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...
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):

\[
\begin{align*}
\frac{dG}{dt} &= -P_1(G-G_b)-XG + D(t) \\
\frac{dX}{dt} &= -P_2X + P_3(I-I_b) \\
\frac{dI}{dt} &= -n(I-I_b) + \gamma(G-h^3) + U(t)
\end{align*}
\]

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 (\( \mu \)U/L), \( I_b \) is the basal insulin level (\( \mu \)U/mL) and \( P_1, P_2, P_3, h, n, \gamma \) 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 on, previous knowledge and information is often Inaccessible. This absence of data on or wide knowledge of, the system makes expanding a model from previous tests or exams with the system to expand a fuzzy model and previse the result is compared with responses of 21st order metabolic model of Sorensen (Sorensen, 1985). For comparison we consider Bergman’s three-state minimal patient model (Bergman et al., 1981):

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\begin{align*}
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The two premises of each rule are defined by the input membership function centers (\( c_i \)) and their respective spread (\( \sigma_j \)).

**Recursive least squares algorithm:** 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 \( b_j \). The two premises of each rule are defined by the input membership function centers (\( c_i \)) and their respective spread (\( \sigma_j \)).

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

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

\[
f(x|\theta)=\frac{\sum_{j=1}^m \mu_j(x)}{\sum_{j=1}^m \mu_j(x)}
\]

and if we define the regression vector \( \xi \) as:

\[
\xi(x)=\frac{\mu_j(x)}{\sum_{j=1}^m \mu_j(x)} \quad \text{for } i=n
\]

Using \( Y \) and \( \Phi \) we determine \( \phi \):

\[
\phi = (\Phi^T \Phi)^{-1} \Phi^T Y
\]

1974
we can use Eq. (6) to calculate the output:

\[ f(x|\hat{\theta}) = \hat{\theta}^T \xi_i(x) \]  

where \( Y_mx \) is output matrix of training data and \( \Phi_mx \) is transpose of \( \xi_i(x) \).

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 \( \Phi \) each time the \( \hat{\theta} \) is updated. RLS calculates \( \hat{\theta}(k) \) at each time step \( k \) from the past estimate \( \hat{\theta}(k-1) \) 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. Turkey sandwich 2oz turkey = 2 protein servings, 2 slices bread = 2 grain servings, 1 Tbsp. reduced fat mayonnaise = 1 fat serving. 1 small peach = 1 fruit serving. 1 cup carrots = 1 vegetableserving. Unsweetened ice tea.

**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.

**Dinner:** 1 cup skim, 1/2% or 1% fat milk = 1 milk serving. 1 cup of raw vegetables = 1 vegetable serving (broccoli, cucumber red pepper).

**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 dinner and 30 g carbohydrate in evening snack.

**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 (814.767 mg/kg body weight), dinner: CHO (841.767 mg/kg body weight), evening snack: CHO (841.767 mg/kg body weight).
Table 3: Training data points for healthy person type 1

<table>
<thead>
<tr>
<th>Time of test (min)</th>
<th>Blood glucose (mg/dL)</th>
<th>Blood insulin (mU/mL)</th>
</tr>
</thead>
<tbody>
<tr>
<td>57</td>
<td>70.7600</td>
<td>12.4988</td>
</tr>
<tr>
<td>310</td>
<td>70.3662</td>
<td>9.9237</td>
</tr>
<tr>
<td>539</td>
<td>80.1825</td>
<td>9.9834</td>
</tr>
<tr>
<td>1055</td>
<td>70.1988</td>
<td>1</td>
</tr>
<tr>
<td>1148</td>
<td>79.9887</td>
<td>8.9566</td>
</tr>
</tbody>
</table>

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

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

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 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 achieved by the web GlucoSim Simulator. In Table 4 a comparison between data points 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

<table>
<thead>
<tr>
<th>Time of test (min)</th>
<th>Blood glucose (mg/dL) by RLSA</th>
<th>Blood glucose (mg/dL) by glucosim</th>
<th>Blood insulin (mU/mL) by RLSA</th>
<th>Blood insulin (mU/mL) by glucosim</th>
</tr>
</thead>
<tbody>
<tr>
<td>70</td>
<td>76.4572</td>
<td>76.2649</td>
<td>127.5892</td>
<td>127.4577</td>
</tr>
<tr>
<td>350</td>
<td>82.3978</td>
<td>82.0265</td>
<td>90.7029</td>
<td>90.7966</td>
</tr>
<tr>
<td>730</td>
<td>88.0924</td>
<td>88.4669</td>
<td>98.1665</td>
<td>98.7534</td>
</tr>
<tr>
<td>915</td>
<td>71.6914</td>
<td>71.0334</td>
<td>107.8137</td>
<td>107.7623</td>
</tr>
</tbody>
</table>

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 achieved 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 algorithm 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 insulin 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 achieve 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.

REFERENCES


