V. Lohitha Reddy* et al.
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Active Contours With New Signed Pressure Force Function For Echocardiographic Image Segmentation

V.LOHITHA REDDY
M.Tech Student
Dept. of Electronics and Communication Engineering,
Kakatiya Institute of Technology and Science
Warangal, India

SYED ZAHEERUDDIN
Asst.Professor.
Dept. of Electronics and Communication Engineering
Kakatiya Institute of Technology and Science
Warangal, India

Abstract— **In the present paper a novel region based active contour method is developed by formulating a new signed pressure force (SPF) function. The method has been applied to the echocardiographic images for getting the desired boundary. The method is useful for finding the automatic boundary detection of other images (Microbiological, MRI, CT, Natural and welding joint etc.) as well. Level set method in combination with original SPF has not been able to give satisfactory results during the segmentation of echocardiographic images. There are lots of noises present in the echocardiographic images those create difficulties in the segmentation process. The proposed method resolves all these difficulties in such a manner that the output image is having the proper boundary detection without any disturbances and noises. The very important advantage of this method is that it gives a very fast response in terms of time taken by CPU and the number of iterations. Fast response is very important in the clinical area especially in diagnosis purpose. The presented model is an advancement of Selective Binary and Gaussian Filtering Regularized Level Set (SBGFRLS) method. Proposed model is more robust against images with weak edge and intensity inhomogeneity when compared with the performance of earlier methods.**

Keywords—**Active Contours; Level Set Method; Echocardiographic; Image Segmentation; Signed Pressure Force Function.**

I. INTRODUCTION

Segmentation is a well-known step which is carried out for the clinical diagnosis from medical images. But the major problem encountered during the segmentation of echcardiographic images. The literature shows that the active contour based segmentation techniques are being extensively used in medical imaging [1-5]. Active contour models can be categorized as edge based active contour models [1-4, 6, 9, 10, 11] and region based active contour models [5, 7, 8, 12-14].

Some of the edge based active contour models are used as the edge-detector. The operation of edge detector depends on the gradient of the image to stop the initial contour on the boundary of the interested objects. This technique has advantage when the objects and background of segmented image are heterogeneous. Drawbacks of these active contour models are that the satisfactory results cannot be achieved in case of objects with discrete or with the presence of blur boundaries or noise. Some active contour models as in [6] introduce the balloon force to shrink and enlarge the capture range of the force. However some undesired effects occur during balloon method. If weak balloon force is there then contour is not able to pass through the narrow part of the object, and if the balloon force is large, the contour will pass through the weak edges of the object. Region based active contour models have several advantages over edge based active contour models. Region based active contour models use the statistical information inside and outside the initial curve to evolve the contour towards the boundaries of the desired object. This renders it the less sensitive to noise and gives better performance in case of weak edges. It is also suitable for regions having no edges. Another advantage is the less sensitivity about the location of the initial contour to make it, in turn, easy to detect exterior and interior boundaries efficiently. One of the most popular edge based active contour model is Geodesic Active contour model(GAC) which utilizes image gradient to construct an edge stopping function(ESF) to stop the contour evolution on the object boundaries. One of the popular region based active contour model is Chan-Vese(C-V) model[5].

Selective Binary and Gaussian Filtering Regularized Level set(SBGFRLS) method[15] shares the advantages of the C-V and GAC models. Which utilizes the statistical information inside and outside the contour to construct a region-based signed pressure force(SPF) function.

In this paper, a level set method for active contour model is developed with a new signed pressure force function. Proposed model is faster than the SBGFRLS method. This model used for echocardiographic images in this paper but it is equally useful for other images also.

II. SBGFRLS MEHOD

A. Signed pressure force(SPF) function

The SPF function has values in the range [-1,1].It modulates the signs of the pressure forces inside and outside the region of interest so that the contour shrinks when outside the object ,or expands when inside the object.

$$spf(I(x)) = \frac{I(x) - \frac{c_1 + c_2}{2}}{\max\left(\left|I(x) - \frac{c_1 + c_2}{2}\right|\right)}, x \in \Omega \quad (1)$$

Where,

$$c_1 = \frac{\int_\Omega I(x).H(\phi)dx}{\int_\Omega H(\phi)dx} \quad (2)$$

$$c_2 = \frac{\int_\Omega I(x).(1 - H(\phi))dx}{\int_\Omega (1 - H(\phi))dx} \quad (3)$$

Here,

H(.) is Heaviside function.

The intensities inside and outside the object are homogeneous. It is intuitive that $Min(I(x)) \le c_1, c_2 \le Max(I(x))$, and the equal signs cannot be obtained simultaneously whenever the contour is. Hence there is

$$Min(I(x)) < \frac{c_1 + c_2}{2} < Max(I(x)), x \in \Omega$$

(4)

B. Level set formulation

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

(5)

The regular term $div(\frac{\nabla \phi}{|\nabla \phi|})|\phi|$ is un-necessary because Gaussian filter can be utilized to smooth the level set function to keep the interface regular. Also the term $\nabla spf.\nabla \phi$ can be removed because the method utilizes the statistical in formation of the regions. Thus the final level set model is

$$\frac{\partial \phi}{\partial t} = spf(I(x))\alpha|\nabla \phi|, x \in \Omega \quad (6)$$

III. PROPOSED 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 echocardiographic images. It is not able to detect all boundaries. So here in the proposed model a new SPF function

$spf_n(I(x))$ is developed to overcome thid problem. Proposed model also takes less time to converge and the lesser number of iterations to converge when compared with other models.

$$spf_n(I(x)) = \frac{((c_1 * c_2) * (I(x) - \frac{c_1 + c_2}{2}))}{\max\left(\left|(c_1 * c_2) * (I(x) - \frac{c_1 + c_2}{2})\right|\right)}, x \in \Omega$$

(7)

Where $spf_n(I(x))$ is the new SPF function proposed method.

The significance of new SPF function can be explained by referring below figure(1), which explains that $Min(I(x)) \le c_1, c_2 \le Max(I(x))$.Hence

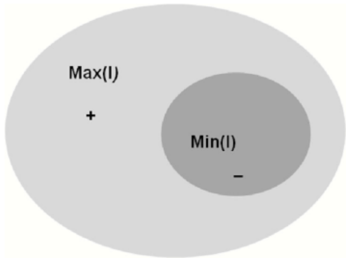

Fig. 1. Signs of SPF function inside and outside of the object

$$Min(I(x)) < \frac{c_1 + c_2}{2} < Max(I(x)), x \in \Omega$$

(8)

Level set formulation of proposed method is

$$\frac{\partial \phi}{\partial t} = spf_n(I(x)).(div(\frac{\nabla \phi}{|\nabla \phi|}) + \alpha)|\nabla \phi| + \nabla spf_n(I(x).\nabla \phi, x \in \Omega$$

(9)

Similar to SBGFRLS method, the regular term $div(\frac{\nabla \phi}{|\nabla \phi|})|\phi|$ and $\nabla spf.\nabla \phi$ can be removed because of the similar reasons as explained earlier. The final level set equation for the proposed method thus given

$$\frac{\partial \phi}{\partial t} = spf_n(I(x))\alpha|\nabla \phi|, x \in \Omega \quad (10)$$

IV. IMPLEMENTATION

A novel level set method, which utilizes a Gaussian filter to regularize the selective binary level set function after each iteration. The procedure of penalizing level set function to be binary is optional according to the desired property of evolution. If we want local segmentation property, the procedure is necessary; otherwise, it is unnecessary.

In our method, the level set function can be initialized to constants, which have different signs inside and outside the contour. This is very simple to implement in practice. In the traditional level set methods, the curvature-based term $div(\nabla\phi/|\nabla\phi|)|\nabla\phi|$ is usually used to regularize the level set function ϕ. Since ϕ is an Signed Distance Function that satisfies $|\nabla\phi| = 1$[13], the regularized term can be rewritten as $\Delta\phi$, which is the Laplacian of the level set function ϕ. As pointed out in [21] and based on the theory of scale-space [22], the evolution of a function with its Laplacian is equivalent to a Gaussian kernel filtering the initial condition of the function. Thus we can use a Gaussian filtering process to further regularize the level set function. The standard deviation of the Gaussian filter can control the regularization strength, just as the parameter μ. Since we utilize a Gaussian filter to smooth the level set function to keep the interface regular, the regular term $div(\nabla\phi/|\nabla\phi|)|\nabla\phi|$ is unnecessary. In addition, the term $\nabla spf_n . \nabla\phi$ can also be removed, because our model utilizes the statistical information of regions, which has a larger capture range and capacity of antiedge leakage. Finally, the level set formulation of the proposed model can be written as follows:

$$\frac{\partial\phi}{\partial t} = spf_n(I(x))\alpha|\nabla\phi|, x \in \Omega$$

The main procedures of the proposed algorithm are summarized as follows:

1. Initialize the level set function ϕ as

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

Where $\rho > 0$ is constant, Ω_0 is subset in the image domain Ω and $\partial\Omega_0$ is the boundary of Ω_0.

2. Compute $c_1(\phi)$ and $c_2(\phi)$ using equations respectively.
3. Evolve the level set function according to Eq.10.
4. Let $\phi = -1$ if $\phi > 0$; otherwise, $\phi = -1$.

This step has the local segmentation property. If we want to selectively segment the desired objects, this step is necessary; other-wise, it is unnecessary.

5. Regularize the level set function with a Gaussian filter, i.e. $\phi = \phi * G_\sigma$.
6. Check whether the evolution of the level set function has converged. If not, return to step 2.

Step 4 serves as a selective segmentation procedure, because it makes the deviation $|\nabla\phi|$ that is far from the interface of level set function ϕ close to zero, and only the $\phi(x)$ near the interface will evolve. Thus the evolution has local segmentation property. We can start the contour near the object of interest to obtain the de-sired segmentation. On the other hand, step 4 should be removed if we want to detect all the objects.

In step 5, the standard deviation σ of the Gaussian filter G_σ is a critical parameter, which should be chosen properly.

If σ is too small, the proposed method will be sensitive to noise, and the evolution will be unstable. On the other hand, if σ is too large, edge leakage may occur, and the detected boundary may be inaccurate. In our experiments σ ranges from 0.8 to 1.5.regurgitation

V. EXPERIMENTAL RESULTS

All the echocardiographic images are from patients who were suffering from mitral regurgitation. Parasternal long axis and apical two and four chamber view are included for diagnosing the regurgitation by analyzing the size of chambers.

Fig. 2. is the collection of original images associated with nine patients suffering from mitral regurgitation. Apical four views are in fig 2a and 2i.other images i.e. fig 2b, 2c, 2d, 2e, 2f, 2g and 2h are on parasternal long axis view.

Fig. 4 is the results obtained using the proposed method. It can be seen that the proposed model is able to detect all chambers boundaries. A human eye can very efficiently detect the chambers of the heart from fig.4a through 4i. The proposed method has been able to detect the proper boundaries in those images also in which when processed through C-V and SBGFRLS models could not be detected. Such images are for example of (i) fig. 3a and 4a, (ii) fig. 3f and 4f, (iii) fig. 3h and for (iv) fig. 3i and 4i

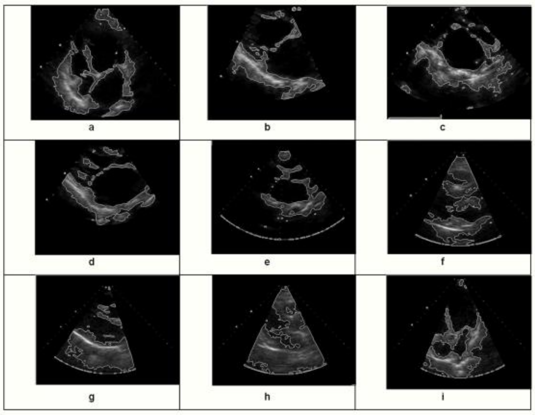

Fig. 2. Original echocardiographic Images showing the parasternal and apical view of the heart

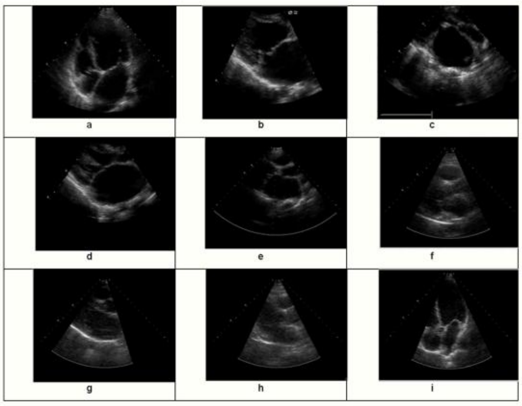

Fig.3.Boundary detection of echocardiographic images with SBGFRLS method

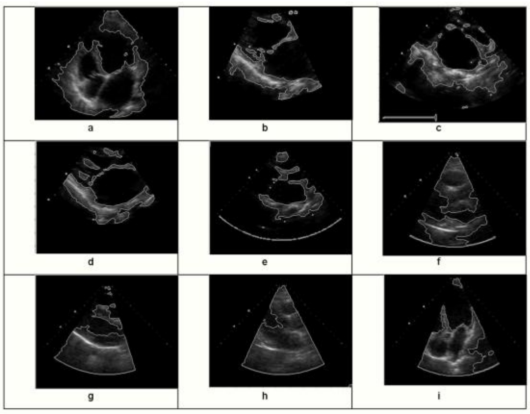

Fig.4.Boundary detection of echocardiographic images with proposed method

VI. DISSCUSSION

The proposed method is also the most efficient when compared with the SBGFRLS method in terms of the number of iterations and time takes to converge. It takes lowest time and iterations. Table 1 shows the iterations and time taken by SBGFRLS method and proposed method. From observations from the table 1 it seen, whereas the SBGFRLS method takes 100 to 200 iterations, the proposed model takes only 30 to 60 iterations to converge, and whereas the SBGFRLS method take the total time to converge ranging from 2.15 to 4.68 seconds respectively, the proposed method takes total time ranging from 0.64 to 1.13 seconds only.

Table 1.Comparision between SBGFRLS and Proposed method

Images	SBGFRLS method		Proposed method	
	Iterations	Time (sec.)	Iterations	Time (sec.)
1	150	3.92	40	0.86
2	150	2.78	40	0.61
3	100	1.65	30	0.52
4	150	3.77	40	0.59
5	200	4.15	50	0.76
6	150	2.36	50	0.85
7	200	3.09	40	0.60
8	150	2.05	60	0.95
9	200	3.19	50	0.69

VII. CONCLUSION

The proposed model presents a method to detect boundaries of echcardiographic images automatically. Automatic detection of boundaries enables the clinicians to determine the chambers efficiently and carry out easy diagnosis. The proposed method is efficient in terms of detecting the proper boundaries with the highest clarity. It exhibits much higher CPU efficiency which is of very high significant to the clinicians for carrying out speedy diagnosis. The new SPF developed in this paper can also be used with all types of active contours.

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