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A Comparison of Fuzzy Types 1 and 2 in Diabetics Control, Based on Augmented Minimal Model

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Abstract *– In this study, a novel and optimized control policy over type 1 diabetes was sought to explore. A nonlinear model of type 1 diabetes (Augmented Minimal Model) was taken into consideration, which has been implemented in MATLAB-SIMULINK environment. The regarded model is one of the proposed diabetes models which consider the conditions of patient. There are uncertainties in this model due to factors such as blood glucose concentration, daily meals and sudden stresses. In addition to different approaches toward the elimination of these uncertainties, distinct control policies could be conducted to monitor blood glucose levels. In this article, a meal disturbance is inserted into diabetic model to consider the real environment and eliminate the regarded uncertainties in the simulation. Moreover, fuzzy control theory was utilized as a logical tool that is used to transform words into actions. To enhance the system performance, a fuzzy type-2 algorithm with independent coefficient had been implemented. Finally, fuzzy type-1 and fuzzy type-2 controllers were compared. It was concluded fuzzy type-2, had a better performance compared to fuzzy type-1. Blood glucose level experienced a lower maximum level in fuzzy type-2. Moreover, it was clarified the controller performance improves considerably by conducting fuzzy type-2 and the controller maintained blood glucose level in the desired range better in comparison to fuzzy type-1.*

Keywords*: Control, Diabetes, Fuzzy Type-2, Minimal Augmented Model.*

INTRODUCTION

Diabetes which faces not only western countries, but also lesser developed societies, is a sever health issue. Conventional control policies over insulin infusion rates, were unable to keep the blood glucose concentration in the desired range, due to its complex and nonlinear nature [1, 2].

Diabetes is a group of metabolic diseases which flaws in insulin action or insulin production would cause high levels of blood glucose concentration. Diabetes is the leading cause of nontraumatic lower limb amputation, kidney failure and a major cause of heart diseases and stroke. Due to the inclination of under developed countries to the western diet and lifestyle, the number of diabetic subjects is unfortunately on rise [3, 4]. Using multiple-dose insulin injections (three to four injections per day of basal and prandial insulin) is a recommended therapy for type 1 diabetes by American Diabetes Association [5]. Keeping the blood glucose concentration as close as possible to the normal value was proven to be lifesaving in diabetic subjects. Also, exact controlling of blood glucose concentration yields in preventing or slowing down the progress of diabetes. It was proven that accurate control of diabetes would be beneficial for patients with long life expectancy [6]. Also, it was concluded that all therapies for diabetic control are effective in lowering plasma triglyceride levels. In contrast, a strict metabolic control is required to affect plasma cholesterol and LDL cholesterol levels [7]. Therefore, precise monitoring of blood glucose concentration is crucial and is in high importance. As a result, many researches have been undertaken to regulate blood glucose level in diabetic patients [8-9]. A favorable control policy requires a significant amount of knowledge or trial and error [8].

Several studies had been under taken to design fuzzy logic based controllers without the need of an expert's experience and knowledge, by the use of evolutionary algorithms [9-11]. Also, controllers based on fuzzy logic succeeded in several control problems where the conventional control theories failed. The optimized fuzzy control method was demonstrated as an effective and intuitive control algorithm [12]. Attempts were made by several scholars to control diabetes type one, Lehmann et al. sought the possibility of using a physiological model of glucose-insulin interaction as a tool for automated insulin dosage regulation [13]. Also, a predictive control policy over glucose concentration in type 1 diabetes was proposed utilizing a nonlinear model [14-21]. A tutorial was published for training fuzzy type 2 in MATLAB setting. Wu, modeled and examined the influences of both insulin and glucagon on blood glucose concentration. In addition, he took time-independent parts for endogenous insulin and glucagon production into consideration. Also, the regarded model incorporates the effects of exogenous "disturbance" factors on plasma insulin and blood glucose [22, 23]. In a previous study, we had linearized a nonlinear metabolic model by the means of gap metric method, afterwards by using a fuzzy-PI control policy, blood glucose level was successfully maintained in the desired range [24].

Moreover in our recent research, we used the augmented minimal model with fractional PID controller [25]. This paper was intended to make a comparison between fuzzy type-1 and type-2, in order to clarify which control policy is more desirable in keeping blood glucose level closer to the normal level. The rest of the paper is organized as follows. The Augmented Minimal Model (AMM) would be introduced in the second section. Next, in the third section AMM will be implemented and simulated in the MATLAB-SIMULINK environment. In the fourth section, fuzzy type 2 principles are considered and the controller is integrated with AMM. The results are provided in the fifth section and a comparison of fuzzy type-1 and type-2 is made. Finally, a comprehensive discussion would bring the paper to a conclusion.

Augmented Minimal Model

The case of type one polygenic disease has been thoroughly studied throughout years and its physiological causes are relatively clear. Therefore, the eye of the tutorial community recently has been centered on modeling and understanding of type two polygenic diseases (see [10]). One amongst the goals of this study is to demonstrate the benefits of explaining the aldohexose metabolism of type one and type two diabetics with one stripped down model (the AMM in our case). By inserting some well-known physiological variations between healthy subjects and diabetics to AMM, we tend to manufacture new input-output information sets. Then AMM will be matched with the given information. In equation (1) the AMM coupled nonlinear set of equations is given. Each of the state parameter of the (1) are introduced and their values are available in table1. Also, constant values of (1) for healthy and diabetic patients are given in Table 2.

$$\begin{cases} \frac{dI}{dt} = -\gamma_I . I(t) + \beta . \max[G(t) - \theta_I, 0] + D_I(t) \\ \frac{dN}{dt} = -\gamma_N . N(t) + \alpha . \max[\theta_N - G(t), 0] \\ \frac{dX}{dt} = -P_2 . X(t) + P_3 . I(t) \\ \frac{dG_I}{dt} = -P_1 G_I(t) - X(t) G(t) \\ \frac{dG_N}{dt} = -P_4 . G_N(t) + P_5 . N(t) \\ G(t) = G_b + G_I(t) + G_N(t) + D_G(t) \end{cases} \tag{1}$$

Table 1. Nomenclature

I	Deviation of plasma insulin concentration from its basal value	15 mU/L in healthy subjects
N	Deviation of plasma glucagon concentration from its basal value	75 ng/L in healthy subjects
X	Insulin action	min%
G_I	Deviation of blood glucose concentration from its basal value due to insulin action	mg/dL
G_N	Deviation of blood glucose concentration from its basal value due to glucagon action	mg/dL
G_b	Basal value of blood glucose concentration	Assumed 90mg/dl in this study
G	Concentration of blood glucose	mg/dL
D_I	Insulin disturbance	mU/L/min
D_G	Glucose disturbance	mg/dL

Table 2. AMM Parameters for healthy and diabetics subjects

	Healthy	Type 1	Type 2
γ_I	0.42	N/A	[0.43,0.56]
β	0.106	0	$[9\times10^{-4}, 0.08]$
θ_I	103	N/A	[101,114]
γ_N	5.8×10^{-4}	$[0, 1.2\times10^{-3}]$	$[4.5\times10^{-4}, 9.5\times10^{-4}]$
α	0.0037	$[4\times10^{-4}, 1.2\times10^{-3}]$	[0.0023,0.0049]
θ_N	83	[75,93]	[77,91]
P_1	0.022	0.013	[0.004,0.036]
P_2	0.075	0.063	[0.034,0.155]
P_3	1.3×10^{-5}	910-6	$[3.1\times10^{-6}, 1.3\times10^{-5}]$
P_4	0.04	0.04	[0.027,0.05]
P_5	0.016	0.016	[0.015,0.017]

Modeling

As it can be concluded from equation (1), with internal secretion injection, the internal secretion concentration and as a result of it, the blood glucose concentration would vary with time severely. Therefore, a powerful control method is needed to maintain the blood glucose concentration in the normal range (110-120[mg/dL]) in diabetic patients. Figure 1, shows the implementation of this nonlinear model in MATLAB-SIMULINK setting. Meanwhile, table 3 gives function block parameters of diabetics.

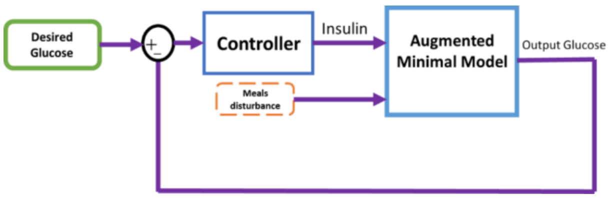

Fig. 1. Diabetes Blood aggregated model with an input box control, an input and an output with meal disturbance

Table 3. Function Block Parameters of Diabetics

G_b	γ_I	β	θ_I	γ_N	α
110	0.56	0.08	114	$9.5e^{-4}$	0.005
θ_N	P_1	P_2	P_3	P_4	P_5
91	0.036	0.155	$1.3e^{-5}$	0.05	0.017

In traditional fuzzy sets, the membership functions sweep the intervals individually by crisp points. But in fuzzy type-2, a distance for the functions is considered. As figure 2 shows, P1 to P9 can build a single membership function.

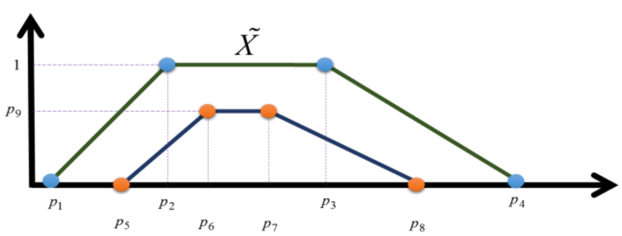

Fig. 2. The position of a simple fuzzy typ2 sets

The usual rules of the fuzzy structure are given in (2), (3).

$$R^n : \text{IF } x_1 \text{ is } \tilde{X}_1^{\,n} \text{ and } \dots \text{ and } x_2 \text{ is } \tilde{X}_2^{\,n} \text{ THEN } y \text{ is } Y^n \tag{2}$$

$$\begin{aligned}
R^1 &: \text{If } x_1 \text{ is } \tilde{X}_{11} \text{ and } x_2 \text{ is } \tilde{X}_{21}, \text{ THEN y is } Y^1 \\
R^2 &: \text{If } x_1 \text{ is } \tilde{X}_{11} \text{ and } x_2 \text{ is } \tilde{X}_{22}, \text{ THEN y is } Y^2 \\
R^3 &: \text{If } x_1 \text{ is } \tilde{X}_{12} \text{ and } x_2 \text{ is } \tilde{X}_{21}, \text{ THEN y is } Y^3 \\
R^4 &: \text{If } x_1 \text{ is } \tilde{X}_{12} \text{ and } x_2 \text{ is } \tilde{X}_{22}, \text{ THEN y is } Y^4
\end{aligned} \tag{3}$$

To compute the output value, calculation of the main fuzzy type-2 values are needed, which is calculated as equations (4)-(6).

The membership functions of the actual errors (deviation from desired blood glucose concentration) in diabetics are as the inputs of the control policy of fuzzy type-2, are given in figure 3. Moreover, figure 4 illustrates the membership functions of blood insulin infusion rates as the output of the fuzzy type-2 controller.

$$y_l = \min_{k\in[1,N-1]} \frac{\sum_{n=1}^{k} \bar{f}^n \underline{y}^n + \sum_{n=k+1}^{N} \underline{f}^n \underline{y}^n}{\sum_{n=1}^{k} \bar{f}^n + \sum_{n=k+1}^{N} \underline{f}^n} \equiv \frac{\sum_{n=1}^{L} \bar{f}^n \underline{y}^n + \sum_{n=L+1}^{N} \underline{f}^n \underline{y}^n}{\sum_{n=1}^{L} \bar{f}^n + \sum_{n=L+1}^{N} \underline{f}^n} \tag{4}$$

$$y_r = \max_{k\in[1,N-1]} \frac{\sum_{n=1}^{k} \underline{f}^n \bar{y}^n + \sum_{n=k+1}^{N} \bar{f}^n \bar{y}^n}{\sum_{n=1}^{k} \underline{f}^n + \sum_{n=k+1}^{N} \bar{f}^n} \equiv \frac{\sum_{n=1}^{R} \underline{f}^n \bar{y}^n + \sum_{n=R+1}^{N} \bar{f}^n \bar{y}^n}{\sum_{n=1}^{R} \underline{f}^n + \sum_{n=R+1}^{N} \bar{f}^n} \tag{5}$$

$$y = \left(y_l + y_r\right)/2 \tag{6}$$

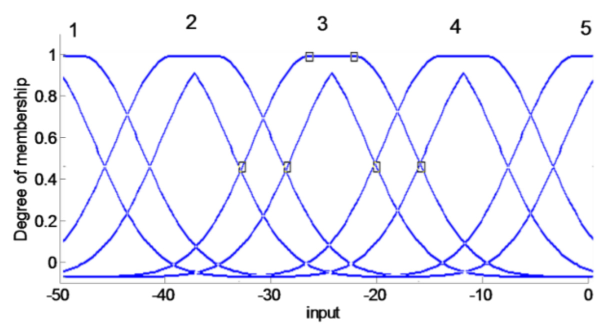

Fig. 3. Membership Functions for the input (desired and actual errors diabetes)

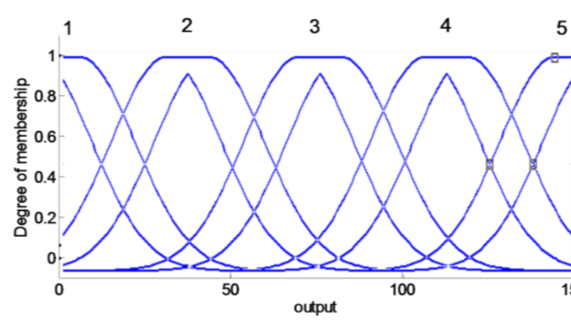

Fig. 4. Membership functions for the output (blood insulin infusion rate)

Mutual rules of input and output are described in Table 4:

Table 4. Fuzzy rules

Rule No.	Input	Output
1	Mf_1	Mf_5
2	Mf_2	Mf_4
3	Mf_3	Mf_3
4	Mf_4	Mf_2
5	Mf_5	Mf_1

The control policy which was obtained by the combination of these membership functions in fuzzy type-2, is shown in figure 5. It clearly shows that when the difference between the desired and the actual levels of blood glucose is high, further injections will be made. As it is illustrated in figure 5, the level of uncertainty is also considered in the proposed control policy.

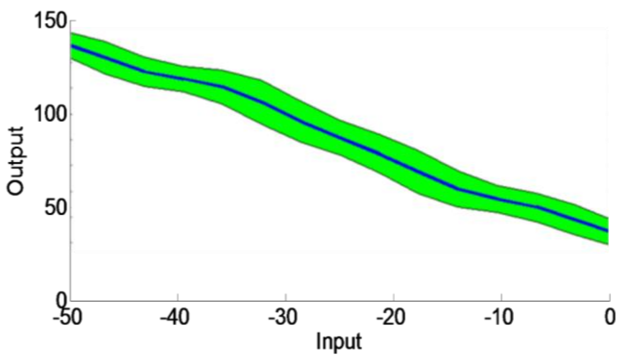

Fig. 5. Policy derived from fuzzy type-2 controller

The same process is done with conventional fuzzy type-1. Figure 6 depicts the membership functions of the actual errors (deviation from desired blood glucose concentration) in diabetics for fuzzy type-1 controller. These membership functions are the inputs of fuzzy type-1 control method.

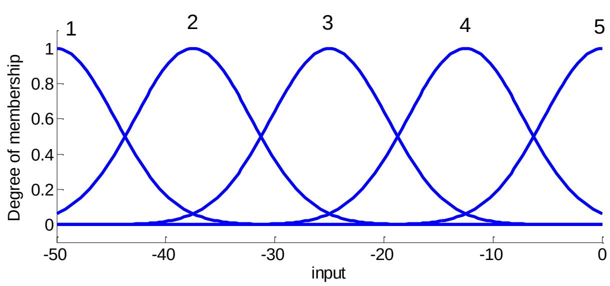

Fig. 6. Fuzzy type-1 Membership Functions for the input (desired and actual errors diabetes)

Also, Figure 7 depicts the membership functions of blood insulin infusion rates as the output of the fuzzy type-1 controller.

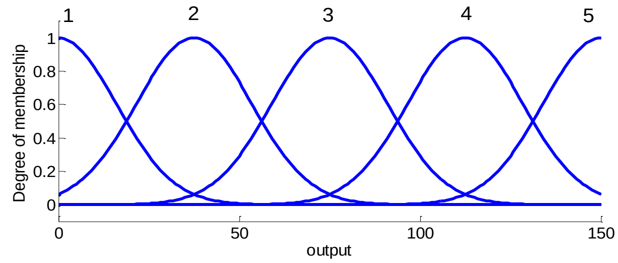

Fig. 7. Fuzzy type-1 Membership Functions for the output (desired and actual errors diabetes)

Eventually, the fuzzy type-1 control policy derived from the combination of these input-output membership functions is shown in figure 8. As it can be seen in the figure, unlike fuzzy type-2 control policy, fuzzy type-1 would not take any level of uncertainty into consideration.

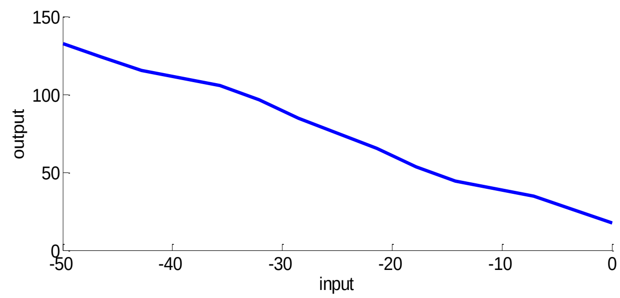

Fig. 8. Policy derived from fuzzy type-1 controller

RESULTS AND DISCUSSION

Figure 9 illustrates the comparison of blood glucose level using fuzzy type-1, type-2 and without utilizing any controller. As it can be seen in figure 9, a controller is needed to maintain the blood glucose level in the desirable range. Also, it is clear that the glucose range is decreased during the control process. Moreover, while fuzzy type-1 controller showed promising results in controlling blood glucose level, fuzzy type-2 exceeds its performance in keeping the blood glucose level closer to the desired value (110[mg/dL]). As it is known, its amount initially has a sharp increase, which figure 9 clearly illustrates this pattern. Also, by conducting fuzzy type-2 the patient will experience a lower maximum level of blood glucose concentration.

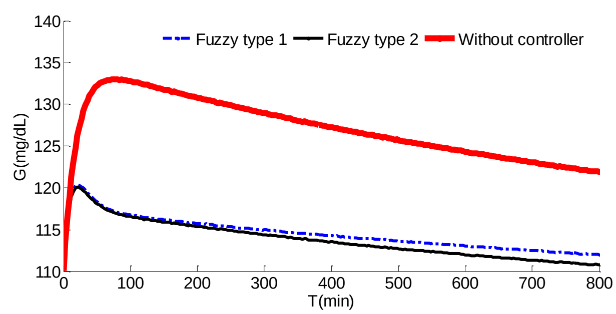

Fig. 9. Blood glucose in the closed loop system

Insulin injection rates as a function of time is depicted in figure 10, this precise injection which is monitored by the controller made the accurate control of blood glucose concentration possible.

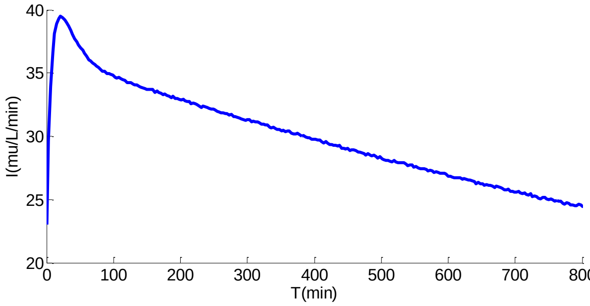

Fig. 10. Insulin injections to control blood glucose

Other parameters which are important in this model such as deviation from the base line, changes in the insulin action, Variation of plasma glucagon concentration, SD deviation from baseline, levels of plasma insulin concentration and Deviation and change in blood glucose from baseline levels of glucagon are depicted in figures 11-15 for type-2 fuzzy controller.

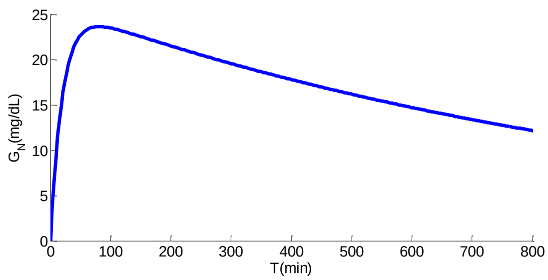

Fig. 11. Deviation from the baseline levels of blood glucose due to insulin action in the closed loop system

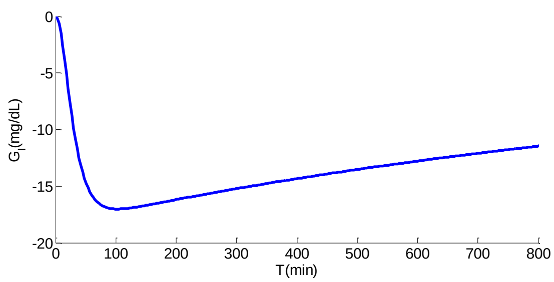

Fig. 12. Changes in insulin action in the closed loop system

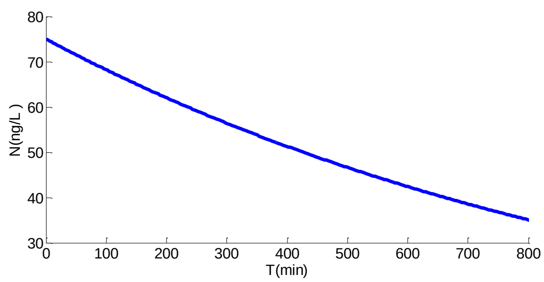

Fig. 13. Changes in plasma glucagon concentration deviation from the baseline values in the closed loop system

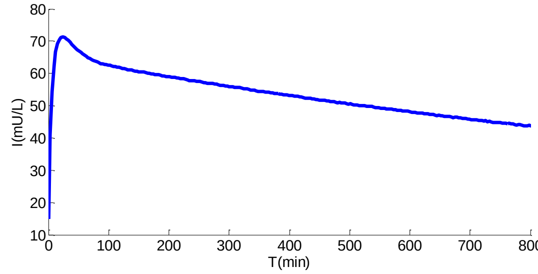

Fig. 14. SD changes from baseline levels of plasma insulin concentration in the closed loop system

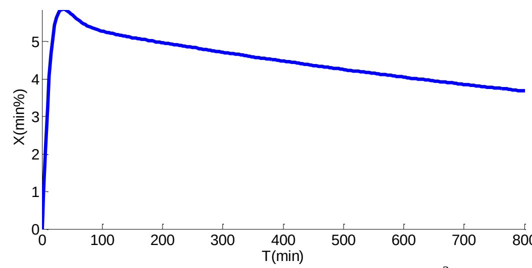

Fig. 15. Deviation change in blood glucose ($\times 10^{-3}$) from baseline levels of glucagon in the closed loop system

CONCLUSION

In this paper, a nonlinear model based on minimal augmented model has been used to simulate type one diabetes in MATLAB-SIMULINK environment. The proposed model has a robustness under blood glucose changes caused by a meal. The novelty of this paper lays in utilizing fuzzy type-2 to consider the uncertainties during the process and to monitor the blood glucose concentration level by regulating insulin infusion rates. Thereafter, a comparison between type-1 and type-2 fuzzy control theories was made. It was shown that fuzzy type-2 offers a favorable control over blood glucose levels in comparison to fuzzy type-1 for diabetic patients. Fuzzy type-2 successfully decreased the maximum glucose concentration experienced by the subject compared to fuzzy type-1. Moreover, fuzzy type-2 exceeds fuzzy type-1 in keeping the blood glucose level as close as possible to the desirable value. To conclude, as we proved here, fuzzy type-2 controller can serve as an effective and powerful controller in the case of type 1 diabetes and could reduce its drastic effects on diabetic patients. In a nutshell, the fuzzy sets as it was clarified in this study, can serve as an effective and powerful controller following the desired values.

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