Combination of Polar Edge Detection and Active Contour Model for Automated Tongue Segmentation

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Abstract

Tongue diagnosis is an important diagnosis method in Traditional Chinese Medicine (TCM) and recently the development of automated tongue image analysis technology has been carried out. Automated tongue segmentation is difficult due to the complexity of pathological tongue, variance of tongue shape and interference of the lips. In this paper we present a novel method for automated tongue segmentation by combining polar edge detector and active contour model. First a novel polar edge detector is proposed to effectively extract the edge of the tongue body. We then introduce a method to filter out the edge that is useless for tongue segmentation. A local adaptive edge bi-thresholding technique is also proposed. Finally an initialization and active contour model are proposed to segment the tongue body from the image. Experimental results demonstrate that the novel tongue segmentation can segment the tongue accurately. A quantitative evaluation on 50 images indicates that the mean DCP (the distance to the closest point) of the proposed method is 5.86 pixels, and the average true positive (TP) percent is 97.2%.
Keywords: automated tongue segmentation, active contour model, polar edge detection, tongue diagnosis.

1. Introduction

Tongue diagnosis, an indispensable diagnosis method in TCM, has been widely applied to clinical analysis and application for thousands of years. Many Chinese Medicine doctors utilize the features of the tongue such as color, texture and coating to differentiate syndromes and diagnose diseases. The simplicity, inexpensiveness and non-invasiveness of tongue diagnosis make it very competitive in the development of remote diagnosis.

However, one important problem in tongue diagnosis is its practice is subjective, qualitative and difficult in automated diagnosis. Recently it is a trend to utilize the image processing and pattern recognition technology in aid of the quantitative analysis of tongue image. Currently there are two main issues in automated tongue analysis. The first is the objective representations of tongue's color, texture and coating with the help of image analysis technology [2, 3, 4, 5]. The other is automated tongue segmentation [1, 6].

Tongue segmentation is one of the most prerequisite steps in automated tongue diagnosis system and is very difficult due to the complexity of pathological tongue, variance of tongue shape and interference of the lips. Previous works on tongue segmentation usually use the regular gradient operator to detect the boundary of tongue body, and then utilize an active contour model to crop the tongue area [1, 6]. Gradient on parts of tongue boundary by regular detector is poor and inconsecutive, thus is difficult to be distinguished from the disturbing edge and can badly affect the final segmentation result.

In this paper we proposed a novel tongue segmentation method by combining the polar edge detector, edge filtering, edge binarization, and active contour model. First, we presented a polar edge detector and then introduce a method to filter out the edge useless for tongue segmentation. A local adaptive edge bi-thresholding technique is also introduced. Finally an initialization and an active contour model are used to segment the tongue body from the image.

The organization of this paper is as follow. Automated tongue segmentation algorithm is proposed in section 2. Experiment and performance evaluation are presented in section 3 and finally conclusions are given in section 4.

2. Automated Tongue Segmentation

In this section we proposed an integrated method of low-level and high-level domain knowledge for tongue segmentation. We first present a polar edge detection method to effectively distinguish the edge of the tongue body. Then we present an edge filtering process and local adaptive edge binarization method. Finally we present an initialization and active contour model for automated tongue segmentation.

2.1 Polar Edge Detection of Tongue Image

A typical tongue image and the intensities in six directions are shown in Fig. 1. The edges of tongue body in these directions are also labeled in Fig. 1(b). It can be observed that the intensities of tongue boundary usually are local minimum in radial direction. This motivates us to present a novel edge detector, polar edge detector.

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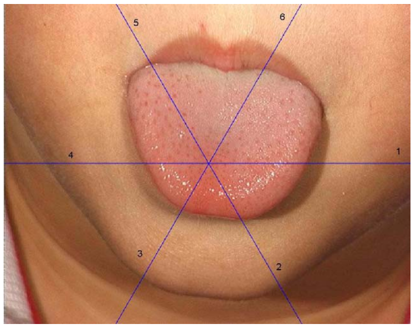
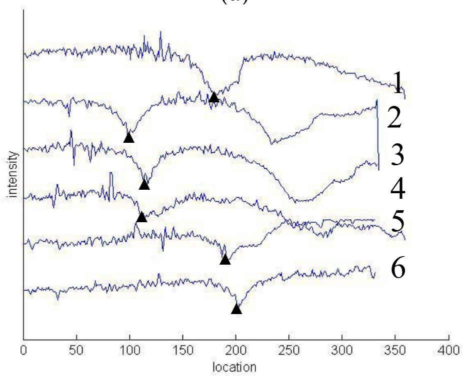


(a)



(b)

Fig. 1 (a) Original image; (b) The variation of intensity in six different directions.

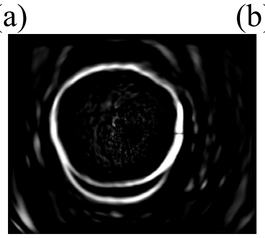
Given a tongue image I, let (x_0, y_0) be the origin of the polar coordinates, then each pixel $I'(r, \theta)$ in polar image can be computed by,

$$I'(r,\theta) = I(r\sin\theta + x_0, r\cos\theta + y_0)\,, \tag{1}$$

where $I(r\sin\theta + x_0, r\cos\theta + y_0)$ in original image is computed by bilinear interpolation. Similarly, the inverse transform can be represented as,

$$I(x, y) = I'(\sqrt{(x-x_0)^2 + (y-y_0)^2}, arctg(\frac{x-x_0}{y-y_0}))\,. \tag{2}$$

(a) (b)



(c)

Fig. 2 (a) Original image; Edge image by Sobel operator; (c) Edge image by polar edge detector.

Whereafter a horizontal Gaussian smoothing operator with windows N×1 and standard deviation σ is used to smooth the polar image. Finally we proposed an 1×(2k+1) horizontal edge detector [1, 1, … , 1, -2k, 1, … , 1, 1] to detect the edge in polar image,

$$E(i, j) = \sum_{i=1}^{k}(I(i, j+k) + I(i, j-k) - 2I(i, j))\,, \tag{3}$$

where $I(i, j)$ is a pixel of polar image, $E(i, j)$ is the corresponding intensity of the polar edge image. The edge images of Fig. 2(a) detected by Sobel and by the proposed method are shown in Fig. 2(b) and Fig. 2(c), respectively. The polar edge detector is superior to Sobel edge detector.

2.2 Filtering and Binarization of Edge Image

The aim of edge filtering is to alleviate the effect of tongue's textures. We use a Sobel operator to find binary edge image and then we use an N×N Gaussian operator with deviation σ to smooth edge image and subsequently a threshold T to binarize image. Then a morphological method is adopted to filter out the blocks with small size.

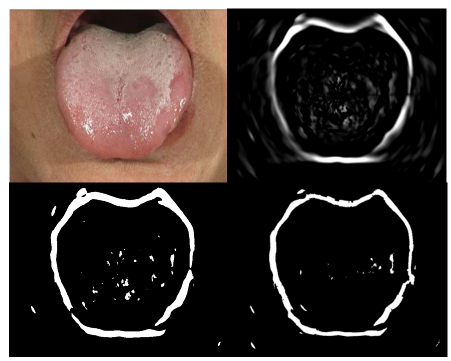


Fig. 3 Top left: Original image; Top right: Edge image by polar edge detector; Down left: Global binarization; Down right: Local adaptive binarization

After edge filtering, we propose a local adaptive bi-thresholding method to binarize polar edge image. Unlike global bi-thresholding where a uniform threshold value is selected to binarize image, every K lines of the polar edge image have their own local threshold value in the proposed thresholding method. Then a morphological method is used to filter the edge without enough length.

Fig. 3 illustrate a tongue image, its edge image, and the bi-level edge images by global bi-thresholding and the proposed method. As shown in Fig. 3, the proposed method is more suited to binarize the edge image.

2.3 Initialization and Active Contour Model

We adopt a heuristic snake initialization method. First we choose the nearest edge point from the origin as the tongue boundary in each direction. Next we choose the longest continuous edge segment as one part of tongue boundary. Then we use the chosen tongue boundary segment and the continuity property to direct the heuristic initialization of tongue boundary.

We use the active contour model in [7] to align the contour to energy minima in the tongue image. The time-delayed discrete dynamic programming formulation guaranteed the convergence of the active contour in a finite number of iterations since the total energy is monotonically decreasing with the number of iterations. Fig. 4 shows a tongue image, and its initialization and final result. As Fig 4 shown, the proposed method can correctly initialize the tongue boundary and the contour can converge to the boundary of tongue body.

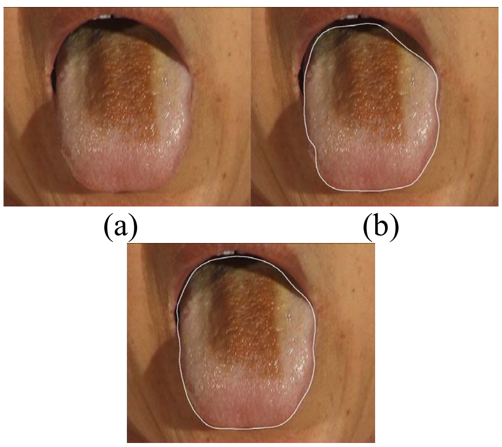


Fig. 4 (a) Original image; (b) Initialization of active contour; (c) Final output.

2.4 The Algorithm Revisited

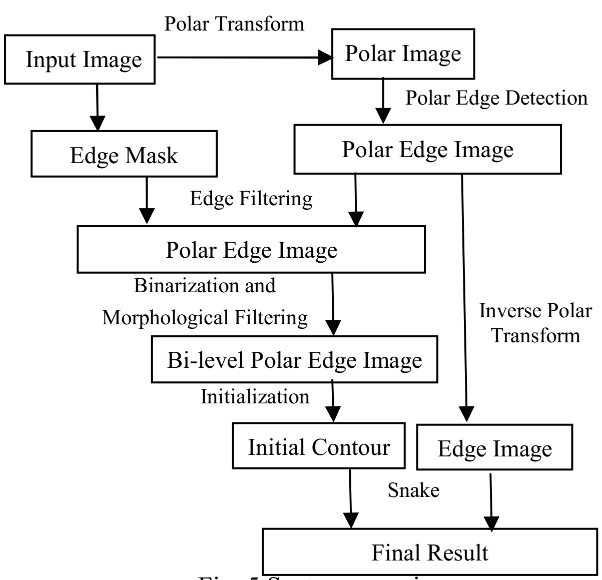


Fig. 5 System overview.

Fig. 5 is a flowchart of the proposed method. The input image first is transformed to polar image and a polar edge detector is used. Then we use the original image to construct edge mask to filter the polar edge image. The filtered polar edge image is binarized by a local adaptive bi-thresholding method. We use the bi-level edge image to initialize the active contour model. Finally a discrete dynamic programming formulation is used to evolve the contour to tongue's boundary.

3. Experimental results and discussions

3.1 Qualitative Evaluation

We use four different tongue images with various texture, shapes and poor defined boundary to evaluate the proposed scheme's effectiveness. From Fig. 6, we can observe that the proposed scheme segment all the tongue images correctly.

Fig. 6 Tongue segmentation results

3.2 Quantitative Evaluation

Quantitative evaluation of medical image segmentation algorithm is an untrivial job. The complexity and difficulty of medical image segmentation make it impossible to obtain a definitive gold standard. Practically researchers often adopt manual result as the gold standard. However, manual results vary with different observers and the collection of them is very tedious. Thus definitive metrics are necessary to evaluate the segmentation algorithm. Chalana proposed boundary error metrics [8], while Udupa used area error measures [9] to quantitatively evaluate the segmentation method. We adopt both boundary metrics and area error metrics and use 50 tongue images to evaluate the proposed scheme.

A. Boundary Error Metrics

Let $A = \{a_1, a_2, \cdots, a_m\}$ denotes the automated segmentation results, and $M = \{m_1, m_2, \cdots, m_n\}$ denotes the manual contour, where each a_i or m_j is a point on the corresponding contour. Here we define two boundary error metrics, the Hausdorff distance and the mean of distance to the closest point (DCP) distance. The DCP for a_i to M is defined as,

$$d(a_i, M) = \min_j(\|m_j - a_i\|_2) . \qquad (4)$$

The Hausdorff distance (HE) between two curves A and M is defined as,

$$hd(A, M) = \max(\max_i\{d(a_i, M)\}, \max_j\{d(m_j, A)\}) , \qquad (5)$$

and the mean DCP distance (MD) of two curves A and M can be defined as,

$$md(A, M) = \frac{1}{m+n}\left(\sum_i d(a_i, M) + \sum_j d(m_j, A)\right). \qquad (6)$$

The average Hausdorff distance and mean DCP distance of the proposed scheme are 24.43 and 5.86 pixels, respectively. The normalized HD and MD, computed by dividing HD and MD by the number of pixels of manual contours are 1.96% and 0.48%, as shown in Table 1.

Table Evaluation results by boundary metrics

HD	MD	Norm. HD %	Norm. MD %
24.43	5.86	1.96	0.48

B. Area Error Metrics

Three area error metrics, false negative volume fraction (FN), false positive volume fraction (FP) and true positive volume fraction (TP) are defined as follows:

$$FN = \left|A_a - A_a \bigcap A_m\right| / \left|A_a\right| , \qquad (7)$$

$$FP = \left|A_m - A_a \bigcap A_m\right| / \left|A_a\right| , \qquad (8)$$

$$TP = \left|A_a \bigcap A_m\right| / \left|A_a\right| , \qquad (9)$$

where A_m and A_a are the area of tongue body determined by manual delineations and the proposed method. The mean of error measures are listed in Table 2. The average percentage of pixels misclassified as tongue body is 4.7%. The average percent of tongue body pixels incorrectly segmented by our method is 2.8%, and the average true positive percentage was 97.2%.

Table 2 Evaluation results by area metrics

FP %	FN %	TP %
4.7	2.8	97.2

4. Conclusions

This paper proposed an integrated method for automated tongue segmentation. The main steps of the proposed method are:

- Polar edge detection. We proposed an innovative polar edge detector to extract tongue boundary.
- Edge filtering and bi-level thresholding. This step is used to filter out the unwanted edge and binarize edge image.
- Active contour model. We use a heuristic initialization and active contour model for final segmentation.

Experiment results demonstrate the effectiveness of the novel tongue segmentation algorithm. We used 50 tongue images to quantitatively evaluate the performance of the proposed scheme. The mean DCP (the distance to the closest point) is 5.86 pixels, and the TP percent is 97.2%.

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