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Tongue Diagnosis: A Non-Invasive Approach to Detect Diabetes Mellitus & Diabetic Retinopathy Using Colour, Texture & Geometry Features

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ABSTRACT: Diabetes Mellitus is one of the major health problems worldwide. To detect DM & NPDR in its early stages, a non-invasive approach is proposed which uses colour, texture & geometry features for diagnosis. A tongue colour gamut is established with 12 colours representing the tongue colour features. The texture values ofblocksstrategicallylocatedonthetonguesurface, with the additional mean of all eight blocks are used to characterize the nine tongue texture features. Finally, 13 features extracted from tongue images based on measurements, distances, areas, and their ratios represent the geometry features. With the combination of these features we can distinguish DM, NPDR & healthy person from their tongue images.

KEYWORDS: Diabetes Mellitus, Non proliferative Retinopathy, Colour Gamut.

I. INTRODUCTION

The belief that the general health of a person is reflected in his tongue is from the days of Hippocrates.Tongue diagnosis is one of mostly widely used diagnostic methods among the four diagnostic processes in traditional Chinese medicine (TCM). The usefulness of tongue diagnosis lies in its simplicity and immediacy-inspection of the tongue can instantly clarify one's pathological problems that people seeking health care can have their tongues routinely examined. However, this is limited by the fact that the clinical competence of tongue diagnosis is decided by the experience and knowledge of the practitioners. The diagnostic results based on the subjective analysis of the examiners may be unreliable and inconsistent. Which means different doctors may achieve different results for the same visual experience of tongue. Therefore, it is important to have an objective and quantitative diagnostic process for tongue diagnosis to reduce human bias and errors.

Among all features that can be extracted, the tongues chromatic, geometric & texture features play most important role in evaluating a person's health condition. According to Traditional Chinese Medicine, TCM practitioners believe that pathological changes of internal organs can affect the colour appearance of the tongue body. The shape of a human tongue and its relation to a patients' state, either healthy or diseased (and if diseased which disease), is quantitatively analysed usinggeometryfeatures.

Diabetes mellitus (DM) and its complications leading to diabetic retinopathy (DR) are soon to become one of the 21st century's major health problems. This represents a huge financial burden to healthcare officials and governments. A fasting plasma glucose (FPG) test is the standard method practiced by many medical professionals to diagnose DM.



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FPG test is performed after the patient has gone at least 12 hour without food, and requires taking a sample of the patient's blood (by piercing their finger) in order to analyze its blood glucose levels. Even though this method is accurate, it can be considered invasive, and slightly painful (piercing process). Therefore, there is a need to develop a non-invasive yet accurate DM and NPDR detection method.

To do this we have extracted three major attributes of tongue- Colour, texture & geometry. We have used the Colour Gamut to showcase the possible colours observed on a tongue image. Gabor filter of second order is used to determine the texture of tongue. Geometric features are determined using mathematical formulas. A combination of all these features is used to classify a tongue image into normal, diabetic or NPDR category. There are separate researches where colour, texture & geometry features are studied solely. But when these three features are combined, it gives better results.

Paper is organized as follows. Section II describes the related work and literature survey. The features are discussed in detail in section III. Section IV describes the algorithm used in the paper. Section V presents experimental results showing results of images tested. Finally, Section VI presents conclusion.

II. RELATED WORK

With the advancement of technology, various (TDS) hardware systems have been developed for acquiring accurate and high-quality tongue images. The most important aspect of any tongue image acquisition module is the ability to obtain a reproducibletongueimageundervaryinglight conditions. The tongue image obtained using a commercial digital camera without an illuminator is unsuitable for tongue diagnosis. The commercial digital camera has its own internal colour bias and environmental noise can severely distort colour intensity. The colour distortion of the image can be induced by the variation of colour temperature of light sources, the inhomogeneity of light intensity and other unexpected light or reflections. The ideal solution is the isolation of the light environment and the use of a sufficient sunlight lamp. Thus, a practical solution is to perform colour correction with a distorted image. Several colour correction methods such as polynomial regression and topology resolve-map model have been pro- posed for medical image recently by using ColourChecker. Since the ColourChecker embedded in image provides the basic colour information of the ColourChecker, the colour distortion of the acquisition system can be estimated more accurately.

Space resolution of the acquisition module is another important characteristic of TDS hardware resources. TDSs have been recently developed using high-resolution CCD, which can acquire a much larger volume of information on thetonguesurface. The CCD camera, with a resolution of over 8 megapixels with suitable lenses, is believed to acquire more detailed colour information. According to the trend of TDSs, the preferred direction for future development is the implementation of an accurate colour acquisition system because the colour features of the tongue provide significant diagnostic information. A 3CCD camera and hyper spectral imaging are specialized for colour image acquisition, and they have thus been adopted in TDSs.

The tongue segmentation methods, which are based on high-level image segmentation techniques, have been improved to achieve a higher degree of accuracy, but full automation of the segmentation process poses continuing problems. In most cases, the colour and the shape information of a tongue are used for tongue segmentation. The active contour model is an effective method to segment the tongue object, where the contour is determined by the sum of energies, namely gradient around the contour position, elastic force and curvature of contour, and these energies are calculated from the colour information of the tongue edge. The gradient around the contour position is determined by changes of intensities. The elastic force is related with smoothness of the object contour. To improve its performance, a tongue template force or colour gradient vector should be applied to the energies. It is important to improve the accuracy of not only the segmentation error because the edge pixels of the tongue are blurred. Image resolution and focus time are also significant factors in segmentation. A user-friendly interface for segmentation checking and modification may offer a solution to segmentation error.



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For the tongue classification, the clinical features, such as a colour of tongue body and coating, distribution of tongue coating, teeth-mark, fissure and shape of tongue, should be quantified, and relations between the features and the technical properties, which are extracted from a tongue image, should be identified. For this purpose, a statistical withmassivedatawasperformed analysis by several researchers Massivetongueimagedatahavebeenacquiredinclinicalsettings, andthenclassificationtechniques, such as SVM and Bayesian networks, have been proposed. Since these machine-learning techniques take advantage of the data to capture characteristics of interest of their unknown underlying probability distribution, the classification rule is changeable according to sample data for the technical properties. Therefore, it isimportant to identify and standardize the meaningful properties of a tongue. Tongue classification and diagnosis is a difficult process, but extensive and accurate tongue image data can be used to determine standard tongue diagnosis parameters. In the future, the performance of TDSs will continue to improve with the advancement of acquisition devices and classification techniques. For accurate tongue diagnosis, the various types of TDSs have been developed with diverse techniques. However, the differences of TDSs can be minor effect in terms of a collaborative research or competitiveness in the clinical. Especially, an erroneous diagnosis can result from image resolution, different lighting condition and the posture of a tongue. To solve this problem, an International Standard for the functions and elements of TDS should be proposed. So far, we reviewed the various TDSs in the manuscript. The image acquisition device, light sources, input user interface, colour correction, segmentation, features for the tongue classification and safety can be contents of the standard.

III. TONGUE COLOUR, TEXTURE & GEOMETRY FEATURES

1) Colour Feature

Three aspects of tongue colour are considered- the tongue colour gamut to classify tongue related colours with tongue-unrelated colours, colour centres value of main colour categories and colour distribution of typical image features. Representative colours are then extracted & combined together to form the tongue colour distribution in the CIEx chromaticity diagram to provide an intuitionist way to describe all visible colours according to its colour stimulus & thus the relative position of tongue colour& its colour composition would be observed easily. 12 colour centers are predefined to meet the demanding them in tongue diagnosis of TCM



Fig 1. Definition of 12 colour centres in CIE chromaticity diagram



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Fig 2. 12 colours from the colour gamut

For each foreground pixel, corresponding RGB values are first extracted, and converted to CIELAB by transferring RBG to CIEXYZ using

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} 0.4124 & 0.3576 & 0.1805 \\ 0.2126 & 0.7152 & 0.0722 \\ 0.0193 & 0.1192 & 0.9505 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix}$$
(1)
Followed by CIEXYZ to CIELAB via
$$\begin{cases} L *= 166.f \left(\frac{Y}{Y_0} \right) - 16 \\ a *= 500. \left[f \left(\frac{X}{X_0} \right) - f \left(\frac{Y}{Y_0} \right) \right] \\ b *= 200. \left[f \left(\frac{Y}{Y_0} \right) - f \left(\frac{Z}{Z_0} \right) \right] \end{cases}$$
(2)

where $f(x) = x^{1/3}$ if x > 0.008856 or f(x) = 7.787x + 16/116 if $x \le 0.008856$.

 X_0, Y_0 , and Z_0 in 3 are the CIEXYZ tri stimulus values of the reference white point.TheLABvaluesarethencomparedto12 coloursfrom the tongue colour gamutand assigned the colour which is closest to it (measured using Euclidean distance). After evaluating all tongue foreground pixels, the total of each colour is summed and divided by the total number of pixels. This ratio of the 12 colours forms the tongue colour feature vector v, where

 $v = [c_{1}, c_{2}, c_{3}, c_{4}, c_{5}, c_{6}, c_{7}, c_{8}, c_{9}, c_{10}, c_{11}, c_{12}]$ and c_i represents the sequence of colours.

2) Texture Feature

Texture feature extraction from tongue images is presented in this section. To better represent the texture of tongue images, eightblocksofsize64×64strategicallylocatedon thetonguesurfaceareused.Ablocksizeof64×64waschosendue to the fact that it covers all eight surface areas very well, while achieving minimum overlap. Larger blocks would cover areas outside the tongue boundary, and overlap more with other blocks. Smaller block sizes would prevent overlapping, but not cover the eight areas as efficiently. The blocks are calculated automatically by first locating the center of the tongue using а segmented binarytongue foregroundimage. Followingthis, the edgesofthetongueareestablishedandequalpartsaremeasured from its center to position the eight blocks. Block 1 is located at the tip; Blocks 2 and 3, and Blocks 4 and 5 are on either side, Blocks 6 and 7 are at the root, and Block 8 is the center. The Gabor filter is а linear filter used in image processing, at andiscommonlyusedintexturerepresentation. To compute the texture value of each block, the 2-D Gabor filter is applied and defined as



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$$G_k(x, y) = \exp\left(\frac{x^2 + \gamma^2 \cdot y^2}{-2\sigma^2}\right) \cos\left(2\pi \frac{x'}{\lambda}\right)$$
(3)

where $x' = x \cdot cos\theta + y \cdot sin\theta$, $y' = -x \cdot sin\theta + y \cdot cos\theta$, σ is the variance, λ is the wavelength, γ is the aspect ratio of the sinusoidal function, and θ is the orientation. A total of three σ (1, 2, and 3) and four θ (0°, 45°, 90°, and 135°) choices were investigated to achieve the best result. Each filter is convolved with a texture block to produce a response

$$R_{k}(x, y): R_{k}(x, y) = G_{k}(x, y) * im(x, y)$$
(4)

where im(x, y) is the texture block and * represents 2-D convolution. Responses of a block are combined to form FR_i , and its final response evaluated as follows:

 $FR_{i}(x, y) = max(R1(x, y), R2(x, y), \dots, Rn(x, y))$ (5)

which selects the maximum pixel intensities, and represents the texture of a block by averaging the pixel values of FR_i . In the end, σ equal to 1 and 2 with three orientations (45°, 90 ° and 135°) was chosen.

3) Geometry Features

In state-of-the-art computerized tongue image analysis, colour and texture features are the most prevalent. There exists little or no literature on tongue image analysis using geometry features, whereas in traditional medicines such as traditional Chinese medicine (TCM) the shape of a tongue can be used to determine a patients' illness. This includes various measurements of length, area, and angle extracted from tongue images. Every image is segmented with the background removed and tongue foreground remaining. From each tongue image consisting of a tip, body, and root, 13 geometry features derived from measurements, distances, areas, and their ratios are extracted. Using these features we define 5 tongue shapes based on TCM.

We describe 13 geometry features extracted from tongue images. These features are based on measurements, distances, areas, and their ratios.

1) Width: The width w feature (see Fig.3) is measured as the horizontal distance along the x-axis from a tongue's furthest right edge point (x_{max}) to its furthest left edge point (x_{min})

$$w = x_{max} - x_{min} \qquad (6)$$

2) Length: The length *l* feature (see Fig. 3) is measured as the vertical distance along the y-axis from a tongue's furthest bottom edge (y_{max}) point to its furthest top edge point (y_{min})

$$l = y_{max} - y_{min}(7)$$

3) Length-width ratio: The length-width ratio lwis the ratio of a tongue's length to its width

$$lw = l/w(8)$$



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4) Smaller half-distance: Smaller half-distance z is the half distance of *lor w*depending on which segment is shorter (refer to Fig. 3)

$$z = min(l, w)/2. (9)$$

5) Center distance: The center distance (*cd*) (refer to Fig. 4) is distance from w'^sy-axis center point to the center point of 1 (*ycp*)

$$cd = \frac{(max(y_{xmax}) + max(y_{xmin}))}{2} - ycp \quad (10)$$

6) Center distance ratio: Center distance ratio (cdr) is ratio of cd to l

$$cdr = cd/l$$
 (11)

- 7) Area: The area (a) of a tongue is defined as the number of tongue foreground pixels.
- 8) Circle area: Circle area (*ca*) is the area of a circle within the tongue foreground using smaller half-distance z, where r = z (refer to Fig. 5):

$$ca = \pi r^2$$
. (12)



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Fig 5 Illustration of feature 8

Fig 6 Illustration of feature 10

9) Circle area ratio: Circle area ratio (*car*) is the ratio of *ca* to *a*

$$car = ca/a$$
 (13)

10) Square area: Square area (*sa*) is the area of a square defined within the tongue foreground using smaller halfdistancez (refer to Fig. 6):

$$sa = 4 z^2 \tag{14}$$

11) Square area ratio: Square area ratio (sar) is the ratio of sato a

$$sar = sa/a(15)$$

12) Triangle area: Triangle area (tar) is the area of a triangle defined within the tongue foreground (see Fig. 7). The right point of the triangle is x_{max} , the left point is x_{min} , and the bottom is y_{max} .



Fig 7 Illustration of feature 12 13) Triangle area ratio: Triangle area ratio (tar) is the ratio of ta to a



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tar = ta/a (16)

IV. PROPOSED METHODOLOGY

The flow of proposed algorithm is as follows.

- 1. Input image is selected from tongue image database.
- 2. Pre-process the image to remove noise
- 3. For colour features,
 - 1. 12 colours are extracted & converted to corresponding LAB values.
 - 2. The Euclidian distance is calculated
 - 3. Mean, average & standard deviation is calculated.
- 4. For texture features,
 - 1. The tongue image is divided in 8 blocks strategically located on tongue.
 - 2. Gabor filter is used for texture feature extraction of each block
- 5. For geometry features, extract various shape features and their ratios using mathematical formulae.
- 6. For matching,
 - 1. Divide the database into training and testing set.
 - 2. SVM is used for training and classification
 - 3. Determine whether the input image is DM/NPDR/Healthy.
- 7. Use Sequential feature selection (SFS), to select best features for matching.
- 8. Result

V. EXPERIMENTAL RESULTS

Stepwise result is shown as below. First we select an input image from the database. The image is resized to obtain a standard data set. To remove any noises from the image the image is filtered.



Fig 8 Input Image

Fig 8 shows the GUI of the program. We can select any of the three features to be calculated on the selected tongue image. The colour features are extracted from the input image. 12 colours as mentioned in section III are calculated.



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Based on these 12 colours, a colour vector is determined. The colours are plotted on the chromaticity diagram. Fig 9 shows the colour gamut in which the region of colours present on tongue image is highlighted.



Fig 9 Colours plotted on the chromaticity diagram

For texture feature extraction, first the image is divided into blocks. Each block is then convolved with 2D Gabor filter. This will give us the texture features of the input tongue image. Fig10 shows the block separation of input tongue image. We obtain different values for texture for tongue images from Healthy, DM & NPDR dataset.



Fig 10 Block separation

When user clicks on the "Geometry Feature" on the GUI, geometry features are displayed. Using mathematical formulas the values of 13 geometric features is calculated. All the geometric features are described in section III. Fig 11



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shows the extraction of geometric features of the input image. The area, triangular area & the square area are highlighted in the image below.



Fig 11 Geometry features

After all the colour, texture & geometry features are extracted, they are analysed. SVM is used for classification. After training, the classifier is able to distinguish between healthy & NPDR patients with the help of the extracted features. The final result is displayed as shown in Fig. 12.



Fig 12 Classification result

VI. CONCLUSION

We have implemented a non-invasive technique to use tongue images and detect diabetes mellitus & non proliferative diabetic retinopathy using colour, texture & geometry features together. This method requires minimum human intervention & can be used at the diabetes screening laboratories. Further, we can include algorithms to determine the age group of the patients.

References

- J. H.Hipwell, F. Strachan, J. A. Olson, K. C. McHardy, P. F. Sharp, and J. V. Forrester, "Automated detection of micro aneurysms in digital redfree photographs: A diabetic retinopathy screening tool," Diabetic Med., vol. 7, pp. 588–594, 2000.
- [2] M. E. MartinezP erez, A. Hughes, S. Thom, A. Bharath, and K. Parker, "Segmentation of blood vessels from red-free and fluorescein retinal images," Med. Image Anal., vol. 11, pp. 47–61, 2007.



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- [3] T. Spencer, J. A. Olson, K. C. McHardy, P. F. Sharp, and J. V. Forrester, "An image-processing strategy for the segmentation of microaneurysms in fluorescein angiograms of the ocular fundus," Comput. Biomed. Res., vol. 29, pp. 284–302, 1996.
- [4] M. Niemeijer, B. van Ginneken, J. Staal, M. S. A. Suttorp-Schulten, and M. D. Abramoff, "Automatic detection of red lesions in digital colour fundus photographs," IEEE Trans. Med. Imag., vol. 24, no. 5, pp. 584–592, May 2005.
- [5] M. Niemeijer, B. van Ginneken, M. J. Cree, A. Mizutani, G. Quellec, C. I. Sanchez, B. Zhang, R. Hornero, M. Lamard, C. Muramatsu, X. Wu, G.Cazuguel, J.You, A.Mayo, Q.Li, Y.Hatanaka, B.Cochener, C.Roux, F.Karray, M.Garcia, H.FujitaandM. D.Abramoff, "Retinopathyonline challenge: Automaticdetectionofmicroaneurysmsindigital colourfundus photographs," IEEE Trans. Med. Imag., vol. 29, no. 1, pp. 185–195, Jan. 2010.
- [6] J. J. Μ. D. Abramoff, Μ. Niemeijer, М. Α. Viergever, and B. Staal, van Ginneken, "Ridgebasedvesselsegmentationincolourimagesoftheretina," IEEE Trans. Med. Imag., vol. 23, no. 4, pp. 501–509, Apr. 2004.
- B.Zhang, F.Karray, Q.LiandL.Zhang, "Sparserepresentation classifier formicroaneurysmdetection and retinal blood vesselextraction," Inf. Sci., vol. 200, pp. 78–90, 2012.
- B. Zhang, X. Wu, J. You, Q. Li, and F. Karray, "Detection of microaneurysms using multi-scale correlation coefficients," Pattern Recog., vol. 43, pp. 2237–2248, 2010.
- B. Zhang, L. Zhang, L. Zhang, and F. Karray, "Retinal vessel extraction by matched filter with first-order derivative of Gaussian," Comput. Biol. Med., vol. 40, pp. 438–445, 2010.
- [10] Prevention of Blindness From Diabetes Mellitus, World Health Organization, Geneva, Switzerland, 2006.