Fractional Order Sliding Mode Blood Glucose Control Using Functions Approximation Techniques

Saeed Khorashadizadeh
Assistant professor of Control Engineering, Faculty of Electrical and Computer Engineering
University of Birjand
Birjand, Iran, 97175/615
s.khorashadizadeh@birjand.ac.ir

Abstract—**In this paper, based on function approximation techniques and sliding mode control strategy, a robust controller for blood glucose regulation is presented. Recently, there has been an increasing trend towards application of fractional order calculus in various fields. Healthcare of patients involved in diabetes mellitus is not exception and various researches have been carried out in this area. In order to design a robust controller, uncertainties should be estimated and compensated. Different estimators can be used for this purpose such as neural networks and fuzzy systems, due to their property of universal approximation. However, there are many tuning parameters in these estimators. Based on the orthogonal functions theorem, we can design other uncertainty estimators such as the Fourier series expansion and Legendre polynomials. Thus, in this paper, the Fourier series expansion is applied for uncertainty estimation in fractional order control of blood glucose. The efficiency of the proposed controller, i.e. robustness and high accuracy, in presence of physical disturbances like food intake and parametric uncertainties is verified via simulations.**

Keywords-Fractional calculus; function approximation techniques; blood glucose regulation)

I. INTRODUCTION(HEADING 1)

Diabetes is discussed as a serious condition in which the body's production and use of insulin are impaired, causing glucose concentration level to increase in the bloodstream. Insulin is a hormone generated by specific cells, called beta cells, in the pancreas. In order to transfer blood glucose into cells, insulin is required. Two types of diabetes have been recognized. In type I diabetes mellitus (T1DM), the b-cells in the pancreas that are responsible for producing insulin are destroyed by the immune system of the patients. Thus, the current solution for treatment is the delivery of exogenous insulin to maintain the glucose levels close to normal.

Based on continuous glucose monitoring (CGM) systems and insulin pumps technologies, a controller that automatically monitors and regulates the blood glucose level can be designed. In other words, it can play the role of an artificial pancreas system to replace the conventional treatment strategies in T1DM. In recent decades, various approaches have been presented in the literature for intelligent control of blood glucose. In this paper, the 3rd order minimal model of Bergman [1] is adopted.

Various approaches have been presented to design a feedback controller for blood glucose regulation, such as fuzzy logic control [2-5], recurrent neural networks [6], model predictive control (MPC) [7], high order sliding mode control [8], optimal control [9] and back-stepping sliding mode control [10]. Also, based on fractional order control, interesting approaches have been introduced in the field of blood glucose regulation [11-15].

Fractional calculus is a generalization of ordinary differentiation- integration operations to an arbitrary fractional order. This field of mathematics was viewed as an only theoretical topic with no practical applications for 300 years [16]. However, recently, it has been used in different fields of engineering and physics. Fractional-order controllers provide extra parameters for tuning. Hence, using this idea in modern nonlinear control techniques like SMC can be useful.

According to the universal approximation theorem [17], fuzzy estimators can approximate any real continuous nonlinear function. Also, this theorem has been developed for neural networks such as radial basis function networks (RBFN) [18]. Based on the orthogonal functions theorem [19], Fourier series can also approximate nonlinear functions. This theorem states that a set of basis functions that their mutual inner products are zero, can be used for approximation of nonlinear functions with small approximation error. In Fourier series, these basis functions are sinusoidal terms and in Legendre polynomials, these basis functions are some polynomials that satisfy the orthogonality condition. Moreover, this theorem states that the approximation error is bounded. Also, the coefficient of each basis function in the final representation of the desired nonlinear function can be calculated by some integrations. In other words, the space of nonlinear functions can be spanned by that set of orthogonal functions. In [20], the controller designed based on the Fourier series has been practically implemented. This uncertainty estimator is simpler and less computational. Using this estimator, some controllers have been presented [21-23] in the field of robust and adaptive control. Thus, in this paper, this estimator is adopted for robust regulation of blood glucose.

This paper is organized as follows. Section 2 introduces fractional calculus. Section 3, describes the glucose-insulin

model. Section 4 explains the Fourier series expansion. Section 5 develops the proposed controller. Section 6 illustrates simulation results. Finally, section 7 concludes the paper.

II. FRACTIONAL CALCULUS

Let us first introduce Caputo definition and results needed here with respect to fractional calculus which will be used later.

Definition 1. The α th-order Caputo fractional derivative of function $f(t)$ is given by [24]

$$ {}_{t_0}^{C}D_t^{\alpha} f(t) = \frac{1}{\Gamma(n-\alpha)} \int_{t_0}^{t} \frac{f^{(n)}(\tau)}{(t-\tau)^{\alpha-n+1}} d\tau, \quad t > t_0 \qquad (1) $$

where t_0 and t are the bounds of the operation, $n = \min\{k \in \mathbb{N} / k > \alpha > 0\}$, and $\Gamma(n)$ denotes the famous Gamma function, which is defined as

$$ \Gamma(n) = \int_{a}^{\infty} t^{n-1} e^{-\tau} d\tau \qquad (2) $$

Definition 2. Fractional integration of the order $\alpha \geq 0$ of $f \in L^1([0,T])$, is defined as [25]

$$ {}_{t_0}^{C}I_t^{\alpha} f(t) = \frac{1}{\Gamma(\alpha)} \int_{t_0}^{t} (t-\tau)^{\alpha-1} f(\tau) d\tau \qquad (3) $$

for $t \in (0,T]$.

Definition 3. The Caputo fractional derivative of order $\alpha > 0$ of $f \in C^n([0,T])$, is defined as $D^{\alpha} f(t) = I^{n-\alpha} D^n f(t)$, where $n = [\alpha]$ [25].

Lemma 1: The Caputo fractional derivative of a function in quadratic form is given by the following [26]

$$ \frac{1}{2} {}_{t_0}^{C}D_t^{\alpha} (\mathbf{x}^T(t)\mathbf{P}\mathbf{x}(t)) \leq \mathbf{x}^T(t)\mathbf{P} {}_{t_0}^{C}D_t^{\alpha}\mathbf{x}(t), \quad \forall \alpha \in (0,1], \forall t \geq t_0 \qquad (4) $$

where $\mathbf{x}(t) \in \Re^{\beta}$; and $\mathbf{P} \in \Re^{\beta \times \beta} > 0$ is a constant matrix.

III. GLUCOSE - INSULIN DYNAMIC

Many models for describing glucose-insulin process has been presented. Bergman's minimal model has been proposed in 1980 by Doctor Richard Bergman. The main advantage of the Bergman minimal model is its simplicity. Following is the Bergman Minimal Model (BeM) [27]

$$ \begin{aligned} {}_{t_0}^{C}D_t^{\alpha} x_1(t) &= -p_1\left[x_1(t) - G_b\right] - x_1(t)x_2(t) + D(t) \\ {}_{t_0}^{C}D_t^{\alpha} x_2(t) &= -p_2 x_2(t) + p_3\left[x_3(t) - I_b\right] \\ {}_{t_0}^{C}D_t^{\alpha} x_3(t) &= -n\left[x_3(t) - I_b\right] + \gamma t\left[x_1(t) - G_b\right]^{+} + u(t) \end{aligned} \qquad (5) $$

in which $x_1(t)$, $x_2(t)$ and $x_3(t)$ are plasma glucose concentration, the insulin influence on glucose concentration reduction, and insulin concentration in plasma respectively, $u(t) \in R$ is injected insulin rate in (mU/min), G_b is the basal pre-injection level of glucose (mg/dl), I_b is 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). The term $\gamma t\left[\mathrm{B}_1(t) - G_b\right]^{+}$ represents the pancreatic insulin secretion after a meal in take at t = 0. As this work is focused on Insulin therapy which is usually administrated to Type I diabetes mellitus patients, γ is assumed to be zero to represent the true dynamic of this disease and p should also be considered zero. The parameter n is the first order decay rate for insulin in blood. This disturbance can be modeled by a decaying exponential function of the following form [28]:

$$ D(t) = A\exp(-Bt) \qquad B > 0 \qquad (6) $$

The pump can be modeled as a first order linear system:

$$ {}_{t_0}^{C}D_t^{\alpha} u(t) = \frac{1}{a}(w(t) - u(t)) \qquad (7) $$

where $w(t)$ is insulin rate command in pump as input, and the parameter a is pump time constant.

IV. THE FOURIER SERIES EXPANSION

According to [29], if the function $F(t)$ defined on $[t_1, t_2]$ satisfies the Dirichlet's conditions, then it can be expressed as

$$ F(t) = a_0 + \sum_{k=1}^{\infty} a_k \cos(\omega_k t) + b_k \sin(\omega_k t) \qquad (8) $$

where a_0, a_k and b_k are the Fourier series coefficients, $\omega_k = 2k\pi/T$ are the frequencies of sinusoidal functions and T is the fundamental period of $F(t)$. The truncation error is defined as

$$ \varepsilon_m(t) = F(t) - F_m(t) \qquad (9) $$

where $F_m(t) = a_0 + \sum_{k=1}^{m} a_k \cos(\omega_k t) + b_k \sin(\omega_k t)]$ is the Fourier series approximation.

$$ a_0 = \frac{1}{T} \int_{t_1}^{t_2} g(t) dt \qquad (10) $$

$$ a_k = \frac{2}{T} \int_{t_1}^{t_2} f(t) \cos(\frac{2k\pi}{T} t) dt \qquad (11) $$

$$ b_k = \frac{2}{T} \int_{t_1}^{t_2} f(t) \sin(\frac{2k\pi}{T} t) dt \qquad (12) $$

Note that $F_m(t)$ can be written as

$$F_m(t) = \theta^T \xi(t) \tag{13}$$

in which

$$\theta = \begin{bmatrix} a_0 & a_1 & b_1 & \dots & a_m & b_m \end{bmatrix}^T \tag{14}$$

and

$$\xi(t) = \begin{bmatrix} 1 & \cos(\omega_1 t) & \sin(\omega_1 t) & \dots & \cos(\omega_m t) & \sin(\omega_m t) \end{bmatrix}^T \tag{15}$$

It should be mentioned that in control systems, the function $g(t)$ is not available and (10)-(12) cannot be applied for calculation of the Fourier series coefficients. In fact, these coefficients should be adjusted online using adaptation laws derived from the stability analysis.

V. The Proposed Controller

Taking the fractional derivative of (5) three times and using (7) results in

$$ {}_{t_0}^{C}D_t^{4\alpha} x_1(t) = f(t) + w(t) \tag{16}$$

where $f(t)$ is a complicated function of $x_1(t)$, $x_2(t)$ and $x_3(t)$ which is assumed unknown and should be estimated in the control law. In other words, based on (9), we have

$$f(t) = \theta^{*T} \xi(t) + \varepsilon(t) \tag{17}$$

$$\hat{f}(t) = \hat{\theta}^T \xi(t) \tag{18}$$

Assume that $f^* = \theta^{*T} \xi(t)$ is the best approximation of $f(t)$ using m frequencies. Since $f(t)$ is uncertain, θ^* is unknown and its estimation $\hat{\theta}$ is used. The adaptation law tries to make $\hat{\theta}$ converge to θ^*. Define the sliding surface as

$$s = ({}_{t_0}^{C}D_t^{\alpha} e + \lambda)^3 \tag{19}$$

in which

$$e = x_1(t) - x_{1d}(t) \tag{20}$$

is the tracking error, $x_{1d}(t)$ is the desired blood glucose level and λ is a design parameter. Also, (19) can be rewritten as

$$s = {}_{t_0}^{C}D_t^{3\alpha} e + 3\lambda\, {}_{t_0}^{C}D_t^{2\alpha} e + 3\lambda^2\, {}_{t_0}^{C}D_t^{\alpha} e + \lambda^3 e \tag{21}$$

Taking the fractional derivative of (21) results in

$$ {}_{t_0}^{C}D_t^{\alpha} s = {}_{t_0}^{C}D_t^{4\alpha} e + 3\lambda\, {}_{t_0}^{C}D_t^{3\alpha} e + 3\lambda^2\, {}_{t_0}^{C}D_t^{2\alpha} e + \lambda^3\, {}_{t_0}^{C}D_t^{\alpha} e \tag{22}$$

Based on (20), we can write

$$ {}_{t_0}^{C}D_t^{4\alpha} e = {}_{t_0}^{C}D_t^{4\alpha} x_1(t) - {}_{t_0}^{C}D_t^{4\alpha} x_{1d}(t) \tag{23}$$

Substitution of ${}_{t_0}^{C}D_t^{4\alpha} x_1(t)$ from (16) into (23) results in

$$ {}_{t_0}^{C}D_t^{4\alpha} e = f(t) + w(t) - {}_{t_0}^{C}D_t^{4\alpha} x_{1d}(t) \tag{24}$$

According to (24), (22) can be given by

$$\begin{aligned} {}_{t_0}^{C}D_t^{\alpha} s = {} & f(t) + w(t) - {}_{t_0}^{C}D_t^{4\alpha} x_{1d}(t) \\ & + 3\lambda\, {}_{t_0}^{C}D_t^{3\alpha} e + 3\lambda^2\, {}_{t_0}^{C}D_t^{2\alpha} e + \lambda^3\, {}_{t_0}^{C}D_t^{\alpha} e \end{aligned} \tag{25}$$

Based on the sliding mode control strategy, the control law is obtained by ${}_{t_0}^{C}D_t^{\alpha} s = 0$. As a result, it follows from (25) that

$$\begin{aligned} w(t) = {} & {}_{t_0}^{C}D_t^{4\alpha} x_{1d}(t) - f(t) \\ & -3\lambda\, {}_{t_0}^{C}D_t^{3\alpha} e - 3\lambda^2\, {}_{t_0}^{C}D_t^{2\alpha} e - \lambda^3\, {}_{t_0}^{C}D_t^{\alpha} e \end{aligned} \tag{26}$$

Since $f(t)$ is unknown, it cannot be used in the control law and its estimation as given by (18) should be used. Thus, the control law is modified as

$$\begin{aligned} w(t) = {} & {}_{t_0}^{C}D_t^{4\alpha} x_{1d}(t) - \hat{f}(t) - u_r \\ & -3\lambda\, {}_{t_0}^{C}D_t^{3\alpha} e - 3\lambda^2\, {}_{t_0}^{C}D_t^{2\alpha} e - \lambda^3\, {}_{t_0}^{C}D_t^{\alpha} e \end{aligned} \tag{27}$$

in which u_r has been considered for compensation of the truncation error of the Fourier series expansion $\varepsilon(t)$. Based on the orthogonal functions theorem that states the approximation error is bounded, we can assume that

$$|\varepsilon(t)| \le \rho \tag{28}$$

in which ρ is a known positive constant. Using Lyapunov stability theorem, the adaptation law for $\hat{\theta}$ and the robust control term u_r can be obtained as

$$ {}_{t_0}^{C}D_t^{\alpha} \hat{\theta} = \beta s \xi(t) \tag{29}$$

$$u_r = \rho\, sign(s) \tag{30}$$

in which Based on Barbalat's lemma [30], the asymptotic convergence of the tracking error can be guaranteed.

Table 1 The model parameters

Bergman minimal model	
$P_1(\min)^{-1}$	0
$P_2(\min)^{-1}$	0.0123
$P_3(\min)^{-1}$	8.2×10^{-8}
$n(\min^{-1})$	0.2659
I_b	7
G_b	70
$B_1(0)$	200

$B_3(0)$	50

Remark: To attenuate the possible problem of chattering phenomenon caused by the sign function, the proportional-integrator structure proposed in [31-33] or the modification proposed in [34] can be used.

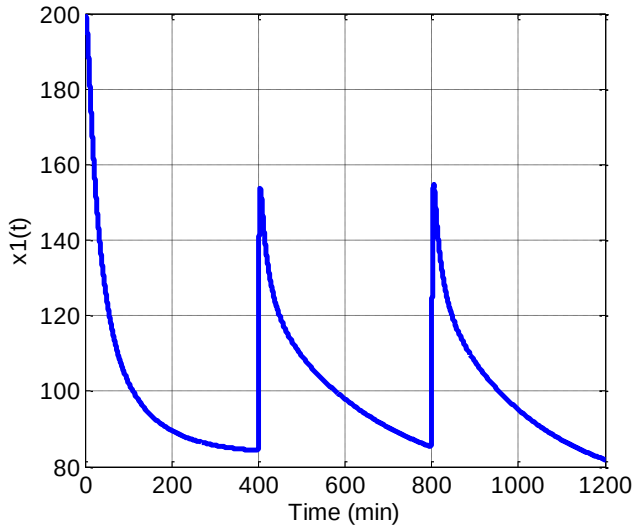

Fig.1 Glucose concentration

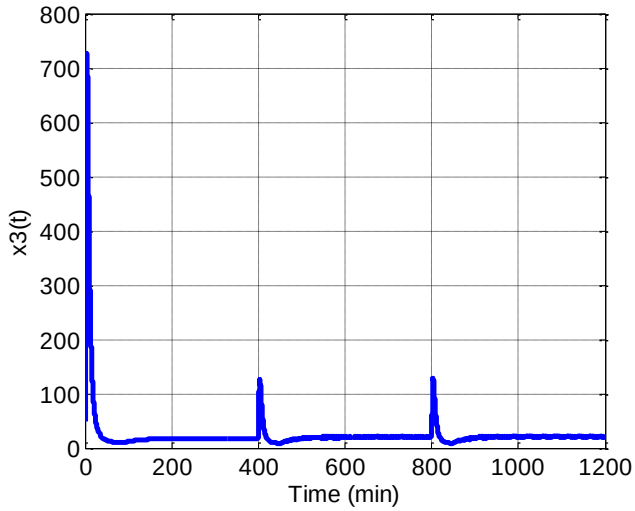

Fig. 2 Plasma insulin concentration

VI. Simulation Results

Consider the model described in [35]. Its parameters are given in Table 1. The parameter of the controller have been set to $\lambda = 0.015,\ \rho = 1,\ \beta = 0.0001, \alpha = 0.86$. The blood glucose level is presented in Fig. 1. As shown in this figure, the controller can reduce the blood glucose concentration from the initial value of 200 (mg/dl) to the approximate value of 80 (mg/dl) which is our desired level. In comparison with controller designed in [35], the proposed controller is superior. The reason is that when the external disturbance $D(t) = 80\exp(-0.5t)$ affects the control system at $t = 400,800(\min)$, the increase in the glucose level is less that of the controller designed in [35].

The Plasma insulin concentration in (mU/L) is illustrated in Fig.2. As shown in this figure, the proposed controller outperforms the controller designed in [35]. The initial increase of Plasma insulin concentration for the proposed controller is much less than that of the controller designed in [35]. The control signal $w(t)$ which is the insulin injection with pump has been presented in Fig.3.

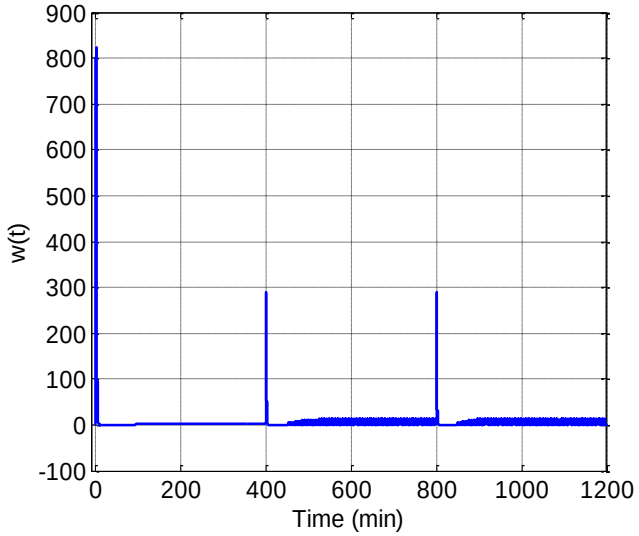

Fig. 3 Control low (insulin injection with pump)

Conclusion

In this paper, a fractional order controller for blood glucose regulation in type I diabetes patients has been presented. Uncertainties have been estimated and compensated using the Fourier series expansion which is less computational in comparison with other uncertainty estimators. The sliding mode control strategy has been adopted to make the controller robust against external disturbances. Simulation results verify the satisfactory performance of the proposed controller in comparison with a previous related work.

References

[1] R. N. Bergman, L. S. Philips, C. Cobelli, "Physiologic evaluation of factors controlling glucose tolerance in man". J. Clin. Investig. 68(6), pp. 1456–1467, 1981.

[2] C. Wai Ting, C. Quek, "A novel blood glucose regulation using TSK-FCMAC: a fuzzy CMAC based on the zero-ordered TSK fuzzy Inference scheme." IEEE Trans. Neural Netw. 20(5), pp. 856–871, 2009.

[3] P. Grant, "A new approach to diabetic control: fuzzy logic and insulin pump technology". Med. Eng. Phys. **29**(7), pp. 824–827, 2007.

[4] Z. Kang, J. Pan, W. Zhang, X. Zou, "A TS Fuzzy Model-Based Algorithm for Blood Glucose Control in Diabetic Patients". *IEEE 3rd Advanced Information Technology, Electronic and Automation Control Conference*, pp. 1110-1113, 2018.

[5] H. Heydarinejad, H. Delavari, D. Baleanu, "Fuzzy type-2 fractional Backstepping blood glucose control based on sliding mode observer". *International Journal of Dynamics and Control*, 1-14, 2018.

[6] F. Allam, Z. Nossair, H. Gomma, I. Ibrahim, M. Abdelsalam, "Evaluation of using a recurrent neural network (RNN) and a fuzzy logic controller (FLC) in closed loop system to regulate blood glucose for type-1 diabetic patients." Int. J. Intell. Syst. Appl. 4(10), pp. 58–71, 2012.

[7] C. Kosse, A. Gonzalez, D. Burdakov, "Predictive models of glucose control: roles for glucose-sensing neurones", *Acta Physiologica*, *213*(1), 7-18, 2015

[8] A. G. G. Hernandez, L. Fridman, A. Levant, Y. B. Shtessel, R. Leder, C. R. Monsalve, S. I. Andrade, "High-order sliding-mode control for blood glucose: practical relative", Control Eng. Pract. **21**(5), pp. 747–758, 2013.

[9] M. Kawashima, K. Taguchi, Y. Kitada, M. Yamauchi, T. Ikeda, K. Kajita, T. Ishizuka, "Development and validation of a scoring system for prediction of insulin requirement for optimal control of blood glucose during glucocorticoid treatments", *Diabetes research and clinical practice*, *140*, pp. 72-80, 2018.

[10] N. Tadrisi Parsa, A. R. Vali, R. Ghasemi, "Back stepping sliding mode control of blood glucose for type I diabetes", Int. J. Med. Health Biomed. Pharm. Eng. **8**(11), pp. 749–753, 2014.

[11] H. Heydarinejad, H. Delavari, H. "Adaptive fractional order sliding mode controller design for blood glucose regulation-4-3." In *Theory and Applications of Non-integer Order Systems*, pp. 449-465, 2017

[12] M. Goharimanesh, A. Lashkaripour, A. Abouei Mehrizi, "Fractional order PID controller for diabetes patients. *Journal of Computational Applied Mechanics*, *46*(1), 69-76, 2015

[13] I. N'doye, H. Voos, M. Darouach, J. G. Schneider, Static output feedback $\mathcal{H}\infty$ control for a fractional-order glucose-insulin system. *International Journal of Control, Automation and Systems*, *13*(4), 798-807, 2015.

[14] I. N'Doye, H. Voos, M. Darouach, J. G. Schneider, and N. Knauf, "An unknown input fractional-order observer design for fractional-order glucose-insulin system." In *IEEE EMBS Conference on Biomedical Engineering and Sciences (IECBES)*, pp. 595-600, 2012.

[15] I. Ndoye, H. Voos, M. Darouach, J. G. Schneider, and N. Knauf, "H∞ static output feedback control for a fractional-order glucose-insulin system". *IFAC Proceedings Volumes*, *46*(1), pp. 266-271, 2013.

[16] S. S. Majidabad, H. T. Shandiz, A. Hajizadeh, "Nonlinear fractional-order power system stabilizer for multi-machine power systems based on sliding mode technique". *International Journal of Robust and Nonlinear Control*, *25*(10), pp. 1548-1568, 2015

[17] L. X. Wang, *A Course in Fuzzy Systems and Control*. Englewood Cliffs, NJ: Prentice-Hall, Aug. 1996.

[18] Gupta, M., Jin, L., & Homma, N., Static and dynamic neural networks: from fundamentals to advanced theory. John Wiley & Sons, 2004.

[19] E. Kreyszig, Advanced Engineering Mathematics, John Wiley & Sons, 2007

[20] S. Khorashadizadeh, and M. M. Fateh, Uncertainty estimation in robust tracking control of robot manipulators using the Fourier series expansion. Robotica, 35(2), 310-336, 2017.

[21] M.C. Chien and A. C. Huang, Adaptive Impedance Control of Robot Manipulators based on Function Approximation Technique. Robotica22: 395-403, 2004.

[22] Y. F. Chen and A. C. Huang, Controller design for a class of underactuated mechanical systems. IET Control Theory & Applications 6: 103-110, 2012.

[23] M. C. Chien and A. C. Huang, Adaptive impedance controller design for flexible-joint electrically-driven robots without computation of the regressor matrix. Robotica 30: 133-144, 2012.

[24] M. A. Duarte-Mermoud, N. Aguils-Camacho, J. A. Gallegos, and R. Castro-Linares, "Using general quadratic Lyapunov functions to prove Lyapunov uniform stability for fractional order systems". Commun Nonlinear Sci Numer Simulat 22, pp. 650-659, 2015.

[25] J. A. Gallegos, and M. A. Duarte-Mermoud, "Convergence of fractional adaptive systems using gradient approach", ISA Transactions pp. 69: 31-42, 2017.

[26] N. Aguils-Camacho, M. A. Duarte-Mermoud, and J. A. Gallegos, "Lyapunov functions for fractional order systems". Commun Nonlinear Sci Numer Simulat 19, pp. 2951-2957, 2014.

[27] N. P. Balakrishnan, G. P. Rangaiah, L. Samavedham, "Review and analysis of blood glucose (BG) models for type 1 diabetic patients". Ind. Eng. Chem. Res. **50**(21), pp. 12041–12066, 2011.

[28] M. E. Fisher, "A semi closed-loop algorithm for the control of blood glucose levels in diabetics". IEEE Trans. BioMed. Eng. **38**(1), pp. 57–61, 1991

[29] Erwin Kreyszig, *Advanced Engineering Mathematics*, John Wiley & Sons, 2007.

[30] J. J. Slotine and W. Li, *Applied Nonlinear Control*. Englewood Cliffs, NJ: Prentice-Hall, 1991.

[31] M. B. Fard and S. Khorashadizadeh, Model free robust impedance control of robot manipulators using fourier series expansion. In *AI & Robotics (IRANOPEN), 2015* (pp. 1-7).

[32] S. Khorashadizadeh, M. M. Fateh, "Adaptive fourier series-based control of electrically driven robot manipulators". In *2013 3rd International Conference on Control, Instrumentation, and Automation (ICCIA)*, pp. 213-218, 2013.

[33] R. Shahnazi, H. M. Shanechi, and N. Pariz, "Position control of induction and DC servomotors: a novel adaptive fuzzy PI sliding mode control". *IEEE Transactions on Energy Conversion*, *23*(1), pp. 138-147, 2008.

[34] S. Khorashadizadeh, and M. M. Fateh, "Robust task-space control of robot manipulators using Legendre polynomials for uncertainty estimation". *Nonlinear Dynamics*, *79*(2), pp. 1151-1161, 2015.

[35] H. Heydarinejad, H. Delavari, H. "Fractional order back stepping sliding mode control for blood glucose regulation in type I diabetes patients." In *Theory and Applications of Non-integer Order Systems*, pp. 187-202, 2017.