



Using Sliding Mode Controller and Eligibility Traces for Controlling the Blood Glucose in Diabetic Patients at the Presence of Fault

A. Noori^{*a}, M. A. Sadrnia^a, M. B. Naghibi Sistani^b

^a Faculty of Electrical and Robotics Engineering, Shahrood University of Technology, Shahrood, Iran

^b Department of Electrical Engineering, Faculty of Engineering, Ferdowsi University of Mashhad, Mashhad, Iran

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ABSTRACT

Some people suffering from diabetes use insulin injection pumps to control the blood glucose level. Sometimes, the fault may occur in the sensor or actuator of these pumps. The main objective of this paper is controlling the blood glucose level at the desired level and fault-tolerant control of these injection pumps. To this end, the eligibility traces algorithm is combined with the sliding mode control. The eligibility traces algorithm is one of the newest solving methods of the Reinforcement Learning approach. The major disadvantage of the sliding mode control method is the chattering phenomenon. In this paper, the novel idea is the combination of these methods to remove the chattering phenomena in simulation results. To demonstrate the superiority of the proposed method, it is compared with another combinatory method that is the sliding mode control and Artificial Neural Networks. Simulation results reveal that the combination of the eligibility traces algorithm and the sliding mode control can control the blood glucose level and insulin with a higher speed and bring them to the desired level, even in the case the sensor and actuator faults are present in the system. When the proposed hybrid method is used, the injected dosage of the drug is lower, which will result in reduced side effects. Finally, the noise, as well as the uncertainty in system parameters and initial conditions are applied to the system to investigate the performance of the proposed controller, under the faulty condition.

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1. INTRODUCTION

Nowadays, diabetes is spreading widely all around the world as an epidemic illness. It is mainly caused by decreasing levels of activity and increasing prevalence of obesity^{1,2}. Two common types of diabetes include type 1 diabetes (due to the diminished production of insulin) and type 2 diabetes (diminished response by the body to insulin). The human's body requires to maintain the glucose concentration level within the 70-110 mg/dl range. In the case the glucose concentration level of a person exceeds this range, then this person has the plasma glucose problem [1].

There are two general methods to control diabetes. In the first method, the diabetic patient controls his/her

disease through injecting insulin or using pills based on a certain schedule. In the second method, diabetic patients use insulin injection pumps. One type of these devices can make an intelligent detection of the glucose level, but the insulin is injected by the patient. In another type, the insulin level is detected and the device intelligently injects the insulin to the diabetic patient. Such devices may have sensor or actuator faults. The main objective of the paper is controlling the blood glucose level while controlling faults that are applied to the system.

Nowadays, intelligent methods are taken into account as significant tasks for controlling the blood glucose level in diabetic patients. Moreover, quickness in controlling the glucose level while injecting the minimum dosage of the drug will result in mitigating the side effects. In relation to the blood glucose control

*Corresponding Author Email: amin_noori@ieee.org (A. Noori)

¹ <http://www.idf.org/home/index.cfm>

using intelligent methods, the following papers can be mentioned:

The Q-learning algorithm is used to regulate the glucose level in type-1 diabetic patients. Through exploration in the environment, the agent will learn to select the best action, which is the optimal dosage on insulin [2-6]. Fuzzy Logic controller is used to regulating glucose concentration in type-1 diabetic patients. Membership functions are defined based on the glucose concentration, insulin concentration, time and speed of the glucose concentration reduction [7, 8].

Data mining and machine learning methods are adopted for adjusting the glucose concentration in diabetic patients [9]. It is demonstrated that among the proposed methods, SVM has higher accuracy. Neural Networks are utilized to control glucose concentration in Diabetes type 2 patients [10]. The work done authors in [11], is the other example in which the cancer is controlled by using novel medical methods.

As said before, in one type of insulin pump, the blood glucose level is measured and the insulin dosage is injected in a smart manner. The basic problem with such devices is that they may have faults. In other words, the sensor device may show a false value for the blood glucose level or the injection pump may inject a high/low dosage of insulin to the diabetic patient. This may be dangerous/seriously problematic for the patient and may lead to his death. Hence, Medical systems are very sensitive. As a result, their correct performance has a specific importance. Fault occurrence in such systems will cause irreparable physical harm. Hence, quick, exact and on-time fault detection in medical systems has attracted considerable attention in recent years. The following investigations and works can be mentioned about the fault detection and control in various systems: On fault detection, the following works can be stated.

Skach et al. [12], have utilized the RL method for fault detection and isolation in a system with the uncertainty. Yih et al. [13] have combined the RL and Fuzzy Logic to detect system faults. Qiming et al. [14] used the eligibility traces algorithm to detect and isolate sensor and actuator faults of the considered system. Fuzzy Logic Control and adaptive thresholding are employed for fault detection and isolation purpose in [15-17].

Using the Q-learning algorithm, Jingang et al. [18] detected the system faults with high accuracy.

Following works have focused on the fault-tolerant control in the diabetic system: Mahmoudi et al. [19] used the Kalman Filter for the state estimation and FDI purpose. A Bayesian algorithm is utilized to detect faults in a blood glucose control system [20]. Here, online fault detection is carried out and the PCA approach is used to extract the features [21].

The following papers and investigations can be mentioned for the fault detection and control: In [22],

Temporal Difference (TD) method in the RL framework is adopted for the fault control in nonlinear systems. For designing the observer and estimating states, an Extended Kalman filter is used. Fault detection and control in nonlinear systems is investigated. To this aim, RL and NNs are used [23]. For more effective tracking and controlling of the linear system against the fault, residual calculation method and its combination with H_∞ are used. In the RL part, Q-learning algorithm is used for the optimal tracking purpose [24]. By assuming there is no information about the occurred fault in the system, the RL method is utilized to detect and control the unknown fault [25]. Fault detection and control in nonlinear continuous systems are investigated in [26]. Moreover, for analyzing the system stability, the Lyapunov theory is employed. Fault detection and control are carried out in multivariable discrete-time systems by using the RL method. The system controlling procedure is performed as output-tracking and error-tracking [27]. An advanced algorithm, named Auto-step algorithm in the RL method is used in [28]. In this work, it is shown that the proposed approach, which uses the RL method and Auto-step algorithm, has higher accuracy in fault detection and isolation and has a faster convergence. Fault detection and control in submarines are performed, by using the multi-objective RL [29]. Artificial Neural Networks (ANNs) and online fault detection and monitoring analysis technique are used [30]. A rule-based classifier ensemble is used to identify and avoid bearings failure. In this regard, GA is employed to reduce the number of extracted features [31]. The combinatory of Reinforcement Learning and PSO is employed to design a PID controller for an Automatic Voltage Regulator system control [32]. The impact of the number of faults and the fault location in a power system are investigated. The objective is to achieve the maximum reduction in the short circuit current level in all buses. GA is used to perform optimization computations, to undermine the effect of the fault [33].

In this paper, the main purpose is to control the level of blood glucose. Besides, the authors have focused on the case that the fault is occurring in the sensor or actuator of the studied system. It is revealed that the proposed method can detect the fault and keep the blood glucose and insulin levels within acceptable ranges. To meet our objectives, a hybrid method is used, i.e. the eligibility traces algorithm and the sliding mode control. In previous works, the eligibility traces algorithm has not been used for the fault control purpose. This method is one of the most efficient methods for solving methods in the Reinforcement Learning approach. There is a backward view to update the value of the state-action pair. The backward view means that the value of the state-action pair at the next time step and total value of the state-action pair at previous time steps are both

involved in updating the state-action pair at each time step. This will speed up the learning procedure and decrease the time required to reach the optimal policy. The sliding mode control is one of the classic control methods. The main issue with this classic method is the chattering phenomena. In this paper, the novel idea is combining two mentioned methods to remove the chattering in simulation results. Moreover, a hybrid method, i.e. the sliding mode control and ANNs, is used to make a comparison and demonstrate the preferable performance of the proposed method. Simulation results reveal that the eligibility traces algorithm in combination with the sliding mode control can control the blood glucose and insulin levels with a high speed, in the presence of sensor and actuator faults in the studied system. In this case, the injected dosage is lower. This indicates the reduced side effects. Finally, the performance of the proposed controller is investigated for the case the noise and uncertainty in system parameters and initial conditions are applied to the studied system.

The rest of the paper is organized as follows. In section 2, the mathematical model used in the paper and the constant coefficients are described. Sliding mode control, which is one of the controlling methods of nonlinear systems is expressed. Also, the Lyapunov function is defined and a brief description is represented about the stability proof using this theory. In section 3, the adopted method (eligibility traces algorithm) for controlling and regulating the glucose concentration are discussed. In section 4, the control strategy in the case of fault occurrence for eligibility traces methods are stated. In section 5, represented concepts and fundamentals are used and glucose concentration control in diabetic patients is stated. Finally, to investigate the proposed control strategy, different simulations are performed in MATLAB Software.

2. MATHEMATICAL MODEL

There are various mathematical models to describe the dynamics of a diabetic patient [34-43]. The mathematical model used in this paper was introduced by Sandhya and Deepka Kumar [44]. They described the dynamics of a diabetic patient with three nonlinear differential equations. These equations are stated as Equations (1)-(3)

$$\frac{dG}{dt} = -m_1G + m_2I + m_1G_b \quad (1)$$

$$\frac{dX}{dt} = -m_2X + m_3I - m_3I_b + m_6I_b \quad (2)$$

$$\frac{dI}{dt} = -m_3I + m_4G + m_4m_5 - m_6I + m_6I_b \quad (3)$$

The third-order model is comprised of a glucose compartment, G , the generalized insulin variable for the remote compartment, X , and the insulin compartment, I . The generalized insulin variable for the remote compartment mediates glucose uptake within the glucose space to the peripheral and hepatic tissues. This model includes basal values i.e. G_b and I_b , which is the advantage of this model. In Equation (3), the variable u is the injected dosage of the drug to control the glucose concentration. Constant values of the system are given in Table 1.

3. REINFORCEMENT LEARNING

In solving a problem using the RL method, two elements have key roles. These elements are the agent and environment. At each time step, the agent receives new information through the trial and error in the environment and updates its experiences. This method is neither a supervised and nor an unsupervised learning method. The best action is not dictated to the agent. The agent itself learns to select the best action at each moment such that the optimal policy can be obtained. This is performed through the trial and error in the environment and receiving rewards and penalties in a high number of iterations. In addition to the agent and environment, the RL method has three additional

TABLE 1. System constant values [44]

Parameter	Description	Value
G_b	This is the basal preinjection value of plasma glucose (mg/dl)	80
I_b	This is the basal preinjection value of plasma insulin (μ U/ml)	7
m_1	Insulin independent rate constant of glucose rate uptake in muscles, liver and adipose tissue (min^{-1})	0.0317000
m_2	The rate of decrease in tissue glucose uptake ability (min^{-1})	0.0123
m_3	The insulin-independent increase in glucose uptake ability in tissue per unit of insulin concentration I_b (min^{-2} (μ U/ml))	4.92×10^{-6}
m_4	The rate of the pancreatic β -cells' release of insulin after the glucose injection and with glucose concentration above h [$(\mu$ U/ml) min^{-2} (mg/dl)-1]	0.0039
m_5	The threshold value of glucose above which the pancreatic β -cells release insulin	79.0353
m_6	The first order decay rate for insulin in plasma (min^{-1}) pancreatic β -cells release insulin	0.2659

components, including the action, reward, and state [45]. At each moment, the agent receives the state of the environment (s_t), takes the action a_t , transits to the next state (s_{t+1}) and receives the immediate reward (r_{t+1}) [45]. Figure 1, depicts a chain including states and actions.

Equation (4), represents an estimation of the value function, under the policy π , (denoted by V^π) [46]

$$V^\pi(s) = E_\pi\{\sum_{k=0}^{\infty} \gamma^k r_{t+k+1} | s_t = s\} \tag{4}$$

where γ is the discount factor, within [0,1] range. k denotes the time step. In this relation, the value of each state under the policy π is based on calculating the expected value of sum of the forgetting factor multiplied by the received rewards from the current moment (s_t) to the end of the episode. Based on the Equation (4), the impact of rewards received by the agent in the current state (s_t), at each time step will be multiplied by γ^k . Equation (5) describes this definition for the value of a state-action pair at each time step [45].

$$Q^\pi(s, a) = E_\pi\{R_t | s_t = s, a_t = a\} = E_\pi\{\sum_{k=0}^{\infty} \gamma^k r_{t+k+1} | s_t = s, a_t = a\} \tag{5}$$

3. 1. Eligibility Traces

The eligibility traces algorithm is an interaction between Monte-Carlo (MC) and Temporal Difference (TD) learning methods. In the MC method, the agent goes to the end of the episode and updates the value of all state-action pairs. In the TD method, at each time step, the value of the state-action pair is updated. In the eligibility traces algorithm, updating the value of state-action pairs is performed after some steps. In addition to the forward view, at each state (s_t), there is a backward view, as well. The backward view causes the minimum error in the optimal drug dosage [45]. The eligibility at each state is obtained according to Equation (6).

$$e_t(s, a) = e_t(s, a) + \delta \tag{6}$$

Policy update (δ) is calculated as Equation (7) [45].

$$\delta = r + \gamma Q(s_{t+1}, a_{t+1}) - Q(s, a) \tag{7}$$

where r is the received immediate reward and $Q(s_{t+1}, a_{t+1})$ is the value of the state-action pair at the next time step ($t+1$). For updating the value of the state-action pair, Equation (8) is used [45].

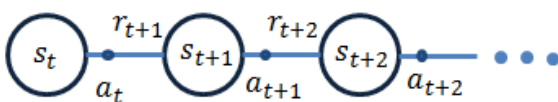


Figure 1. States and actions chain

$$Q(s, a) = Q(s, a) + \alpha \delta e(s, a) \tag{8}$$

where α is the learning rate. The eligibility update is calculated as Equation (9) [45].

$$e_t(s, a) = \gamma \lambda \times e_t(s, a) \tag{9}$$

where λ determines how many steps later, the value of the state-action pair should be updated. It has a constant value within [0,1] range. Assuming that the agent is at state (s_t); according to this relation, updating the eligibility for previous states and the current state is multiplied by $\gamma \lambda$ [45].

In this paper, the sliding mode control is utilized to control the glucose concentration in a diabetic patient. First, it is required to express this concept. Sliding mode control is a simple method to control nonlinear systems. This approach is robust enough to control the system against the noise and disturbance. In designing the controller using the sliding mode control, a sliding surface is defined and states of the system should converge to this surface.

Here, nondeterministic nonlinear systems are introduced. By nondeterministic systems, we mean systems which contain noise and disturbance [47].

4. PROPOSED CONTROL STRATEGY UNDER FAULTY CONDITIONS

In this section, The structure of the fault-tolerant control is represented in a diabetic patient model. It is assumed that the system is affected by the sensor and actuator faults. Additionally, the internal disturbances and noise have impact on system performance.

The eligibility traces is one of the RL methods, which is used in this paper for controlling the glucose concentration in diabetic patients.

Figure 2, depicts the glucose controlling method using the eligibility traces algorithm. In this method, NNs are used for estimating system states. All equations in this paper are considered based on [23]. In Figure 2, u^R is the selected action by the eligibility traces algorithm in the RL problem. The proper selection of u^R will be effective for determining the optimal dosage in the blood glucose concentration control.

The action selection is performed in random, through the e-greedy policy, which is calculated as Equation (10) [45].

$$a_t = \begin{cases} a_t^* & \text{with probability } 1 - \varepsilon \\ \text{random action} & \text{with probability } \varepsilon \end{cases} \tag{10}$$

According to Equation (10), the best action (a_t^*) is selected with $1-\varepsilon$ probability and the rest are selected with equal probabilities.

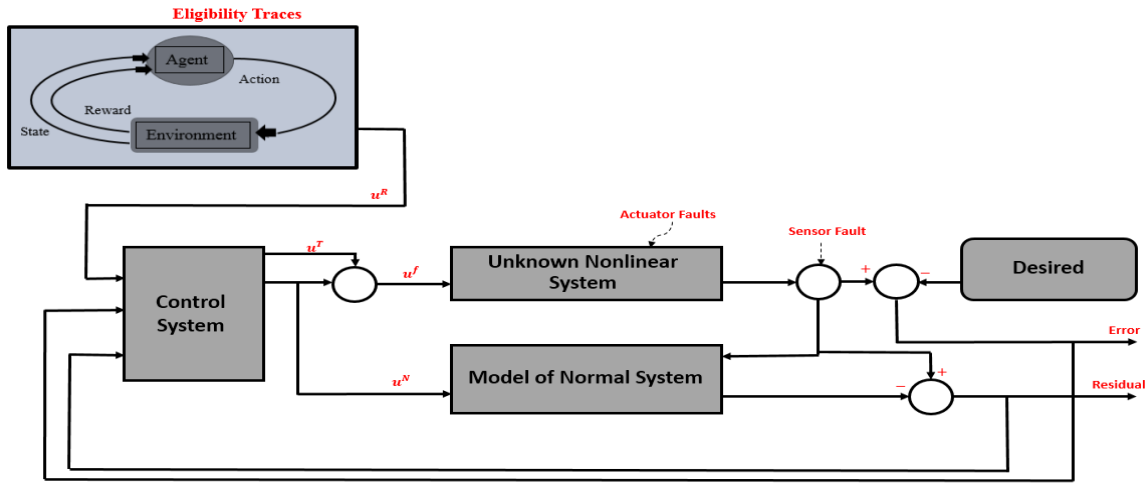


Figure 2. Glucose concentration control using the eligibility traces algorithm, under the faulty condition

5. IMPLEMENTATION OF THE PROPOSED STRATEGY FOR BLOOD GLUCOSE LEVEL USING THE ELIGIBILITY TRACES ALGORITHM

In this section, the implementation of the proposed control structure for controlling the blood glucose level in diabetic patients is described in detail.

For the stated system in this paper, the sliding surfaces will be as Equations (11) and (12).

$$s^N = \begin{pmatrix} 2 \\ 0 \end{pmatrix} e_3^N + \begin{pmatrix} 2 \\ 1 \end{pmatrix} \lambda_c^1 e_2^N + \begin{pmatrix} 2 \\ 2 \end{pmatrix} \lambda_c^2 e_1^N \quad (11)$$

$$s^R = \begin{pmatrix} 2 \\ 0 \end{pmatrix} Re_3 + \begin{pmatrix} 2 \\ 1 \end{pmatrix} \lambda_c^1 Re_2 + \begin{pmatrix} 2 \\ 2 \end{pmatrix} \lambda_c^2 Re_1 \quad (12)$$

The control input u^N used in the system in this paper is stated as Equation (13)

$$u^N = \eta_N sgn(s^N) - \begin{pmatrix} 2 \\ 0 \end{pmatrix} (\hat{f}_N(\hat{X}^N) - x_d^{(n)}) - \begin{pmatrix} 2 \\ 1 \end{pmatrix} \lambda_c^1 e_3^N - \begin{pmatrix} 2 \\ 2 \end{pmatrix} \lambda_c^2 e_2^N \quad (13)$$

Equation (14) is used to calculate the injected dosage of the drug [23].

$$u^f = u^N + u^T \quad (14)$$

where u^T is the tolerant control input and can be calculated as Equation (15)

$$u^T = \eta_R sgn(s^R) - \begin{pmatrix} 2 \\ 0 \end{pmatrix} (\hat{f}_f(\hat{X}^N) - \hat{f}_N(\hat{X}^N)) - \begin{pmatrix} 2 \\ 1 \end{pmatrix} \lambda_c^1 Re_3 - \begin{pmatrix} 2 \\ 2 \end{pmatrix} \lambda_c^2 Re_2 \quad (15)$$

Considered states are two dimensional, including blood glucose and insulin. The reward function is defined as Equation (16) [23].

$$r(t) = -\lambda_R (s^R \dot{s}^R) \quad (16)$$

where λ_R is a constant positive parameter. \dot{s}^R is the differential of s^R and can be calculated as Equation (17). According to Equation (16), when the term $s^R \dot{s}^R$ is positive, the energy of the system will increase and the stability will be decreased. As a consequence, the reward will be negative. Otherwise, the stability will be increased and the reward will be positive.

$$\dot{s}^R = \begin{pmatrix} 2 \\ 0 \end{pmatrix} (f(x^f) - f(x^N)) + \begin{pmatrix} 2 \\ 0 \end{pmatrix} (F_a + F_s^{(n)} + d + u^f + u^N) + \begin{pmatrix} 2 \\ 1 \end{pmatrix} \lambda^1 Re_3 + \begin{pmatrix} 2 \\ 2 \end{pmatrix} \lambda^2 Re_2 \quad (17)$$

The control input u^T is calculated based on the selected action by the agent, represented by Equation (18) [23].

$$u^T = -u^R - (\eta_R sgn(s^R)) \quad (18)$$

where η_R is a constant positive value. u^R is the action selected by the agent. The blood glucose concentration control using the eligibility traces algorithm is given in Figure 3. The flowchart shown in Figure 3 relates to the algorithm learning process. As can be seen, the algorithm is trained with the specified steps. Then, for the practical application of the algorithm, the obtained Q table can be employed for unlimited steps. Noteworthy, simulation results are related to the learning process of the algorithm. As shown, the blood glucose level is controlled and has reached the desired value, even in the presence of the fault.

6. SIMULATION

In this paper, the proposed method is compared with the proposed method of [23] in that article a combinatory method of sliding mode and ANN is used [48]. A Radial Basis Function Network (RBFN) is used as an observer of a faulty system. The block diagram related to the

glucose concentration control using NNs is shown in Figure 4.

According to Figure 4, the control input u^f is the drug dosage injected into the patient's body to regulate the blood glucose level. In each iteration, this dosage is determined such that in the presence of the sensor or actuator fault, the blood glucose concentration can be controlled and maintained at the desired value.

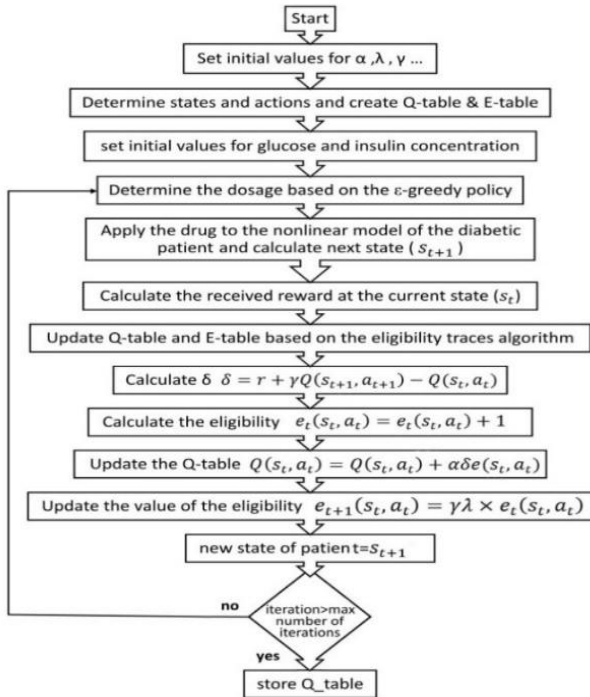


Figure 3. Glucose concentration control using the eligibility traces algorithm

Simulations are carried out by using MATLAB Software. Initial conditions considered for diabetic patients are: $I_0 = 25$, $X_0 = 10$ and $G_0 = 250$ [45]. Desired values of parameters (which should be reached) are 85 for the glucose, 18 for the generalized insulin and 50 for the insulin. Faults applied to the system actuator and sensor are demonstrated in Figures 5 and 6, respectively.

Figure 7, depicts the blood glucose concentration control in a diabetic patient in the presence of sensor and actuator faults. It should be noted that in all subsequent figures the RFTC expresses the combination of the RL method (Eligibility Traces) and the sliding mode control for fault- tolerant control and NFTC expresses the combination of the neural network and the sliding mode control.

As can be seen in Figure 7, both methods can control and sustain the blood glucose concentration at the desired level. But, the RFTC method can control the blood glucose at a higher speed and bring it to the desired value. Figure 8, depicts the insulin concentration for controlling the blood glucose concentration by using both methods.

According to Figure 8, the deviation from the desired value of insulin in the RFTC method is lower than the NFTC method. However, in those cases that the insulin value is less than the desired one, the selected method can control and bring it to the desired value. The injected dosage of the drug for controlling the blood glucose level by using both methods can be observed in Figure 9.

As shown in Figure. 9, the injected dosage of the drug by using the RFTC method is lower compared to the case using NN and sliding mode control. The total injected dosage of the drug determined by using both methods is given in Table 2.

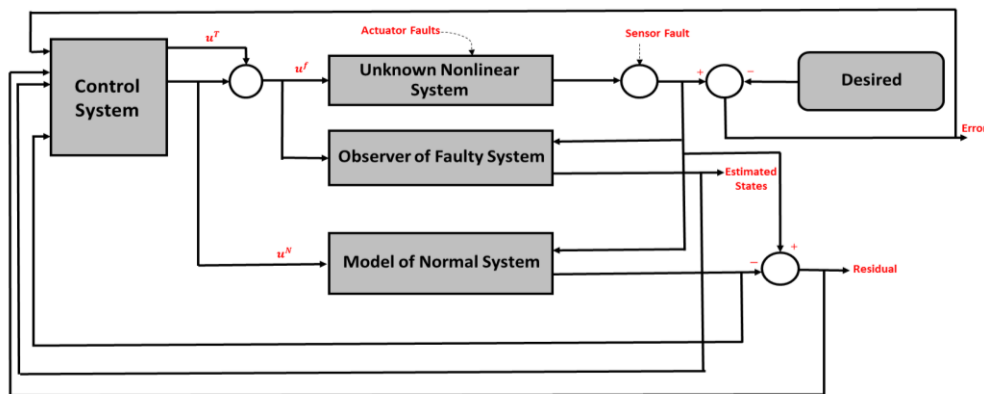


Figure 4. Glucose concentration control using NNs, under faulty condition.

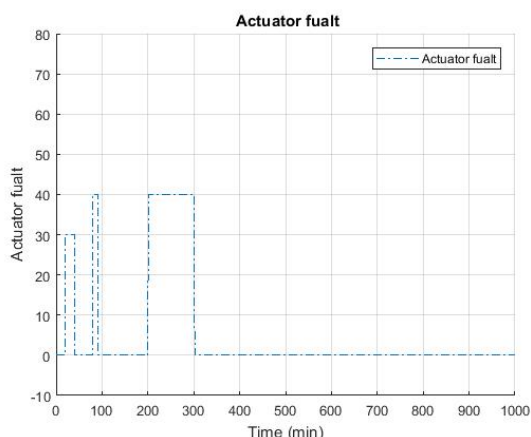


Figure 5. Fault applied to the system actuator

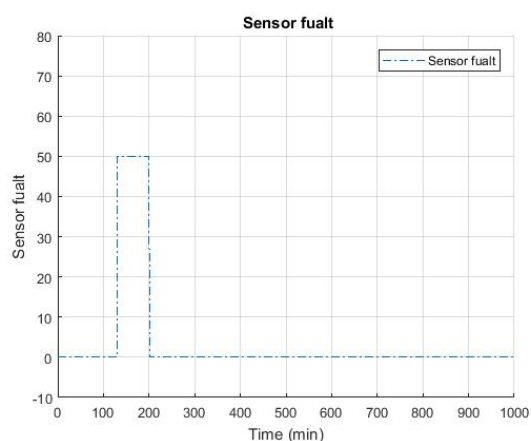


Figure 6. Fault applied to the system sensor

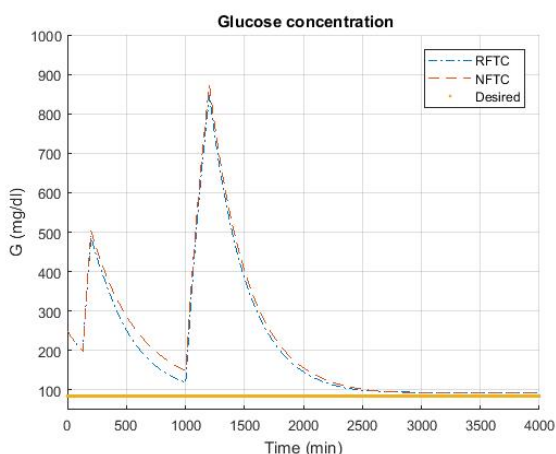


Figure 7. Blood glucose concentration in a diabetic patient in the presence of both sensor and actuator faults

6. 1. Uncertainties in System Parameters and Initial Conditions

In this section, the blood glucose control is investigated by using both previously mentioned methods, for four diabetic patients. First,

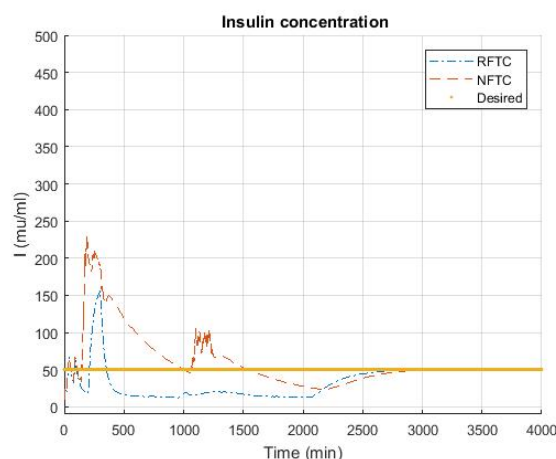


Figure 8. Insulin concentration in a diabetic patient in the presence of sensor and actuator faults

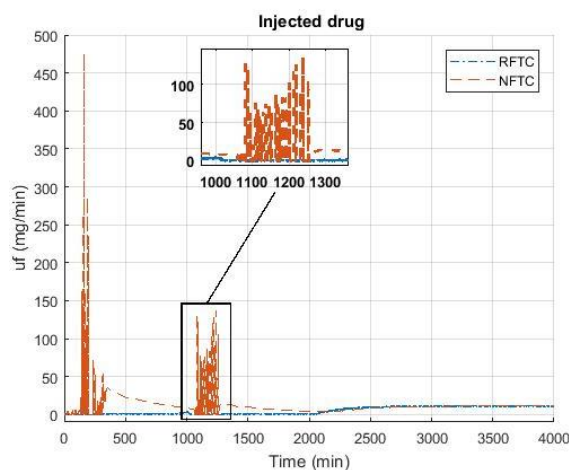


Figure 9. Injected dosage of the drug for a diabetic patient using RFTC and NFTC methods.

TABLE 2. Total injected dosage (u^f) determined by using RFTC and NFTC.

Employed Method	Total Injected Dosage of Drug
RFTC	3.1432×10^4
NFTC	5.8819×10^4

considering uncertainties in system parameters and initial conditions, the insulin and glucose concentrations will be calculated for four other patients. To this aim, 5% of changes in initial conditions and the constant coefficients of the main patient are taken into account. Blood glucose changes for four patients in the presence of faults, using RFTC and NFTC methods are shown in Figure 10. Figure 11 shows the blood insulin concentration in these four diabetic patients. As can be

seen in Figure 10, the eligibility traces algorithm and sliding mode controller can control and bring the

glucose concentration to the desired value faster than the other method. According to Figure 11, the insulin

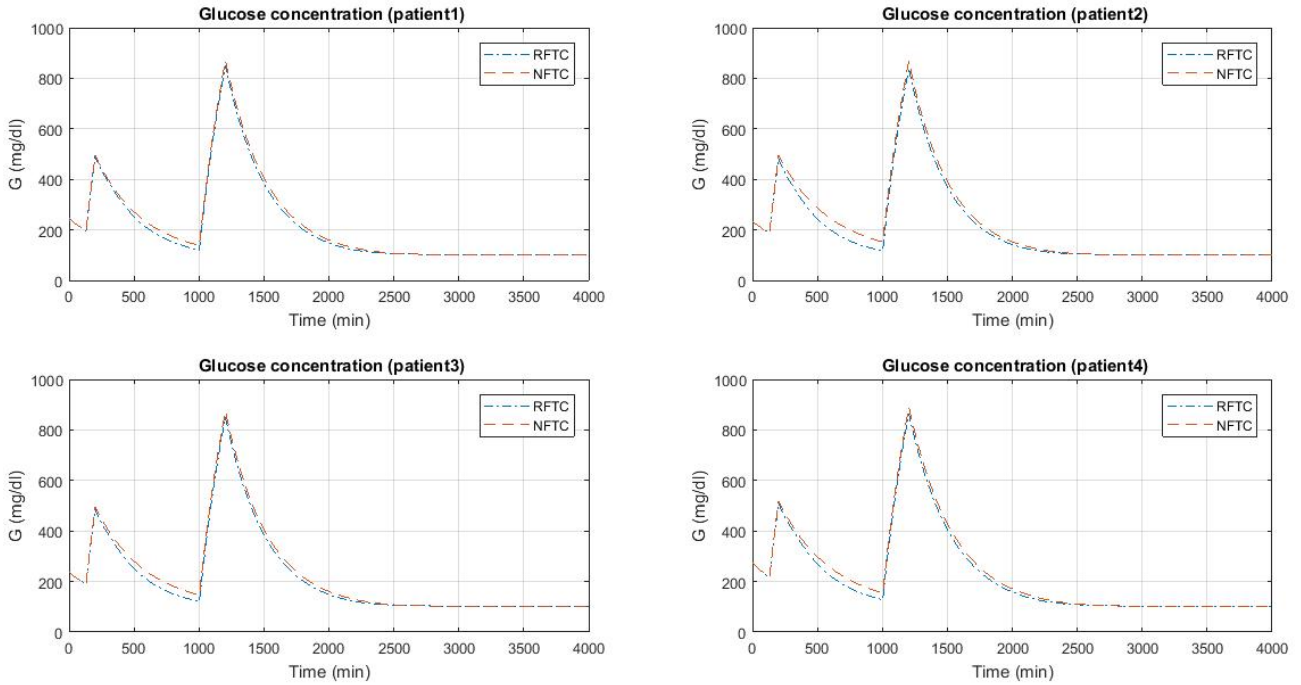


Figure 10. Blood glucose in four diabetic patients using the RFTC and NFTC methods

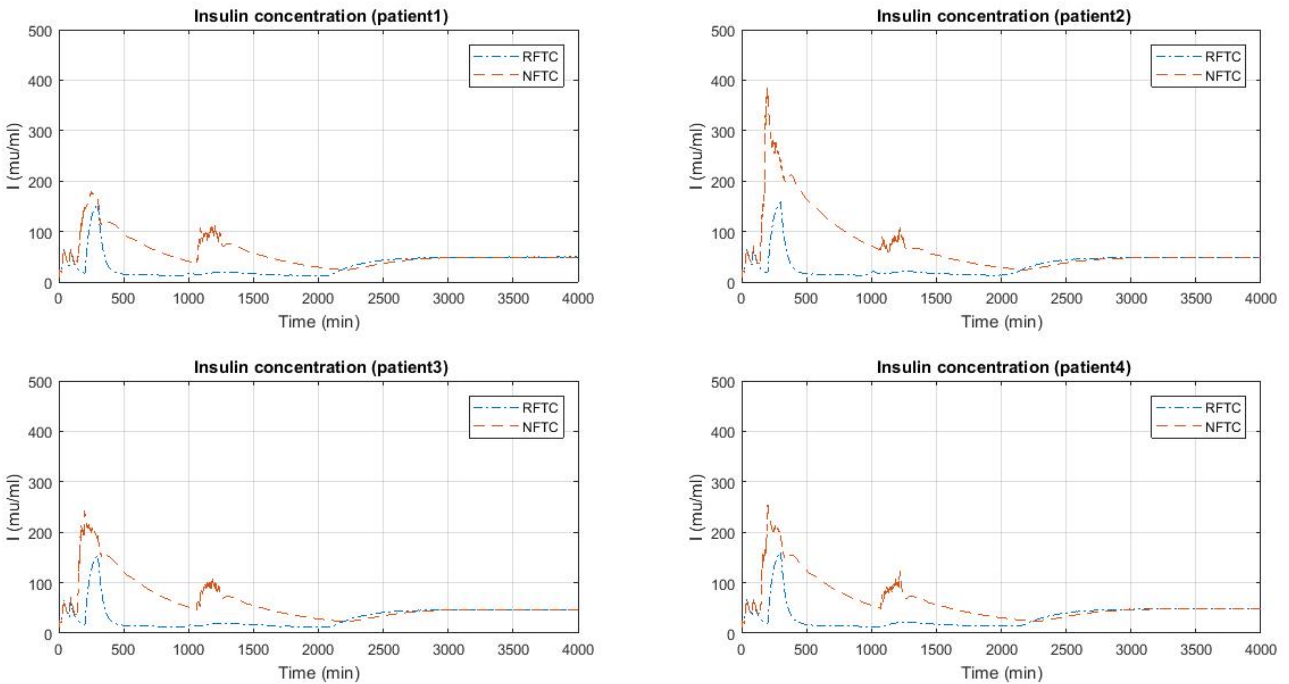


Figure 11. Blood insulin level in four diabetic patients using the RFTC and NFTC methods

concentration in four diabetic patients using the eligibility traces algorithm and sliding mode controller (RFTC) is less than the case that the neural network and sliding mode controller (NFTC) is used. Although in some cases the insulin concentration is less than the desired one, both methods are capable of controlling and bringing the blood insulin concentration to the desired value.

6. 2. Applying Noise to the System under the Parametric and Initial Condition Uncertainties

Since conditions of the environment are continuously changing, the behavior of the system should be investigated by applying the noise. Under this condition, random white noise is added to system equations and the new relations will be as Equations. (19)-(21)

$$\frac{dG}{dt} = -m_1G + m_2I + m_3G_b + w_1 \quad (19)$$

$$\frac{dC}{dt} = -m_2X + m_3I - m_3I_b + m_6I_b \quad (20)$$

$$\frac{dI}{dt} = -m_3I + m_4G + m_4m_5 - m_6I + m_6I_b + w_2 \quad (21)$$

where the noise is only applied to state variables in the RL. The blood glucose concentration in the presence of the fault and applied noise for patient 1 is demonstrated in Figure 12. Figure 13, shows insulin changes in this patient.

As can be observed in Figure 12, both methods can control the blood glucose and the desired level can be reached in case the noise is applied to the system. But the overall performance of the RFTC method is better.

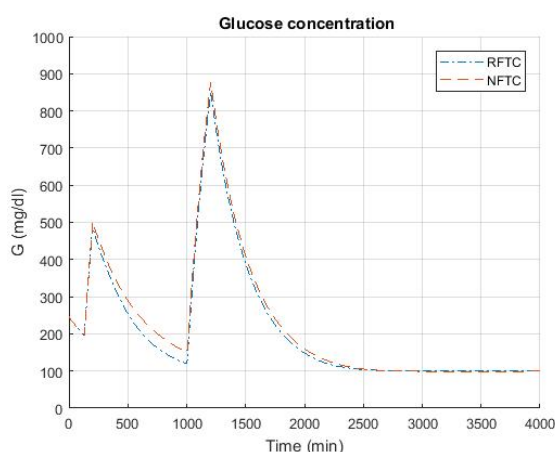


Figure 12. Blood glucose in the presence of noise and fault for a diabetic patient using the RFTC and NFTC methods

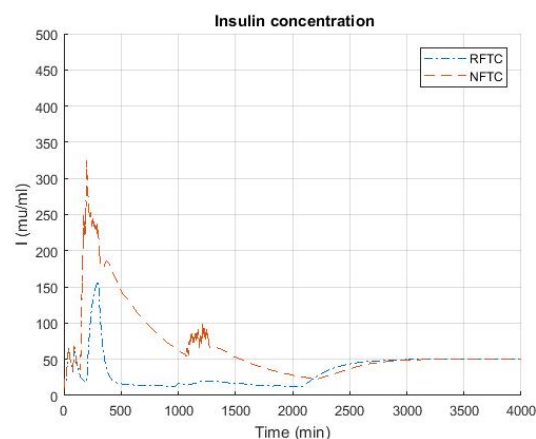


Figure 13. Blood insulin in the presence of noise and fault for a diabetic patient using RFTC and NFTC methods

7. CONCLUSION

In this paper, two hybrid intelligent methods are used for controlling the blood glucose concentration in diabetic patients under the condition that the system is affected by faults.

Some patients with diabetes use insulin injection pump to inject insulin. Fault occurrence in such devices may result in serious problems. As a consequence, fault detection in these devices is significantly important and crucial. In this paper, the sliding mode control is combined with the eligibility traces algorithm to control the blood glucose level, in the case the sensor and actuator faults are present in the system. As far as the knowledge of the authors, the proposed method has not been used for the fault control in the diabetic system. The proposed method can enhance the learning speed and eliminate the chattering phenomena, resulted from the sliding mode control. The reward function is defined based on the Lyapunov function, which guarantees the system stability.

To demonstrate the superior performance of the proposed method, it is compared with another hybrid method, i.e. the sliding mode control and the artificial neural networks. simulation results indicate that the proposed hybrid method can speed up the blood glucose level control, while injecting a lower dosage, in the case the fault is present in the system. Reduced dosage injection implies mitigated side effects associated with the considered drug. Even in the case, the uncertainty in initial conditions and noise in system parameters are applied, both selected methods can control the level of the blood glucose and insulin while bringing them to the preferred value.

8. REFERENCES

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Using Sliding Mode Controller and Eligibility Traces for Controlling the Blood Glucose in Diabetic Patients at the Presence of Fault

A. Noori^a, M. A. Sadrnia^a, M. B. Naghibi Sistani^b

^a Faculty of Electrical and Robotics Engineering, Shahrood University of Technology, Shahrood, Iran

^b Department of Electrical Engineering, Faculty of Engineering, Ferdowsi University of Mashhad, Mashhad, Iran

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بسیاری از افراد مبتلا به دیابت برای کنترل میزان گلوکز خون از پمپ‌های تزریق انسولین استفاده می‌کنند. این پمپ‌ها ممکن است دچار عیب در حسگر و یا عملگرشان شوند. هدف اصلی در این مقاله علاوه بر کنترل میزان گلوکز روی مقدار مطلوب، رفع عیوب وارد شده به پمپ‌های تزریق نیز می‌باشد. برای رسیدن به این هدف، از ترکیب روش مسیره‌های شایستگی و کنترلر مد لغزشی استفاده شده است. روش مسیره‌های شایستگی یکی از جدیدترین روش‌های حل مسئله در یادگیری تقویتی می‌باشد. روش کنترلر مد لغزشی یک روش کنترل کلاسیک بوده و از معایب عمده این روش وجود چترینگ در پاسخ می‌باشد. در این مقاله نوآوری اصلی ترکیب این دو روش برای حذف چترینگ در پاسخ می‌باشد. برای نشان دادن برتری روش پیشنهادی، این روش با حالت ترکیب کنترلر مد لغزشی و شبکه‌های عصبی مقایسه شده است. نتایج حاصل از شبیه‌سازی نشان داده است که در حالت ترکیب روش مسیره‌های شایستگی با کنترلر مد لغزشی در حضور عیب حسگر و عملگر میزان گلوکز و انسولین با سرعت بیشتر به مقدار مطلوب رسیده‌اند. دوز داروی تزریقی نیز در این حالت کمتر بوده که این امر باعث کاهش اثرات زیان‌بار دارو خواهد شد. در نهایت نیز با وارد کردن نویز به سیستم و عدم قطعیت در پارامترهای سیستم و شرایط اولیه، عملکرد کنترلر پیشنهادی در رخداد عیب مورد بررسی قرار گرفته است.

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