

# Tongue Diagnosis System Based on PCA and SVM

Jin-Woong Park, Sun-Kyung Kang, Sung-Tae Jung

**Abstract**—In this study, we propose a tongue diagnosis method which detects the tongue from face image and divides the tongue area into six areas, and finally generates tongue coating ratio of each area. To detect the tongue area from face image, we use ASM as one of the active shape models. Detected tongue area is divided into six areas widely used in the Korean traditional medicine and the distribution of tongue coating of the six areas is examined by SVM(Support Vector Machine). For SVM, we use a 3-dimensional vector calculated by PCA(Principal Component Analysis) from a 12-dimensional vector consisting of RGB, HIS, Lab, and Luv. As a result, we detected the tongue area stably using ASM and found that PCA and SVM helped raise the ratio of tongue coating detection.

**Keywords**—Active Shape Model, Principal Component Analysis, Support Vector Machine, Tongue diagnosis

## I. INTRODUCTION

In recent years, growing interest in the oriental medicine around the globe has led to the standardization of the Korean traditional medicine. Among others, extensive research is underway on how to process tongue images for the standardization of tongue diagnosis which judges health condition from tongue [1]. Until now, tongue diagnosis has been dependent largely on subjective judgment of oriental doctors based on their experience, not standardized sufficiently yet. However, the development of information technology has made tongue diagnosis possible by machine, instead of judgment of an oriental medical doctor. In this paper, we propose a method of generating tongue coating ratio of each area by detecting the tongue area from face image and dividing the tongue area into six areas for tongue diagnosis.

Fig. 1 depicts the proposed system. To divide the tongue area from an image, we detected the tongue area first from face images using ASM (Active Shape Model)[2], one of the major object detection methods, which requires an understanding on the shape of tongue. For the training of the shape of tongue, we conducted training on shape model and profile model by using face images manually marked landmarks the shape of tongue.

Based on the result of ASM training on the image, we detect the tongue area. After that, we divide it into six areas using coordinates of edges of the tongue and Lagrange polynomial interpolation. Then, we detected the tongue coating area from the divided image by using SVM[4],[5]. For SVM, we use a

3-dimensional vector calculated by PCA(Principal Component Analysis) from a 12-dimensional vector consisting of RGB, HIS, Lab, and Luv. As a result, we detected the tongue area stably using ASM and found that PCA and SVM helped raise the ratio of tongue coating detection.

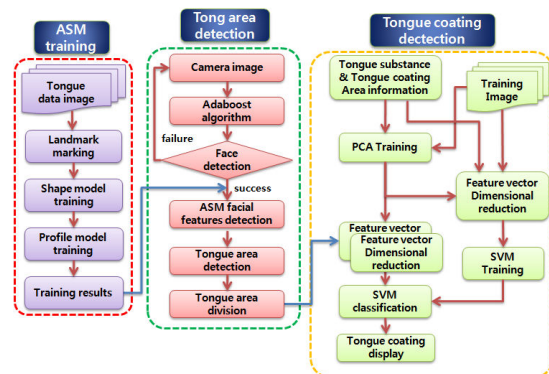


Fig. 1 Structure of proposed tongue diagnosis system

## II. DETECTION AND DIVISION OF TONGUE AREA

### A. Detection of Tongue Area Using ASM

In the study, we used a method of detecting face area including tongue by means of an Adaboost algorithm, in order to detect a portion including tongue from face images. Once face area is detected, we detected face landmarks with ASM. ASM allows for finding landmarks more effectively on the basis of statistical characteristics of the models for contour information of the object. To develop a statistical model for the shape of face and tongue based on the image, we defined the shape made by 56 dots along face contour and tongue as in Fig. 2 (a). These dots are called landmarks, which are placed on contour of face and tongue of the image. Fig. 2 (b) shows a sample face image marked manually with 56 landmarks.

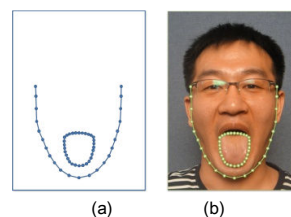


Fig. 2 Detection of tongue area (a) Landmarks (b) A face image manually marked with landmarks

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A set of landmarks,  $X$  is defined as in (1), where  $(a_i, b_i)$  refers to 2-dimensional coordinates of each landmark:

$$X = [a_0, b_0, a_1, b_1, \dots, a_{55}, b_{55}] \quad (1)$$

The 56 landmarks refer to characteristics of an object, which are used to form shape and profile models. In  $m$  training images to form these models,  $x_i$  is a set of landmark for each training image, and the average of training sets,  $\bar{x}$  is calculated as in (2).

$$\bar{x} = \frac{1}{m} \sum_{i=1}^m x_i \quad (2)$$

Covariance matrix  $S_s$  to calculate the correlation of training sets with the shape of collected training sets is as in (3).

$$S_s = \frac{1}{m-1} \sum_{i=1}^m (x_i - \bar{x})(x_i - \bar{x})^T \quad (3)$$

In covariance matrix  $S_s$ , we can calculate eigen value  $\lambda_i$  and eigen vector  $\Phi_i$  which satisfies (4):

$$(S_s - \lambda_i)\Phi_i = 0 \quad (4)$$

Eigen vector is arranged in order of bigger eigen value as in (5):

$$\Phi = (\Phi_1, \Phi_2, \dots, \Phi_k) \quad (5)$$

The shape of tongue in each training image can be calculated using average shape  $\bar{x}$ , parameter vector  $b = (b_1, b_2, \dots, b_k)^T$ , and eigen vector  $\Phi$  as in (6):

$$\hat{x} = \bar{x} + \Phi b \quad (6)$$

Parameter vector  $b$  is a vector meaning weight of each eigen vector, which makes a difference in the shape of tongue. As in the case of normal distribution, data is distributed within the threefold range of standard deviation, weight is limited to the range as in (7):

$$-3\sqrt{\lambda_i} \leq b_i \leq 3\sqrt{\lambda_i} \quad (7)$$

It is possible to form various models in (6) by changing parameter vector  $b$  in the allowable range. Profile models are used to place landmarks by template matching. Profiles use one-dimensional vectors of changing pixels selected along a line vertical to the border of landmarks. Profile vector  $g$  of each landmark of training image is calculated to generate average profile vector  $\bar{g}$  for the entire training images. In addition, covariance matrix of profile vectors  $S_g$  is calculated. A Mahalanobis distance [3] in (8) shows where a profile vector is similar to a profile model:

$$\text{Mahalanobis distance} = (g - \bar{g})^T S_g^{-1} (g - \bar{g}) \quad (8)$$

A new shape is created by moving each landmark in the profile model. However, some landmarks of the new shape may be located in instable places as each landmark is moved independently, and therefore, it is necessary to adjust the shape using shape model so that the new shape can be within the trained range.

$x$  refers the new shape created by moving landmarks, and we can generate a shape similar to  $x$  from trained shape model. A shape  $\hat{x} = T(\bar{x} + \Phi b)$  approximating  $x$  is calculated by finding  $b$  and  $T$  repeatedly minimizing the value of (9), where  $T$  is a transformation to map a shape model into a shape space of the image. The resulting shape  $\hat{x}$  is used to repeat the above process:

$$\text{distance}(x, T(\bar{x} + \Phi b)) \quad (9)$$

Using shape and profile models as above, we detected tongue area surrounded by landmarks of tongue.

*B. Division of the detected area into subareas*

In general, tongue is divided into six areas in tongue diagnosis as in Fig. 3. We divided tongue area on the basis of the correlation between tongue and internal organs of the body used for the Korean traditional medicine into gall bladder and liver on left and right side, kidney and bladder at the top, lung and heart at the bottom, and stomach and spleen at the center.

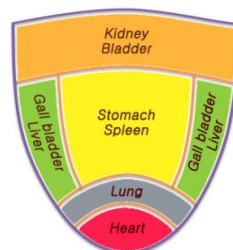


Fig. 3 Relationship between body parts and tongue areas

Tongue diagnosis is to examine the condition corresponding organs by dividing tongue into tongue substance and tongue coating and observing the state of tongue surface; such as the color of tongue. Since it is possible to judge a health problem from abnormality in a certain area of tongue.

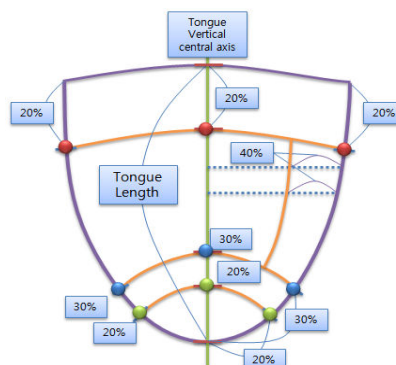


Fig. 4 References for area division

We divided tongue as in Fig. 4. Bottom area is the portion connecting the point of 20% and 30% of the vertical axis from lowest bottom of tongue and points equivalent to 20% and 30% from the bottom pixels of both edges of tongue. Top area is the portion connecting three points: points of 20% from the top pixels of both edges of tongue and a point equivalent to 20% from the top of a vertical axis. From these reference points, a 2-dimensional curve separates the bottom area from the top.

Left and right areas begin from the point equivalent to 40% of the length of vertical axis from pixel coordinates of left and right edges of tongue in remaining portion of the tongue image excluding the bottom.

The central area is the remaining tongue area excluding top, bottom, and left and right side areas.



Fig. 5 Subareas of tongue

Fig. 5 shows subareas of tongue divided by the propose division method.

### III. DETECTION OF TONGUE COATING

In the paper, we calculated a feature vector by means of PCA on training image of tongue coating and tongue substance and divided into tongue coating and tongue substance with SVM to detect tongue coating for tongue area. PCA is a method of analyzing the shape of data in data space composed of many axes to identify a principal component axis and reducing the dimension of the data space by projecting data onto the principal component axis.

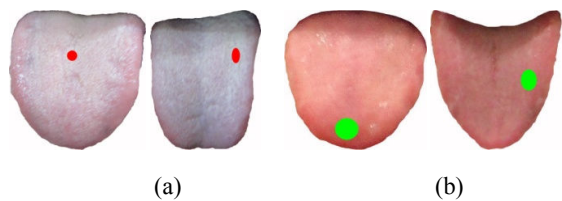


Fig. 6 Defining tongue coating and tongue substance for PCA (a)Tongue coating area (b)Tongue substance area

We conducted a PCA on 20 training images with tongue coating and 20 images with tongue substance. Each training image is marked with tongue coating region and tongue substance region with different color as in Fig. 6. The average color of the pixels marked with a region is used for principal component analysis. Although reference color value for those images is RGB, we used 12-dimensional color values, adding various color vectors HSV, Lab, and Luv tongue coating to find values which can better show the difference between tongue

coating color and tongue substance colors. We reduced the 12 dimensions of characteristic vectors into three, using the most important three values from the results of the PCA on the 12 dimensional color values.

Following the PCA, we carried out SVM training, reducing the dimension of characteristic vectors into three by applying results of the PCA for the colors of tongue substance and tongue coating of the training images.

Upon completion of SVM training, we calculated 12-dimensional color values for pixels of each test image to detect tongue coating and 3D feature vectors based on the results of the PCA, followed by identifying a pixel as tongue coating or tongue substance from the results of the SVM training[4],[5].



Fig. 7 Tongue coating detected

Fig. 7 is an example of tongue coating detected for each subareas. After detecting tongue coating of each area as in this picture, health condition of each organ is indicated by calculating tongue coating ratio of each area. Table I outlines area-specific tongue coating and health condition based on tongue coating detection in Fig. 7.

TABLE I  
AREA-SPECIFIC TONGUE COATING RATIO AND HEALTH CONDITION OF THE TONGUE IMAGE IN FIG. 7 (UNIT : %)

Area	Body Part	Tongue Coating Ratio	Health Condition
Left and Right	Gall Bladder Liver	70.2	Weak function
Top	Kidney Bladder	76.1	Weak function
Central	Stomach Spleen	99.3	Need Caution
Bottom-1	Lung	55.9	Abnormal
Bottom-2	Heart	7.9	Normal

### IV. EXPERIMENTAL RESULT

For the ASM training, 56 landmarks were marked manually on a total of 100 images, two per person, taken from 50 people who stuck out their tongue with a digital camera. Also for PCA and SVM training to classify tongue substance and tongue coating, 20 tongue images were taken from patients with a symptom at an oriental clinic who have higher ratios of tongue coating. We also took 20 tongue images of healthy people who have no tongue coating.

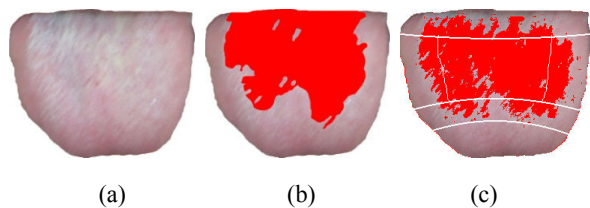


Fig. 8 Detection and comparison of tongue coating (a)Input image (b)Tongue coating area marked by an oriental doctor (c)Resulting tongue coating detection

To test for the validity of the proposed method, we compared tongue coating area marked manually by an oriental doctor and tongue coating image detected by the proposed method as in Fig. 8. An analysis of 10 tongue images in total revealed that tongue coating area detected by the proposed method was coincided as much as 71.8~88.4% with tongue coating area marked manually by a highly experienced oriental doctor as in Table II.

TABLE II  
ANALYSIS ON DETECTED TONGUE COATING (UNIT : %)

	Coincidence Index	Tongue Coating Distribution by Area					
		Kidney	L.Liver	R.Liver	Stomach	Lung	Heart
1	80.4	0.5	3.2	5.0	11.6	2.0	1.0
2	83.9	8.6	47.9	40.4	83.1	1.5	0.4
3	74.6	3.3	6.4	34.0	23.8	11.0	1.0
4	81.6	3.0	18.6	8.9	21.5	3.8	1.6
5	88.0	15.0	10.6	12.5	81.9	2.2	0.5
6	82.8	36.9	37.3	43.3	93.9	31.0	1.2
7	88.4	77.1	76.8	63.5	99.4	56.0	7.9
8	85.9	5.7	78.4	80.6	92.9	80.4	52.6
9	71.8	12.8	57.4	48.0	24.7	3.4	0.8
10	85.4	9.9	3.6	2.3	1.0	1.5	2.0

Many of the existing methods [6]-[8] used highly distinctive colors by choosing certain color values from color values such as RGB, HSV, Lab, and Luv or by administering a statistical analysis. Since we used 3D feature vectors in this paper, we chose three color values from them for SVM training and applied the SVM. Table III summarizes the results of the analysis on good detection based on the three colors. Detection results were best when using S of HSV, b of Lab, and u of Luv, and the coincidence index is lower than in PCA. This result indicates that the proposed method of using PCA and SVM together helps raise the accuracy of tongue coating detection.

TABLE III  
ANALYSIS OF RESULTS OF TONGUE COATING DETECTION USING FIXED COLOR VALUE (UNIT : %)

Image	Coincidence Index		
	Sbu	Hbu	Hsu
1	81.0	70.5	77.6
2	41.6	29.5	37.1
3	62.3	33.9	54.3
4	40.0	27.1	34.7
5	24.3	20.7	21.4
6	61.5	46.1	54.9

7	74.8	58.4	70.3
8	56.0	61.4	56.2
9	53.1	38.3	49.3
10	84.7	33.0	84.7

V. CONCLUSION

This study proposed a method of detecting tongue area from face images, dividing tongue area into subareas, and detecting tongue coating for subareas. We used an ASM-based method because of its ability to detect a certain portion of an image on the basis of landmarks. We also developed a method of dividing reference area for the standardization of tongue diagnosis by marking left and right side from the vertical axis and top and bottom areas using a Lagrange polynomial interpolation. PCA and SVM-based marking of tongue coating area for the divided subareas was found to allow for analysis of health condition of the body part corresponding to each subarea.

Further studies are considered necessary to diagnose diseases from the perspective of the Korean traditional medicine and establish appropriate treatments of each disease by developing a method of defining the type and degree of tongue coating and analyzing the distribution of tongue coating in the subareas in the future.

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