Comparison of MLP and Elman Neural Network for Blood Glucose Level Prediction in Type 1 Diabetics

S.A. Quchani, E. Tahami

Biomedical Engineering Department of Azad University, Mashhad, Iran

Abstract— **One of the most dangerous symptoms of Type 1 diabetes is the frequent and grate oscillation of blood glucose level that can lead the patient to unconscious and coma states . So being able to predict and finally prevent these two symptoms would simplify the management of the diabetic patients. This paper attempts to comparison the performance of MLP and Elman neural networks to predict the blood glucose levels in type1 diabetics. Data set, used in this paper consists of the protocol of a 10 Iranian type1 Diabetic women and include features such as type and dosage of injected insulin, The period of time (in hour) between two consecutive measurements of the blood glucose level, carbohydrate intake , exercise and the blood glucose level measured at start of the given period of time. Finally we concluded that the usage of Recurrent Neural Network such as Elman can be an appropriate model to predict the long term blood glucose level in type 1 diabetics also we could successfully increase the accuracy of prediction and reduce the number of layers and neurons used in the construction of Neural Networks.**

Keywords—**Diabetes, Blood glucose prediction, Elman, MLP, Neural Network**

I. Introduction

Diabetes mellitus is one of the most widespread chronic diseases known in the world that mostly extending in developed and developing countries, so that it is forecasted 220 million people will have this disease till 2010. Now Diabetes mellitus is one of the most common chronic diseases with approximately 1.5 million affected people, just in Iran [1] .

Most dangerous and basic symptoms associated with this disease are related to the frequent and grate oscillation of blood glucose level known as a hypoglycemic and hyperglycemic which can lead the patient to unconscious or coma states and finally some other complications such as heart attack , blindness, diabetics foot and mental disturbance.

Because of this, the methods that can reduce the number of blood glucose level registration and also predict and prevent these two fundamental symptoms are the best ways to control and cure the diabetes.

Different computer-assisted approaches have been attempted to predict blood glucose levels and insulin requirements such as mathematical minimal models [2-12] Most of these models also incorporate prediction of the patient s response to insulin and recommendations on supplements, adjustments, or dietary modification. These approaches have been based on complicated algorithms or mathematical models or combinations of the two. Still, there are many detectable and undetectable factors that are difficult to measure and incorporate into a model, making the model more or less uncertain. The ideal prediction tool should minimize the impact of such factors.

In this paper we attempted to compare the performance of MLP and Elman neural networks in blood glucose levels prediction and improved the accuracy of prediction and also reduce the number of layers and neurons used in the construction of neural network in comparison with previous researches in this case.

II. Data and Method

A. Data

Dataset used in this paper consists of the protocols of a 10 Iranian type1 Diabetic women with the ages between 17 and 26 that include features such as:

- Dosage of injected short acting insulin (unit)
- Dosage of injected long acting insulin (unit)
- Period of time between two consecutive measure ments of the blood glucose level(hour)
- Stress level (unit)
- Carbohydrate intake (gr)
- Exercise(unit)
- Blood glucose level measured at the start of the given period of time(FBGL) (mg/dlit)

The recorded data that was used covers a continuous period of 75 days for some of patients and 135 days for another. For each day we have recorded data just in the morning and afternoon and during this interval. 75% of this recorded data is used to train the neural network and 25% is used to test the neural.

It is noticeable that the carbohydrate intake was an estimate in grams. Exercise is expressed on a four step scale from one to four, which one means doing nothing and four expresses heavy exercise. A scale from one to four was also

F. Ibrahim, N.A. Abu Osman, J. Usman and N.A. Kadri (Eds.): Biomed 06, IFMBE Proceedings 15, pp. 54-58, 2007
www.springerlink.com '

used for stress, which one means relaxing and four expresses heavy stress .In this paper First, Blood Glucose Level (FBGL) has been recorded before breakfast and Next, Blood Glucose Level (NBGL) has been recorded before launch in each day. A sample of data is shown in Table 1.

Table 1 Sample of dataset

FBGL	Short Acting Insulin	Long Acting Insulin	Stress Level	Exercise Level	Carbohydrate	Time Interval	NBGL

B. Methodology

Designed algorithm for prediction of e blood glucose level has five steps. In first step data are divided in two groups of testing and training sets. In second step data must be normalized for using in neural network. In third step data are fed into the neural network and finally in forth step the output of neural network must be renormalized to return in the correct blood glucose ranges. Block diagram of our designed algorithm has shown in Fig. 1.

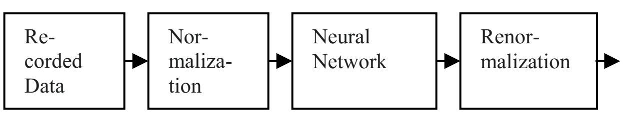

Fig.1 Block diagram of designed algorithm for prediction of blood glucose level in type one diabetics

It must be emphasized that the present method results in an individual model , valid for that particular patient under a limited period of time because the blood glucose affected by some physiological conditions such as age, weight, sex and even some other non physiological factors . However, the method itself has general validity, since the blood glucose variations over time have similar properties in any diabetic patient.

C. Multilayer neural networks

Multilayer perceptron neural networks are capable of learning and parallel processing, which are valuable specifications; and commonly are being used for solving complicated problems. In these networks, learning process is accomplished by specific algorithms which adjust existing weights between neuron connections.

Neural network used in proposed intelligent algorithm, is a 3 layer MLP which has a hidden layer with 5 neuron and 1 neuron in output layer. Learning criteria is based on back propagation. MATLAB is used to design MLP neural network. Neuron active functions of each layer are used to determine the threshold of output layer. For output layer logsig activation functions and for hidden layer tansig activation functions have been used

Neural network weights, by considering back propagation algorithm , are improving automatically in iteration stages calculated by (2) , in other words weight x in each moment equals to weight in previous moment plus gradient error function g_k in each stage, which is multiplied by learning rate a_k and this will repeated so many times until the weights vector reaches its optimal degree which is calculated by (3), versus this optimal degree, error criterion reaches its minimum. Error criterion is mean square error MSE here.

$$X_{k+1} = X_K - a_k g_k \tag{1}$$

$$MSE = \frac{1}{N}\sum_{k=1}^{N}(t(k) - a(k))^2 \tag{2}$$

t(k) is expected output , a(k) is real network output and N is number of iterations.

It should be pointed out that in initializing the algorithm, some initial quantities are being chosen randomly for weights and then these quantities will improve during performance of the algorithm. Bias quantity which adjust the activation function also designate and shift the threshold amount of each activation function. As the initial quantities were random for weights, initial quantities for bias are also random. The entire network construction and parameters is tabulated in Table 2.

Table 2 MLP Neural Network construction

Number of input	7
Network Configuration	[5 1] tansig pure line
Learning Rate	0.01
Number of epochs	300
Training goal accuracy	0.1

Fig. 2 shows the results of blood glucose level time series prediction with the MLP neural network for one of diabetics. Finally the mean absolute error between recorded and predicted blood glucose levels for testing and training sets is tabulated in Table 3.

F. Ibrahim, N.A. Abu Osman, J. Usman and N.A. Kadri (Eds.): Biomed 06, IFMBE Proceedings 15, pp. 54-58, 2007
www.springerlink.com ' Springer-Verlag Berlin Heidelberg 2007

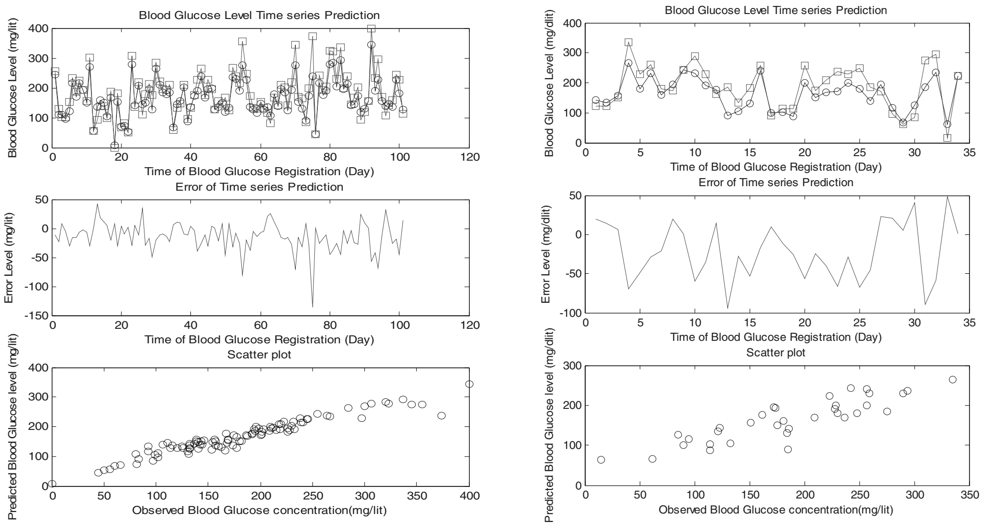

Fig.2 The plots show the blood glucose level time series prediction for two parts which part (A) is related to the training set and part (B) is related to the testing set. At the top of each part the small circles indicate real recorded blood glucose levels and the small squares indicate predicted blood glucose levels. Predicted Error and scatter function are plotted in the next terms.

Table 3 Mean of prediction Errors for training and testing of MLP Neural Network

Steps of prediction	Mean absolute error of prediction
Training step	22.5289 (mg/dlit)
Testing step	24.1449 (mg/dlit)

D. Recurrent Neural Network

In contrast to feed-forward networks partially recurrent neural networks, especially the Elman net, offer a good compromise between complexity and capability. After modifying the network by introducing additional feedback loops in the context layer of the Elman net as shown in figure 3 it is able to learn the process that their current state heavily depends on events that took place in the past.

The Elman Recurrent Neural Network is used in this paper has an identical construction with the MLP Neural Network in number of neurons, number of layers, Type of activation functions and also training algorithm .The only difference between two types of neural network is just related to the delays used in the feedback loops of Elman Recurrent Neural Network .The Elman Neural Network we used in this paper is shown in Fig. 3.

According to the Fig. 3 the outputs of the Elman Recurrent Neural Network at each time step can be calculated as follows where $a_j(k)$ is the output of the hidden layer, IW_{ij} are the weights of the input layer, LW_{ij} are the weights of the feed back and V_j are the weights of the output layer.

$$a_j(k) = \tan sig(X_i \cdot IW_{ij} + a_j(k-1).LW_{ij}) \quad (3)$$

$$BGL = pureline(a_j(k) \cdot V_j) \quad (4)$$

Fig. 4 shows the results of blood glucose level time series prediction with the Elman Recurrent neural network for one of diabetics.

The mean absolute error between observed and predicted blood glucose levels for testing and training sets are shown in Table 4.

Table 4 Mean of prediction Errors for training and testing of Elman Recurrent Neural Network

Steps of prediction	Mean absolute error of prediction
Training step	5.4597 (mg/lit)
Testing step	10.4023 (mg/lit)

F. Ibrahim, N.A. Abu Osman, J. Usman and N.A. Kadri (Eds.): Biomed 06, IFMBE Proceedings 15, pp. 54-58, 2007
www.springerlink.com ' Springer-Verlag Berlin Heidelberg 2007

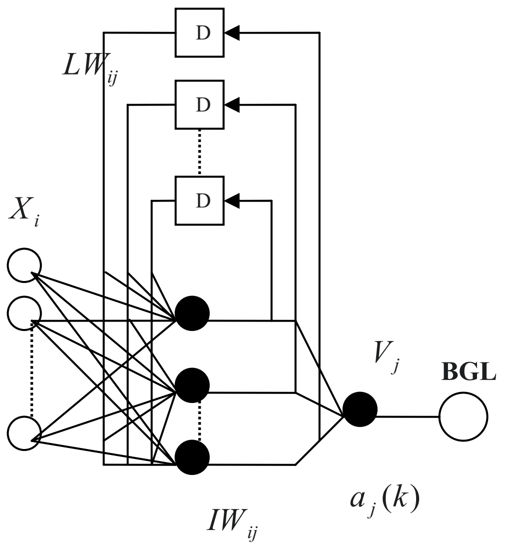

Fig.3 Elman Recurrent Neural Network

By comparing Tables 3 and 4 we can conclude that the Elman Recurrent Neural Networks have more appropriate accuracies than the MLP Neural Networks in the blood glucose level prediction process.

This result adapted to the real blood glucose regulatory system of the body because the glucose metabolism is characterized by the fact that the current state heavily depends on events (meals, insulin injections , exercise) that took place in the past and this factor an be provided with time delays in the construction of Elman Recurrent Neural Networks.

III. Conclusions

On of the most dangerous and basic symptoms associated with the diabetes disease are related to the frequent oscillation of blood glucose level known as a hypoglycemic and hyperglycemic that can lead the patient to unconscious and coma states .For this reason it is necessary to use, methods which can decrease the registration number of blood glucose level and also predict and prevent these two fundamental symptoms.

In this paper we could successfully compare the performance of MLP and Elman neural networks and then we conclude that the performance of Elman Recurrent Neural Network is better than the MLP Neural Network for blood glucose levels prediction also we could increase the accuracy of prediction and reduce the number of layers and neurons used in the construction of neural network in comparison with previous researches in this case which make the algorithms faster and simpler. To improve the accuracy of blood glucose time series prediction we suggest that the number of effectiveness features must be increased and the intervals between data registration must be decreased also optimization of Neural Network construction with other intelligent methods such as Genetic algorithms or Fuzzy Logics are another ways to achieve this goal.

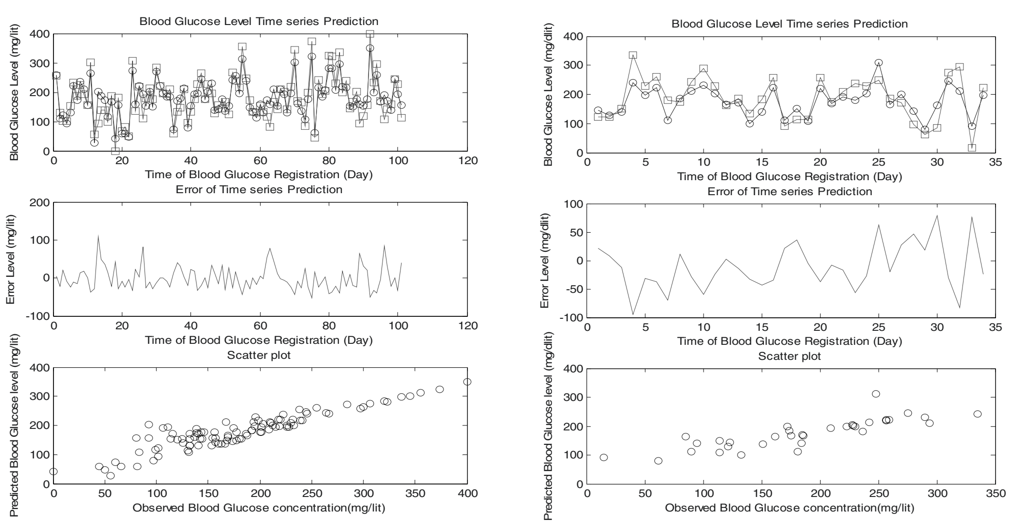

Fig.4 The plot show the blood glucose level time series prediction for two parts that part (A) related to the training set and part (B) is related to the testing set. At the top of each part the small circles indicate the recorded blood glucose levels and the small squares indicate the predicted blood glucose levels. Predicted error and scatter function are plotted in the next terms.

F. Ibrahim, N.A. Abu Osman, J. Usman and N.A. Kadri (Eds.): Biomed 06, IFMBE Proceedings 15, pp. 54-58, 2007

References

1. B. Larijani, M.D; F. Zahedi, M.D; Sh. Aghakhani, M.D Epidemiology of Diabetes Mellitus in Iran Shiraz E-Medical Journal , Vol. 4, No. 4, October 2003
2. Martin H. Kroll, "Biological variation of glucose and insulin includes a deterministic chaotic component" BioSystems 50 (1999) 189 201
3. E.Carson et al. , 1992 A Spectrum of Approaches for Controlling Diabetes , IEEE Transactions onControl Systems, No.12 Andreassen, S., Benn, J., Hovorka, R., et al. A probabilistic approach to glucose prediction and insulin dose adjustment: Description of metabolic model and pilot evaluation study. Comput.Methods Programs Biomed. 41, 153, (1994).
4. Deutsch, T., Lehmann, E. D., et al. Time series analysis and control of blood glucose levels in diabetic patients. Comput. Methods Programs Biomed. 41, 167, (1994).
5. Lehmann, E. D., Deutsch, T., et al. AIDA: An interactive diabetes advisor. Comput. Methods Programs Biomed. 41, 183, (1994)
6. A. De Gaetano, O. Arino, Mathematical modelling of the intravenous glucose tolerance test, J. Math. Biol. 40 (2000) 136 168.
7. R.N. Bergman, Pathogenesis and prediction of diabetes mellitus: Lessons from integrative physiology, in: Irving L.Schwartz Lecture, Mount Sinai J. Medicine 60 (2002) 280 290.
8. D.L. Bennett, S.A. Gourley, Asymptotic properties of a delay differential equation model for the interaction of glucose with plasma and interstitial insulin, Appl. Math. Comput. 151 (2004) 189 207.
9. J. Li, Y. Kuang, C. Mason, Modeling the glucose-insulin regulatory system and ultradian insulin secretary oscillations with two time delays, submitted for publication.
10. Leaning M. S. and Boroujerdi M. A., "A system for compartmental modeling and simulation," Comput. methods programs biomed., vol. 35, 1991
11. Tresp V., Moody J., and Delong W.-R., \Neural modeling of physiological processes," Computational Learning Theory and Natural Learning Systems, vol. 2, 1994, S. Hanson et al., eds., MIT Press.
12. A. Drozdov, H. Khanina, A model for ultradian oscillations of insulin and glucose, Math. Comput. Modeling 22 (1995) 23 38.

Address of the corresponding author:

Author: Ehsan Tahami
Institute: Biomedical Engineering of Azad university of mashhad
Street: Ghasem abad ostad usefi
City: Mashhad
Country: Iran
Email: ehsantahami@yahoo.com

F. Ibrahim, N.A. Abu Osman, J. Usman and N.A. Kadri (Eds.): Biomed 06, IFMBE Proceedings 15, pp. 54-58, 2007