ACTIVE CONTOURS BASED OBJECT DETECTION & EXTRACTION USING WSPF PARAMETER: A NEW LEVEL SET METHOD

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ABSTRACT

This In this paper, we propose a new region based Active Contour Model (ACM) that employs weighted signed pressure force (WSPF) as a level set function. Further, a flood fill algorithm is used for object extraction. Weighted Signed pressure force (WSPF) parameters, is able to control the direction of evolution of the region. The proposed system shares all advantages of the C–V and GAC models. The proposed ACM based on the weighted intensities of inside and outside region of the contour. Flood Fill method is employed for retrieving the object after successful detection in the image. The proposed method is very much effective for images with sharp edges and is having inter -pixel accuracy. In this method level set function can be changed according to given image for better results. In addition, the computer simulation results show that the proposed system could address object detection within an image and its extraction with highest order of efficiency. The major contribution of this paper is the implementation of weighted intensities instead of average intensities for level set function formulation.

KEYWORDS: *Image segmentation, signed pressure force parameters, flood fill algorithm, threshold segmentation.*

I. INTRODUCTION

In the last few decades, image segmentation has been established as a very active research area in computer vision. One of the major problems that we come across during the image processing analysis is to extract the region of interest (i.e. segmentation). Segmentation subdivides an image into its constituent parts. Extensive study for segmentation has been made and many techniques have been proposed. Active contour models [2] have been one of the most successful methods for image segmentation.

The basic idea in active contour models (or snakes) is to evolve a curve, in order to detect objects in that image. Level set theory in active contours increases the flexibility. The existing active contour models can be categorized into two classes: edge-based models [2,4,5,7,11,17,18,20] and region-based models [6,8,9,12,14,15,16] .The Edge based models rely on a gradient based stopping function to stop the curve evolution whereas Region-based models utilize the image statistical information to construct constraints and can successfully segment objects with weak boundaries. Most popular edge based model is GAC model [4, 5].GAC model utilizes image gradient to construct an edge stopping function (ESF) to stop the contour evolution on the object boundaries. The GAC model can only extract the object when the initial contour surrounds its boundary, and it cannot detect the interior contour without setting the initial one inside the object. Thus, we can say that the GAC model possesses local segmentation property which can only segment the desired object with a proper initial contour. A model that does not use the gradient of the image for the stopping process is generally known as Region based model. One of the most popular region based model is the C-V model [6] which utilizes the statistical information inside and outside the contour to control the evolution. The C–V model [6] has the global segmentation property to segment all objects in an image.

One of the region based model utilizes SPF parameter as a level set function [1] .In that model the average of intensities of inside and outside region of contour is used. A new level set function is designed in this paper which is known as Weighted Signed Pressure force (WSPF) function and a region growing algorithm [3] known as Flood Fill algorithm is also applied with WSPF function in this paper. The proposed WSPF function has opposite signs, so the contour can shrink when it is outside the object or expand when inside the object and it uses the weighted intensities of inside and outside region of contour. This intensity variation is employed for efficient results and intensity variation totally depends upon the image. In addition it incorporates a unique aspect of selective local or global segmentation, which can segment the desired objects as well as accurately segment all the objects with interior and exterior boundaries. After detection of desired object, Flood fill algorithm is employed to retrieve it from the image.

The rest of the paper is organized as follows. In section 2, we discuss the existing works in the field of image segmentation with reference to the segmentation. In addition, we present the merits and demerits of these systems in brief. Section 3 deals with the proposed model that counters the demerits of the existing systems while offering the merits. In section 4, we present the simulation results and analysis of the proposed system. And section 5 provides the conclusion of the paper.

II. BACKGROUND

2.1. The GAC model

One of the most successful edge based geometric active contour model is the Geodesic Active Contour (GAC) model [4, 5]. The GAC model proposed by Caselles et al. and Malladi et al., as well as the Snake model, are EGAC models, which means that the contour evolution speed is based on the edge information in images. Let Ω be a bounded open subset of R^2 and I: [0, a] X [0, b] $\rightarrow R^+$ be a given image. Let C (q): [0, 1] $\rightarrow R^2$ be a parameterized planar curve in Ω. The GAC model is formulated by minimizing the following energy functional:

$$E^{gac}(C) = \int_0^1 g\left(\left|\nabla I\left(C(q)\right)\right|\right)|c'(q)|dq \quad (1)$$

$$C_1 = g(|\nabla I|)\, k\, N - (\nabla g.N)\quad N \quad (2)$$

Where k is the curvature of the contour and N is the inward normal to the curve. Usually a constant velocity term α is added to increase the propagation speed. Then Eq. (2) can be rewritten as

$$C_1 = g(|\nabla I|)(k + \alpha)N - (\nabla g.N)N \quad (3)$$

The corresponding level set formulation is as follows:

$$\frac{\partial \phi}{\partial t} = g|\nabla \phi|\left(div\left(\frac{\nabla \phi}{|\nabla \phi|}\right) + \alpha\right) + \nabla g.\nabla \phi \quad (4)$$

Where α is the balloon force, which controls the contour shrinking or expanding**.**

2.2. The C-V model

Chan-Vese model **[6]** is the first region based geometric active contour model which can be seen as a special case of the Mumford -Shah Problem **[9]**. The evolution function given by Chan- Vese is as follows:

$$\frac{\partial \phi}{\partial t} = \delta_\varepsilon(\phi)[\lambda_1(I - c_1)^2 - \lambda_2(I - c_2)^2] + \mu.k + v] \quad (5)$$

Where $\mu \geq 0$, $v \geq 0$, $\lambda_1 > 0$, $\lambda_2 > 0$ are fixed coefficients, c_1 and c_2 are two target values that are mean intensities of the image areas inside and outside the contours, respectively, κ is the mean curvature of the contours and is the δ_ε is the Delta function.

For a given image I in domain Ω, the C – V model is formulated by minimizing the following energy functional:

$$E_{CV} = \lambda_1 \int_{inside(C)} |I(x) - c_1|^2 dx + \lambda_2 \int_{outside(C)} |I(x) - c_2|^2 dx, \quad (6)$$

Where c_1 and c_2 are two constants which are the average intensities inside and outside the contour, respectively, with the level set method, we assume.

$$\begin{cases} C = \{x \,\varepsilon\, \Omega: \phi(x) = 0\} \\ \text{Inside } (C) = \{x \,\varepsilon\, \Omega: \phi(x) > 0\}. \\ \text{Outside } (C) \ \{x \,\varepsilon\, \Omega: \phi(x) < 0\} \end{cases}$$

By minimizing Eq. (6) we solve c_1 and c_2 as follows:

$$C_1(\phi) = \frac{\int_\Omega I(x).H(\phi)dx}{\int_\Omega H(\phi)dx}, \tag{7}$$

$$C_2(\phi) = \frac{\int_\Omega I(x).(1-H(\phi)dx}{\int_\Omega (1-H(\phi)dx} \tag{8}$$

$H(\phi)$ is the Heaviside function and $\delta_\varepsilon(\phi)$ is the Dirac function. Generally, the regularized versions are selected as follows:

$$\begin{cases} H(\phi) = \frac{1}{2}\left(1 + \frac{2}{\pi}\arctan\left(\frac{z}{\varepsilon}\right)\right), \\ \delta_\varepsilon(\phi) = \frac{1}{\pi}\frac{\varepsilon}{\varepsilon^2 + z^2}, \quad \phi \,\varepsilon\, R \end{cases}$$

2.3. Flood Fill method

Flood Fill method is used to retrieve the selected object in an image, it is also known as region growing or region marking technique. Region growing **[3]** is a simple region-based image segmentation method that is classified as a pixel based image segmentation method since it involves the selection of initial seed points. In the search for color regions, the most important tasks are to find out which pixels belong to which regions how many regions are in the image and where these regions are located. These steps usually take place as part of a process called region labeling or region coloring. During this process neighboring pixels is pieced together in a stepwise manner to build regions in which all pixels within that region are assigned a unique number ("label") for identification. One efficient fast method is region marking through flood filing in which a region is filled in all directions starting from a single point or "seed" within the region. We must first settle on either the 4 or 8-connected definition of neighbourhood for determining when two pixels are "connected" to each other, since under each definition we can end up with different results.

III. PROPOSED MODEL

In this section, we have given the analysis regarding the limitations of the existing methods that are presented in the earlier section. Further, we propose our method that has similar advantages and also fixes the drawbacks of previous methods. For clean and clear background the existing algorithms works fine. Problems occurs when the background is noisy and interior intensities are not homogeneous and also with images having weak edges or without edges. Existing methods does not works well with images having sharp and deep cavities.

In order to counter the limitations, we employed a new level set method that is based on Weighted Signed Pressure Force (WSPF) parameter is proposed. In this method level set function is designed such that the weighted intensities of inside and outside region of contour are considered where as in level set method based on SPF parameter considered the average intensities of inside and outside region of contour. This parameter improves the traditional level set methods as the calculation of SDF and re-initialization **[13]** is not required. Initially level set function is penalized to be binary, and then a Gaussian filter is used to regularize to cover the entire contour. It is a well-known fact that the Gaussian filter can make the evolution more stable. In addition, this model is incorporated with flood fill algorithm to extract the detected object. The proposed model has a property that makes it suitable for both selective local or global segmentation, which can not only extract the desired objects, but also accurately extract all the objects with interior and exterior boundaries. The proposed model has improved sub-pixel segmentation accuracy which makes it possible to segment the images with deep cavities.

3.1. WSPF Function

WSPF function depends on the average intensities inside and outside the contour (c_1 and c_2).The existing SPF function based model **[1]**, uses average of c_1 and c_2. WSPF function works like SPF function but it uses weighted sum of c_1 and c_2. Region information can be used to improve the robustness of an active contour; both to noise and to weak edges those parametric active contours formulations that have incorporated region information can all be written in the following way:

$$\alpha X_t=[\alpha(s)X_s]_s-[\beta(s)X_{ss}]_{ss}+w_R R(X)N+F_{ext}(X) \tag{9}$$

where R(x) is a *region function* and ω_R is a positive weighting parameter. The region function is derived from the image and (for the sake of concreteness) has values in the range [-1, 1]. The region function modulates the sign of the pressure forces using so that the contour shrinks when it is outside the object of interest and expands when it is inside the object. These external forces are sometimes called signed pressure forces **[10]**. The SPF function has opposite signs around the object boundary, so the contour can shrink when it is outside the object or expand when inside the object. SPF function as given in **[1]** is formulated as:

$$\text{Spf}\ (\text{I(x)}) = \frac{I(x)-\frac{c1+c2}{2}}{\max(|I(x)-\frac{c1+c2}{2}|)}\ \ x\ \varepsilon\ \Omega$$

Where as our model has WSPF function which is formulated as:

$$\text{wspf(I(x))}=\frac{I(x)- w(c1+c2)}{\max(|I(x)- w(c1+c2)|)}\ x\varepsilon\Omega \tag{10}$$

Where c_1 and c_2 are defined in Eqs. (7) and (8), respectively and w is the parameter which can be selected according to given image and its value is between 0.45 to 0.55.Substituting the WSPF function from Eq. (10) for the ESF in Eq. (4), the level set formulation of the proposed model is as follows:

$$\frac{\partial\phi}{\partial t}=\text{wspf}(I(\text{x}))\left(div\left(\frac{\nabla\phi}{|\nabla\phi|}\right)+\propto\right)|\nabla\phi| + \nabla wspf\big(I(x)\big)\nabla\phi \tag{11}$$

In addition, the term $\nabla wspf.\ \nabla\varphi$ in Eq. (11) can also be removed, because our model utilizes the statistical information of regions, which has a larger capture range and capacity of anti-edge leakage. Finally, the level set formulation of the proposed model can be written as follows:

$$\frac{\partial\phi}{\partial t} = \text{wspf}(I(\text{x})).\alpha|\nabla\phi|, \qquad x\ \varepsilon\ \Omega \tag{12}$$

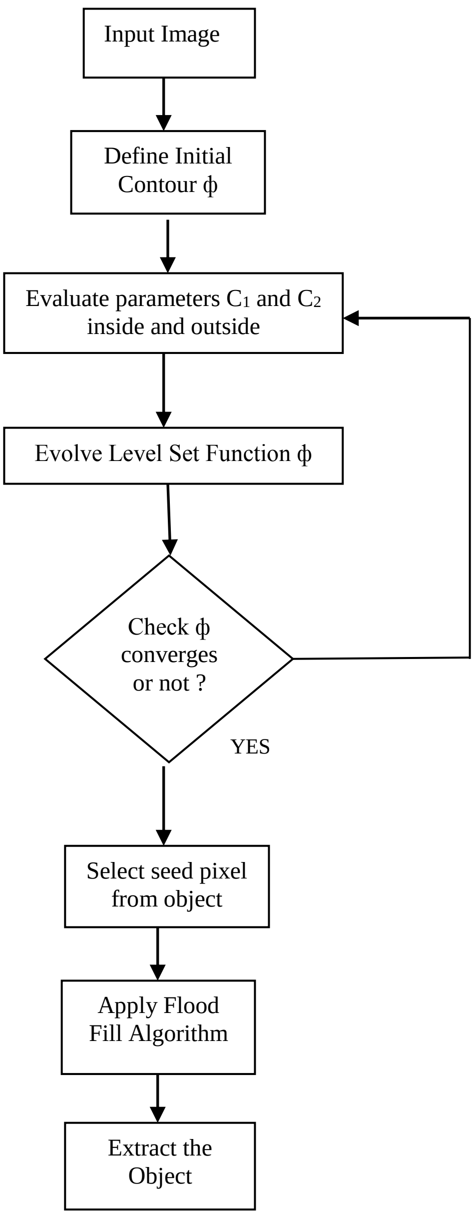
3.2. Algorithm

1. Select input image from database.
2. Define initial level set function ϕ to be binary function as :

$$\phi\ (x, t) = \begin{cases} -\gamma & : \text{ x is in inside domain} \\ \gamma & : \text{ x is in outside domain} \\ 0 & : \text{ x is lies on the boundary.} \end{cases}$$

3. Compute parameter as : C_1 (ϕ) and C_2 (ϕ)
4. Expansion or shrinkage of level set function ϕ according to energy minimization or maximization.
5. Using Gaussian filter regularize the level set function.
6. If level set function converges then stop otherwise go to step 3.
7. If it converges select a seed pixel within object contour.
8. Algorithm for flood fills.

3.3. Flowchart



IV. RESULTS AND DISCUSSION

This section is dedicated to presenting the results of the WSPF based segmentation technique as well as image extraction using Flood fill algorithm. Comparison results of segmentation techniques, discussed in section 2, with WSPF based ACM are also discussed. We compared the active contour model based on the WSPF function explained in previous chapter and the C-V **[6]** and GAC **[4, 5]** model (having traditional level set formulation). Comparison with SPF based ACM **[1]** is also discussed in this section. The proposed method applied to a set of real images and in all of them the main object can be found with acceptable amount of error. The initial level set is the square enclosing the image. So there is no need for specific initialization for every single object.

Our method has been applied to synthetic and real images of different modalities. For our method, the evolution of the level set function converges in 25 iterations, $w=0.54$, $\sigma=1$.The size of the test image is 200*200 pixels.

Figure 1 shows the segmentation results of a real image with objects having weak edges. Fig. 1(a) shows the input image to our model. The Fig.1 (b) shows the segmentation result, it is the closed contour obtained by our model and the Fig.1(c) shows the results of our model i.e. object extraction from input image.

Figure1 Experiment for a real image (a) Input Image. (b) Object detection using WSPF function (closed contour) (c) Object extraction.

Figure 2 demonstrates the global segmentation property of our method. If initial contour is far from the desired object then it is difficult to detect it.Fig.2 (a) shows the input image having many objects in it (a galaxy with stars). Our method could accurately detect all objects as shown in the Fig.2 (b) and any of the objects can be extracted from the image.Fig.2 (c) shows the extraction of only galaxy from input image.

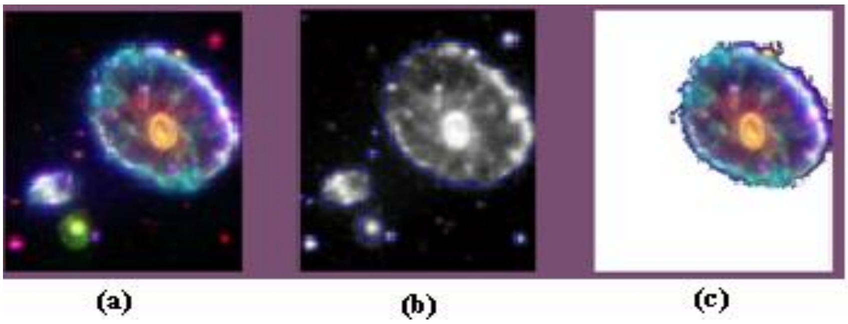


Figure2 Experiment for a galaxy image which explains the Global segmentation property. (a) Input Image. (b) Object detection using WSPF function (closed contour) (c) Object extraction.

Figure 3 also demonstrates the global segmentation property of our method. If initial contour is far from the desired object then it is difficult to detect it.Fig.3 (a) shows the input image having two objects in it. Our method could accurately detect both the objects as shown in the Fig.3 (b) and any of the objects can be extracted from the image.Fig.3 (c) shows the extraction of only left object from input image.

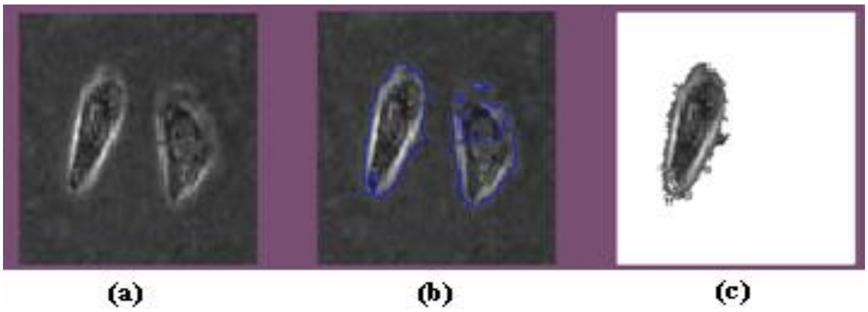


Figure3 Experiment for a real microscope cell image explaining the global segmentation property (a) Input Image. (b) Object detection using WSPF function (closed contours) (c) Object extraction.

The experiment in Figure 4 validates that our method can achieve sub-pixel segmentation accuracy. As can be seen from Fig. 4(b), with the SPF based model the two middle fingers stick together, which is not desired. The segmentation result by our method is shown in Fig. 4(c), which achieves sub-pixel segmentation accuracy of the finger boundaries. The final contour accurately reflects the true hand shape and the Fig.4 (d) shows the object extraction using our model.

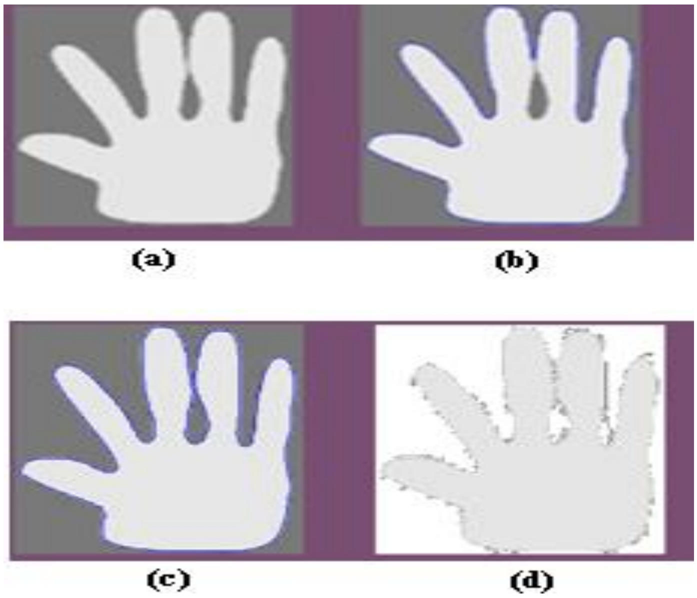


Figure4 Experiments for a hand phantom image (a) Input image (b) Result of the SPF based model. (c) Result of our method (d) Object extraction.

Figure 5 shows the segmentation results of a galaxy image. As can be seen from Fig. 5(b), with the SPF based model the galaxy is detected with a star in single contour, which is not desired. The segmentation result by our method is shown in Fig. 5(c), in which contour splits and separate the galaxy with star. The final contour accurately reflects the true shape of galaxy and the Fig.5 (d) shows the object extraction using our model.

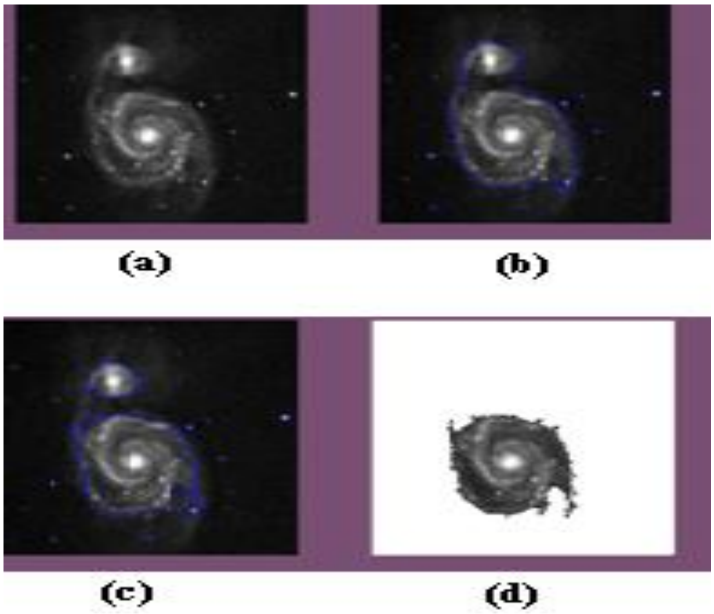


Figure5 Experiments for a galaxy image (a) Input image (b) Result of the SPF based model. (c) Result of our method (d) Object extraction.

Figure 6 shows the segmentation results of a synthetic image with objects having weak edges and interior holes. The GAC model with the traditional level set method is used in the comparison. Fig. 6(a) shows the initial contour of our model. The Fig.6 (b) shows the segmentation result of the GAC model. The Fig.6(c) shows the result of our WSPF model and the Fig.6 (d) shows the object extraction using our model.

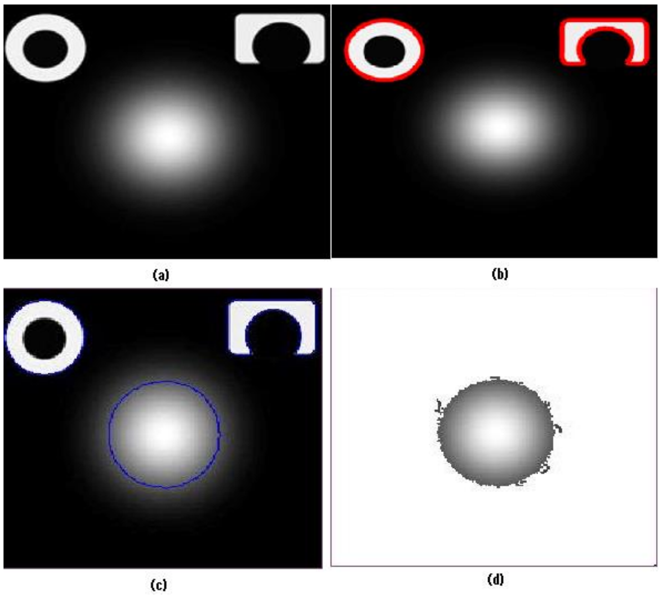


Figure6 Comparison with GAC model (a) Input image (b) Result of the GAC model [1]. (c) Result of our method (d) Object extraction.

Figure 7 shows the comparison of our method with CV model. The limitation of CV model is that if initial contour is far from the desired object then it is difficult to detect it.Fig.7 (a) shows the input image having three objects in it. In case of C-V model if initial contour is nearer to middle object then it will detect only middle object and fails to extract all the objects as shown in Fig.7 (b).Whereas our method could accurately detect all the objects, as shown in the Fig.7(c) and any of the three objects can be extracted from the image.Fig.7 (d) shows the extraction of left object of input image.

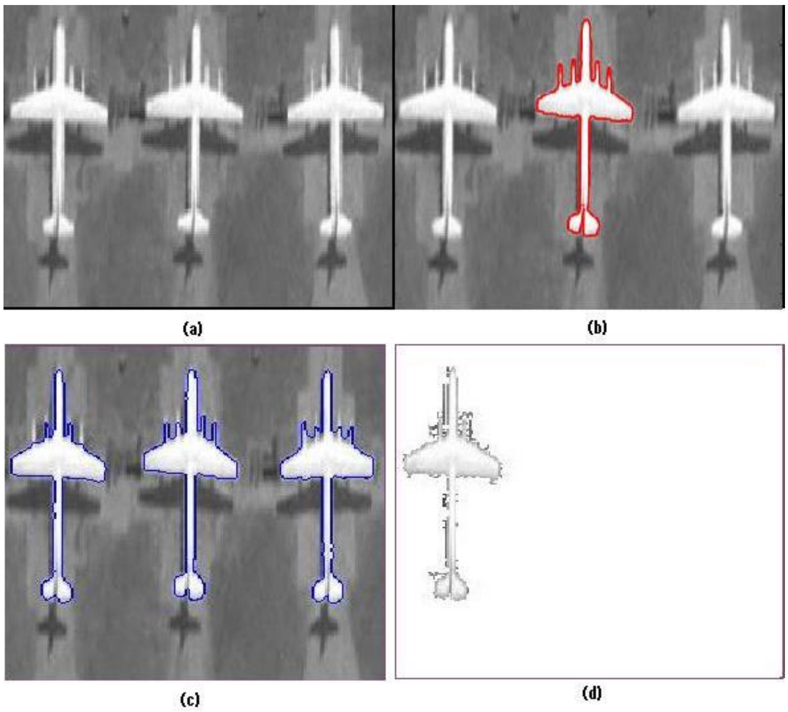


Figure7 Comparison with C-V model (a) Input image (b) Result of the C-V model [1]. (c) Result of our method (d) Object extraction.

V. CONCLUSIONS AND FUTURE SCOPES

Experimental results show that the proposed criterion can achieve results with promising accuracy. The accuracy of the result is governed by the convergence criteria, used in energy minimization. To make the results more accurate, tighter convergence criteria is required.We have proposed a new image segmentation technique, which can produce desired segmentation outputs on difficult image segmentation problems where traditional segmentation methods cannot create satisfying results. We have developed a fast and efficient model for object detection and extraction and it has both local and global segmentation property. The mathematical implementation of our active contour is achieved by means of Weighted Signed Pressure (WSPF) Function as a level set function and Flood Fill algorithm as a region growing method **[3]** for object extraction. By introducing contours as a SPF function, splitting a contour into multiple contours is possible which provide flexibility in the use of active contours. Our experimental results showed clearly that the proposed active contour model based on the WSPF function has sub-pixel accuracy and also it shares the advantages of SPF based model **[1]**, GAC **[4, 5]** and C-V models **[6].** It should be tested on a larger database to make some statistics of the percent of failure. Further, the computational time should be reduced significantly. The model could also be tested up against more available models to compare the performance.

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