Tongue image analysis for Detection of Diabetes mellitus

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Abstract

Diabetes mellitus (DM) and its complications become one of the major health problems. Tongue diagnosis is an important diagnostic method in traditional Chinese medicine (TCM). The proposed paper explains how diabetes is detected in an early edge using a non-invasive approach as tongue image analysis.

The tongue image database is collected using a DSLR camera with specific resolution. The geodesic flow was evaluated in the lower part, and the Geo-gradient vector flow was evaluated in the upper part. Polar edge detector and ACM technique used for clearing edges during segmentation. Using the tongue color gamut, tongue foreground pixels are first extracted and assigned to one of 12 colors representing this gamut. The ratio of each color of the entire image is calculated and forms a tongue color feature vector. Experimenting 120 Healthy and 180 Disease tongue samples, results classified with an average accuracy of 84.34% using KNN and SVM classifier.

Keywords- Diabetes mellitus (DM), traditional chinese medicine (TCM), active contour model (ACM), polar edge detector, KNN

1. Introduction

The belief is that the health status of the internal organs can be reflected on the tongue [1]. Hence, visual examination is an important aspect of TCM [1] [2]. The tongue is one of the important internal organs of the body as it is connected to every other organ of the body. The human tongue contains numerous features that can be used to diagnose disease, with color features being the most important. Traditionally, medical practitioners would examine these color features based on years of experience [3][4]. Many other techniques used for the detection of diabetes, but all these are invasive. It requires time as well as follows some rules like fasting and all.

To overcome these issues, medical imaging used a non-invasive process for early detection of diabetes. As it is non-invasive, no instrument is brought into physical contact with the body for the detection of disease [5]. So this paper states the detection of diabetes mellitus in early edge by tongue image analysis using different color features.

1.1 Issues found in the Existing System

The following are some reasons that it's necessary to develop tongue image analysis for the detection of diabetes.

- The tongue image database is rarely collected in hospitals. So tongue image construction is one of the important tasks. Various methods are observed in a research paper to collect an image dataset. Features obtained from images depend on how are constructed. So for increasing accuracy, uniform and accurate image acquisition is important with the proper tool.
- The irregular shape, tongue color, saliva present on the tongue, image construction time and why is changes person to person. So its effect on segmentation result, feature extraction, and finally on output accuracy [6].
- Color gamut separation and correction are affecting color feature extraction. Hence the proper method is necessary [8].

Although some research has been done in skin color characterizing [15] and color analysis [10] [11], to date, there has been no comprehensive study on tongue color distribution analysis. This might be due to not enough high-quality tongue images and there is not a "complete" tongue image database covering people of various health statuses. Based on the investigation of the tongue color space, feature extraction methods are proposed for diagnostic classification purposes, such as classification of healthy and non-healthy people.

This paper represents the following design model for the classification of samples into healthy and diabetes disease affected.

1.2 Protocol design and methods

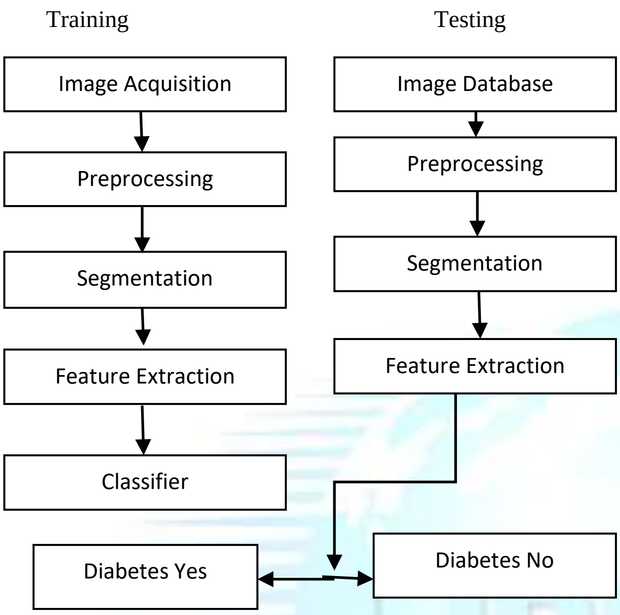

Fig.1.2 Design Algorithm

The remainder of this paper is organized as follows. Section II summarizes tongue image acquisition and preprocessing of images. Color correction and the composition of the tongue image database. Section III, to establish the segmentation process and tongue color space, distribution characteristics of tongue colors are thoroughly described, including the tongue color gamut and its boundary model. Section IV presents the Clustering process and corresponding result and discussion. Finally, the references in Section V.

2. Tongue Image Acquisition & Preprocessing

2.1 Tongue Image Acquisition

Tongue image acquisition plays a vital role in the early detection of diabetes. In Hospital no one physician/ Doctor will use tongue image as the only source for diagnosis, but they use the tongue as a preliminary examination of tongue analysis [12].

The tongue image database is composed of 300 images (one image per person) split into 120 healthy samples and 180 disease samples. DSLR camera with 24-bit resolution (fig.2) used for image capturing. The image captured in JPEG format that ranged from 257*189 pixels to 443*355 pixels. The images were color corrected for eliminating noise caused by illumination and device handle. The age of persons lies between 30 to 85 years. Healthy samples collected through a blood test. In disease class, samples were collected from inpatient with illness determines by their admission note as well as a lab report.

2.2 Tongue image preprocessing

Tongue image preprocessing is essential for accurate and effective feature extraction.

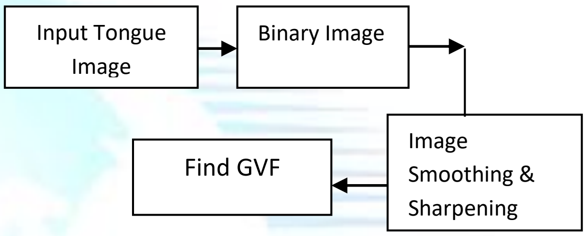

Fig.2.2 Steps in Image Preprocessing

The first Input image is converted o binary image. The next step is to find different color space as RGB, CMYK, LAB, CIE, etc.. Image smooth is done by a Gaussian convolution method to remove noise and sharpening done by Gradient process also Sobel operator used for edge detection. Techniques Edge detectors are essential tools for tongue diagnosis and one of the most popular techniques [16]. The Prewitt, Sobel, and Laplacian filters are commonly used edge detectors for medical image processing. Finally, the image GVF is finding out.

3. Segmentation and Color feature extraction

3.1 Tongue segmentation

Segmentation is one of the most prerequisites and difficult steps in an automated tongue diagnosis system.

3.1.1 Need

- The complexity of the pathological tongue, the variance of the tongue shape, and interference of the lips make automated tongue segmentation very challenging
- The result of tongue segmentation directly influences the performance of the entire system[14]
- Noise in an image, Diffused boundaries, redundant edges
- A boundary may be blurred due to moving object

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- Miss-focus of a camera device
- Low signal to noise ratio of the capture device

In previous research, Classical gradient and ACM used combine but certain drawbacks will be there as a weak boundary in consecutive problems will be indifferent edges. So to overcome all that, we are using a combination of polar edge detector and ACM technique.

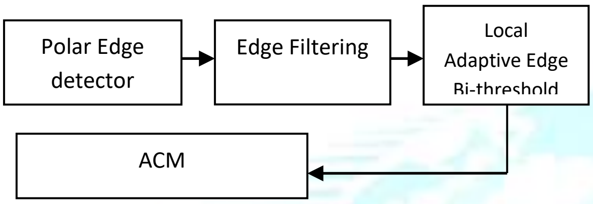


Fig.3.1 Tongue Image Segmentation

Polar edge detector:- This method used to extract the edge of the tongue body. Firstly finding the intensities in 6 directions and then get the second derivative of the Gaussian filter used for dark line detection.

Edge Filtering:-Edge filtering used to minimize the effect of texture and coating of the tongue. Gaussian operator (Sobel operator) used for detecting the edges and removing useless edges. For this standard deviation is finding out and by determining threshold binary edge is cleared out.

Local Adaptive Edge Bi-threshold After edge filtering, we introduce a local adaptive bi-thresholding method to binarize the polar edge image. Local adaptive thresholding is used to convert an image consisting of grayscale pixels to just black and white scale pixels. Local adaptive thresholding chooses different threshold (T) values for every pixel in the image based on an analysis of its neighboring pixels. After edge filtering and binarization, a morphological method is further used to post-filter an edge without enough length.

Active contour model (ACM) This also called the Snake model. For the medical image segmentation ACM model is widely used as it has very good resulted as compare to others. A snake is an energy minimizing, deformable spline influenced by constraint and image forces that pull it towards object contours and internal forces that resist deformation. Snakes may be understood as a special case of the general technique of matching a deformable model to an image employing energy minimization. In two dimensions, the active shape model represents a discrete version of this approach, taking advantage of the point distribution model to restrict the shape range to an explicit domain learned from a training set. Snakes do not solve the entire problem of finding contours in images since the method requires knowledge of the desired contour shape beforehand. Rather, they depend on other mechanisms such as interaction with a user, interaction with some higher-level image understanding process, or information from image data adjacent in time or space [13].

A simple elastic snake is defined by a set of n points v_i for $i=0,- - - - n-1$, the internal elastic energy term $E_{internal}$, and the external edge-based energy term $E_{external}$. The purpose of the internal energy term is to control the deformations made to the snake, and the purpose of the external energy term is to control the fitting of the contour onto the image. The external energy is usually a combination of the forces due to the image itself E_{image} and the constraint forces introduced by the user E_{con}.

The energy function of the snake is the sum of its external energy and internal energy, or

$$E^*_{snake} = \int_0^1 E_{snake}(v(s))\, ds = \int_0^1 \left(E_{internal}(v(s)) + E_{etxernal}(v(s)) + E_{con}(v(s))\right) ds$$

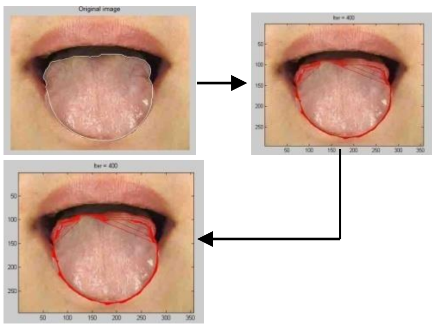


Fig.3.1.2 Tongue segmentation

3.2 Color Features Extraction

Tongue colors are only a subset of the total visible colors [8]. CIELAB is a nonlinear transformation of RGB where the Euclidean distance between two colors is equal to their perceptual distances. Algorithms that process color images often produce better results in CIELAB. RGB operates on three channels: red, green, and blue[17]. The lab is a conversion of the same information to a lightness component L*, and two-color components - a* and b*[2]. Lightness is kept separate from color so that you can adjust one without affecting the other. Lab chromaticity is the recommended method for boosting colors. Hence initially we convert RGB image to LAB image.

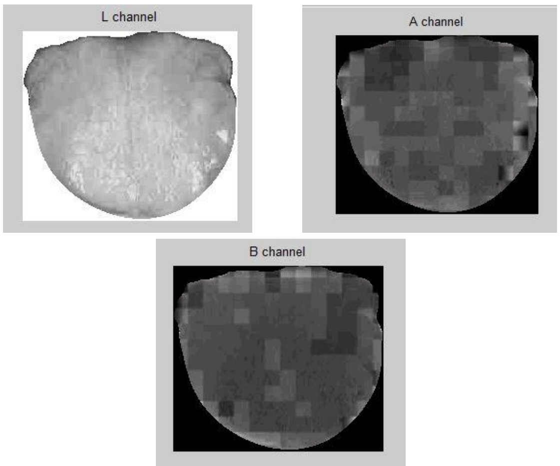


Fig.3.2 LAB Channel Image

Every foreground tongue pixel color is first compared to the proposed 12 color centers and assigned to its nearest color [9]. Each tongue image has been decomposed into 12 colors, with the first 8 colors belonging to the tongue substance and the last 4 colors belonging to the tongue coating. Therefore, we combined all the image pixels of the 8 colors (cyan, red, blue, purple, deep red, light red, light purple, and light blue) as the tongue substance, while image pixels of the 4 remaining colors (black, gray, white, yellow) are the tongue coating [4] [10].

The figure shows separated examples for various kinds of tongue images in terms of different amounts of the tongue coating.

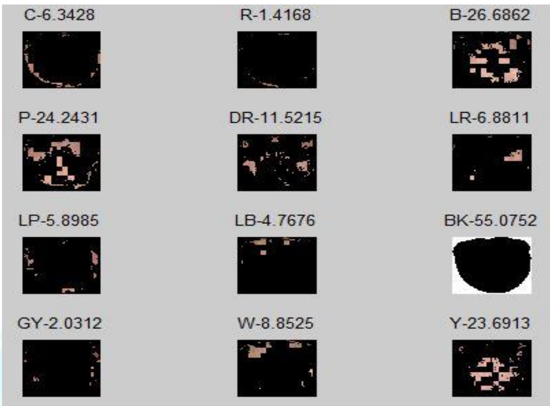
Fig.3.2.1 Color Features

4. Clustering and Result Discussion

4.1 Clustering

K means clustering used as a classifier [6] to do the image classification as Healthy or abnormal images. KNN algorithm several times with different values of K and choose the K that reduces the number of errors. KNN based on measuring the distances between the test data and each of the training data to decide the final classification output.

The clustering process will repeat 3 times to avoid local minima [11],[14]. Parameters are to be considered as distance, sqEuclidean, emptyaction, singleton, Replicates. Finally will get clustered image as shown in fig.4.1



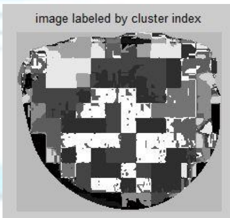
1
. Clustering

4.2 Result & Discussion

The tongue image database is composed of 300 images (one image per person) split into 120 healthy samples and 180 disease samples. All samples are verified by the Blood test and FPG test. Half of the images used for training and half used for testing. The process is repeated 4 times to get accuracy. The result has taken by using KNN classifier. The same result is also verified using the SVM classifier also. Accuracy is found using

Average Accuracy =(sensitivity + specificity) / 2

The resulting accuracy is 81.23 %. Instead of considering all 12 color features if we use only selected best features that can discriminate, then accuracy is increased up to 84.34 %.



Sr. No	**Features**	**Accuracy**
1	cyan, red, blue, purple,	81.23%.

	deep red, light red, light purple, light blue, black, gray, white, yellow	
2	cyan, blue, deep red light purple, white	84.34 %

Table 4.2 Result

Following fig. shows typical Healthy and DM samples

Fig.4.2.1 Typical DM samples

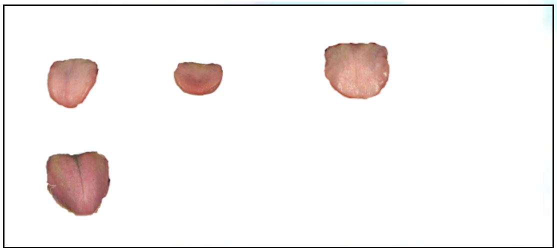


Fig.4.2.2 Typical Healthy samples

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