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Preclinical Diagnosis of Diabetes with Tongue Infrared Thermography and PSO Algorithm

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Abstract

The tongue use as an initial biomarker for disease diagnosis in Greek, western and Chinese culture. The tongue provides a non-invasive method to diagnose diseases in health care. The tongue shows gamut of symptoms due to disease and disorder. The traditional tongue diagnosis requires quantitative experience. In western medicine the tongue symptom use as one of the criteria for disease diagnosis. The tongue reflexology shows functioning of internal organs in body. Recent studies attribute chronic pancreatitis to saliva secretion. In this paper, we propose to diagnose diabetes with tongue thermal image. The Particle swarm optimization (PSO) algorithm to cluster thermally active pixels with similar intensity. The clustered tongue thermal region show drastic change for normal and diabetic person. The study involved 25 normal person and 25 type 1 diabetic person. The proposed approach diagnoses diabetes with 86% accuracy.

Keywords: *Tongue, type 1 diabetes, Pancreas, salivary gland, insulin, Thermal image Particle swarm optimization.*

Introduction

Diabetes, a heterogeneous disorder cause due to etiologic, pathophysiologic and genetic mechanisms. The insulin deficiency in body cause glycemic index of blood to increase. The insulin deficiency cause due to partial insulin production or no production by pancreas. Over 300 million people in the world affect by diabetes and the numbers are still increasing. The diabetes classify as type 1 diabetes, type 2 diabetes, gestational diabetes and monogenic diabetes. The type 1 diabetes cause due to insufficient insulin in body to regulate blood glycemic index. The insulin production in pancreas affect due to β- cell destruction. The β cells induce insulin production and secretion in pancreas. The β cell destruction causes due to autoimmune disorder. The type 1 diabetes further classify as type1A and idiopathic or type 1B diabetes.

The tongue reflexology use in traditional Chinese medicine for disease diagnosis. The Greek and Chinese medicine relates tongue to internal body organs. The tongue reflects different organs such as epigastric, abdominal cavity, gall bladder, liver, spleen areas, pancreas and stomach. The tongue color and tongue coating reflects health of internal organs. The tongue coating such as pale white, thick solid white color reflects operation of digestive system, metabolic and nutritive condition of tongue. The tongue coating use as biomarker to evaluate overall body health. The tongue free from stinging, swelling, burning and scarring reflect healthy tongue. The tongue diagnosis provides information about abnormal functioning of digestive tract and metabolism. Traditionally, doctors look at tongue to diagnose yeast infection, cancer, oral hygiene, candida growth, iron, B12 deficiency and herpes. In this paper, we propose computer aided diabetes diagnosis with tongue thermal image. The tongue thermal image process with Particle Swarm Optimization (PSO) to outline thermally active region.

Related Work:

A novel non-invasive method performed to diagnose Diabetes mellitus based on Sparse Representation Classifier (SRC) with facial block colour characteristics. The non-invasive capture device along with image correction is utilized to capture facial image. The facial image comprising of 4 facial blocks and the facial block placed around the face. From facial colour range, the Six centroids are used to estimate the facial colour characteristics of each block. The facial blocks denote by facial colour characteristics. For Sparse Representation Classifier, Diabetes mellitus facial colour sub dictionary and Healthy facial colour sub dictionary are used in SRC process[1].

The novel invasive method is used to discover Non-proliferative Diabetic Retinopathy (NPDR) and Diabetes Mellitus. From tongue, image three different features extract namely texture, geometry and colour in Diabetic Retinopathy. Initially, the tongue images capture by using the non-invasive device along with image correction. Tongue colour range is separated with twelve colours, each colour represents tongue colour characteristics[2].

Human tongue colour has certain statistical distribution characteristics. The diagnostic feature extraction for tongue colour can be performed through analyzing these characteristics in-depth to describe the tongue colour space. There are three tongue colour space characteristics. The tongue colour range describes, colours centres with 12 colour types of tongue and tongue colour representing the colour distribution of particular image characteristics were analysed[3].

The Munsell colour checker is used to enhance correction accuracy of tongue colours. The Munsell colour checker is designed with the help of tongue colour space.Tongue colour space is implemented by whole visible colours. Initially the tongue colour space is depends on the comprehensive tongue database. The visible colours categorize as tongue or non-tongue colours. From tongue colours, the tongue colour checker colours designed to attain maximum correction performance. Secondly, In colour checker, the minimum sufficient number of colors is created by comparing the correction accuracy when the range is different (ranges from ten to two hundred). Finally, for optimum colour selection technique, the objective function is presented. Two color selection techniques that is greedy & clustering based selection technique is used to solve objective function[4].

The colour images are created by digital camera. The created information is dependent with the imaging characteristics of particular cameras. This is the major problem of tongue image analysis. Since, the tongue image analysis depends on the accurate performance of colour information. The optimized correction method is performed to adjust the captured tongue images in several device dependent colour spaces into target independent colour space. By comparing different correction algorithm, the correction algorithm system is created with ridge regression, polynomial-based regression, neural network mapping, and support vector regression algorithms[5].

Methodology

The tongue reflexology show changes in abnormality of organs in body. The tongue diagnosis is based on tongue color. The tongue color and tongue thermal activity boundary detect with pixel clustering. The tongue has different color such as dark-red, red, light red, purple and white. The thermally active region of tongue determine with infrared thermography camera. The tongue thermal activity change due to organ operation. The tongue thermally active region extracts to determine normal functioning of pancreas. The Infrared thermal camera acquires tongue thermal image. The low pass filter applies on thermal image to remove noise. The thermally active region in tongue cluster with particle swarm optimization (PSO). The PSO algorithm cluster pixel with similar intensity for thermally active region detection and extraction. The thermal region clustering aid in diabetes diagnosis.

Particle swarm optimization algorithm (PSO):

The PSO algorithm is based on social behavior of birds in a flock. The PSO algorithm processes alternative solution to particular optimization problem. The alternative solution to each problem is referred to as particle. For an ‘n’ number of variables, the alternative solutions represent by n dimensional point with search space. The fitness function applies to detect particle relation to optimal solution. The alternative solutions are flown through search space by adjusting the particle solution with respect to best position. The best solution select based on the swarm of particle. The alternative solution performance measure through solution relation to optimization problem.

The alternative solution has information such as current position of solution (xi), current velocity of a particular solution (vi) and best optimal solution (yi).

The best position for a solution determine by solution visit to particular position in swarm. Hence, the particular position yields higher fitness value. The higher fitness value saves in memory. The objective function of fitness value denote by f and the alternate solution for each position with respect to time denote by

$$\mathbf{y}_i(t+1) = \begin{cases} \mathbf{y}_i(t) & \text{if } f(\mathbf{x}_i(t+1)) \geq f(\mathbf{y}_i(t)) \\ \mathbf{x}_i(t+1) & \text{if } f(\mathbf{x}_i(t+1)) < f(\mathbf{y}_i(t)). \end{cases} \quad (1)$$

The information about alternative solution exchange between members in swarm. The information exchange provides best solution and its position in swarm. The information help particles to adjust to best solution. The particles deploy either in star or ring topologies. The star topologies aid particular particle to initiate communication with all other particles. The best optimal solution determines and all particles move to global best solution. The algorithm refers to as *gbest* PSO. The ring topology, determine particles that overlap with each other. The particles communicate with other particles to determine best particle solution. Once done, the solution adjusts to best neighborhood space. The above process is referred to as *lbest* PSO.

In gbest PSO the best solution determine by swarm of particles represented by

$$\hat{\mathbf{y}}(t) \in \{\mathbf{y}_0, \mathbf{y}_1, \ldots, \mathbf{y}_s\} = \min\{f(\mathbf{y}_0(t)),\ f(\mathbf{y}_1(t)), \ldots, f(\mathbf{y}_s(t))\} \quad (2)$$

Where

's' represents particles in swarm.

In lbest PSO the neighborhood determine by

$$N_j = \{\mathbf{y}_{i-l}(t), \mathbf{y}_{i-l+1}(t), \ldots, \mathbf{y}_{i-1}(t), \mathbf{y}_i(t), \mathbf{y}_{i+1}(t), \ldots, \mathbf{y}_{i+l-1}(t), \mathbf{y}_{i+1}(t)\} \quad (3)$$

The best particle solution in Nj neighborhood represent by

$$\hat{\mathbf{y}}_j(t+1) \in N_j \mid f(\hat{\mathbf{y}}_j(t+1)) = \min\{f(y_i)\}, \quad \forall y_i \in N_j. \quad (4)$$

The neighborhoods determine by particle indices and topographical particles. In a swarm, the gbest PSO is simply equivalent to lbest PSO. The best optimum solution for gbest PSO determine by

$$\mathbf{v}_i(t+1) = w\mathbf{v}_i(t) + c_1\mathbf{r}_1(t)(\mathbf{y}_i(t) - \mathbf{x}_i(t)) + c_2\mathbf{r}_2(t)(\hat{\mathbf{y}}(t) - \mathbf{x}_i(t)) \quad (5)$$

$$\mathbf{x}_i(t+1) = \mathbf{x}_i(t) + \mathbf{v}_i(t+1) \quad (6)$$

Where,

w - inertia weight.

C_1, C2 represents acceleration constants.

r_1, (t), r_2 (t) represents vector sampled with uniform distribution.

In equation (5), the inertia term saves previous velocity in memory. The previous velocity in memory alters inertia weight. The high inertia weight induces exploration and low inertia weight causes exploitation.

The Y_i (t) – x_i represents particles experience to determine best location for solution. The cognitive component saves previous best positions in memory.

The social component - x_i (t) represents entire swarm prediction where the best solution is. The PSO influence by parameters such as ω, c_1 and c_2. The theoretical studies show certain bound on values given by

$$w > \frac{1}{2}(c_1 + c_2), \quad w < 1 \tag{7}$$

In such cases, the PSO shows convergent behavior. The particle adjustment limit by allocating predefined search space and limiting particle velocity.

The PSO algorithm updates the search space until the iterations are met or the velocity is close to zero. The fitness function applies to measure particle quality. However, all the particles converge to an optimum point, which cause particle stagnation. The particle stagnation overcomes by local convergence. In local convergence, the global best particle index update with velocity given by

$$v_{\tau,j}(t+1) = -x_{\tau,j}(t) + \hat{y}_j(t) + wv_{\tau,j}(t) + \rho(t)(1 - 2r_{2,j}(t)) \tag{8}$$

Hence, the position update is represented by

$$x_{\tau,j}(t+1) = \hat{y}_j(t) + wv_{\tau,j}(t) + \rho(t)(1 - 2r_{2,j}(t)). \tag{9}$$

Where, $-x_T$ represents reset of particle position for global best position v_T represents direction for search and addition of random search term $_2$(t).

Where, determines search space for optimal solution. The initialize to 0 with defined by

$$\rho(t+1) = \begin{cases} 2\rho(t) & \text{if } \#\text{successes} > s_c \\ 0.5\rho(t) & \text{if } \#\text{failures} > f_c \\ \rho(t) & \text{otherwise.} \end{cases} \tag{10}$$

The failure state occur when $f(\hat{\mathbf{y}}(t)) \geq f(\hat{\mathbf{y}}(t-1))$ and variable are incremented. The success state occurs when $f(\hat{\mathbf{y}}(t)) < f(\hat{\mathbf{y}}(t-1))$. The values of f_c and S_c vary dynamically represented by

$$s_c(t+1) = \begin{cases} s_c(t) + 1 & \text{if } \#\text{failures}(t+1) > f_c \\ s_c(t) & \text{otherwise.} \end{cases} \tag{11}$$

$$f_c(t+1) = \begin{cases} f_c(t) + 1 & \text{if } \#\text{successes}(t+1) > s_c \\ f_c(t) & \text{otherwise.} \end{cases} \tag{12}$$

The success state becomes hard to achieve when multiple failures occur. The failures cause due to over confident convergent behavior, which make the search space to be smaller surrounding global best position. The success rate and failure rate represent by equation

$$\begin{gathered} \#\text{successes}(t+1) > \#\text{successes}(t) \Rightarrow \#\text{failures}(t+1) = 0 \\ \#\text{failures}(t+1) > \#\text{failures}(t) \Rightarrow \#\text{successes}(t+1) = 0. \end{gathered} \tag{13}$$

The algorithm reaches a stop position when becomes a small value or when stopping criteria is met.

Result and Discussion

The thermal flow on the tongue surface is measured using the thermal camera. Fluke infrared thermal camera is utilised to capture the thermal images of tongue from normal and diabetic patients. The recorded thermal image is applied to PSO segmentation and texture analysis to identify the variation in the flow of heat over the surface of the tongue. Before applying to the algorithm the thermal image should be pre-processed with image filters and Haar wavelet transformation. Pre-processing the thermal image results in elimination of noises added during the image-processing unit within the thermal camera. The noise from surrounding environment affects the pixel values of the recorded Thermal Image. To overcome this additional noise the thermal image is initially pre-processed with the Gaussion High pass and Low Pass filters. Gaussian Low pass filter is used to smoothen the input image. This results in blurred output of the input image. Gaussian smoothing is used to remove the high frequency noises and enhance the structures in diabetic tongue and normal tongue image. The excessive edges generated by the noises were smoothen and the enhanced image is generated.

The high pass filter sharpens the input image by highlighting the fine details in the input image. Gaussian high pass filter is applied over the diabetic tongue and normal tongue thermal images.

The filtered thermal image process with HAAR Wavelet transformation. The HAAR wavelet transformation extracts the features from the input image. Identifying the edges in the input image is more important in segmentation process. The filters applied over the input image removes the noise but the resultant image was blurred. To enhance the edges from the filter output the HAAR wavelet transformation is applied which process over the time frequency medium, which enhance the time frequency resolution of provided image.

The HAAR wavelet transformation enhances colour regions of thermal flow, which assists the colour analysis to identify sharp edges in resultant image of wavelet transform. The colour analysis is used to enhance the thermal flow by increasing the contrast of colour pattern of input image. Red colour represents the higher heat flow, Yellow moderate heat flow and green represents low heat flow. Thus, the exact region of heat flow can be measured from the results of colour analysis. Figure 1 and 2 represents the original and colour analysis image of diabetic tongue and normal tongue image. The heat flow is higher at the centre segments of the diabetic tongue, which is not present in normal tongue thermal image. The normal tongue thermal image shows the uniform heat flow but diabetic tongue image shows increase in heat flow in middle regions of the tongue.

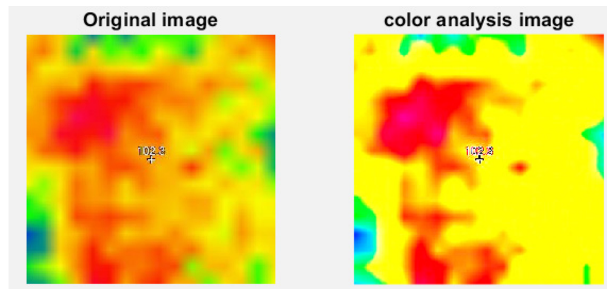

Figure 1: Colour analysis for Diabetic Tongue Image.

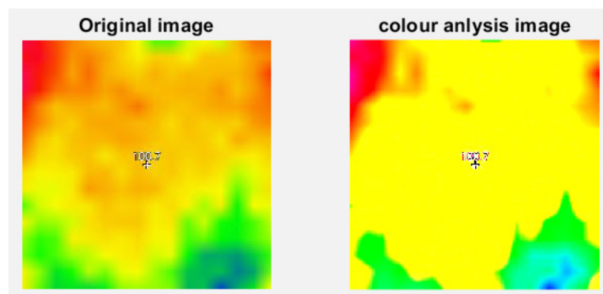

Figure 2: Colour analysis on Normal Tongue image.

The output of the colour analysis is applied to the Particle swarm optimisation technique to perform image segmentation to identify the exact location of heat change in diabetes and normal tongue thermal image. PSO algorithm groups the data set into regions. The image segmented using PSO algorithm is well grouped into regions of homogeneous colours and provides the knowledge about the presence of number of regions in the input image. Figure 3 shows the PSO output for Diabetic tongue thermal image and normal tongue thermal image. The group of heat zones and spreading out of temperature was segmented clearly. It shows the thermal hotspots on the surface of diabetes tongue. The figure 3 shows the grouping of heat zones in the normal tongue thermal image. The comparative analysis shows absence of heat zones in normal tongue. The heat flow is evenly dissipated throughout the tongue surface.

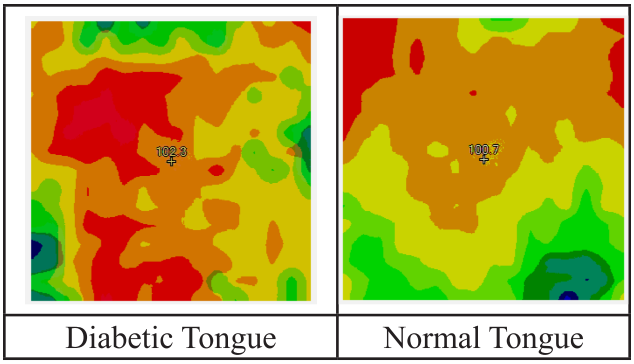

Figure 3: PSO segmentation for Normal and diabetic tongue images.

Local Binary pattern (LBP) is an efficient tool to perform texture analysis over the input images. LBP converts the pixel values of the image into binary codes based on the threshold value of the centre pixel. Eight neighbour points of every centre frequency was grouped together. The pixel value greater than or equal to centre value is assigned as 1 and the value smaller than centre pixel value is assigned as 0. The input image was grouped into local structure with a centre pixel value. Histogram analysis is performed over each structure of LBP. The combined histogram output of each structure of normal tongue thermal image and diabetic tongue thermal image, are spitted sparse and tight histogram plots are shown in figure 4 and 5. The output of Efficient LBP image and Pixel wise LBP image shows the change in tongue thermal image pixel intensity.

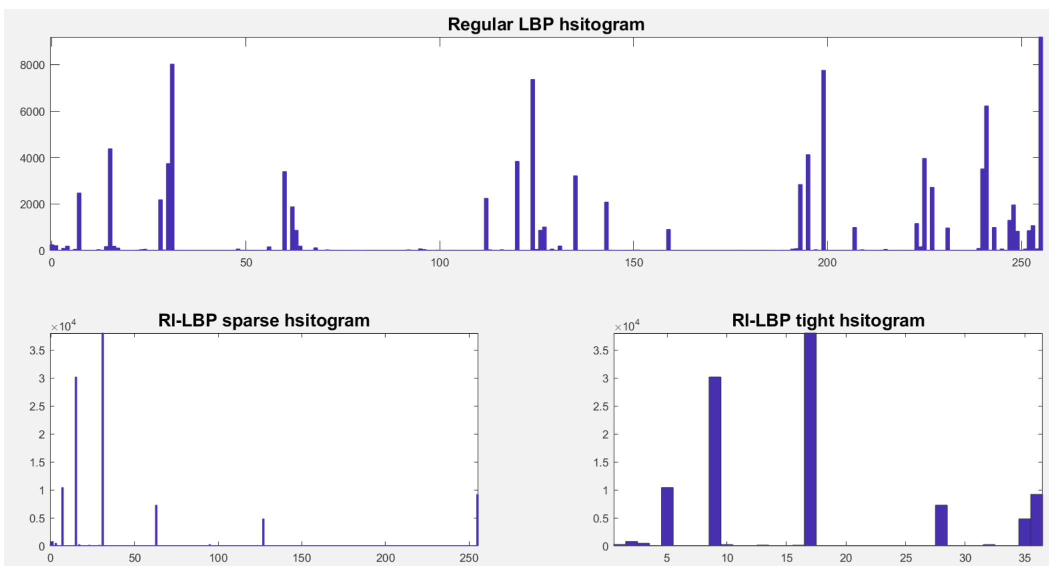

Figure 4: Histogram for Local Binary Pattern for Diabetic Tongue Image

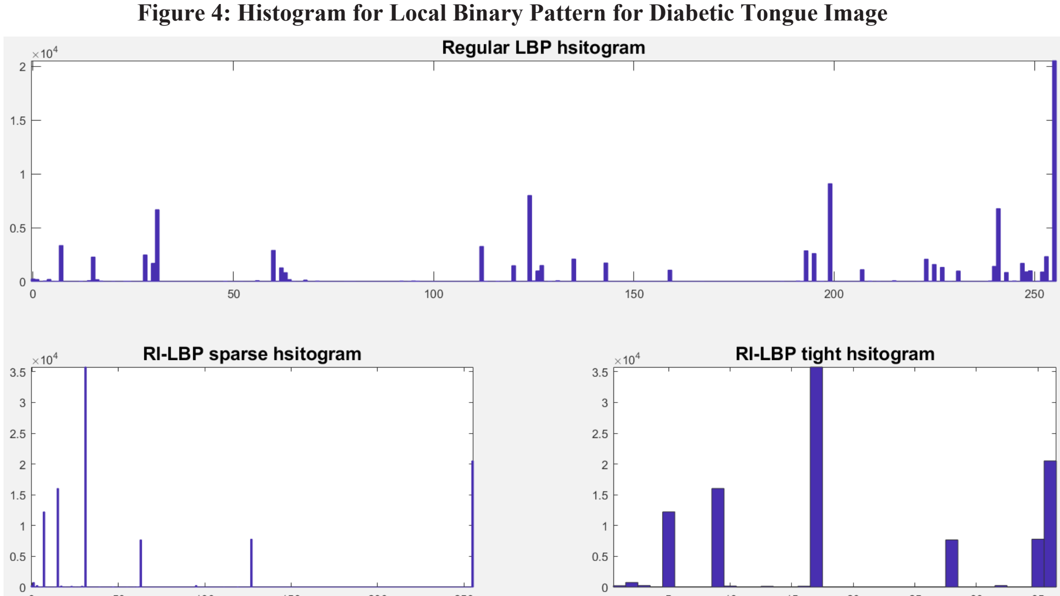

Figure 5: Histogram for Local Binary Pattern for Normal Tongue Image

Conclusion

In this paper, we propose to a non-invasive approach to diagnose diabetes at an earlier stage through tongue thermal image. The tongue thermal colour differences acquire via fluke thermal camera for normal and diabetic person. The PSO algorithm apply to cluster thermally active pixel in image. The texture extract from clustered thermal image for diabetes diagnosis. The texture show change in tongue texture, geometry and colour. The effectiveness of proposed method validate by processing thermal tongue images of 25 normal person and 25 type1 diabetic person. The tongue thermal features show positive correlation for diabetic person.

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