The 13th Industrial Electronics Seminar 2011 (IES 2011)
Electronic Engineering Polytechnic Institute of Surabaya (EEPIS), Indonesia, October 26, 2011

Tongue Image Analysis for Diabetes Mellitus Diagnosis Based on SOM Kohonen

Muh. Fuad Al Haris[1,2] I Ketut Eddy Purnama[1] Mauridhi Hery Purnomo[1]
[1]Department of Electrical Engineering, Faculty of Industrial Technology ITS, 60111, Surabaya, Indonesia
[2]Department of Information Technology, Polytechnic State of Banyuwangi, Jl. Raya Jember, Banyuwangi, Indonesia
f_haris@yahoo.co.id, ketut@ee.its.ac.id, hery@ee.its.ac.id

Abstract

Tongue diagnosis is an important diagnostic method for evaluating the condition of internal organ by looking at the image of tongue . However, due to its qualitative, subjective and experience-based nature, traditional tongue diagnosis has a very limited application in clinical medicine. Moreover, traditional tongue diagnosis is always concerned with the identification of syndromes rather than with the connection between tongue abnormal appearances and diseases. This is not well understood in Western medicine, thus greatly obstruct its wider use in the world. In this paper, we present a novel computerized tongue inspection method aiming to address these problems. First, two kinds of quantitative features, chromatic and textural measures, are extracted from tongue images by using popular digital image processing techniques. Then, SOM Kohonen are employed to model the relationship between these quantitative features and diseases. The effectiveness of the method is tested on 35 patients affected by Diabetes Mellitus as well as other 30 healthy volunteers, and the diagnostic results predicted by the previously trained SOM Kohonen classifiers are compared with the HOMA-B .

Keyword: SOM Kohonen, Tongue Diagnosis, HOMA-B

1. Introduction

Tongue diagnosis [1], [2] is one of the most important diagnostic methods, which is used to observe any abnormal changes in the tongue (also the body of the tongue or substance of the tongue) and the coating of the tongue in making diagnosis of disease [1]. The beauty of tongue diagnosis lies in its simplicity and immediacy: whenever there is a complex disorder full of contradictions, examination of the tongue instantly clarifies the main pathological process. Therefore, it is of great value in both clinic applications and self-diagnosis. Moreover, tongue diagnosis is one of the few diagnostic techniques that accord with the most promising direction in the 21st century: no pain and no injury.

Tongue diagnosis has played such a prominent role in the diagnosis and the subsequent treatment of diseases, it has attracted an increasing amount of attention both in clinical medicine and in biomedicine. However, traditional tongue diagnosis has its inevitable limitations. First, the clinical competence of tongue diagnosis is determined by the experience and knowledge of the physicians. Second, environmental factors, such as differences in light sources and their brightness, have a great influence on the physicians in obtaining good diagnostic results from the tongue. Finally, traditional tongue diagnosis is intimately related to the identification of syndromes, and it is not very well understood by Western medicine and modern biomedicine. Therefore, it is necessary to build an objective and quantitative diagnostic standard for tongue diagnosis.

In this paper, we propose a computerized tongue inspection method based on quantitative features and SOM Kohonen [3]. First, two kinds of quantitative features, chromatic and textural measures, are extracted from tongue images by using popular digital image processing techniques. Then, Som Kohonen are employed to model the relationship between these quantitative features and diseases.

2. Previous Works

Recently, researchers have been developing various methods and systems to circumvent these problems. Supatman and M. H. Purnomo [4] suggested identifying the dirtiness tongue texture's image using a texel (texture element) as a basic element in image processing to identify the typhoid fever in 2007. From the experiments using 89 data (40 data of learning and 49 data of recognition), the system can identify the four models of the differences of tongue's dirtiness from the image tongue according to the titer typhoid 1/100(84.61%), 1/200(92.85%), 1/400(90.00%) and 1/800(75.00%). In 2004 Bo Pang, David Zhang, [5] suggested that a novel computerized tongue inspection method to identification of syndromes rather than with the connection between tongue abnormal appearances and diseases. First, two kinds of quantitative features, chromatic and textural measures, are extracted from tongue images by using popular digital image processing techniques. Then, Bayesian networks are employed to model the relationship between these quantitative features and diseases. The effectiveness of the method is tested on a group of 455 patients affected by 13 common diseases as well as other 70 healthy volunteers, and the diagnostic results predicted by the previously trained Bayesian network classifiers are reported.application. In 2005 Bo Pang, David Zhang, [6], suggested a tongue-computing model (TCoM) for the diagnosis of diabetes mellitus based on quantitative measurements that include chromatic and textural metrics. These metrics are computed from true color tongue images by using appropriate techniques of image processing.

3. Tongue Diagnosis Using SOM Kohonen

The self – organizing neural networks described in this section, also called *topology-preserving maps*, assume a topological structure among the cluster units. This property is observed in the brain, but is not found in other artificial neural networks. There are m cluster units, arranged in a one-or two-dimensional array, the input signals are n-tuples.

The weight vector for a cluster unit serves as an exemplar of the input patterns associated with that cluster. During the self –organization process, the cluster unit whose weight vector matches the input pattern most closely (typically the square of the minimum Euclidean distance) is chosen as the winner. The winning unit and its neighboring units (in terms of the topology of the cluster units) update their weights. The weight vectors of neighboring units are not in general close to the input pattern.

3.1. Architecture

The architecture of the Kohonen self-organizing map is shown in Figure 1. The input for $X_1 - X_n$ is 324 total features from a tongue image. Tongue image is divided into 6 areas. For each areas has 22 color features and 32 texture festures. And the output $Y_1 - Y_n$ is level of severity of pancreatic. There are 5 levels, namely: health, acute, subacute, cronic and degenerative.

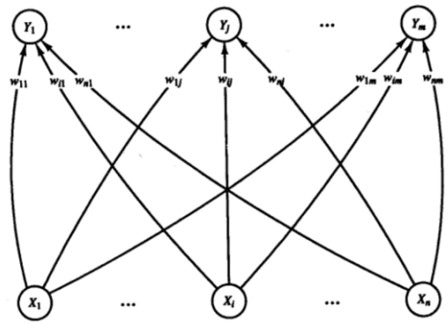

Figure 1. Kohonen self-organizing map

3.2. Algorithm

Step 0. Initialize weights w_{ij}

Set topologycal neighborhood parameters
Set learning rate parameters

Step 1. While stpping condition is false , do Step 2-8
Step 2. For each input vector x, do step 3-5
Step 3. For each *j*, compute:

$$D(j) = \sum_i (w_{ij} - x_i) \quad (1)$$

Step 4. Find index J such that $D(J)$ is a minimum
Step 5. For all units j within a specified neighborhood of J and for all i:

$$w_{ij}(new) = w_{ij}(old) + \alpha\left[x_i - w_{ij}(old)\right] \quad (2)$$

4. Experimental Process

In this paper, we used Canon PowerShot SX20 IS camera, used super macro mode, ISO 100, additional lighting with ring flash camera covered by paper to get soft lighting. To ensure the distance between camera and object fixed 5 cm was used tools as buffer chin. Before image acquisition is done, the patient is done , the patient should be fasting and temporarily stop the use of diabetes medication or insulin injections within 2x24 hours to ensure no effect of the drug on the condition of the pancreas. Typical image of tounge from patients with diabetes mellitus is shown in Figure 2, together with an image of a normal tounge for comparison. The system framework consists of eye image capture, image preprocessing, texture feature extraction and symptomatic analysis. The detailed process is shown in Figure 3.

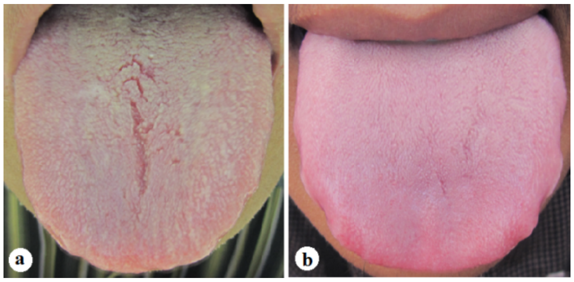

Figure 2. (a) A typical image of the tongue from a patient with Diabetes Mellitus, and (b) a typical normal tongue image.

4.1. Quantitative Color Features

The color always has to be given relative to a specific color space. The extraction of the features of the color can be performed in different colorspaces, which usually include RGB, HSV, CIEYxy, CIELUV and CIELAB. Different from the other color spaces, the HSV color space is an intuitive system in which a specific color is described by its hue, saturation and brightness values. This color space is often used in software systems to aid in interactive selection and manipulation of color. However, the HSV space has discontinuities in the value of the hue around red, which make this approach sensitive to noise. Therefore, in our system we use the remaining four color spaces (RGB, CIEYxy, CIELUV and CIELAB) for the extraction of quantitative features of the color.

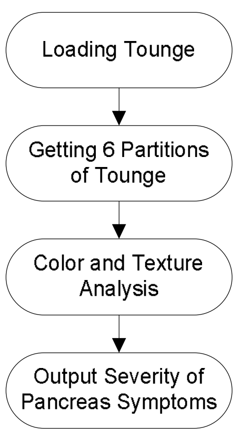

Figure 3. System Flowchart

The metrics for color that are used in our algorithms are the means and standard deviations of the colors of each pixel within a region of the tongue, using all of the four color spaces. Thus, there are a total of 22 different metrics in four color spaces as follows. $CM_i (i = 1,2,...,11)$: Means of each plane of color in the spaces, and $CM_i (i = 12,13,...,22)$: Standard deviation of each plane of color in the four color spaces.

Since both of the L channels in CIELUV and CIELAB indicate the sensation of the lightness in human vision system, we only use it once in the calculation of the features of the color.

Table 1. Color Features

Color Partition	Value	
	Mean	Standard Deviation
R	170.5219	10.9794
G	138.7956	24.3665
B	135.3916	20.6999
X	0.3091	170.5665
Y	0.2964	140.6263
Z	0.2789	136.6892
L	60.5963	110.4725
U	20.3011	120.9738
V	6.9111	130.1374
A	11.6642	129.4454
B	6.5518	130.4921

4.2. Quantitative Texture Features

Methods for extracting the features of the texture can be categorized roughly as follows: feature-based, model-based, and structural. In featurebased methods, some characteristic or characteristics of the textures are chosen and regions are sought in which these characteristics are relatively constant (or the boundaries between the regions). In this paper, two feature-based texture operators, which are derived from the co-occurrence matrix, are implemented to extract different textural features from images of the tongue. These two descriptors are the second moment and the contrast metrics based on a cooccurrence matrix, which are shown respectively as follows:

$$W_M = \sum_{g_1} \sum_{g_2} P^2(g_1, g_2) \quad (3)$$

$$W_M = \sum_{g_1} \sum_{g_2} |g_1 - g_2| P(g_1, g_2) \quad (4)$$

Where $P(g_1, g_2)$ is a co-occurrence matrix and g_1 and g_2 are two values of the gray level. W_M measures the smoothness or homogeneity of an image and it will reach its minimum value when all of the $P(g_1, g_2)$ have the same value. W_C is the first moment of the differences in the values of the gray level betweenthe entries in the co-occurrence matrix. Both of the two textural descriptors are calculated quantitatively and they have little correlation with the sensation of the human vision system.

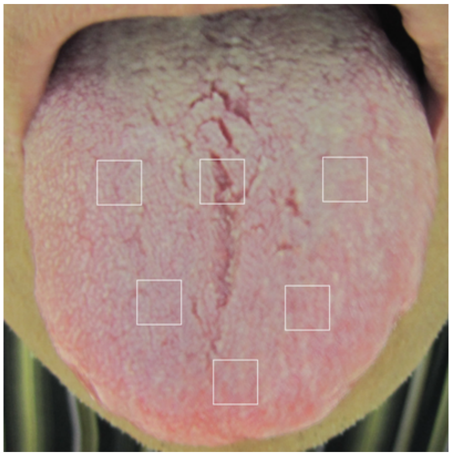

Figure 4. Partition of Tongue

Table 2

Numbers indicating different partion of a tongue	Position of Tongue Partition
1	Top Right edge of the tongue
2	Center of the tongue
3	Top Left edge of the tongue
4	Bottom Left of the tongue
5	Bottom Right of the tongue
6	Tip of the tongue

It has been found in clinical practice that there is some relation between abnormal changes of different parts of the tongue and diseases. That is, different diseases may cause pathological changes at different parts of the tongue. Therefore, we calculate the above two textural metrics for each partition (see Figure 4) of a tongue. For convenience, we denote each partition of a tongue with a number, as shown in Table 1. Thus, we obtain a set of textural features for each partition of tongue, which contains a total of 32 textural metrics as follows.

$$\begin{cases} TM_i = W_{M,i} \\ TM_{i+16} = W_{C,i} (i = 1,2,...16) \end{cases} \quad (i = 1,2,...,16) \qquad (5)$$

Where $W_{M,i}$ and $W_{C,i}$ denote the measurements of W_M and W_C for each partition, respectively.

Table 3. Texture Features

Parameter	0º	45º	90º	135º
Contrast: 1 px	0.1130	0.1419	0.1033	0.1352
Contrast: 2 px	0.1748	0.1960	0.1535	0.1855
Contrast: 3 px	0.2129	0.2482	0.1791	0.2254
Contrast: 4 px	0.2535	0.2974	0.2052	0.2652
Homogeneity: 1 px	0.9435	0.9291	0.9483	0.9324
Homogeneity: 2 px	0.9126	0.9020	0.9233	0.9072
Homogeneity: 3 px	0.8936	0.8761	0.9104	0.8874
Homogeneity: 4 px	0.8737	0.8524	0.8975	0.8679

5. Result

The experimental samples include 65 images from tongue, but after feature extraction 60 images can be used. The resting 5 images cannot be used due to environment factors, including covered by can not be used due to environmental factors such as the slight influence of outside light coming in the area of the tongue, blurred image because the time taken to move the tongue, the tongue shape folded or less panhandle. Among the 60 tongue images, 31 images are the tongue of persons who affected by abnormal pancreas caused by diabetes with varying condition and other 29 images are shot from healthy tongue, and they are divided into two sets: the training set and test set. In this section, we present the experimental results for the diagnosis of diabetes mellitus.

The results presented in this section are divided into three parts. The first part evaluates the performance of the color metrics in each color space (RGB, CIEYxy, CIELUV, CIELAB). The second part evaluates the performance of textural metrics in different partitions of the tongue. Based on the results in the first two parts, we eliminate those metrics that do not perform well. The third part reports the performance of a combined metric that includes the surviving metrics from the first two experiments. To provide a quantitative measurement to evaluate the capability of the different metrics in differentiating diabetes mellitus from other diseases, we used grade of differentiation (GOD), which can be calculated as follows:

$$GOD_i = \left| \frac{A_{i,mean} - O_{i,mean}}{A_{i,mean}} \right| \qquad (6)$$

Where A_i ,mean is the mean of metric *i*, which is evaluated on the samples with diabetes mellitus, and $O_{i,mean}$ is the mean of metric *i*, which is evaluated on all of the other samples.

Finally, for the classification of an image of the tongue (to determine whether it is associated with diabetes mellitus or not) based on the set of metrics, we first use a (so-called) nearest distance rule for the classification of each metric. Then, we employ the consensus of all of the metrics in the set to obtain each conclusion.

5.1. Performance on metrics for color

The objective of this section is to discover which metrics do not perform well for diagnosis of diabetes mellitus. Figure 5 shows the results for the GODs of different metrics (means) in four color spaces (as defined in Section 2.2). For the measurement of the mean, the metric that gives the best performance is CM11 (the B chromatic plane in the CIELAB space), whereas the metric that gives the worst performance is CM2 (the B plane in the RGB space). Moreover, all of the metrics that are related to lightness or brightness (CM4 and CM7) exhibit poor performance. However, the four chromatic metrics in the two CIE perceptual uniform color spaces (CM8–CM11) perform exceptionally well.

Figure 6 illustrates the results of the GODs of different metrics (standard deviation) in the four color spaces. The best performing metrics are CM12 (deviation of R in the RGB space) and CM18 (deviation of L in the CIELUV/AB space), whereas the worst performing metric is CM15 (deviation of Y in the CIEYxy space). A very interesting contrast can be seen for the four chromatic channels that correspond to CM19–CM22 in Figure 6 that show a very poor performance, whereas they perform well in Figure 5.

The diagnostic results of diabetes mellitus based on the 22 chromatic metrics and a subset, which is selected according to the performance presented in this section, of the total chromatic metrics are shown in Table 2. It can be seen that, the ratios of the correct classification are 56.14%, when using all chromaticmetrics and rise up to 66.67%, when a subset of these metrics are used. Also, the values of FAR are decreased through this feature selection.

Table 4. Diagnostic results of diabetes mellitus by using chromatic metrics (number of correct and false classifications to total number)

	CM1–CM22	CM8–CM14, CM16, CM18
Correct/total	32/57	38/57
False/total	142/399	126/399

This section evaluates the suitability of different textural metrics for diagnosing diabetes mellitus. Two kinds of textural features (WM and WC) are implemented for five artitions of the tongue, providing a total of 10 different metrics whose GODs are shown in Figure 7. It can be seen that all of the metrics of WM provide a much better performance than those of WC. TM5 (WM measurement of the root of the tongue) provides the best performance. Such a difference might be the result of the different degrees to which WM and WC correspond to the perception of the human vision system to a specific texture, especially in an image of the tongue.

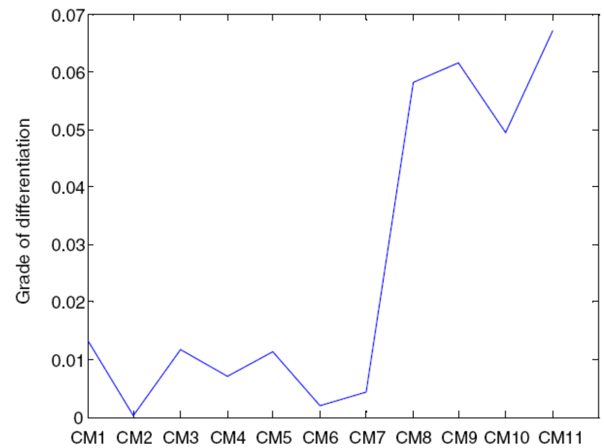

Figure 5. GODs of the means in the four color spaces.

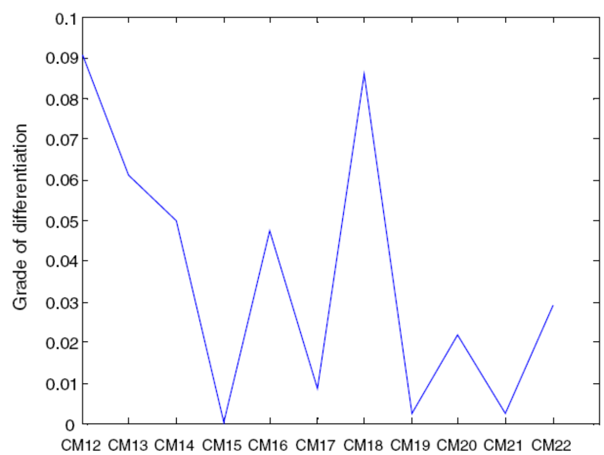

Figure 6. GODs of the standard deviations in the four color space

A problematic result is the relatively low value of GOD for the WM measurement at the tip of the tongue, as shown in Figure 7. Actually, because ofthe existence of hyperplastic filiform papillae, the picture of the tip of a tongue affected by diabetes mellitus is very different from other diseases. However, all of the textural metrics that were introduced in this paper fail to report such a difference.

Table 3 shows the diagnostic results of diabetes mellitus by using the whole textural metrics and a subset of these metrics, respectively. Similar to that case of the chromatic metrics, the feature selection also improves the performance. Note that, although the ratios of correct classification increase, compared with those by using chromatic metrics, the ratios of false classification go up also.

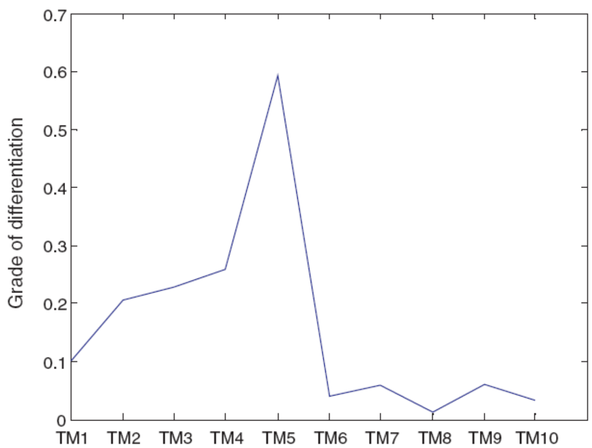

Figure 7. GODs of textural measurements in different partitions of the tongue.

Table 5. Diagnostic results of diabetes mellitus by using textural metrics (number of correct and false classifications to total number)

	TM1–TM10	TM1–TM5
Correct/total	41/57	47/57
False/total	215/399	176/399

5.3. Evaluation basis for diagnosis

Results of classification will be compared with homeostatic model assessment (HOMA)-B (26) test to quantify beta-cell function (see Table III). From 12 patients that show a very clear broken tissue in their iris, they also have a great abnormality in insulin productivity.

$$HOMA - B = \frac{360\, x\, insulin(ulU/ml)}{glu\cos e(mg/dL) - 63}\% \qquad (7)$$

The normal value of fasting glucose is 70-110 mg/dL, and HOMA-B is 70-150%. Classification divided into 4 levels to indicate severity of pancreas organ namely acute for the value of HOMA-B 55-70%, subacute for the value of HOMA-B 40-54%, chronic for the value of HOMA-B 20-39%, and degenerative for the value of HOMA-B 0-19%.

From Table 6, it can be concluded the system can correctly classify 91.7% of abnormal pancreas condition in accordance with the level of severity of pancreatic by evaluating the image of tongue

TABLE 6
COMPARISON TABLE FOR HOMA-B AND CLASSIFICATION

Patient	Fasting Blood Glucose (mg/dL)	Fasting Blood Insulin (ulU/ml)	HOMA-B (%)	Classification Result
A	149	14.8	62.06	Acute
B	171	16.06	53.62	Acute
C	179	8.96	27.85	Chronic
D	188	16.73	48.25	Subacute
E	221	16.58	37.83	Chronic
F	248	5.25	10.23	Degenerative
G	253	16.68	31.65	Chronic
H	260	11	20.13	Chronic
I	270	33.12	55.68	Subacute
J	271	24.07	41.71	Subacute
K	442	2.15	2.04	Degenerative
L	513	47.24	37.84	Chronic

6. Conclusion

In this paper, we proposed a distinct computerized tongue diagnosis approach for the diagnosis of diabetes mellitus based on a quantitative analysis of the pathological changes on the surface of a tongue. Both chromatic and textural features are used to build the mapping from a tongue image to corresponding diseases by a statistical way. Experiments are implemented on a large tongue image database, and the results are promising.

The main contribution of this research is that computerized tongue image analysis approach is proposed for the building of the mapping from tongue signs to Western medicine defined diseases. This will undoubtedly boost the modernization process of the traditional tongue diagnosis and, more importantly, shorten the gap between the tongue diagnosis and clinical application.

References

[1] B. Kirschbaum, “Atlas of Chinese Tongue Diagnosis. Seattle”, WA: Eastland, 2000.

[2] G. Maciocia, “Tongue Diagnosis in Chinese Medicine. Seattle”, WA: Eastland, 1995.

[3] Laurene Fausett, ”Fundamentals of Neural Networks Prentice Hall”, Englewood Cliffs, NJ 07632, 1994.

[4] Supatman, M. H. Purnomo, “Identification of Tongue Image Texture With Gaussian Markov Random Field Method for Typhoid Disease Early Detection”, 2007.

[5] B. P. Zhang, D. Li, N. Wang, “Computerized Tongue Diagnosis Based on Bayesian”, Biomedical Engineering, IEEE transactions on Biomedical Engineering, no 10, vol. 51, October 2004, pp. 1803-1810.

[6] B. P. Zhang, D. Li, N. Wang, "Tongue Image Analysis for Appendicitis Diagnosis", Information Sciences, vol. 175, 2005, pp.160–176.