IJMS
Vol 38, No 1, March 2013

Original Article

Determination of Blood Glucose Concentration by Using Wavelet Transform and Neural Networks

Vajravelu Ashok[1], PhD; Nirmal Kumar[2], PhD

Abstract

Background: Early and non-invasive determination of blood glucose level is of great importance. We aimed to present a new technique to accurately infer the blood glucose concentration in peripheral blood flow using non-invasive optical monitoring system.
Methods: The data for the research were obtained from 900 individuals. Of them, 750 people had diabetes mellitus (DM). The system was designed using a helium neon laser source of 632.8 nm wavelength with 5mW power, photo detectors and digital storage oscilloscope. The laser beam was directed through a single optical fiber to the index finger and the scattered beams were collected by the photo detectors placed circumferentially to the transmitting fiber. The received signals were filtered using band pass filter and finally sent to a digital storage oscilloscope. These signals were then decomposed into approximation and detail coefficients using modified Haar Wavelet Transform. Back propagation neural and radial basis functions were employed for the prediction of blood glucose concentration.
Results: The data of 450 patients were randomly used for training, 225 for testing and the rest for validation. The data showed that outputs from radial basis function were nearer to the clinical value. Significant variations could be seen from signals obtained from patients with DM and those without DM.
Conclusion: The proposed non-invasive optical glucose monitoring system is able to predict the glucose concentration by proving that there is a definite variation in hematological distribution between patients with DM and those without DM.

Please cite this article as: Ashok V, Kumar N. Determination of Blood Glucose Concentration by Using Wavelet Transform and Neural Networks. Iran J Med Sci. 2013;38(1): 51-56.

Keywords ● Diabetes mellitus ● Noninvasive ● Neural networks

[1]Electronics and Communication Engineering, Nandha College of Technology, Erode, India;
[2]Electrical and Electronics Engineering, Info Institute of Engineering, Coimbatore, India

Correspondence:
Vajravelu Ashok, PhD;
Electronics and Communication Engineering,
Nandha College of Technology,
L 238 Periyar Nagar,
Erode, India
Tel: +91 424 2430333
Fax: +91 424 2431725
Emails: ashokvajravelu@gmail.com
vashok.research@gmail.com
Received: 13 December 2011
Revised: 6 February 2011
Accepted: 8 April 2012

Introduction

Currently, diabetes mellitus (DM) is more prevalent than any other hereditary metabolic diseases. It is a chronic disorder of carbohydrate, fat, and protein metabolism caused by lower amounts or absence of insulin. It can lead to several complications such as blindness, cardiac arrest, kidney failure, etc.[1] According to the statistics issued by the World Health Organization (WHO), the prevalence of DM was 171 million,[2] in 2000 and 285 million in 2010. The prevalence is likely to rise by more than two-third between 2010 and 2030.[3]

Haemoglobin A1c (HbA1c) plays a significant role in DM. The HbA1c test or glycosylated HbA1c test is a laboratory test that reveals the average blood glucose over a period of the previous two to three months (long-term control test). It helps assess whether patients have had optimal glycemic control and the control status between checkups. HbA1c can, therefore, provide a reliable reflection of long-term blood glucose control because its value is not affected by brief or infrequent fluctuations in blood glucose levels affecting the viscosity of blood.[4] HbA1c, which affects the blood flow, is abnormal in patients with DM. This concept has been taken in the present study.

Generally, three techniques are in practice for the early detection of DM; invasive, minimally invasive, and non-invasive. The first two methods have certain limitations such as patients preparation, reagent preparation, piercing the skin that can cause infection, need to sophisticated instruments, and skilled technicians. Thus, the non-invasive method is preferred to avoid these drawbacks,. Optical techniques come under different categories of non-invasive methods. Among them, scattering changes are adopted. These scattering changes are of two types, namely spatially resolved diffuse reflectance and optical coherence tomography. Out of the two, the spatially resolved diffuse method is adopted in our study.[5]

Patients and Methods

The suggested system works on the principle of Doppler effect. This principle also applies to light and other electromagnetic radiations. Here, a laser beam is focused on the moving objects like the RBC or stationary particles like tissue structures in the skin. The shift in the frequency of the back scattered light gives a measure of the velocity. Since the vessel diameter is not known because of its elasticity, the flow rate cannot be measured.

Developing Laser System

Using the He-Ne laser system, photo detectors (as optical detectors) are arranged in an axial fashion at 19 different angles for the detection of transilluminated and scattered laser beam from the index finger. The index finger is placed in the sensing arrangement and each detector is capable of detecting the optical signal up to ±10° away from the point of observation. For the surface measurement, a laser beam directed by a single optical fiber is transmitted through the index finger. The transmitting and receiving fibers are positioned in parallel with their centers separated by 1 mm and encased in epoxy resin with black painted mica housing to maintain this separation. The scattered beam is then detected by the photo detector and is stored in a personal computer through Digital Storage Oscilloscope.[6]

Decomposition of Signals

The stored signals are then processed by wavelet transform. Wavelets are, in fact, techniques that analyze the signals using mathematical functions. These functions divide the signal information into different frequency components, without any modification of signal shape, amplitude, and frequency components. Wavelets are used in the fields of electrical engineering, mathematics, medical science, quantum physics, and seismic geology.[7]

Haar Wavelet Structure

The wavelet transform can be implemented by a two channel perfect reconstruction (PR) filter bank. A filter bank is a set of filters, which are connected by sampling operators. Figure 1 shows an example of a two-channel filter bank applied to a one dimensional signal. In general, figure 1 is a two channel wavelet structure which consists of an analysis and synthesis bank.

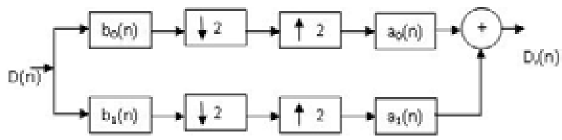

Figure 1: Two channel wavelet structure.

D(n) is an input signal. In the analysis bank, $b_0(n)$ is a low pass filter while $b_1(n)$ is a high pass filter. In the synthesis bank, $a_0(n)$ is the reconstruction low pass filter (LPF) and $a_1(n)$ is the reconstruction high pass filter (HPF).

In this study, only the analysis bank was required and it was modified as shown in figure 2.

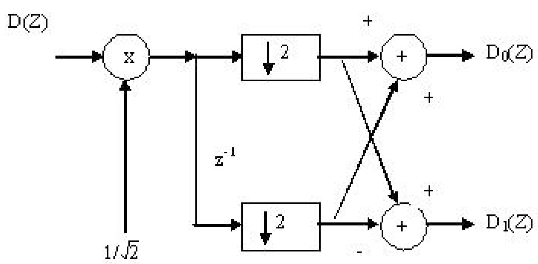

Figure 2: Modified Haar wavelet analysis bank.

Shifting the down sampler to the input causes reduction in the computational complexity by a factor 2. With this method, computational complexity as well as the time required for computation is reduced by a quarter of the original structure.[8]

Data Collection

The data for the research were obtained from 900 individuals. Among them, 750 patients had DM and were undergoing treatment in government and private hospitals during 2007-2011, and the remaining were patients from the same hospital without DM. The data were collected from the patients on a daily basis. The data contained information on the patients' personal details as well as their medical profile such as pathology, biochemistry, and lipid profile along with the corresponding developed system sensor outputs. Further analysis was done using these data. The blood samples were collected twice the time of examining the patients in fasting and post parandial conditions.

The experiments were carried out on the index finger of the patients at a room temperature of 32±5°C. In each case, the arm was strapped in the horizontal position (at heart level) by a special arrangement to minimize any kind of movement. The probe was not in direct contact with the skin, in order to enhance the air flow and to prevent humidity condensation which could possibly modify the skin's optical properties and microcirculations.

Once the probe is applied, the power spectra were recorded to detect any difference in frequency and amplitude response. The measurements were repeated at least twice for each patient in order to check the reproducibility of the method. The time duration between the two records was one minute.

Preparing Data to Implement Neural Network Techniques

The decomposed outputs are classified into several groups as follows: group I: 0-150 mg/dl, group II: 151-250 mg/dl, group III: 251-350 mg/dl, group IV: 351-450 mg/dl, and group V: ≥451 mg/dl. The prediction of blood glucose concentration was done using back propagation network (BPN) with gradient descent algorithm and radial basis function (RBF),[9] with extreme learning machine.

Proving the Validation Using Six Sigma Concept

A statistical analysis chart for continuous real time process of human blood flow is used for the verification.

Results

The feasibility of the laser system technique in measuring peripheral blood glucose concentration has been reported in this present investigation. We focused on successful clinical utilization. Of the 750 patients with DM, 457 (61%) were females. Table 1 displays the statistical details of the clinical baseline characteristics of the sampled patients.

This study predicts the blood glucose concentration in the peripheral blood by using developed laser system.

As demonstrated in table 2, the transillumination profiles of some subjects were taken randomly and verified with the help of coefficient of variation (CV) between the blood glucose concentration and transilluminated voltage. The CV is the ratio of the standard deviation σ and the mean μ, computed to measure the precision for the dispersion of data sets on ratio scale.[10]

Because of the anisotropy factor, the maximum scattered signal was obtained at 29° and 337° from the index finger. These two angles are selected for further analysis.[6] The scattered signals obtained are decomposed by the modified Haar wavelet transform into approximation and detailed coefficient with an error rate ranging between the classical Haar Wavelet method and proposed as -140 dB and -200 dB to -260 dB, respectively (figure 3).

Table 3 gives the prediction of blood glucose for different groups using BPN and RBF Networks expressed as means±standard error. In figure 3,

Table 1: Mean (±SD) of the clinical baseline characteristics of the patients with DM

Parameters	Mean (±SD)
Age (years)	53.2 (±9.5)
Body mass index (kg/m^2)	35.9 (±9.6)
HbA1c(%)	8.8 (±2.2)
Years with DM	12.0 (±9.8)
Hematocrit (%)	42.8 (±4.3)
Systolic bleed pressure (mmHg)	136.3 (±15.48)
Diastolic bleed pressure (mmHg)	82.4 (±5.07)
Blood glucose (mg/dL)	127.3 (±45.31)
Na (mmol/L)	142.5 (±2.18)
K (mmol/L)	4.4 (±0.39)
Cholesterol (mg/dL)	224.0 (±32.59)
HDL-Cholesterol (mg/dL)	51.5 (±11.17)
LDL-Cholesterol (mg/dL)	137.3 (±1.50)
Triglycerides (mg/dL)	183.7 (±87.44)
Daily insulin dosage (unit)	51 (±19)

Table 2: Coefficient of variations in transilluminated voltages in relation to the corresponding blood glucose concentration

Serial Number	Blood glucose concentration (mg/dL)	Transillumination voltage (mV)
01.	89	1.0347
02.	112	1.0342
03.	120	1.0335
04.	122	1.0331
05	300	1.0265
06.	352	1.0262
07.	374	1.027
08.	404	1.0252
09.	589	1.0235
CV	0.395466	0.35205

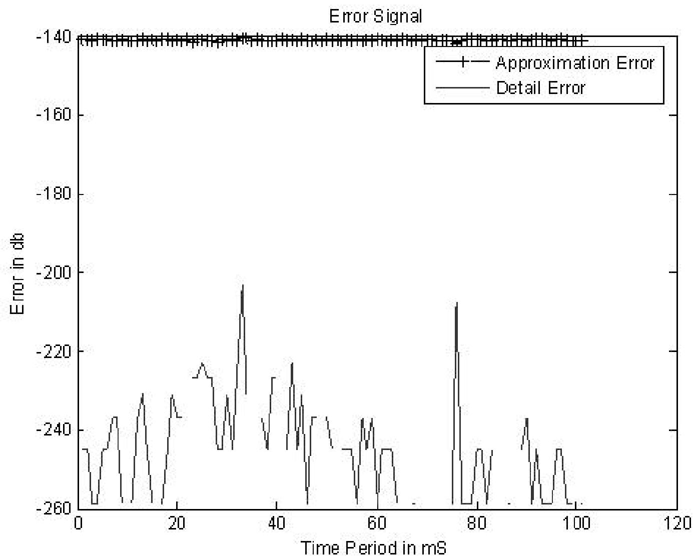

Figure 3: Results of error rate compared with existing and proposed modified Haar wavelet transform.

Table 3: The prediction of blood glucose concentration for different groups using BPN and RBF networks displayed as in mean±standard error with the values in mg/dl

Groups	Clinical outputs (mg/dL)	Practical outputs (mg/dl)		BPN accuracy in (%)	RBF accuracy (%)
		BPN	RBF		
Group 1 (0-150 mg/dl)	133 (±16.2)	131.06 (±15.8)	132.06 (±14.7)	98.49	99.24
Group 2 (151-250 mg/dl)	220 (±19.3)	218.62 (±17.0)	219.62 (±17.0)	99.09	99.54
Group 3 (251-350 mg/dl)	307 (±20.1)	304.43 (±19.1)	305.43 (±21.3)	99.02	99.34
Group 4 (351-450 mg/dl)	392 (±21.4)	390.92 (±21.3)	391.92 (±19.1)	99.48	99.74
Group 5 (≥451 mg/dl)	512 (±25.3)	510.52 (±24.3)	511.52 (±25.3)	99.60	99.80

the legends, + shows the approximation error and the legends, – indicates the detailed error.

As displayed in figure 3, the notation '+' depicts approximation error and '-' shows the detail error.

By trial and error process, it is found that these architectures are most suitable. The data of 450 patients were randomly used for training, 225 for testing, and the remaining 225 for validation. These parameters render good predictive capabilities of possible relationships between dependent and independent variables.

A glimpse of the foregoing tabulated data shows that the outputs from RBF radial basis function with extreme learning machine algorithm,[11,12] are nearer to their clinical values than BPN,[13] outputs. The significant variations can be seen from signals obtained from patients with and without DM. They are compared using six sigma statistical analysis chart for 200 ms (figure 4).

The signals received from the patients without DM reach the centre limit line approximately at regular intervals. However, in patients with DM, the signal variations are large. It reveals that the distributions of the blood particles are not uniform in patients with DM.

We showed that with the proposed non-invasive blood glucose monitoring system, the optical signals are transmitted to the index finger. The scattered signals were collected from the stratum corneum, dermis, epidermis layers, subcutaneous tissue, interstitial fluid and blood vessels in both the arterial and venous blood. Using the continuous modified Haar wavelet transform, the signals are decomposed. Then the back propagation neural network, with gradient descent algorithm and radial basis function with extreme learning machine algorithm were implemented to predict the blood glucose classification and concentration.

Discussion

The method presented here, shows the average efficiency of the architectures by testing the real time signal data sets obtained through indigenous laser based developed system,[6] from the human skin and capillaries of the index finger. It provides the information about the determination of blood glucose concentration by back propagation neural network and radial basis function architectures. Table 4 presents the comparative results of different studies.

Venkatesan and Anita (2006) discussed the use of radial basis function (RBF) as a hidden layer in a supervised feed forward network.[14] RBF used smaller number of locally tuned units and was adaptive by nature. The performance was compared with the most commonly used multilayer perceptron network and classical logistic regression. They used diabetes database for empirical calculations and the results showed that RBF performed better than the other models. The correction prediction percentage was found to be 97 to 98% and it was improved to 99.24 to 99.80% in this research work by using dynamic RBF neural networks.

Jayalakshmi and Santhakumar (2010) mooted a method that was implemented the improved form of Gradient Descent back propagation algorithm.[15] This has been done to increase the

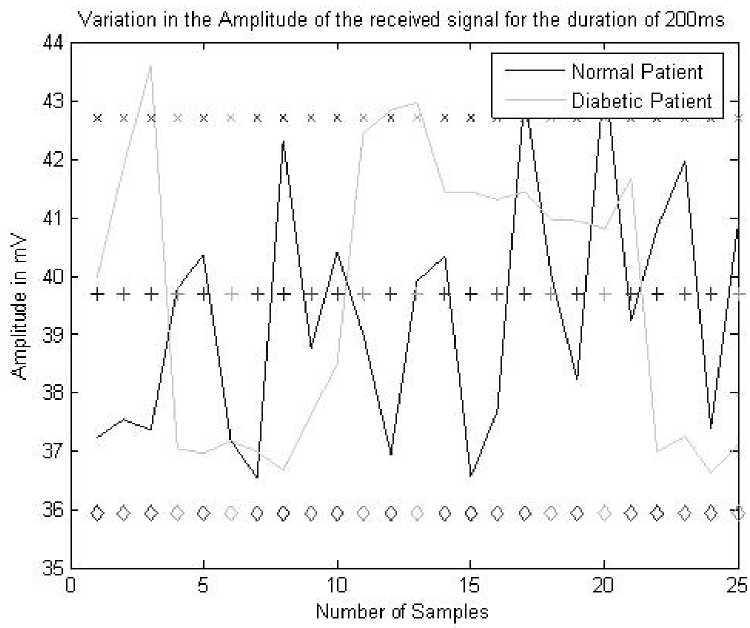

Figure 4: Blood flow variation chart in patients with and without DM.

Table 4: Comparative Results of other Articles

	Authors and Years	Network	Average testing efficiency (%)
1	Venkatesan and Anita (2006)[14]	RBF	98.0
2	Jayalakshmi and Santhakumaran (2010)[15]	BPN	99.73
3	Proposed Method (2011)	BPN	99.136
		RBF	99.53

accuracy of the network, and by missing data replacement, data preprocessing and introducing the performance vector (PV). It has been proved that the new method improved the system performance by more than 7%. This method is not a real time analysis but done offline on existing Pima Indian Diabetes dataset.

As depicted in table 4, Venkatesan and Anita using RBF algorithm determined the blood glucose concentration in the measure of average testing efficiency as 98.0% and Jayalakshmi and Santhakumaran determined it as 99.73% using BPN algorithm, and with the proposed method the average testing efficiency were found to be 99.136% by BPN and 99.53% using RBF algorithms.

Conclusion

The management of DM is mainly based on the continuous analysis of blood glucose level. Our results showed that the proposed non-invasive optical glucose monitoring system is able to predict the glucose concentration. The experimental outputs proved that there was a definite variation in the hematological distribution between the patients with and without DM. This was made possible using the six sigma concept. As the continuous monitoring of blood glucose concentration is important for the management of DM, this study proves to be clinically relevant and useful.

Conflict of interest: None declared

References

1 World Health Organization. Technical Report Series No. 310: Diabetes Mellitus. Geneva: WHO, 1965.
2 Cepuch C, Ojoo A, Amugune B, Kusemerewa D, Goffin E, Saunders Ph, et al. Practical Pharmacy for Developing Countries. Diabetes Mellitus.2011;25:1-11.
3 Gakidou E, Mallinger L, Abbott-Klafter J, Guerrero R, Villalpando S, Ridaura RL, et al. Management of diabetes and associated cardiovascular risk factors in seven countries: a comparison of data from national health examination surveys. Bull World Health Organ. 2011;89:172-83. doi: 10.2471/BLT.10.080820.
4 Cohen RM, Franco RS, Khera PK, Smith EP, Lindsell CJ, Ciraolo PJ, et al. Red cell life span heterogeneity in hematologically normal people is sufficient to alter HbA1c. Blood. 2008;112:4284-91. doi: 10.1182/blood-2008-04-154112. PubMed PMID: 18694998; PubMed Central PMCID: PMC2581997.
5 Non-Invasive Glucose Monitoring Techniques: A review and current trends [Internet]. Poddar R, Andrews JT, Shukla P, Sen P: Cornell University Library. arXiv:0810.5755 [physics.med-ph]- [cited 2008 Oct 31]. Available from: http://arxiv.org/abs/0810.5755
6 Ashok V, Nirmalkumar A, Jeyashanthi N. A Novel Method for Blood Glucose Measurement by Noninvasive Technique Using Laser. International Journal of Biological and Life Sciences. 2011;7:127-33.
7 Rafiqul Islam M. Wavelets, its Application and Technique in signal and image processing. Global Journal of Computer Science and Technology. 2011;11:47-58.
8 Ashok V, Balakumaran T, Gowrishankar C, Vennila I, Nirmal kumar A. The Fast Haar Wavelet Transform for Signal & Image Processing. International Journal of Computer Science and Information Security. 2010;7:126-30.
9 Abu Zitar R. Towards Neural Network Model for Insulin/Glucose in Diabetics. International Journal of Computing & Information Sciences. 2003;1:25-32.
10 Mahmoudvand R, Hassani H, Wilson R. Is the Sample Coefficient of Variation A Good Estimator for the Population Coefficient of Variation? World Applied Sciences Journal. 2007;2:519-22.
11 Oyang YJ, Hwang SC, Ou YY, Chen CY, Chen ZW. Data classification with radial basis function networks based on a novel kernel density estimation algorithm. IEEE Trans Neural Netw. 2005;16:225-36. doi: 10.1109/TNN.2004.836229. PubMed PMID: 15732402.
12 Suresh S, Saraswathi S, Sundararajan N. Performance enhancement of extreme learning machine for multi-category sparse data classification problems. Engineering Applications of Artificial Intelligence. 2010;23:1149-57. doi: 10.1016/j.engappai.2010.06.009.
13 Ashok V, Rajan Singh S, Nirmalkumar A. Determination of blood glucose concentration by back propagation neural network. Indian Journal of Science and Technology. 2010;3:916-8.
14 Venkatesan P, Anitha S. Application of a radial basis function neural network for diagnosis of diabetes mellitus. CURRENT SCIENCE. 2006;91:1195–9.
15 Jayalakshmi T, Santhakumaran A. A Novel Classification Method for Diagnosis of Diabetes Mellitus Using Artificial Neural Networks. International Conference on Data Storage and Data Engineering. 2010;159-63. doi: 10.1109/DSDE.2010.58.