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Diabetes Mellitus Discovery based on Tongue Texture Features using Log Gabor Filter Mechanism

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ABSTRACT: Diabetes mellitus can be defined as a metabolic disorder of multiple aetiology, which characterized by chronic hyperglycemia (symptoms of carbohydrate, fat and protein metabolism). These are resulting from defects in insulin secretion, insulin action or both. Diabetes mellitus is gradually becoming an epidemic, affecting almost every single country. This diabetes mellitus has given a large amount of burden on governments and healthcare officials. In this paper, we propose a method to detect DM initial stage based on three groups of features extracted from tongue images. They include color, texture, and geometry tongue color features with a log gabor filter mechanism. Concerning biological vision criteria, the log-Gabor filters mimic closely analysis the tongue texture features. Relational statistics of natural images have similar shape of trained images which supports the proposed log Gabor filter as an adequate scheme for matching biomedical features. In this proposed system we tested the proposed filters both in texture segmentation and texture recognition aspects. This study shows that, as expected, the resulting filters perform better than the traditional ones with real textures.

KEYWORDS: Diabetes, Log gabor filter, Tongue, Texture

I. INTRODUCTION

iabetes is a group of metabolic diseases caused by hyperglycemia this is because of defects in insulin secretion, insulin action and both. Next stage chronic hyperglycemia of diabetes is associated with long term damage, dysfunction, and failure of different organs of body, especially the eyes, kidneys, nerves, heart, and blood vessels. This deficiency leads to destruction of the b-cells of the pancreas with consequent insulin deficiency to abnormalities that result in resistance to insulin action and reaction process. The basis of the abnormalities found in carbohydrate, fat, and protein metabolism in diabetes is deficient action of insulin on target tissues. Deficiency of insulin results from inadequate insulin secretion otherwise diminished tissue responses to insulin at the complex pathways of hormonal reaction in the body. Improper insulin secretion and defects in insulin action that is frequently coexist in the same patient and it is often unclear which abnormality is the primary cause of the hyperglycemia. The symptoms of marked hyperglycemia include which includes polyuria, polydipsia, weight loss, sometimes with polyphagia, and blurred vision impairment. The growth and susceptibility to certain infections may also accompany chronic hyperglycemia in so many patients. Life-threatening consequences of uncontrolled diabetes are hyperglycemia with keto acidosis and the non ketotic hyperosmolar syndrome. Long-term complications of diabetes causes retinopathy with potential vision loss, nephropathy leading to renal failure, peripheral neuropathy with foot ulcers, amputations, Charcot joints, and autonomic neuropathy causing gastrointestinal, genitourinary, and cardiovascular symptoms and sexual dysfunction. Patients with diabetes have an increased incidence of atherosclerotic cardiovascular, peripheral arterial and cerebrovascular disease. Hypertension and abnormalities of lipoprotein metabolism are often found in people with diabetes. The vast majority of cases of diabetes fall into two broad etiopathogenetic categories. In one category, type 1 diabetes, the cause is an absolute deficiency of insulin secretion. Individuals at increased risk of developing this type of diabetes can often be identified by serological evidence of an autoimmune pathologic process occurring in the pancreatic islets and by genetic markers. In the other, much more prevalent category, type 2 diabetes, the cause is a combination of resistance to insulin action and an inadequate compensatory insulin secretary response. In the latter category, a degree of hyperglycemia sufficient to cause



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pathologic and functional changes in various target tissues, but without clinical symptoms, may be present for a long period of time before diabetes is detected. During this asymptomatic period, it is possible to demonstrate an abnormality in carbohydrate metabolism by measurement of plasma glucose in the fasting state or after a challenge with an oral glucose load.

Classification of Diabetes Mellitus and Other Categories of Glucose Regulation:

Assigning a type of diabetes to an individual often depends on the circumstances present at the time of diagnosis, and many diabetic individuals do not easily fit into a single class. For example, a person with gestational diabetes mellitus may continue to be hyperglycemic after delivery and may be determined to have, in fact, type 2diabetes. Alternatively, a person who acquires diabetes because of large doses of exogenous steroids may become normoglycemic once the glucocorticoids are discontinued, but then may develop diabetes many years later after recurrent episodes of pancreatitis. Another example would be a person treated with thyroids who develops diabetes years later. Because thiazides in themselves seldom cause severe hyperglycemia, such individuals probably have type 2 diabetes that is exacerbated by the drug. Thus, for the clinician and patient, it is less important to label the particular type of diabetes than it is to understand the pathogenesis of the hyperglycemia and to treat it effectively.

Tongue Diagnosis Based Analysis:

Tongue diagnosis [1] is one of the most important diagnostic methods those are used to observe any abnormal changes in the tongue and the coating of the tongue in making diagnosis of disease [2]. 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 with pain and no injury. Tongue diagnosis has played such a prominent role in the diagnosis and the subsequent treatment of disease and 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. So, that it is necessary to build an objective and quantitative diagnostic standard for tongue diagnosis.

II. LITERATURE SURVEY

[1] Microaneurysm detection from diabetic retinopathy patient's non-dilated pupil digital images. It is an extension to automated DR screening system described earlier. The system intends to help the ophthalmologists in the diabetic retinopathy screening and treating process to detect symptoms faster and more easily than the existing. The algorithm was working on very poor quality images too. Although further development of this algorithm is still required, the results are satisfying. [2] Monitoring the progression of early diabetic retinopathy is a prerequisite for assessing the efficacy of new drugs and treatment regimens. Quantification of retinal pathology by digital image-processing offers an accurate and highly repeatable technique for monitoring fundal changes. The region-growing approach to the quantification of microaneurysms in digitized fluorescein angiograms represents an improvement on existing techniques, in terms of its true-positive rate for a given false-positive rate. The complete delineation of each microaneurysm, as opposed to a mere marking of its location, facilitates the use of other parameters, such as size, energy, and morphology, in the study of the natural history of these lesions. [3] Niemeijer, Meindert presented the robust detection of red lesions in digital color fundus photographs which is a critical step in the development of automated screening system for diabetic retinopathy. This existing study proposed a novel red lesion detection method is presented based on a hybrid approach, combining prior works by Spencer and Frame with two important new contributions. The first contribution is a new red lesion candidate detection system based on classification of pixels. Using these technique red lesions is separated from the background of the image. Then removal of the connected vasculature object is considered possible red lesions in the image. After that an extensive number of new features are added to those parameters. The detected candidate objects are classified by features extracted and with a k-nearest neighbor classifier approach. Evaluation was performed on image test set representative of those normal feature found in a screening set. [4] In this paper, evaluation has been done using accuracy of hard classifications and values of soft



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classifications. Other evaluation measures might be more appropriate, depending on the application at hand. For example, if one is interested in examining the tortuosity of the vessels, the width of the vessels might not be important, only the centerlines. The measures used do not take into account the number of branches, the connectedness of the vessels or the number of branching points, which all might be relevant in specific applications. [5] Accurate extraction of retinal blood vessels is an important task in computer aided diagnosis of retinopathy. The Matched Filter (MF) is a simple yet effective method for vessel extraction. However, a MF will respond not only to vessels but also to nonvessel edges. This will lead to frequent false vessel detection. The author proposed a novel extension of the MF approach that is the MF-FDOG, to detect retinal blood vessels. MF-FDOG is composed of the original MF which is a zero-mean Gaussian function and the FDOG- first-order derivative of Gaussian function. The vessels are detected by thresholding the retinal image's response to the MF, while the threshold is adjusted by the image's response to the FDOG. The proposed MF-FDOG method is very simple but however it is simple it reduces significantly the false detections produced by the original MF and detects many fine vessels that are missed by the MF. [6] Among the four diagnostic processes of TCM: inspection process, auscultation process and olfaction process inquiry and pulse feeling and palpation, the examination of tongue is one of the most important approaches to get significant evidences for diagnosing the patient's health conditions. However, owing to its drawbacks in quantification and standardization, the development of tongue diagnosis is stagnated. Computerized methods for TCM allow researchers to identify required information more efficiently, discover new relationships which are obscured by merely focusing on Western medicine, and bridge the gaps between Western Medicine and TCM. Therefore, getting the overall information about tongue surface is very important for computerized tongue diagnosis system. In this chapter, an AOTF based HTIS which can capture hyper spectral images of human tongue at a series of wavelengths is developed and used in tongue diagnosis. The basic principles and instrumental systems of the new system, the data pre-processing method as well as some applications are presented. Compared with the push broom hyper spectral tongue imager used in our previous works this new type of hyper spectral tongue imaging system has the advantage of having no moving parts and can be scanned at very high rates. As the hyper spectral tongue images can provide more information than the CCD based images, we can find some successful applications in computerized tongue diagnosis such as tongue body segmentation, tongue color analysis and discrimination, tongue cracks extraction and classification, sublingual veins analysis, etc. Preliminary experiments show that the AOTF based hyper spectral tongue imaging system is superior to the traditional CCD based methods because the hyper spectral images can provide more information about the tongue.

III. PROPOSED SYSTEM

Tongue Image Preprocessing:

Once the tongue images are captured using the capturing device, automatic segmentation process will be applied in each image in order to separate its foreground pixels from the background. The segmentation result is a binary image which clearly defining foregrounds portion pixels such as a tongue surface area and its edges from its background pixels. This segmentation process allows three groups of features like color, texture and geometry to be extracted from a tongue foreground image in the proceeding steps.

Color Feature Extraction:

The tongue color gamut represents all the colors that appear on the tongue image surface within the red boundary.

Tongue Texture Features:

Fig. 1 represents the texture of tongue images, eight blocks of size 64×64 strategically located on the tongue surface are used. A block size of 64×64 was chosen due to the fact that it covers all eight surface areas very well, while achieving minimum overlap. The blocks are calculated automatically by first locating the center of the tongue using a segmented binary tongue foreground image. Following this, the edges of the tongue are established and equal parts are measured 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 at the center. The Gabor filter is a linear filters used in image processing, and is commonly used in texture representation.



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Fig 1: Eight Texture block location

Then to compute the texture value of the entire tongue block, the 2-D Log Gabor filter is applied. There are some similarities between the Gabor filter, the log-Gabor filter has seen great popularity in image processing. Because of these similarities it is essential to define the 2-dimensional log-Gabor filter. This added dimension gives the features that makes the filter is not only designed for a particular frequency but also is designed for a particular orientation. The orientation component is a Gaussian distance function according to the angle in polar coordinates:

$$G(f,\theta) = \exp\left(\frac{-(\log(f/f_0))^2}{2(\log(\sigma_f/f_0))^2}\right) \exp\left(\frac{-(\theta-\theta_0)^2}{2\sigma_\theta^2}\right)$$

In the Gaussian equation four parameters are discussed: f_0 the center frequency, σ_f the width parameter for the frequency, θ_0 the center orientation, and σ_{θ} the width parameter of the orientation.

The two dimensional filter consists of a component based on frequency (a) and a component based on orientation (b). The two components are combined to form the final component (c).

In the spatial domain the response of Gabor and Log-Gabor filters are nearly identical. On the left is the real part and on the right is the imaginary part of the impulse response.





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The bandwidth in the frequency is given by:

$$B = 2\sqrt{2/\log(2)} \left(\|\log(\sigma_f/f_0)\| \right)$$

The angular bandwidth is given by:

$$B_{\theta} = 2\sigma_{\theta}\sqrt{2\log 2}$$

In many practical applications many filters are designed to form a filter bank. Because the filters do not form orthogonal basis, the design of the filter bank is somewhat of an art and may depend upon the particular task at hand. , The angular bandwidth, minimum and maximum frequencies, the filter bandwidth, orientations, the filter scaling and the number of scales are the necessary parameters. After collect the texture feature the geometry features of the tongue is calculated and stored in the database. Then the numerical calculations are made up and classified as a healthy feature value or Diabetes Mellitus feature value.



IV. EXPERIMENT AND ANALYSIS

Fig 3: Accuracy comparison chart

This experimental result chart describes the working principle of the proposed system with log gabor filter application. The various testing input tongue images are given as an input to analyze healthy or diabetes mellitus and the texture accuracy is calculated and deployed. This result evaluation is done based on the comparison of the numerical values got when the texture vale and tongue geometry values are compared with the database values.

PSNR Analysis:

The above chart shows the accuracy comparison between Existing and proposed system which are used as an input image for the Diabetes mellitus detection. The Example or sample dataset which used to test the proposed disease detection implementations are the sample images taken from the biomedical dataset.

PSNR is a matrix parameter which is used to measure the quality of a resultant signal, just after compression. High PSNR values gives higher quality. The value can be calculated as

 $PSNR=10 \log_{10} [R^2/MSE]$ (1)



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where PSNR is Peak Signal to Noise Ratio, R is the maximum fluctuation in image input value, MSE is the Mean Squared Error.MSE can be calculated as

 $MSE = [\Sigma_{m,n} [l_1(m,n) - l_2(m,n)]^2] / [M*N]$ (2)

IV. CONCLUSION

In this study, we proposed a tongue dataset diagnosis approach for the diagnosis of diabetes mellitus based on a texture feature analysis of the tongue eight block texture numerical value changes. Both geometric and textural features are the measures to identify the diabetic mellitus features from the tongue image retrieved numerical results. Experiments are implemented on the database of tongue images and the results are retrieved and analyzed. The main contribution of this research is that computerized tongue image analysis approach to detect the initial stages of diabetic mellitus is proposed. This will undoubtedly boost the modernization process of the disease detection unlike traditional tongue diagnosis based on the gabor filter and, more importantly increase the disease detection application.

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