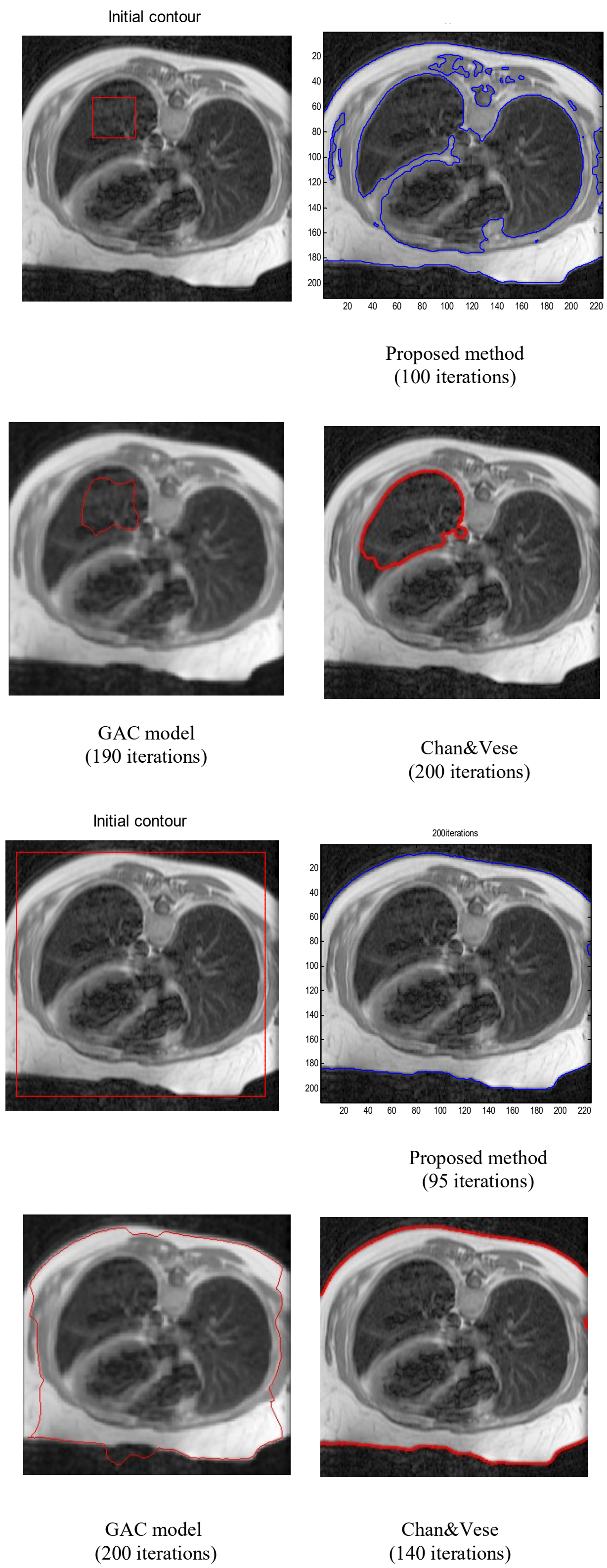

Fig. 3 Segmentation of chest image.

Example 3

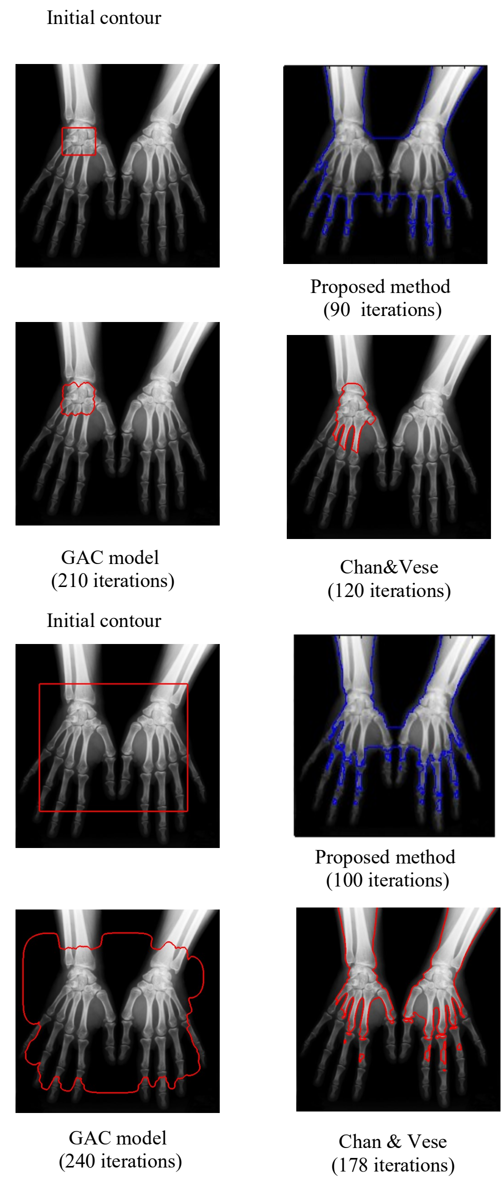

Fig. 4 Segmentation of Arms_XRay image.

Example 4

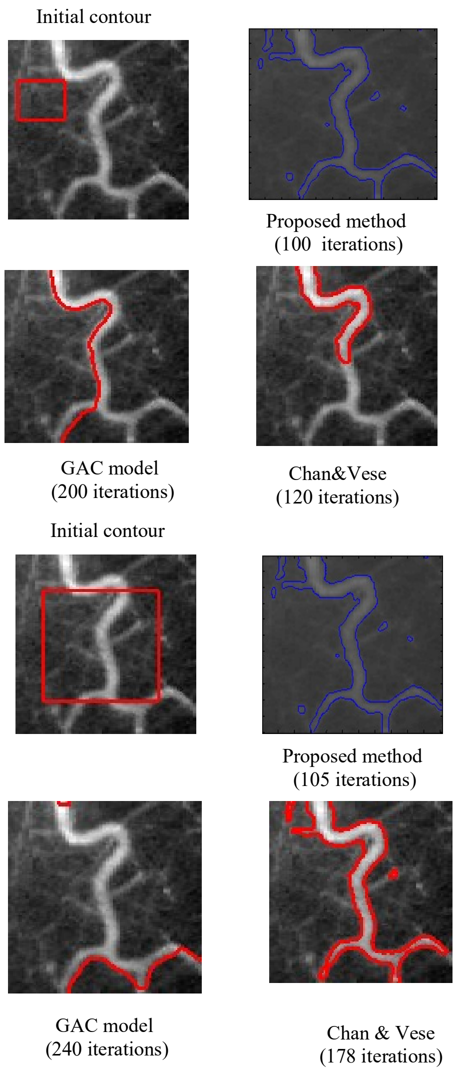

Fig. 5 Segmentation of Vessel_CTA1 image.

Four experiments are conducted to validate the adequacy of the Proposed method method. three representative are taken as baselines on medical images. Chan & Vese, the GAC model and Proposed method (This method utilizes the advantages of both GAC and C-V model). For the sake of comparison, the initial contour used is the same for all the methods.

Experiment1 applied the three methods to medical image with Brain image, as shown in Fig 2. The left column in the first row of Fig 2 shows the initial contour, which is inside the Brain, the others column of the first row and second row show the corresponding segmentation results of Proposed method , GAC method and Chan & Vese algorithm, respectively. We have found that, the evolution of the Proposed method and GAC model converge at 120 iterations, while for the Chan & Vese algorithm, the evolution converge at 132 iterations. Proposed method and Chan & Vese algorithm detect the exterior whereas the snakes model fails to detect the brain.

The left column in the third row shows the initial contour, which is around the brain image, the others columns of third and fourth row show the corresponding segmentation results. We see that the contour of the brain is accurately detected by Proposed method and Chan & Vese algorithm but the GAC method fails to detect the contour.

In Experiment 2,compares the Proposed method , the GAC method and Chan & Vese algorithm by applying them to a chest image. The left column in the first row shows the initial contour which is inside the chest, the initial contour of third row is around the chest, the others columns of first and second row show the corresponding segmentation results of the three models .The segmentation by Proposed method and Chan &Vese algorithm are obviously more accurate than the corresponding segmentation results of the GAC model.

Experiment 3 applied the three methods on a medical image containing Arms_XRay image as shown in Fig 4. The left column in the first row shows the initial contour which is inside the Arms_XRay, the other columns show the corresponding segmentation results of the three models. The results show that GAC method missed the boundaries because its image gradient-based stopping function cannot well deal with the weak boundaries; Chan & Vese also failed to detect the boundaries, Proposed method almost correctly outlined the object with a smooth contour .

In Experiment 4, these three methods were applied to an Vessel_CTA1 image, as shown in Fig 5. The left column in the first row shows the initial contour which is inside the Vessel_CTA1 (of the left Ort). The initial contour of the third row is a middle of the Vessel_CTA1, the other columns show the corresponding segmentation results of the three models. The obtained results illustrate that Proposed method (for Initial contour 1) detected the part of boundaries around the mass, but the result is not complete; GAC method failed to detect the complete region; Chan & Vese method obtained the same curve outlining the mass to be captured but the Proposed method gives the best results .

From Table I, Table II , Table III and Table IV , it can be see that Proposed method succeed for segmentation the image:

Table I. The coefficients: times, Dice, Hausdorff and MSSD of the three method s obtained for the segmentation of Brain image.

Methods	Time (S)	Dice coefficient	Hausdorff coefficient	MSSD coefficient
Snakes	10.57	0.22	41.44	406.17
Chan&Vese	2.16	0.68	15.62	22.68
Proposed method	1.10	0.77	14.88	20.19

Table II. The coefficients: times, Dice, Hausdorff and MSSD of the three method s obtained for the segmentation of Chest image.

Methods	Time (S)	Dice coefficient	Hausdorff coefficient	MSSD coefficient
Snakes	11.88	0.31	45.10	140.00
Chan&Vese	2.15	0.90	6.00	12.30
Proposed method	1.20	0.95	10.20	11.23

Table III. The coefficients: times, Dice, Hausdorff and MSSD of the three method s obtained for the segmentation of Arms_XRay image.

Methods	Time (S)	Dice coefficient	Hausdorff coefficient	MSSD coefficient
Snakes	10.77	0.41	55.10	150.00
Chan&Vese	3.15	0.80	16.00	14.30
Proposed method	1.60	0.90	14.10	13.23

Table IV. The coefficients: times, Dice, Hausdorff and MSSD of the three method s obtained for the segmentation of Vessel_CTA1 image.

Methods	Time (S)	Dice coefficient	Hausdorff coefficient	MSSD coefficient
Snakes	12.88	0.51	75.10	154.00
Chan&Vese	2.18	0.85	26.00	24.30
Proposed method	1.00	0.91	16.20	11.43

V. CONCLUSION

To conclude, we compare different methods of segmentation based on active contours and level set algorithms. To evaluate performances of the different methods, we have used four test medical images. The obtained experimental results show that segmentation Proposed method give the best results than Chan & Vese model and GAC method. The Proposed method reduces the expensive re-initialization of the traditional level set method to make it more efficient. This method combines the merits of the traditional GAC and C–V models, which possesses the property of local or global segmentation. Proposed method is general and robust which can be applied to implementing the algorithms: of some classical ACMs such as GAC model , C–V model ,PS model , LBF model , and so on.…

For all the problems, any method is always ideal for segmentation.

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