Geometric and Tongue-Mouth Relation Features for Morphology Analysis of Tongue Body

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Abstract. Traditional Chinese Medicine diagnoses a wide range of health conditions by examining morphology features of the tongue, such as fat, thin and normal. This paper presents an approach of classification for recognizing and analyzing tongue morphology based on geometric features and tongue-mouth relation feature. The geometric features are defined using various measurements of width and length of the tongue body, and ratio between them. In addition, an innovative and important feature is proposed based on the relationship between the width of the tongue body and the width of the oral cavity, named as tongue-mouth relation feature. All these features are used to train a SVM classifier. Experimental results show that the tongue-mouth relation feature is helpful to improve the recognition accuracy for tongue morphology, and the proposed method, tested on a total of 200 tongue samples, achieved an accuracy of more than 92%.

Keywords: Tongue morphology · Tongue-mouth relation feature · SVM

1 Introduction

Diagnosis based on condition of the tongue [1–3] is one of the most important and valuable diagnostic methods in traditional Chinese medicine (TCM) and has been widely used in clinical analysis and applications for thousands of years. According to the principles of TCM, analyzing the appearance of an individual's tongue can provide a greater understanding of his or her overall health. Whenever there is a complex disorder in vivo, examining the tongue may instantly clarify the main pathological processes. However, traditional tongue diagnosis has inevitable limitations that impede its medical applications. First, the clinical competence of tongue diagnosis is determined by the experience and knowledge of the practitioners. Second, tongue diagnosis is usually based on the detailed visual discrimination, so it depends on the subjective analysis of the examiners and the diagnostic results may be unreliable and inconsistent.

In recent years, some research has been done to improve computerized or automated tongue diagnosis by applying the techniques of image analysis and pattern recognition. Chiuet al. [4, 5] proposed a structural texture recognition algorithm which adopted the RGB model for mapping the tongue colors to some known categories and used certain features to verify or identify certain properties of coating on the tongue. [6] presented a

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novel computerized tongue inspection method based on two kinds of quantitative features, chromatic and textural measure, and Bayesian networks are employed to model the relationship between these quantitative features and diseases. [7–9] introduced three kinds of tongue image segmentation method. [10] gave a scheme to extract tongue cracks, one of pathological features in tongue diagnosis, which extracts the whole of the line by employing anisotropic nonlinear filter. Base on their work, [11] proposed a new method using statistic feature to identify if a tongue is a cracked tongue. [12] proposed a teeth-marked tongue recognition method performing better than the work [13, 14], which are concentrated on features of convex and the change of brightness of tongue. An in-depth analysis on the statistical distribution characteristics of human tongue color that aims to propose a mathematically described tongue color space for diagnostic feature extraction is presented in [15]. [16] elaborated a research result about a noninvasive method to detect diabetes mellitus and non-proliferative diabetic retinopathy based on three groups of features including color, texture, and geometry extracted from tongue images.

The theory of TCM claims that tongue morphology can objectively reflect some physiological and pathologic changes of human. For example, the fat tongue may indicate spleen-kidney yang-deficiency, gasification disorder and internal stagnation of fluid dampness, while the thin tongue is arising from qi-blood deficiency and yin-blood insufficiency. Recently, some research has been done for tongue morphology recognition. Wei [17] established an automatic tongue body analysis which was based on the curve-fitting parameters. Xu [18] studied and analyzed the tongue shape to establish a kind of tongue diagnosis method, which measured the tongue's length, width and height and established an optimum formula between the body surface area and the sum of the width and height. However, these methods neglect tongue-mouth relation feature, according to tongue diagnosis, which is also key factor to recognize tongue as fat tongue, thin tongue and normal tongue. In addition, machine learning method is not used in these methods. In this paper, we propose a novel medical biometric approach that automatically classifies and recognizes tongue morphology. First, we combined geometric features with tongue-mouth relation feature to represent the tongue morphology. Then, a multi-class SVM is trained based on these statistic features to build a classifier for tongue morphology.

The remainder of this paper is organized as follows. Section 2 introduces how to extract geometric features with tongue-mouth relation feature, and train SVM classifier. Section 3 gives the experimental results and discussion. Finally, this study is concluded in Sect. 4.

2 Feature Extraction and SVM Classifier

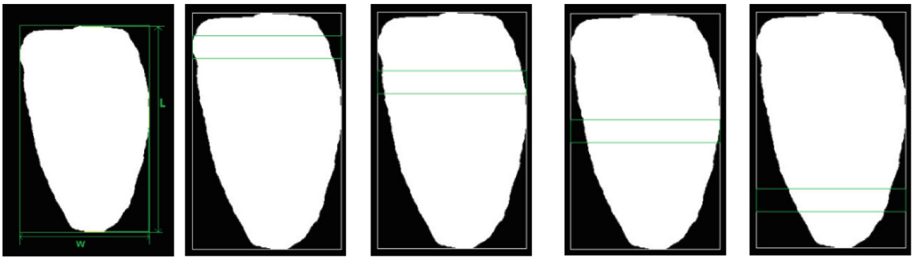
This section describes the method to extract the geometry features of tongue and the tongue-mouth relation. First, Automatic contour extraction extracts the geometric contours of the tongue body from its surroundings by using a segmentation method based on histogram projection and matting [9]. Image in Fig. 1 shows that the accurate and precise tongue body in Fig. 1(b) can be segmented from original tongue image showed in Fig. 1(a), which is captured by standard tongue image acquisition.

(a) (b)

Fig. 1. Tongue image segmentation (a) initial tongue image includes the lips, parts of the face, or the teeth; (b) tongue body image

2.1 Geometry Features

After extracting tongue body image, we extract the geometry features based on tongue body region. The width and the length of a tongue were often used in researches related to the analysis of tongue body [19]. Here, the tongue length is the distance between tongue root and tongue tip; the tongue width refers to the distance of the leftmost and rightmost of the different tongue position as showed in Fig. 2.



(a) (b) (c) (d) (e)

Fig. 2. Length of tongue body and width of different part of tongue body. (a) Width and Length of tongue body. (b) Width of tongue root. (c) and (d) With of tongue middle. (e) Width of tongue tip

Given a tongue body image, the pixels which are rendered in the RGB color space are first converted to the grayscale value. Then, the binarization algorithm is conducted for grayscale image, which uses one calculated threshold value to classify pixels into object or background. The new value of each image pixel is modified as:

$$f(x, y) = \begin{cases} 0, & f(x, y) \leq 10 \\ 255, & f(x, y) > 10 \end{cases} \quad (1)$$

in which f(x, y) is the gray value of image pixels. We selected 10 as the threshold. It is very intuitive to get the contour of the tongue in the binary image (see Fig. 2(a)). Drawing a minimum circumscribed rectangle for the tongue body contour, the coordinate of the up-left point of the rectangle is set to (0, 0). The width and the length of the rectangle are denoted as W (width) and L (length) of tongue, respectively, showed in Fig. 2(a). The ratio of the tongue width and length is calculated as follows:

$$F = W/L \tag{2}$$

The relationship between tongue width and length is a very important feature on the judgment of tongue morphology. For fat tongues, the width is basically equal to or more than the length, while the length of thin tongues is much larger than the width.

Then, we extract four width of different position of tongue body based on four different rectangles, showed as green box in Fig. 2(b)–(d), they are located at tongue root, tongue middle and tongue tip respectively. The width of each rectangle is W and the length is 0.1L. The x coordinate sequence of left boundary and right boundary is denoted as

$$x_l = \left\{ x_{li} | i = 1, 2, \cdots, n \right\} \text{ and } x_r = \left\{ x_{rj} | j = 1, 2, \cdots, m \right\}$$

respectively. Here, x_{li} represents the x coordinate of the ith pixel on left boundary and x_{rj} represents the x coordinate of the jth pixel on right boundary. The x coordinate of a boundary of different position is presented by the mean value of all pixels' x coordinate on left boundary or right boundary. The widths of four tongue body positions are defined as:

$$W_k = \frac{1}{n}\sum_{i=1}^{n} x_{li} - \frac{1}{m}\sum_{j=1}^{m} x_{rj},\ k = 1, 2, 3, 4 \tag{3}$$

$$F_i = W_i \big/ W,\ i = 1, 2, 3, 4 \tag{4}$$

Finally, four geometric features are defined as Eq. 4. In our research, we found that the width of the tip and the root part of fat tongue are smaller than the tongue width, in contrast, the width of each part of thin tongue, except the root part, will not be larger than the tongue body width.

2.2 Tongue-Mouth Relation Feature Extraction

The objective of this subsection is to extract the tongue-mouth relation feature on the initial image. The method used to find oral cavity is based on the rectangle drawn in Sect. 2.1. The changes on the rectangle are moving the distance of 0.3 W to the left and move up the distance of 0.4L, moreover the width is set to 1.6 W and the length is unchanged. Thus we get a new rectangle that is named imgROI. The function of creating the new rectangle is defined as follows,

$$\begin{aligned} imgROI.x &= x - 0.3W \\ imgROI.y &= y - 0.4L \end{aligned} \tag{5}$$

$$\begin{aligned} imgROI.W &= 1.6 * W \\ imgROI.L &= L \end{aligned} \tag{6}$$

The oral cavity is surrounded by the rectangle while applying the new rectangle on the initial image. Then split the local image which is contained in the rectangle from the initial image, thus we get the image of oral cavity named mouth.

The detail steps calculating the width of the oral cavity are described as follow:

1. Converting the image mouth to the red channel image.
2. Splitting the red channel image by using threshold operation of parameter inversion. The threshold is selected according to the local area information.
3. There are several contours after image segmentation. These contours are descending sort according to the size of areas which are surrounded by contours. Then, remove areas which are over small or over wide or near the image edge.
4. Retaining two of the largest regions in the residual areas if the number of the rest area is greater than 3. Otherwise, all remaining areas are retained.
5. All pixels for each region are combined together as the oral cavity region.
6. Drawing the minimum enclosing rectangle for oral cavity area.

The area surrounded by the tongue is the gap between the upper lip and the tongue when the tongue is stretched out. Let the width of the rectangle represents the width of the oral cavity area named as mouth.W. The ratio represented the tongue-mouth feature is defined as follow,

$$F_m = (mouth.W - W)/W \tag{7}$$

For fat tongue samples (see Fig. 3(a)), the oral cavity width is less than the width of the tongue. However, for thin tongue samples (see Fig. 3(c)), the oral cavity width is far larger than the width of the tongue.

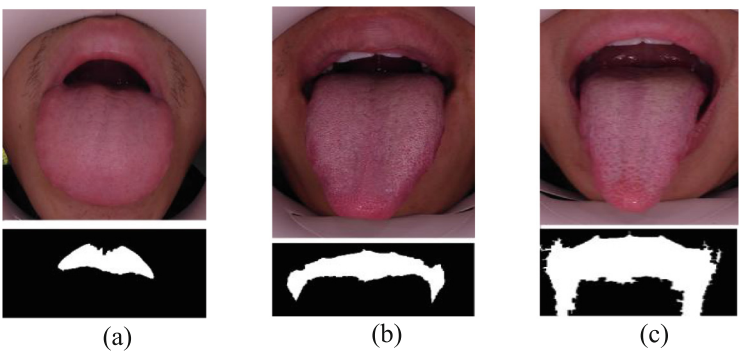


Fig. 3. The space of oral cavity (a) fat tongue; (b) normal tongue; (c) thin tongue

2.3 SVM

Support vector machine is a supervised learning model. Originally it was worked out for linear two-class classification with margin, where margin means the minimal distance from the separating hyperplane to the closest data points. SVM learning machine seeks for an optimal separating hyperplane, where the margin is maximal. The SVM classifier supports binary classification, multiclass classification and regression, the structured SVM allows training of a classifier for general structured output labels. The linear SVM can extended to nonlinear one when the problem is transformed into feature space using a set of nonlinear basis function. In the feature space – which can be very high dimensional – the data points can be separated linearly. An important advantage of the SVM is that it is not necessary to implement this transformation and to determine the separating hyperplane in the possibly very-high dimensional feature space, instead a kernel representation can be used, where the solution is written as a weighted sum of the values of certain kernel function evaluated at the support vectors [20].

In this study, the RBF kernel is chosen to train the SVM model because it has only one parameter for model selection and fewer numberical difficulties. The definition of RBF function is,

$$K(x_i, x) = \exp(-\gamma \left\| x_i - x \right\|^2) \tag{7}$$

The parameter gamma(γ) which tunes the training error and the generalization capability needs to be optimized for best performance.

3 Experimental Results and Discussion

Based on the proposed methods of the tongue morphology feature extraction, this section describes the tongues classification using SVM.

3.1 Dataset

According to the diagnosis experience given by the experts, there are three classes of tongue morphology: fat, normal and thin. In our experiment, the image database contains over 200 tongue images and covers various types of tongues. Every image in the database is independently labeled by three or more experts of TCM with opinion agreement.

The typical sample (see Fig. 3) refers to the representative tongue image in the category of tongue. In this study, we select 10 images from the fat tongue type, 10 images from the normal tongue type and 10 images from the thin tongue type to form a set of typical sample. The testing set consists of the rest images in the image database.

3.2 Experimental Results

In this section, we will verify whether the extracted features are valid. As mentioned in Sect. 3.1, some typical samples are selected from the image database to form the SVM training set, and the remaining images are used for testing.

The experiment is conducted on two different feature sets. One set contains all of the six features mentioned in Sect. 2, and another one contains five features which not include the feature representing the relationship between the width of oral cavity and the tongue.

True positive rate (TP) are calculated to evaluate the classification. TP measures the proportion of positives that are correctly identified. In Table 1, we compute TP of two different feature sets on three tongue types respectively according experimental results. The set of five features contains the ratio between tongue width and length and the ratio between different tongue part width and tongue width. These features are much affected by the length of the tongue when it is stretching outside of the mouth, especially the ratio of tongue width and length. Even though the volunteers are required to open their mouth and stretch out their tongue when taking pictures, there are still some images are not perfectly. The experiment shows that the correct rate of classification is greatly improved after added new feature. And it indicates that classification based on all features can recognize the fat tongue and thin tongue correctly, while a few of normal tongue are always recognized as fat tongue or thin tongue, showed as Table 2. Compared with accuracy rate 80% in [17], fat TP rate (93.4%) and thin TP rate (88.57%) [18], the proposed method achieves better performance.

Table 1. True positive base on five features or six features

Feature set	Fat TP	Normal TP	Thin TP
Five features	78.74%	71.67%	76.92%
Six features	98.43%	86.67%	92.31%

Table 2. Classification results of proposed method based on six features

	Fat	Normal	Thin
Fat	125	4	0
Normal	1	52	1
Thin	1	4	12

4 Conclusion

This paper presents a classification approach for automatically recognizing and analyzing tongue morphology based on geometric features and tongue-mouth relation feature. First, we develop five geometric features by using various measurements of width and length of the tongue body, and ratio between them. Then, our main contribution, an innovative tongue-mouth relation feature, the relationship between the width of the tongue body and the width of the oral cavity is computed to add into feature vector representing tongue morphology. Finally, a SVM classifier is trained to classify the tongue into three categories such as fat tongue, normal tongue and thin tongue. Experimental results demonstrated that the tongue-mouth relation feature is helpful to improve the recognition accuracy for tongue morphology, and the proposed method achieves better accuracy.

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