Object Segmentation by Comparison of Active Contour Snake and Level Set in Biomedical Applications

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***Abstract*— Automatic foreground object segmentation is a fascinating, a demanding research area, and an exigent problem in biomedical applications. Existing works cannot segment concave objects and completely dependent on initial curve that is initialized manually by the users, and must be closer to the object. Due to these limitations, most of them were considered as semi-automatic approaches. In this paper, we incorporated active contours (level-set) based on Bhattacharya distance to the Chan and Vese energy functional such that are not only minimized the differences within each region but also maximized the distance between the two regions as well. Compared with active contour snake, the proposed model gave more accurate results that segment the foreground objects automatically.**

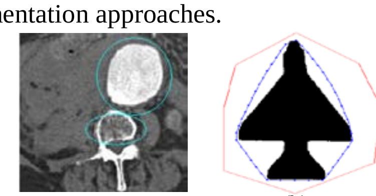
I. Introduction

The object segmentation is generally used for brain tumor, which nowadays is a decisive issue of medical side applications. Trying to locate an object contour purely by running a low level image processing task such as canny edge detection is not particularly successful technique because mostly the edges are not continuous and serious edges can be present because of noise [1].

Since the last two decades, large volume of works has been published on for object segmentation that is mainly categorized into region or boundary-based methods [2]. Some emblematic works have been done for region-based category such as splitting and merging [3], watershed and motion-based segmentations presented by [4, 5], and a primitive method has been reported for video object extraction by [6]. However, the abovementioned approaches produce artifacts due to occlusion.

Some methods did the segmentation manually whereas some did it automatically. Currently, no one can point out which is the most advantageous solution due to different constrictions [7]. The author of [8] used a method based on similarity close measure to classify the belonging of the pixel followed by region growing to get the objects. But for segmentation, a set of markers were required, and it was also very hard for this method to discriminate which part should be segmented if there is an unknown image, which were considered the limitations of this method. In [9], the author segmented the objects based on linking the area information. The color histograms were employed for building up the videos, but this method was not being applicable in real life because it needed the color information first. An automatic image segmentation approach was proposed by [10] that was the comprehensive version of different models, but this approach was completely dependent on the initialization that must be closer to the target, and whenever a new segmentation problem bumped into, manual redesign of segmentation criteria was required. Furthermore, it was also necessary to situate and understand an image that where the objects are located [11].

To solve the abovementioned problem the active contour models were introduced by [12] that tried to move the contour towards the object of interest. Some boundary based methods were developed by [13-15] that mostly started with initial curve and used the gradient information to locate the object boundaries. All the aforementioned approaches had limited accuracy, because of initial curve dependency that was explicitly defined and initialized by the user manually, which must be near the boundary of the desired object to be segmented. Also, if more than two objects needed to be segmented, two different contours needed to be initialized as shown in Fig. 1(a). Snakes are not useful for complex images where edges are concave as shown in Fig. 1(b). Due to this reason these approaches are known as semi-automatic segmentation approaches.



(a) (b)

Figure 1. Weakness of Active Contour Snake in-term of two objects as in (a) and in-term of Concave Edges as in (b). In (b) the red solid line indicates the initial contour while the blue dotted line shows the final contour.

In this research, a model is proposed that solved the limitations of the active contour snake and can segment the foreground objects automatically from the corresponding image. In this paper, we incorporated active contours level-set based on Bhattacharya distance [16] to the Chan and Vese energy functional [17] such that not only the differences within each region are minimized but the distance between the two regions is maximized as well.

II. Methodology

An active contour model is a deformable spline influenced by constraint and image forces that pull it towards object contours. It tries to move into a position where its energy is minimized. Active contour tries to improve by imposing desirable properties such as continuity and smoothness to the contour of the object, which means that the active contour approach adds a certain degree of prior knowledge for dealing with problem of finding the object contour.

A. Active Contour Snake

In the field of image segmentation, since it was first introduced by [12], active contour model has attracted much attention. A snake is a parametric curve that tries to move into a position where its energy is minimized. The author of [12] calculated the snake energy by introducing the following energy functions.

$$E_{snake} = \int_0^1 E_{\text{int}}(C(x)) + E_{img}(C(x)) + E_{con}(C(x))\, dx \qquad (1)$$

where E_{int} represents the internal spline energy of the snake, caused by stretching and bending that stands for smoothness along the curve, E_{img} indicates the forces of the image that measures the attraction of the image feature such as contours and guides the active contour towards the desired image properties, and E_{con} denotes the external constraints forces that measures the external constraints either from higher level shape information or user applied energy, which can be caused to account for user defined constraints The external constraints forces are also called external snake forces, denoted by E_{ext} that is the combination of image forces E_{img} and external constraints forces E_{con}. So equation (1) can be written as.

$$E_{snake} = \int_0^1 E_{\text{int}}\left(C\left(x\right)\right) + E_{ext}\left(C\left(x\right)\right) dx \qquad (2)$$

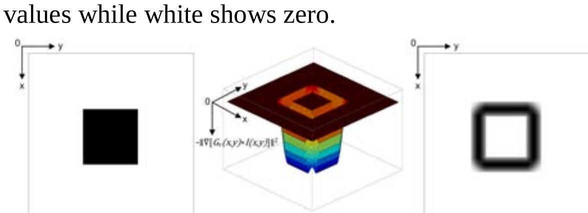
The energy function associated with the snake is given as:

$$E_{internal} = \alpha(s)\left|\frac{dv}{ds}\right|^2 + \beta(s)\left|\frac{dv^2}{ds^2}\right|^2 \qquad (3)$$

where $\alpha(s)$ is a measure of the elasticity of the snake that makes the action of the snake like a membrane and control the tension along the spine, and $\beta(s)$ is a measure of the stiffness of the snake that makes the action of the snake like a thin plate and controls the rigidity of the spine. If the stiffness of the snake is equal to zero, then the function is discontinuous in its tangent that may develop a corner at that point, and if the elasticity and stiffness of the snake are the same, then this also allows a break in the contour, a positional discontinuity. If we want to detect the edge of the object, the external energy function of the gradient of the image is given as.

$$E_{ext} = -\left|\nabla\left(G_\sigma\left(x, y\right) * I\left(x, y\right)\right)\right|^2 \qquad (4)$$

where $G_\sigma (x, y)$ is a two dimensional Gaussian with standard deviation σ. The whole energy is known as "image energy" and is illustrated in Fig. 2, in which (a) is a block square .on white background, (b) shows image energy derived by Eq. 4, and (c) is the same as (b), dark shades refer to negative values while white shows zero.



(a) (b (c)

Figure 2. Graphical representation of the image energy [1].

To overcome the limitations of the snake, we incorporated active contour (level-set) based on Bhattacharya distance to the Chan and Vese energy functional to segment the foreground objects automatically.

B. Active Contour Level Set

Level set has an important role in image segmentation that is based on progressive fruition of the differences among neighboring pixels to find object boundaries. Basically, level-set converges at the object's boundaries where the differences are high. It has many advantages, for example, the ability to seamlessly split apart a single surface, and merge it without losing its identity [18]: Level set signifies the contours by implicit surface; they do not delineate the contours explicitly, and the implicit surface is articulated by implicit contour function as:

$$\Omega\left(t\right) = \{x | \varnothing\left(x, t\right) < 0\}$$

$$\delta\Omega\left(t\right) = \{x | \varnothing\left(x, t\right) = 0\}$$

This is known as level set function. The graphical representation of the level set surface is given in Fig. 3.

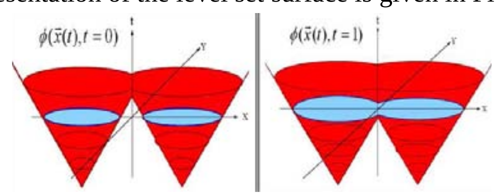


Figure 3. Graphical representation of level set function surface (red) that moved and plot the distance from each point (x, y) to the Interface in Blue. Topological change of two separate fronts (left) into a single front (right) handled naturally via higher dimensional function. After [19].

Recently, Chan and Vese (CV) proposed in [17] a novel form of active contour for object segmentation based on level set framework. Unlike other active contour models which rely much on the gradient of the image as the stopping term and thus have unsatisfactory performance in noisy images, the CV active contour model does not use the edge information but utilizes the difference between the regions inside and outside of the curve, making itself one of the most robust and thus widely used techniques for image segmentation. Its energy function is defined by.

$$F(C) = \int_{in(c)} \left|I\left(x\right) - C_{in}\right|^2 dx + \int_{out(c)} \left|I\left(x\right) - C_{out}\right|^2 dx \qquad (5)$$

where $x \in \Omega$ (the image plane) $\subset R^2$, $I:\Omega \rightarrow Z$ is a certain image feature such as intensity, color, or texture, and c_{in} and c_{out} are respectively the mean values of image feature inside *[in(C)]* and outside *[out(C)]* the curve *C*. Considering image segmentation as a clustering problem, we can see that this model forms two segments (clusters) such that the differences within every segment are minimized. However, the global minimum of the above energy functional does not always guarantee the desirable results. The unsatisfactory result of the CV AC in this case is due to the fact that it is trying to minimize the dissimilarity within each segment but does not take into account the distance between different segments.

Our methodology is to incorporate an evolving term based on the Bhattacharyya distance to the CV energy functional that minimizes the dissimilarities within the object and maximizes the distance between the two regions. The proposed energy function is:

$$E_0(C) = \beta F(C) + (1-\beta) B(C) \qquad (6)$$

$$where \;\; \beta \in [0,1], B(C) \equiv \int_x \sqrt{f_1(x)\, f_2(x)\, dx}$$

the Bhattacharyya coefficient [16] with Eq.7 and 8.

$$f_1(x) = \frac{K_\sigma(x) * [H(\phi(x)) I(x)]}{K_\sigma(x) * H(\phi(x))} \qquad (7)$$

$$f_2(x) = \frac{K_\sigma(x) * [1 - H(\phi(x)) I(x)]}{K_\sigma(x) * [1 - H(\phi(x))]} \qquad (8)$$

where $f_1(x)$ and $f_2(x)$ are the local fitting functions [18], which depend on the level set function ϕ, and need to be updated in each contour evaluation, and $H(\bullet)$ and $\delta'(\bullet) \equiv H'(\bullet)$ respectively the Heaviside and the Dirac functions [20]. Note that the Bhattacharyya distance is defined by $[-\log B(C)]$ and the maximization of this distance is equivalent to the minimization of $B(C)$. Note also that to be comparable to the $F(C)$ term, $B(C)$ is multiplied by the area of the image because its value is always within the interval $[0, 1]$ whereas $F(C)$ is calculated based on the integral over the image plane. In general, we can regularize the solution by constraining the length of the curve and the area of the region inside it. Therefore, the energy functional is defined by

$$E(C) = \gamma \int_\Omega \left|\nabla H(\phi(x))\right| dx + \eta \int_\Omega H(-\phi(x))\, dx + \beta F(C) + (1-\beta) B(C) \qquad (9)$$

where $\gamma \geq 0$ and $\eta \geq 0$ are constants.

The intuition behind the proposed energy functional is that we seek for a curve which 1) is regular (the first two terms) and 2) partitions the image into regions such that the differences within each region are minimized (i.e., the $F(C)$ term) and the distance between the two regions is maximized (i.e., the $B(C)$ term). The level set implementation for the energy functional in (8) can be derived as.

$$\frac{\partial \phi}{\partial t} = |\nabla \phi| \left\{ \begin{array}{l} \gamma k + \eta + \beta\left[(I - C_{in})^2 - (I - C_{out})^2\right] - \\ (1-\beta) \left[\begin{array}{l} \frac{B}{2}\left(\frac{B}{A_{in}} - \frac{B}{A_{out}}\right) + \\ \frac{1}{2}\int_\Omega \delta(x-1)\left(\frac{1}{A_{out}}\sqrt{\frac{f_1}{f_2}} - \frac{1}{A_{in}}\sqrt{\frac{f_2}{f_1}}\right) \end{array} \right] \end{array} \right\} \qquad (10)$$

where A_{in} and A_{out} are respectively the areas inside and outside the curve C. Thus, the proposed model overcame the limitation of active contour snake in object segmenting

III. Experimental Results

The segmentation results active contour snake and level set that are described in the previous section were done image-based. The evaluation of level set in a certain image is performed independently, due to which the proposed model is able to segment more than one object automatically presented in the image using one initial contour, independent of its distance from the objects that is one of the limitations of the active contour snake as shown in Fig. 1(a). The sample segmentation results of the active contour snake are shown in Fig. 4, in which the experiments are performed on human body at different angles.

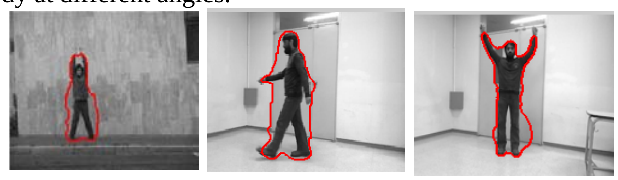


Figure 4. Sample segmentation results of active contour model (snake).We can see that the processed image is in concave form, and the snake cannot segment the foreground object well.

So, it is obvious from Fig. 4 that the active contour snake cannot detect the objects which are in concave form. Some experimental results are shown in Fig. 5, in which the images consisted of more than one objects.

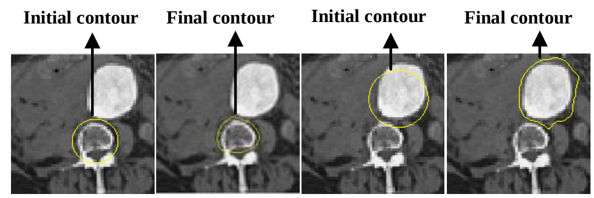


Figure 5. Sample segmentation results of active contour model (snake). If there is more than one object, then active contour snake needs a separate initial contour for each object.

Further results are illustrated in Fig. 6, which shows the segmentation result of more than one object using active contour snake with one initial contour.

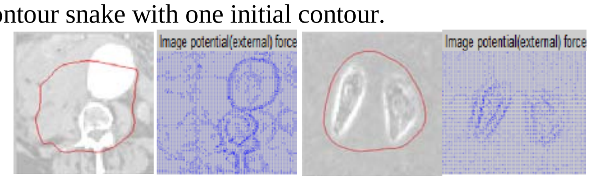


Figure 6.Sample segmentation results of active contour model (snake). If there is more than one object, and we want to segment all the objects from the image via one initial curve, so in this case the active contour snake cannot segment. The blue image shows the external force of the snake.

It is also obvious from Fig. 6 that by using one initial curve; the active contour snake cannot segment more than one object that present in the image.

To solve the abovementioned limitations of the active contour snake, the proposed model segments the concave objects well of different side, the results of which are shown in Fig. 7 (a), (b), and (c). The proposed model also segments all the objects using one initial contour, if the number of objects present in the processed image is two or more than two as shown in Fig. 7 (d). The overall results of the proposed model in-term of concave objects and if the number of the objects are more than two, presented in Fig. 8.

(a) **(b)** **(c)** **(d)**

Figure 7.Sample segmentation results of the proposed model. Compare with Figure. 4, it is obvious that the proposed approach works well, if there are concave objects in the image.

IV. CONCLUSION

In the proposed model, the limitations of some of the existing works were solved, because most of them cannot segment concave objects and completely dependent on the initial curve that is initialized manually by the users and must be closer to the object. Due to these limitations, most of them were considered as semi-automatic approaches. So to solve these limitations, we incorporated active contour level-set based on Bhattacharya distance to the Chan and Vese energy functional that minimizes the dissimilarities within the object and maximizes the distance between the two regions. The results of the proposed model are compared with active contour snake that are shown in Fig. 4, 5, 6, 7, and 8. It is obvious from the above figures (described in section 4) that the proposed model segments the objects well either in concave form or the number of objects are more than one.

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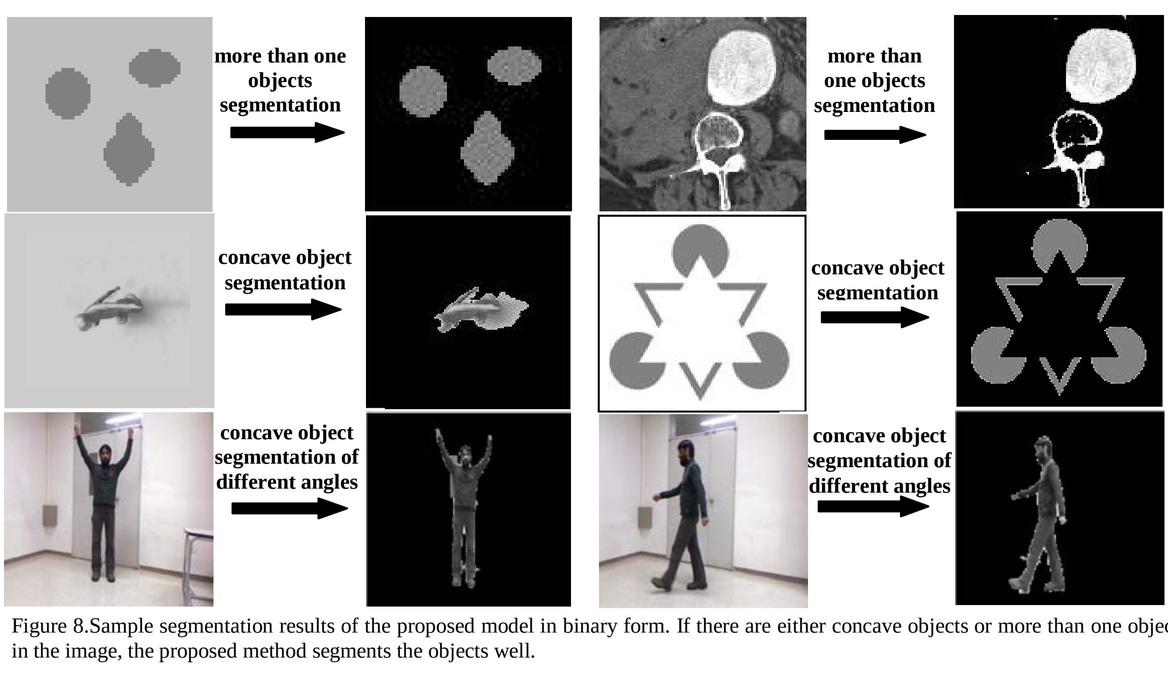

Figure 8.Sample segmentation results of the proposed model in binary form. If there are either concave objects or more than one object in the image, the proposed method segments the objects well.