Abstract

Classical active contour models provide an elegant framework for optimal estimation in image processing. However, their adaptability to image noise and convergence speed have been major challenges. In this paper, we address the problems by combining advanced active contour techniques such as Gradient Vector Flow (GVF), quadratic snake interaction, and the adaptive initialization of multiple snakes. Through two independent experiments, we show that our snake model can effectively segment objects in images with high level noise such as CAPTCHAs and medical images. First, we show that our algorithm is fast enough for practical applications by measuring the time efficiency in successful segmentation experiments of a CAPTCHA challenge data set. Second, we consider medical image segmentation that requires high degree of noise tolerance. We test our algorithm against a tumor image with higher noise than CAPTCHAs. With an adaptive initialization approach, our preliminary segmentation results show our technique is effective to the application to real medical images with tumors.

Keywords: Active Contours, Quadratic Snakes, Snake Multiplicity, GVF, Adaptive Initialization

1 Introduction

Flexible automated systems capable of extracting structures and regions of interest from digital images encompass a broad range of applications. For example, applications such as automated road extraction and object detection in medical images would boost the productivity of technicians enormously. Manual marking and extraction of those objects is an extremely slow and laborious process considering the degree of complexity that those objects can possess in the real world. Towards the ultimate goal of fully automated image object extraction, there has been a great deal of progress in the computer vision and image processing communities. But after 30 years of research, (see [1] for a thorough review), there is still no system attaining the speed, robustness, and level of automation necessary for practical application on arbitrary imagery.

Classical active contour models [2; 3; 4] provide an elegant framework for optimal estimation in image processing; rather than writing an algorithm to extract the object or region of interest, we simply consider an energy functional a minimum of which is achieved at a good solution. Then, given a new image, we use general optimization techniques to find a contour minimizing the energy functional.

Although the classical models should fundamentally work well, in practice, their adaptability to image noise and convergence speed become major challenges. For noise, image enhancement based on object types such as oriented filtering applied to road extraction applications, can greatly improve extraction results [5]. For convergence speed, Xu and Prince’s gradient vector flow (GVF) [6] technique makes it possible to achieve fast convergence of snakes initialized far from the boundary of the object. GVF also improves convergence to objects with concave boundaries where the classical snake models fail.

Rochery et al. have proposed a geometric model for higher-order active contours, in particular quadratic snakes, for extraction of linear structures like roads [7]. The idea is to use a quadratic formulation of the contour’s geometric energy to encourage anti-parallel tangents on opposite sides of a road and parallel tangents along the same side of a road. These priors increase the final contour’s robustness to partial occlusions and decrease the likelihood of false detections in regions not shaped like roads.

In this paper, we propose a multiple quadratic multiple snake model that uses the GVF external force. We show that our approach is fast enough for practical applications by measuring the time
efficiency of our snake model in successful segmentation experiments of a CAPTCHA challenge data set. We also show preliminary segmentation results in the application for real medical images with tumors using our adaptive initialization technique.

2 Methods

2.1 Quadratic snake model

This section briefly overviews our quadratic snake model by extending the original snake model [2] with quadratic geometric energy [7].

We define a closed 2D spline \( \tilde{\gamma}(p) = [x(p), y(p)]^T, p \in [0, 1] \) that minimizes energy functional

\[
E(\tilde{\gamma}) = \int E_s(\tilde{\gamma}, \tilde{\gamma}_p, \tilde{\gamma}_{pp}) dp = E_g + E_i, 
\]

where \( \tilde{\gamma}_p \) and \( \tilde{\gamma}_{pp} \) are first and second partial derivatives of a contour \( \tilde{\gamma} \), respectively.

\( E_g \) is the geometric energy defined by

\[
E_g(\tilde{\gamma}) = \int \left( \frac{1}{2} \alpha \tilde{\gamma}_p^2 + \frac{1}{2} \beta \tilde{\gamma}_{pp}^2 \right) dp - \delta \int \int \tilde{I}(p_1) \cdot \tilde{I}(p_2) \Psi (\| \tilde{\gamma}(p_1) - \tilde{\gamma}(p_2) \|) \cdot dp_1 dp_2, 
\]

(2)

The first integral represents the stretch energy and bending energy, respectively. \( \alpha \) and \( \beta \) are the weights of those energy terms. A large stretch energy encourages the contour to be straightened, on the other hand, a large bending energy forces the contour to be straightened. \( \tilde{I}(p) \) is the unit-length tangent to \( \tilde{\gamma} \) at point \( \gamma(p) \), and \( \Psi(z) \), given the distance \( z \) between \( p_1 \) and \( p_2 \), is used to weight the interaction between those two points. For positive \( \delta \), \( E_g(\tilde{\gamma}) \) is minimized by contours with short length and parallel tangents.

The quadratic term is responsible for interactions between points on the snake. The sigmoid function \( \Psi(\cdot) \) defines the radius of the region in which anti-parallel tangents should be discouraged:

\[
\Psi(z) = \begin{cases} 
1 & \text{if } z < d - \epsilon, \\
0 & \text{if } z > d + \epsilon, \\
\frac{1}{2} \left( 1 - \frac{z - d}{\epsilon} \right) \sin \pi \frac{z - d}{\epsilon} & \text{otherwise.} 
\end{cases} 
\]

(3)

\( d \) is approximate width of the region of interest and \( \epsilon \) is the sharpness of the sigmoid function.

\( E_i \) is the image energy that depends on the image intensity \( I(x, y) \) as follows

\[
E_i(\tilde{\gamma}, I) = -\int \lambda |\nabla I|^2 dp, 
\]

(4)

where \( \lambda \) is a weight.

Contour \( \gamma \) is a solution of the following Euler equation:

\[
-\frac{d^2}{dp^2} \left( \frac{\partial E_s}{\partial \tilde{\gamma}_pp} \right) + \frac{d}{dp} \left( \frac{\partial E_s}{\partial \tilde{\gamma}_p} \right) - \frac{\partial E_s}{\partial \tilde{\gamma}} = 0. 
\]

(5)

2.2 GVF external force

To improve the convergence, we adopt Xu and Prince’s gradient vector field (GVF) [6] technique. The GVF is a vector field \( \vec{V}(x, y) = [u(x, y) \; v(x, y)]^T \) that minimizes an energy functional given by

\[
E(\vec{V}) = \int \int \mu (u_x^2 + u_y^2 + v_x^2 + v_y^2) + |\nabla I|^2 |\vec{V} - \nabla I|^2 \; dx \; dy, 
\]

(6)

where

\[
u_x = \frac{\partial u}{\partial x}, \quad u_y = \frac{\partial u}{\partial y}, \quad v_x = \frac{\partial v}{\partial x}, \quad v_y = \frac{\partial v}{\partial y}. 
\]

Minimizing the functional leads to an Euler equation given by

\[
\mu \nabla^2 \vec{V} - (\vec{V} - \nabla I) |\nabla I| = 0. 
\]

(7)

The Laplacian creates a slow varying field in homogeneous regions causing elimination (diffusion) of noise and false boundaries. With large \( |\nabla I| \), the energy is dominated by the second term. Therefore the energy achieves the minimum, when \( \vec{V} = \nabla I \), encouraging the snake to snap to the object boundary.

2.3 Snake multiplicity

A single quadratic snake [7] is unable to extract enclosed regions and multiple disconnected characters in an image. We address this limitation by introducing a family of cooperating snakes that are able to split, generate offspring (anti-snakes), disappear, and merge if necessary.

In our formulation, specifying the points on \( \tilde{\gamma} \) in a counterclockwise direction creates a shrinking snake, whereas specifying the points on \( \tilde{\gamma} \) in a clockwise direction creates a growing snake.
2.3.1 Splitting a snake
We split a snake into two snakes whenever two of its arms are squeezed too close together.

2.3.2 Deleting a snake
A snake $\gamma$ is deleted if it has perimeter less than $L_{\text{delete}}$.

2.3.3 Generating an anti-snake
The evolution of the snake continues until it either attaches itself to a boundary of the character or gets deleted. In the first case an anti-snake is generated by offsetting the original snake by $d_{\text{offset}}$ pixels inside the object.

2.3.4 Merging two snakes
We merge two growing snakes when they come too close to each other.

2.4 Adaptive initialization
With the ability of anti-snake generation, it is possible that we simply initialize a single shrinking snake along the boundary of an image and extract all inner objects. For medical images with complex shape objects, however, more sophisticated initialization is generally required to obtain correct convergence. For this purpose, we employ an adaptive initialization approach in which we initialize multiple shrinking/growing snakes depending on the intensity of image regions.

3 Experiments
3.1 Time efficiency of multiple quadratic snakes

Table 1. Convergence time (sec) and accuracy vs noise levels

<table>
<thead>
<tr>
<th></th>
<th>Low</th>
<th>Medium</th>
<th>High</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ave</td>
<td>2.91</td>
<td>2.79</td>
<td>3.36</td>
</tr>
<tr>
<td>Std</td>
<td>0.31</td>
<td>0.23</td>
<td>0.51</td>
</tr>
<tr>
<td>Accuracy</td>
<td>0.8</td>
<td>0.9</td>
<td>0.4</td>
</tr>
</tbody>
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by measuring the time efficiency of our snake model in successful segmentation experiments of a CAPTCHA challenge data set.

To create the CAPTCHA image set used for the experiment, we used the popular Drupal CAPTCHA API [8], which produces CAPTCHAs characterized by distortion and tilting of the characters followed by the addition of line noise. We generated $480 \times 160$ CAPTCHAs each containing five characters. The average measured line noise levels are 6.5 dB, 5.2 dB, and 4.4 dB for Low, Medium, and High, respectively. After pre-processing the CAPTCHAs with an oriented filter followed by median filter, we measured the convergence speed and accuracy of our multiple snake algorithm against the CAPTCHA data set containing 10 samples in each noise level. The accuracy is determined by recognition rate using a SVM (Support Vector Machine) pre-trained by similar CAPTCHA data.

Table 1 presents results of the numerical experiment, that is, the pixel-wise extraction of CAPTCHAs corrupted by the three noise modes (Figure 1). We found that noise level Low and Medium show similar results (Medium is even slightly better than Low) due to the fact that the pre-processing results of both levels become quite comparable. In the context of CAPTCHA recognition by machines, even accuracy with 1% is considered to be a substantial threat to a system. Our proposed algorithm extracted CAPTCHA characters with practical accuracy and time cost.

3.2 Segmentation of a tumor in a medical image

In this experiment, we apply our multiple snake algorithm to segment a tumor from a real medical image. We tested two types of initialization approach. One is the simple initialization with a shrinking snake along the boundary of the image; and the other is manually setting multi-

In this experiment, we show that our approach is fast enough for practical applications.

Figure 1. CAPTCHA samples. (a) Original CAPTCHAs. (b) Pre-processed CAPTCHAs.
ple growing/shrinking snakes based on the background of the image. Figure 2 shows the segmentation results using the two types of initialization. The boundary initialization could not capture the details of the tumor due to a blurred region of the tumor. With the adaptive initialization, both shrinking and growing snakes correctly captured the tumor.

4 Conclusion

We have shown that our multiple snake algorithm is fast enough for practical applications by measuring the time efficiency of our snake model in successful segmentation experiments of a CAPTCHA challenge data set. With an adaptive initialization technique, our preliminary segmentation results indicate the effectiveness against real medical images with tumors. For the system to be more practical, however, we should automate the initialization procedure in future.

References


