SEGMENTATION OF SINGLE ORIENTED IMAGES WITH CAGE ACTIVE CONTOURS

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Abstract:- **Image segmentation primarily based on parametrized active contours. Active contours are of geometric and parametric types. Geometric active contours are used for curve topologies and parametric active contours are used for set of discrete points. Contours are used for identifying the shape of the object. The points which are touching to form the boundary make a set. With help of this level sets the contour is formed. The evolving contour is parametrized in keeping with a reduced set of manipulate points that shape a closed polygon and have a clear visual interpretation. The parametrization, referred to as mean value coordinates, stems from the strategies used in computer pictures to animate digital fashions.The framework allows to effortlessly formulate region based energies to segment an image. The Gaussian model is one of the region based energy term in the segmentation. The behavior of the method is shown on synthetic and real images and examines the overall performance with trendy level set methods.**
Keywords—Mean value coordinates, Active contours,level sets.

I.INTRODUCTION

Active contours are used in the field of digital image processing to find the contour of an object. They are used in image analysis to detect and locate objects, and to describe their shape. Active contour is a powerful tool for segmentation in image processing. There are advantages of active contour over image segmentation methods that are thresholding and region grow.

The goal of image segmentation is to produce a simple and meaningful representation of the image making it easier to analyze. Image segmentation is defined as the dividing of an image into non overlapping regions made up of pixels.

Image features are either edge-based or region-based terms. Edge-based terms usually depend on the gradient of the image for stopping the evolution of the curve and Region-based segmentation looks for equality inside a sub-region. These uses information about the pixels inside and outside the segmentation regions. Thus, they can have a better performance of segmentation than edge-based contours, especially for images with weak object boundaries and noise.

Among the region-based methods, Chan–Vese model is a representative and popular one. Chan–Vese (CV) model is used to detect objects whose boundaries are not detected by the gradient. Active contours are of two types they are parametric and geometric contours. Geometric active contours are used for curve topologies and parametric active contours are used for set of discrete points.

In this paper we are segmenting connected objects using parametric active contours. The parameters are based on the deformable models. In our work we use mean value coordinates as the parameters to deform the evolving contour. Mean value coordinates have several advantages, namely control points are used to form the closed polygon that consists of any shape. Any point inside or outside of this polygon may be described in terms of parameters with respect to the control points. We can easily deal with region-based approaches. This is an advantage over other previous approaches, which are only deal with edge-based energies.

II.RELATED WORK

A. Active contours

Active contours are used for image segmentation and boundary tracking since the first introduction of snakes by Kass et al. The idea is to start with first boundary shapes represented in a type of closed curves, i.e. contours, and changed by applying shrink or expansion operations according to the constraints of images. Those shrink or expansion operations, called as contour evolution, are done by minimizing of an energy function.

The technique of active contours has become popular for a range of applications, specially image segmentation and motion monitoring. This is based on the use of deformable contours which is matching to various object shapes and motions. Contours are used for identifying the shape of the object. Hence active Contours are advanced way of image segmentation because it provides certain properties to the image before performing segmentation which makes the technique of finding the boundary comparatively easier.

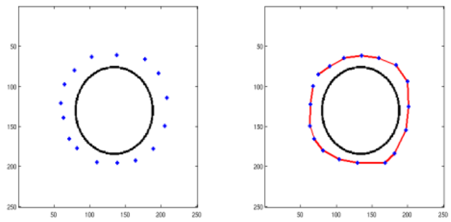

Fig.1. Contour Initialization

B.Level Sets

The level set approach was first delivered by using Osher and Sethian. They represented a contour implicitly via a - dimensional Lipschitz - non-stop – function ϕ(x, y):Ω→ℜ described on the image plane.On the image plane. The function ϕ(x, y) is referred to as level set function, and a particular level, normally the zero level, of ϕ(x, y) is defined as the contour.

Level set processes are able to address the curve topology and accordingly can segment multiple unconnected areas. Level set strategies have advantages like performing computation for curves and surfaces. Level set is in particular used for satellite tv for pc imagery, biomedical imaging system video photograph analysis and so on.

Chan and Vese presented a technique to adapt a curve by minimizing the variance within the inside area, Ω_1, and outside area, Ω_2. The energy minimization is

$$\mathrm{E}(C) = \frac{1}{2}\iint_{\Omega_1}(I-\mu_1)^2\,dxdy + \frac{1}{2}\iint_{\Omega_2}(I-\mu_2)^2\,dxdy$$

where the terms are based on the contour length. Image I corresponds to the observed data.

The $\mu 1$ and $\mu 2$ refer to mean intensity values in the interior and exterior region.

The energy to be minimized is given by

$$\mathrm{E}(C) = \iint_{\Omega_1} e_1\,dxdy + \iint_{\Omega_2} e_2\,dxdy$$

Here e1 and e2 correspond to the log-likelihood function.

III. PROPOSED METHOD

A. Cage Active Contours

Cage Active Contours (CAC) is a segmentation framework that combines computer graphic deformation techniques and parameters of the active contours. It introduces the idea of parameterizing a contour according to a reduced set of control points, known as cage points, which drive the evolution of the contour. We use the term cage to refer to the polygon that lets into deform the evolving contour. Therefore we call our method Cage Active Contours(CAC).

Let us denote $v = \{v_1 ...... v_N\}$ the set of cage vertices related to our parameterization, and allow Ω_1 and Ω_2 be the set of pixels of the interior and exterior, respectively, of the evolving interface C.The cage vertices v may be manually positioned from the evolving contour C, as is done on this work.

B.Mean value coordinates

Mean value coordinates need to form a closed polygon that may have any shape. These are used to simplify and improve methods for parameterization.Mean value coordinates are used to deform the evolving contour.

The mean value coordinates of a point p,given a set of vertices $\boldsymbol{v}_i$ of a polygon of N points, $j = 1 \ldots N$, are computed as

$$\phi_i(p) = \frac{\omega_i}{\sum_{j=1}^{N}\omega_j} \qquad i=1\ldots..N$$

and ω_i is computed as

$$\omega_i = \frac{\tan\left(\frac{\alpha_{i-1}}{2}\right) + \tan\left(\frac{\alpha_i}{2}\right)}{\| v_i - p \|}$$

where " $v_i - p$ " is the distance between the vertex $\mathbf{v}_i$ and the considered point p, α_i is the signed angle of $[v_i, p, v_{i+1}]$,see in fig.2.

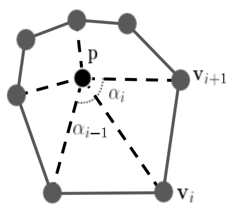

Fig. 2.Mean Value coordinates of vertex points

Given the affine coordinates $i(p)$ of a point p, the point p can be recovered with

$$p = \sum_{i=1}^{N}\phi_i(p)v_i$$

Where ϕ_i (p) is the corresponding affine coordinate of the point p with respect to the vertex v_i and N is the number of vertices.

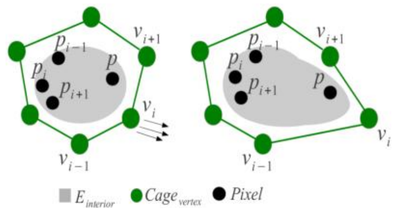

Fig.3. Influence of a vertex over the points on the plain.

If the vertices **v**i of the polygon move to positions v', the "deformed" point p' can be recovered as

$$p' = \sum_{i=1}^{N} \phi_i(p) v_i'$$

C. Gaussian Energy function

The Gaussian energy decreases when the values of each region have stable statistics. In other words, the curve will stop evolving when each region has points whose values have a higher probability.

$$\mathrm{E}_{gauss} = \sum_{h=1}^{2} \sum_{p \in \Omega_h} -\log(p_h(I(p)))$$

Where Ph is the probability an intensity of p,I (p) belong to the normal distribution.

In order to minimize the energy, calculate the gradient the derivative of the energy with respect to each control point vi.

$$\nabla_{v_j} \mathrm{E}_{gauss} = \sum_{h=1}^{2} \sum_{p \in \Omega_h} \frac{I(p) - \mu_h}{\sigma_h^2} \nabla I(p) \phi_i(P)$$

IV.IMPLEMENTATION

The binary mask M is used as initialization for the algorithm and its outer boundary is an approximation to the object boundary we want to segment. Several choices are available to compute the inner Ω_1 and outer pixels Ω_2. For instance, Ω_1 may be composed of the pixels of *M*, Ω_1 = *M*, and Ω_2 may be taken as the set Ω_2 = Ω*M*, where Ω is the whole image support. This is the Way in which Ω_1 and Ω_2 are defined for the level sets.

Minimization of the energy is performed by means of a gradient descent process that iteratively updates the cage vertex positions. At each step of the gradient descent, Ω_1 and Ω_2 are recomputed. The inputs of this system are the image on one hand and the components of Cage Active Contours on the other, the initial contour, the initial cage and the energy function.

The uniform sampling method is based on extracting at the initialization stage the contour *C* associated to the mask *M*. The contour is represented as neighboring pixels that forms the contour and may be ordered either in clockwise or counter-clockwise way. Let **c***i* be the points of the discretized contour. The affine coordinates of c_i are computed before the gradient descent is commenced. For every generation of the gradient descent technique, the "deformed" contour C is recovered.

The sets Ω_1 and Ω_2 can be easily extracted by describing them using integer pixel positions, and its associated affine coordinates are computed. Then *E*(**v**) and ∇ *E*(**v**) can be evaluated and the cage vertices are updated. This approach implies computing Ω_1, Ω_2 and its associated affine coordinates at each iteration of the gradient descent. Thus, it is a computationally intensive method. The advantage of this approach is that, at each iteration, the image is sampled at integer pixel positions, and thus, in a uniform way.

A. Gradient Descent

In order to segment the image, the Energy function with respect to the contour must be minimized. Since there are a few restrictions on the cage, the iterative gradient descent algorithm is integrated into the Segment Object.

The Calculate Gradient method iteratively updates the cage V= { $v_1 \ldots\ldots\ldots v_N$ } represented as v^k in iteration k to $v^{k=1}$ for iteration k + 1 through the update:

$$v^{k+1} = v^k + \alpha^k s^k$$

Where s^k is the so called search direction and α^k the step. Usually the steepest descent direction $s^k = -\nabla_{v^k} \mathrm{E}$ is taken as the search direction. In this work we take the negative of the normalized gradient vector obtained as follows:

$$s^k = -\left(\frac{\nabla_{v_1^k} \mathrm{E}}{\|\nabla_{v_j^k} \mathrm{E}\|_{\max}}, \frac{\nabla_{v_2^k} \mathrm{E}}{\|\nabla_{v_j^k} \mathrm{E}\|_{\max}}, \ldots\ldots \frac{\nabla_{v_N^k} \mathrm{E}}{\|\nabla_{v_j^k} \mathrm{E}\|_{\max}} \right)$$

Where

$$\|\nabla_{v_j^k} \mathrm{E}\|_{\max} = \max\left\{ \|\nabla_{v_j^k} \mathrm{E}\| : j = 1 \ldots N \right\}$$

After this update, the Deform Points function is applied to the Contour so that it is updated with respect to the new cage.

In CAC gradient descent is used by means of a two stage process.

First stage:

The goal in this stage is to obtain a segmentation as close as possible to the solution by restricting the step and direction in which the cage vertices may evolve At each iteration of the gradient descent each cage vertex v_j^k is restricted to move along the line that passes through the center point of v_c and v_j^k. That is, the gradient vector $\nabla_{v_j^k} E$ is projected on the line joining v_c and v_j before normalizing it. This can be seen in figure 4 with red lines representing the gradient vector while the blue lines their projection on the line that passes through its corresponding vertex v_j and the center point v_c.

In this first stage, the step α is constant for each iteration and corresponds to a motion of α = β pixels of the cage vertices4, which is the maximum distance points are allowed to approach edges or other vertices to ensure the cage, does not cross over.

This condition has to be satisfied independently, for each cage vertex, in order to stop the first stage and begin the second stage.

$$\left(\nabla_{v_j^k} E\right)^T \nabla_{v_j^{k-2}} E > 0, \left(\nabla_{v_j^{k-1}} E\right)^T \nabla_{v_j^{k-3}} E > 0, \left(\nabla_{v_j^k} E\right)^T \nabla_{v_j^{k-1}} < 0, \forall k \in V$$

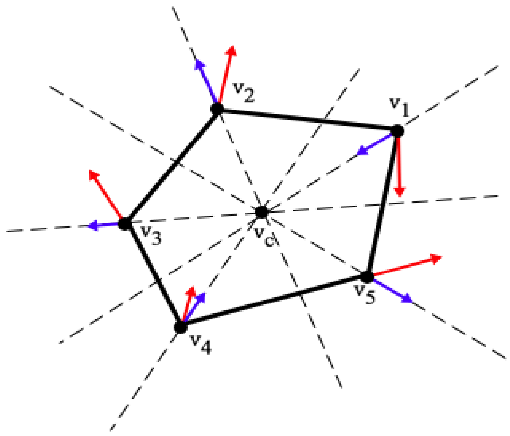

Fig.4. Depiction of the first stage restriction.

Second stage:

When the cage meets the above condition, an approximation of the segmentation is met and the second stage begins. The restrictions on the direction of the gradient are immediately removed. The objective of this stage is to move the cage vertices in the direction given by the gradient only if the energy is minimized. Once the energy can no longer be reduced, it is considered that the cage has reached a minimum of the energy and the inner region of the contour deformed by the cage is the final segmentation of the object.In the undesirable case where the cage does not reach the second stage after a long time, we have added a maximum number of iterations which ends the segmentation when reached returning the current segmentation as the final one.

V. EXPERIMENTAL RESULTS

In this section, we present the experimental results of CAC method on synthetic and real images. Here we use uniform sampling and we constrain edges to not cross between each other. Cage vertices are automatically placed in a uniform way around the initial evolving contour. Fig. 5. Shows the results for two synthetic images, one X-ray Image of vessel. Our method successfully extracts the object boundaries for these two synthetic images, as shown in Fig. 5. The third in Fig. 5 show the results of our method for real image of blood vessel. In this image, part of the vessel boundaries is quite weak, which renders it a nontrivial task to segment the vessels in the images.

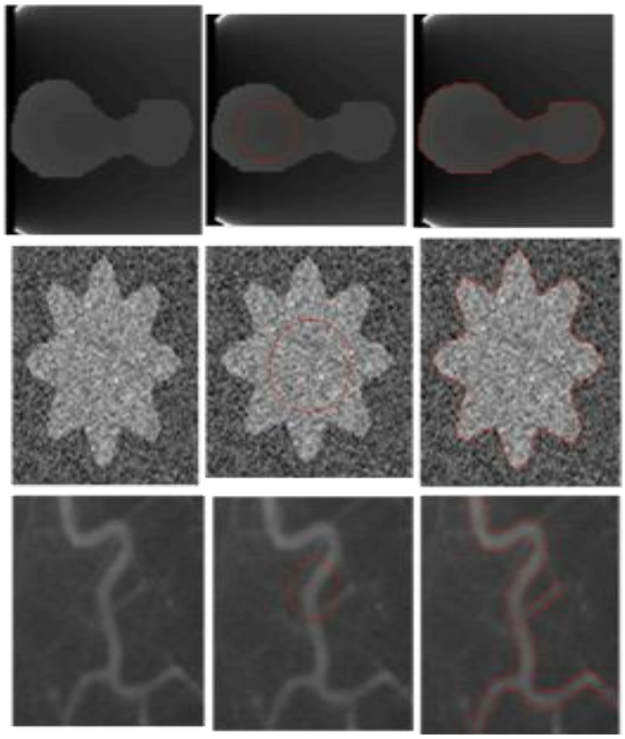

Fig.5. Results for two synthetic images and X-ray image of vessel. The curve evolution process from the initial contour to the final contour is shown in every row for the corresponding image.

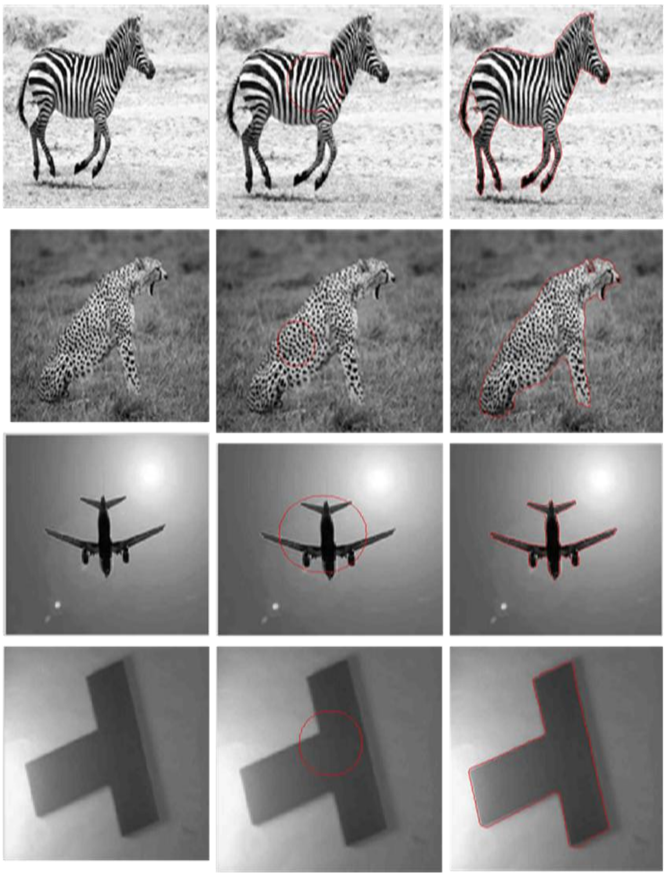

Fig.6.Results of real images using gaussian model. The curve evolution process from the initial contour to the final contour is shown in every row for the corresponding image.

VI CONCLUSION

In this work, we present a new segmentation method, Cage Active Contours. Cage Active Contours (CAC) is a segmentation framework that combines computer graphic deformation techniques and parameters of the active contours. The evolution is driven by a reduced set of control points that modify the shape of the segmentation contour via an affine transformation. Mean value coordinates are used to deform the evolving contour and are used to parameterize the points of the space with respect to the cage points. Experimental results have demonstrated the advantages of our method over several well-known methods for image segmentation.

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