Diabetic Control Using Genetic Fuzzy-PI Controller

Masoud Goharimanesh, Ali Lashkaripour, Shadi Shariatnia, and Aliakbar Akbari

Abstract

This paper deals with diabetes type 1 as a nonlinear model, which has been simulated in MATLAB-SIMULINK environment by the means of Gap Metric method. A proportional controller turns three independent linear integrals into this nonlinear model. To enhance the system performance, a Fuzzy algorithm independent coefficient has been implemented. In this study, Genetic Algorithm amends the controller by improving fuzzy membership functions. Finally, the control method tuned by standard tuning procedure and the optimized form of it are compared.

Keywords: Fuzzy, PID, gap metric, genetic algorithm, diabetes.

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 [1] proved that precise control of diabetes is beneficial in patients with long life expectancy and no psychological, social or cultural problems. It was also concluded by Pietri et al. [2] 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.

PID (proportional-integral-derivative) controller, considered to be the best controller, is a mechanism, which is aimed to minimize the difference between a set value and process variables. O'Dwyer et al. [3] published a handbook, in which PID controller tuning rules are discussed. Skogestad and Sigurd [4]also presented analytic rules for PID controller tuning. In an experiment done by Årzén et al. [5]. It was shown that only minor control performance degradation in PID controllers results in significant CPU usage reduction. 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 et al. [10] designed an auto-tuning fuzzy PID controller based on genetic algorithm. Controllers, based on fuzzy logic, succeeded in many control problems where the conventional control theories failed. Moreover, the control policy requires a significant amount of knowledge or trial and error. To solve this issue Raju et al. [11] proposed a fuzzy controller with the fuzzy sliding surface. Shao and Shihuang [12] studied a fuzzy self-organizing controller, where the control policy is able to develop and improve by itself. Studies have been carried out to design fuzzy logic based controllers without the need of an expert's experience and knowledge, by conducting genetic algorithm [13-15]. In another study, Trebi-Ollennu et al. [16] demonstrated the fuzzy genetic algorithm optimization as an effective and intuitive algorithm. Lehmann et al. [17] explored the possibility of using a physiological model of glucose-insulin interaction as a tool for automated insulin dosage adjustment. Hovorka, Roman, et al. [18] also came up with a predictive control over glucose concentration in type 1 diabetes utilizing a nonlinear model. The rest of this paper is organized as follows. In Section 2, a nonlinear model for diabetes will be introduced. In Sections 3 and 4 the paper focuses on the linearizing method based on gap metric and its implementation. The novel part of this paper is located in Sections 5 and 6, where the fuzzy PID controller is tuned by genetic algorithm.

2. Diabetes Type 1 Nonlinear Model

In this section, the nonlinear model discussed in [19] will be introduced and simulated in MATLAB-SIMULINK environment. In the regarded model, (1), (2) and (3) are the governing equations of blood glucose system. There are three principal state parameters in this set of equations, G, X and I which are glucose concentration, insulin concentration and remote concentration respectively. The latter is utilized as time

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Manuscript received 5 July 2013; accepted 18 Dec. 2013.

delay for insulin injection. Table 1, shows the parameters with their corresponding values in these equations.

$$\dot{G} = -p_1 G - X\,(G + G_b) + \frac{G_{meal}}{v_1} \quad (1)$$

$$\dot{X} = -p_2 X + p_3 I \quad (2)$$

$$\dot{I} = -n\left(I + I_b\right) + \frac{u}{v_1} \quad (3)$$

Table 1. Parameter values in equations 1 to 3 [19].

Parameters	Values
G (Nominal)	81.5 mMol L^{-1}
I (Nominal)	10.5 mU L^{-1}
X (Nominal)	0.00546 min^{-1}
G_b	4.5 mMol L^{-1}
v_1	12 L
p_1	0 min^{-1}
I_b	4.5 mU L^{-1}
p_2	0.025 min^{-1}
p_3	0.000013 mU L^{-1} min^{-2}
n	5/54 min^{-1}
G_{meal}	5.54 mMol L^{-1} min^{-1}
u (Nominal)	16.5 mU L^{-1} min^{-1}

Diabetes is a disease that either the patient has a high blood glucose concentration due to the lack of insulin production, or the body's cells do not respond correctly to the insulin that exists. The lack of insulin production is regarded as type 1 diabetes, where the patient needs to take regular insulin infusion and blood tests to ensure if the blood glucose level is normal. Figure 1 shows the implementation of this nonlinear model in MATLAB-SIMULINK environment. Meanwhile, Figure 2-a and Figure 2-b illustrate the insulin concentration and the blood glucose concentration affected by insulin injection as a variable of time, respectively.

3. Linearize Model Using GAP Metric

Linearizing every nonlinear model in operation intervals can ease the simulation and controller design. One approach is gap metric technique. The idea of the gap between the patterns of two linear systems was introduced in 1935 by Hausdorff [20]. A topology was described for close operators by Newburgh [21]. The introduction of gap by Krein and Krasnoselsk [22] dates back to 1947. The original paper of this work was based on Russian and many researchers have reviewed their results[23]. The notion of identity between Newburgh's metric and the gap metric was first established by Berkson [24].

In this study, the gap metric has been employed as a standard measure to extract linear equations of unstable systems in order to make them suitable to handle and work with. Here, this metric works on eight sets of closed subspaces of available diabetic records. If the gap metric value of two functions is relatively small, a same controller can be applied both in the former and the latter subspace. The gap metric calculations can be simulated using MATLAB software. The result, as shown in Table 3, is an 8x8 diagonal symmetric matrix in which all the inputs have been compared and the gap value is presented. Based on a prescribed scale, the gap metric values under this criterion form a family. Finally, the middle member of every family is preferred for subsequent operations. The transfer functions adopted from reference [19] are shown in Table 2. Each of these functions is located for a fixed interval. The gap metric value is 0.07 as in the reference [19]. Table 3, shows an eight squared matrix which is filled by gap metric algorithm. As it shows, with the criteria mentioned above, three clusters are extracted. Three transfer functions are introduced in (4), (5) and (6). Each e^{-is}, shows the delay for each insulin dynamic during the injection process [19].

$$\frac{-8.4114}{256s+1}e^{-4s} \quad (4)$$

$$\frac{-10.8114}{274s+1}e^{-2s} \quad (5)$$

$$\frac{-13.0286}{296s+1}e^{-2s} \quad (6)$$

It is obvious that working with linear systems is much easier to handle, rather than operating calculations on nonlinear ones. Hence, according to the gap metric results, we can introduce three families in which a same controller can be applied. A linear equation represents each subdivision for subsequent calculations.

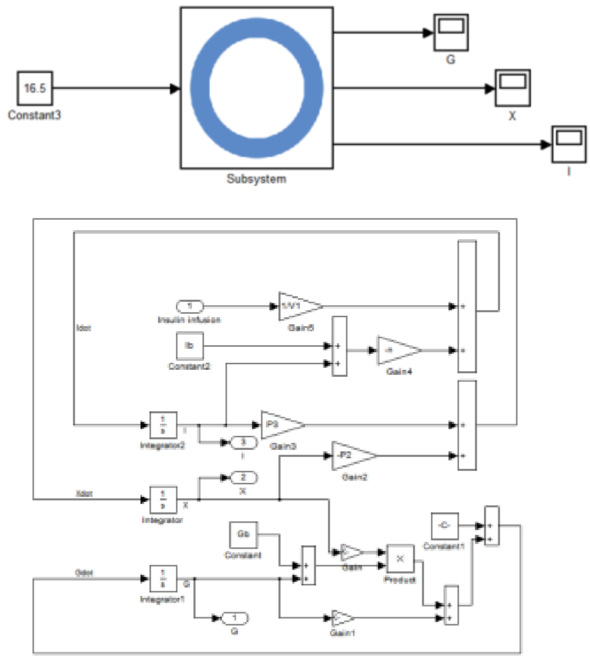

Figure 1. Nonlinear model in Simulink.

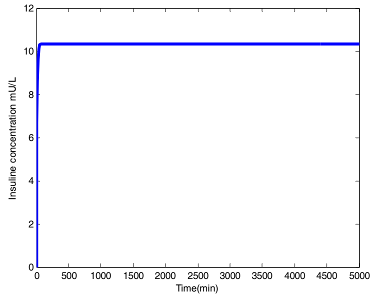

Figure 2-a. Insulin injected into nonlinear model.

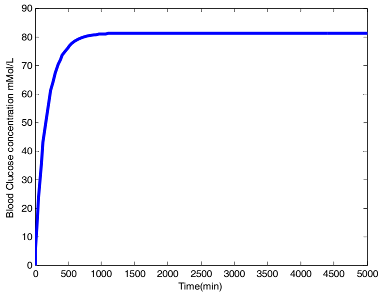

Figure 2-b. Result of nonlinear model.

4. Linear Model Implementation

In Figure 3, the three models, mentioned above, are implemented in SIMULINK. By designing a feedback controller, the blood glucose concentration would be maintained close to a desirable amount. ODE45, as a powerful solver with time step variable, is used to solve the differential process. In this model, a fuzzy controller is added to control the blood glucose. Design and tuning of this part will be discussed later.

Table 2. Proposed Linear Transfer functions [19].

	Interval	Transfer functions
1	81.5-84.9	$\frac{-7.7714}{249s+1}e^{-3s}$
2	84.9-88.61	$\frac{-8.4114}{256s+1}e^{-4s}$
3	88.61-92.61	$\frac{-9.1429}{256s+1}e^{-4s}$
4	92.61-96.97	$\frac{-9.9657}{274s+1}e^{-2s}$
5	96.97-101.7	$\frac{-10.8114}{274s+1}e^{-2s}$
6	101.7-107	$\frac{-12.1143}{282s+1}e^{-3s}$
7	107-112.7	$\frac{-13.0286}{296s+1}e^{-2s}$
8	112.7-119.6	$\frac{-14.8571}{322s+1}e^{-2s}$

Table 3. Gap metric matrix.

	Mi1	Mi2	Mi3	Mi4	Mi5	Mi6	Mi7	Mi8
M1i	0.000976	0.026341	0.068291	0.078047	0.118046	0.159996	0.171703	0.195117
M2i	0.026341	0.000976	0.04195	0.051706	0.092681	0.134631	0.146338	0.169752
M3i	0.068291	0.04195	0.000976	0.011707	0.05073	0.093656	0.105363	0.129753
M4i	**0.078047**	0.051706	0.011707	0.000976	0.040975	0.0839	0.095607	0.119997
M5i	0.118046	0.092681	0.05073	0.040975	0.000976	0.042926	0.055608	0.079998
M6i	0.159996	0.134631	0.093656	**0.0839**	0.042926	0.000976	0.012683	0.037072
M7i	0.171703	0.146338	0.105363	0.095607	0.055608	0.012683	0.000976	0.02439
M8i	0.195117	0.169752	0.129753	0.119997	0.079998	0.037072	0.02439	0.000976

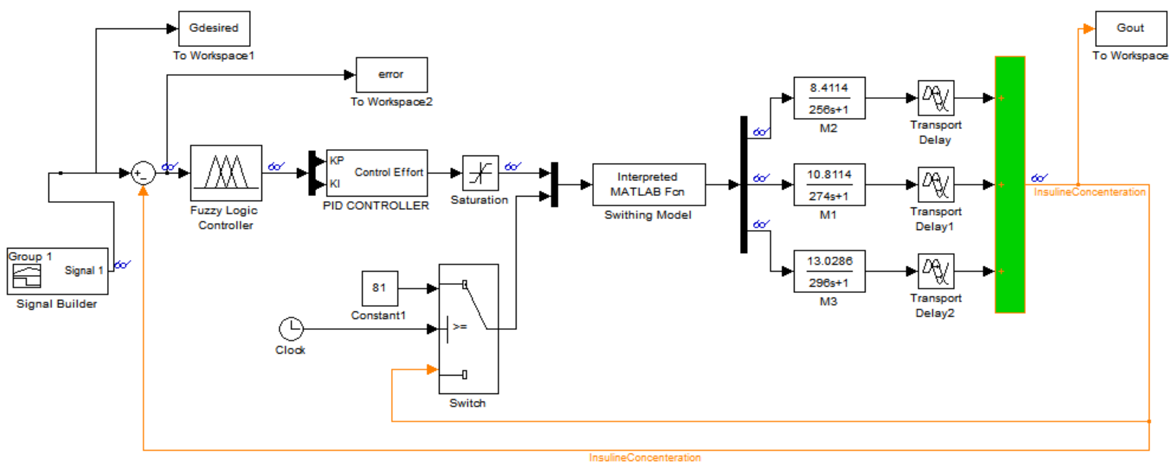

Figure 3. SIMULINK model implementation.

5. Conventional PI Controller

The PID controller is the most common form of feedback controller. It became a standard tool when process control emerged in 1940s. PID controllers have survived many changes in technology, from mechanics and pneumatics to microprocessors via electronic tubes, transistors and integrated circuits. The microprocessors have had a dramatic influence on PID controllers. PID controller calculates an error value as the difference between a measured process variable and a desired set point. The controller attempts to minimize the error by adjusting the process control inputs. The PI controller block is shown in Figure 4.

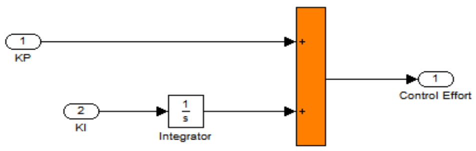

Figure 4. PI controller.

6. Fuzzy PI Controller Design Using Genetic Algorithm

The fuzzy set theory was introduced by Lotfi Zadeh [25, 26]. Fuzzy logic can serve as a useful tool dealing with complex systems which are faced with challenges and issues that are associated with reasoning and decision making. Selecting a system totally depends on its internal complexity.

In this paper, a fuzzy set, based on MAMDANI, with one input as error and two outputs for tuning proportional and integral gain of PID controller is considered. In Figure 5, this organization in MATLAB FUZZY TOOLBOX is shown.

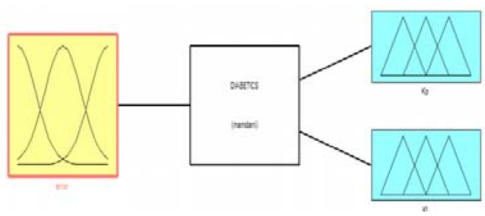

Figure 5. FUZZY set.

The membership functions or output parameters, K_p and K_I are demonstrated in Figure 6 and Figure 7, respectively. This process is different for the input, and would be changed and tuned by an optimization algorithm like GA. Figures 8 and 9 show the before and after of tuning of membership functions for input set respectively. This process is going to be described in rest of the paper. Fuzzy rules are simple in this section and are not maneuvered on. The rules are listed in Table 4.

Table 4. Fuzzy rules.

	ERROR	K_p	K_I
1	L	L	L
2	M	M	M
3	H	H	H

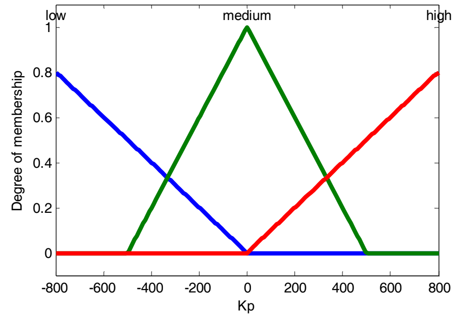

Figure 6. First output of fuzzy set (Proportional gain).

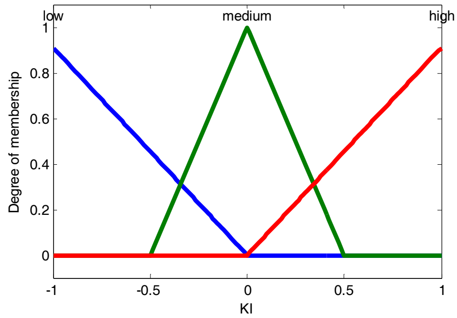

Figure 7. Second output of fuzzy set (Integrative gain).

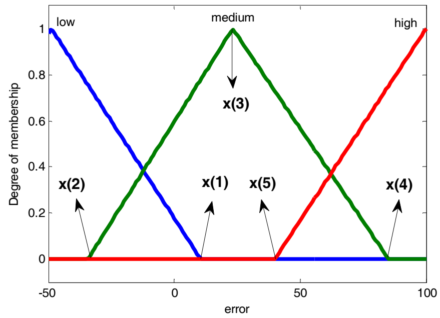

Figure 8. FUZZY input membership function, before tuning.

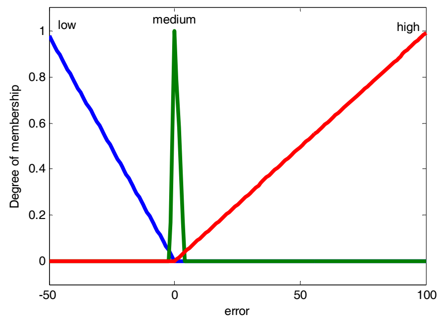

Figure 9. FUZZY input membership function, after tuning.

The optimization process for a problem like this needs a cost function to minimize, such that the constraints are satisfied. Inequality constraints are shown in (7) and (8). These formulas hold the membership function of the input set in a regular region.

$$\begin{cases} x_2 - x_3 \le 0 \\ x_3 - x_4 \le 0 \end{cases} \tag{7}$$

$$\begin{bmatrix} 0 & 1 & -1 & 0 & 0 \\ 0 & 0 & 1 & -1 & 0 \end{bmatrix} \le \begin{bmatrix} 0 \\ 0 \end{bmatrix} \tag{8}$$

Genetic algorithm is a special type of evolutionary algorithms, which uses reverted biology techniques such as inheritance and mutation.

In fact, genetic algorithms utilize Darwin's principle of natural selection to find the optimal formula for predicting or matching patterns. Genetic algorithms are often a good option for prediction based on regression techniques. Briefly, genetic algorithm is a programming technique which employs genetic evolution as a problem-solving model. The problem, which has to be solved, is the input and solutions are coded according to a pattern that is called fitness function. Each solution evaluates the candidate, while most of them are randomly selected. The flowchart of this algorithm is illustrated in Figure 10; also the assigned variables to implement the method in MATLAB are available in Table 5.

The result of the optimization problem is shown in Figure 11. The membership function is tuned by genetic algorithm and can be used as a controller in SIMULINK. These graphs compare the rate of blood glucose concentration, while implementing FUZZY-PI controller, with the desired values. It can be clearly realized that the controller results maintain a relatively smooth trend with small differences by desired amounts.

As Figure 12 shows, the optimized fuzzy-PI controller is compared with the conventional fuzzy-PI. The proposed method shows a smooth response.

Table 5. Properties of the conducted genetic algorithm.

Option	Value
Crossover function	Heuristic
Crossover fraction	0.8
Elite number	2
Initial penalty	10
Mutation function	Adaptive feasible
Penalty factor	100
Population initial range	[-1,1]
Population size	100
Population type	Bit string
Selection function	Stochastic uniform

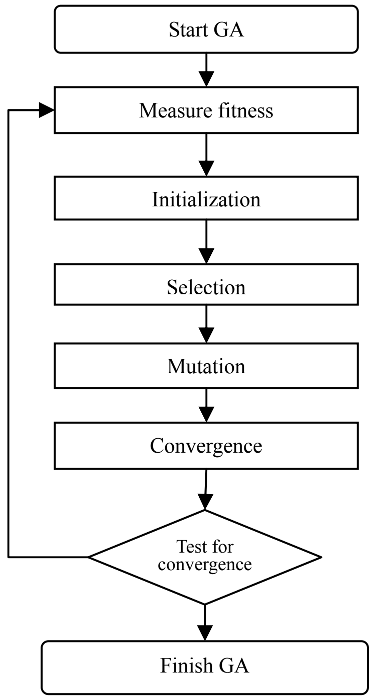

Figure 10. Biological genetic algorithm process flow.

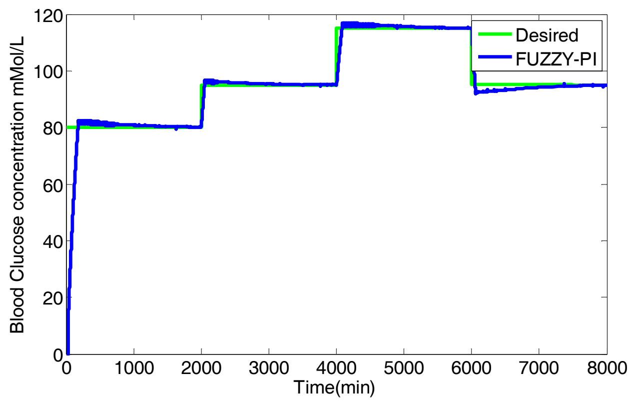

Figure 11. Optimized fuzzy- PI controller result.

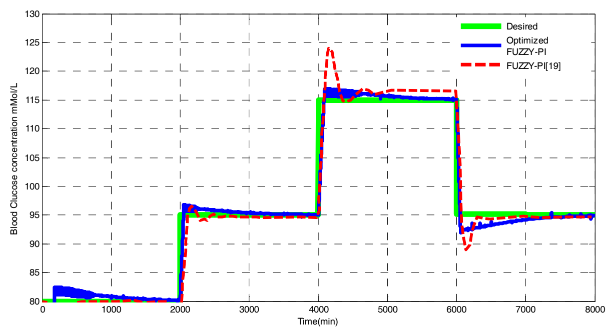

Figure 12. Comparison of proposed controller with the conventional fuzzy- PI controller.

7. Conclusion

In this paper, a linearized model, based on gap metric, has been used to simulate the 1st type of diabetes. The novelty of this paper is in using an evolutionary algorithm like GA to tune the membership function during the process. Optimized fuzzy sets, as we proved, can serve as an effective and powerful controller in following the desired values.

Appendix

Symbol	Parameter description
G	Blood glucose concentration
I	Insulin concentration
X	Insulin concentration
G_b	Basal plasma glucose
v_1	Insulin distribution volume
p_1	Glucose effectiveness factor
I_b	Basal plasma insulin
p_2	Delay in insulin action
p_3	Patient parameter
n	Fractional disappearance rate of insulin
G_{meal}	External glucose input
u	Insulin infusion rate
M_{ij}	Gap metric proposed transfer functions

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