New Approach for Stabilizing of Glucose Concentration Level Using Non-Linear Control Strategies: Improvement of Sliding Mode Control and Fuzzy Logic Technique

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Abstract— **Diabetes is a serious disease during which the body's production and use of insulin is impaired, causing glucose concentration level to increase in the bloodstream. The blood glucose dynamics is described using the Bergman minimal model. In this paper, higher-order sliding mode control techniques, in specific prescribed convergence law, super-twisting control algorithm, is used to robustly stabilize the glucose concentration level of a diabetic patient in presence of the parameter variations and meal disturbance. Intelligent systems have appeared in many technical areas, such as consumer electronics, robotics and industrial control systems. Many of these intelligent systems are based on fuzzy control strategies which describe complex systems mathematical model in terms of linguistic rules. By advent of these methods, new techniques have appeared from which fuzzy logic been applied extensively in medical systems. This paper surveys the utilization of fuzzy logic control. Based on this method, fuzzy logic controller is designed to tackle a control problem of the resulting highly nonlinear plant. It was shown also that the proposed schemes can perform well in simulation experiments. Finally the obtained results from these two methods, are verified based on comparison via digital computer simulation by MATLAB.**

Index Terms—— **Diabetes, higher-order sliding mode control, super-twisting control algorithm, fuzzy logic control.**

I. Introduction

COMPLEXITY of a human biological system typically allows its relations to be expressed only in a nonlinear way. Because of this complexity, it is not simple to achieve insulin-dependent diabetic therapies autonomously. Diabetes mellitus is a metabolic disorder of endogenous insulin allowing excessive amount of glucose to stay in blood. In general, blood glucose is transformed into energy required by human activities, such as, walking, and this transformation requires insulin functionality. However, in diabetes mellitus, since a human body fully or partially lacks the insulin functionality, unchanged glucose remains in blood.

A condition of high blood glucose profiles results in several complications, such as, eye, kidney, and nerve damage, called hyperglycemia. Thus, in order to avoid the hyperglycemia, a continuous supply of exogenous insulin is required, and the insulin dependent diabetic therapy usually does this. On the contrary, too much insulin supply may lead to a condition of low blood glucose profiles resulting in drowsiness, mental malfunctioning, irritability, and loss of consciousness [1]. This condition is called hypoglycemia and also dangerous to the diabetic. Thus, the insulin-dependent diabetic therapy must concern both hyperglycemia and hypoglycemia by providing an appropriate amount of exogenous insulin timely.

Implementing tight glucose control in critically ill patients is the most important issue in diabetes management. The current medical treatments suggest three to four daily glucose measurements and an equivalent number of subcutaneous insulin injections [2]. Finding less invasive and less frequent methods has been the subject of interest for many researchers who are working in this area. An alternative approach is to deliver insulin using a closed-loop device like a pump, which works like an artificial pancreas [3,4]. This closed-loop device would include a glucose sensor imbedded under the skin and an insulin pump implanted in the abdomen. The sensor can measure blood glucose concentration and pass the information to a feedback control system that would calculate the necessary insulin delivery rate using robust higher-order sliding mode control algorithms [5–7], to keep the patient under metabolic control. Imprecisely defined classes play an important role in human thinking. Fuzzy set theory derives from the fact that most natural classes and concepts are fuzzy rather than crisp nature. On the other hand, people can approximate well enough to perform many desired tasks. The fact is that they summarize from massive information inputs and still function effectively. For complex systems, fuzzy logic is quite suitable because of its tolerance to some imprecision. In the following sections a brief description is given of the key contribution which fuzzy control, estimation, and measurements technology have made in each of the topics which have been identified in a medical literature search.

In this paper, higher-order sliding mode control techniques, in specific prescribed convergence law, super-twisting control algorithm, is used to robustly stabilize the glucose concentration level of a diabetic patient in presence of the parameter variations and meal disturbance. Intelligent systems

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have appeared in many technical areas, such as consumer electronics, robotics and industrial control systems. Many of these intelligent systems are based on fuzzy control strategies which describe complex systems mathematical model in terms of linguistic rules. By advent of these methods, new techniques have appeared from which fuzzy logic been applied extensively in medical systems. This paper surveys the utilization of fuzzy logic control. Based on this method, fuzzy logic controller is designed to tackle a control problem of the resulting highly nonlinear plant. It was shown also that the proposed schemes can perform well in simulation experiments. Finally the obtained results from these two methods, are verified based on comparison via digital computer simulation by MATLAB.

II. The Human Insulin-Glucose Model

To procure the mathematical models of the human insulin glucose system, several approaches are taken by researchers. In these approaches, empirical and fundamental methods are preferably used by them. These approaches aim to describe the insulin-glucose dynamics as a couple of mathematical equations that should be easy to manipulate for the insulin therapies and should fully describe the characteristics of the internal insulin-glucose metabolism [8].

Basically, the empirical method uses a model structure (formula or equation) which is determined theoretically with several parameters. The behavior of this model structure is determined by only the input-output data of the system from a number of experiments. In this method, capturing the system behavior or data is the most time-consuming process. In an example of the linear structure of the insulin-glucose system, to represent glucose effects, two parameters are used, and to represent insulin effects, other two parameters are also used in order to close the model to the actual system. In addition to the input-output data, semi empirical method utilizes other physiological factors, such as dynamic behavior and kinetics to create a closer model of diabetic patients [8].

In the fundamental methods, a mathematical representation of the human internal system which is already known sufficiently by researchers constructs an insulin glucose model. This system behavior includes kinetics and material transport. According to investigating the internal system, a lot of data from the literature can be used to determine the system parameters. Usually the model averages studied behaviors. In particular, in constructing a fundamental diabetes model, the authors in [9] applied the insulin-release data of the β cells of the pancreas from a number of examinations to a mathematical representation.

III. History of Closed-Loop Control Methods

Over the last half century, automated systems for delivery of insulin have been a topic of much interest, envisioned as an intelligent treatment paradigm for the insulin-deficient patient. The concept of an artificial pancreas and the evolving algorithms during this time parallel the rise of the electronic, digitized computer age. The control of blood glucose levels has been likened to industrial processes in which a monitoring system (glucose sensor) evaluates an input (glucose levels) and uses a control system (e.g. algorithm programmed into a computer) to predictably control the output of that system (insulin infusion rate, see figure 1).

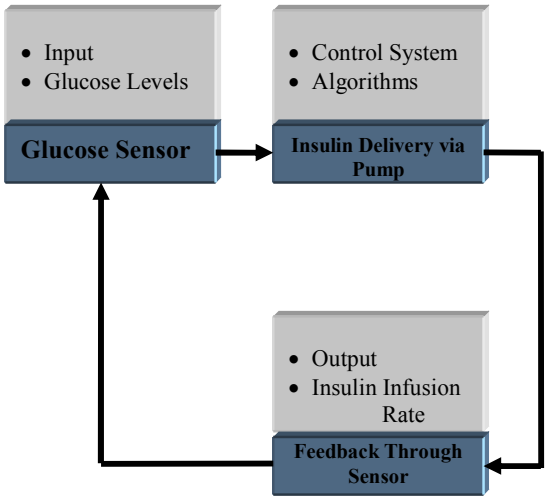

Fig.1. Principles of control systems applied to glycemic control

This system of artificially maintaining glycemic control requires three main components:

1. Glucose sensing device (continuous or very frequent).
2. Control device for analyzing blood glucose data and computing insulin dosing (computer or microprocessor).
3. Insulin delivery device (usually a subcutaneous mechanical pump, potentially an implantable pump).

Only within the last decade have continuous glucose sensing devices (the afferent limb of a closed loop system) been approved by regulatory agencies after overcoming accuracy and stability issues. Three currently-available models which are inserted into subcutaneous tissue have been approved in the USA due to success in clinical trials (Medtronic Guardian or Paradigm, Dexcom Seven, and Abbott Navigator). A fourth, the Gluco-Day sensor, a microdialysis device (Menarini), is approved in parts of Europe. Even without closed loop control, a recent 6-month study found that usage of these devices led to a substantial improvement in hemoglobin A1C without an increase in hypoglycemic episodes in persons with Type 1 diabetes [10]. Intravenous (IV) glucose sensors have been investigated in smaller trials [11] but IV devices are not typically used. In contrast to subcutaneous sensors, intravenous sensors are accompanied by more severe risks such as thrombosis, embolization, and intravascular infection.

There have also been advances in insulin pump technology over the past 2 decades. Commercially-available insulin pumps deliver insulin by the subcutaneous route, though

intraperitoneal delivery (leading to faster absorption and action than subcutaneous) is being studied in limited research settings [11]. Nonetheless, subcutaneous insulin delivery does not compare favorably with the physiological secretion of beta-cells directly into the blood stream, and confers risks when used in the setting of closed-loop management. For example, delay of subcutaneous insulin absorption and action, even with fast-acting analog insulin, constitutes a fundamental problem of most closed loop systems in persons with diabetes: the efferent delay. Specifically, elevated glucose levels after meals due to this delay lead to late and often excessive insulin delivery, leading in turn to hypoglycemia (overcorrection hypoglycemia). Stated in engineering terminology, there is an instability characterized by large oscillations in the controlled variable (glucose) due to marked efferent delay. Recently, a "semi-closed loop" or "hybrid" system involving open-loop insulin delivery before meals has been shown to lead to tighter glycemic control than fully closed loop treatment [12]. The attractiveness of a hybrid system rests on the well-known delay between administration of subcutaneous fast-acting insulin and its action. Insulin given before the meal in this fashion can be thought of as "anticipatory" rather than reactive.

There have been multiple mathematical concepts with initial linear equations using first-order dynamics utilized in algorithms for closed loop glycemic control [13]. These early concepts could not be fully tested in animal or human studies and were rudimentary in terms of their ability to control blood glucose. Over the years, there came a clear need for models of glucose-insulin interaction that described the dynamics of carbohydrate homeostasis. A very early concept, Bolie's two-compartment model [13], gave way to Cerasi's three-compartment model [14,15]. Later, the Bergman/Cobelli well-known minimal model of carbohydrate metabolism was published [16], and continues to provide an important contribution to some closed loop algorithms. This model generates indices of insulin action and insulin secretion and utilizes frequent glucose and insulin measurements during glucose clamp testing or intravenous glucose tolerance testing. It assumes a closed-loop relationship between glucose, insulin secretion and insulin action between a single glucose compartment and two insulin compartments [16]. It has been instrumental in defining the disposition index, a constant product of insulin sensitivity and insulin secretion [17]. Cobelli et al have modified the original model in order to improve the accuracy of estimating insulin action and glucose secretory characteristics [18].

The ultimate role of any insulin delivery system is provision of insulin in a manner mirroring, as closely as possible, the human beta-cell. Beta-cell physiology and pathophysiology is an important topic of research and recent work emphasizes the acute effects of incretins and the chronic effects of amyloid [19]. Earlier beta cell reviews were silent on these issues and instead emphasized the many hormonal and non-hormonal input signals which regulate pancreatic insulin secretion [20]. These reviews of pancreatic beta cell secretion reveal something very important to this discussion. The strongest single regulatory factor affecting beta-cell insulin secretion is the concentration of glucose.

IV. Insulin-Glucose Regulation Model

Until now, a wide range of models has been used to describe the insulin–glucose regulatory system dynamics in the human body. One of the pioneers in this task was Dr Richard Bergman, who developed the so-called 'Minimal Model.' Bergman minimal model, which is a commonly referenced model in the literature, approximates the dynamic response of a diabetic patient's blood glucose concentration to the insulin injection using the following nonlinear differential equations [21]:

$$\begin{cases} \dot{G}(t) = -p_1[G(t) - G_b] - X(t)G(t) + D(t) \\ \dot{X}(t) = -p_2 X(t) + p_3[I(t) - I_b] \\ \dot{I}(t) = -n[I(t) - I_b] + \gamma[G(t) - h]^+ t + u(t) \end{cases} \quad (1)$$

where t = 0 shows the time glucose enters blood, '+' sign shows the positive reflection to glucose intake and G(t), the glucose concentration in the blood plasma (mg/dl); X(t), the insulin's effect on the net glucose disappearance, the insulin concentration in the remote compartments (1/min); I(t), the insulin concentration in plasma at time t (μU/ml); G_b, the basal pre-injection level of glucose (mg/dl); I_b, the basal pre-injection level of insulin (μU/ml); p_1, the insulin-independent rate constant of glucose uptake in muscles and liver (1/min); p_2, the rate for decrease in tissue glucose uptake ability (1/min); p_3, the insulin-dependent increase in glucose uptake ability in tissue per unit of insulin concentration above the basal level [(μU/ml)/min^2]; n, the first-order decay rate for insulin in blood (1/min); h, the threshold value of glucose above which the pancreatic β cells release insulin (mg/dl); γ, the rate of the pancreatic β cells' release of insulin after the glucose injection with glucose concentration above the threshold [(μU/ml)/min^2/(mg/dl)].

To show the complete dynamics of the glucose–insulin regulatory system, two other terms are considered in Equation (1). D(t) shows the rate at which glucose is absorbed to the blood from the intestine, following food intake. Since in diabetic patients, the normal insulin regulatory system does not exist, this glucose absorption is considered as a disturbance for the system dynamics presented in (1). This disturbance can be modeled by a decaying exponential function of the following:

$$D(t) = 0.5e^{-0.05t} \quad (2)$$

where t is in (min) and D(t) is in (mg/dl/min). u(t), which is the controller, defines the insulin injection rate and replaces the normal insulin regulatory system of the body, which does not exist in diabetic patients. Therefore, the goal is to employ higher-order sliding model technique to design the appropriate control function, u(t) to compensate the uncertainties and disturbances and to stabilize the blood plasma glucose concentration of a diabetic patient at the basal level. It should be mentioned that the dynamics of the pump is neglected in the model introduced in Equation (1).

It is worth noting that in reality D(t) is supposed to reduce

to zero or some constant value in finite time, and the asymptotic model (2) is an approximation of a real process. Since higher-order sliding model control (SMC) accounts for the worst case scenario, i.e. considering D(t) and its derivatives at their maximum values, the controller design will be the same for model (2) or any other more realistic models.

The system introduced in Equation (1) can be rewritten in state-space form as follows:

$$\begin{cases} \dot{x}_1 = -p_1[x_1 - G_b] - x_1 x_2 + D(t) \\ \dot{x}_2 = -p_2 x_2 + p_3[x_3 - I_b] \\ \dot{x}_3 = -n[x_3 - I_b] + \gamma[x_1 - h]^+ t + u(t) \end{cases} \quad (3)$$

Stabilizing the glucose concentration in the diabetic patient's blood at the basal level G_b is an output-tracking problem thus, the tracking error is defined as the difference between the glucose concentration level and its basal value in the diabetic patient's blood as

$$e = G_b - G(t) = G_b - x_1 \quad (4)$$

Given the dynamical system introduced in Equation (3), the controller u(t) must be designed such that e→0 in presence of the uncertainties, parameter variations, and disturbances, oral food intake, D(t). First the relative degree of the system must be defined. Assuming y = x_1, the relative degree would be defined with the number of successive differentiation until the control appears in the equation. Relative degree r means that the controller u(t) first appears explicitly in the r^{th} total derivative of σ. Using (3), the control function appears in the equations after the third differentiation, i.e :

$$x_1^{(3)} = \varphi(x,t) - p_3 x_1 u(t) \quad (5)$$

Since $p_3 \neq 0$, $x_1 = 0$ and $p_3 x_1 \in [1.2\times10^{-4}, 3\times10^{-2}]$, system (3) has a well-defined relative degree, r = 3. This allows us to design the controller for the system in Equation (3) that satisfies e→0.

V. High-Order SMC Technique: Super – Twist Control Design

The super-twist control algorithm continuously controls the system with relative degree, r = 1, in presence of bounded disturbances. In order to achieve relative degree 1, the sliding variable is designed as :

$$\sigma = \ddot{e} + c_1 \dot{e} + c_0 e \quad (6)$$

where c_1 and c_0 are real-valued constants chosen such that Equation (6) has the desired behaviour. To check the existence condition of the sliding mode control, the dynamics of the sliding variable must be derived using (6) as

$$\dot{\sigma} = \dddot{e} + c_1 \ddot{e} + c_0 \dot{e} \quad (7)$$

Using (4) , (5) and (7) can be written as :

$$\begin{aligned} \ddot{\sigma} &= \dddot{G}_b - \ddot{x}_1 + c_1 \ddot{e} + c_0 \dot{e} = \\ &- \ddot{x}_1 + c_1 \ddot{e} + c_0 \dot{e} = \\ &- \varphi(x,t) + p_3 x_1 u(t) + c_1 \ddot{e} + c_0 \end{aligned} \quad (8)$$

Combining and simplifying the terms in (8) will give

$$\dot{\sigma} = \psi(t) + p_3 x_1 u(t) \quad (9)$$

Where

$$\psi(t) = -\varphi(x,t) + c_1 \ddot{e} + c_0 \dot{e} \quad (10)$$

For the sliding mode to exist Ψ˙(t) must be bounded by a positive real number [22(10)], i.e.

$$|\dot{\psi}(t)| \leq N \quad (11)$$

From Equations (3)–(5) it is obvious that the above condition is met and therefore sliding mode exists and the controller can be designed for the system of (3). Consider the following first-order nonlinear differential equation:

$$\dot{\sigma} + \alpha|\sigma|^{1/2} + \beta \int sign(\sigma) d\tau = f(t) \quad (12)$$

where $|\dot{f}(t)| \leq L$. It has been proven [22] that the solution of this nonlinear differential equation and its first time derivative will converge to zero in a finite time if $\alpha \geq 0.5\ (L)^{(1/2)}$ and $\beta \geq 4L$, where L is a real positive constant. The super-twist control function can then be designed as

$$u = -\alpha_1 |\sigma|^{1/2} - \beta_1 \int sign(\sigma) d\tau \quad (13)$$

The super-twist control algorithm (13) provides finite time convergence of the sliding variable (6) to zero but asymptotic convergence of the tracking error e due to the equation $\sigma = \ddot{e} + c_1 \dot{e} + c_0 e$, i.e. the blood glucose will be stabilized at its basal level asymptotically. The asymptotic convergence would not create any problem since in case of insulin–glucose regulatory, the process itself is inherently asymptotic.

VI. Simulation Results (Part 1)

A. Comparison Between PID Algorithm and Sliding Mode Control

PID algorithms are offshoots of proportional derivative (PD) systems. A PD system from the company Nikkiso, in Japan, is used in hospital settings with continuous glucose monitoring, in order to control glucose. Garry Steil and his colleagues have been instrumental in conceptualizing and testing PID algorithms for closed loop control.

The results of the simulations with PID algorithm are included in this part of paper. MATLAB is used to simulate the closed-loop system in order to show the validity of the proposed design according to Fig. 2.

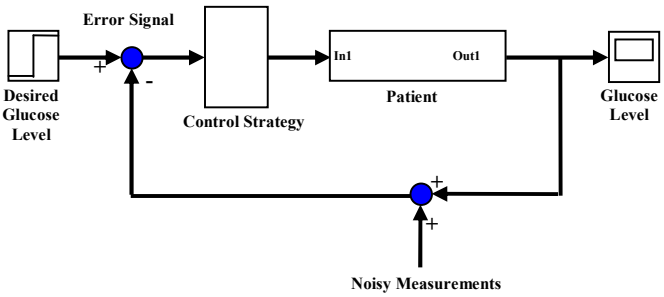

Fig.2. Simulation of closed-loop system by MATLAB using PID controller

By assumption K_p=0.12, K_i=0.00985 and K_D=5 (for PID controller) and $c_0=3.4\times10^{-4}$, c_1=0.0255, α=63.36 and β=0.3493 (for SMC), Fig. 3 shows the response of a sick person to the presence of the meal disturbance in t=0 using two methods.

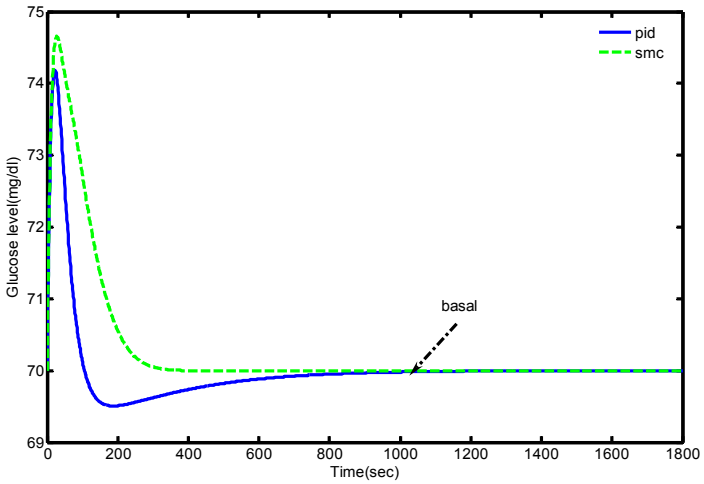

Fig. 3. Comparison proposed methods (PID & SMC) in blood glucose regulatory

It is obvious that the glucose is completely stabilized at the basal level by using high-order SMC technique faster than PID algorithm.

In the next part, MATLAB is used to simulate the closed-loop system in order to show the response of a sick person to the presence of sudden variations in blood glucose concentration level. Fig. 4 illustrates the performance of closed-loop system in these conditions.

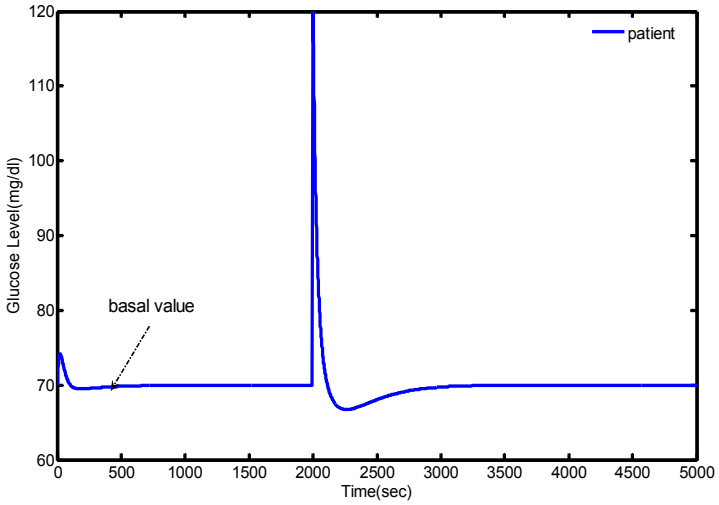

Fig. 4. Curve of the response of a sick person to the presence of the sudden disturbances in blood glucose concentration level using PID controller

As similar way, these conditions are used to simulate the closed – loop system in order to show the response of a sick person to the presence of sudden variations in blood glucose concentration level using high-order SMC technique. Fig. 5 illustrates the performance of closed-loop system using this method.

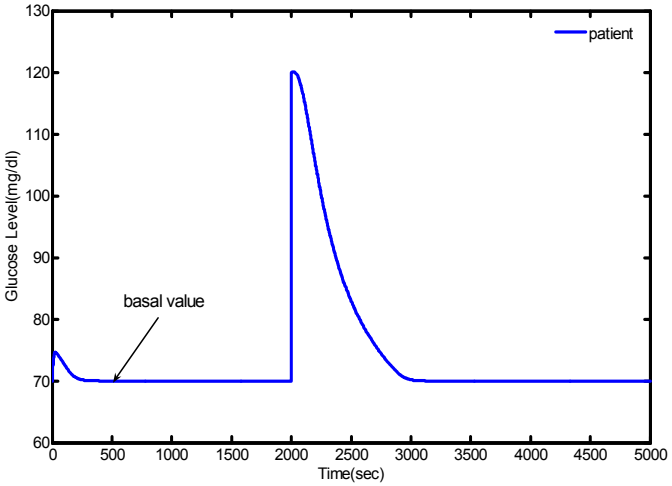

Fig. 5. Curve of the response of a sick person to the presence of the sudden disturbances in blood glucose concentration level using SMC method

B. Robustness Analysis

To validate the proposed SMC method in Equation (13), the control function is applied to system (3) and the response of a sick person in presence of the meal disturbance is examined.

To check the robustness of the control algorithm to the parameter variations, a set of parameters for three different patients have been used. Figure 6 shows the results obtained from the simulation. It is obvious that the transient responses of the different patients to the same controller are different, but in all three cases, the glucose is completely stabilized at the basal level in a reasonable time interval.

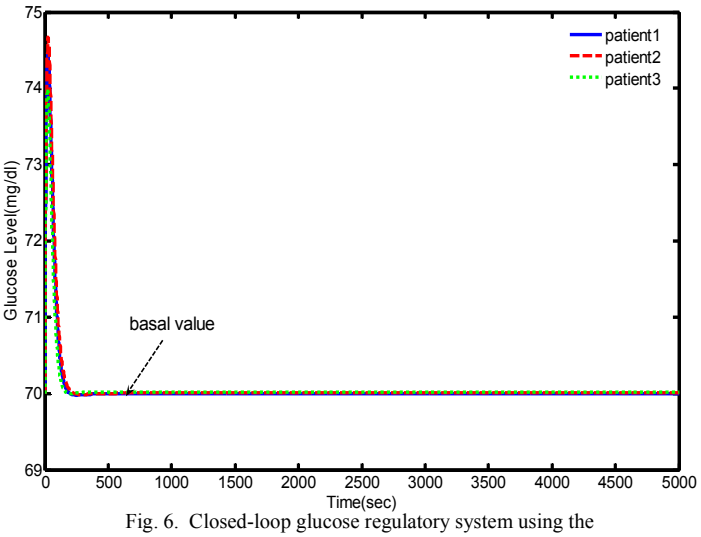

Fig. 6. Closed-loop glucose regulatory system using the proposed controller for robustness analysis using SMC method

The values that have been used in implementing the model and its parameters are given in Table I.

To check the robustness of the PID algorithm to the parameter variations, a set of parameters for three different patients have been used too. Figure 7 illustrates the results obtained from the simulation.

Table I. Parameter Values

Parameter	Patient I	Patient II	Patient III
p_1	0.0306	0.0290	0.0395
p_2	0.0107	0.0072	0.0142
p_3	5.3×10^{-6}	2.16×10^{-6}	9.94×10^{-6}
γ	0.0042	0.0038	0.0046
n	0.2640	0.2645	0.2814
h	80.2576	77.5783	82.9370
G_b	70	70	70
I_b	7	7	7

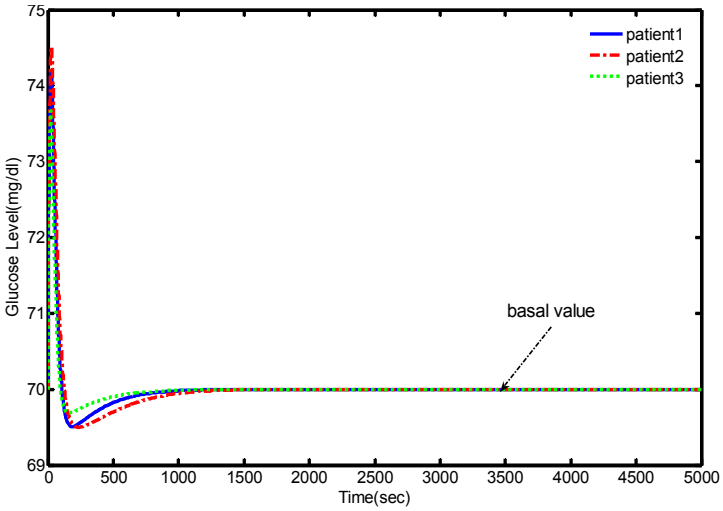

Fig.7. Closed-loop glucose regulatory system using the proposed controller for robustness analysis using PID method

VII. Simulation Results (Part 2)

A. Comparison Between PID Algorithm and Fuzzy Logic Technique

Various therapeutic situations are related to control problems. Although the early medical systems appeared at the same time as the article by Zadeh (1965), there has been little communication between the research fields, but recently this has changed due to the developments in computer systems, and rapid development of the literature searching methods motivated by the internet and the World Wide Web. Many systems are being developed which utilize fuzzy logic and fuzzy set theory.

Fuzzy logic control is also an advanced process control, which imitates the logic of human thought, and much less rigid than the calculations computers generally perform [23]. There are three steps for the process of a fuzzy logic algorithm: fuzzification, rules, and defuzzification.

1) *Fuzzification:* the input of a controller is an exact number, for example, the concentration of glucose is 100 mg/dL. What the fuzzification does is to fuzzify the concentration such as low concentration, high concentration, and proper concentration. Every exact number has the weight of all these low, high, and proper concentrations.

2) *Rules:* After defining the fuzzy concept of input, we should make rules to decide what the output should be: more drug, a little drug, or no drug. For example, we define the following rule: if the concentration of glucose is high and the rate of glucose is rising, then the drug should be more.

3) *Defuzzification:* After the rule, we get the output of fuzzy concept, for example, more of 0.8 and little of 0.2. But the output which is the object model's input must be an exact number that needs to be defuzzified. By defuzzification, the output gets an exact number. Fig. 8 shows configuration of a fuzzy system.

In this paper, it is assumed that there are two different inputs of the concentration of glucose and the change rate of concentration, and one output of the change rate of insulin injection. Fuzzy logic controller is designed according to the structure of Mamdani.

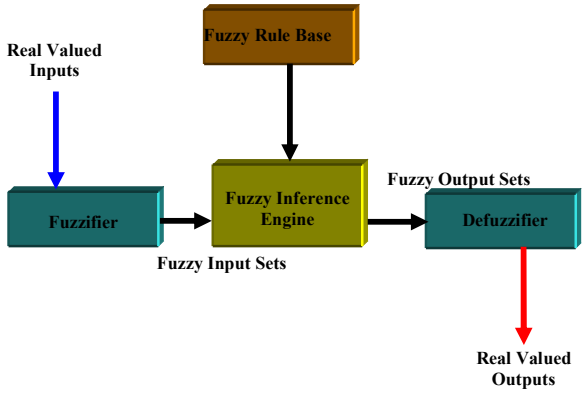

Fig. 8. Configuration of a fuzzy system with fuzzifier and defuzzifier

It can be seen all required data for fuzzy logic controller in Table. II-IV. Fig. 10 shows member functions that they have been used for input variables. It is illustrated output member function by Fig. 9. It is important that the doctor prescribes suitable value of blood glucose concentration level and so proposed controller identifies the change rate of concentration according to the blood glucose concentration. It has been selected input and output member functions as triangular.

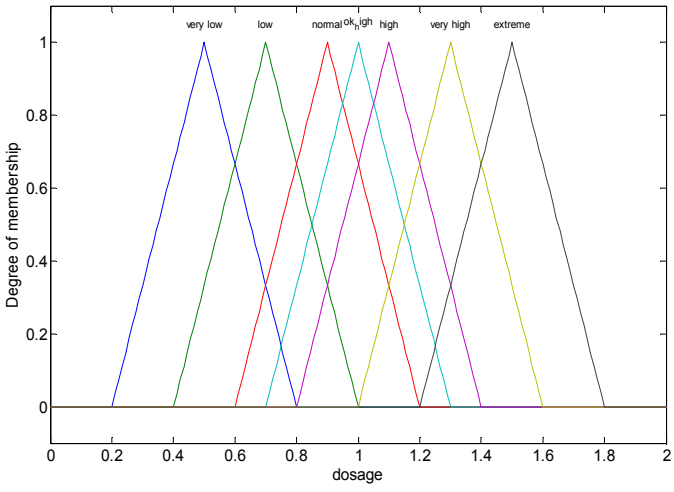

Fig. 9. Output membership function

Table II. Input Variables Characteristics

Input Variables	Range	Membership Functions						
Blood Glucose Concentration	[40 400]	very low	low	normal	OK_high	high	very high	extreme
The Change Rate of Blood Glucose	[-20 20]	negative	zero	positive				

Table III. Output Variable Characteristics

Output Variables	Range	Membership Function						
The Change Rate of Insulin Injection	[0 2]	very low	low	normal	OK_high	high	very high	extreme

Table IV. Rules for Fuzzy Logic Controller

Blood Glucose Concentration	The change Rate of Concentration		
	negative	positive	zero
extreme	extreme	extreme	extreme
very high	very high	very high	extreme
high	high	high	high
OK_high	OK_high	OK_high	OK_high
normal	normal	normal	normal
low	very low	low	low
very low	very low	very low	very low

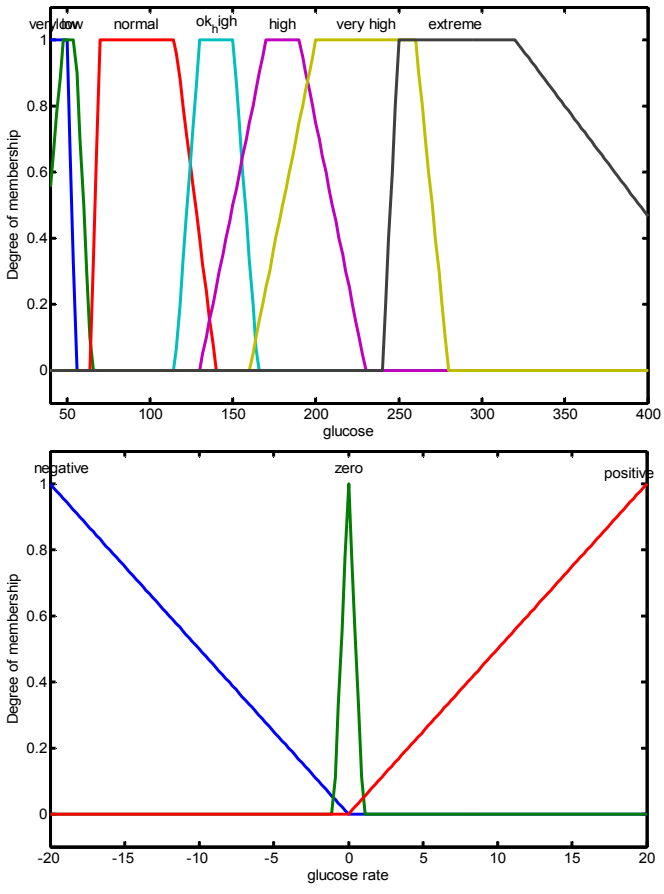

Fig. 10. Input membership functions

Two types of algorithms are used for a feedback controller design that stabilizes the blood glucose concentration of a diabetic patient at the desired level in this paper. Now, we can compare performance of these methods in the same conditions. By assumption of this, we will obtain to Fig. 11 for accurate comparison between PID method and fuzzy logic method.

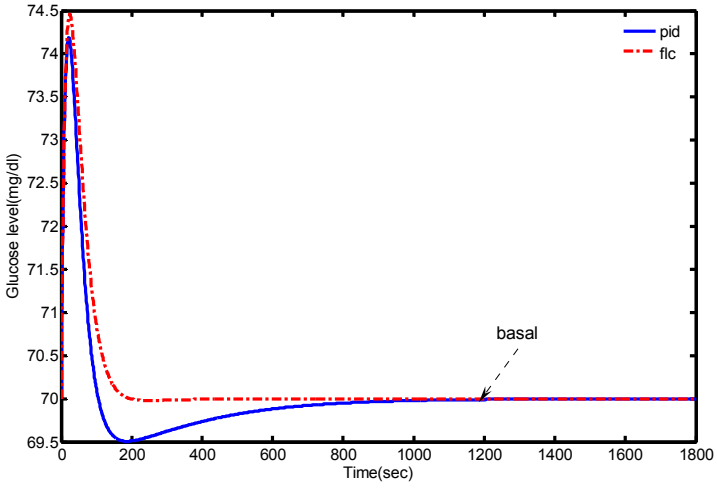

Fig. 11. Comparison proposed methods (PID & FLC) in blood glucose regulatory

In this part, The results of the simulations with the fuzzy logic control are included. MATLAB is used to simulate the nonlinear model of system. The values that have been used in implementing the model and its parameters are given in Table

I. At first, we can indicate to the effect of noise in measurement. This can create by unexpected disturbance. Unexpected disturbance may happen, for example, a patient might eat an apple in nonmeal time, and this should be considered but obviously is difficult to deal with by using the traditional discrete time methods. Taking this into account, simulation experiments, has been shown in Fig. 12. It is assumed a white noise by 0.15 amplitude for the error measurement in blood glucose evaluation. Fig. 12 shows the response of a sick person to the presence of noise in the meal disturbance in t=0 and t=2000 Sec.

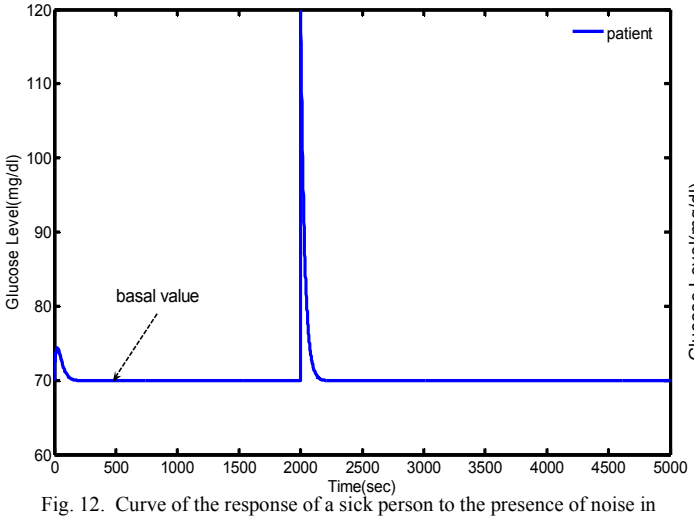

Fig. 12. Curve of the response of a sick person to the presence of noise in the meal disturbance in blood glucose concentration level by fuzzy logic controller

It is easy to see that the performance of proposed controller is suitable and it can be stabilize glucose value at the basal level in the presence of noise in the meal disturbance.

B. Robustness Analysis

To check the robustness of the fuzzy logic control to the parameter variations, a set of parameters for three different patients have been used. Figure 13 shows the results obtained from the simulation. It is obvious that the transient responses of the different patients to the same controller are different, but in all three cases, the glucose is completely stabilized at the basal level in a reasonable time interval.

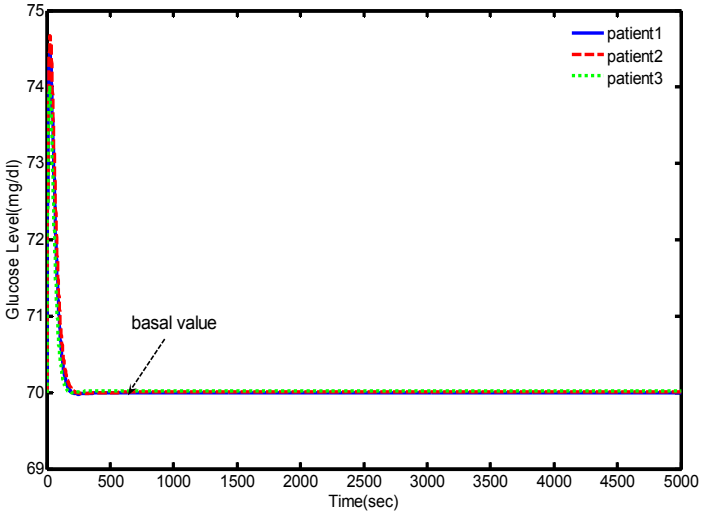

Fig. 13. Closed-loop glucose regulatory system using fuzzy logic controller for robustness analysis

VIII. Simulation Results (Part 3)

SMC and FLC methods are used for a feedback controller design that stabilizes the blood glucose concentration of a diabetic patient at the desired level in this paper. Now, we can compare performance of these methods in the same conditions. By assumption of this, we will obtain to Fig. 14 for accurate comparison between high-order SMC technique and fuzzy logic method.

It is obvious that the glucose is completely stabilized at the basal level by using fuzzy logic control faster than high-order SMC technique.

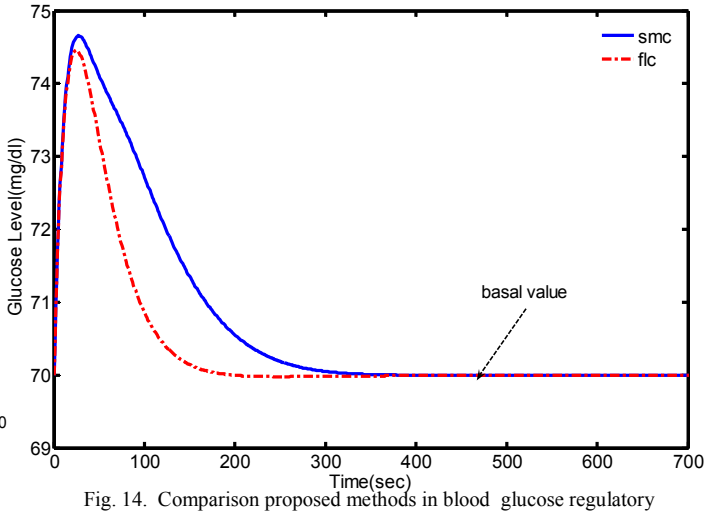

Fig. 14. Comparison proposed methods in blood glucose regulatory

IX. Conclusion

The diabetes management as one of the challenging control problems in human regulatory systems has been discussed. The treatment of the disease via robust feedback control design has been considered. In this research, two types of algorithms are used for a feedback controller design that stabilizes the blood glucose concentration of a diabetic patient at the desired level.

Higher-order sliding mode control techniques, in specific prescribed convergence law, super-twisting control algorithm, is used to robustly stabilize the glucose concentration level of a diabetic patient in presence of the parameter variations and meal disturbance. In fact, This stabilization has been done in presence of the external disturbances such as food intake and model parametric uncertainties, which affect high-accuracy and robustness of the entire system. The robust high-accuracy performance of the super-twist controller is checked and confirmed by computer simulations.

Intelligent systems have appeared in many technical areas, such as consumer electronics, robotics and industrial control systems. Many of these intelligent systems are based on fuzzy control strategies which describe complex systems mathematical model in terms of linguistic rules. By advent of these methods, new techniques have appeared from which fuzzy logic been applied extensively in medical systems. This paper surveys the utilization of fuzzy logic control. Based on this method, fuzzy logic controller is designed to tackle a

control problem of the resulting highly nonlinear plant. It was shown also that the proposed schemes can perform well in simulation experiments. Finally the obtained results from these two methods, are verified based on comparison via digital computer simulation by MATLAB.

The main purpose of the current paper is to employ proposed methods and design a robust control in order to maintain blood glucose level at the basal value. The theoretical results are checked via computer simulations. Also, for future studies, the effect of measurement noise is to be assessed and attenuated, as well as chattering analysis is to be performed. It is obvious that the glucose is completely stabilized at the basal level by using fuzzy logic control faster than high-order SMC technique.

APPENDIX

G(t)	The Glucose Concentration in the Blood Plasma for at Time t
X(t)	The Iinsulin's Effect on the Net Glucose Disappearance
I(t)	The Insulin Concentration in Plasma at Time t
G_b	The Basal Pre-injection Level of Glucose
I_b	The Basal Pre-injection Level of Insulin
p_1	The Insulin-independent Rate Constant of Glucose Uptake in Muscles and Liver
p_2	The Rate for Decrease in Tissue Glucose Uptake Ability
p_3	The Insulin-dependent Increase in Glucose Uptake Ability in Tissue per unit of Insulin Concentration Above the Basal Level
n	The First-Order Decay Rate for Insulin in Blood
h	The Threshold Value of Glucose Above which the Pancreatic β Cells Release Insulin
γ	The Rate of the Pancreatic β Cells' Release of Insulin After the Glucose Injection with Glucose Concentration Above the Threshold

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