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An Unprecedented Automated Fuzzy Model for Diabetes Mellitus

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Abstract: Finding an expert fuzzy model for glucose-insulin system seems to be essential because this model is always changeable according to parameters such as body weight, individual age, time and numbers of meals, physical activities and etc. In this study we try to obtain a fuzzy model for diabetes mellitus. At first a certain diet is introduced and the amount of carbohydrate in each meal is calculated, then by introduced diet the amount of blood glucose and insulin as outputs of diabetes mellitus system are determined. Although there are some models about glucose-insulin system but in this study we use automated method, recursive least squares, in order to find a fuzzy relation between inputs and outputs of system for producing a fuzzy model of glucose-insulin system. At last the performance of obtained model with regard to the same inputs is compared with responses of 21st order metabolic model of Sorensen.

Key words: Automated methods, fuzzy model, Recursive Least Squares Algorihtm (RLSA)

INTRODUCTION

The World Health Organization (WHO) apprises that over 180 million people in the world have diabetes and this statistic is estimated to be 360 million people by 2030 (Cobelli *et al*., 2009). Diabetes mellitus, a case due the disability of the pancreas in controlling blood glucose amount, can lead to stickler longsome difficulties and dying. Diabetes can lead to: diabetic retinopathy causing blindness, diabetic neuropathy increasing the risk of leg wound and organ Lack and diabetic nephropathy which terminate to a general inadequacy. Furthermore, the danger of heart sickness and brunt rose in people who are stricken from diabetes (Hipszer, 2001).

Diabetes has two types. In type 1 diabetes, the immune system of body lay on the beta cells in the pancreas and so the body entirely ceases generating any insulin. Type 1 diabetes could be Manageable if the insulin generated outward to the body can be handy injected to replace for what the body cannot generate. So, individuals with type 1 diabetes must cash quotidian insulin transfusion to be alive. Type 2 diabetes is the outcomes when the body cannot generate sufficient insulin or incapable to consume insulin rightly. Type 2 diabetes is usually link to overweight and way of life. It frequently starts after adulthood and is further prevalent than Type 1 diabetes. But, the sickness can be governed by diets and other lifestyle variations. For a healthy individual, the glucose amounts should be kept Among 70 and 120 mg/dL before meals and under 180 mg/dL after meals (Abonyi *et al*., 2003).

Fuzzy models are, somewhat, clear to commentary and analysis. But, the clarity of a fuzzy model can't be gained spontaneously, particularly in the case of spontaneous data-driven fuzzy modeling techniques. This is because when spontaneous data-driven techniques are exerted to build fuzzy models from data, a specified grade of abundance and thus complication, is imposed to the produced fuzzy model (Setnes *et al*., 1998). Various procedures have been suggested for the reduction of the fuzzy model, mostly focusing on the simplification of the fuzzy rules, according to resemblance measures (Setnes and Babuska, 2001) or genetic algorithms (Pedrycz and Sosnowski, 2005). In this study we acquired fuzzy model for both type1 and type 2 diabetes unlike other articles that try to use automated methods for just diagnosing diabetes (Tsipouras *et al*., 2008). It is obvious that physical characteristics vary from person to person and so different patients have different responses to the same treatment, which in turn can cause parameter variations in the system so it seems important to find a model which is especially for each person.

Finding an intelligent fuzzy model for glucose-insulin system appears to be necessary because this model is always variable based on parameters like body weight, individual age, time and numbers of meals, physical activities and etc. Therefore, in this research activity has been tried to obtain a fuzzy model with the aid of RLS algorithm for diabetes mellitus. In order to achieve this purpose, a specific diet is presented and the amount of carbohydrate in each meal is calculated, then by presented diet the amount of blood glucose and insulin as outputs of

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diabetes mellitus system are specified. Although there are some models about glucose-insulin system but in this paper we use automated method, RLS algorithm, in order to find a fuzzy relation between inputs and outputs of system for producing a fuzzy model of glucose-insulin system. At last the performance of obtained model with regard to the same inputs is compared with responses of 21st order metabolic model of Sorensen.

METHODOLOGY

Glucose modeling: Various models of glucose-insulin systems exist in the literature including, for instance, the much comprehensive 21st order metabolic model of Sorensen (Sorensen, 1985). For comparison we consider Bergman's three-state minimal patient model (Bergman *et al*., 1981):

$$\begin{aligned} dG/dt &= -P_1(G-G_b)-XG + D(t) \\ dX/dt &= -P_2X + P_3(I-I_b) \\ dI/dt &= -n(I-I_b) + \gamma(G-h)^+ + U(t) \end{aligned} \quad (1)$$

where G is the plasma glucose concentration (mg/dL), G_b is the basal plasma glucose (mg/dL), X is the generalized insulin variable for the remote compartment (1/min), I is the insulin concentration (μU/L), I_b is the basal insulin level (μU/mL) and P_1, P_2, P_3, h, n, γ are parameters of the model.

The physiological parameters that are used in the above model are always considered to be constant but in fact these parameters are not constant at all. Each individual have a special body weight and diet which is not considered in these models. We are going to suggest a model that considered uncertainties such as body weight and diet which other models are not capable to regarding them.

Automated methods: It is often hard or inconceivable to carefully model intricate physical processes or engineered systems using an ordinary nonlinear mathematical approach with limited previous informations. Ideally, the analyzer uses the information and knowledge obtained from previous tests or exams with the system to expand a model and previse the result, but for new systems where little is known or where empirical analyses are too expensive to carry out, previous knowledge and information is often Inaccessible. This absence of data on or wide knowledge of, the system makes expanding a model using ordinary means acutely hard and often inconceivable. Moreover, forming a linguistic rule-base of the system may be impracticable without managing extra witnessings. Luckily, for conditions such as these, fuzzy modeling is very feasible and can be used to expand a model for the system using the ''confined'' accessible information. Batch Least Squares (BLS), Recursive Least Squares (RLS), Gradient Method (GM), Learning from Example (LFE), Modified Learning from Example (MLFE) and Clustering Method (CM) are some of the algorithms accessible for expanding a fuzzy model (Passino and Yurkovich, 1998). In this study we only use recursive least squares algoritm for producing a fuzzy model of glucose-insulin system. The reason of this selection is expressed in the next part.

Recursive least squares algoritm: In this study we demonstrate the development of a nonlinear fuzzy model for the data that are obtained by diabetes mellitus test. The algorithm constructs a fuzzy model from numerical data which can then be used to predict outputs given any input. When using the RLS algorithm to develop a fuzzy model it is helpful to have knowledge about the behavior of the data set in order to form a rule-base. Parameter m is the number of input data-tuples, parameter n the inputs for each data-tuple and parameter j the outputs for each data-tuple. The consequence in each rule is denoted by the output membership function centers b_i. The two premises of each rule are defined by the input membership function centers (c_i) and their respective spread (σ_i):

IF $premise_1$ and $premise_2$ and $premise_3$ and $premise_4$THEN *consequence*

where $premise_1$ is carbohydrate content of the meal, $premise_2$ is time of the meal, $premise_3$ is body weight and $premise_3$ is duration of simulation. We calculate the membership value that each input data-tuple has in the specified rules of the rule-base and multiply these two values by one another, resulting in the membership value that the input data-tuple has in a particular rule. This is accomplished by:

$$\mu_i(x) = \Pi_{j=1}^{n} \exp\left(\frac{-1}{2}\left(\frac{x-c_j^i}{\sigma_j^i}\right)^2\right) \quad (2)$$

where x are the input data-tuples and c^i_j and μ^i_j are the rule-base parameters. (Passino and Yurkovich, 1998) suggested the following equation to predict the output given an input data-tuple x_j:

$$f(x|\theta) = \frac{\Sigma_{i=1}^{R} b_i \mu_i(x)}{\Sigma_{i=1}^{R} \mu_i(x)} \quad (3)$$

and if we define the regression vector ξ as:

$$\xi_i(x) = \frac{\mu_i(x)}{\Sigma_{i=1}^{R}\mu_i(x)} = \frac{\Pi_{j=1}^{n} \exp\left[\frac{-1}{2}\left(\frac{x-c_j^i}{\sigma_j^i}\right)2\right]}{\Sigma_{i=1}^{R}\Pi_{j=1}^{n} \exp\left[\frac{-1}{2}\left(\frac{x-c_j^i}{\sigma_j^i}\right)2\right]} \quad \text{for i = n} \quad (4)$$

Using Y and Φ we determine $\hat{\theta}$:

$$\hat{\theta} = (\Phi^T\Phi)^{-1}\Phi^T Y \quad (5)$$

Table 1: Sample menu for 1600 calories

Number of servings from food groups	1600 calories
Milk	3
Fruit	4
Vegetable	4
Protein	6
Grain	6
Fat	3

Table 2: The amount of nutrients in 1 service from each group

Food group	Carbohydrate (g)	Protein (g)	Fat (g)	Calories
Grains	15	0-3	0-1	80
Fruits	15	-	-	60
Milk				
Fat-free, low -fat, 1%	12	8	0-3	100
Reduced-fat, 2%	12	8	5	120
Whole	12	8	8	160
Non-starchy vegetables	5	2	-	25
Meat				
Lean	-	7	0-3	45
Medium-fat	-	7	4-7	75
High-fat	-	7	8+	100
Fats	-	-	5	45

we can use Eq. (6) to calculate the output:

$$f(x|\hat{\theta}) = \hat{\theta}^{T}\xi(x) \quad (6)$$

where $Y_{m\times j}$ is output matrix of training data and $\Phi_{m\times n}$ is transpose of ξi(x).

The RLS algorithm is very similar to the BLS (Batch Least Squares) algorithm; however, the RLS algorithm makes updating $\hat{\theta}$ much easier. The algorithm is a recursive version of the BLS method (Timothy, 2004). It operates without using all the training data and most importantly without having to compute the inverse of $\Phi^{T}\Phi$ each time the $\hat{\theta}$ is updated. RLS calculates $\hat{\theta}(k)$ at each time step k from the past estimate $\hat{\theta}(k\text{-}1)$ and the latest data pair that is received x^k, y^k.

Carbohydrate counter: In this part we introduce a sample diet and calculate the amount of carbohydrate in each meal (http://www.bcbsm.com/index.shtml). In Table 1 sample menu which consists of 1600 calories is expressed.

In the Table 2 six major food groups is given. Note that grains group includes: breads, cereals, grains, starchy vegetables, crackers, snacks, beans, peas and lentils.

Sample menu for 1600 calories:

Breakfast: 1 cup blueberries = 1 fruit serving,1 cup skim, 1/2% or 1% fat milk = 1 milk serving Coffee.

Lunch: Turkey sandwich 2oz turkey = 2 protein servings, 2 slices bread = 2 grain servings, 1 Tbsp. Reduced fat mayonnaise = 1 fat, 1 small peach = 1 fruit serving, 1 cup carrots = 1 vegetableserving, Unsweetened ice tea.

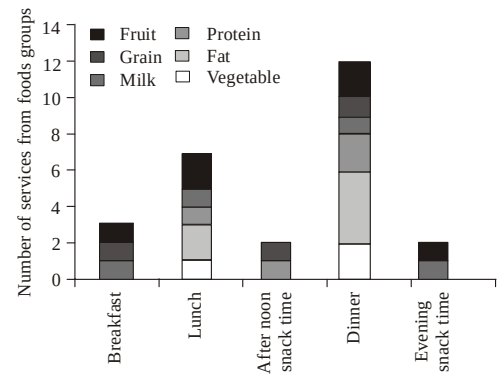

Fig. 1: Number of servings from food groups

Afternoon snack: 6 oz (2/3 cup) low-fat yogurt = 1 milk serving, 1 cup of raw vegetables = 1 vegetable serving (broccoli, cucumber red pepper).

Dinner: 1 cup skim, 1/2 % or 1% fat milk = 1 milk serving 4 oz. Chicken breast = 4 protein servings, 1 medium baked potato (6 oz) = 2 grain servings 3 Tbsp. low-fat sour cream = 1 fat serving.

Salad: 2 cup lettuce = 1 vegetable serving, 1 cup mixture of green peppers, tomatoes, onions = 1 vegetable servings, 2 Tbsp. reduced fat salad dressing = 1 fat, 1 cup strawberries = 1 fruit, Non-caloric beverage.

Evening Snack: 1 Small Apple = 1 fruit serving, 3 cups non-fat popcorn = 1 grain serving.

It can be calculated that in this sample menu an individual consumes 42 g carbohydrate in breakfast, 50 g carbohydrate in lunch, 17 g carbohydrate in afternoon snack, 67 g carbohydrate in dinner and 30 g carbohydrate in evening snack. The number of servings from food groups for above sample menu is displayed in Fig. 1.

SIMULATION AND RESULTS

In order to obtain fuzzy model numerical calculations are needed, to perform this calculations MATLAB software is used. We are using the web base GlucoSim Simulator (GlucoSim, 2012) for obtaining Glucose-Insulin response. The inputs are carbohydrate content of the meal, time of the meal, body weight and duration of simulation. By information that obtained in last part we start the simulations for Healthy Person Type 1 and Healthy Person Type 2. It can be shown that this fuzzy model is expansible for Unhealthy Person Type 1 and 2 but in this paper we only obtain the fuzzy model for Healthy Person Type 1 and 2. The body weight (kg) of individual is considered 49.895 kg and the duration of simulation (h) is 24 h. We can write the content of the meals in this shape, breakfast: CHO (841.767 mg/kg body weight), lunch: CHO (1002.104 mg/kg body weight),

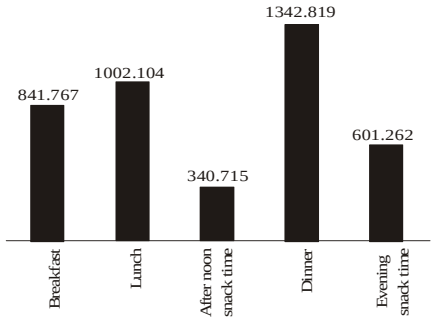

Fig. 2: The amount of CHO (mg/kg body weight) per each meal

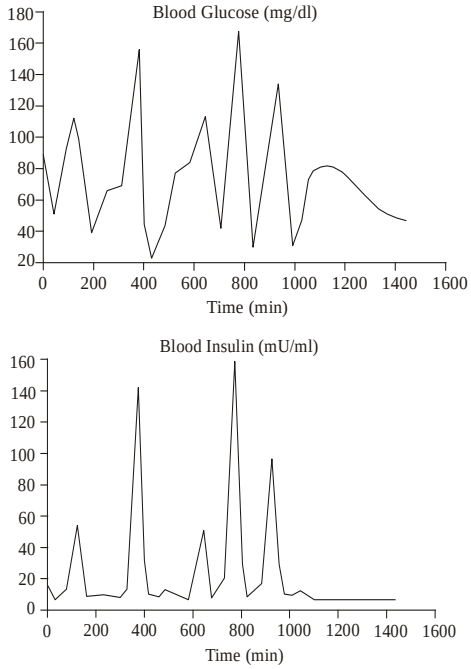

Fig. 3: Sample glucose and insulin data output from the GlucoSim simulator [Passino and Yurkovich (1998)] for healthy person type 1

Table 3: Training data points for healthy person type1

Time of test (min)	Blood glucose (mg/dL)	Blood insulin (mU/mL)
57	70.7600	12.4988
310	70.3662	9.9237
539	80.1825	9.9834
1055	70.1988	1
1148	79.9887	8.9566

afternoon snack: CHO (340.715 mg/kg body weight), dinner: CHO (1342.819 mg/kg body weight), evening snack: CHO (601.262 mg/kg body weight). We also asume that the times of the meals are: breakfast at 08:30, Lunch at 13:30, afternoon snack at 18:00, dinner at 20:00 and evening snack at 22:00. The amount of CHO (mg/kg body weight) per each meals is shown in Fig. 2 and also the glucose and insulin response of type 1 and 2 diabetes are shown respectively in Fig. 3 and 4.

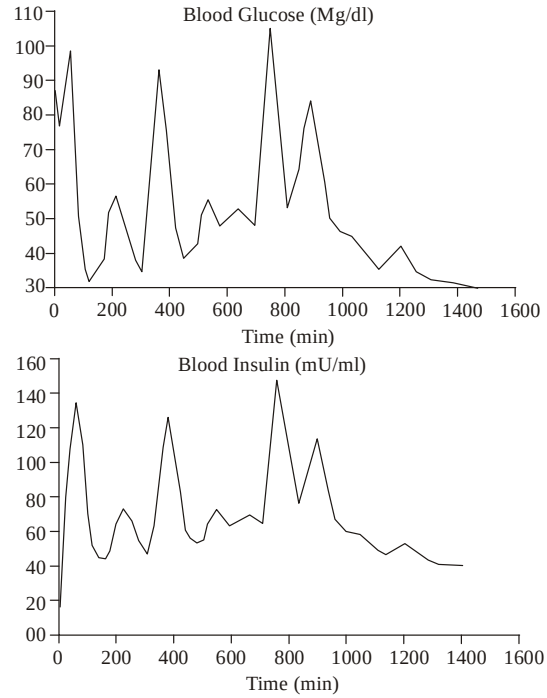

Fig. 4: Sample glucose and insulin data output from the GlucoSim simulator (Passino and Yurkovich, 1998) for healthy person type 2

Table 4: Comparison between data point obtained by RLSA and the GlucoSim simulator for healthy person type 1

Time of test (min)	Blood glucose (mg/dL) by RLSA	Blood glucose (mg/dL) by glucosim	Blood insulin (mU/mL) by RLSA	Blood insulin (mU/mL) by glucosim
67	81.3754	81.1765	13.2113	13.1867
320	82.1665	82.8095	12.6469	12.7989
549	81.9729	81.2366	9.3644	9.6348
1065	74.1290	74.8647	11.9839	11.4323
1158	81.9058	79.5311	8.0479	8.9526

Table 5: Training data points for healthy person type2

Time of test (min)	Blood glucose (mg/dL)	Blood insulin (mU/mL)
60	93.3908	133.0318
340	71.5487	75.7060
720	75.8892	83.3346
905	76.5433	111.9588

By executing the simulation we can obtain 1440 data. We are using 10 data points for training the fuzzy system for Healthy Person Type 1. These data are are listed in Table 3.

By achieved RLSA model for Healthy Person Type 1, we try to obtain amount of blood glucose and blood insulin in other moments and compare with the amount of that achived by the web GlucoSim Simulator. In Table 4 a comparison between data point obtained by RLSA and the Glucosim simulator for healthy person type 1 has been done.

We can see that by RLSA, we can appropriately obtain fuzzy model for Healthy Person Type 1. We can expand, these results for other data points. Now we obtain

Table 6: Comparison between data point obtained by RLSA and the glucosim simulator for healthy person type 2

Time of test (min)	Blood glucose (mg/dL) by RLSA	Blood glucose (mg/dL) by glucosim	Blood insulin (mU/mL) by RLSA	Blood insulin (mU/mL) by glucosim
70	76.4572	76.2649	127.5892	127.45777
350	82.3978	82.0265	90.7029	90.7966
730	88.0924	88.4669	98.1665	98.7534
915	71.6914	71.0334	107.8137	107.7623

fuzzy model for Healthy Person Type 2. We are using 8 data points for training the fuzzy system for Healthy Person Type 2. These data are are listed in Table 5.

By achieved RLSA model for Healthy Person Type 2 we try to obtain amount of blood glucose and blood insulin in other moments and compare with the amount of that achived from the web GlucoSim Simulator. In Table 6 a comparison between data point obtained by RLSA and the Glucosim simulator for healthy person type 2 has been done.

We can see that by RLSA, we can appropriately obtain fuzzy model for Healthy Person Type 2. We can expand these results for other data points.

CONCLUSION

Every individual have a certain glucose-insulin model which is exclusive for itself. The proposed model is changeable according to body weight, time and amount of meals. Whatever the model is more accurate the better controllers can be designed in order to overcome diabetes. In this study the RLS algoritm used for developing fuzzy systems from input-output data. By achieved RLSA model for Healthy Person Type 1 and Type 2 we can obtain blood glucose and blood insuline in other moments. We can calculate the CHO (mg/kg body weight) for each individual and then get diabetes test, so that we can obtain fuzzy model from input-output data and we can achive blood glucose and blood insulin in other moments according to inputs, without the need to take diabetes test again. It is interesting to know the uncertainties such as body weight, time and amount of meals, which the other models are incapable of taking them, can be considered by this model.

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