Integral Sliding Mode Control with Dual-Hormone for an Artificial Pancreas

Saoussane Mahour, Mohamed Tadjine, and Messaoud Chakir

Abstract-Low concentration of glucose, "hypoglycemia" is the most critical complication for type 1 diabetes patients, may lead to coma or death. For this purpose, a dual-hormonal control of glycaemia is required, using insulin to recover the period of hyperglycemia and glucagon to treat hypoglycemia. In this study, an extended mathematical model of blood glucose is presented, taking into account the dynamics of the glucagon hormone. An Integral Sliding Mode Control ISMC was developed using a hysteresis switch between two hormones, "insulin and glucagon". The numerical simulation results show that the proposed controllers have many advantages, such as robustness to parameter variance, change in the initial condition, and external disturbance.

Keywords- Integral sliding mode control, dual hormone, artificial pancreas, lyapunov stability.

NOMENCLATURE

AP	Artificial Pancreas
BGL	Blood Glucose Level
ISMC	Integral Sliding Mode Control
PID	Proportional-Integral-Derivative
TIDM	Type 1 Diabetes Mellitus

I. INTRODUCTION

Diabetes is a chronic metabolic illness caused by a lack production or deficient action of insulin (concentration of glycemia above 180 mg/dl). Type 1 diabetes is the one of this disease, the human body's does not aptitude to secret the insulin by the beta cells of pancreas, which causes several risks to these patients' health [1] .The symptoms of this diabetes includes urination, thirst ,losing weight ,hunger increased appetite and feeling tired [2].Control blood glucose decreases the risk of long-term diabetes-related complications, such as kidney disease, heart disease, blindness, and peripheral vascular and nerve damage [1]. The two methods of treatment for type 1 diabetes patients are multiple daily injections or continuous subcutaneous infusion via a portable pump. In recent years, the development of a novel device to build automated insulin delivery systems and to manage the blood glucose, known as the artificial pancreas[3]. however, intensive insulin treatment, including the artificial pancreas, can raise the risk of hypoglycemia with potentially severe complications, including coma or death [4]. Moreover, a closed-loop system retaining the dual hormone insulin infusion and glucagon has confirmed its efficacy in avoiding and treating hypoglycemia[5], [6]; bihormonal systems would better emulate the endocrine pancreas function [7]. Several authors[5], [8], [9]have stated that a bihormonal closed-loop algorithm could provide asafe blood glucose regulation and significantly reduce the risk and time spent in hypoglycemic

Manuscript received July 17, 2024; revised December 10, 2024.

S.MAHOUR, M. TADJINE and M.CHAKIR are with Process Control Laboratory at EcoleNationalePolytechnique, Algiers, Algeria. (e-mail: <u>saoussane.mahour@g.enp.edu.dz</u>, <u>mohamed.tadjine@g.enp.edu.dz</u>, <u>messaoud.chakir@g.enp.edu.dz</u>)

Digital Object Identifier (DOI): 10.53907/enpesj.v4i2.280

episodes [10] compared to usual insulin therapy. However, the dual-hormone systems have shown better results during exercise studies [10]. Besides, recent studies[11] have demonstrated that adding glucagon delivery to the closed-loop system with automatic exercise detection reduces hypoglycemia after aerobic exercise. To maintain the BGL in the normal range, approximately between 70-120 mg/dl for a healthy human and deal with hypoglycemia and hyperglycemia conditions, several control strategies have been designed and tested for the artificial pancreas: neural control[12], $H\infty$ control[13], PID control[14], model predictive control[15], sliding control[16]. Among these controllers, Sliding Mode Control has received much attention in biomedical studies due to its unique features such as strong robustness, fast convergence rate, and simplicity[17], [18]. Sliding mode control is an efficient approach to dealing with the model uncertainties, nonlinearities, and bounded external disturbance[4]. The control technique has a number of advantages when compared with other nonlinear controllers. It has been implemented on photo-voltaic system [19] Leukemia therapy [20] and blood glucose regulation[4], [16].

This study aims to develop a control algorithm that maintains the blood glucose concentration in subjects with T1DM in a safe range using an integral sliding mode control and adopting a dual hormone strategy by adding glucagon administration to insulin delivery. Numerical simulations illustrate the contribution of glucagon to achieving control goals, with no hypoglycemic or hyperglycemic events observed. The remainder of this paper is organized as follows: Section 2 describes the nonlinear model of the insulin-glucose-glucagon system and synthesizes the dual hormone controller applying to the integral slide mode method; section 3 discusses the obtained results; Section 4 concludes the paper.

II. MATERIALS AND METHODS

Mathematical model

Many researchers have studied the glucose-insulin-glucagon endocrine and metabolic regulatory system. Therefore, different models for the glucoregulatory system are available [21], [22], [23] with different structures and degrees of complexity. The model developed by Ben Abbes et al (2013) [24]and extended by Mahour et al. (2022) [25]was chosen for this study to represent the diabetic patient (virtual subject). The mathematical description of the system is given as follows:

$$\dot{x}_{1}(t) = -P_{1}x_{1}(t) - P_{2}x_{1}(t)e^{S_{1}i_{2}(t)} + K_{gr}m_{4}(t) + P_{3}g_{6}(t)$$
(1)

$$\dot{i}_{2}(t) = -W_{in2}(\dot{i}_{2}(t) - \dot{i}_{3}(t))$$
⁽²⁾

$$i_{3}(t) = -W_{in1}(i_{3}(t) - U_{ins}(t))$$
(3)

$$\dot{m}_4(t) = -W_{r2} \big(m_4(t) - m_5(t) \big) \tag{4}$$

$$\dot{m}_{5}(t) = -W_{r1}\left(m_{5}(t) - U_{rep}(t)\right)$$
(5)

$$\dot{g}_6(t) = -W_{g2} \big(g_6(t) - g_7(t) \big) \tag{6}$$

$$\dot{g}_7(t) = -W_{g1}\left(g_7(t) - U_g(t)\right)$$
(7)

$$y(t) = x_1(t) \tag{8}$$

 x_1 : Glycemia concentration,

 i_2, i_3 : Insulin concentration in distant compartments,

 m_4, m_5 : Quantity of ingested carbohydrate.

 g_6, g_7 . Glucagon concentration in distant compartments,

 P_I : Constant expressing the decline of glucose affected by glucose uptake by cells, independent of the insulin blood concentration,

 P_2 : Gain in the double action of the pair insulin– glucose on glucose

P₃: Glucagon action on glucose production,

 S_1 : Gain in the action of insulin on glucose.

 K_{gr} : Carbohydrates action on glucose production.

 \mathbf{U}_{ins} , \mathbf{U}_{rep} , $\mathbf{U}_{\mathbf{g}}$: Injected insulin; ingested carbohydrates and injected glucagon,

 W_{in1} , W_{in2} : Values related with the distribution of insulin,

 W_{r1} , W_{r2} : Constants related with the distribution of carbohydrates,

 W_{g1}, W_{g2} : Constants related with glucagon diffusion,

Controller design

Consider system described by (1)-(8) is presented as follows form:

$$\dot{x}(t) = f(t, x(t)) + g_1(t)u_1(t) + g_2(t)u_2(t);$$
(9)

Where x(t) is a measurable states, u_1 and u_2 are the control inputs, f(x, t) and g(x, t) are unknown nonlinear time-variant functions.

Reference trajectory of x(t) is a known bounded $x_r=1g/l$. This value was chosen so that the blood glucose level of the patient with T1DM would remain within safe limits by the medical community: 80 and 100 mg /dL .The dual hormone control has two-control actions: u_1 is represented by the injection of insulin in the bloodstream, and u_2 is represented by the amount of glucagon administered in the bloodstream. A simple switching logic with hysteresis is applied to choose which hormone is active at each moment. In the algorithm, when the blood glucose is under 0.8 g/l, the glucagon controller is switched on so that the glucose concentration increases to the desired value of 1 g/l; then, the blood glucose exits the safe range. The insulin controller is switched on, and the glucagon controller is deactivated.

Integral sliding mode Controller design

Control problem of blood glucose concentration in diabetes patients requires the tracking of the normal glucose level. For the first state of the system to track their reference value, we define the error and integral of error as follows:

$$e(t) = x_1(t) - x_r(t);$$
(10)

$$e_l(t) = \int e(t)dt; \tag{11}$$

Now, consider a third order sliding surface that incorporate the tracking error:

$$S(t) = \ddot{e}(t) + \beta_1 \dot{e}(t) + \beta_2 e(t) + \alpha e_l(t); \quad (12)$$

$$S(t) = \ddot{x}_{1}(t) + \beta_{1} \dot{x}_{1}(t) + \beta_{2} (x_{1}(t) - x_{r}(t)) + \alpha \int (x_{1}(t) - x_{r}(t)) dt; \quad (13)$$

Differentiation of (13) with respect to time can be calculated by

$$\dot{S}(t) = \ddot{x_1}(t) + \beta_1 \ \ddot{x}_1(t) + \beta_2 \ \dot{x}_1(t)$$

$$+ \alpha \ x_1(t);$$
(14)

The overall control law for blood glucose regulation of patient can be written as:

$$U_{1} = \frac{1}{\varphi_{1}} \left(g_{1} + \beta_{1} \left(-P_{1} \dot{x}_{1}(t) - P_{2} x_{1} t e S_{1} i t t - P_{2} S_{1} x_{1} t i t e S_{1} i t t + Kgrm 1 t \right)$$

$$P_{2} x_{1} t e S_{1} i t t - P_{2} x_{1} t e S_{1} i t t + Kgrm 1 t$$

$$P_{3} g_{1} t + \beta_{2} - P_{1} x_{1} t - P_{2} x_{1} t e S_{1} i t t + Kgrm 1 t$$

$$P_{3} g_{1} t + \beta_{2} - P_{1} x_{1} t - P_{2} x_{1} t e S_{1} i t t + Kgrm 1 t$$

$$P_{3} g_{1} t + \beta_{2} - P_{1} x_{1} t - P_{2} x_{1} t e S_{1} i t t + Kgrm 1 t$$

$$P_{3} g_{1} t + \beta_{2} - P_{1} x_{1} t - P_{2} x_{1} t e S_{1} i t t + Kgrm 1 t$$

$$P_{3} g_{1} t + \beta_{2} - P_{1} x_{1} t - P_{2} x_{1} t e S_{1} i t t + Kgrm 1 t$$

$$P_{3} g_{1} t + \beta_{2} - P_{1} x_{1} t - P_{2} x_{1} t e S_{1} i t t + Kgrm 1 t$$

$$P_{3} g_{1} t + \beta_{2} - P_{1} x_{1} t - P_{2} x_{1} t e S_{1} i t t + Kgrm 1 t$$

$$P_{3} g_{1} t + \beta_{2} - P_{1} x_{1} t - P_{2} x_{1} t e S_{1} i t t + Kgrm 1 t + Sgrm 1 t + Sgr$$

Blycemia

0

5

$$U_{2} = \frac{1}{\varphi_{2}} \Big(g_{2} + \beta_{1} \Big(-P_{1} \dot{x}_{1}(t) \\ - P_{2} \dot{x}_{1}(t) e^{S_{1} i_{1}(t)} \\ - P_{2} S_{1} x_{1}(t) \dot{i}_{1}(t) e^{S_{1} i_{1}(t)} \\ + K_{gr} \dot{m}_{1}(t) + P_{3} \dot{g}_{1}(t) \Big) \\ + \beta_{2} \Big(-P_{1} G x_{1}(t) \\ - P_{2} x_{1}(t) e^{S_{1} i_{1}(t)} \\ + K_{gr} m_{1}(t) + P_{3} g_{1}(t) \Big) \\ + \alpha (x_{1}(t) - x_{r}(t)) \\ + ksign(s) \Big);$$
(16)



10

Time (h)

15

20

Fig.1: Concentration of blood glucose with hyperglycemia and external disturbance

III. RESULTS AND DISCUSSION

In this section, we analyzed the behavior of proposed nonlinear controller under critical conditions, such as hypoglycemia (low blood glucose concentration) and hyperglycemia (high blood glucose concentration). Table .1 lists the value of the parameters have been used of the simulation in MATLAB.

The simulation in fig.1 shows a virtual patient confronted with hyperglycemia and external disturbance. Initially, the blood glucose concentration is around 4 g/l and the patient consumes 80 g of carbohydrates at 12:00 p.m. The blood sugar levels remain within the acceptable range of 0.9 to 1.20 g/L, avoiding critical periods of hyperglycemia or hypoglycemia. The blood sugar converges towards the target value of 1 g/L. The external disturbance does not impact the system's response, demonstrating the controller's robustness to such changes

The integral action integrated with the sliding mode technique results in a significant reduction in steady-state error.

Fig.2the control inputs Uins and Ug (insulin and glucagon injections) in the case of ISMC. This method exhibits unwanted chattering and fluctuations in the control inputs curve. It can be seen that the level of insulin administered into the body is at its maximum after the intake of carbohydrates, reaching a value of 13 U/min. To compensate for the high quantity of insulin and to avoid a hypoglycemic episode, the controller injects the glucagon. This approach ensures a safer management of blood glucose levels by preventing both hyperglycemia and hypoglycemia.

	Table 1.	
meters used	during the simulation.	

Dara

Tarameters used during the simulation.					
Parameter	Value	Units			
P_1	0.003	min-1			
P_2	0.0008	min-1			
P_3	0.04	min-1			
\mathbf{S}_1	60	pmol/min			
Kgr	0.04	mg/(dl/min)			
Wg_1	0.2	min-1			
Wg_2	0.02	min-1			
Win ₂	0.009	min-1			
Win_1	0.006	min-1			
Wr_2	0.02	min-1			
Wr_1	0.008	min-1			



Fig 2: Control input (insulin and glucagon injected)

The effect of different initial conditions was simulated to check the robustness of the ISMC controller. Fig.3 presents the results obtained. Three different simulation scenarios were assumed. In the first scenario, the blood sugar level is initial X01=0.3g/l; in the second scenario, it is X01=0.4 g/l; and in the third scenario, it is X03=0.5 g/l. It can be noted that the blood glucose curves follow the same shape and converge to the desired value with the lowest error in beginning.

Fig.4 displays the control inputs by the controller for various initial conditions during a hypoglycemia episode. It is clear that the amount of administered glucagon varies based on the patient's initial conditions.

Fig.5 presents the tracking error in the presence of hypoglycemia with different initial conditions. Initially, the error is at maximum, indicating a significant difference between the real glucose level and the reference value. The error reduces to zero after injecting glucagon into the different patients using ISMC.



Fig.3: Concentration of blood glucose with different initial conditions.



Fig.4: Control inputs by the ISMC



Fig.5: Tracking error under different initial conditions

Fig.6 shows the level of sugar in blood of three different patients with hypoglycemia, and Table.2 summarizes the

parameters. It can be noted that all three patients' blood glucose levels were stabilized to reference value, validating the rejection of parameter uncertainty and robustness to parameter variations by the controller ISMC.

Fig.7 illustrates the control inputs (injected glucagon) of the three different patients using ISMC. It can be noted that the amount of administered glucagon is different for different patients depending on the parameters of patients in beginning.

 Table 2.

 Parameters used for three different patients.

Parameters	Patient 1	Patient 2	Patient 3
P ₁	0.004	0.003	0.002
P_2	0.0009	0.0008	0.0007
P ₃	0.05	0.04	0.03
\mathbf{S}_1	70	60	50



Fig.6: Concentration of blood glucose for three different conditions



Fig.7: Control inputs for three different conditions

IV. CONCLUSION

Over the past few decades, the design of a robust controller has been an appropriate choice for the closed-loop of an artificial pancreas. This paper proposed the integral sliding mode with bihormonal control (ISMC) to regulate blood glucose. The dual hormone can potentially reduce insulininduced hypoglycemia's effects and provide additional blood ^[15] glucose safety. The ISMC was also submitted to test the robustness property. Satisfactory results were observed from the simulation. In addition, the robustness of the proposed ^[16] controller to parameter variations of different diabetic patients, external disturbances, and changes in the initial condition was confirmed ^[17]

REFERENCES

- M. Dansa, V. H. P. Rodrigues, et T. R. Oliveira, « Blood glucose regulation in patients with type 1 diabetes by means of output-feedback sliding mode control », in *Control Applications for Biomedical Engineering Systems*, Elsevier, 2020, p. 25-54. doi: 10.1016/B978-0-12-817461-6.00002-0.
- [2] M. Farman *et al.*, « A control of glucose level in insulin therapies for the development of artificial pancreas by AtanganaBaleanu derivative », *Alex. Eng. J.*, vol. 59, n° 4, p. 2639-2648, août 2020, doi: 10.1016/j.aej.2020.04.027.
- [3] D. Majdpouret al., « Fully Automated Artificial Pancreas for Adults With Type 1 Diabetes Using Multiple Hormones: Exploratory Experiments », *Can. J. Diabetes*, vol. 45, n° 8, p. 734-742, déc. 2021, doi: 10.1016/j.jcjd.2021.02.002.
- [4] Sh. Asadiet V. Nekoukar, « Adaptive fuzzy integral sliding mode control of blood glucose level in patients with type 1 diabetes: In silico studies », *Math. Biosci.*, vol. 305, p. 122-132, nov. 2018, doi: 10.1016/j.mbs.2018.09.006.
- [5] J. R. Castle *et al.*, « Novel Use of Glucagon in a Closed-Loop System for Prevention of Hypoglycemia in Type 1 Diabetes », *Diabetes Care*, vol. 33, nº 6, p. 1282-1287, juin 2010, doi: 10.2337/dc09-2254.
- [6] F. H. El-Khatib, S. J. Russell, D. M. Nathan, R. G. Sutherlin, et E. R. Damiano, « A Bihormonal Closed-Loop Artificial Pancreas for Type 1 Diabetes », *Sci. Transl. Med.*, vol. 2, n° 27, avr. 2010, doi: 10.1126/scitranslmed.3000619.
- [7] F. H. El-Khatib, J. Jiang, et E. R. Damiano, « A Feasibility Study of Bihormonal Closed-Loop Blood Glucose Control Using Dual Subcutaneous Infusion of Insulin and Glucagon in Ambulatory Diabetic Swine », J. Diabetes Sci. Technol., vol. 3, nº 4, p. 789-803, juill. 2009, doi: 10.1177/193229680900300428.
- [8] M. Reiter, F. Reiterer, et L. Del Re, « Bihormonal glucose control using a continuous insulin pump and a glucagon-pen », in 2016 European Control Conference (ECC), Aalborg, Denmark: IEEE, juin 2016, p. 2435-2440. doi: 10.1109/ECC.2016.7810655.
- [9] S. J. Russell, F. H. El-Khatib, D. M. Nathan, K. L. Magyar, J. Jiang, et E. R. Damiano, « Blood Glucose Control in Type 1 Diabetes With a Bihormonal Bionic Endocrine Pancreas », Diabetes Care, vol. 35, no 11, p. 2148-2155, nov. 2012, doi: 10.2337/dc12-0071.
- [10] N. Taleb et al., « Efficacy of single-hormone and dual-hormone artificial pancreas during continuous and interval exercise in adult patients with type 1 diabetes: randomised controlled crossover trial », Diabetologia, vol. 59, no 12, p. 2561-2571, déc. 2016, doi: 10.1007/s00125-016-4107-0.
- [11] J. R. Castle et al., « Randomized Outpatient Trial of Single- and Dual-Hormone Closed-Loop Systems That Adapt to Exercise Using Wearable Sensors », Diabetes Care, vol. 41, no 7, p. 1471-1477, juill. 2018, doi: 10.2337/dc18-0228.
- [12] B. S. Leon, A. Y. Alanis, E. N. Sanchez, F. Ornelas-Tellez, et E. Ruiz-Velazquez, « Inverse optimal neural control of blood glucose level for type 1 diabetes mellitus patients », J. Frankl. Inst., vol. 349, no 5, p. 1851-1870, juin 2012, doi: 10.1016/j.jfranklin.2012.02.011.
- [13] F. Chee, A. V. Savkin, T. L. Fernando, et S. Nahavandi, « Optimal\$H^infty\$Insulin Injection Control for Blood Glucose Regulation in Diabetic Patients », IEEE Trans. Biomed. Eng., vol. 52, no 10, p. 1625-1631, oct. 2005, doi: 10.1109/TBME.2005.855727.
- [14] H. M. Paiva, W. S. Keller, et L. G. R. Da Cunha, «Blood-Glucose Regulation Using Fractional-Order PID Control », J. Control Autom. Electr. Syst., vol. 31, no 1, p. 1-9, févr. 2020, doi: 10.1007/s40313-019-00552-0.

- [15] T. B. Aradóttir et al., « Model predictive control for dose guidance in long acting insulin treatment of type 2 diabetes », IFAC J. Syst. Control, vol. 9, p. 100067, sept. 2019, doi: 10.1016/j.ifacsc.2019.100067.
- [16] A. Abu-Řmileh, W. Garcia-Gabin, et D. Zambrano, « A robust sliding mode controller with internal model for closed-loop artificial pancreas », Med. Biol. Eng. Comput., vol. 48, no 12, p. 1191-1201, déc. 2010, doi: 10.1007/s11517-010-0665-3.
- [17] M.-C. Pai, « Discrete-time output feedback quasi-sliding mode control for robust tracking and model following of uncertain systems », J. Frankl. Inst., vol. 351, no 5, p. 2623-2639, mai 2014, doi: 10.1016/j.jfranklin.2014.01.005.
- [18] Y. Niuet D. W. C. Ho, « Design of Sliding Mode Control Subject to Packet Losses », IEEE Trans. Autom. Control, vol. 55, no 11, p. 2623-2628, nov. 2010, doi: 10.1109/TAC.2010.2069350.
- [19] R. Pradhan et B. Subudhi, « Double Integral Sliding Mode MPPT Control of a Photovoltaic System », IEEE Trans. Control Syst. Technol., vol. 24, no 1, p. 285-292, janv. 2016, doi: 10.1109/TCST.2015.2420674.
- [20] Y. Islam, I. Ahmad, M. Zubair, et K. Shahzad, « Double Integral sliding mode control of Leukemia Therapy », Biomed. Signal Process. Control, vol. 61, p. 102046, août 2020, doi: 10.1016/j.bspc.2020.102046.
- [21] W. Boutayeb, M. E. N. Lamlili, A. Boutayeb, et M. Derouich, « Mathematical Modelling and Simulation of <i>β</i>-Cell Mass, Insulin and Glucose Dynamics: Effect of Genetic Predisposition to Diabetes », J. Biomed. Sci. Eng., vol. 07, no 06, p. 330-342, 2014, doi: 10.4236/jbise.2014.76035.
- [22] C.-L. Chen et H.-W. Tsai, « Modeling the physiological glucose– insulin system on normal and diabetic subjects », Comput. Methods Programs Biomed., vol. 97, no 2, p. 130-140, févr. 2010, doi: 10.1016/j.cmpb.2009.06.005.
- [23] P. S. Shabestari, S. Panahi, B. Hatef, S. Jafari, et J. C. Sprott, « A new chaotic model for glucose-insulin regulatory system », Chaos Solitons Fractals, vol. 112, p. 44-51, juill. 2018, doi: 10.1016/j.chaos.2018.04.029.
- [24] I. B. Abbes, P.-Y. Richard, M.-A. Lefebvre, I. Guilhem, et J.-Y. Poirier, « A Closed-Loop Artificial Pancreas Using a Proportional Integral Derivative with Double Phase Lead Controller Based on a New Nonlinear Model of Glucose Metabolism », J. Diabetes Sci. Technol., vol. 7, no 3, p. 699-707, mai 2013, doi: 10.1177/193229681300700315.
- [25] M. Saoussane, T. Mohammed, et C. Mesaoud, « Adaptive controller based an extended model of glucose-insulin-glucagon system for type 1 diabetes », Int. J. Model. Simul., vol. 43, no 3, p. 282-293, mai 2023, doi: 10.1080/02286203.2022.2068214.

Saoussane Mahour received Engineering and Master degree in Control Engineering in 2015 from Ecole Nationale Polytechnqiue (ENP) of Algiers, Algeria. She is actually a PhD student in Automatic Control in the same school. Her current research interests are control in biological system, Non Linear and Robust Control.

Mohamed Tadjine received her PhD degree in Control and Manufacturing Management from 'Institut National Polytechnique de Grenoble' (INPG), (France) in 1994. In 1997, he joined the Ecole Nationale Polytechnique where he is currently Professor in Control Engineering Department. His main research areas are: Non Linear and Robust Control, Observer Design, Fault Detection and Fault Tolerant Control, Application in healthcare and biological systems.

Messaoud Chakir received his PhD degree in Automatic & Control in 2017 from the Ecole Nationale Polytechnique. He is a lecturer-researcher interested in the main research areas of: Robotics, Fault Detection and Fault Tolerant Control, Optimal Control, Application in healthcare and biological systems.