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Research Paper

Level Set Approach to Image Segmentation

Engineering

KEYWORDS : Active contour, curvature, energy minimization, segmentation, snake model, curve evolution.

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ABSTRACT

Image segmentation is one of the most important step in the image analyses. Its aim is to divide image in some parts which correlate strongly by objects. Segmentation is difficult task because of big variety of objects, shape as well as different quality. In this paper various methods of finding active contour is discussed. First method of image segmentation is based on principle paradigm of edge or gradient by minimizing the energy of an image. Later section we discuss about the practical limitation of the model. Another paradigm is that the detection of active contour whose stopping term does not depend on the gradient. After that we discuss how this method is advantageous or more beneficial in finding the interested regions from an image.

1. INTRODUCTION

Active contours are used in the domain of image processing to locate the contour of an object. Trying to locate an object contour purely by running a low level image processing task such as canny, sobel and prewitt edge detections are not particularly successful. Often the edge is not continuous, i.e. edges are broken or not connected, and spurious edges can be present because of noise. An active contour tries to improve on this by imposing desirable properties such as continuity and smoothness to the contour of the object.

In section II, discussion of the basic active contour method which is introduced in “international journal of computer vision”. How image is segmented based on minimizing energy terms and how it can be formulated in different energy terms. Section III, describes effect of noise on the image which degrade the results and also illustrates the practical problem of broken edges in an image. Section IV, discussion of disadvantages of edge based active contour and its solution of finding the active contour.

2. CLASSICAL ACTIVE CONTOUR

The concept of active contours models was first introduced in 1987 [1] and has later been developed by different researchers. An active contour is an energy minimizing that detects specified features within an image. It is a flexible curve which can be dynamically adapted to required edges or objects in the image.

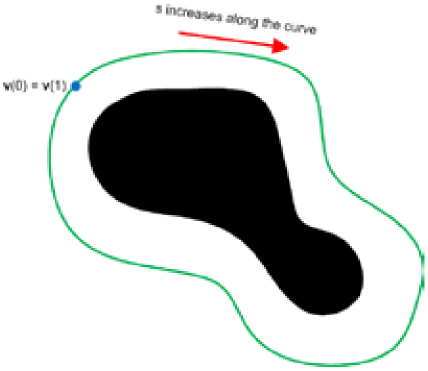

Fig. 1 Illustration of a parametric snake curve v(s). The blue dot marks the starting point and end point of the snake curve.

The position of the snake is given by the parametric curve v(s) = [x(s); y(s)]T with S∈ [0; 1],in practice the curve is often closed which means that v(0) = v(1). Furthermore the curve is assumed to be parameterized by arc length. A closed parametric snake curve is illustrated in Fig. 1. Each point along the curve is under the influence of both internal and external forces [2]. Fitting active contours to shapes in images is an interactive process. The contour will then be attracted to features in the image extracted by internal energy creating an attractor image [3].

A. The Original Snake by Kass, Witkin & Terzopoulos

Snakes, developed by Kass et al. [1], is a method of molding a closed contour to the boundary of an object in an image. The snake model is a controlled continuity closed contour that deforms under the influence of internal forces, image forces, and external constraint forces. The internal contour forces provide a piecewise smoothness constrain [4]. Kass et al. introduced the following energy functional for calculating the snake energy

$$E^{*}_{snake} = \int_{0}^{1} E_{snake}(v(s))ds$$

$$E_{snake} = \int_{0}^{1} E_{int}(v(s)) + E_{ext}(v(s))ds$$

$$E_{snake} = \int_{0}^{1} E_{int}(v(s)) + E_{img}(v(s)) + E_{con}(v(s))ds$$

The snake energy consists of three terms. The first term E_{int} represents the internal energy of the snake while the second term E_{img} denotes the image forces; the last term E_{con} Gives rise to external constraint forces. The sum of the image forces E_{img} And the external constraint forces E_{con} Is also simply known as the external snake forces, denoted by E_{ext}. The internal energy of the snake is written as

$$E_{int} = \frac{1}{2}(\alpha(s)\|V_s(s)\|^2 + \beta(s)\|V_{ss}(s)\|^2)$$

Where the first-order term$\|Vs(s)\|^2$gives a measure of the elasticity, while the second-order term $\|Vss(s)\|^2$ gives a measure of the curvature. This means that in parts of the snake where the curve is stretched, the elasticity term will have a high value, while in parts of the snake where the curve is kinked; the curvature term will have a high value. The influence that these terms have on the overall snake energy is controlled by the confidents α(S)And β(S), The image forces E_{img} Attracts the snake to the desired features in the image. If the snake should settle on edges in the image, then the image energy can be defined as $E_{img} = -\|\nabla I(x,y)\|^2$, with I being the image function. Thus the snake will position itself in parts of the image with high gradient values. The external constraint forces E_{con} are attributed to some form of high level image understanding, most likely defined by human interaction. The external energy E_{ext} consists of both the image energy And $E_{int}(v(s))$ the external constraint forces, E_{com} (V(S)) ,however in order to simplify the analysis we will disregard the external constraint forces.

B. The image energy forces E_{img}(V(s))

Let us take closer look at the image energy E_{img}(V(s)). A crucial step in the Snake model is finding a suitable term for the image energy; this is because the snake will try to position itself in areas of low energy. Often the snake should be attracted to edges in the image and when this is the case a suitable energy term is $E_{img} = -\|\nabla I(x,y)\|^2$ where I is the image function. In order to remove noise from the image and increase the capture range of the snake. The image can be convolved with a Gaussian kernel before computing the gradients. This gives the following image energy term

$$E_{img} = -\|\nabla[G_\sigma(x,y) * I(x,y)]\|^2$$

Where $G_\sigma(x,y)$ is a two dimensional Gaussian with standard deviation σ. When strong edges in the image are blurred by the Gaussian the corresponding gradient is also smoothed which results in the snake coming under the influence of the gradient forces from a greater distance, hereby increasing the capture range of the snake.

C. The internal energy of the snake $E_{int}(v(s))$

The internal energy of the snake is defined as in (2). The first order term$\|Vs(s)\|^2$ Measures the elasticity of the snake, while the second order term $\|Vss(s)\|^2$ Measures the curvature energy. The influence of each term is controlled by the coefficients and σ(S) and β (S). The more the snake is stretched at a point v(s) the greater the magnitude of the first order term, whereas the magnitude of the second order term will be greater in places where the curvature of the curve is high. It should be noted that if the snake is not under the influence of any image energy, and only moves to minimize its own internal energy. Then, for a closed curve, it will take the form of a circle that keeps shrinking and for a open curve the snake will position itself to form a straight line that also shrinks. The internal forces of the snake are however necessary in order to preserve desirable properties such as continuity and smoothness of the curve.

3. PROBLEMS IN CLASSICAL ACTIVE CONTOUR

As discussed in previous section, fitting term of the snake model is depending on the edge or gradient of an image. In practical system there is some noise or other factors that degrade the quality of an image and made task of segmentation more difficult. These factors are noise, broken edges; non uniform illumination etc. lets discuss how they create problems.

A. Presence of noise in an image

The image segments in the first column in Fig. 2 show close-ups of four ramp edges that transition from a black region on the left to a white region on the right

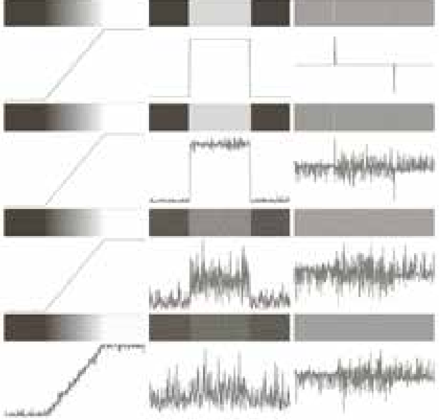

Fig. 2 Intensity profiles and its derivative with different amount of noise.

The image segment at the top left is free of noise. The other three images in the first column are corrupted by additive Gaussian noise with zero mean and standard deviation of 0.1, 1.0 and 10.0 intensity levels respectively. The graph below each image is horizontal in intensity profile passing through the center of the image. All images have 8 bits of intensity resolution, with 0 and 255 representing black and white, respectively [5]. Second column shows the first order differentiation for respective images. Resultant images are getting poorer as density of the noise is increasing. Right-most column shows the second order derivative which is very useful for detecting the location of the edge by detecting zero crossing. Minor amount of noise can produce large number of undesired variation in second order derivation.

To remove effect of noise, image is smoothed out by low pass filter. Due to this process noise is somewhat removed but it also affect the gradual transition of the intensity level which is edge though it is not affected by noise. So this is disadvantage of model which is depending on edge of an image corrupted by noise.

B. Presence of broken edge

Because of noise or same property of an object to background all edge detection operators produce broken edge. This creates several problems for detecting the boundary of objects. These discontinuities in edge should be removed by edge linking procedure but they also have somewhat limitations.

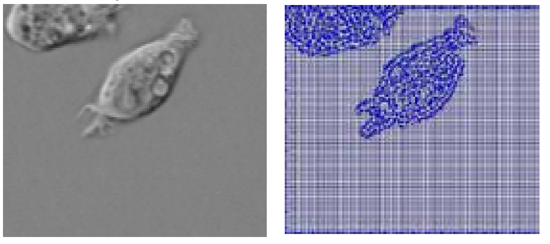

Fig. 3 Image of cell and its gradient image.

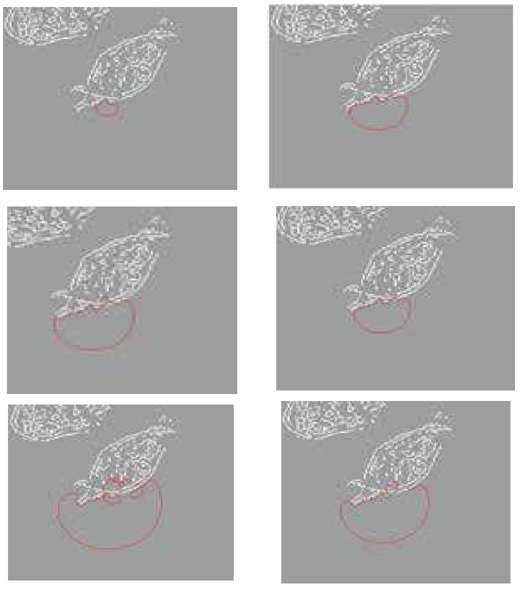

Fig. 4 Simulation result of evolving initial contour to the broken edge.

Fig. 3 shows original image and its gradient of an image. Fig. 4 shows simulation results which evolve the active contour to the broken edge. There is problem of multiple curves passing through isolated object an image. This happens because the evolving of the curve is only depending on its neighbor point not other point in the curve [6]. This type of looping problem can be avoided by using proper algorithm for curve evolution.

4. ACTIVE CONTOUR WITHOUT EDGE

All these classical snakes and active contour models rely on the edge function, depending on the image gradient, to stop the curve evolution; these models can detect only objects with edges defined by gradient. In practice, the discrete gradients are bounded and then the stopping function is never zero on the edges, and the curve may pass through the boundary, especially for the model in [1], [8]-[10]. If the image is very noisy, then the isotropic smoothing Gaussian has to be strong which will smooth the edges. In this section, we propose a different active contour model, without a stopping edge function, i.e. a model which is not based on the gradient of the image for the stopping process. The stopping term is based on Mumford–Shah segmentation techniques. In this way, we obtain a model which can detect contours both with and without gradient, for instance objects with very smooth boundaries or even with discontinuous boundaries. In addition, our model has a level set formulation, interior contours are automatically detected, and the initial curve can be anywhere in the image [7].

Our method is the minimization of an energy based-segmentation. Let us first explain the basic idea of the model in a simple case. Assume that the image u_0 is formed by two regions of approximately piecewise-constant intensities, of distinct values

u_0^i and u_0^o. Assume further that the object to be detected is represented by the region with the value u_0^i. Let denote its boundary by C_0. Then we have $u_0 = u_0^i$ inside the object and $u_0 = u_0^o$ outside the object. Now let us consider the following "fitting" term:

$$F_1(C) + F_2(C) = \int_{inside(C)} |u_0(x,y) - c_1|^2\, dx\, dy + \int_{outside(C)} |u_0(x,y) - c_2|^2\, dx\, dy$$

Where C is any other variable curve, and the constants c_1, c_2 , depending on C, are the averages of u_0 inside C and respectively outside C.

This can be seen easily. For instance, if the curve C is outside the object, then $F_1(C) > 0$ and $F_2(C) \approx 0$. If the curve C is inside the object, then $F_1(C) \approx 0$ but $F_2(C) > 0$. If the curve C is both inside and outside the object, then $F_1(C) > 0$and $F_2(C) > 0$. Finally, the fitting energy is minimized if $C = C_0$, i.e., if the curve C is on the boundary of the object. These basic remarks are illustrated in Fig 5.

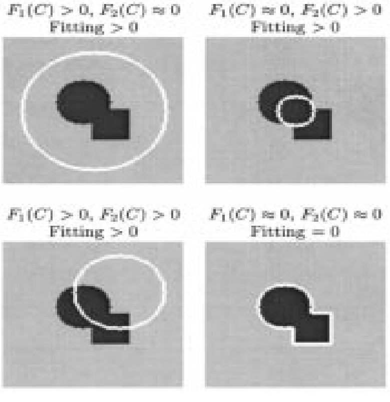

Fig. 5 all possible cases in the position of the curve the fitting term is minimized only in the case when the curve is on the boundary of the object

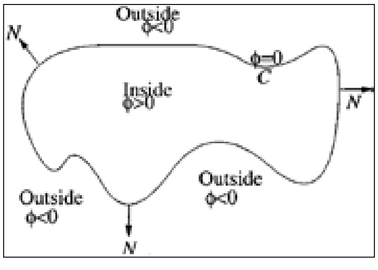

Fig. 6 Curve $C = \{(x,y): \emptyset(x,y) = 0\}$ propagating in normal direction

In the level set method, $C \subset \omega$ is represented by the zero level set of a Lipschitz function $\emptyset, \Omega \to R$ such that

$$C = \partial\omega = \{(x,y) \in \Omega : \emptyset(x,y) = 0\}$$
$$inside(C) = \omega = \{(x,y) \in \Omega : \emptyset(x,y) > 0\}$$
$$outside(C) = \Omega \backslash \overline{\omega} = \{(x,y) \in \Omega : \emptyset(x,y) < 0\}$$

For the level set formulation of our variation active contour model, we replace the unknown variable C by the unknown variable $\emptyset$. Using the Heaviside function H,

$$H(z) = \begin{cases} 1, & if\ z \geq 0 \\ 0, & if\ z < 0 \end{cases}$$

$$\delta_0(z) = \frac{d}{dz} H(z)$$

Then, the energy $F(c_1, c_2, \emptyset)$ can be written as

$$F(c_1, c_2, \emptyset) = \mu \cdot \int_\Omega \delta_0(\emptyset(x,y)) |\nabla \emptyset(x,y)|\, dx\, dy + v \cdot \int_\Omega H(\emptyset(x,y))\, dx\, dy + \lambda_1 \int_\Omega |u_0(x,y) - c_1|^2 H(\emptyset(x,y))\, dx\, dy + \lambda_2 \int_\Omega |u_0(x,y) - c_2|^2 (1 - H(\emptyset(x,y)))\, dx\, dy$$

Where, c1 and c2 are the average intensity within the objects and outside the objects respectively. Thus we can define boundary of objects by function rather than the edge of the image.

Fig. 6 Simulation results for level set method for different iterations.

5. FUTURE ENHANCEMENT

Above section introduce new model for extracting the objects from an image. This mathematical model shows that stopping term of model does not depends of edge but depends on a function so objects and background is clearly identified based on response of the function. In section II and III, we discussed about use of edge and its limitations. Though edges have demerits, they can be used as one of the parameter which can direct contour toward the boundary of objects.

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CONCLUSION

In this paper we discussed about need of segmentation in image processing then we describe one domain of segmentation that is active contour detection. There are two approaches for detecting active contours, first is based on edge and second is independent of edge. A model of detecting active contour whose fitting term depends on the edge or gradient is very sensitive to noise and degrade its result and also produce poor response in several unfavorable conditions like broken edges. In such cases a model, which's fitting term depend on the function rather than gradient will provide better and reliable results. Thus active contour without gradient is better way to segment an image rather than gradient based model.

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