Automatic classification of tongue texture color and tongue coating color based on BP neural network

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Abstract. Tongue diagnosis is an important part of the traditional Chinese medicine diagnosis, and it is one of the main criteria for clinical diagnosis of TCM. Tongue texture color and tongue coating color are the main research contents of tongue diagnosis. This paper first uses computer technology to achieve separation of tongue texture and tongue coating on the tongue image. According to the position information, the tongue texture and tongue coating template are discriminated, and the color information of tongue texture area and tongue coating area are obtained respectively. Finally, the automatic classification of tongue texture color and tongue coating color is realized through neural network.

1. Introduction
Tongue diagnosis is an important part of the four diagnosis of traditional Chinese medicine and one of the main bases of clinical diagnosis of traditional Chinese medicine. Tongue texture color and tongue coating color are the main research contents of tongue diagnosis. The tongue is divided into two areas: tongue texture and tongue coating. Tongue color refers to the color of tongue quality, and coating color refers to the color of tongue coating. The tongue is the muscle vein of the tongue, located in the smooth area of the tongue. Tongue coating is a thin coating on the back of the tongue, which is located in the middle of the tongue.

At present, FCM fuzzy clustering algorithm is commonly used to separate tongue texture and tongue coating. In this paper, the algorithm is improved, which can automatically determine the number and location of clustering centers, improve the accuracy of segmentation and operation speed.

At present, the research on tongue texture color and tongue coating color mainly focuses on the quantitative analysis of color, and the automatic classification of tongue texture color and tongue coating color mainly uses statistical methods. Neural network imitates human brain and adopts adaptive algorithm. It has strong fault tolerance, self-learning, self-organizing function and induction ability. Therefore, this paper uses BP neural network to classify the color of tongue texture and tongue coating.

2. Segmentation of tongue texture, tongue coating and background
FCM fuzzy clustering algorithm is used to realize automatic segmentation of tongue quality, tongue coating and background. The number and position of the tongue image clustering center can be determined by the peak position and the number of peaks of the chromaticity histogram of the tongue image. The specific algorithm is as follows:
(1) Convert Original tongue image from RGB space to HIS space to obtain hue histogram, as shown in Figure 1.

(2) The high frequency component of the signal corresponds to the mutation region of the signal. Therefore, Figure 1 is filtered by Butterworth low-pass in frequency domain. It can remove the small and medium burr of the histogram and make the histogram smooth. The filtering results are shown in Figure 2.

(3) Obtain the number and position of the peak points in Figure 2, where the number of peaks is the number of clustering centers, and the position of peaks is the initial position of clustering centers. The FCM clustering segmentation effect is shown in Figure 3.

![Figure 1. Hue histogram of tongue image](image1.png)  
![Figure 2. Low pass filtering results of Fig1](image2.png)  
![Figure 3. FCM clustering segmentation effect](image3.png)

3. Automatic recognition of tongue texture template, tongue coating template and background template

After FCM clustering segmentation, there are three gray levels, 255, 150 and 0, which correspond to three different regions. So we need to determine which of the three gray levels corresponds to the tongue quality, tongue coating and background. According to the feature that tongue coating is surrounded by tongue quality, this paper realizes the automatic recognition of tongue quality and tongue coating.

The identification steps are as follows:

(1) Get the template of grayscale 0, 150 and 255. The original tongue image is shown in Figure 4 (a), and the FCM clustering segmentation image is shown in Figure 4 (b). In this paper, E0 is used to represent the gray level 0 template, as shown in Figure 4 (c), E150 is used to represent the gray level 150 template, as shown in Figure 4 (d), and E255 is used to represent the gray level 255 template, as shown in Figure 4 (e).
Figure 4. The process of separating three gray level templates

(2) Judge background template.
According to the value of the background template in the upper left corner of the image must be 1, and the value of the tongue quality and tongue coating template in the upper left corner must be 0, the background template can be found in three templates.

If e255 (1, 1) = = 1 background = e255; else if e0 (1, 1) = = 1 background = e0; else if e150 (1, 1) = = 1 background = e150

(3) Judgment of tongue texture and tongue coating template
The remaining two gray level templates are used to determine which gray level corresponds to the tongue quality, and the other gray level corresponds to the tongue coating. Take Figure 4 as an example. In the second step, we can find that the background template is e255.

The binary morphological operations are carried out on e0 and e150 respectively to remove the small connected components, only the largest connected components are retained, and the set of coordinates of all pixels in the largest connected components is obtained. Because the tongue coating is sometimes at the root of the tongue, we can judge the position information of two gray level templates from three directions. When one template is surrounded by another template in any two directions of the left, right and lower three directions, it can be judged that the template is tongue coating template, and the other template is tongue quality template.

4. Automatic classification of tongue texture and tongue coating color on tongue images using BP neural network
Due to the limited number of tongue image samples, this paper does not classify all tongue texture colors and tongue coating colors. In this paper, the color of tongue texture is divided into red, purple, light, deep purple and light red. The color of tongue coating is divided into white and yellow.

The BP neural network of tongue texture color classification has three inputs. The input data are the values of H, S and I in the tongue region, which represent the information of hue, saturation and brightness in the tongue texture region. The network has three output terminals: y3y2y1 = 000(red), y3y2y1 = 001(deep purple), y3y2y1 = 010(light red), y3y2y1 = 011 and y3y2y1 = 100(light red).

The number of samples of each type of five tongue colors is 8, including 5 samples of each type of training set and 3 samples of each type of test set.
The mean square error of the network is set to $\text{net.trainparam.goal}=1e^{-3}$, and the number of iterations is $\text{net.trainparam.epochs}=10000$. The effect of mean square error iteration is shown in Figure 5. It can be seen from the figure that when the iterative operation is more than 2000 times, the mean square error is very small.

![Figure 5. Mean square error iteration effect](image)

The BP neural network of tongue coating classification is established. There are three input nodes in the input layer of the network. The input data are the values of $H$, $S$ and $I$ in the tongue coating area, which represent the information of hue, saturation and brightness in the tongue coating area. The output layer has an output terminal $Y_1$, when $Y_1 = 0$, it represents moss white, $Y_1 = 1$, it represents moss yellow.

The number of samples of each type of two kinds of tongue coating color is 30, including 20 samples of each type of training set and 10 samples of each type of test set. The mean square error and the number of iterations of the network are the same as those of the tongue texture color classification network.

After obtaining the network through the training set, the network is verified through the test set. Set $T$ as the ideal output result (the first three columns 0 represent white moss, the first four to six columns 1 represent yellow moss), is shown in table 1, $A$ is the experimental output, is shown in table 2. Mean square error equal to $\text{sum} \left( (t - a)^2 \right) = 0.094$.

**Table 1. Ideal output T.**

|          | white moss | white moss | white moss | yellow moss | yellow moss | yellow moss |
|----------|------------|------------|------------|-------------|-------------|-------------|
| T        | 0          | 0          | 0          | 1           | 1           | 1           |

**Table 2. Experiment output result A.**

|          | white moss | white moss | white moss | yellow moss | yellow moss | yellow moss |
|----------|------------|------------|------------|-------------|-------------|-------------|
| A        | 0.00342    | 0.00428    | -0.00413   | 0.931       | 1.043       | 1.052       |

5. Conclusions
In this paper, the color information of tongue texture and tongue coating area are automatically obtained by computer, and the color information is used as the input of BP neural network, and the tongue texture color and coating color are used as the output to realize automatic classification of tongue texture color and coating color, and obtain high accuracy. However, as the number of tongue image samples is not enough, it has not been realized for all kinds of tongue texture color and coating color. In the follow-up study, the number of samples will be increased to further improve the recognition accuracy and the number of classification types.
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