ADAPTIVE SNAKE MODEL WITH AUTOMATIC FORCE RECTIFICATION

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Abstract

— Most applications of snake model are domain-specific, while specifying fixed snake coefficients to an image in problem. In this paper, we propose content-triggered adaptive snake model (CASM) to lead all the parameters of snake model to be automatically adapted for various images in the noisy environment. First, the CASM applies a fast estimation method to find the possible ranges of gradient magnitudes of object boundary. As soon as the gradient magnitude of progressing snaxels falls in those ranges, CASM will adapt the weights within the snake forces of these snaxels according to encountered changes in gray levels and influences of various forces in the resided snake segments. And, it simultaneously renormalizes their external and internal forces. After primary convergence, CASM fires a compensation evolution to rectify the unqualified snaxels far from the object boundary. The unqualified snaxels, which are discovered by block-based texture analysis, can be pushed inward or pulled outward to the object border by so-called directional compensation evolution in revived evolutions. The simulation results demonstrate that CASM can improve the performance of snake very much, and outperform Gradient Vector Flow (GVF) in noisy images.

Keywords: Adaptive snake model, Concavity

1. INTRODUCTION

Energy-minimizing active contour model (Snakes) has been first concretely proposed in 1987 [1] for localizing the regions of interest. A snake is a deformable curve attracted by the internal and external forces using energy minimization to identify a closed object's border via progressive inflation or shrink evolution. The internal force resident within the snake contour controls smoothness of snake evolution, and the external force arisen from the variations of image pixels guides the snake toward desired image features. Snakes are widely applied to many image processes, such as image object segmentation shape modeling and, especially for medical applications [2]. For traditional snake models, the common problems such as initialization and concavity fitness have been lessened [2-5]. Rather, with those improved models, the weakness of snake is still problematic for image segmentation in the noisy image as follows.

1. The snake can not easily progress into deep boundary concavities or the snake will difficultly evolve especially with the interference of background edges. Although the GVF approach [5] has extended the influence of external forces to solve the deep concavity in problem, the undesired interference from the edge-like background noise is still remained unsolved.
2. The snake location initialization is problematic that the edge-like background textures exist.
3. Generally speaking, except for application-specific image segmentation, effectively controlling the normalizations and the model factors used to various snake forces is rather difficult for a high-performance convergence.

Basically, the derivation of traditional snake functional has been quite complete. Hence, to confirm the proper snake model coefficients via labor intensive examinations can mostly make the snake attain a quite accurate fitness to the boundary of targeted object. Unfortunately, the images have very plenty of characteristics to difficultly conclude the assignments of model coefficients weighted to internal and external forces. Naturally, the snake is unsuitable for the varying image or videos. Hence, the snake model is substantially re-modeled [2, 5], or the extension of external forces are addressed [2-5]. However, they might not simultaneously solve the snake problems mentioned above in noisy images.

In this paper, we propose a content-triggered adaptive snake model to directly improve the snake prototype to simultaneously solve the above-mentioned problems in noisy backgrounds without complex pre-processing and the creation of extra forces.

2. ESTIMATION OF LIKELY BOUNDARY GRADIENT MAGNIUDES

The fast analysis method comes from the following postulate. Given a straight scan line through the object, the variations of gradient magnitudes across the first and the last scanned object borders could be more distinguishable than that across backgrounds, the object inside or even other scanned borders under a proper observed scope. And, the locations of first (or last) encountered object borders in two successive scan lines shall not be too far. For the convenience of algorithm illustration, we assume that the target object is located inside the initial snake contour. With above postulates, the proposed method is composed of two parts. The first part to find the called object border intervals is implemented as follows.

Step1: Select suitable horizontal and vertical scan lines based on the range of initial snake contour to scan the inside area of initial snake contour. Divide each scan line into intervals of even width.

Step2: Take a horizontal (or vertical) scan line in the top-to-down (or left-to-right) order, and compute the sum of gradient magnitudes (SGMs) for each interval of this scan line. Decide a lower bound as an initial threshold, and then increase it progressively.

Step3: Add the threshold once an immersion step and identify the edge-residing intervals according to two conditions. The SGM of edge-residing interval is kept larger than the threshold; while 1) both the SGMs of its closest left and right intervals are less than the threshold after incrementing the threshold once, or 2) the SGMs of at least two successive intervals at either the closest right side or left side of edge-residing interval are exceeded through incrementing the threshold twice. Continuously enlarge the threshold until either at least two edge-residing intervals appear or only a single edge-residing interval can be obtained, then go to Step 4.

Step4: The first edge-residing interval and the last one, of which perhaps only one can be found, are the border intervals and divided into sub-intervals, among which the sub-interval of largest SGM is identified as the target border interval where the object boundaries are considered likely encountered. If the scan line is the final one, enter the second pass; otherwise, go back to Step 2.

The largest gradient magnitude over some threshold is extracted from every border sub-interval and denoted as the prediction border gradient-magnitude (PBGM). Herein, the standard deviations of gradient magnitudes in scanning lines are directly concerned with the widths of immersion step and PBGM zone, by which the gradients of background variations can be bypassed and the true border gradient-magnitude (TBGM) be covered as much as possible. So, the sizes of both immersion step and PBGM zone is determined by minimizing the entropy of class uncertainty proposed in [6].

3. MODEL COEFFICIENT ADAPTATION OF ACTIVE CONTORU

A parametric active contour can be expressed by assembling position vectors $v(s,t) = (x(s,t), y(s,t))$ at position s of snake contour and time t. The internal energy can be written

$$E_{\text{int}} = \alpha_s \,|\, v'(s,t) \,|^2 + \beta_s \,|\, v''(s,t) \,|^2 \quad , \tag{1}$$

where the first and second terms control the snake's continuity and curvature, respectively, and $v'(s,t)$ and $v''(s,t)$ denote the first and second derivatives of $v(s,t)$ with respect to *s*; α_s and β_s are the weighting factors of tensile force and flexural force, respectively. In practical, the effect of external constrain force $E_{con}(v(s,t))$ could be absorbed into α_s and β_s. Thus, the total energy function is represented by

$$E_{sanke} = E_{\text{int}}(v(s,t)) + E_{ext}(v(s,t)) \quad , \tag{2}$$

where $E_{\text{int}}(v(s,t))$ and $E_{ext}(v(s,t))$ are internal and external energies, respectively. A snake to minimize E_{snake} must satisfy the Euler equation

$$\alpha_s v''(s,t) - \beta_s v''''(s,t) - \nabla E_{ext}(v(s,t)) = 0 \quad .. \tag{3}$$

For steering the moving of snake to attain (3), the partial derivative of $v(s,t)$ with respect to t can be directly given as the left hand side in (3):

$$\frac{\partial v(s,t)}{\partial t} = \alpha_s v''(s,t) - \beta_s v''''(s,t) - \nabla E_{ext}(v(s,t)) \quad .. \tag{4}$$

When the snake asymptotically stabilizes to make $\frac{\partial v(s,t)}{\partial t}$ in (4) vanish, and then (3) is solved. In the numerical reality, the snake is made up by linking the discrete snaxels treated as the elements of snake contour. Hence, we modify $v(s,t)$ as notation $v_i(t)$ to stand for the position of ith snaxel at time t, while a periodic boundary condition $v_0(t) = v_N(t)$ for N-snaxel snake. The motion behavior of classical snake is governed by the results of first-order differential equations for all snaxels :

$$r_i \frac{\partial v_i(t)}{\partial t} + \alpha_i v_i''(t) + \beta_i v_i''''(t) = E_{extt}(v_i(t)) \quad , \tag{5}$$

where $v_i(t)$ is the velocity of ith snaxel, r_i is the damping coefficient and $E_{extt}(v_i(t))$ is the external force used to the ith snaxel. The internal tensile forces

$$v_i''(t) = 2v_i(t) - v_{i-1}(t) - v_{i+1}(t) \tag{6}$$

are discrete approximation to the second derivative of coordinate functions with respect to s. It acts to maintain a uniform spacing between snaxels and contour smoothing. The tensile forces can be made scale invariant by dividing the right hand side of (6) by the distance between neighboring snaxels. The internal flexural forces

$$v_i''''(t) = 2v_i''(t) - v_{i-1}''(t) - v_{i+1}''(t) \tag{7}$$

are discrete approximation to the fourth derivative of the coordinate function with respect to s. By observing (6) and (7), we know that the weighting factors α_i and β_i are to control the resistance of the contour to respectively stretching and bending deformations.

As we known, the evolution movement of prototype snake only depends on the local information such as gradient strengths of neighboring pixels and contour's local shapes no matter if a more global image analysis has been previously exploited. Therefore, the basic improvement to the snake model is to adapt all the coefficients and the force normalization in the snake model to fit the current status of moving snaxels. Hence, α_i , β_i and r_i in (5) used to CASM are time variant. In reality, to control the

normalization between internal and external forces is also a very significant issue to capture snaxels at desired positions, i.e., the proximity to object boundaries of interest. Here, we introduce a time-variant coefficient to dynamically normalize the internal and external forces. After approximating the temporal derivatives with forward finite differences in (5) by letting Δt as a time unit of evolution motion, the recursive update of position from time t to time t+Δt by CASM is shown by

$$v_i(t+\Delta t) = v_i(t) - (-1)^q \frac{\Delta t}{\gamma_i(t)} \cdot [K_I(t) \cdot (\alpha_i(t) v_i''(t) + \beta_i(t) v_i''''(t)) - E_{extt}(v_i(t)] \quad (8)$$

where $K_I(t)$ is utilized to normalize the internal forces and the external forces through the proposed alternative alignment of their maximums in the snaxels of same attribute (either PBGM or non-PBGM snaxels). In normal, q is set to 0 in (8).

A. ADAPTING WEIGHTING FACTORS OF THE TENSILE AND FLEXURAL FORCES

A snaxel on the snake contour becomes so-called a PBGM snaxels, if its gradient magnitude falls in the region of PBGM-zone group. Then, the contribution of tensile and flexural forces relative to the local contour fitness degree (LCFD) is evaluated. The LCFD is defined as the SGM of three pixels centered at this PBGM snaxels such that there is no extra computation for attaining LCFD because of already existed computation of external forces. According to the concept of adaptive filtering, the tendency of modifying a snake parameter can be decided by observing the influence on the current LCFD being either positive or negative, while changing this parameter. Hence, when the LCFD becomes higher, the increasing (or decreasing) force is supporting a positive (or negative) contribution, and vice versa. Thus, LCFD is incremented (or decremented) and the tensile force of this snaxel is also increased (or decreased), then its weighting factor is weighted up. This is because the tensile force perhaps provides the corresponding /positive influence on LCFD. Relatively, as the sign of change in the tensile force is opposite to that in LCFD, is weighted down due to the inverse influence offered by the tensile force in LCFD. With the similar way to the adaptation of weighting coefficient up/ down is depending on checking the signs of changes in the flexural force and LCFD.

B. RE-NORMALIZATION BETWEEN THE INTERNAL AND EXTERNAL FORCES

The effectiveness of total force is highly sensitive to the normalization between the internal and external forces. When the snake's initial contour is distant from the target object boundary in edged noisy images, it may fail to locate itself to the object border supporting the energy minimization. Rather, enhancing the internal forces to solve this problem might cause much more snaxels to overwhelm the object borders. Hence, to control the trigger of re-normalization in proper occasions on the critical snaxels appears an efficient method to overcome above-mentioned problems. Here, we propose a simple method to set the basic normalization and the re-normalization used in (8). The basic normalization is utilized on the snaxels, which does not yet approach the object boundary. For maintaining the attraction to the object boundary, the basic normalization is implemented by letting the maximal internal force as a constant multiple of the maximal external force in these snaxels. The occasions of using basic normalization and re-normalization is depicted as follows. If more than one snaxel on the snake contour are the PBGM pixels, the snake will start to retard the snake progress of these PBGM pixels to lessen the overwhelming of boundary edges as much as possible. Such re-normalizing of internal and external forces of PBGM snaxels is an effective way to enhance the effect of external force to catch the snaxels at the borders.

C. MODIFYING DAMPING FACTORS

When a snaxel is close to the object boundary with oscillation-like seesaw motion, it implies that the snake force is pulling and dragging this snaxel in turn. In the meanwhile, the object boundary's edge has been very possibly passed over by this snaxel. Hence, for both reducing the snake redundant movements and exploiting such an occasion to seize the snaxel at right place, the damping factor is risen to attenuate the entire snake force for rapidly decreasing the snaxel activity. According to the concept mentioned above, when a PBGM snaxel with snaxel index i moves backwards and forwards, the damping factor in (8) is increased with a easiest way: $r_i = 2r_i$. A simple criterion to judge if this PBGM snaxel enter or not an oscillation-like status at time t is given by checking the parameter K of changes in the directions of successive three movements:

$$K = \sum_{k=0}^{1} \operatorname{sgn}((v_i(t-k\Delta t) - v_i(t-(k+1)\Delta t)) \cdot (v_i(t-(k+1)\Delta t) - v_i(t-(k+2)\Delta t)) \quad (9)$$

where function sgn() is to extract the sign of value in parentheses. The motion of this snaxel is considered saw-toothed at time t if $K=2$, while an oscillation-like status can be confirmed.

For rectifying convergence errors, we find the unqualified snake segments composed of successive incorrectly converged snaxels (ICSs) after the primary convergence. Then, a reference line is set to link two endings of an unqualified segment. Around that segment's center, an ICS is selected as an evolution trigger using unity force magnitude as an initial force to re-open a so-called directional compensation evolution and induce other ICSs near it to evolve to the untouched object borders. During the directional compensation evolution, the directions of internal forces on those ICSs are pointing either inside or outside to the object borders. Such direction control relies on automatically setting index q in (8) as either 0 or 1 according to the counterclockwise included angle of internal force direction of ICS and the reference line. Thus, a reference line acts as an evolution launch line. For an unqualified curve, with such a simple way to control the force direction,

the ICSs protruding toward the desired boundary piece progressively dilate this curve, and others toward their launch line can smooth the dilating of curve in harmony.

4. EXPERIMENTAL RESULTS

For a manually-drawn object with a large concavity and artifact line noises, as Fig. 1 shown, we can see better concavity fitness resulted from CASM than the GVF model. Due to the extension of gradient influence, the converged contour has obviously failed segments, which is totally blocked at background lines. On the contrary, the CASM model does overcome edge-like noises in background. For the practical medical applications, CASM can easily provide the better fitness for object profiles than the traditional model, as Fig.2 shown. Particularly, the GVF model can even not obtain similar performance to the traditional model under close computation costs used to obtain suitable fixed model parameters, as Fig.3 shown. This is because the evolution of GVF snake is also heavily influenced by edges inside the object especially in natural images.

5. CONCLUSION

In this work, based on the snake prototype, a characteristic-adapted adaptive snake model (CASM) is addressed by effectively adapting its parameters to automatically fit the characteristics along the paths of snake evolution. For increasing the efficiency, the proposed adaptation is merely performed to rectify the forces of critical snaxels in the proximity of object boundary of interest. Such a solution can basically cope with the snake common problems in the noisy environment, and particularly, it can be applied to a wider range of images rather than a specified image without a priori image knowledge. Observing the experimental results, CASM can make the snake achieve better fitness to the object profile over GVF approach in segmenting the noisy images.

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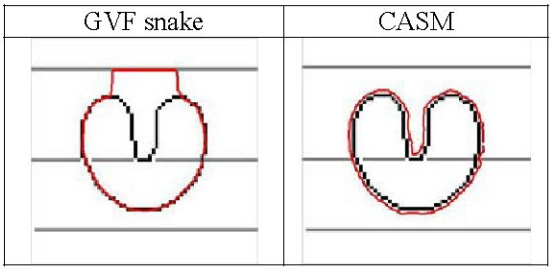

Figure 1. Comparisons of GVF and CASM models with converged red-line contours for the segmentation of artificial object with a deep concavity in a noisy background with horizontal lines

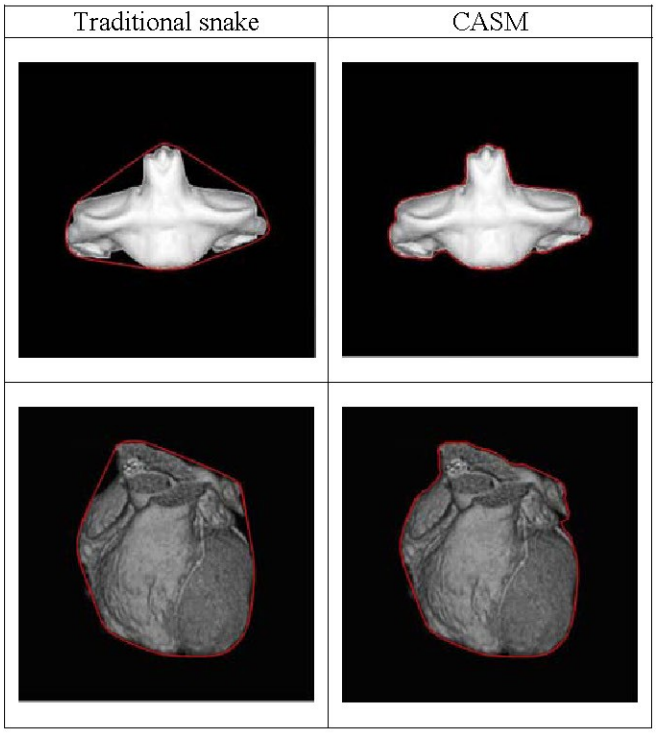

Figure 2. Comparisons of traditional snake and CASM model with converged red-line contours in segmenting the medical pictures

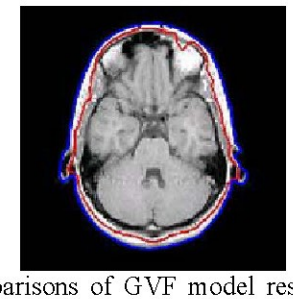

Figure 3. Comparisons of GVF model result with red-line contour and CASM model result with blue-line contour in segmenting the brain medical image.