An Intelligent System for Tongue Diagnosis in Traditional Chinese Medicine

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ABSTRACT

Tongue features diagnosis is an integral aspect of Traditional Chinese Medicine to study the health of individuals. In this research, we propose an automatic approach for discerning the general tongue types based on the classification of salient tongue features in different color spaces. The Gray-Tone Spatial-Dependence Matrix is used to extract tone and texture information from each tongue photo. Methods such as the Support Vector Machine, Self Organizing Map, Back-Propagation Neural Networks are used for classification of the features obtained. Cross validation is also carried out to assess the efficacies of these methods.

INTRODUCTION

In traditional Chinese medicine (TCM), tongue features such as the color, texture, shape and coating reveal the well-being of a person that is characterized by a particular body syndrome. For instance, the damp-heat (湿热) body syndrome shows symptoms of light-red tongue body and thin tongue coating. In this research, we propose an automatic system that identifies the different features of the tongue based on training using classification algorithms. This is the first step towards an automatic diagnostic system based on general tongue types.

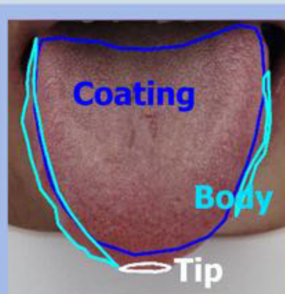


Figure 1: Illustration of Tongue

In this research, the following tongue features are extracted and quantified using mathematical models. The color spaces provide the chromatic information about the colors in the tongue and three distinct color spaces, including RGB, HSV and LAB, are used as features for classification. The Gray-Tone Spatial-Dependence Matrix, a function of the spatial relationship between point-pairs, describes the texture-context feature of the picture.

Feature	Classifications	Model
Body color	red versus amaranth	Color spaces (RGB, HSV and LAB)
Coating color	white versus yellow	Color spaces (RGB, HSV and LAB)
Coating texture	thinness versus thickness	Gray-Tone Spatial-Dependence Matrix
Tongue tip	red versus not red	Color spaces (RGB, HSV and LAB)
Tongue morphology	plumpness versus slenderness	Polynomial curve fitting

Table 1: features, classifications and related models

METHODOLOGY

Support vector machine:

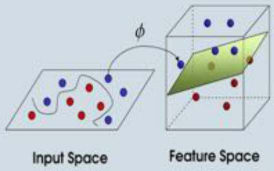


Figure 2: Support vector mechine

This supervised learning model maps examples into higher space by kernel Φ, so that a clear margin can be found to divide them. Each new example can then be judged, based on the side of the gap it falls on, which category it belongs to.

Find a hyperplane w for vector x: $(w \cdot x)+b=0, w \in R^N, b \in R$

Minimize $\frac{2}{\|w\|}$ to obtain the maximal margin.

Back-propagation neural networks:

The BPNN consists of three layers, namely the input layer, hidden layer and output layer. After conducting forward propagation, the gradient of cost function of the network regarding of each neuron can be fed to the optimization method, and then the minimum of cost function will be found by updating the weights of all the nodes.

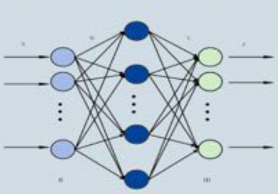
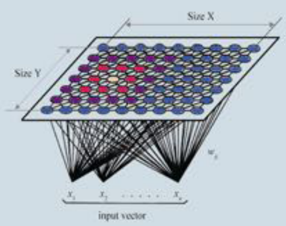


Figure 3: Back-propagation neural network

Self-organizing map



Using unsupervised learning, the SOM is trained to produce a map, a low-dimensional representation of the input, for classification purposes. The nodes or neurons are its predominant components. Each node is

$$\|\vec{x}-\vec{w}_{j^*}\| = \min_{j\in\{1,2,\cdots,m\}}\{\|\vec{x}-\vec{w}_j\|\}$$

$$\Rightarrow \|\vec{x}-\vec{w}_{j^*}\| = \sqrt{(\vec{x}-\vec{w}_{j^*})(\vec{x}-\vec{w}_{j^*})^T} = \sqrt{\vec{x}\vec{x}^T - 2\vec{w}_{j^*}\vec{x}^T + \vec{w}_{j^*}\vec{w}_{j^*}^T} = \sqrt{2(1-\vec{w}_{j^*}\vec{x}^T)}$$

$$\Rightarrow \vec{w}_{j^*}\vec{x}^T = \max_j(\vec{w}_j\vec{x}^T)$$

Only best matching unit (node that produces the smallest distance) is entitled to adjust its weight vector:
$$\begin{cases} \vec{w}_{j^*}(t+1) = \vec{w}_{j^*}(t) + \Delta\vec{w}_{j^*} = \vec{w}_{j^*}(t) + \alpha(\vec{x}-\vec{w}_{j^*}) & \\ \vec{w}_j(t+1) = \vec{w}_j(t) & j \neq j^* \end{cases}$$
α is its learning rate.

Naive Bayes classifiers:

The Naive Bayes Classifier is based on Bayesian theorem(listed below) with strict independence assumptions among features and is particularly proper when the inputs are in high dimensionality. Also, its maximum-likelihood training can be conducted by merely evaluating a closed-form expression.

$$P(\omega_i|x) = \frac{P(x|\omega_i)P(\omega_i)}{P(x)} \quad (i = 1, 2, \cdots, c)$$

where P(A|B) stands for the conditional probability of A given that event B has happened.

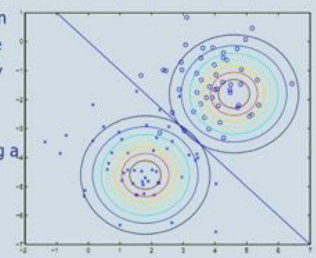


Figure 5: Naive Bayes classifiers

Method for morphology classification:

It is believed that the shape of tongue is similar to an eclipse, therefore, in this method, the outline of the tongue was fitted by an eclipse which gave the minimum square error. Quartic polynomial was also applied to conduct linear regression of the outline, whose parameters could quantify the morphology of the tongue.

RESULTS

In this research, the efficacy of each method is evaluated with k-fold cross validation in which k=5. The table below shows all the best results of the four classifiers.

Features	SVM	BP	SOM	Bayes
Body color	**88.46**	84.62	73.08	76.92
Coating color	80.77	84.62	**88.46**	76.92
Coating texture	**88.46**	80.77	84.62	73.08
Red tip	**93.33**	80	**93.33**	100*
Tongue morphology	84.62	80.77	**88.46**	61.54

Table 2: best results of each classifier

We tried all of the three color spaces since each one has its merits and faults; namely, they can contribute to different accuracies of classification. The accuracies listed above are the best ones we obtained, among which, RGB leads to the highest accuracy of body color while that of coating color comes from LAB space. Our results, on the whole, are around 90 percent and it is worth noting that when using Bayes classifier to test the red tip feature, we get an accuracy of 100 percent*. However, Bayesian theorem is based on normal distribution whereas we have only three samples with red tip, which means that our data are not sufficient to support the assumption; therefore, it cannot be justified that the 100% result is indeed reasonable. Additionally, in classifying the morphology of tongue, in that this judgment should be based on the oral cavity of the individual, it would be rather difficult for machine to make accurate judgment merely according to imagery, therefore detailed personal information should be collected ahead.

CONCLUSIONS AND FUTURE WORK

In short, SVM, to some extent, functioned well in binary classification and it paved the way for the further development of intelligent system. In future research, specific algorithms are required to automatically separate different parts of the tongue. Moreover, the effectiveness of Bayes classifier and multi-classification should be further studied after obtaining more data and then obtained information can be used to realize our goal of recognizing what the general tongue type is.

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