A New Controlling Approach of Type 1 Diabetics Based on Interval Type-2 Fuzzy Controller

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Abstract

Augmented Minimal Model which is developed in consideration of the patient is taken into attention and uncertainties in this model which can occur by factors such as blood glucose, daily meals or sudden stress in considered. In addition to eliminate the effects of uncertainty, different control methods may be utilized. In this article, fuzzy control as a logical tool is used to transform words into control actions. To enhance the system performance, an interval type-2 Fuzzy controller has been implemented. To date, because of computational complexity of using a general type-2 fuzzy set (T2 FS) in a T2 fuzzy logic system (FLS), most people only use an interval T2 FS, the result being an interval T2 FLS (IT2 FLS). A daily meal disturbance is injected to model to consider the real environment for simulation. Finally, the control method tuned by standard tuning procedure and simulation results show the efficiency of method in regulating the blood glucose level in presence of daily meal disturbance.

Keywords: Diabetes, Interval Type-2 Fuzzy, Minimal Augmented Model, Uncertainty.

1 Introduction

It is lifesaving to keep the blood glucose concentration as close as possible to a normal value in diabetic patients. Therefore many researches have been undertaken in diabetes control. In 1978 Tchobroutsky proved that precise control of diabetes is beneficial in patients with long life expectancy and no psychological, social or cultural problems [1]. It was also concluded by Pietri et al., that all diabetic control therapies are effective in lowering plasma triglyceride levels, whereas it requires strict metabolic control to affect plasma cholesterol and LDL cholesterol levels [2]. PID controller, a mechanism which is aimed to minimize the difference between set value and process variables was discussed by O'Dwyer et al. in a handbook and the controller tuning rules were obtained [3]. Skogestad presented analytic rules for PID controller tuning [4]. In an experiment done by Årzén it was shown that in PID controllers by only a minor control performance degradation, a significant amount of CPU usage reduction will be obtained [5].

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Researchers have improved the steady state and transient performance of the PID controller by conducting fuzzy theory, named PID type fuzzy controller [6-9]. Wu, Chia-Ju, et al. designed an auto-tuning fuzzy PID controller based on genetic algorithm [10]. Two control algorithm a fuzzy-PID control and classical PID control method are used for insulin infusion. The result of fuzzy-PID is more ideal than the classical PID and also the glucose is stabilized at the basal level about 2 hours [11]. Automated method is used, RLS (Recursive Least Squares) algorithm, in order to find the relation between inputs and outputs of system for producing a glucose-insulin fuzzy model system. By obtain RLSA model for healthy person type 1 and type 2. Blood glucose and blood insulin in other moments. CHO (mg/kg body weight) was calculated for every personal and gain diabetics test, as a consequent fuzzy model is achieved from input-output data. Uncertainties would be noticed to this model [12]. Controllers based on fuzzy logic succeeded in many control problems where the conventional control theories failed. A type-1 fuzzy controller is used for Diabetics patients by GA and the AMM model is considered in this article. Uncertainties in the meal disturbance and variations of model parameters were noticed in simulations. On the other hands, the controller is robust [13]. Fuzzy PI controller is applied for regulation of blood glucose level. Mamdani type structure was used in the controller. So as to show the operation of proposed controller. It was test under standard meal disturbance for 10h. The Bergman model is utilized in this paper and also it is supposed that Insulin is injected by insulin pump every 10 min [14]. The fuzzy controller considers control algorithm by insulin infusion according to multiple daily injection regime. So as to control algorithm combine knowledge about patient treatment the inner-loop and outer-loop controller are designed using a Mamdani-type fuzzy shame and these feedback loops overcome the variability the glucose-in-insulin dynamics from patient to patient. The model of the type 1 diabetes mellitus present in 3 parts: 1) Insulin-glucose compartmental made 2) glucose input via Gastric Emptying 3) subcutaneous insulin injection. Moreover, the control policy requires a significant amount of knowledge or trial and error [15]. To solve this issue Raju et al. proposed a fuzzy controller with the fuzzy sliding surface [16]. Shao and Shihuang studied a fuzzy self-organizing controller, where the control policy is able to develop and improve by itself [17]. Studies have been carried out to design fuzzy logic based controllers without the need of anexpert’s experience and knowledge, by conducting genetic algorithm [18-20]. In another study, Trebi-Ollennu et al. demonstrated the fuzzy genetic algorithm optimization as an effective and intuitive algorithm [21]. Lehmann et al. explored the possibility ofusing a physiological model of glucose-insulin interaction as a tool for automated insulin dosage adjustment [22]. Hovorka, Roman, et al. also came up with a predictive control over glucose concentration in type 1 diabetes utilizing a nonlinear model [23]. They consider the uncertainties of system dynamics [24-30]. Mendel, Wu, reviewed and gives some benefit points in their papers. Wu, also published a tutorial for training type-2fuzzy in MATLAB [31-32]. In this paper an interval fuzzy logic controller is proposed to consider physicians experience with different efficiencies. The daily meal is considered as distribution which imposed to diabetic system. The proposed method controls glucose level in presentment of disturbance effectively. The rest of the paper is organized as follows. First of all the model of AMM is introduced. Then the proposed interval type-2fuzzycontroller is introduced and the principles are considered and the controller is implemented to the AMM. A comprehensive discussion concludes the paper.

2 Augmented Minimal Model

Since the case of kind one polygenic disease is wide studied and its physiological cause's area unit comparatively clear, studies are centered recently on modeling and understanding type two polygenic diseases (see e.g. Hwang, W.R. and W.E. 1994). Among different proposed models, which describe the diabetic system characteristics in this paper we consider the Augmented Minimal Model (AMM) considering to following specifications. In compare with other models, AMM contains the effects of both insulin and glucagon on blood glucose concentration. It also includes time independent parts for
production of endogenous, insulin and glucagon. Furthermore, it considers the effect of exogenous insulin or daily meal as disturbance. Applying some well-known physiological variations between healthy subjects and diabetics to Sorenson’s model of diabetics (SM), one tends to manufacture new input-output information sets and match the AMM once more to that information.

The AMM coupled nonlinear equation is shown below (Mihalis G. Markakis, Georgios D. et al. 2008):

\[
\begin{align*}
\frac{dI}{dt} &= -\gamma_I I(t) + \beta \max[G(t) - \theta_I, 0] + D_I(t) \\
\frac{dN}{dt} &= -\gamma_N N(t) + \alpha \max[\theta_N - G(t), 0] \\
\frac{dX}{dt} &= -P_2 X(t) + P_3 I(t) \\
\frac{dG_I}{dt} &= -P_G I(t) - X(t) G(t) \\
\frac{dG_N}{dt} &= -P_G N(t) + P_N N(t) \\
G(t) &= G_b + G_I(t) + G_N(t) + D_G(t)
\end{align*}
\]

Where of the state parameters, output and constant values are considered in table 1 and table 2, respectively.

<table>
<thead>
<tr>
<th>States Description</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>deviation of plasma insulin concentration from its basal value</td>
<td>15 mU/L in healthy subjects</td>
</tr>
<tr>
<td>deviation of plasma glucagon concentration from its basal value</td>
<td>75 ng/L in healthy subjects</td>
</tr>
<tr>
<td>insulin action</td>
<td>min%</td>
</tr>
<tr>
<td>deviation of blood glucose concentration from its basal value due to insulin action</td>
<td>mg/dL</td>
</tr>
<tr>
<td>deviation of blood glucose concentration from its basal value due to glucagon action</td>
<td>mg/dL</td>
</tr>
<tr>
<td>basal value of blood glucose concentration</td>
<td>assumed 110mg/dl in this study</td>
</tr>
<tr>
<td>concentration of blood glucose</td>
<td>mg/dL</td>
</tr>
<tr>
<td>Intravenous insulin</td>
<td>mU/L/min</td>
</tr>
<tr>
<td>glucose disturbance</td>
<td>mg/dL</td>
</tr>
</tbody>
</table>
Table 2: AMM Parameters for healthy and diabetics subjects

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Healthy</th>
<th>Type 1</th>
<th>Type 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\gamma_1$</td>
<td>0.42</td>
<td>N/A</td>
<td>[0.43,0.56]</td>
</tr>
<tr>
<td>$\beta$</td>
<td>0.106</td>
<td>0</td>
<td>$[9 \times 10^{-4}, 0.08]$</td>
</tr>
<tr>
<td>$\theta_1$</td>
<td>103</td>
<td>N/A</td>
<td>[101,114]</td>
</tr>
<tr>
<td>$\gamma_N$</td>
<td>$5.8 \times 10^{-4}$</td>
<td>0.003</td>
<td>$[4.5 \times 10^{-4}, 9.5 \times 10^{-4}]$</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>0.0037</td>
<td>0.0008</td>
<td>[0.0023,0.0049]</td>
</tr>
<tr>
<td>$\theta_N$</td>
<td>83</td>
<td>83</td>
<td>[77,91]</td>
</tr>
<tr>
<td>$P_1$</td>
<td>0.022</td>
<td>0.013</td>
<td>[0.004,0.036]</td>
</tr>
<tr>
<td>$P_2$</td>
<td>0.075</td>
<td>0.063</td>
<td>[0.034,0.155]</td>
</tr>
<tr>
<td>$P_3$</td>
<td>$1.3 \times 10^{-5}$</td>
<td>910-6</td>
<td>$[3.1 \times 10^{-6}, 1.3 \times 10^{-5}]$</td>
</tr>
<tr>
<td>$P_4$</td>
<td>0.04</td>
<td>0.04</td>
<td>[0.027,0.05]</td>
</tr>
<tr>
<td>$P_5$</td>
<td>0.016</td>
<td>0.016</td>
<td>[0.015,0.017]</td>
</tr>
</tbody>
</table>

3 Proposed interval Type-2 Fuzzy Controller

Type-2 Fuzzy Logic is an emerging and promising area for achieving Intelligent Control. Using interval type-2 fuzzy logic for minimizing the effects of uncertainty produced by the instrumentation elements, environmental noise, etc. A type-2 fuzzy logic system consists basically of three blocks fuzzification, inference and defuzzification as similar to type-1. But the only difference is in the third block of the type-2 fuzzy which is not only defuzzifier but also accomplished by a type-reducer processing block. This difference is mainly associated with the nature of the membership functions where type-reducer is needed due to the added degree in the kind of fuzzy sets. In this article, we proposed the fuzzy controller is structure by singleton fuzzification and produce the inter-face engine Mamdani and the center of sets method type reducer [33] and KM algorithme for defuzzification. The input variable are the plasma glucose construction and the change rate of error respectively, and the insulin injection rate take into account as the output. Figure 1 presents a type 2 fuzzy logic system.
In the sequel some important definitions are presented:

**Definition 3.1.** A type-2 fuzzy set \( A \) is characterized by a type-2 membership function \( \mu_A(x,u) \) where \( x \in X \) and \( u \in J_x \subseteq [0,1), [23], \)
\[
A = \{(x,u), \mu_A(x,u) \forall x \in X, \forall u \in J_x \subseteq [0,1]\} \tag{3.2}
\]
where \( 0 \leq \mu_A(x,u) \leq 1 \) and typically written as
\[
A = \int_{x \in X} \int_{u \in J_x} \mu(x,u)/(x,u) \quad J_x \subseteq [0,1] \tag{3.3}
\]
where \( \bigcup \) denotes union over all admissible \( x \) and \( u, J_x \in [0,1] \) is a restriction that is equivalent to \( 0 \leq \mu_A(x) \leq 1 \) for type-2 membership function and \( J_x \) denotes primary membership of \( \tilde{A} \) where \( J_x \subseteq [0,1] \) for \( x \in X \).

**Definition 3.2.** The IT2 FLS can be expressed as Mendel, J.M.
\[
\tilde{A} = \int_{x \in X} \int_{u \in J_x} 1/(x,u) \quad J_x \subseteq [0,1] \tag{3.4}
\]
Where the position of \( \mu(x,u) \) in (3.3) is replaced by (3.2). When all \( \mu_A(x,u) = 1 \) then \( \tilde{A} \) is an interval T2 FS (IT2 FS). There exist an uncertainty in the Primary membership of a type-2 fuzzy set \( \tilde{A} \) consists of bounded region known as footprint of uncertainty (FOU) as in figure 2.
Definition 3.3. There are two type-1 membership function that bound the FOU (\(\tilde{A}\)) that is the lower membership function (LMF) denoted by \(\mu_\tilde{A}(x), \forall x \in X\) and the upper function denoted by \(\mu_\tilde{A}(x), \forall x \in X\)

\[
\mu_\tilde{A}(x) = \text{FOU}(\tilde{A}) \quad \forall x \in X
\] (3.5)

And

\[
\mu_\tilde{A}(x) = \text{FOU}(\tilde{A}) \quad \forall x \in X
\] (3.6)

For an IT2 FS

\[
J_x = \left[\mu_\tilde{A}(x), \mu_\tilde{A}(x)\right], \forall x \in X
\] (3.7)

These upper and lower bound are clarified in figure 2.

4 Method

Firstly, the model is used in the absent of controller. The figure 3 shows Diabetics model box in which demonstrate the constant parameters from table 2. The mask set on the parameters in order to performing simulations for every patients.

Figure 3: Diabetes Blood aggregated model with an input box control, an input and an output noise

In the figure 4 show the diabetic model states especially blood glucose changes. As you demonstrate in figure 4, it rise from normal value (110 ml) then it increase about 145 ml due to the absence of the controller. Furthermore, it stabilize in the same number owing to the lack of Insulin infusion, it would not decreased noticeably.

Figure 4: Blood glucose changes in open-loop system

Figure 5 shows the implementation of proposed controlling method on diabetic model. The parameter \(e\) shows the different between measure blood glucose level and its basal level and the parameter \(de/dt\) demonstrate blood glucose return speed to its basal level. Table 3 shows the parameters in controlling
As it was mentioned the internal secretion concentration and therefore the blood glucose concentration suffering from internal secretion injection as a variable of time, severally.

Table 3: Function Block Parameters Diabetics

<table>
<thead>
<tr>
<th>$G_b$</th>
<th>$\gamma_I$</th>
<th>$\beta$</th>
<th>$\theta_i$</th>
<th>$\gamma_N$</th>
<th>$\alpha$</th>
<th>$\theta_N$</th>
<th>$P_1$</th>
<th>$P_2$</th>
<th>$P_3$</th>
<th>$P_4$</th>
<th>$P_5$</th>
</tr>
</thead>
<tbody>
<tr>
<td>110</td>
<td>0.56</td>
<td>0.08</td>
<td>114</td>
<td>$3e^{-3}$</td>
<td>0.008</td>
<td>83</td>
<td>0.036</td>
<td>0.155</td>
<td>$1.3e^{-5}$</td>
<td>0.05</td>
<td>0.017</td>
</tr>
</tbody>
</table>

Figure 5: Diabetes Blood aggregated model with an input box control, an input and an output noise

Table 4: Fuzzy rules

<table>
<thead>
<tr>
<th>$\dot{e}$ (\dot{e})</th>
<th>$\dot{e} \ll 0$</th>
<th>$\dot{e} &lt; 0$</th>
<th>$\dot{e} = 0$</th>
<th>$\dot{e} &gt; 0$</th>
<th>$\dot{e} \gg 0$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$e \gg 0$</td>
<td>Very high</td>
<td>high</td>
<td>middle</td>
<td>low</td>
<td>Very low</td>
</tr>
<tr>
<td>$e &gt; 0$</td>
<td>High</td>
<td>middle</td>
<td>middle</td>
<td>low</td>
<td>low</td>
</tr>
<tr>
<td>$e = 0$</td>
<td>middle</td>
<td>Low</td>
<td>high</td>
<td>Very high</td>
<td>Very high</td>
</tr>
<tr>
<td>$e &lt; 0$</td>
<td>Low</td>
<td>Low</td>
<td>middle</td>
<td>high</td>
<td>high</td>
</tr>
<tr>
<td>$\dot{e} \ll 0$</td>
<td>Very low</td>
<td>Low</td>
<td>middle</td>
<td>high</td>
<td>Very high</td>
</tr>
</tbody>
</table>

As it was mentioned the type-2 fuzzy controller eliminates the blood glucose variation considering to uncertainty effects. In traditional fuzzy sets, the membership functions put on figures individually by crisp points, but in type-2 fuzzy, a distance for the functions is considered.

The usual structure of rules proposed in fuzzy controller is as follows:

$$R^n: \text{IF } e \text{ is } \tilde{X}_i^n \text{ and } \ldots \text{ and } \dot{e} \text{ is } \tilde{X}_2^n \text{ THEN } y \text{ is } \tilde{Y}^n$$

(4.8)
The Gaussian type-2 fuzzy set is one in which a membership grade of every domain point is a Gaussian type-1 set contained in [0,1]. The proposed membership functions for inputs and output of diabetic control system which is error, error-deviation and blood glucose infusion rate are define in figure6 and figure7 respectively and also the output membership function are also defined in figure 8.

![Figure 6: Membership Functions for the input 1(desired and actual error diabetes)](image)

![Figure 7: Membership Functions for the input 2 (desired and actual error-deviation diabetes)](image)

![Figure 8: Membership functions for the output (blood insulin infusion rate)](image)

According to above membership function mutual rules, input and output are described in the following table:

Control policy obtained in the following figure, is clearly shown. This figure shows that when the difference between the desired levels of blood glucose is high, further injections will be increased. As shown in figure 9, the level of uncertainty is also considered.
Close-loop system requires to provide glucose sensor that will measure blood glucose level and then control system calculate the information to keep glucose blood in the stable rage by delivered insulin. Furthermore, mechanical pump can deliver the desired amount of insulin such as artificial pancreas. Biomedical systems usually have inaccuracy and uncertainty in model parameters. In order to reduce such problems, fuzzy logic controllers are used to calculate uncertainty in insulin-glucose synthesis. Such uncertainty leads to rules whose antecedents or consequents are uncertain, which translates into uncertain antecedent or consequent membership functions [34]. Type-1 fuzzy systems whose membership functions are type-1 fuzzy sets, are unable to directly handle such uncertainties. Such sets are fuzzy sets whose membership grades themselves are type-1 fuzzy sets; they are very useful in circumstances where it is difficult to determine an exact membership function for a fuzzy set. So as shown in simulation result of figure 10 shows that the level of blood glucose is back to its optimal value; however, if we consider initial value of blood glucose states 110 mg/dl condition of the patient is at a relatively high concentration. In other words, By consuming a greater amount of glucose during meal, the blood glucose peak increased and the controller demonstrate the remarkable performance.
We consider that interval fuzzy-2 controller is so proper according to its fast response and high accuracy. As the figure 8 shows the results, the glucose range is decreased during the control process. The simplicity of proposed controller provides new method for perform a controller with less TM (time margin). TM parameter in the amount of time (min) it takes the blood glucose level to achieve the normal limitations (60-120 ml). The figure 11 shows the value of insulin injection. It considerate a rising at the first of process and decreasing dramatically during the rest of treatment process. Insulin is used in the form shown below.

The other parameters which are important in this model like deviation from the base line, changes in the insulin action, changes in plasma glucagon concentration, SD changes from baseline levels of plasma insulin concentration and deviation change in blood glucose from baseline levels of glucagon are depicted below in figures 12 to 16.
5 Conclusion

In this paper, a nonlinear model based on augmented minimal model has been used to simulate the 1st type of diabetes. The proposed model has robustness under meal glucose changes. Whatever the model is more accurate and the better controller can be designed in order to overcome diabetes. The novelty of this paper is in using type-2 fuzzy to considerate the uncertainties during the process that it enjoyed faster response and higher accuracy compared with type-1 fuzzy under the normal condition and in the presence of uncertainties in parameters of model. The comparison with last studies illustrate the proposed controller reduce the blood glucose in less time. Furthermore, less insulin dosage in difference with optimal controller is used [13]. The fuzzy sets as we proved, can serve as an effective and powerful controller in following the desired values.
Acknowledgements

The research was performed in collaboration with Dr. Mahdi Yaghoobi and Dr. Salahshour. Their advice and experience is greatly appreciated.

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