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Enhancement of morphological snake based segmentation by imparting image attachment through scale-space continuity

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ABSTRACT

In this paper, we propose a new multi-scale morphological approach to curve evolution useful for object extraction through segmentation. The homogenous image structures that characterize the segmentation process are edges and terminations. Normally the conventional *morphological snake* (MS) technique employs morphological binary level-set operators for realizing forces. These operations handle definite components of the PDE (partial differential equation) used for modeling the dynamic system. The proposed model can segment with reasonably high level of accuracy and efficiency while ensuring smooth segmentation at object boundaries with scale space continuity. Application of discrete image force in MS is a per pixel decision based on the sign of image force PDE component. In the continuous domain however, the intensity of the image force PDE component is the primary factor for snake evolution. In our model we embed scale-space continuity into the morphological operators dictated by MS in order to realize the image force both in intensity and direction. Thus, our model confirms to the speed, agility and robustness of morphological snakes with regard to segmentation while ensuring enhanced efficiency of segmentation under noise. We have rated the performance both on qualitative and quantitative basis against benchmark results, on a set of 2D gray-scale real images both in absence and presence of noise. A comparative study has also been carried among our method, MS, geodesic active contour (GAC) and Distance Regularized Level Set Evolution (DRLSE).

1. Introduction

Morphological snakes and geodesic active contours make up the most widely used algorithms for image segmentation and object tracking and in similar problems of computer vision. Curve evolution in a parameter free environment along with the ability to adapt to shapes of unknown topology make up some of the reasons for their extensive applications. Here, a curve evolves to fit and track an object in unknown image topologies by deforming its shape. This deformation occurs in an attempt to minimize internal and external energies along its boundary. Lowering the internal energy keeps the curve smooth and in such cases the external energy attracts the snake towards image structures such as edges and terminations.

Curve deformation occurs by iteratively solving a partial differential equation (PDE) that leads to lowering of both internal and external energies of the snake over time. Concept of *geodesic active contours* [1] as well as the method suggested by Shi and Karl [2] introduced the use of level-sets for curve evolution. The former techniques are rather slow and require large number of iterations for the snake to reach equilibrium. *Morphological Snakes* [3,4] handle this problem by using morphological operations of dilation and/or erosion and morphological line operations, with which the solution of the snake PDE in successive iterations is always embedded in a binary level-set. Such morphological operators convect a balloon force component responsible for bringing the snake to regions of interest (ROI), an internal smoothing component responsible for smoothing high curvature segments and an image force component that attracts the snake towards edges. While MS presents a much faster alternative for snake evolution in comparison to GAC, its fixed threshold margin regularization for balloon force can have negative effects. Since the image attachment term relies on the balloon force tern to bring the snake to ROI, a noisy pixel environment can lead to irregular snake attachment. This occurs when the balloon force component does not agree with image attachment under the effect of a universal threshold margin. In particular there are two scenarios where balloon force may disagree with image force in a noisy pixel environment:

- For a low threshold margin, the balloon force may fail to bring the snake to ROI causing the snake to halt under the effect of image force, at *bad local minima*.
- For a high threshold margin, a prominent balloon force may lead the snake beyond actual ROI or *good local minima*, unperturbed by the less strong image force.

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In the proposed work, we remove such threshold margin regularization of the balloon force component. This is conducted by formulating a discrete adaptive force that depends on a multitude of threshold margins instead of a single margin. Such multitude of threshold margins can be obtained in a multi-scale environment. Multi-scale snake evolution begins over a blurred version of the image with consecutive de-blurring, followed by snake evolution in each epoch. In the continuous domain, this adaptive force resembles the image force under scale space continuity, as applicable for Kass snakes [11]. The force is termed *adaptive* as it solves the aforesaid scenarios by automatically exchanging roles of image *exploration* and *attachment*. In this paper we formulate a morphological operator to convect adaptive force that renders the agility of MS but with greater robustness in segmentation. In Section 3.1 the formulation of the adaptive force under scale space continuity, from the snake evolution PDE, is shown. Here, we also come up with a morphological operator that can convect this adaptive force. In Section 3.2, the significance of the adaptive force is illustrated, with respect to image attachment in noisy localities. Finally extensive comparative results among MS, GAC, proposed method and DRLSE [5] techniques, are presented in Section 4.

2. Theoretical background

With the introduction of *Kalman snakes* [7,8] and snakes where image forces were applied through scale space continuity [3,4,9–11], simple feature localization was made possible but with low throughput. Segmentation of multiple features however is not possible with the aforesaid methods. A brief survey of methods used in deformable models prior to the application of level-sets has been presented by McInerney and Terzoupoulos in [12]. The level-set method [1,13–15] form a more efficient and robust approach to curve deformation compared to parametric active contour models [16–19], where the curve deformation PDE is solved numerically. The property of topology preservation along with the sub-pixel accuracy of geometric deformable models is coupled with the level-set technique to obtain a methodology as in [20], which improves segmentation quality but with overhead in time. This overhead persists in the ground work active contour models of Chan and Vese [21], Feng et al. [22] and Goldenberg et al. [23], as well as in statistical region based active contour models [24,25]. Moreover edge detection in a complex and noisy environment persists to be a challenge. *Countourlet* transform integrated with the active contour model [26,27] can detect edges in a noisy environment but it still does not address the limitations of active contours with respect to throughput. In comparison to countourlet transform, the edge detection technique of Marr and Hildreth suffers at noisy edges but provides an elegant theoretical background for convecting image forces. Luis Alvarez et al. [3,4] introduced a curve evolution technique that uses the latter edge detection technique but is fast as it utilizes morphological binary operations to solve the level-set PDE. This model however performs only fairly near noisy edges and is less smooth in comparison to the classical active contour model suggested by Caselles et al. [1].

2.1. Morphological snake evolution using binary level sets

The Osher–Sethian [1,28,29] level-set method describes a curve that evolves with time in an implicit form as the level-set of an embedding functional. If $C(t)=\{(x,y)|\,u(t,(x,y))=0\}$ represents the curve with $u:\Re^+\times\Re^2\rightarrow\Re$ being the implicit representation of the curve then the curve evolution can be obtained in terms of this implicit functional as given by the PDE:

$$\frac{\partial u}{\partial t}=\underbrace{g(I)|\nabla u|\,\mathrm{div}\left(\frac{\nabla u}{|\nabla u|}\right)}_{1a}+\underbrace{g(I)|\nabla u|\nu}_{1b}+\underbrace{\nabla g(I)\nabla u}_{2} \tag{1}$$

Here, ν represents a balloon force parameter and $g(I)$ is an energy functional on the image $I:\Re^2\rightarrow\Re^+$, which is low at the proximity of the edges and is given by

$$g(I)=\frac{1}{\sqrt{1+\alpha|\nabla G_\sigma * I|}} \tag{2}$$

The PDE consists of two energy terms as given in Eq. (1). Part 1 of Eq. (1) represents the internal energy consisting of smoothing component 1a, which smoothens the curve at high curvature segments and an inflation and/or deflation term 1b that brings the curve to interesting areas of the image space which can be found in the model methodized by Caselles et al. [1]. Luis Alvarez et al. [3,4] suggests a morphological model for curve deformation that solves the PDE Eq. (1), maintaining an appreciable level of throughput by improving upon convergence speed associated with numerical algorithms. This methodology has been adopted from the work of Osher and Sethian [29], which suggests that a curve is described by the boundary of a binary piecewise constant function $u:\Re^2\rightarrow\{0,1\}$ that takes a value $u(p)=1$ for every p inside the curve and a value $u(p)=0$ for every p outside the curve, where p represents an ordered pair (x,y). Through the application of morphological operations on this level-set method, the curve is made to implicitly evolve with time, starting with a zero level set $u(t=0,p)$. The morphological operations convect:

- Balloon force
- Smoothing force
- Image force

The first two control the internal energy of the curve, whereas the third attracts the curve towards the ROI. The component equation that convects the balloon force is provided by part 1b of the PDE in Eq. (1), given as

$$\frac{\partial u}{\partial t}=g(I)|\nabla u|\nu \tag{3}$$

which is evident from the models presented in [1,14,30,31]. The morphological operations of *dilation* and *erosion* over u serves as an infinitesimal generator of Eq. (3), where dilation and erosion operations are defined as

$$(D_d u)(p)=\sup_{q\in dB} u(p-q)$$

$$(E_d u)(p)=\inf_{q\in dB} u(p-q) \tag{4}$$

In both the cases, d is the radius of the operator, B is a disk of radius unity and p,q represent distinct ordered pairs (x,y). dB is the dth homothetic of B i.e. $dB=\underbrace{B\oplus B\oplus\ldots}_{d\ times}$.

Here, $g(I)$ controls the balloon force at different segments of the curve. Given the value of ν, the solution of PDE component Eq. (3) is given by the morphological operations of dilation or erosion. At the $(n+1)$th iteration, the solution to PDE Eq. (3) is approximated as

$$u^{n+1}(x_i)=\begin{cases}(D_d u^n)(x_i) & \text{if } g(I)(x_i)>\theta \text{ and } \nu>0\\ (E_d u^n)(x_i) & \text{if } g(I)(x_i)>\theta \text{ and } \nu<0\end{cases} \tag{5}$$

where $g(I)$ is discretized with the threshold θ. Next, morphological operators are devised for infinitesimal generation of the smoothing component of PDE Eq. (1), given as

$$\frac{\partial u}{\partial t}=g(I)|\nabla u|\,\mathrm{div}\left(\frac{\nabla u}{|\nabla u|}\right) \tag{6}$$

The discrete operation $(F_d u)(x)=SI_d u(x)+IS_d u(x)/2$ forms the infinitesimal generator of the PDE component Eq. (6) as suggested by Luis Alvarez et al. [3,4] and mathematically supported by Catte et al.