World Applied Sciences Journal 28 (12): 2010-2015, 2013
ISSN 1818-4952

DOI: 10.5829/idosi.wasj.2013.28.12.100

A New Approach for Parametric Active Contour Segmentation

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Abstract: Parametric active contour models cannot provide enough precision for object segmentation. Since, based on analyzing the diffusion process of GVF, an improved external force field called as (center of local mass) CLM is proposed in this paper. The results show that our proposed algorithm provides good convergence and have very good segmentation.

Key words: Active contours or snakes · Gradient vector flow · Image segmentation

INTRODUCTION

Active contours or snakes have been widely used in many applications of image processing and computer vision. Ever since the introduction of the active contours by Kass *et al*. [1], active contour models have received wide popularity with the computer vision community. It quickly found use in the different kinds of images or videos with applications such as image segmentation [2], image tracking [3, 4] and object detection [5].

In general, there are two different implement methods of active contours: parametric active contours [6, 7, 8] and geometric active contours (or geodesic active contours) [9, 10].

Parametric active contours represent curves and surfaces explicitly in their parametric forms during deformation. This representation allows direct interaction with the model and can lead to a compact representation for fast real- time implementation. Adaptation of the model topology, however, such as splitting or merging parts during the deformation, can be difficult using parametric models. Geometric deformable models, on the other hand, can handle topological changes naturally. These models represent curves and surfaces implicitly as a level set of a higher- dimensional scalar function.

Since, parametric snakes have the advantage over geometric snakes in convergence speed, we focus on the enhancement of parametric active contours, in this paper.

Snake is a controlled continuity spline which can deform dynamically and moves towards the desired image features under the influence of internal and external forces, appearing in an energy functional, which convert the problem of finding objects into the process of energy minimizing subject to certain constraints. The internal forces serve to model to the salient image features such as lines, edges and terminations. these two types of energy are dependent to the shape and position of snake on the image as follows:

$$E = E_{\text{int}} + E_{ext} \tag{1}$$

where E_{int} is internal energy and E_{ext} is the external energy. The deformable curve is generally initialized by automatic or manual process around the object of interest. The snake algorithm then deforms iteratively the model and finds the configuration with the minimum total energy, which hopefully corresponds to the best fit of the snake to the object contour in the image.

In the implementation of traditional snakes, the location of the initial snake is critical and is required to be set close to the object boundary. Otherwise, it will potentially evolve to the local minima due to the limited capture range. In order to enable the curves to converge the edge of objects rapidly, many improved models of image force field were put forwarded. The balloon modes [6], enlarge the capture range of snakes, but could not enter into the concavities of the objects' edge. The distance potential force [11], defined based on the Euclidian distance improves the capture range. However, the snake with such external force does not evolve onto concave boundary as traditional snakes behave.

In this paper, we discuss at length the diffusion process of GVF force field and propose an improved external force field called as CLM. The CLM snakes have

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a large capture range and ability to capture concavities. Those advantages are demonstrated by examples and comparisons with other snake models.

The remaining part of this paper is organized as follows. In section 3 and 4, we introduce briefly snake models and the shortcomings of these snakes are highlighted. Then, the proposed external force is explained in details at the end of section 5. Conclusions of this paper are presented in section 6 and, Finally, the acknowledgement is presented in section 7.

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Internal Energy: The internal energy serves to impose a piecewise smoothness and consecutiveness constraint. The internal energy of the contour depends on the shape of the contour and the weighting parameters α and β is defined as:

$$E_{\text{int}} = \int_0^1 \left[\alpha \left| c'(s) \right|^2 - \alpha \left| c''(s) \right|^2 \right] ds \tag{2}$$

where α and β are weighting parameters that control the snake's tension and rigidity, respectively. The first term, $|c'(s)|$ will have larger values if there is a large gap between successive points on the contour and minimizing it will minimize the total length of the contour. The second term, $|c''(s)|$ will be larger where the contour is bending and requires the contour to be as smooth as possible. Increasing both coefficients may enhance the effect of the physical properties of the model, but diminish the influence of the external energy.

External Energy: The external energy function is derived from the image and it takes on its smaller values at the features of interest, such as edges and boundaries. the external energy function is designed to lead the active contour toward edges of the matching degree image.

Since, the first external force proposed by Kass has a limited attraction range, many different models are proposed to solve this problem. In this section, we briefly depict and compare these models.

Traditional Method: Given a gray level image I(x, y), viewed as a function of continuous position variables (x, y), a typical example of the external force designed to lead a snake toward step edges as follows:

$$E_{ext}(x, y) = -|\nabla I(x, y)| \tag{3}$$

where ∇ is the gradient operator. The equation is fitted for the objects that has homogeneous. The external force of traditional snake is defines by the gradient of image as in Eq. (3) has a very limited capture range. An efficient way to increase capture range of snake is boundary smoothing. Since, an enhancement energy model can defined as follows:

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

where $G_\sigma(x, y)$ (in this paper we use 10*10 model) is a two dimentional Gaussian function with standard derivation σ. It is easy to see that larger σ will cause the boundary blurry, but this has both positive and negative effects: the range of the potential field will be increased, but the edge localization will be come less accurate and distinct.

Distance Potential Force: The distance potential force [11], defined based on the Euclidian distance can be applied to increase the capture range of snake. Hence, the external force of snake is replaced by the normalized distance potential force as follows:

$$E_{ext} = -k \frac{\nabla d(x,y)}{|\nabla d(x,y)|} \tag{5}$$

where k is a constant coefficient, d is the distance between a point (x, y) and the nearest edge points in the binary boundary map. Distance potential force snake have high capture range but it cannot extract concave object correctly. In this method, the Gaussian filter can be used before or after of edge detection operator.

Gradient Vector Flow: Gradient Vector Flow (GVF) was defined in [11] as an external force to push the snake into object concavity. It is the vector field v(x, y)=[u(x, y), v(x, y)] that minimizes the energy functional.

$$E_{GVF} = \iint \mu(u_x^2 + u_y^2 + v_x^2 + v_y^2) + |\nabla f|^2 |V - \nabla f|^2 \, dxdy \tag{6}$$

where μ is the regularization parameter governing the tradeoff between the first term and the second term in the integrand and ∇f is the gradient of the edge map derived from the image. The GVF field outperforms the distance forces by providing a large capture range and the ability to capture boundary concavities.

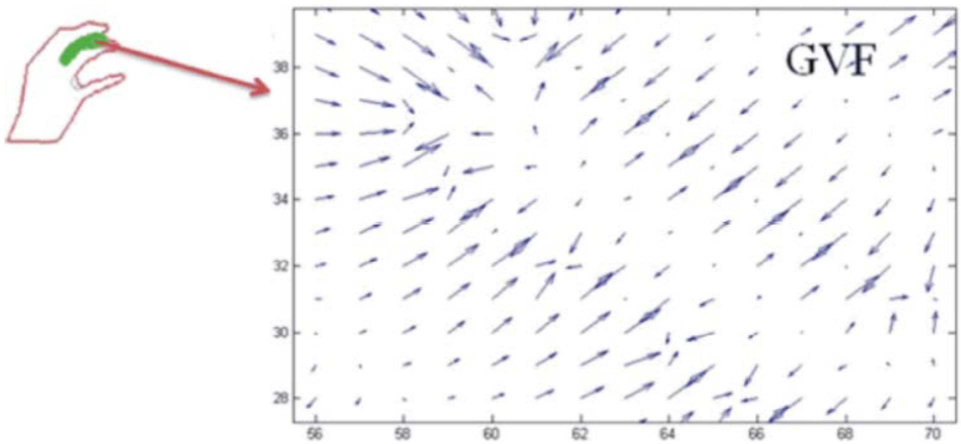

Fig. 1: Gradient vector flows of the pixels between hand's fingers

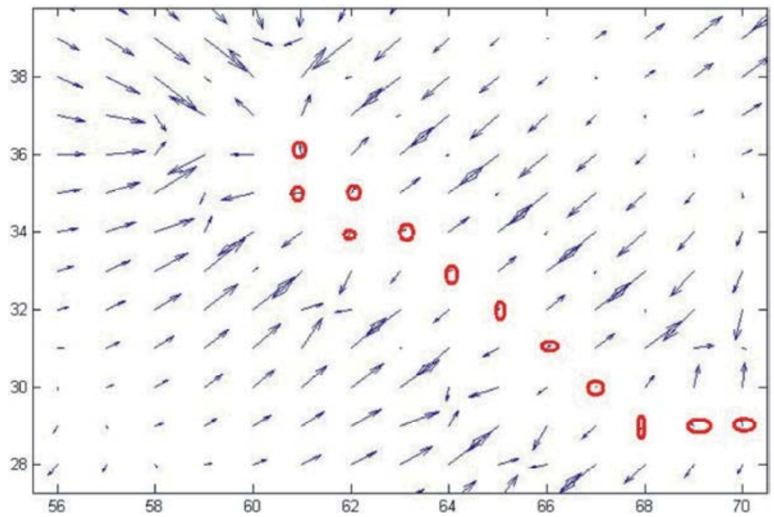

Fig. 2: Centre of local mass(CLM)- these pixels are shown in red spots

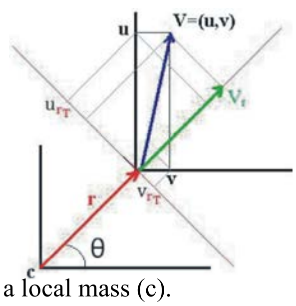

Fig. 3: Vector flows of a pixel rather than a local mass (c).

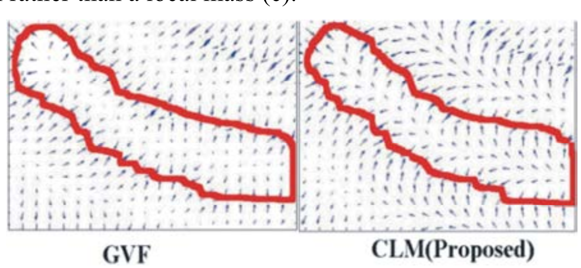

Fig. 4: Comparing vector flows of the gradient vector flow and the proposed method for pixels between hand's fingers

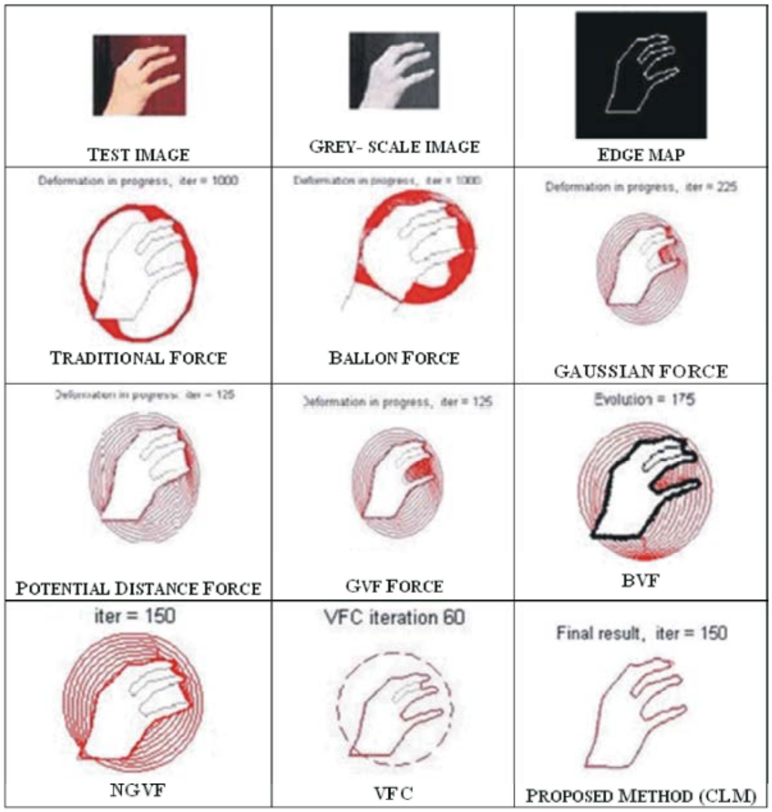

Fig. 5: Comparing results from other method with the proposed method (CLM) that obtained from GVF

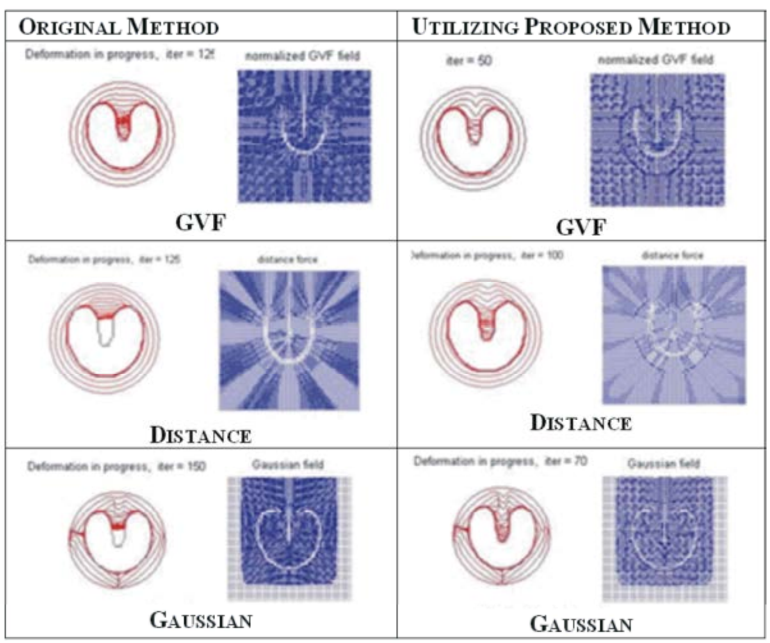

Fig. 6: Utilizing proposed method on existing methods and comparing obtained results

Proposed Method: Since, the points with equal distance between two edges, under attraction of that edges, have insignificant vector flows. The contour, therefore, would cease, at these points, due to the fact that the external force in these points would be slightly. Consequently, the segmentation process would not completely done. and hence, these models, as shown as, Fig. 5., can not provide enough precision for object segmentation.

Based on analyzing the diffusion process of GVF, we have proposed a segmentation algorithm that is to somewhat is similar to the classical GVF method. As shown as in the Fig. 1., there are some points among concavities area that they have insignificant vector flow. In this paper, we proposed a method to charge these points toward concavities. As shown as in the Fig. 2, the proposed method selects these points that their vector flows have two conditions as below:

- Their vector flow amount is smaller than a threshold.
- Vector flows of their surrounding pixels are scattered around.

In this stage, by considering points that were selected at the previous stage (central pixels), we calculate sum of the vector flows of their surrounding pixels. If vector flows of pixels, that surrounding the central pixel, are scattered significantly around, then those central pixels are selected, as shown as in Fig. 2 these calculation can be done as follows:

$$S_{CLM} = \sum_{|r|<d} |(u,u)| \cos\alpha = \sum_{|r|<d} \frac{u.r_x + v.r_y}{|r|} \quad (7)$$

where, as shown as in Fig. 3, c is the central pixel, V=(u, v) is a surrounding pixel and r is the distance between them. After calculating S_{CLM} for all pixels, we choose the pixels that their S_{CLM} is smaller than a threshold value. This centre local masses are shown in the Fig. 2. In this paper, we have called this points as centre of local mass(CLM). Finally, after selecting these points, we optimize the value of this points with regarding to concave area position. The results of the proposed method against the gradient vector flow (GVF) are shown in Fig. 4. As the image shows, the proposed method would effectively pull toward the concavity areas.

Consequently, Fig. 5 illustrates individual perfo-rmance of segmentation using a variety segmentation models and the proposed method with similar initial contours. Clearly, in the previous methods, snake is ceased by the narrow concavities of the object. However, the proposed method confidently gets around this problem and finally addresses on the ideal boundary.

CONCLUSIONS

Parametric active contour models can not provide enough precision for object segmentation. Since, based on analyzing the diffusion process of GVF, an improved external force field called as (center of local mass) CLM is proposed in this paper. Experimental results of the proposed method, then, compared with existing method.

Finally, we have depicted the performance of our algorithm by utilizing proposed method upon previous methods and then comparing obtained results. The results show that our proposed algorithm provides good convergence and have very good segmentation.

ACKNOWLEDGMENT

This paper uses MATLAB snake demo toolbox developed by Xu C. And Prince J., which helps author to learn active contour model. The valuable suggestions from reviewers are important for authors to improve the paper.

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