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An Improved Fuzzy PI Controller for Type 1 Diabetes

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Abstract: Diabetes mellitus, an illness due the inefficiency of the pancreas in managing plasma glucose level, can result intensive side difficulties and death. Since the diabetes system is a nonlinear system the control of it associated with specific problems. For effective control, the use of fuzzy logic theory seems to be appropriate. In this study, Bergman model of type 1 diabetes is considered and is tried to design a fuzzy Proportional Integral (PI) controller base on Mamdani-type structure. In the design procedure, less linguistic rules are used so the proposed controller is less complicated than other existing fuzzy controllers. In order to evaluate the performance of the proposed controller, a control input and a disturbance input are derived from authoritative references and the system is tested on standard initial states for 10 h. The comparison with previous studies shows that the proposed controller reduces the blood glucose level in less time; however less insulin dosage in comparison with other optimal controllers is used.

Keywords: Bergman model, fuzzy Proportional Integral (PI) controller

INTRODUCTION

Diabetes mellitus is a metabolic illness created by inadequate generation or shortage counteraction to insulin. There are two types of diabetes: type I and type II. In type I diabetes, the pancreatic beta cells, which are the only cells in the body that produce the hormone insulin and adjusts blood glucose, have been damaged by the body immune system (Topp *et al*., 2000).

If the blood glucose level not properly controlled, diabetes can results side difficulties like nerve hurt, brain hurt, mutilation and finally death. Diabetes dependent side difficulties are a pandemic around the world which has high medical, economic and social costs (Thomson *et al*., 2001; Alberti and Zimmet, 1998). Tight control of blood glucose levels has also been shown to lessen the fatality of diabetic and non-diabetic, severe care unit patients by up to 50% (Berghe *et al*., 2001). Diabetic persons monitor food consumption and everyday works in order to preserve blood sugar levels at a sufficient level. For facilitation of management, individuals are encouraged to diets in order to minimize handy monitoring and infusion, reduction of intervention and problem. This regime can results intense restrictions of the subjects' lifestyle, an institutional psychology and the problem of continuously keeping a strict diurnal regimen over long years.

For a diabetic person it is necessary to perform the procedures of blood glucose regulation manually. Therefore, a system that automatically monitors and controls the blood glucose level of a diabetic individual permits the patient to have more participation in the ordinary daily activities with risk reduction of long-term side effects.

Recent therapy for type I diabetes include monitoring the plasma glucose level and injecting insulin if required. Usually, patients pursue a strict regimen to avoid side effects, although the efficacy of this regimen is a function of the patient's insight and experience. A generic day for a diabetic person should include injecting insulin with long-term effect nearly three times and injecting insulin with immediate effect before meals, to decrease spike in blood sugar after meals. The patient is needed to make intuitive decisions when they deviate from ordinary diet or exercise templates and correct their regimen to adapt the disorderliness. Consequently, error is occurred and control is frequently not optimal. Utmost generally accessible glucose measurement instruments acting by measuring the blood glucose content of a small finger-prick blood instance, a nettlesome procedure upon repeated application. Consequently, some diabetic persons gage blood sugar as rarely as once per day, or less. Although last progresses have lead to semi-aggressive systems for example the GlucoWatch Biographer from Cygnus (Garg *et al*., 1999). This instrument offers sampling rates up to one readership every 20 min and can gage and save data constantly for up to 12 h before new sensor pads are needed.

In recent years much studies have been made for intelligent control of blood glucose. Among them we focus the 3rd order minimal model of Bergman *et al*.

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(1981) have been used because this study is also based on this model. In Li and Hu (2007), an ordinary PID controller proposed in order to reduce the time of lowering blood glucose. In Beyki *et al*. (2010), the parameters of Hammerstein controller were optimized in order to minimizing the time that takes for blood glucose to come back to its basal level. In Yasini *et al*. (2008), a closed-loop control system according to fuzzy logic control introduced and the performance of this controller is tested on three different patients. In addition some attempts have been done for robust blood-glucose controlling to eliminate disturbance of glucose-insulin system (Kovács *et al*., 2006; Garcia-Gabin *et al*., 2008).

In this study, Bergman model of type 1 diabetes is applied. Then is tried to design a fuzzy Proportional Integral (PI) controller based on Mamdani-type structure. The proposed controller has less linguistic rules than other existing controllers in literatures (Yasini *et al*., 2008). In order to evaluate the efficiency of the suggested controller, the system is tested on standard initial states for 10 h. The comparison with previous studies shows that the proposed controller reduces the blood glucose level in less time, however less insulin dosage in comparison with other optimal controllers is used.

METHODOLOGY

Current models of type I diabetes: Many efforts have been made to model diabetes. Among them, the three well-known models are mentioned in this part. The easiest model characterizing the answers of plasma glucose and insulin to an oral or intravenous administration of glucose, was the leading study of in 1961 (Bolie, 1961). This simple 2nd order model contains only plasma glucose and insulin. Also some research activities have been done according to this model (Makrogluo *et al*., 2006; Wahab *et al*., 2006). Another model that has been proposed for diabetes and is a little more complicated than the Bolie model, is the 3rd order minimal model of Bergman. The Bergman model, in addition to the two variable of Bolie model, also includes third variable namely remote compartment insulin exploitation. The Bergman model is very common and many researchers have done their research, according to this model. Among the existing models, the Sorensen model that was introduced in 1985 is the most complicated model. It is composed of six compartments and 21 states. These compartments include the equations demonstrating the physiological structure of the brain, heart, lungs, liver, intestine, kidney and peripheral tissues (Sorensen, 1985).

Bergman model: The equations of Bergman model, which is utilized in this study, are listed below Bergman *et al*. (1981):

Table 1: Parameters of bergman model

Parameters	Normal	Patient
P_1	0.0317	0.000
P_2	0.0123	0.020
P_3	4.92E-06	5.30E-06
γ	0.0039	0.005
n	0.2659	0.3000
h	79.0353	78000000.000
G	$_b$70.0000	70.000
I_b	7.0000	7.000
G_o	291.2000	220.000
I_o	364.8000	50.000

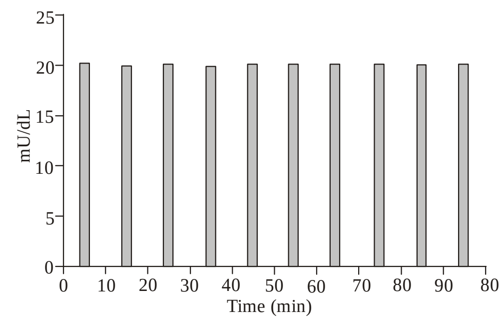

Fig. 1: Exogenous insulin injection rate

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

In above equations, the control variable is the exogenous insulin injection rate, U(t) (mU/min), whereas the exogenous glucose injection rate D(t) (mg/dL min) demonstrates the disturbance.

Other variables display parameters of system (1). The physiological parameters are G_B the basal glucose level (mg/dL), Y_B basal insulin level (mU/dL), V_L the insulin distribution volume (dL) and p_1, p_2, p_3, p_4 show the model parameters. The numerical values of patient and normal individual that we worked with them are mentioned in Table 1 (Kaveh and Yuri, 2006). It is noteworthy that these parameters belong to a diabetic individual. In the blood glucose control subject matters, the input *D(t)*, is regarded as disturbance. This input has the following equation as follows Geoffrey Chase *et al*. (2002):

$$D(t) = 0.5\exp(-0.5\,t)\ ,\ t \geq 0 \quad (2)$$

where, *t* is in (min) and *D(t)* is in (mg/dL/min). In this study, it is assumed that insulin is injected by insulin pump once every 10 min. The maximum amount of insulin that the insulin pump is capable to inject it is shown in Fig. 1 where the horizontal axis is (min) and vertical axis is (mU/dL). Selected limitations of insulin injection are expressed according to Geoffrey Chase *et al*. (2002). An appropriate controller can change the control signals in order to decrease blood glucose level to basal level as soon as possible.

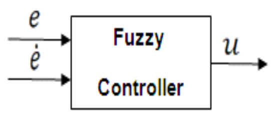

Fig. 2: Fuzzy-PD controller

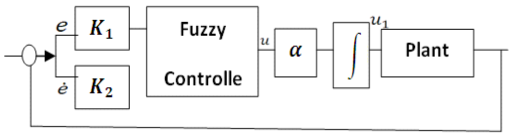

Fig. 3: The enhanced fuzzy-PI controller

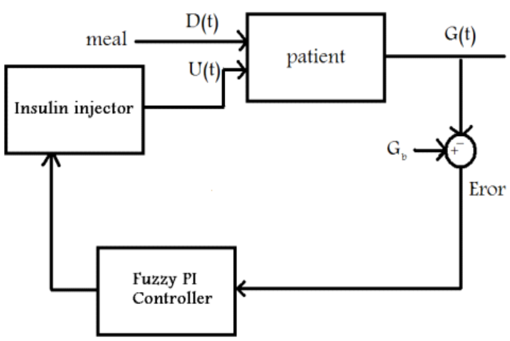

Fig. 4: Block diagram of the control scheme

The proposed approach: As mentioned before, an enhanced fuzzy PI controller is used in this study. In order to design the enhanced fuzzy PI controller at first fuzzy PD controller is introduced. Assume that the fuzzy controller by considered circumstances is a two-input and one output as shown in Fig. 2. The two inputs of the fuzzy PD controller are the error *e* and the change rate of error $\dot{e}$ respectively and the output of the fuzzy controller is *U* Huang *et al*. (1999). In fact the parameter *e* represents the difference between measured blood glucose level and its basal level and the parameter $\dot{e}$ represents return speed of blood glucose to its basal level.

Based on fuzzy-PD controller above, we can create the enhanced fuzzy-PI controller as is shown in Fig. 3:

$$\begin{aligned} u_1 &= \alpha\int\left(A + PK_1 e + DK_2\dot{e}\right)dt \\ &= \alpha At + \alpha K_2 De + \alpha K_1 P\int e\,dt \end{aligned} \quad (3)$$

The above equations are taken from Huang *et al*. (1999), where K_1 and K_2 are weighting parameters for *e* and $\dot{e}$, respectively. Moreover, α is the integral constant. Therefore the enhanced fuzzy controller becomes a parameter variable PI controller, its tantamount commensurate control and integral control parts are $\alpha K_2 D$, $\alpha K_1 P$. Different parts of recommended approach are shown in Fig. 4.

SIMULATION AND RESULTS

In order to simulate the proposed fuzzy PI controller, MATLAB software is applied. General scheme of the designed fuzzy PI controller is shown in Fig. 5.

Mamdani-type structure is used in the proposed fuzzy PI controller with two inputs and one output. Linguistic entrance variables are plasma glucose deviation G(t) (mg/dL) and its changes rate, i.e., dG/dt and the only output variable is the exogenous insulin injection rate, U(t) (mU/min). This parameter is also considered as a control variable. Triangular membership functions, because of their simple application, are used in the design process. These membership functions are chosen with respect to fuzzy clustering of inputs and output.

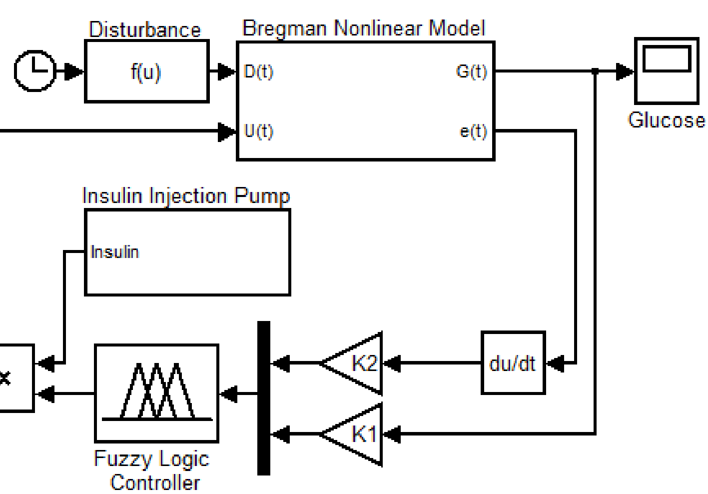

Fig. 5: General scheme of designed fuzzy-PI controller

Table 2: Parameters of triangular membership functions

Input variables	Membership	FunctionsInterval
Glucose concentration	Low	[56.7 94.24 119.1]
	Medium	[68.84 120.4 170]
	High	[110 172.34 290]
Glucose deviation	Low	[-20 -20 0]
	Medium	[1 0 1]
	High	[0 20 20]
Insulin infusion rate	Very Low	[0 0.10 .0.2]
	Low	[0.1524 0.2524 0.3]
	Medium	[0.287 0.333 0.4]
	High	[0.355 0.623 0.762]
	Very High	[0.737 0.837 1]

Table 3: Fuzzy IF-THEN rules

	Glucose deviation rate		
Glucose deviation	Negative	Zero	Positive
High	M	H	V.H
Medium	L	M	H
Low	Z	Z	V.L

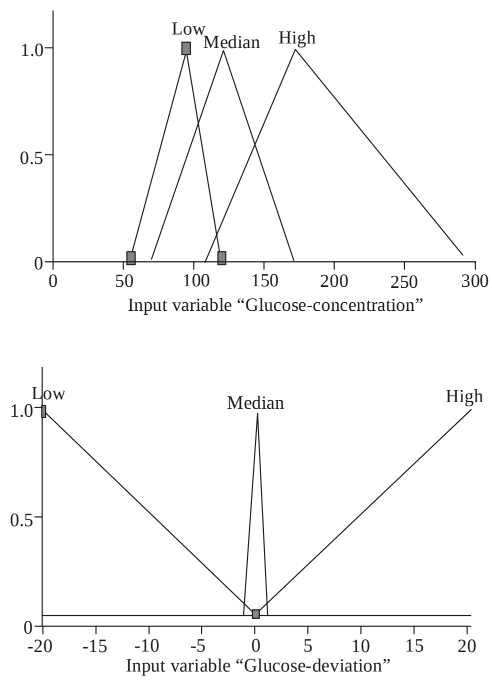

Fig. 6: Input membership functions

Specification of inputs and output variables are given in Table 2. The membership functions forms of inputs and output are given in Fig. 6 and 7, respectively. The relationship between inputs and output of the designed fuzzy controller is defined by 9 IF-THEN rules as is shown in Table 3. The logical relationship between linguistic rules are AND (minimum) method whereas for defuzzification of output CENTROID method is used. The Linguistic rules in more detail are given in Table 3. The surface of the controller is also displayed in Fig. 8.

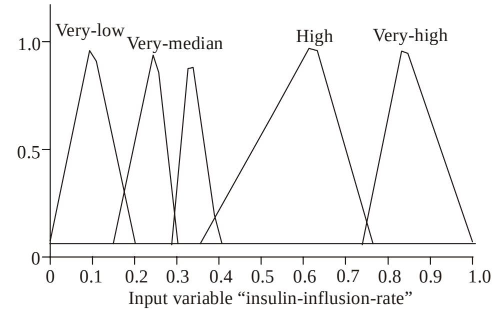

Fig. 7: Output membership functions

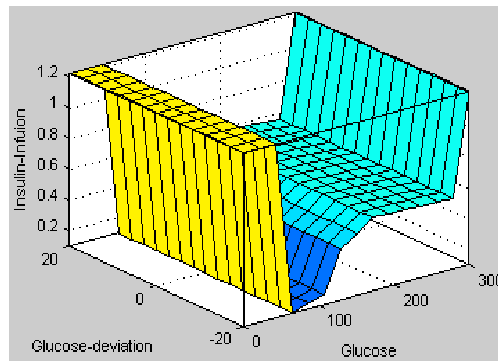

Fig. 8: The surface of fuzzy controller

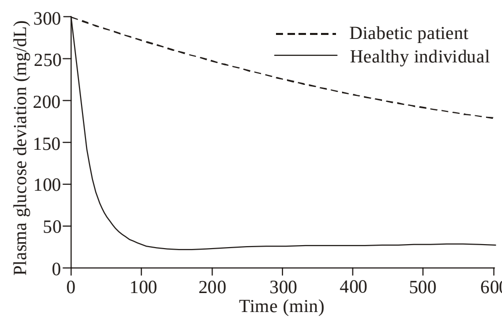

Fig. 9: Plasma glucose deviation response of healthy individual and diabetic patient

By using the values presented in Table 1, plasma glucose deviation response of healthy individual and diabetic patient after consuming a meal and with no insulin injection is obtained and for comparison both responses are gathered in the same plot. As can be seen in Fig. 9, the plasma glucose deviation level of a healthy individual decrease rapidly from its initial state i.e., 290 (mg/dL) to its basal level and for a diabetic individual the blood glucose level decrease slowly and after 10 h is reached to 190 (mg/dL). It is noteworthy that basal level of blood glucose is among 70 and 120 mg/dL before meal and under 180 mg/dL after meal (Hipszer, 2001).

The designed fuzzy PI controller is applied for regulation of blood glucose level. In order to evaluate the

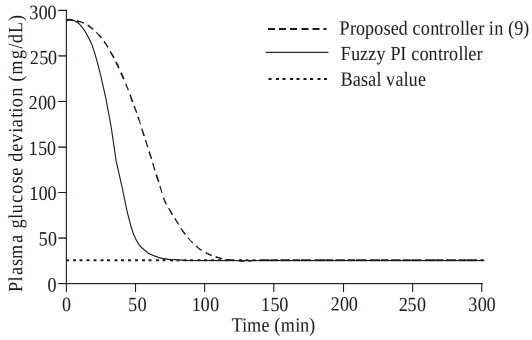

Fig. 10: Glucose profiles of patient using the enhanced fuzzy PI controller and the proposed controller in Yasini *et al*. (2008)

performance of fuzzy PI controller, the parameter *TM* (Time Margin) is introduced. *TM* parameter is the amount of time (min) that it takes the blood glucose level to reach the normal limits of 70-110. The obtained TM parameter in Li and Hu (2007) is 87.5 and in Beyki *et al*. (2010) is claimed to be 70. This parameter in our study as shown in Fig. 10 is much less than others and is about 50. In relation with linguistic rules, 9 linguistic rules are used whereas in comparison with Yasini *et al*. (2008) less IF-THEN rules are used. It means that the enhanced fuzzy PI controller is less complicated than the proposed controller in Yasini *et al*. (2008). It is necessary to recall that the maximum amount of insulin injection is 30 (mU/dL) (Sorensen, 1985) and this value in Beyki *et al*. (2010) is 61 (mU/dL), while this value seems to be irrational because the insulin pump is incapable to inject this amount. In the case of glucose regulation, the initial value of blood glucose level, as mentioned in Table 1, should be 291.2 but according to Fig. 7 of Yasini *et al*. (2008) it is started from 75 so the regulation appears to be wrong. In order to have more clarity instead of 0 to 600 Fig. 10 is plotted from 0 to 300.

CONCLUSION

In this study, an enhanced fuzzy PI controller was proposed for regulation of blood glucose level. Mamdani-type structure was used in the fuzzy PI controller. In order to demonstrate the performance of proposed controller, it was tested under standard meal disturbance for 10 h. The simplicity of proposed controller provides a novel approach for implementing a controller with less *TM* in comparison with other researches. In addition, less insulin dosage in comparison with other controllers shows that the performance of the proposed controller is perfect. Furthermore, compared to other available fuzzy controllers less linguistic rules were used in proposed fuzzy controller so it is less sophisticated.

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