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Controlling Blood Glucose Levels in Diabetics By Neural Network Predictor

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Abstract— **In this study we develop a system that uses some variables such as, level of exercise, stress, food intake, injected insulin and blood glucose level in previous intervals, as input and accurately predicts the blood glucose level in the next interval. The system is split up to make separate prediction of blood glucose level in the morning, afternoon, evening and night, using data from one patient covering a period of 77 days. We have used RBF neural network, and compared our result with MLP neural network that was implemented by the others. The assessment of the analysis resulted in a Root Mean Square Error of (0.04±0.0004) mmol/l.**

I. Introduction

DIABETES mellitus is one of the most common chronic diseases, which can be lead to serious long-term complications and death. In type I diabetes, the disease is caused by the failure of pancreas, to produce sufficient insulin [2], and in type II the body is resistant to the insulin it makes, which leads to an uncontrolled increase of blood glucose, unless the patient uses insulin or drug. Maintaining blood glucose levels of diabetic patients within the normal range by exogenous insulin administration can decrease these complications [3].

There are several factors that affect the blood glucose level, such as the amount of food, the insulin dosage, the level of exercise and stress. In addition, there are a number of internal processes, such as absorption and production of glucose by the liver and renal. The large number of factors makes it difficult to predict how the glucose level will behave in the next few hours.

It is desirable to make an accurate prediction, so that controlling actions can be taken before the glucose level goes beyond the ideal bounds [1].

Currently, there are a number of computer based systems commercially available where the patient can enter insulin injections, blood glucose measurements and meals, which store and display this information. These systems are very useful for self-monitoring and consultation with the physician. Such computer based systems are potentially more useful if they can be able to analyze past therapy, to predict future blood glucose levels and to provide therapy recommendations.

So far, different approaches are used to manage blood glucose level. Some of them are based on compartment or algorithmic model [4, 5]; also we can see such a system as a control system, where insulin is used to control the blood glucose level. For non-diabetics, the body continuously 'monitors' the blood glucose level and the pancreas releases insulin if needed. If the goal is to create an artificial pancreas, the system will have to continuously measure the glucose level and taking action in the form of releasing insulin. This is a closed loop system [1]. An overview of different kinds of control systems is given by R.Blazzi ,G.Nucci and C.Cobelli [6], and in some researches we can see blood glucose level predicting by chaos approach [7,8].Neural networks are widely used in the field of health care for a range of different purposes. It also can be found in the field of diabetic treatment [1, 2, 9].

The goal of our study is to design an artificial neural network which uses several affective factors during an interval as input, and gives the level of blood glucose at the next interval, as output.

Multidimensional of physiological interactions, highly nonlinear, stochastically, time variant, and patient specific are the reasons which made us consider that, neural networks are particular suitable models and we try to model the input-output behavior of a diabetic not any of the internal processes explicitly.

Because the effect of some factors can be very different from person to person, the model is created for only one specific patient.

II. Procedure

A. Data

We used the data which P.Kok [1] has used in his research. His data covers a continuous period of 77 days from one patient.

A shorter period would result in even less data than we have now. But a longer period would cover long-term changes in the glucose metabolism, which makes our result unreliable. These changes may be caused by factors that are not taken into account in our model.

In P.Kok's records, for each day, the patient filled in a table similar to the one in figure 1, which is a sample of a typical day and a day consists of eight measurement points:

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night, breakfast, after breakfast, lunch, after lunch, dinner, after dinner and before sleeping. We will consider four intervals: morning, afternoon, evening and night and we create separate neural net for each interval, by this method we consider the changes of glucose metabolism that depends on the time of day. There are measurement points at the start of the interval, during the interval and at the end of the interval (e.g. breakfast, after breakfast and lunch for the morning interval).

TABLE I
SAMPLE OF PATIENTS DATA USED FOR MODELING [1]

9 apr 04								
Friday	NT	BB	AB	BL	AL	BD	AD	BS
Time		8:27		12:25		17:29		23:42
Glucose level		7.8		6.6		7.4		8.3
Short act. insulin		7		7		9		0
Long act. insulin		22		0		0		3
Carbohydrates		81	0	93	16	92	30	8
Exercise		3		2		3		2
Stress		2		2		2		2

For each interval, following data is entered: time of glucose measurement, glucose measurement value, amount of short acting insulin, amount of long acting insulin, food intake, exercise and stress. Most of the values are only present at the start and the end of the interval and values during the interval are ignored. The patient recorded the glucose measurements in mmol/l and the insulin dosage in units. The short acting insulin that was NovoRapid and the long acting insulin was Lantus. The carbohydrate intake is estimated in grams. Exercise is expressed on a scale from one to five, which one means doing nothing and five means, heavy exercise. A same scale was used for stress, which one means relaxing and five, heavy stress.

The unit of the variables is not really that important and can be any unit, as long as it is consistent within all of the data. The data will be scaled appropriately in the neural network [1].

As we know, the distribution of data can change the result of our model. To overcome this problem we created 20 holdout conditions, each of them consist of a random distribution of the data over these three data sets. The train data set contained 40% of the data, the validation data set 30% and the test data the remaining 30% and for investigation of training result, the average performance of the neural networks over the 20 holdout conditions is taken.

B. *Neural Network*

A *radial-basis function* ***(RBF)*** *network* in its most basic form that involves three entirely different layers, is used for each interval (morning, afternoon, evening and night). The input layer is made up of source nodes (sensory units). The second layer is a hidden layer of high enough dimension, which serves a different purpose from that in a multilayer perceptron. The output layer supplies the response of the network to the activation patterns applied to the input layer. The transformation from the input space to the hidden-unit space is *nonlinear,* whereas the transformation from the hidden-unit space to the output space is *linear* [10].

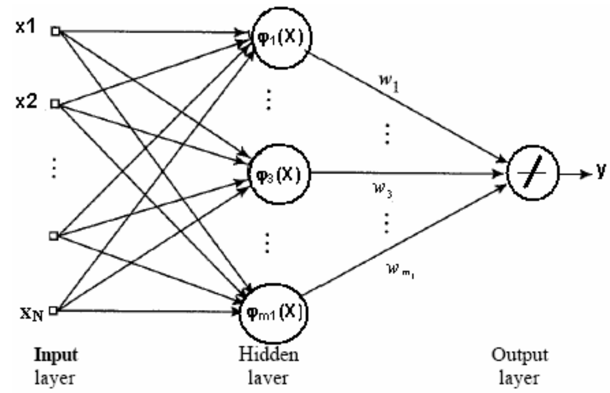

Fig. 1. A scheme of RBF Neural Network

The nonlinear function that is used for each hidden neuron is the following Gaussian function:

$$\varphi_i(X) = \exp(-X^2) \tag{1}$$

Number of hidden neurons (m_1) in our experiment was equivalent to number of training input vectors and learning is equivalent to finding a surface in a multidimensional space that provides a best fit to the training data, with the criterion for "best fit" being measured in some statistical sense. Correspondingly, generalization is equivalent to the use of this multidimensional surface to interpolate the test data.

Scaling: The data had to be scaled, so that the neural network could process the data. We divided all of the data by a number which is the largest number in the training data.

C. *Criterion Function*

For choosing an optimal neural network we compared the performance of the neural networks by defining two criterion functions, the root mean square error and the performance coefficient.

The root-mean-square-error (RMSE) is given by:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - T_i)^2} \tag{2}$$

Where y is the output of the neural network, T is the target output (the measured value) and N is the number of samples. In RMSE, network output is compared to the target, the error is calculated as the difference between the target output and the network output. We will always express the RMSE in mmol/l. And the performance coefficient is given by:

$$\begin{cases} pc = -cc \cdot sc & if \quad cc < 0 \quad and \quad sc < 0 \\ pc = cc \cdot sc & otherwise \end{cases} \tag{3}$$

Where pc is the performance coefficient, cc is the correlation coefficient and sc is the slope coefficient.

cc and sc are given by:

$$cc = \frac{\left(\sum_{i=1}^{N}(T_i - \overline{T})(y_i - \overline{y})\right)^2}{\left(\sum_{i=1}^{N}(T_i - \overline{T})^2\right)\left(\sum_{i=1}^{N}(y_i - \overline{y})^2\right)} \quad (4)$$

$$y = sc \cdot t + a$$

$$sc = \frac{N\sum_{i=1}^{N} T_i y_i - \sum_{i=1}^{N} T_i \sum_{i=1}^{N} y_i}{N\sum_{i=1}^{N} T_i^2 - \left(\sum_{i=1}^{N} T_i\right)^2} \quad (5)$$

Where y is the output of the neural network, T is the target output and N is the number of samples. We also assume that both the cc and the sc will be between 0 and 1.If both sc and cc measures are close to 1 we can say that the neural network performs well, for this reason we combined them in performance coefficient. To get an unbiased measure of performance, the criterion functions are calculated using the test data set.

D. Input Vector

Peter Kok[1] considered these 19 inputs from the raw data, and he tried to find the best inputs for each interval from these input by trial and error.

1. Glucose level during interval
2. Short acting insulin during interval
3. Food intake during interval
4. Exercise during interval
5. Glucose level at start of interval
6. Long acting insulin during past 24 hours
7. Stress during interval
8. Glucose level at start of interval on previous day
9. Short acting insulin during interval on previous day
10. Food intake during interval on previous day
11. Exercise during interval on previous day
12. Resulting glucose at end of interval on previous day
13. Glucose level at start of previous interval
14. Short acting insulin during previous interval
15. Food intake during previous interval
16. Exercise during previous interval
17. Exercise average over past 24 hours
18. Interval length during interval
19. Exercise added up squared values during past 24 hours

In our study we used these inputs, but for choosing optimal inputs in different intervals, first we take all of the 19 inputs into consideration, and then we try to eliminate unimportant inputs by pruning method. In this method, after training the network with all of the input and measuring the criterion functions, we calculate the magnitude of weight vector for each input, and then we eliminate the inputs that the magnitude of their weight vector is low. After elimination an input, again we measure the criterion functions, if we see that CC or RMSE becomes worth by this elimination, we don't omit it, but if the result becomes better, we will leave out that input and by repeating this procedure optimal inputs for each interval will be find. By this technique we have obtained the following result:

For morning interval, eliminating the input (3,4,8,9,11,12,13,14,16,19), and in afternoon, evening and night interval, omitting the input (3,4,6,7,8,9,11,12,13,14,16,17,19), got the best result.

We bring the average result of network performance for training, validation and test data set in the following table:

TABLE II
PERFORMANCE RESULT

Criterion function	morning	afternoon	evening	night
RMSE Training data	0	0	0	0
RMSE Validation data	0.0710	0.0491	0.0263	0.0119
RMSE Test data	0.0826	0.0513	0.0373	0.0118
pc Training data	1	1	1	1
pc Validation data	0.9997	0.9996	0.9994	0.9999
pc Test data	0.9996	0.9994	0.9994	0.9999

In the following figure we provided a plot of target output (the measured value) versus the output of the neural network (predicted value).The performance plot gives a quick impression on how well the neural network has been trained. In each figure, star markers indicate train data; triangular markers are validation data and round markers represent test data.

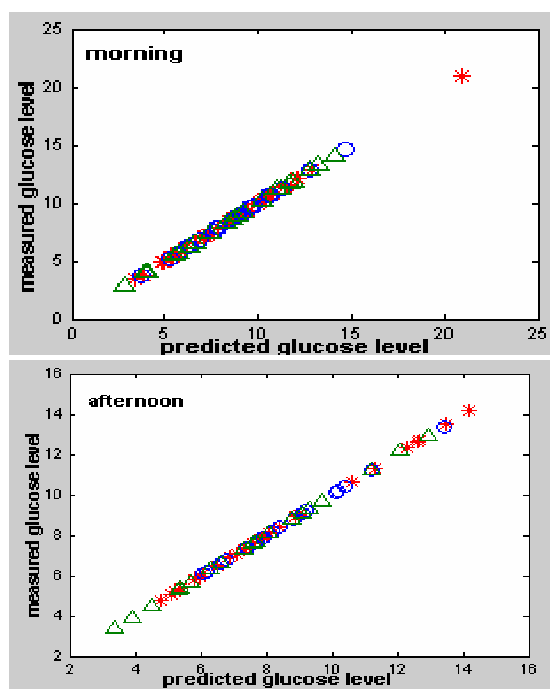

Fig. 2. Predicted blood glucose levels against measured blood glucose levels in the morning and afternoon.

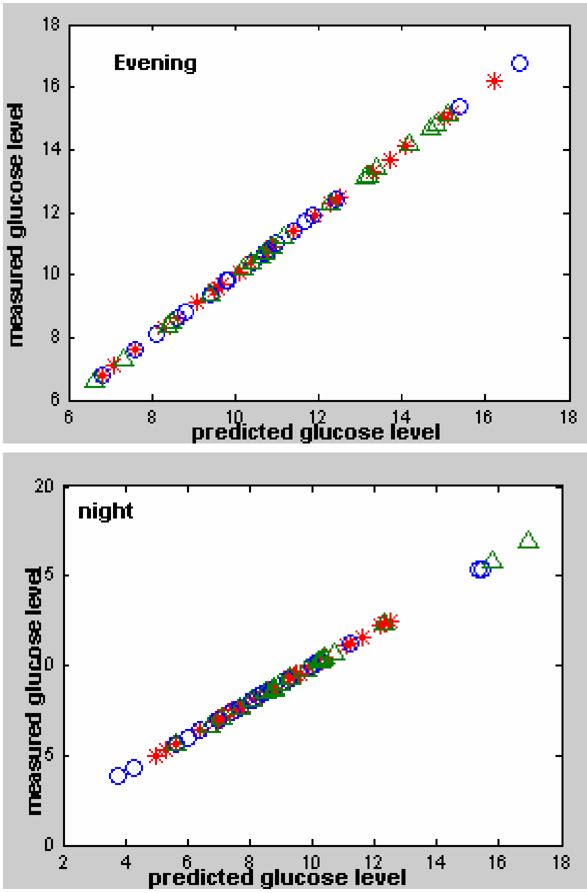

Fig. 3. Predicted blood glucose levels against measured blood glucose levels in the evening and night interval

III. Result Of Validation

In order to show the reliability of our results, we will select the test and train data from data set randomly, and then we will give train data to the network, if its RMSE becomes less than 0.08, we will give test data to network and after measuring its RMSE and pc, again we choose another distribution of test and training data. By repeating this procedure for 20 times we obtained a vector of RMSE and pc for test data. We calculated the average and variance of these vectors. If the measured variance becomes large we can't trust the result, because this shows that if we test the network again, maybe we will not get an acceptable result. But in our study we achieved small RMSE and large pc with very small variances. You can see the validation result in the following table:

TABLE III
Validation Result s For RBF Network

	Avg. RMSE	Var. RMSE	Avg. pc	Var. pc
morning	0.0289	0.0001	0.9971	0.0000
afternoon	0.0378	0.0004	0.9949	0.0000
evening	0.0244	0.0004	0.9976	0.0000
night	0.0063	0.0000	0.9993	0.0000

We ourselves implemented the Peter Kok's experiment with MLP network again, and brought the validation result of it, here. The selected MLP NN for morning and night is a single hidden layer network for morning and night and two hidden layers for afternoon and evening intervals. In this network, when the training RMSE is less than 3, we will go to test phase, because of networks having such a structure, we can't achieve very small RMSE.

TABLE IV
Validation Result s For MLP Network

	Avg. RMSE	Var. RMSE	Avg. pc	Var. pc
morning	3.4476	0.4542	0.0043	0.0002
afternoon	2.8611	0.1057	0.0128	0.0021
evening	2.3660	0.1831	0.0213	0.0006
night	2.2253	0.2693	0.1900	0.0213

IV. Conclusion And Discussion

A comparison of the system to MLP networks which has a root-mean-square error of 2.5 mmol/l and AIDA ('The Automated Insulin Dosage Advisor'), which works based on neural net approaches and has a root-mean-square error of 1.9 mmol/l [1], shows that RBF networks with optimal input selection can predict the blood glucose values more accurately. RBF NN has a root-mean-square error of 0.012 mmol/l. But the system needs to be tested on other data sets and with other patients.

Acknowledgment

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