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Type I Diabetes, Second Order Sliding Mode Control,
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DESIGN OF MODIFIED SECOND ORDER SLIDING MODE CONTROLLER BASED ON ST ALGORITHM FOR BLOOD GLUCOSE REGULATION SYSTEMS

Abstract

The type1 of diabetes is a chronic situation characterized by abnormally high glucose levels in the blood. Persons with diabetes characterized by no insulin secretion in the pancreas (ß-cell) which also known as insulin-dependent diabetic Mellitus (IDDM). In order to keep the levels of glucose in blood near the normal ranges (70–110mg/dl), the diabetic patients needed to inject by external insulin from time to time. In this paper, a Modified Second Order Sliding Mode Controller (MSOSMC) has been developed to control the concentration of blood glucose levels under a disturbing meal. The parameters of the suggested design controller are optimized by using chaotic particle swarm optimization (CPSO) technique, the model which is used to represent the artificial pancreas is a minimal model for Bergman. The simulation was performed on a MATLAB/SIMULINK to verify the performance of the suggested controller. The results showed the effectiveness of the proposed MSOSMC in controlling the behavior of glucose deviation to a sudden rise in blood glucose.

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1. INFORMATION

Diabetes mellitus is one of the most important chronic diseases which results from a high blood sugar for a long time due to insufficient insulin generation in the blood (Bergman, Phillips & Cobelli, 1981). The concentration of glucose in the bloodstream is naturally regulated by two hormones: insulin and glucagon. Both of these hormones are secreted by β-cells and α cells in the Langerhans islands of the pancreas, respectively. The concentration of glucose ranges from 70 to 110 (mg/dL). Accordingly, there are two states, hyperglycemia (glucose concentration is above the normal ranges) and hypoglycemia (low glucose concentration than the normal ranges) (Basher, 2017).

Diabetes is broken down into two major types. The type 1 diabetes mellitus (T1DM) and Type 2 diabetes mellitus (T2DM) in the first type the patient's body can't produce enough insulin and doses of insulin need to be injected into the human body to control blood glucose levels, while the second type starts with insulin resistance, a condition in which cells do not respond properly to insulin. This type of diabetes is a common type and known as noninsulin-dependent diabetes (Sylvester & Munie, 2017).

In order to prevent the effects of high blood glucose levels the best approach is to administer insulin during a moment when blood glucose is supposed to rise. With the Advance of technology, the so-called artificial pancreas emerged its consists of three main components, glucose sensor, insulin pump and control techniques to generate the necessary insulin dose based on glucose measurements (Kaveh & Shtessel, 2006). The block diagram of the closed – loop system for glucose level control shown in Figure 1.

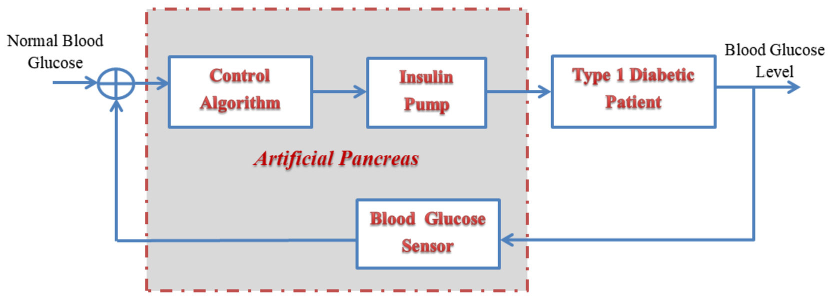

Fig. 1. Block diagram of closed-loop insulin delivery system

There are several studies that use a closed-loop controller to keep blood glucose (BG) diabetic concentration within the appropriate range, such as: (Kaveh and Shtessel, 2006) used higher order sliding mode controller (HOSMC) to regulate the levels of blood glucose. (Garcia-Gabin, et al., 2009) suggested a sliding mode predictive control (SMPC) which is the combining sliding mode control technology with model predictive control (MPC). In a (Abu-Rmileh & Garcia-Gabin, 2011) used a combination of the robust sliding mode control (SMC) and the Smith predictor (SP) structures. Nasrin et al. suggest a Sliding Mode Control (SMC) based on Backstepping technique (Parsa, Vali & Ghasemi, 2014). Waqar et al. suggest a non-linear super twisting control algorithm based on SMC approach has been addressed for regulation of glucose concentration in blood plasma of type 1 diabetes patients (Alam, et al., 2018).

In this paper, the MSOSMC is suggested to regulate the levels of blood glucose, the CPSO algorithm was used for tuning the parameters of the controller. To accomplish these objectives Bergman Minimal (BEM) mathematical model which considered here. The outliner of this paper as follows: The BEM mathematical model of blood glucose system presented in section 2. The details of the SOSMC described in section 3, while the design of the MSOSMC explained in section 4. And the CPSO algorithm illustrated in section 5. The proposed controller's analysis and simulation results will be discussed in section 6, while the final conclusions listed in the last section.

2. BERGMAN GLUCOSE-INSULIN REGULATION MODEL

Specific mathematical models have been suggested to explain the complexities of diabetes and to compare the interaction between models of glucose and the delivery of insulin that helps design a diabetes model. Among these models, the minimal Bergman model, a common reference model in the literature, approaches the dynamic response of blood glucose concentration in a diabetic to insulin injections. Bergman model consists of three differential equations as follows (Sylvester, 2017), (Abu-Rmileh & Garcia-Gabin, 2011):

$$\begin{gathered} \dot{G}(t) = -p_1(G(t) - G_b) - X(t)G(t) + D(t) \\ \dot{X}(t) = -p_2X(t) + p_3(I(t) - I_b) \\ \dot{I}(t) = -n(I(t) + I_b) + \gamma[G(t) - h]^+ t + u(t) \end{gathered} \tag{1}$$

where: $G(t)$ is the plasma glucose concentration in [mg/dL], $X(t)$ proportional to the insulin concentration in the remote compartment [1/min], $I(t)$ is the plasma insulin concentration in [mU/dL], and $u(t)$ is injected insulin rate in [mU/min], $(p_1, p_2, p_3, n, h, \gamma)$ are parameters of the model. The term, $\gamma[G(t) - h]^+$ in the third equation of this model, serves as an internal regulatory function that formulates insulin secretion in the body, which does not exist in diabetics, the $u(t)$ represent the rate of exogenous insulin. The value of p_1 will be significantly reduced; therefore it can be approximated as zero (Parsa, Vali & Ghasemi, 2014). Which $D(t)$ is disturbance signal (meal disturbance) can be modeled by a decaying exponential function of the following form (Fisher, 1991):

$$D(t) = Aexp(-B(t - t_{meal})) \tag{2}$$

where: B represents the absorption rate of the meal, A is meal size and t_{meal} represents the beginning time of meal digestion.

3. SLIDING MODE CONTROLLER DESIGN

SMC is a robust and simple procedure for synthesizing controllers for linear and nonlinear processes based on the Variable Structure Control (VSC) principles.

The discrete control has high switching frequency, which causes a "chattering-phenomenon", it considered undesired property that appear in SMC's control action (Djouima, et al., 2018). There are different methods that have been used to overcome the chattering phenomena such as replacing the sign(s) by boundary function like sat(s), using terminal SMC, integral SMC, and other different methods. One of the most efficient methods to overcome this problem by using Second Order Sliding Mode Control. There are different SOSMC algorithms, such as Sub-Optimal (SO), Twisting (TW) and Super-Twisting (ST) algorithm. ST-SMC does not require the information of ṡ in its formulation and application which is simpler and preferable (Matraji, Al-Durra & Errouissi, 2018).

The ST-SMC utilized similar design steps as standard SMC. The same sliding surface as in Eq. (3) is applied and the control laws are stated in Eq. (8). The sliding surface can be introduced as:

$$s(t) = \gamma e(t) - \dot{e}(t) \tag{3}$$

where $e(t)$ and $\dot{e}(t)$ is error and derivative of the error respectively, $e(t)$ is given by:

$$e(t) = r(t) - y(t) \tag{4}$$

where $r(t)$ is the reference input (Basal Value) and $y(t)$ is the output signal (measured glucose).

The constant γ is chosen to be positive. The choice of γ decides the convergence rate of the tracking error.

The ST algorithm is defined by the following control law (Matraji, Al-Durra & Errouissi, 2018; Levant, 2013):

$$u = u_1 + u_2, \tag{5}$$

$$u_1 = -a_1 sign(s) \tag{6}$$

$$u_2 = -a_2 |s|^{0.5} \mathrm{sign(s)}, \tag{7}$$

where a_1 and a_2 are positive bounded constants. The control law of the super twisting SOSMC is given by:

$$u(t) = -a_1 sign(s(t)) - a_2 |s(t)|^{0.5} \mathrm{sign(s(t))} \tag{8}$$

4. MODIFIED SLIDING MODE CONTROLLER DESIGN

In this paper, a Modified SOSMC based on super twisting is suggested as shown in fig. 2, which considered as improvement to the SOSMC, the control law of the super twisting SOSMC (Eq. (8)) is modified to:

$$u(t) = -a_1 sign\big(s(t)\big) - a_2|s(t)|^{0.5}\mathrm{sign}\big(\mathrm{s(t)}\big) + u_n(s(t)) \tag{9}$$

where $u_n(e(t))$ is nonlinear auxiliary part given by:

$$u_n(e(t)) = \frac{L_1(1-\exp(L_2 e(t)))}{(1+\exp(L_2 e(t)))} \tag{10}$$

where L_1, L_2 are small positive numbers that will be tuning by (PSO and CPSO) algorithms.

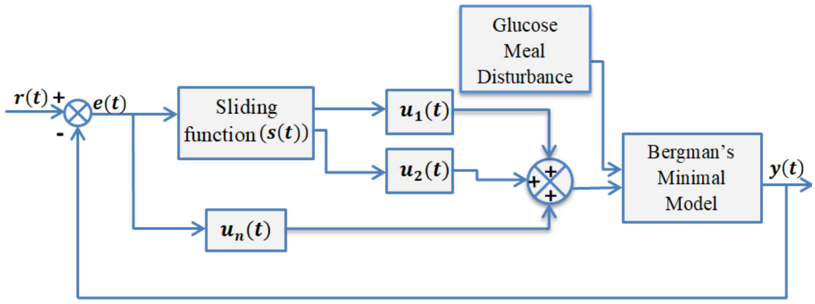

Fig. 2. Modified SOSMC block diagram

5. CHAOTIC PARTICLE SWARM OPTIMIZATION

The Particle Swarm Optimization algorithms (PSO) is the common evolutionary techniques. Which is adopt a random sequence for their parameter. The PSO algorithm is initialized with a population of candidate solutions which is called a particle. *N* particles are moving around in a D-dimensional search space of the problem (Amet, Ghanes & Barbot, 2012).

The position of the i^{th} particle at the i^{th} iteration is represented by $x_i(t) = \big(x_{i1}, x_{i_2}, \ldots, x_{iD}\big)$. The velocity for the i^{th} particle can be written as $v_i(t) = (v_{i1}, v_{i_2}, \ldots, v_{iD})$. The best position that has so far been visited by the i^{th} particle is represented as $pi = (p_{i1}, p_{i_2}, \ldots, p_{iD})$ which is also called pbest. The global best position attained by the whole swarm is called the global best (gbest) and represented as $p_g(t) = (p_{g1}, p_{g2}, \ldots, p_{gD})$. The velocity vector at the i^{th} iteration is represented as $v_i(t) = (v_{g1}, v_{g2}, \ldots, v_{gD})$. At the next iteration, the velocity and position of the particle are calculated according to (11, 12):

$$v_i(t+1) = wv_i(t) + c_1 r_1\big(\text{pbest}_i(t) - x_i(t)\big) + c_2 r_2\big(\text{gbest}_i(t) - x_i(t)\big) \quad (11)$$

$$x_i(t+1) = x_i(t) + v_i(t) \quad (12)$$

where c_1, c_2 are called acceleration coefficients. w is called inertia weight, and r_1, r_2 are random value in the range [0, 1]. The parameters $w,\ r_1$ and r_2 is the key factors that effected the convergence behavior (Wang, Tan & Liu, 2018). In the Chaotic Particle Swarm Optimization algorithms (CPSO) the parameters c_1 and c_2 are modified by using logistic map based on the following equation:

$$M(t+1) = \mu \times M(t) \times \big(1 - M(t)\big) \quad 0 \leq M(t) \leq 1 \quad (13)$$

where μ is s a control parameter with a real number from $[0\ to\ 4]$ and $0 \leq M(t) \leq 1$. Then introduce a new velocity update as in equations (14).

$$v_i(t+1) = wv_i(t) + M(t) \times r_1\big(\text{pbest}_i(t) - x_i(t)\big) + (1 - M(t)) \times \\ \times r_2\big(\text{gbest}_i(t) - x_i(t)\big) \quad (14)$$

Important advantages of the chaotic optimization algorithm (COA) are summarized as: easy implementation, short execution time and speed-up of the search. Observations, however, reveal that the COA also has some problems including: (i) COA is effective only for small decision spaces; (ii) COA easily converges in the early stages of the search process. Therefore, hybrid methods have attracted attention by the researchers (Hadi, 2019) The flowchart that represented this algorithm illustrated below.

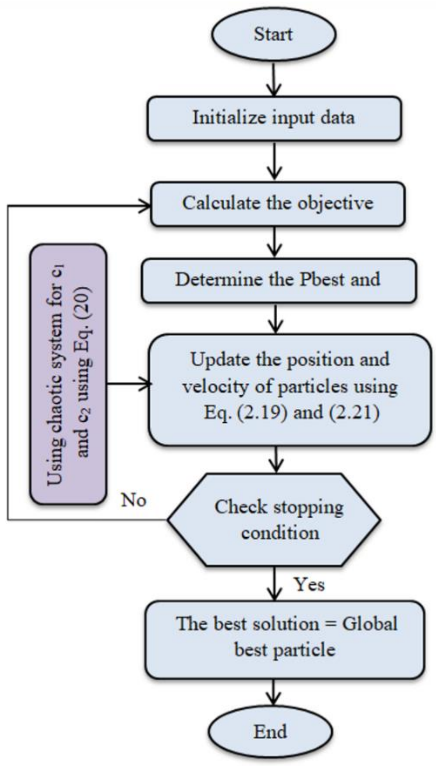

Fig. 3. General flowchart of the CPSO algorithm

6. SIMULATION RESULTS

The results of simulations for BEM model addressed in Eq. (1), parameters of BEM model are available on table (1), and the suggested controller based on the CPSO algorithm are offered in this section for a BG levels of 70 mg/dl. The BEM model response without controller is showen in figure (4). In this paper, the simulations are carried out dynamically for three patients with the initial conditions 220, 200 and 180mg/dl for patients 1, 2 and 3, respectively. In the simulation, the meal glucose disturbance that given in Eq. (2) the value of its parameters are $A = 0.5$, $b = 0.05$, and $t_{meal} = 400$ min.

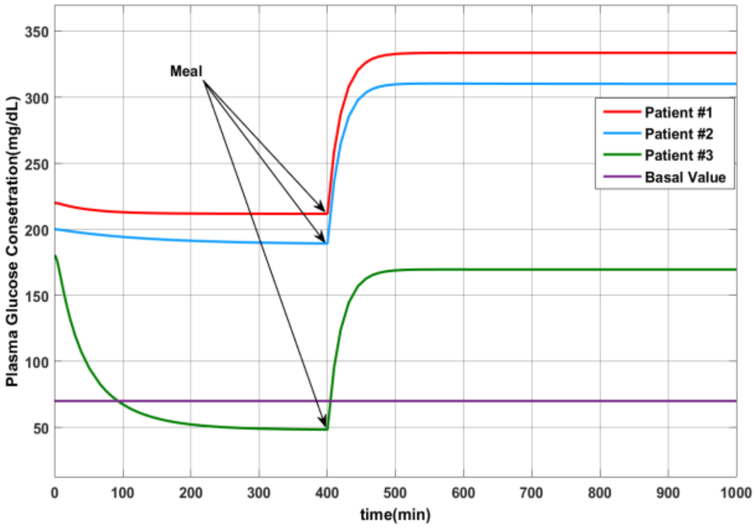

Fig. 4. Glucose output of three patients with disturbance (open-loop glucose regulatory system)

You can note that the glucose value of the normal person is stabilized at the basal level in the presence of the disturbance (meal), while the patient's glucose level remains dangerous outside the range. The simulation second part is the proposed controller is applied to the system and the response of a patients in the presence of the disturbance is tested. To examine the robustness of the control algorithm to the parameter change, three sets of parameters for three different patients have been used. The parameters of CPSO algorithm are considered here as in Table 2.

Tab. 1. Bergman Minimal Model Parameters (Garcia-Gabin, et al., 2009; Abu-Rmileh & Garcia-Gabin, 2011).

Parameter	Normal	Patient1	Patient2	Patient3
p_1	0.0317	0	0	0
p_2	0.0123	0.02	0.0072	0.0142
p_3	4.92	5.3×10^{-6}	2.16×10^{-6}	9.94×10^{-5}
n	0.2659	0.3	0.2465	0.2814
γ	0.0039	–	–	–
h	79.0353	–	–	–
G_b	70	70	70	70
I_b	7	7	7	7

Tab. 2. The parameters of CPSO algorithm

CPSO Parameters	Acronym	Value
Maximum number of iterations	$Iter_{max}$	80
Number of particles	pop_size	20
Acceleration constant	c_1 & c_2	1.5
Inertia weight factor	w	0.9
Random values	r_1 & r_2	0-1
Control parameter	μ	4
Chaotic initial value	$M(1)$	0.3

Table 3 illustrate the optimal parameters for SOSMC and MSOSMC controllers gotten from the CPSO algorithm.

Tab. 3. Optimal controller parameters

Controller	Parameter	Value
SOSMC	γ	0.15
	a_1	9.25
	a_2	0.00013
MSOSMC	L_1	0.037
	L_2	1.5

Figures (5 to 10) shows the response of BEM model for three patients after applying the suggested controllers to regulated the BG level according to Table 3 parameters.

It can be noticed from simulation results (Figures (5 to 10) and Tables (4 to 6)) of the suggested controllers that the glucose output with these controllers tracks the desired BG level with small settling time (t_s), study state error ($e_{s.s}$), and the Mean Absolute Percentage Error ($MAPE$) between the glucose value under the control system and that under the normal model according to the following formula:

$$MAPE = \frac{1}{n}\sum_{t=0}^{n}\left|\frac{BG_{desired}-BG_{measured}}{BG_{desired}}\right| \tag{15}$$

where n is the duration of simulation, $BG_{desired}$ is the glucose value returned by the reference model, and $BG_{measured}$ represents the actual output of the system under the controller.

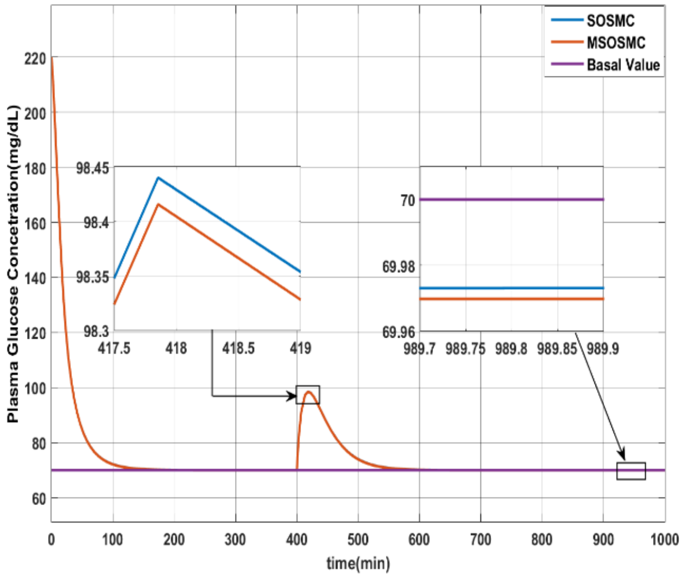

Fig. 5. Blood glucose concentration for patient 1 based on the suggested controllers and CPSO algorithm

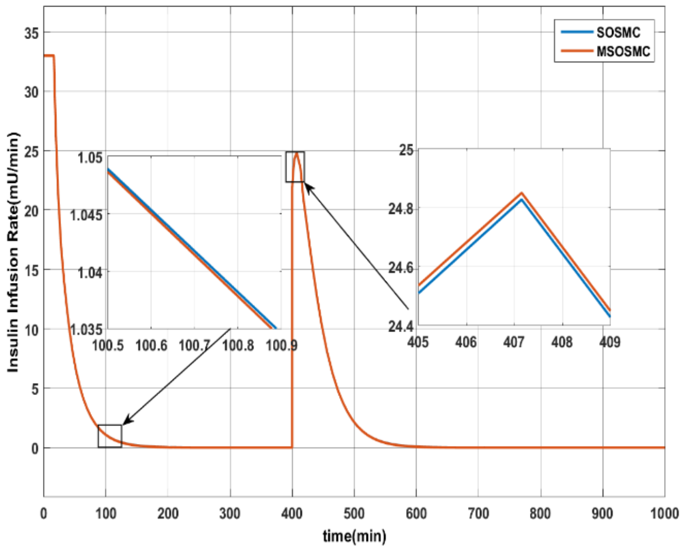

Fig. 6. Insulin infusion rate for patient1 based on the suggested controllers and CPSO algorithm

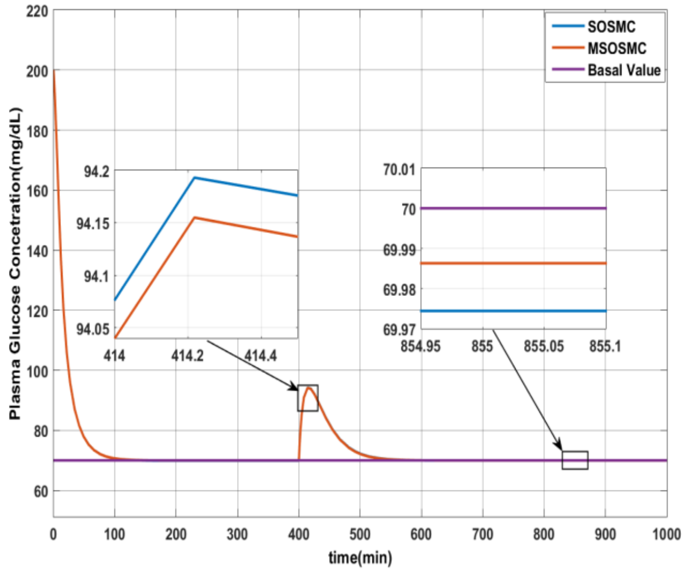

Fig. 7. Blood glucose concentration for patient 2 based on the suggested controllers and CPSO algorithm

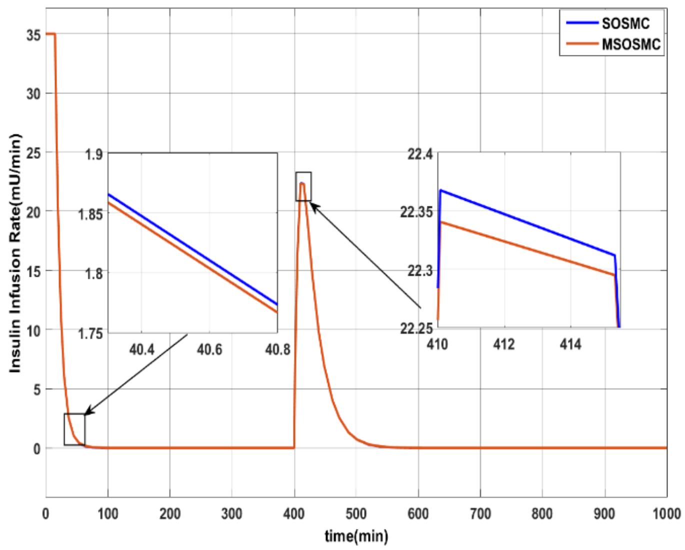

Fig. 8. Insulin infusion rate for patient2 based on the suggested controllers and CPSO algorithm

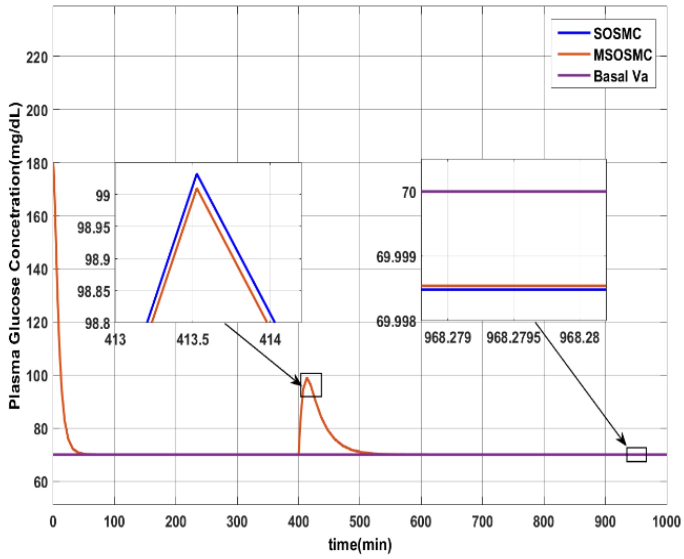

Fig. 9. Blood glucose concentration for patient 3 based on the suggested controllers and CPSO algorithm

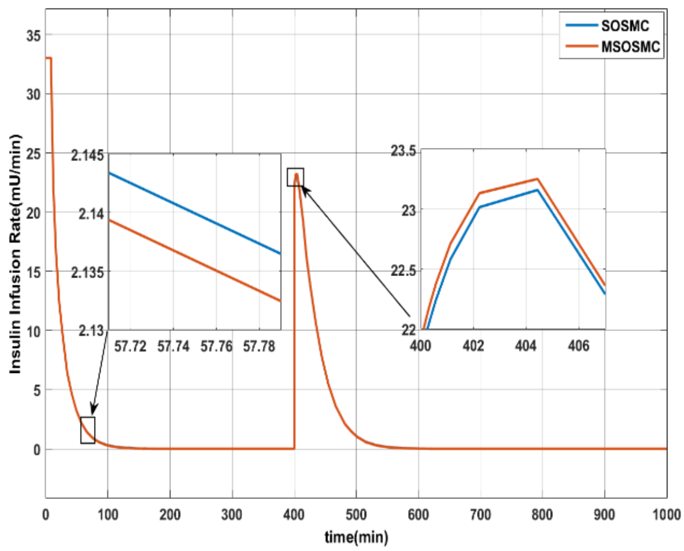

Fig. 10. Insulin infusion rate for patient3 based on the suggested controllers and CPSO algorithm

Tab. 4. The simulation result's evaluation parameters for patient 1

The controller used	t_s (min.)	$MAPE$	$e_{s.s.}$
SOSMC	508.94	0.0565	0.0031
MSOSMC	508.42	0.0564	0.0002

Tab. 5. The simulation result's evaluation parameters for patient 2

The controller used	t_s (min.)	$MAPE$	$e_{s.s.}$
SOSMC	496.14	0.0386	0.0005
MSOSMC	495.16	0.0387	0.0004

Tab. 6. The simulation result's evaluation parameters for patient 3

The controller used	t_s (min.)	$MAPE$	$e_{s.s.}$
SOSMC	476.25	0.0295	0.0008
MSOSMC	475.34	0.0293	0.0007

The comparison between controllers is shown in Tables (4 to 6). This tables illustrates the performance of controllers. The MSOSMC has the best average performance which satisfies the design requirement.

7. CONCLUSIONS

In this paper, a simple modified second order sliding mode controller has been suggested based on ST algorithm and CPSO algorithm. The performance analysis of the suggested control strategy concerning plasma glucose-insulin stabilization is comprehensively demonstrated by computer simulations. To validate the robustness of the suggested controller, the diabetic patient is exposed to external disturbance, that is, a meal. The closed-loop system has been simulated for different patients with different parameters, in the presence of the food intake disturbance and it has been shown that the glucose level is stabilized at its basal value (reference input) in a reasonable amount of time. The effectiveness of the suggested controller compared with the classical SOSMC are verified by simulation results for three patients.

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