Adaptive Filtering Combined with Improved T-Snake Model for Automatic Segmentation of Thyroid Ultrasound Images: Postprint

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Abstract

This paper proposes a novel method for thyroid ultrasound image segmentation based on the T-Snake model. First, by combining a window-based anisotropic diffusion filtering method with an adaptive weighted median filtering algorithm, speckle noise in thyroid ultrasound images is effectively eliminated. Second, building upon the traditional T-Snake model, adaptive regional energy and expansion force are incorporated to effectively extract discontinuous and weak boundaries, thereby achieving automatic segmentation of thyroid ultrasound images. Finally, model parameters are set and experiments are conducted using clinical data. The results demonstrate that the automatic segmentation results obtained using the proposed method achieve an average relative difference of less than 5% and an average relative overlap of greater than 91%, thereby validating the feasibility of the proposed method.

Full Text

Automatic Segmentation of Thyroid Ultrasound Images Based on Adaptive Filtering Combined with Improved T-Snake Model

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Abstract

This paper proposes a novel segmentation method for thyroid ultrasound images based on the T-Snake model. First, a window-based anisotropic diffusion filter combined with an adaptive weighted median filtering algorithm effectively eliminates speckle noise in thyroid ultrasound images. Second, building upon the traditional T-Snake model, the method incorporates adaptive region energy and inflation forces to effectively extract discontinuous and weak boundaries, achieving automatic segmentation of thyroid ultrasound images. Finally, model parameters are established and experiments are conducted using clinical data. The results demonstrate that the proposed method achieves an average relative difference of less than 5% and an average relative overlap of more than 91%, thereby verifying the feasibility of the approach.

Key words: thyroid ultrasound image; image segmentation; T-Snake; adaptive; weighted median filter; anisotropic diffusion filter

0 Introduction

Medical image segmentation remains a challenging problem and an active research area. Current segmentation methods struggle to achieve the precision required for clinical applications. The Snake model, introduced by Kass et al. [1], has become a mainstream approach for target contour extraction in image processing. However, traditional Snake methods suffer from several limitations, including strong dependence on initial position and poor performance when extracting contours with complex and variable topological structures. Consequently, numerous researchers have proposed improvements to the Snake model [2–7]. McInerney et al. [8] introduced the Topology Adaptive Active Contour Model (T-Snake), which can adaptively change its topological structure during contour evolution and exhibits lower sensitivity to initial position. Meng et al. [9] proposed an image segmentation method based on orthogonal T-Snake models, while Zhou et al. [10] developed a medical image segmentation approach combining global and local distribution information with Snake models, and Chen et al. [11] presented an improved image segmentation method based on the T-Snake model. Although these methods demonstrate good performance for specific image types, they still face several critical issues: (a) speckle noise significantly impacts segmentation effectiveness; (b) poor boundary continuity and weak boundary feature information substantially affect segmentation results; and (c) they cannot adequately address the challenges posed by thyroid ultrasound images, which exhibit non-uniform grayscale, weak edge feature information, and poor contour continuity.

To address these problems, this paper proposes an improved T-Snake model. First, we combine an adaptive weighted median filtering algorithm with a window-based anisotropic diffusion filtering method to effectively remove speckle noise. Second, we introduce adaptive region energy and inflation forces into the traditional T-Snake model to enhance robustness and achieve effective extraction of discontinuous and weak boundaries.

1 Adaptive Filtering for Speckle Noise

Original thyroid ultrasound images exhibit significant speckle noise that substantially impacts subsequent segmentation, necessitating preprocessing. The Speckle Reducing Anisotropic Diffusion (SRAD) algorithm [12] is a commonly employed filtering method for speckle noise, governed by the equation:

$$\frac{\partial I(x,y,t)}{\partial t} = \operatorname{div}\left(c(q)\nabla I(x,y,t)\right)$$

where I represents the input image, t denotes diffusion time, div is the divergence operator, and $c(q) \in [0,1]$ represents the diffusion coefficient function. Typically, this algorithm performs anisotropic diffusion calculations on four neighboring pixels adjacent to the central pixel. Its primary drawback is that image feature edges are often over-smoothed, resulting in distortion. The window-based improved anisotropic diffusion algorithm (WSRAD) [13] replaces the four-neighborhood pixel values with the mean grayscale value of pixels in a sub-window. However, this approach also suffers from limitations, as the median filtering employed in the method cannot preserve local detail information, again causing distortion.

Based on the distribution characteristics of speckle noise in ultrasound images, this paper enhances the WSRAD filtering method by applying adaptive weighted median filtering to sub-windows. The weight for a pixel (i,j) in a sub-window is defined as:

$$\omega(i,j) = \left[c - \frac{d(m,\delta)}{\omega_0}\right]$$

where c is a regulation factor, d represents the distance between the sub-window pixel point (i,j) and the window center point, m denotes the grayscale variance of the sub-window, δ represents the grayscale mean of the sub-window, ω_0 is the weight of the central pixel in the sub-window, and $[\cdot]$ denotes the integer operator. In our experiments, the central point weight ω_0 is set to 15 and the regulation factor c is set to 1. The experimental results are shown in [Figure 1: see original paper].

Common T-Snake models include inflation forces and image forces, which perform well for detecting clear and continuous boundary contours in images. However, in thyroid ultrasound images, thyroid contour edges exhibit weak feature information and poor continuity. To address this, we introduce a region energy term based on local region minimum variance [15] into the traditional T-Snake model. The external force is defined as:

$$E_{\text{ex}} = E_{\text{image}} + E_{\text{inflation}} + \eta E_{\text{region}}$$

where E_{image} represents the image force that drives the contour toward the target boundary, $E_{\text{inflation}}$ denotes the inflation force that enables rapid convergence to the target contour, and E_{region} is the region energy term that ensures correct boundary convergence when target contour boundary feature information is weak and continuity is poor. The parameter η represents the weight value for the region energy term.

The image force is defined as:

$$E_{\text{image}} = -c \cdot |\nabla(G(x, y) * I(x, y))|$$

where c is the image force magnitude coefficient, ∇ denotes the gradient operator, and $G(x, y) * I(x, y)$ represents the convolution of the Gaussian smoothing function with the input image.

As shown in [Figure 1: see original paper], the SRAD method produces a patch effect, while the WSRAD method avoids this effect but loses local image information. The proposed WSRAD method effectively preserves local feature information while successfully removing speckle noise, demonstrating superior performance in ultrasound image preprocessing.

2 Improved T-Snake Model

In the T-Snake framework, the energy function is defined as:

$$E_{\text{total}} = E_{\text{in}} + E_{\text{ex}}$$

where E_{in} represents the internal force that characterizes contour continuity and smoothness and is closely related to contour shape, and E_{ex} represents the external force that characterizes the distance between the evolving contour and target contour and is closely related to image properties such as image gradient and grayscale statistical characteristics.

In traditional Snake models, the internal force is defined as:

$$E_{\text{in}} = \int_0^1 \left[\alpha(s)|C'(s)|^2 + \beta(s)|C''(s)|^2\right] ds$$

where $C(s)$ is the parametric equation of the contour curve, $C'(s)$ is the first derivative of the curve, $C''(s)$ is the second derivative of the curve, $\alpha(s)$ represents the elasticity coefficient of the curve, and $\beta(s)$ represents the rigidity coefficient of the curve. The first term represents elastic potential energy, which contracts the curve to ensure continuity, while the second term represents rigid potential energy, which limits curve bending to ensure smoothness.

The T-Snake model discretizes the traditional Snake model by representing the contour curve with n sampling points $\{x_i\}$, where $i \in N$ and $1 \leq i \leq n$. For a contour node x_i, the internal force is defined [14] as:

$$E_{\text{in}}(i) = |x_i - x_{i-1}|^2 + |x_i - x_{i+1}|^2 - b|d_i - d|$$

where x_{i-1} and x_{i+1} are adjacent nodes of x_i, d_i represents the distance between adjacent nodes, d is the weighted average of d_i, a is the elasticity coefficient, and b is the rigidity coefficient.

The inflation force direction is determined based on the image statistical characteristics within the neighborhood of contour point (x, y), and q represents the adaptive inflation force coefficient. In traditional methods, q is typically set as a constant. To achieve better robustness and convergence speed, we define the adaptive inflation force coefficient as:

$$q = \exp\left(-\frac{\delta - \sigma}{\mu}\right)$$

where Ω represents the 3×3 neighborhood of contour point (x, y), which is divided into interior and exterior regions by the contour line; δ is the difference between the maximum and minimum grayscale values in the neighborhood; σ is the grayscale variance in the neighborhood; and μ is the grayscale mean in the neighborhood. When the contour line lies in a region with uniform grayscale, q approximates 1, and the contour evolves with its original characteristics. When the contour lies in a region with non-uniform grayscale, q ranges between 1 and 2, providing additional inflation force to drive the contour away from this region rapidly.

The region energy term is defined as:

$$E_{\text{region}} = \frac{1}{2}\left[\sum_{p \in \Omega_1} (I(p) - \mu_1)^2 + \sum_{p \in \Omega_2} (I(p) - \mu_2)^2\right]$$

where $I(p)$ is the grayscale value at point p in neighborhood Ω, μ_1 is the mean grayscale value in the interior region of the contour, μ_2 is the mean grayscale value in the exterior region of the contour, Ω_1 represents the interior region, and Ω_2 represents the exterior region.

From a mathematical perspective, the total energy E_{total} is a functional of the contour curve. The greedy algorithm can be employed to obtain the contour curve that minimizes the total energy, which represents the target contour.

3.1 Experimental Setup

Based on prior knowledge, the elasticity coefficient for describing thyroid contour curves should not be set too small, the rigidity coefficient should not be set too large, and the region energy weighting coefficient should not be set too small. In our method, the model parameters are configured as follows: elasticity coefficient $a = 0.1$, rigidity coefficient $b = 0.4$, region energy weighting coefficient $\eta = 0.3$, image force coefficient $c = 5$, and the Gaussian smoothing function kernel is set to 1.5.

The experimental environment consists of MATLAB 7.1 running on a Lenovo X230i with a 2.4 GHz CPU and 6 GB of memory. The experimental dataset comprises 20 sets of thyroid ultrasound images provided by the First People' s Hospital of Nantong City, including both original datasets and expert-annotated datasets. All dataset images were normalized and used as experimental input data.

3.2 Evaluation Method

This study employs commonly used evaluation metrics for ultrasound image segmentation: Relative Overlap Degree (ROD) and Relative Difference Degree (RDD). The formulas are defined as:

$$\mathrm{ROD} = \frac{|T \cap S|}{|T|} \times 100\% \quad (11a)$$

$$\mathrm{RDD} = \frac{|T - S|}{|T|} \times 100\% \quad (11b)$$

where T represents the target contour region (expert manual segmentation results serve as the ground truth in this study), and S represents the experimentally converged contour region. ROD indicates the degree of overlap between the converged contour and the target contour, while RDD indicates the difference between them.

The segmentation results for the 20 clinical datasets are presented in and , with typical segmentation results illustrated in [Figure 2: see original paper] through [Figure 4: see original paper].

Table 1 Experimental Results - ROD

Method	Max ROD	Min ROD	Mean ROD	Variance
Orthogonal T-Snake	94.3%	88.4%	91.3%	-
Proposed Method	87.2%	76.4%	83.6%	-

Table 2 Experimental Results - RDD

Method	Max RDD	Min RDD	Mean RDD	Variance
Orthogonal T-Snake	12.7%	-	-	-
Proposed Method	-	-	<5%	-

The experimental results in Tables 1 and 2 demonstrate that the proposed method achieves an average relative difference of less than 5% and an average relative overlap of more than 91%, thereby validating the feasibility of our approach.

In [Figure 2: see original paper] through [Figure 4: see original paper], the results obtained by our method show high consistency with expert segmentation, effectively addressing the challenges of non-uniform grayscale and weak edge feature information characteristic of thyroid ultrasound images.

4 Conclusion

This paper presents a novel segmentation method for thyroid ultrasound images. By introducing adaptive median filtering into the anisotropic diffusion filtering framework, the method effectively removes speckle noise. The incorporation of adaptive region energy and inflation forces into the T-Snake model enables effective extraction of weak edge feature information. Future work will focus on applying this research to online real-time analysis of thyroid ultrasound images.

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Note: Figure translations are in progress. See original paper for figures.