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Non-invasive Blood Glucose Level Measurement from LASER Reflected Spectral Patterns Images

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Abstract : - Texture analysis is used here in the proposed work in order to establish the correlation between the glucose level and texture coefficients. The texture image is stored in jpeg format that is basically the rgb image. The rgb image is converted to gray image and then we analyze the texture by Using a Gray-Level Co-Occurrence Matrix (GLCM).The gray co matrix function creates a gray-level co-occurrence matrix (GLCM) by calculating how often a pixel with the intensity (gray-level) value i occurs in a specific spatial relationship to a pixel with the value j. In the earlier method, infra red light source is used in order to estimate the glucose level in human body as non-invasive method. However, it is observed that IR light source is affected by ambient light noise and results are not repeatable for the same patient under same circumstances. In order to enhance the repeatability of the measurements, LASER light source can be used as LASER light is highly coherent and a reliable reflected pattern can be achieved using the laser array of photodiode or receivers.

Keywords: - *Non-invasive Blood Sugar Computation, LASER reflected Image*

I. INTRODUCTION

Knowing the correct blood glucose concentration is necessary to identify conditions of hypo- and hyperglycemia, that is extremely low and high blood sugar. When a person becomes aware of their current glucose levels, the correct actions can be taken to prevent complications and maintain euglycemia. Tight glycemic control invariably maintained throughout life can extend a patient's life span by 5 to 8 years.

The existing method of glucose level measurement in human body are primarily invasive methods i.e. the blood is taken out from the body using syringes and tested in pathological labs. In fact, its the bio-chemistry test and a reagent kit is used to test the glucose level using a bio-chemistry analyser, basically a colorimeter or spectrometer.

However, in the proposed work, a non-invasive method is proposed i.e. without taking the blood from human body. That is why the proposed method is free from any kind of risk of syringe infection and painless.

Spectral imaging involves the acquisition of a series of 2D images of reflected light, where each image uses a different wavelength (λ) yielding a "spectral cube", R(x, y, λ). Each pixel R(x, y) has a spectrum R(λ). The reflectance spectrum can be described using a variety of light transport computations. The reflected laser pattern is in the form of texture image. From the analysis of texture, an estimate of the glucose level in the human body can be estimated.

II. RELATED WORKS

Spectral imaging requires rapid analysis of spectra associated with each pixel. A rapid algorithm has been developed that uses iterative matrix inversions to solve for the absorption spectra of a tissue using a lookup table for photon path length based on numerical simulations. The algorithm uses tissue water content as an internal standard to specify the strength of optical scattering. An experimental example is presented on the spectroscopy of port wine stain lesions. When implemented in MATLAB, the method is ~100-fold faster than using fmin search [1].

Selectivity is paramount for the successful implementation of noninvasive spectroscopic sensing for the painless measurement of blood glucose concentrations in people with diabetes. Selectivity issues are explored for different multivariate calibration models based on noninvasive near-infrared spectra collected from an animal model [2].

An optical approach allowing the extraction and the separation of remote vibration sources has recently been proposed. The approach has also been applied for medical related applications as blood pressure and heart beats monitoring. In this paper we demonstrate its capability to monitor glucose concentration in blood stream. The technique is based on the tracking of temporal changes of reflected secondary speckle produced in human skin (wrist) when being illuminated by a laser beam. A temporal change in skin's vibration profile generated due to blood pulsation is analyzed for estimating the glucose concentration. Experimental tests that were carried out

in order to verify the proposed approach showed good match with the change of the glucose level at the positive slope stage as it was obtained from conventional reference measurement [3].

Noninvasive blood glucose sensors are still under development stage considering that they are far from being suitable for use in an artificial pancreas. The latter has three main parts: the blood glucose sensor, the insulin pump and the controller. However, for the biosensor analyzed here, some common failures such as signal shifts and unreal picks were found. They must be taken into account, for computing the correct insulin dosage for diabetic persons. Hence, a fault detection system based on discrete wavelets transform (DWT) is applied here. The main idea is, when the fault occurs, to do a proper measurement compensation for sending the corrected value to the predictive functional controller (PFC) algorithm. The study is done by reproducing the fault on the blood glucose measurements. They are obtained from a mathematical model of the endocrine system of an adult diabetic patient. This model was approved by the FDA in 2008. Then, the simulation environment includes faulty blood glucose measurements and a fault diagnosis and identification (FDI) system based on DWT. The FDI system gives to the PFC algorithm the correct information to turn it into a fault-tolerant controller (FTC). The main goal is to deliver the correct insulin dosage to the patient [4].

No reliable non-invasive glucose monitoring devices are currently available. We implemented a mid-infrared (MIR) photo acoustic (PA) setup to track glucose *in vitro* in deep epidermal layers, which represents a significant step towards non-invasive *in vivo* glucose measurements using MIR light. An external-cavity quantum-cascade laser (1010–1095 cm−1) and a PA cell of only 78 mm3 volume were employed to monitor glucose in epidermal skin. Skin samples are characterized by a high water content. Such samples investigated with an open-ended PA cell lead to varying conditions in the PA chamber (i.e., change of light absorption or relative humidity) and cause unstable signals. To circumvent variations in relative humidity and possible water condensation, the PA chamber was constantly ventilated by a 10 sccm N2 flow. By bringing the epidermal skin samples in contact with aqueous glucose solutions with different concentrations (i.e., 0.1–10 g/dl), the glucose concentration in the skin sample was varied through passive diffusion. The achieved detection limit for glucose in epidermal skin is 100 mg/dl (SNR=1). Although this lies within the human physiological range (30–500 mg/dl) further improvements are necessary to non-invasively monitor glucose levels of diabetes patients. Furthermore spectra of epidermal tissue with and without glucose content have been recorded with the tunable quantum-cascade laser, indicating that epidermal constituents do not impair glucose detection [5].

The main concern in noninvasive (NI) glucose monitoring methods is to achieve high accuracy results despite the fact that no direct blood or interstitial fluid glucose measurement is performed. An alternative approach to increase the accuracy of NI glucose measurement was previously suggested through a combination of three NI methods: ultrasonic, electromagnetic, and thermal. This paper provides further explanation about the nature of the implemented technologies, and multi-sensors are presented, as well as a detailed elaboration on the novel algorithm for data analysis [6].

Six putative measurement sites were evaluated for noninvasive sensing of blood glucose by first-overtone near-infrared spectroscopy. The cheek, lower lip, upper lip, nasal septum, tongue, and webbing tissue between the thumb and forefinger were examined. These sites were evaluated on the basis of their chemical and physical properties as they pertain to the noninvasive measurement of glucose. Critical features included the effective optical path length of aqueous material within the tissue and the percentage of body fat within the optical path. Aqueous optical paths of 5 mm are required to measure clinically relevant concentrations of glucose in the first-overtone region. All of the tested sites met this requirement. The percentage of body fat affects the signal-to-noise ratio of the measurement and must be minimized for reliable glucose sensing. The webbing tissue contains a considerable amount of fat tissue and is clearly the worse measurement site. All other sites possess substantially less fat, with the least amount of fat in tongue tissue. For this reason, the tongue provides spectra with the highest signal-to-noise ratio and is, therefore, the site of choice on the basis of spectral quality [7].

III. ALGORITHM

In the proposed work, a correlation between texture analysis and the glucose level of the human body using the texture analysis techniques is presented. The texture from the human body is obtained by using the LASER source made to fall upon the human skin and then the reflected pattern is stored as the LASER signature. This LASER signature is basically the texture type image of biological matter present behind the skin.

By default, the spatial relationship is defined as the pixel of interest and the pixel to its immediate right (horizontally Adjacent.), each element (i, j) in the resultant glcm is simply the sum of the number of times that the pixel with value i occurred in the specified spatial relationship to a pixel with value j in the input image. The entropy information from the texture image of the pattern is computed using the following equation: Where Pi is the no. of pixels of the ith gray level. Higher is the entropy of the texture image, higher is the random pattern obtained from the LASER reflection and that gives the estimate of the higher glucose level.

A statistical method of examining texture that considers the spatial relationship of pixels is the gray-level co-occurrence matrix (GLCM), also known as the gray-level spatial dependence matrix. The GLCM functions characterize the texture of an image by calculating how often pairs of pixel with specific values and in a specified spatial relationship occur in an image, creating a GLCM, and then extracting statistical measures from this matrix. The texture filter functions, described in Using Texture Filter Functions, cannot provide information about shape, i.e., the spatial relationships of pixels in an image. The gray-level co-occurrence matrix can reveal certain properties about the spatial distribution of the gray levels in the texture image. For example, if most of the entries in the GLCM are concentrated along the diagonal, the texture is coarse with respect to the specified offset.

Diabetes is a chronic disease that is caused by disruptions in the normal glycolytic pathways. Glucose is a primary source of energy for living cells. In the body, glucose concentrations are regulated by insulin, a pancreatic hormone.

IV. FEATURE EXTRACTION

Following features are extracted from the GLCM matrix of the laser speckle patterns:

Contrast → It measures the local variations in the gray-level co-occurrence matrix. Contrast is 0 for a constant image.

Correlation → It measures the joint probability occurrence of the specified pixel pairs. Correlation is 1 or -1 for a perfectly positively or negatively correlated image.

Energy → It is the sum of squared elements in the GLCM. Energy is 1 for a constant image.

Homogeneity → It measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal. Homogeneity is 1 for a diagonal GLCM.

I. COMPUTATION OF ENTROPY

The expression of the information entropy of an image is given by:

$$H = -\sum_{i=0}^{L-1} p_i \ln p_i,$$

Where L is the number of gray level, and pi equals the ratio between the number of pixels whose gray value equals i(0 i L _ 1) and the total pixel number contained in an image. The richness of information is measured by entropy in an image.

Following images shows the laser speckle texture patterns in order to extract the glucose level concentration in human blood non-invasively.

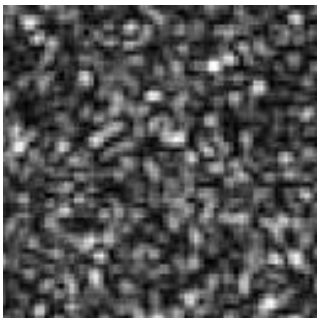


Fig. 1

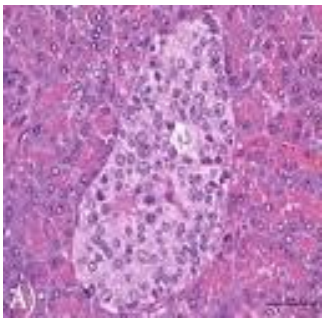


Fig. 2

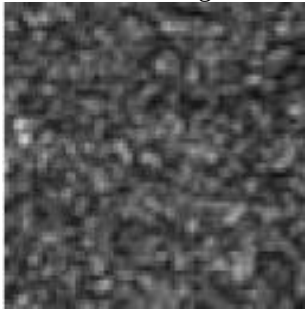


Fig. 3

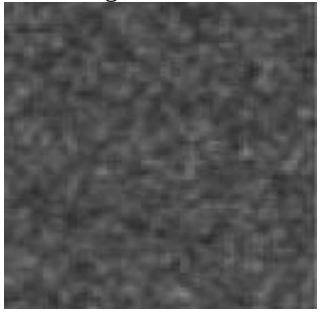
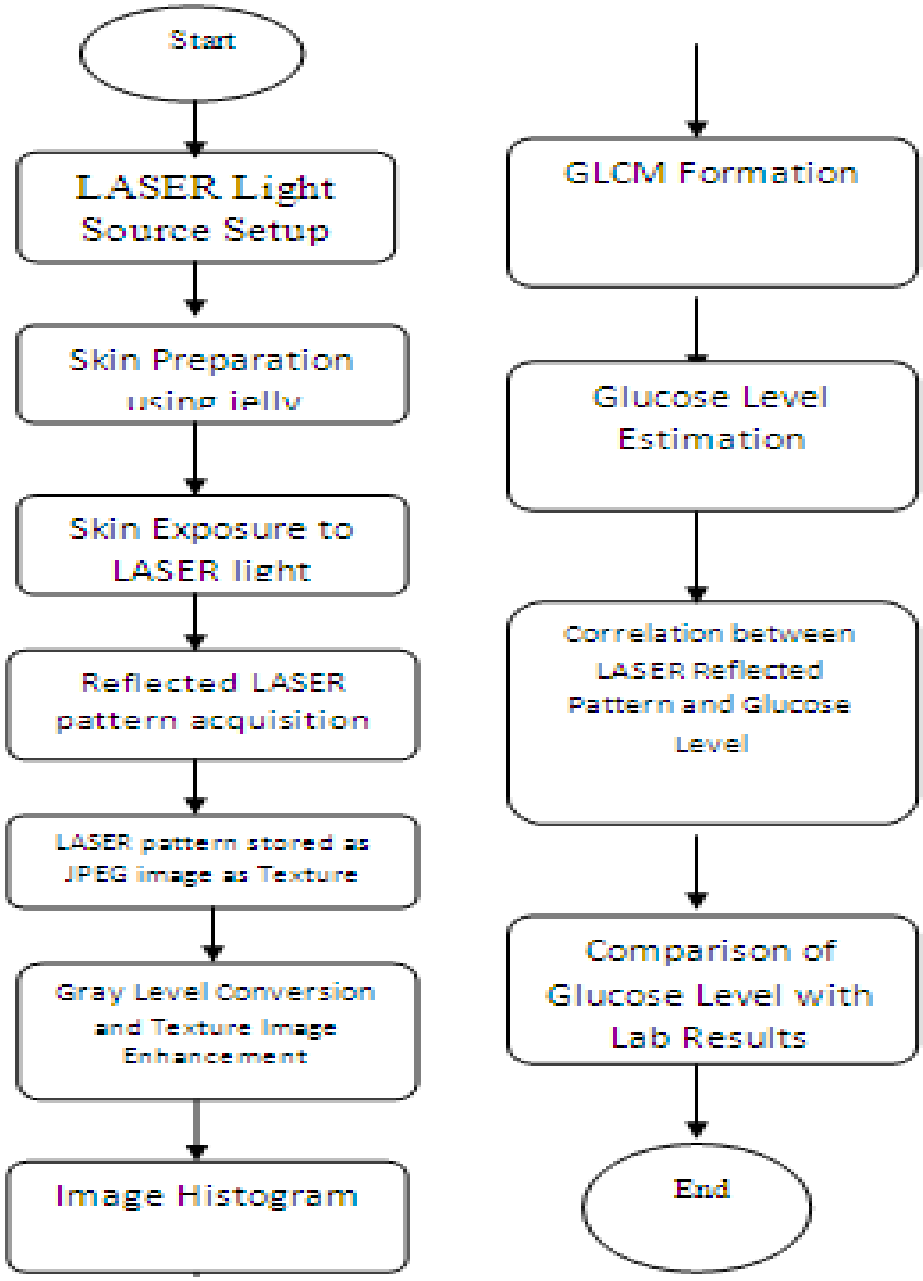


Fig. 4

V. FLOW CHART OFF THE PROPOSED SYSTEM



VI. RESULT

The proposed algorithm has been implemented on the images as shown in fig. 1 to 4. The images are reflected laser speckle patterns from the wrist of different persons. The results for given images are given in the table below:

IMAGE NO.	FIG. 1	FIG. 2	FIG. 3	FIG. 4
CONTRAST (C)	3.89	6.814	3.451	3.49
CORRELATION (CR)	0.557	0.226	.603	.595
ENERGY (E)	0.022	0.019	.024	0.023
HOMOGENEITY (H)	0.532	0.460	.547	.539
STD. DEV. (SD)	130	166	4.0	243
ENTROPY (ENT)	5.90	5.93	5.94	5.62

Further, the final glucose level is determined by integrating all the above tabled parameters according to some weights so that correct glucose level estimate could be made.

$$\text{Glucose Level} = w_1.C + w_2.Cr + w_3.E + w_4.H + w_5.SD + w_6.Ent$$

Where, w_1, w_2, w_3, w_4, w_5 and w_6 are the weights for contrast, correlation, energy, homogeneity, standard deviation and entropy respectively. The value of weights can be determined if the same algorithm is applied over some more images of different sugar levels and categorized according the glucose level.

VII. CONCLUSION

The proposed algorithm is quite robust to variation in the imaging device due to low illumination or resolution limitation due to statistical in nature. Therefore, results do not vary from one extreme to other extreme. The proposed work illustrates the possibility of non-invasive blood glucose level measure and can be extended to other biological parameters. Thus eliminating the need of puncturing the human body for taking out the blood sample. This avoids the possibility of any kind of blood infection due to syringe effect.

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