Detection of the Blood Glucose and Haemoglobin A1C with Palm Perspiration by using Artificial Neural Networks

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Abstract

The invasive measurement techniques that puncture the skin during the detection are generally used for blood glucose and haemoglobin A1C (HbA1C) detection. In this paper, artificial neural network structures were used for the detection of relationship between blood glucose, HbA1C and palm perspiration rate as a non-invasive measurement technique. For this purpose, a comparative study was realized by using feed forward multilayer, Elman and radial basis neural network structures. A data set for 221 volunteers is used for this study. Data of 148 volunteers are used for training of the neural networks and the remaining data were used as test data.

1. Introduction

Diabetes is a major health problem in both developed and developing countries, and its incidence is rising [1,2]. The diabetic patients have to control their glucose rates which are very important for them [3]. The diabetes is manageable if the blood glucose concentration can be appropriately monitored [4]. The long-term excess of glucose rate (hyperglycemia) can cause many problems for diabetes such as blindness, damaged nerves and kidneys (renal failure), or even increase the heart diseases, strokes and birth defects. On the contrary the long term low glucose rate (hypoglycemia) can cause confusion, coma and even death. Monitoring the glycemic state of patients is cornerstone of diabetic care [3,5,6].

Glucose sticks to the haemoglobin to produce a haemoglobin A1C (HbA1C). Blood glucose and HbA1C are most commonly used in the tests that monitoring the glycemic status of diabetes patients. Haemoglobin A1C value reflects mean glucose level during the previous 2-3 months' period and is a useful indicator for risk assessment of diabetic complications [6].

The invasive measurement techniques are generally used for blood glucose and haemoglobin A1C (HbA1C) detection. Invasive techniques are widely used for diagnosis and treatment in medicine. During these invasive techniques, some damage and pain could occur in the human body. Therefore, patients suffer during an invasive technique. So, non-invasive measurements at routine time intervals are very attractive for patients. The perspiration contains the glucose. The rate of blood glucose and HbA1C can be determined by measuring the perspiration rate of the palm [3].

Artificial neural network (ANN) structures for classification systems in medical diagnosis are increasing gradually [7-9]. There have been several studies reported focusing on invasive measurement techniques for blood glucose detection using artificial neural network structures [3,10].

The feed forward multilayer neural network structure is the most common neural network structure which has been successfully used for the disease diagnosis systems [8,11]. The radial basis functions greatly reduce the training time and make related analyses much easier [11-13]. The RBF network structures have been successfully used for the disease diagnosis problems also [9,14]. The Elman neural network structure is commonly a two-layer network with feedback from the first-layer output to the first-layer input [15]. The Elman neural network structure has been used for the blood glucose detection [3].

In this paper, artificial neural network structures were used for the detection of relationship between blood glucose, HbA1C and palm perspiration rate as a non-invasive measurement technique. For this purpose, a comparative study was realized by using feed forward multilayer, Elman and radial basis neural network structures. A data set for 221 volunteers is used for this study. Data of 148 volunteers are used for training of the neural networks and the remaining data were used as test data.

2. Method

2.1. Measurement system and sample collection

Schematic diagram and a photo view of the measurement system for detection of blood glucose with palm perspiration are shown in Fig. 1a and 1b respectively. The measurement system consists of four parts: a sampling tube, a sampling humidity probe placed in it, a measurement unit and a PC for data records.

The sampling tube which is made of plastic has a cylindrical shape with a diameter of 6 cm. It is located in the middle of the palm during the measurement after cleaning the palm surface with alcohol. While locating the sampling tube on the palm surface, it is required for a precise measurement to make that there is no interference between outside and inside of the tube.

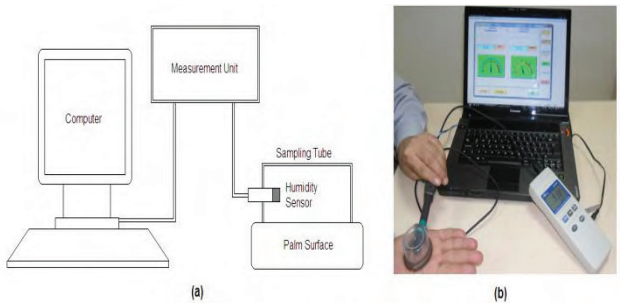

Fig. 1. Schematic diagram (a) and a photo view (b) of the measurement system

A device (Lutron HD-3008 Humidity=Dew Point Meter) is used for measurements in this study. The humidity sensor is made of a thin film capacitance and has a relative humidity range of 10%–95%. It has a relative humidity resolution of 0.1%. The humidity data are measured in 2 s intervals by the Lutron HD-3008 and transferred to the PC via an RS-232 serial port and the data are recorded against time.

2.2. Data preparation

The data from 221 volunteers used in this research were measured at room temperature. An illustration of left and right palm perspiration of a volunteer is shown in Fig. 2a as an example. Right and left palm perspiration versus blood glucose concentration (value yazılmayabilir) was examined for the 221 volunteers. Data from 148 volunteers were used for training the neural network structures and data (for yazılmayabilir) the other 73 volunteers were reserved as test data. The palm perspiration data were measured for each hand and 1 min period and 2 s intervals.

In the previous studies [3,10], the slopes of the palm perspiration data used as the input values of feed forward, Elman and radial basis neural network structures. The calculation method for the slope of palm perspiration ($tg\alpha$) can be shown in Fig. 2b. In the first step of our study, the slopes of the palm perspiration data used as the input values of the neural network structures.

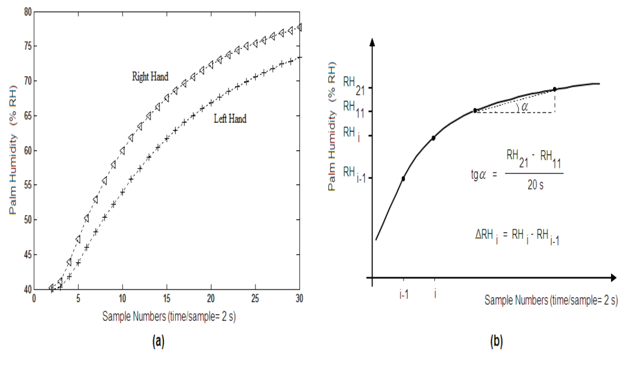

Fig. 2. Raw sensor data and calculations for data preparation.(a) Left and right palm perspiration for a volunteer. (b) Calculation of the palm perspiration slope ($tg\alpha$) and differences (ΔRH_i).

The response values for relative humidity changes very fast at the beginning of measurement. That is, the slope of the transient response is bigger at the beginning and decrease with time. A time series is a set of data collected sequentially over a period of time at regular intervals. Time series data of the transient response provide additional information about the trend and slope of the sensor response [16], This information can be used for detection of relationship between blood glucose, HbA1C and palm perspiration rate. That is why, the palm perspiration deviations and means of the palm perspiration differences were used additionally as the input values of the neural network structures to provide additional information about the trend and slope of the sensor response in the second step. The calculation method for the palm perspiration differences (ΔRH_i) can be shown in Fig. 2b. The palm perspiration deviations are computed according to

$$\Delta RH = RH_{30} - RH_2 \tag{1}$$

where RHi is humidity value of the sample i. And the mean values of the palm perspiration differences is computed according to

$$mean(\Delta RH_i) = \frac{1}{29}\sum_{i=2}^{30}\Delta RH_i \tag{2}$$

2.3. Blood Glucose and Haemoglobin A1C detection by using neural networks

In this study, the feed forward multilayer, Elman and radial basis neural network structures were used for blood glucose and haemoglobin A1C detection. Two different input alternatives were used for these structures. At the first alternative, input values contained palm perspiration slops (2 inputs). At the second alternative, input values contained palm perspiration slops, the palm perspiration deviations and mean values of the palm perspiration differences (6 inputs).

The feed forward multilayer neural network structure used in this study is shown in Fig. 3. This structure has one input layer, two hidden layers, and one output layer. The hidden layer neurons (20 neurons for each hidden layer) and the output layer neurons use nonlinear sigmoid activation functions. Detailed computational issues about the feed forward multilayer neural network structure can be found in references [8,9,15].

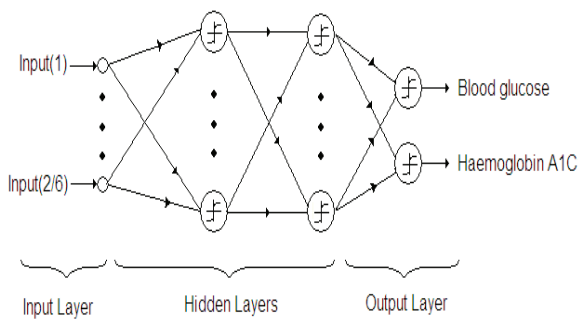

Fig. 3. Implementation of multilayer neural network for blood glucose and haemoglobin A1C detection

The Elman neural network structure used in this study is shown in Fig. 4. This structure has one input layer, one hidden layer, and one output layer. The hidden layer neurons (20 neurons) and the output layer neurons use nonlinear sigmoid activation functions. Detailed computational issues about the feed forward multilayer neural network structure can be found in references [15,16].

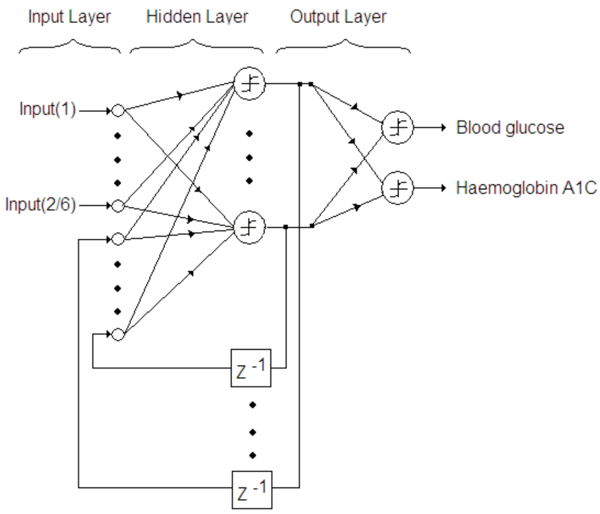

Fig. 4. Implementation of Elman neural network for blood glucose and haemoglobin A1C detection

The radial basis neural network structure used in this study is shown in Fig. 5. This structure has one input layer, one hidden layer, and one output layer. The hidden layer neurons use radial basis activation functions and the output layer neurons use linear activation functions. More detailed computational issues about the radial basis neural network structure can be found in references [9,15,16].

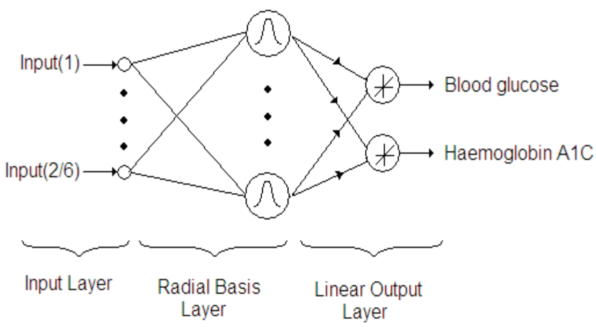

Fig. 5. Implementation of radial basis neural network for blood glucose and haemoglobin A1C detection

In order to test appropriateness of neural network structures, as performance evaluation criteria, the mean relative absolute error (E(RAE)) was used [16].

$$E(RAE) = \frac{1}{n_{test}} \sum_{testset} \left(\left| \frac{\left(Value_{predicted} - Value_{true} \right)}{Value_{true}} \right| \right) \quad \forall Value_{true} \neq 0 \tag{3}$$

where, $Value_{predicted}$ is estimated glucose/HbA1C value, $Value_{true}$ is real glucose/HbA1C value and n_{test} is number of test set data.

3. Results and discussion

The results of the previous studies can not be compared with the results of this study, since the data used in the previous studies [3,10] have been narrow and limited. The methods of the previous studies were used for comparison instead of results. Table 1 shows the E(RAE) performances of the neural network structures for the glucose and HbA1C detection with two different input alternatives.

The results obtained using the second input alternative (this study) were better than the results obtained using the first input alternative (the previous studies) as shown in Table 1. The reason for the better results of second alternative can be seen as additional information provided by the palm perspiration deviations and means of the palm perspiration differences.

From the same table, it can also be seen, that the best rates for the glucose and HbA1C detection was obtained using the radial basis neural network structure with the second input alternative (6 inputs: Palm perspiration slops, the palm perspiration deviations and mean values of the palm perspiration differences) within this study. Hence, it can be said that the radial basis neural network was more successful than other networks used in this study for detection of relationship between blood glucose, HbA1C and palm perspiration rate.

Table 1. The E(RAE) performances of the neural network structures for the glucose and HbA1C detection

Neural Network Inputs	Neural Network Structures	E(RAE) for glucose	E(RAE) for HbA1C
2 inputs: Palm perspiration slops [3,10]	FF multilayer [3]	30.12	18.79
	Elman [3]	29.38	17.87
	Radial Basis [10]	31.16	15.46
6 inputs: Palm perspiration slops, the palm perspiration deviations and mean values of the palm perspiration differences (This study)	FF multilayer	28.36	17.68
	Elman	28.78	16.73
	Radial Basis	23.98	14.91

The results for HbA1C detection were better than that the results of blood glucose detection as it can be seen on the Table 1. This can be because of that, haemoglobin A1C value reflects mean glucose level for a bit long period and it can be a more stable value which affects the palm perspiration rate.

In addition to the above results, the E(RAE) values of the Elman neural network was a bit better than that of the feed forward neural network. This can be because of that the feedback structure of the Elman neural network is more appropriate for the time series nature of the waves.

4. Conclusions

In this study, the forward multilayer, Elman and radial basis neural network structures were used for the detection of relationship between blood glucose, HbA1C and palm perspiration rate as a non-invasive measurement technique.

As the conclusion, the following results can be summarized:

- It was seen that neural network structures could be used for the glucose and especially for HbA1C detection. HbA1C is a useful indicator for risk assessment of diabetic complications. So, the used methods can be helpful as learning based decision support system for contributing to the patients in their early diagnosis decisions
- It was also seen that the using of the palm perspiration deviations and mean values of the palm perspiration differences which give additional information about the trend and slope of the sensor response were useful for detection of relationship between blood glucose, HbA1C and palm perspiration rate.
- The detection rates obtained using the radial basis neural network structure was better than those obtained using other neural network structures.

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7. References

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