Ingenious Snake: An Adaptive Multi-Class Contours Extraction

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Abstract. Active contour model (ACM) plays an important role in computer vision and medical image application. The traditional ACMs were used to extract single-class of object contours. While, simultaneous extraction of multi-class of interesting contours (i.e., various contours with closed- or open-ended) have not been solved so far. Therefore, a novel ACM model named "Ingenious Snake" is proposed to adaptively extract these interesting contours. In the first place, the ridge-points are extracted based on the local phase measurement of gradient vector flow field; the consequential ridgelines initialization are automated with high speed. Secondly, the contours’ deformation and evolvement are implemented with the ingenious snake. In the experiments, the result from initialization, deformation and evolvement are compared with the existing methods. The quantitative evaluation of the structure extraction is satisfying with respect of effectiveness and accuracy.

1. Introduction
ACM, namely Snake for the parametric model, has been studied for a long time and is widely used in the closed contour extraction [1-4]. The vast majority of studies involved the construction and optimization of its external energy conditions [2-4]. For example, improving external dynamic range of the gradient vector flow (GVF) field [2, 4], constructing an external force condition based on the image area content [5], and initializing Snake contours [6,7,8]. Another few studies relate to open snake, namely, open curve contour model [9-11], which is early proposed by Wong et al. [9] and used by Li et al. [10] to enable the dynamic contour extracting the linear or linear objects. Different from closed snake, the internal forces at the ports of open snake are cancelled, and the pull forces at the ports are used as the external force condition at both ends. Considering that open snake can perform axial elongating and radial deforming, we use it to describe the interesting boundaries, or linear objects. Another, existing open snake is faced with the external force defect as well as the initialization problems (e.g., a manual and time-consuming process), which severely limited in their application.

In summary, the existing ACMs only apply for single-class contour with finite level of initialization. The proposed ingenious snake applies to fast-adaptively extract multi-class contours, it can adaptively select the internal force and external force condition for the closed contour deformation and open curve evolution respectively, and finally approaches the interesting contours.

2. Method

2.1. Ingenious Snake
As a special application of ACM, ingenious snake model is still expressed as \( r(s) = (x(s), y(s)) \), \( s \in [0, 1] \). The difference is that it can express both the open curve and the closed contour. The total energy is: \( E_{\text{snake}} = E_{\text{int}} + E_{\text{ext}} \). The internal energy term of the model definition:

\[
E_{\text{int}} = \int_0^1 (\alpha(s)|r_s(s)|^2 + \beta(s)|r_{ss}(s)|^2)\,ds
\]  

Traditionally, the \( \alpha \) and \( \beta \) are set as constant for the closed Snake contour [1], while be set as zero at the both tips for the open Snake curves [11]. The external energy term of ingenious snake \( E_{\text{ext}} \) is composed of image term \( E_{\text{img}} \) and stretch force term \( E_{\text{str}} \):

\[
E_{\text{ext}} = \int_0^1 k_{\text{img}} \cdot E_{\text{img}}(r(s)) + \zeta \cdot k_{\text{str}} \cdot E_{\text{str}}(r(s))\,ds
\]  

The appearance of the logical variable \( \zeta \), namely \( \zeta = 0 \) or \( 1 \), in Eq. (2) differentiates it from the traditional ACM. The model automatically identifies the two port types (namely, open contour and closed contour). For Eq. (2), the port stretch force is generated when \( \zeta = 1 \). The stretching forces are applied to both ends of the open curve, and point at the tangent direction of the front-points. The size of the stretching force is referred to in [10].

If \( \zeta = 0 \), Eq. (2) is reduced to describe the evolution of closed contours. The form is same to its traditional one, where the image energy conditions \( k_{\text{img}} \cdot E_{\text{img}}(r(s)) \) act as the external energy conditions of the contour. The corresponding external force structure can utilize GVF field, that is, \(-V_{\text{GVF}}\), as in [2].

When the automated initial curves are deforming and evolving using the above model Eq. (1) ~ (2), the ingenious snake activates an adaptive coefficient setting of \( \alpha, \beta \) and the logical variable \( \zeta \) in terms of the two port types. Let \( R_i \) be the \( i \)-th initial curve, \( R_i = \{X, \zeta\}_i \), where \( X \) is a point sequence composed of \( N \) points \( x_n, n = 1, ..., N \); and \( \zeta \) represents the on/off logic variable of this curve. For the internal energy condition of the model, as shown in equation (1), we modulate the "elasticity" and "stiffness" coefficients \( \alpha \) and \( \beta \) of the curve front-points by introducing the window functions \( \omega(n), n = 1, ..., N \) of length \( N \):

\[
\omega(n) = \begin{cases} 0, & n = 1, 2, N - 1, N \\ 1, & \text{otherwise} \end{cases}
\]  

Thus, the \( \alpha, \beta \) in the internal force term \( E_{\text{int}} \) of the model are expressed as follows:

\[
\alpha(n) = \alpha_0 \cdot \omega(n) \cdot \zeta + \alpha_0 \cdot (1 - \zeta), \quad n = 1, ..., N
\]

\[
\beta(n) = \beta_0 \cdot \omega(n) \cdot \zeta + \beta_0 \cdot (1 - \zeta), \quad n = 1, ..., N
\]  

For the external energy condition of the model, as expressed in Eq. (2), its discrete external energy \( E_{\text{ext}} \) is denoted by:

\[
E_{\text{ext}}(X) = k_{\text{img}} \cdot E_{\text{img}}(X) + \zeta \cdot (k_{\text{str}} \cdot E_{\text{str}}(X))
\]  

Let \( X_k = (x_{0,k}, ..., x_{1,k}, ..., x_{N,k})^T \), \( k=0,1 \) be the vector containing all the \( k \)-th-dimension coordinates of the point sequence, \( X_k^t \) at iteration \( t \) can be computed iteratively after deriving the Euler-Lagrangian equation:

\[
X_k^t = (A + \gamma I)^{-1} \cdot \left( \gamma X_k^{t-1} - \frac{k_{\text{img}} \partial E_{\text{img}}(X_k^{t-1})}{\partial x_k} - \zeta \cdot \frac{k_{\text{str}} \partial E_{\text{str}}(X_k^{t-1})}{\partial x_k} \right)
\]  

Where \( A \) is composed of coefficients \( \alpha \) and \( \beta \), \( \gamma \) is used to control the step size, and \( I \) is the unit matrix. The parameters \( \zeta = 0 \) and \( \zeta = 1 \) are respectively used to control the updating mode of the two kinds of curves. For the closed contour (\( \zeta = 0 \)), it can approach to the object and make the Eq. (6) convergence with no more than three iteration-steps \( (t_{\text{max}}) \). For one open curve (\( \zeta = 1 \)), the curve keep evolving along the linear structure and stops evolving until it meets some termination terms. For example, stretch force disappearing, or the front-points’ intensities are less than a low threshold.
2.2. Preprocessing
Ingenious snake firstly need to enhance the feature (e.g., ridge characteristics of boundaries or linear structures) of interesting contours. In the preprocessing, K-means classification and morphological operators are used to separate the region shape and a linear structure. Then, the ridges of region edge and linear structure are enhanced respectively. The enhancement of edge ridges is done using the Canny operator following with Gaussian kernel $G_\sigma$ filter. While the ridges of the linear-objects are enhanced by using the multi-scale filter [12]. The resultant ridge feature map is used to generate the GVF fields.

2.3. Automated initialization
2.3.1. Ridge-points Extraction. The GVF field [2] is normalized and denoted by $F(x, y)$, which can be obtained by solving a Euler iteration diffusion equation. Firstly, the GVF field is acquired through computing the ridge feature map. Then, the ridge-points are obtained by the direction estimation of the GVF field. Given the two-dimensional vector $F_x(i,j)$ and $F_y(i,j)$ of a GVF at each point $p(i,j)$, it will be defined as a ridge-point if they satisfy one of the following conditions

$$\begin{cases}
F_x^{(i-1,j)} + F_y^{(i-1,j)} & \leq 0 \quad \text{if } F_x^{(i,j)} > 0 \\
F_x^{(i,j-1)} + F_y^{(i,j-1)} & \leq 0 \quad \text{if } F_y^{(i,j)} > 0
\end{cases}$$

Restricting $F_x^{(i,j)}$ and $F_y^{(i,j)}$ to be greater than 0 can reduce image-marginal noise point. For example, in figure 1, the 2D coronary angiography X-ray image is shown in figure 1(a), figure 1(b) shows the GVF field overlapping with the ridge feature image, wherein the local amplification shows that GVF points to the vessel central gradient vectors. The result of ridge-points extraction via Eq. (7) is shown in figure 1(c).

![Figure 1](image_url)

**Figure 1.** An example of ridge-point extraction: (a) Original coronary X ray radiography image; (b) multi-scale enhancement image GVF field; (c) the results of ridge-point extraction.

2.3.2. Generation of ridgelines. We provide a fast algorithm to automate a tracking process.
- **Starting a tracking process using seed point.** See figure 2, a seed point $p_0$ is randomly generated from the ridge-point set $P$, when the neighbouring two points $p_{-\tau}$ and $p_\tau$ are detected with the angle of the two direction vectors being no less than a big obtuse angle (e.g., $2\pi/3$). Otherwise, the seed point is removed from the ridge-point set.
- **Generation of ridgelines based on tracking.** Given seed point $p_0$, the tracking process continues to search the candidates along the path of opposite directions. Suppose that $\nu_\tau$ and $\nu_{-\tau}$ represent two reverse tracking directions, $p_\tau$ and $p_{-\tau}$ represent two front-points of the tracking. The tracking process is to sequentially update $p_{\pm\tau}$, $\nu_{\pm\tau}$, so as to form a ridgeline in $X$. In $t$-th step of tracking, the ridge-points on the corresponding path of the ridgeline obtained in step $t - 1$ should be deleted, thereby updating the ridge-points set $P$. 


Figure 2. Generation a ridgeline using ridge-point tracking. All the points in the graph are ridge-points, in which the red point is a seed point to start the tracking process, the blue point is the initial detection point, the black point is the front-point of tracking path, and the candidates locate in the fan shaped region.

- **Termination criteria.** A tracking process should be stop with the suitable termination criteria. We devise the terms considering the characteristic of both open curve and closed contour and detail them as follows: (1) No candidates can be used to generate the front-points \( p_r \) and \( p_{rt} \). (2) After a length of path tracking, the distance between the left and right front-points is less than a low-limit \( \epsilon_0 \) (usually \( \epsilon_0 = r_{min} \)). (3) When the whole ridge space \( P \) is empty, there is not seed points to start a new tracking, thus the tracking process is finished.

The resulting ridgelines are used as the initial contours for Ingenious snake in the aforementioned Sections 2.1. Each ridgeline \( R_i = \{ X, \zeta \}_i \) contains the initial coordinate sequence \( X = [x_1, x_2, x_3, \ldots] \) and ridgeline’s port type parameter \( \zeta \). When the termination term meets the second criteria, a closed contour is determined and labelled with \( \zeta = 0 \); Otherwise, if the termination term meets the first criteria, the curve will be determined as an open curve labelled with \( \zeta = 1 \).

3. Experiments

Existing contour extraction methods involve the center of divergence (CoD) method [6], force field segmentation (FFS) method [7], poisson inverse gradient (PIG) method [8] (website: http://cn.mathworks.com/matlabcentral/fileexchange/22871-parametric-active-model-toolbox) and stretching open active contours (SOACs) [11] (website: http://www.cse.lehigh.edu/~idea-lab/soax/). To extract multi-class contours, the proposed method acquired obvious verification on their visual comparisons. Parameters are manually assigned with \( \alpha = 0.1, \beta = 0.5, \gamma = 2, k_{img} = 2, k_{str} = 3 \), \( r_{min} = 2 \) and \( n_{max} = 3 \). In the evolvement, curves are resampled to maintain point spacing strictly with single pixel. The workstation configuration is as follows, Intel (R) Core (TM) i7-6700 CPU @ 3.41GHz, RAM 32G, operating system Win10, and programming language MATLAB r2014a.

3.1. Experimental of Phantom

We constructed the Phantom image to quantify the precision of Ingenious snake. As shown in figure 3, figure 3 (a) is the Phantom with Gaussian mixing noise, in which the linear object with label (1)-(6) is manually generated as the central line gold standard. The initialization ridgelines are shown in figure 3 (b). figure 3(c) shows the result of multi-class contours extraction, which could describe the structure pattern. The segmentation accuracy of the boundary obtained by Dice coefficient is 0.9882. To evaluate the precision of the extracted central lines, we refer to the document [11] and use the Vertex error and Hausdorff distance to evaluate. The results are shown in Table 1, the Vertex error of the 6 lines is on average 0.593 pixels, and the Hausdorff distance is on average 3.011 pixels. The results show that the method can extract multi-class contours with good precision.
Figure 3. Verification of multi-class contours extraction from phantom: (a) Original image, (b) initialization, and (c) extraction results by ingenious Snake. In the subfigure (c), the red lines denote the final result.

Table 1. Evaluation of central lines extraction of the Phantom

| line No. | Vertex error (pixel) | Hausdorff distance (pixel) |
|---------|---------------------|---------------------------|
| (1)     | 0.584               | 4.120                     |
| (2)     | 0.611               | 3.609                     |
| (3)     | 0.568               | 3.104                     |
| (4)     | 0.489               | 2.690                     |
| (5)     | 0.716               | 3.254                     |
| (6)     | 0.591               | 1.290                     |
| mean    | 0.593               | 3.011                     |

3.2. Experimental of medical image

We use different methods to extracted multi-class contours in figure 4. In the MR image, the organ’s boundary and vessels’ central lines are both the interesting contours. The CoD method initializes 42 active contours, most of which are inside the vessels. And its convergent result could not express the vessels. The FFS method initializes outside the objects, and converges at the vessels’ boundary or the organ’s contour, thus it couldn’t distinguish between the vessels and organ. The PIG method only initializes within the organ, while lack completeness for multi-class contours. The SOACs method generates 212 initial ridgelines and eventually converged to 42 contours, as a result, it obtains discontinuous and inaccurate organ boundaries and vessels. The proposed method obtains the multi-class contours at the same time.

Figure 4. Verification of multi-class contours extraction from medical image. The subfigures from left to right show the results from CoD, FFS, PIG, SOACs and proposed method. The subfigures in the row (a) and (b) are the results of the initialization and the corresponding convergent results.
4. Conclusion
Considering that the traditional ACM model cannot solve simultaneously open contour and closed contour, we proposed the ingenious snake to effectively initialize the closed/open contour, and it has a good performance in the multi-class contours extraction. For the follow-up works, we should develop the method with better evolution scheme to describe complex scene, in companied with deep learning.

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