Blood Glucose Level Prediction Using Intelligent Based Modeling Techniques

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Abstract

In this paper, new methods of blood glucose (BG) level modeling and prediction using artificial intelligent (AI) based techniques have been suggested. The obtained data was windowed and normalized prior to the application of AI based modeling techniques for the estimation of appropriate model parameters. The obtained parameters can be used to predict the next pre-breakfast BG level. Performance analysis of the suggested techniques have been evaluated using pre-breakfast BG level data and results obtained show that the techniques especially the hybrid AIS technique can accurately predict next BG level, thus critical emergency can be avoided and at the same time injection of insulin dosages and appropriate meals for a diabetic patient can be prepared ahead of time.

Keywords: Artificial Intelligent (AI), Blood Glucose Level, Diabetes, Parametric Modeling Technique.

1. Introduction

Diabetes mellitus type 1 or insulin-dependent diabetes mellitus (IDDM) is one of the known chronic disease in man. It is an autoimmune disease that results in destruction of insulin-producing beta cells of the pancreas thereby leading to inability of the body to produce the required insulin. It may also lead to insulin-resistance which is typically associated with old age and obesity [1]–[4]. Insulin is one of the most important hormones in the body. It performs several important functions among which is the regulation of body metabolism. Constant monitoring of blood glucose concentration, exercise and periodic insulin injection are some of the standard ways of treating IDDM patient. It is estimated that 4-6 times insulin are often taken daily so as to keep the blood glucose (BG) constant.

There has been an increase in age and society-related diseases like Diabetes mellitus type 1, IDDM in recent times. Diabetes can harm the eyes by damaging blood vessels of the retina, which in turn can cause loss of vision. The effect of diabetes on the retina is popularly known as diabetic retinopathy (DR) and if left untreated for long time can lead to blindness [5], [6]

The BG measurement data used in this work have been obtained from [2] accessed via UCI database [3]. The dataset cover several weeks to months worth of outpatient care on 70 patients. Two different sources, an automatic electronic recording device and paper records have been used in acquiring the data. The automatic electronic recording had an internal clock to time s tamp events, whereas the paper records only gives "logical time" slots (breakfast, lunch, dinner,bedtime) [2]. BG concentration varies in individuals

TABLE I
A typical section from BG dataset

Date	Time	Code	Code Name	Value
04-21-1991	9 : 09	58	Pre-breakfast BG measurement	100
04-21-1991	9 : 09	33	Regular insulin dose	009
04-21-1991	9 : 09	34	NPH insulin dose	013
04-21-1991	17 : 08	33	Regular insulin dose	007
04-22-1991	7 : 35	58	Pre-breakfast BG measurement	216
04-22-1991	7 : 35	33	Regular insulin dose	010
04-22-1991	7 : 35	34	NPH insulin dose	013
04-22-1991	13 : 40	33	Regular insulin dose	002
04-22-1991	16 : 56	33	Regular insulin dose	007
04-23-1991	7 : 25	58	Pre-breakfast BG measurement	257
04-23-1991	7 : 25	33	Regular insulin dose	011
04-23-1991	7 : 25	34	NPH insulin dose	013
04-23-1991	17 : 25	33	Regular insulin dose	007
04-24-1991	7 : 52	58	Pre-breakfast BG measurement	239
04-24-1991	7 : 52	33	Regular insulin dose	010

with normal pancreatic hormonal function, and the normal pre-meal BG ranges approximately 80-120 mg/dl while a normal post-meal BG ranges 80-140 mg/dl. Typical section from the acquired data for a patient and the plot of pre-breakfast BG measurement is shown in Table I and Figure 1 respectively.

The motivation for this work lies in the application of parametric modeling techniques especially autoregressive (AR) and autoregressive moving average (ARMA) models in solving the problem of BG measurement in order to predict pre-breakfast BG level ahead of time. Accurate prediction will definitely assist in preparing the best meal mixture ahead of time for the patient thus avoiding unwarranted emergency situation caused by high BG level. Similarly, predicting ahead will assist in maintaining the BG level at the appropriate safe level. Furthermore, modeling the BG level will also assist in understanding the behavioral pattern of the patients and provide mechanism for simulation and response to meals and other inputs like insulin dosage, drugs, exercise etc.

The suggested parametric models are presented in section 2 while performance analysis of the proposed techniques and conclusion are contained in section 3 and section 4 respectively.

2. Methodology

Parametric model identification techniques have been suggested as the best way for finding the mathematical description of a typical black box [7]. In this work, application of parametric modeling techniques for BG level

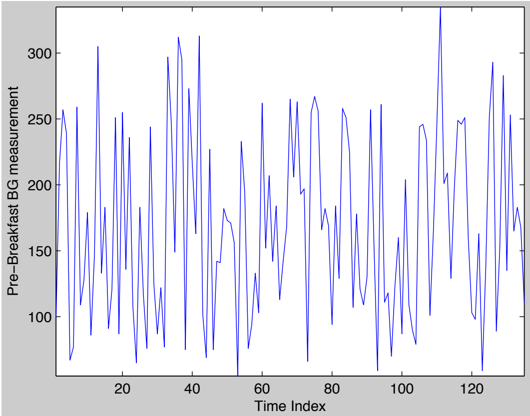


Fig. 1. Pre-breakfast BG level for a diabetic patient

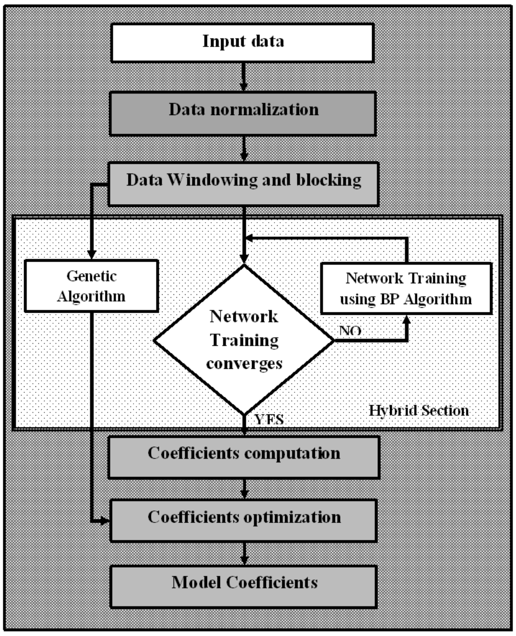


Fig. 2. RVNN-based ARMA model coefficients optimization using GA

prediction has been evaluated and proposed. Figure 2 shows the block diagram for the suggested BG level prediction using parametric modeling approach. Detailed analysis of each of the units is subsequently discussed.

2.1 Data Normalization and Formatting

Past BG measured data are normalized within certain range. Data normalization has been shown to greatly affect the accuracy of the system. Three normalization techniques have been tested in this work, namely z-score, min-max and unitary data normalization techniques. Data normalization involves the application of NT1, NT2 and NT3 data normalization technique defined by :

- **z-score data normalization**

$$X_{new} = \frac{x - \bar{x}}{\sigma_x^2} \tag{1a}$$

- **Min-Max data normalization**

$$X_{new} = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{1b}$$

- **Unitary data normalization**

$$X_{new} = \frac{x}{x_{max}} \tag{1c}$$

where x_{min} and x_{max} are the minimum and maximum values of the data respectively, $\bar{x}$ is the mean value and σ_x^2 is the variance of the data [8]. The above normalization methods are henceforth referred to as NT1, NT2 and NT3 respectively. Therefore, the acquired BG measurement (code 58 in the data) is formatted and normalized using NT1, NT2 and NT3 techniques in this paper.

2.2 Model Parameters Estimation Techniques

Autoregressive (AR) model and Autoregressive moving average (ARMA) model are among the widely used parametric modeling techniques. Mathematically, an ARMA model involves representation of input-output data of a system by a difference equation of the form :

$$y(n) = -\sum_{k=1}^{p} a_k y(n-k) + \sum_{k=0}^{q} b_k x(n-k) \tag{2}$$

where a_k and b_k are the model coefficients, p and q are real-valued model order for the AR and moving average (MA) parts respectively. Similarly, a linear time invariant causal (LTIC) described by the difference equation

$$y(n) = -\sum_{k=1}^{p} a_k y(n-k) + b_0 x(n) \tag{3}$$

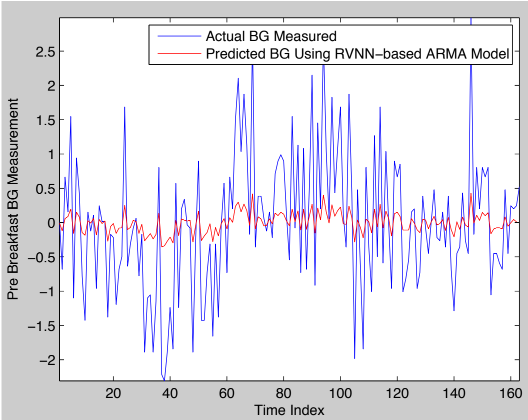
is normally referred to as an AR model. Various methods of estimating the model parameters have been suggested in literatures and these can be broadly divided into two main classes namely optimal and suboptimal model parameters determination techniques [9]–[13]. Recently, the use of real-valued neural networks (RVNN) to estimate the model coefficients have been proposed in [14], [15] and improvement and extension of the technique to complex-valued data domain have also been reported in [16]–[19]. In this work, the optimization of the obtained model coefficients using the techniques proposed in [14]–[19] have been suggested. The newly proposed block diagram is shown in Figure 2. Once the proposed RVNN-based model parameters estimation techniques converged, the estimated coefficients can be optimized using GA.

Genetic Algorithm (GA) is a type of Evolutionary Algorithms (EA) that is based on the principles of biological evolution process. GA emulates nature in searching for the optimal solution of a given problem. By considering many points in the search space simultaneously, GA reduces the risk of converging to local minima, a major shortcoming of BP algorithm. It uses probabilistic rules to guide its search, by favoring the mating of the fitter individuals, the most promising areas in search space are explored [20]. GA is an effective and robust search algorithms that allow to quickly locate areas of high quality solutions even in a large and complex search space [22].

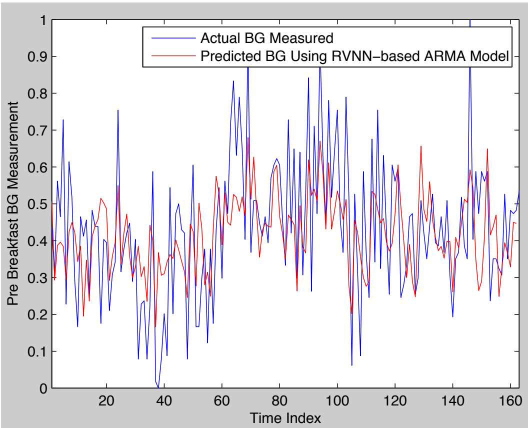
GA distinguishes itself from other search algorithms by working on a population of individuals each representing a possible solution to the problem. Each individual is assigned a fitness score, according to how good a solution to the problem [20]–[24].

2.3 BG Level Prediction

On completion of model coefficients estimation stage in subsection 2.2, the estimated model coefficients can now be used to predict the next BG level. Performance analysis of each of suggested BG level modeling technique is presented in section 3.



(a)



(b)

Fig. 3. RVNN-based ARMA model for BG level prediction using (a) NT1 (b)NT2 data normalization techniques

TABLE II
BG level prediction performance Analysis

Model Type	Ψ
RVNN-based AR model	0.0266
RVNN-based ARMA model	0.0267
Hybrid RVNN-based ARMA model	0.0234

3. Performance Analysis of RVNN-based ARMA Model

The effect of data normalization technique on BG modeling for diabetic patients using the suggested modeling techniques have been evaluated in this work. Shown in Figure 3a-b and Figure 5a are the results obtained using NT1, NT2 and NT3 data normalization techniques respectively for a typical patient. As observed from the figures, the use of NT1 (see Figure 3a) and NT2 (see Figure 3b) data normalization techniques result in poor modeling of the BG signal while the use of NT3 (see Figure 4) data normalization technique gives an accurate modeling of the measurement and prediction. Large variation in pre-breakfast BG measurement and the use of linear activation function have been observed to be responsible for the poor performance of NT1 and NT2.

The Model Error Energy (MEE) measures the goodness of fit between the estimated signal and the original signal in time domain. MEE is given as

$$\Psi = \frac{1}{N}\sum_{n=1}^{N} |(\widehat{y}(n) - y(n)|^2 \tag{4}$$

where N is the data length and $y(n)$ and $\widehat{y}(n)$ are the actual and estimated signal respectively. The best fit occurs when the value is approximately equal to zero. The performance of RVNN-based ARMA model is compared with the performance of RVNN-based AR modeling technique using NT3 data normalization for the whole database. As shown in Figure 5 and Table II, the MEE of RVNN-based ARMA model is almost similar compared to the results obtained using RVNN-based AR modeling technique in predicting BG level. However, better results have been obtained using the hybrid RVNN-based ARMA modeling technique suggested in this work. The model coefficients obtained using RVNN-based ARMA model have been optimized using genetic algorithm (GA). Table III shows results obtained

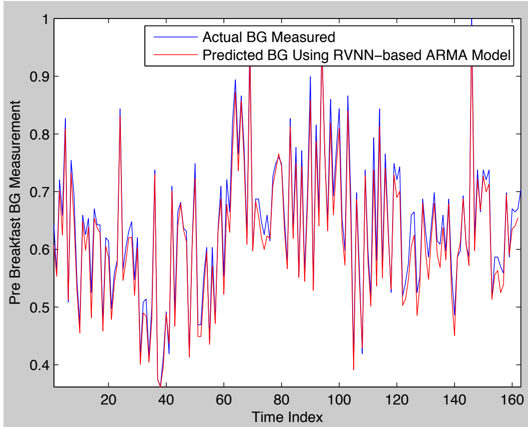


Fig. 4. RVNN-based ARMA model for BG level prediction using NT3 data normalization technique

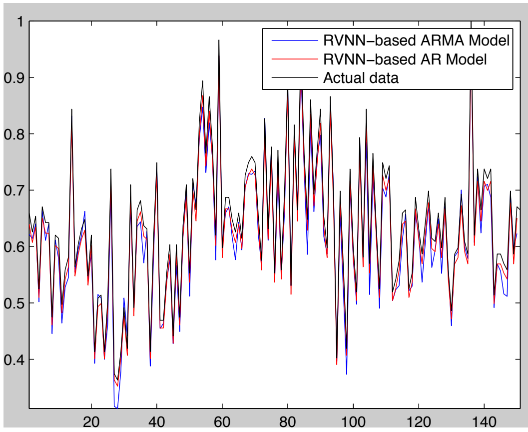


Fig. 5. Performance evaluation of RVNN-based ARMA model and RVNN-based AR model for BG level prediction

TABLE III
BG level prediction performance Analysis

	a_0	a_1	b_0	b_1	Ψ
ARMA(1,1)	1.0000	-0.9682	0.0157	-0.0671	0.0267
Hybrid ARMA(1,1)	1.0000	-0.9682	-0.0180	0.0450	0.0235
Hybrid ARMA(1,1)	1.0000	-0.9682	-0.0423	0.0373	0.0237
Hybrid ARMA(1,1)	1.0000	-0.9682	0.0025	0.0765	0.0235
Hybrid ARMA(1,1)	1.0000	-0.9682	-0.0074	0.0703	0.0234
Hybrid ARMA(1,1)	1.0000	-0.9682	0.0157	0.0959	0.0237

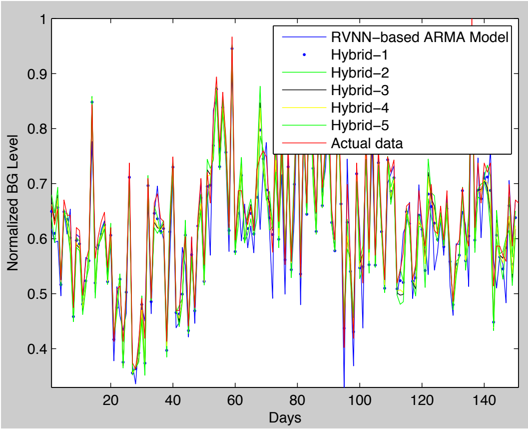


Fig. 6. Performance evaluation of Hybrd RVNN-based ARMA model for BG level prediction

while optimizing the model coefficients of the RVNN-based ARMA model while Figure 6 shows the model output BG level signals. Since the hybrid approach results in lower MEE, and provide better matching of the BG level signal, therefore, better performance of BG level modeling and prediction have been obtained using Hybrid RVNN-based ARMA modeling technique.

4. Conclusion

In the work, new methods of predicting the BG level of diabetic patient have been suggested and evaluated. The developed techniques have been able to predict the next BG level of a diabetic patient to certain degree of accuracy by measuring the model error energy. Furthermore, it have been demonstrated that the use of hybrid RVNN-based ARMA shows better performance when compared to the use of RVNN-based AR model and RVNN-based ARMA model in predicting pre-breakfast BG level. One potential area of application of these modeling techniques could be in treatment of diabetic patients, where it is of utmost concern to control the BG level through the use of insulin dosage, exercise and control of meals intake.

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