A NOVEL GLOBAL THRESHOLD-BASED ACTIVE CONTOUR MODEL

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ABSTRACT

In this paper, we propose a novel global threshold-based active contour model which employs a new edge-stopping function that controls the direction of the evolution and stops the evolving contour at weak or blurred edges. The model is implemented using selective binary and Gaussian filtering regularized level set (SBGFRLS) method. The method has a selective local or global segmentation property. It selectively penalizes the level set function to be a binary function. This is followed by using a Gaussian function to regularize it. The Gaussian filters smooth the level set function and afford the evolution more stability. The contour could be initialized anywhere inside the image to extract object boundaries. The proposed method performs well when the intensities inside and outside the object are homogenous. Our method is tested on synthetic, medical and Arabic-characters images with satisfactory results

KEYWORDS

Imagesegmentation, Active contour,Geodesic active contour,C-V model,Level set method, ZAC model.

1. INTRODUCTION

Active contour model (ACM) is one of the most successful techniques in solving image segmentation problems. The idea underlying the ACM is to evolve a curve or a surface defined within an image from some arbitrary initial shape towards its interior normal direction and stop it on the object boundary [1]. The parametric curve is associated with an energy function. During the deformation, the curve tries to minimize its energy so that the final curve possesses a local minimum when the contour is spatially aligned with the shape or the desired image features. Thus the problem of segmentation becomes an energy minimization problem [2]. To find the desired image features, parametric curves are initialized close to the desired feature and are forced to move toward the local minimum which will be on the desired features under the influence of internal and external forces. The internal forces are defined within the curve or surface to keep the model smooth during the deformation. The external forces are derived from the image data to move the curve toward the object boundary or the desired features within an image. The geodesic active contour models [3, 4] utilize the image gradient in order to construct an edge detector function. The objective of this function is to stop the contour evolution on the object boundary. The general edge detector function can be defined by a positive and decreasing function such as:

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$$g(|\nabla u_0|) = \frac{1}{1+|\nabla G_\sigma(x,y) * u_0(x,y)|} \qquad (1)$$

where u_0 is a given image in Ω and $G_\sigma * u_0$ denotes a smooth version of u_0 after convolving it with the Gaussian function. The values of $g(|\nabla u_0|)$ function will be positive in the homogenous regions and zero on the object boundary.

Due to its flexibility in allowing topological changes, the level set method has been extensively utilized in problems of curve evolution, especially the motion by mean curvature described by Osher and Sethian [5]. In the level set method, the evolution curve is represented implicitly via a Lipchitz function ϕ, as $C = \{(x,y) \mid \phi(x,y) = 0\}$ .The zero level set of the function $\phi(t,x,y)$ represents the evolution curve C at time t. The evolution of the curve C in a normal direction with speed F operates to solve the equation:

$$\begin{cases} \dfrac{\partial \phi}{\partial t} = |\nabla \phi| F \quad in\ [0,\infty] \in R^2 \\ \phi(x,y,0) = \phi_0(x,y)\ in\ R^2 \end{cases} \qquad (2)$$

where $\{(x,y) \mid \phi(x,y) = 0\}$ represents the initial contour. A particular case is the motion by mean curvature in which $F = div(\nabla \phi(x,y) / |\nabla \phi(x,y)|)$ .It follows:

$$\begin{cases} \dfrac{\partial \phi}{\partial t} = |\nabla \phi| div(\dfrac{\nabla \phi}{|\nabla \phi|}) \quad in\ [0,\infty] \mathrm{X} R^2 \\ \phi(x,y,0) = \phi_0(x,y)\ in\ R^2 \end{cases} \qquad (3)$$

Malladi et al.[6] proposed the following level set equation:

$$\begin{cases} \dfrac{\partial \phi}{\partial t} = |\nabla \phi|(-v + \dfrac{v}{(m_1+m_2)}(|\nabla G_\sigma * u_0| - m_2)) \\ \phi(x,y,0) = \phi_0(x,y)\ in\ R^2 \end{cases} \qquad (4)$$

where v isaconstant,and m_1 and m_2 arethemaximumandminimumvaluesoftheimage gradient $|\nabla G_\sigma * u_0|$, respectively . The evolving curve stops at the boundary ,i.e., points with the highest gradient. Caselles et al.[4] proposed a Geometric Active Contour model (GAC) based on the mean curvature motion:

$$\begin{cases} \dfrac{\partial \phi}{\partial t} = g(|\nabla u_0|) \,|\nabla \phi|(div(\dfrac{\nabla \phi}{|\nabla \phi|}) + v) \quad in\ [0,\infty] \mathrm{x} R^2 \\ \phi(x,y,0) = \phi_0(x,y)\ in\ R^2 \end{cases} \qquad (5)$$

where v is a constant. In GAC the curve moves in the normal direction with speed equal to $g(|\nabla u_0|)(div(\nabla \phi / |\nabla \phi|) + v)$. The curve will stop the evolution when the function vanishes.

All the above ACMs are termed as edge-based models [7-10] because they utilize the image gradient as stopping criterion for the evolving curve.Edge-based models do not perform well in the presence of noise and in images with weak edges or without edges. In the case of a discrete gradient, the curve may pass through the edges because the function $g(|\nabla u_0|)$ never approaches zero at these points . These models possess a local segmentation property. They They are sensitive to the position of the initial contour as they are prone to the local minima and can only segment the desired object with a proper initial contour. As a result, these models fail to detect the boundaries when the initial contour is far from the boundary of the desired object. They also cannot detect the interior boundary without setting a proper initial contour inside the desired object. Region-based models represent another category of ACMs [11-16]. These models deploy statistical information inside and outside the contour in order to control its evolution. Region-based models are less sensitive to the position of the initial contour and they perform well in the presence of the noise and with images with weak edges or without edges. These models have a global segmentation property and can detect the interior and exterior boundaries at the same time, regardless of the position of the initial contour in the image. Chan and Vese [11] proposed a widely used region-based model, namely the C-V model. The C-V model is based on Mumford–Shah segmentation techniques [13] and has been successfully implemented in a binary phase segmentations. The C-V model uses the statistical information inside and outside the contour with the aim of controlling the evolution. The C-V model is formulated by minimizing the equation:

$$F\left(c_1,c_2,C\right)=\mu\, Length\left(C\right)+\nu\, Area\left(inside(C)\right)+\lambda_1\int_{inside(C)}\left|u_0(x,y)-c_1\right|^2 dxdy+\lambda_2\int_{outside(C)}\left|u_0(x,y)-c_2\right|^2 dxd \tag{6}$$

where u_0 is a given image in Ω, μ, ν, λ_1, λ_2 are positive parameters and c_1, c_2 are the average intensities inside and outside the curve C ,respectively .With the level set method , one can assume:

$$\begin{cases} C=\left\{(x,y)\in\Omega:\phi(x,y)=0\right\} \\ inside(C)=\left\{(x,y)\in\Omega:\phi(x,y)>0\right\} \\ outside(C)=\left\{(x,y)\in\Omega:\phi(x,y)<0\right\} \end{cases} \tag{7}$$

c_1 and c_2 are solved as:

$$\begin{cases} c_1(\phi)=\dfrac{\int_\Omega u_0(x,y)H(\phi(x,y))dxdy}{\int_\Omega H(\phi(x,y))dxdy} \\ c_2(\phi)=\dfrac{\int_\Omega u_0(x,y)(1-H(\phi(x,y)))dxdy}{\int_\Omega (1-H(\phi(x,y)))dxdy} \end{cases} \tag{8}$$

where $H(\phi)$ refers to the Heaviside function and $\delta(\phi)$ is the Dirac function. The regularization version of H and δ that were implemented in the C-V model are:

$$\begin{cases} H_\varepsilon(z)=\dfrac{1}{2}\left(1+\dfrac{2}{\pi}\arctan\left(\dfrac{z}{\varepsilon}\right)\right) \\ \delta_\varepsilon(z)=\dfrac{1}{\pi}\cdot\dfrac{\varepsilon}{\varepsilon+z},\ z\in R \end{cases} \tag{9}$$

Thecorrespondingvariation level set formulation is then:

$$\frac{\partial\phi}{\partial t}=\delta(\phi)\left[\mu\ div\left(\frac{\nabla\phi}{|\nabla\phi|}\right)|\nabla\phi|-\nu-\lambda_1(u_0-c_1)^2+\lambda_2(u_0-c_2)^2\right] \tag{10}$$

where μ controls the curve smoothness during the deformation, v is a constant to increase the propagation speed, and λ_1 and λ_2 control the image forces inside and outside the contour C, respectively. The values of $\delta_\varepsilon(z)$ tend to be near zero , if ε is too small . In this case, extraction of the desired object may fail if the initial contour starts far from the desired object . The final contour location may not be accurate if ε is large [12]. Zhang et al.[12] proposed an new region-based active contour model , hereafter we refer to this model as Zhang et al. Active contour(ZAC) model . This model shares the advantages of the region based model as described in[11]as well as the edge based models in[3].

To this end, this study complements the work of Zhang et al. [12] by introducing a new edge stopping function (ESF). This paper is organized as follows: Section 2 reviews the ZAC model [12] and Section 3 describes our methodology. Section 4 shows some experimental results and finally the conclusion is made in Section 5.

2. THE ZAC MODEL

Zhang et al. [12] proposed a novel level set method termed as selective binary and Gaussian filtering regularized level set (SBGFRLS). This approach selectively penalizes the level set function to be a binary function. This is followed by using a Gaussian function to regularize it. The Gaussian filters smooth the level set function and afford the evolution more stability. SBGFRLS model reduces the computational coast of the re-initialization step which in turn makes it more efficient than the traditional level set methods [17]. It is worthwhile mentioning that the SBGFRLS method has the advantage of being a general and robust technique. It can be applied to the classical ACMs, such as GAC model [3] as well as C-V model [11]. The proposed model implemented with SBGFRLS approach has a property of selective local or global segmentation. A novel signed pressure force (SPF) [18] is proposed to control the direction of the evolution and to stop the evolving contour at weak or blurred edges. The ZAC model uses statistical information inside and outside the contour to formulate the SPF. The proposed SPF function is assigned with values in the range [-1, 1]. It modulates the signs of the pressure forces inside and outside the region of interest as:

$$spf(u_0(x)) = \frac{u_0(x) - \frac{c_1 + c_2}{2}}{\max(|u_0(x) - \frac{c_1 + c_2}{2}|)}, x \in \Omega \tag{11}$$

where c_1 and c_2 are defined in Eq. (8). The SPF assumes that if the intensities inside and outside the object are homogenous, it is instinctive that $\mathrm{Min}(u_0(x)) <= c_1$ and $\mathrm{Max}(u_0(x)) <= c_2$, accordingly, therefore $\mathrm{Min}(u_0(x)) < \frac{c1+c2}{2} < \mathrm{Max}(u_0(x))$. The SPF function has opposite signs around the object boundary in order to force the contour to shrink when it is outside the object and to expand when it is inside the object. The formulation of the level set function in the proposed method is given as:

$$\frac{\partial \phi}{\partial t} = spf(u_0(x)).\alpha |\nabla \phi|, x \in \Omega \tag{12}$$

The ZAC model utilizes a binary function for the initialization of the level set function φ instead of using the signed distance function as in the traditional level set method. The ZAC model deploys the image statistical information to stop the curve evolution on the desired object boundaries. This makes the ZAC model insensitive to noise and can perform well in the case of an object with weak edges or without edges. The ZAC model is capable of performing both local and global segmentation, in contrast to the C-V model which can only handle global segmentation and extracts all the objects. The ZAC model has less computational complexity than the GAC and C-V models.

3. The Proposed Model

In this paper, we propose a new edge stopping function that controls the direction of the evolution and stops the evolving contour at weak or blurred edges. Our model is implemented using the SBGFRLS method, which grants it a selective local or global segmentation property. Our model adapts the same methodology of the ZAC model described by Zhang et al. [12]. Our novel modification stems from utilizing a new function termed the global threshold function (GTF) instead of using the SPF as in the original ZAC model. The GTF operates similarly to the SPF. Generally, both functions produce similar results. It controls the direction of the evolution and stops the evolving contour at weak or blurred edges. Our proposed model performs well when the intensities inside and outside the object are homogenous and in the binary segmentation phase, in an analogy to the ZAC model. The GTF has opposite signs around the object boundary in order to force the contour to shrink when it is outside the object and to expand when it is inside the object. The proposed GTF is assigned with values in the range [-1, 1]:

$$gtf\,(u_0(x)) = \frac{u_0(x) - t}{\max(|\,u_0(x) - t\,|)}, x \in \Omega \tag{13}$$

where t is a threshold value computed automatically by using the global thresholding method[19]. The procedure of the proposed algorithm consists mainly of:

1. Initialisation of the level set function ϕ into a binary function.
2. Computing the value of t using the global threshold method[19].
3. Computing the values of $gtf\,(u_0(x))$ function according to Eq. (13).
4. Evolving the level set function ϕ according to Eq. (12).
5. If the local segmentation property is desired, let ϕ=1 if ϕ>0; otherwise ϕ= -1.
6. In order to smooth the level set function, Gaussian filter is used to regularize it.
7. When the evolution of the level set function has converged, the procedure stops. Otherwise return to step4.

The contour could be initialized anywhere inside the image to extract all exterior and interior boundaries, even if the initial contour does not surround all the objects in the image. Our model entails all the advantages pertinent to the ZAC model. Our model gives a similar result to the ZAC model in less computational time because the values of t and 0(())gtfux are computed only once. The ZAC model can extract objects with distinctive boundaries while interior intensities are not homogeneous. By contrast, our model extracts both the interior and exterior boundaries as shown in Figure 6.

4. Experimental Results

In each experiment , we select values of ρ , ε , σ , k , and s tobe1,1.5,1,5and1, respectively . The values of α and t were set according to the images. Figure1 exhibits the global segmentation property of the C-V model and our proposed model.The initial contour is initialized far from the objects, as shown in the first column of Figure1 .The second column shows the segmentation results of the C-V model . As is displayed , the C-V model fails to extract all the objects in the image. The third column shows the segmentation result of our model. Clearly, our model extracts accurately all the objects in the image regardless of the position of the initial contour, while the C-V model may be trapped into the local minima and then result in unsatisfactory segmentation.

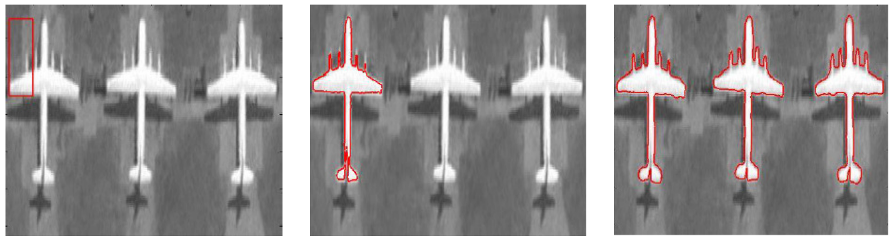

Figure 1. Comparisons of the global property between the C-V model and the proposed method. The first column shows the initial contour, the second column shows the segmentation results of the C-V method and the third column shows the result of the proposed method with t =172 and σ =20. The original image is sourced from Zhang et al. [12].

Figure 2 presents segmentation results of the C-V model and our proposed model in a magnetic resonance image of the left ventricle of a human heart. In an analogy to the ZAC model, our model also can selectively extract the desired object by setting the initial contour inside or surrounding the desired boundaries, while the C-V model will extract all the objects. Furthermore, the evolution direction in our model can be controlled to obtain satisfactory segmentation results, while the C-V model may get disordered results.

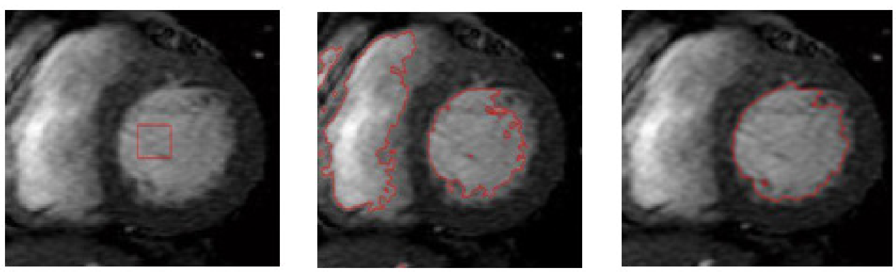

Figure 2. Segmentation results for a magnetic resonance image of the left ventricle of a human heart. The first column shows the initial contour, the second column shows the segmentation results of the C-V model and the third column shows the result of the proposed model with t =111 and α =5.

Figure 3 demonstrates the local segmentation property of the proposed model in an MR image of a corpus callsum. As depicted in the image, our model gives satisfactory results. As our model is based on the ZAC model it can selectively extract the desired object by setting the initial contour inside or surrounding the desired boundaries with satisfactory segmentation results.

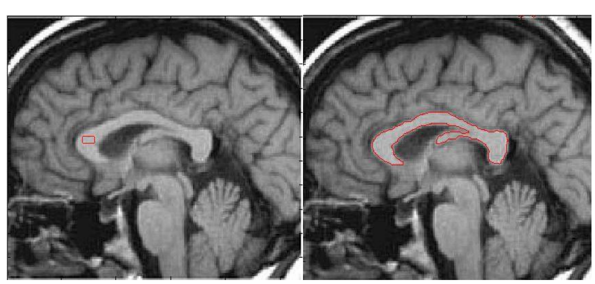

Figure 3. The first column shows the initial contour, the second column shows the segmentation result of the proposed method with α =10.

Figure 4 shows the local segmentation property of our proposed model.The initial contour resides near or surrounding the desired object ,as shown in the first column of Figure 4 . The second column shows the segmentation result of our proposed model.

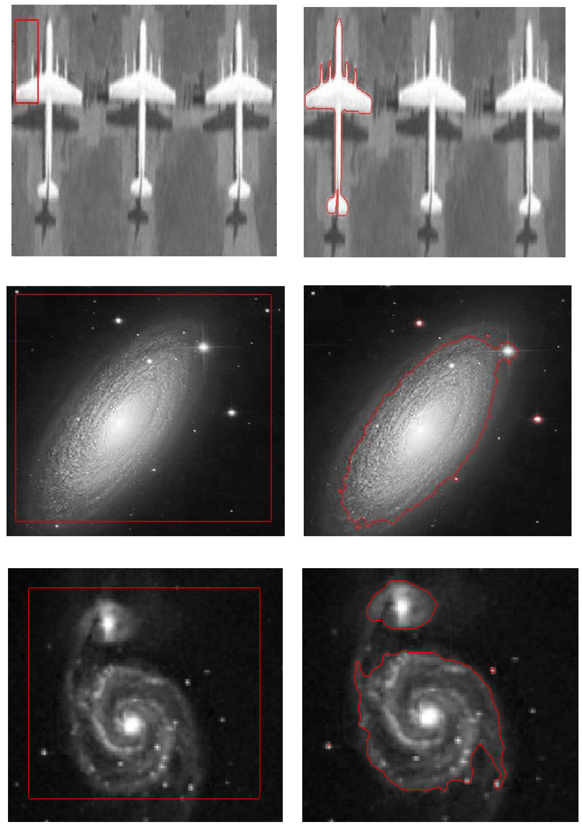

Figure4.Segmentationresultsfromourproposedmodel.Thefirstandsecondcolumn sshowtheinitialcontour,and segmentation results,respectively. t Correspond to 172, 90 and 56.4071, for the first, second and third row, respectively and α =20. The original images are sourced from Zhang et al.[12].

Figure 5 shows the global segmentation results by our proposed model for noisy images .As it can be seen, despite of the presence of significant noise inherit in the image, our model performs well in detecting the desired object boundary.

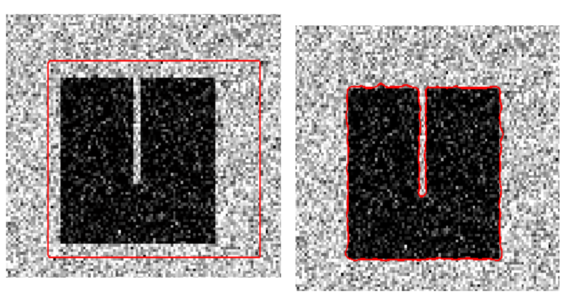

Figure5.Global segmentation results for a noisy image. The first column shows the initial contour ,the second column shows the segmentation result of the proposed method with t =114.1and σ =10. The original image is sourced from Zhang et al.[12].

Figure 6 shows the local segmentation property of the ZAC model and our proposed model. As shown in Figure 6, the ZAC model extracts objects with distinct boundaries whereas interior intensities are not homogeneous. In contrary, our model extracts the interior and the exterior boundaries. This represents the main shortcoming of our proposed model.

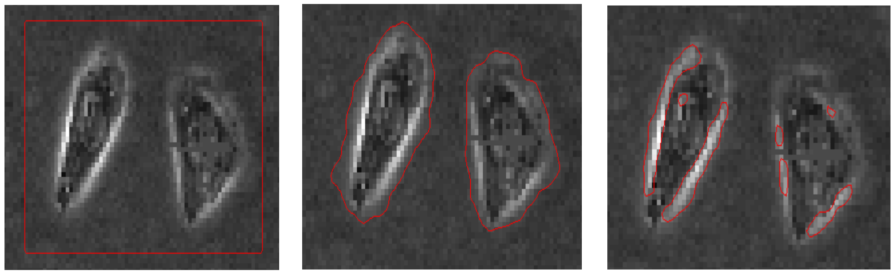

Figure 6.Local segmentation results for a real microscope cell image.The first column shows the initial contour, the second column shows the segmentation results of the ZAC method and the third column shows the result of the proposed method with $t = 94.0314$. The original image is sourced from Zhang et al.[12].

Figure7 exhibits the performance of our proposed method in the case of Arabic-characters segmentation. As shown in this figure, our proposed model attains satisfactory segmentation results.

Figure7.Thefirstcolumnshowstheinitialcontour,thesecondcolumnshowsthesegm entationresultsoftheproposedmethodwith $t = 141.3368$ and $\alpha = 20$.

5. CONCLUSIONS

A novel global threshed-based active contour model with a new edge-stopping function is presented. The main merits of this approach consist in its ability to control the direction of the evolving contour and to stop it on the weak or blurred edges. Our model is implemented using the SBGFRLS method. We tested this method on several categories of images including synthetic, medical and Arabic-characters where a satisfactory performance is attained.

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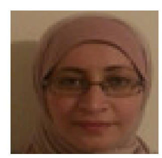

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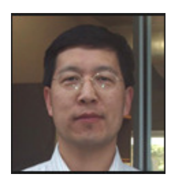

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