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Neural Network-Based Optimal Control for Glucose Regulation in a Simplified Diabetic Model

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ABSTRACT

This paper investigates the application of neural networks for approximating optimal control strategies in regulating blood glucose levels in a simplified model of glucose-insulin dynamics. A linear model of glucose-insulin interaction is used, and an optimal control problem is formulated to minimize deviations from a target glucose level while penalizing excessive insulin infusion. Training data for the neural network is generated by numerically solving the optimal control problem. A feedforward neural network is trained on this data to approximate the optimal control policy. The performance of the neural network controller is evaluated through simulation and compared against the directly calculated optimal control, demonstrating the potential of neural networks for personalized glucose regulation. The limitations of this simplified approach and directions for future research are also discussed.

Keywords: Neural networks (NN), Optimal Control, Glucose Regulation, Diabetes.

التحكم الأمثل القائم على الشبكات العصبية لتنظيم الجلوكوز في نموذج مبسط لمرض السكري

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ملخـــــــص البحــــــــث

تستقصي هذه الورقة تطبيق الشبكات العصبية لتقريب استراتيجيات التحكم الأمثل في تنظيم مستويات جلوكوز الدم ضمن نموذج مبسط لديناميكيات الجلوكوز–الأنسولين. تم استخدام نموذج خطي للتفاعل بين الجلوكوز والأنسولين، وتمت صياغة مشكلة تحكم أمثل لتقليل الانحرافات عن مستوى الجلوكوز المستهدف مع فرض عقوبة على الإفراط في ضخ الأنسولين. يتم توليد بيانات تدريب الشبكة العصبية عن طريق الحل العددي لمشكلة التحكم الأمثل. تم تدريب شبكة عصبية أمامية بناءً على هذه البيانات لتقريب سياسة التحكم الأمثل. تم تقييم أداء المتحكم القائم على الشبكة العصبية من خلال المحاكاة ومقارنته بالتحكم الأمثل المحسوب مباشرةً، مما يدل على إمكانات الشبكات العصبية في تنظيم الجلوكوز الشخصي والتكيفي. كما نوقشت قيود هذا النهج المبسط واتجاهات الأبحاث المستقبلية.

الكلمات الدالة: الشبكات العصبية (NN)، التحكم الأمثل، تنظيم الجلوكوز، مرض السكري.

1. INTRODUCTION

Diabetes mellitus is a chronic metabolic disorder characterized by elevated blood glucose levels (hyperglycaemia), affecting millions worldwide [1]. Effective management of diabetes is crucial to prevent long-term complications such as cardiovascular disease, neuropathy, retinopathy, and nephropathy [2]. These complications impose a significant burden on healthcare systems and reduce patients' quality of life. Continuous glucose monitoring (CGM) and insulin pumps offer the potential for automated insulin delivery systems, often referred to as "artificial pancreas" or closed-loop systems [3]. These systems aim to mimic the function of a healthy pancreas by automatically adjusting insulin delivery based on real-time glucose measurements. This paper explores the use of neural networks to approximate optimal control strategies for glucose regulation. Optimal control theory provides a rigorous mathematical framework for determining the best control actions to achieve a desired objective, such as maintaining glucose levels within a narrow physiological range [4]. However, solving optimal control problems can be computationally intensive, especially for complex systems with nonlinear dynamics, time delays, and constraints. Neural networks offer a promising alternative by learning to approximate the optimal control policy from data [5]. This approach has the potential to enable personalized and adaptive glucose control strategies, adapting to individual patient characteristics, meal intake, exercise, and other factors that influence glucose levels.

2. MATHEMATICAL MODEL AND CONTROL METHOD:

To generate training data that accurately represents the optimal control policy for the neural network, the optimal control problem was numerically solved based on the glucose-insulin dynamic model.

2.1 System Model

A simplified linear model of glucose-insulin dynamics is used [6, 7]:

$$\frac{dG}{dt} = -p_1 G(t) - p_2 I(t) + u(t) + D(t) \quad (1)$$

$$\frac{dI}{dt} = -p_3 I(t) - p_4 G(t) \quad (2)$$

Where $G(t)$ is blood glucose concentration (mg/dL) , $I(t)$ is blood insulin concentration (mU/L) , $u(t)$ is Insulin infusion rate (mU/min) , $D(t)$ is meal disturbance representing glucose absorption from a meal (mg/dL/min) and p_1 , p_2 , p_3 , p_4 are patient-specific parameters (set to 0.1, 0.2, 0.3, and 0.05, respectively). These parameters represent glucose disappearance rate, insulin-dependent glucose uptake, insulin disappearance rate, and insulin secretion rate proportional to glucose, respectively.

2.2 Optimal Control Problem

Objective: To maintain blood glucose levels close to the target level (G target) by adjusting the insulin infusion rate $u(t)$.
Cost Function: A quadratic cost function is formulated to minimize deviations from the target glucose level and penalize excessive insulin infusion7. The objective is to minimize the following cost function over a finite time horizon (T_{opt})

$$J = \int_0^{T_{opt}} [Q(G(t) - G_{target})^2 + Ru(t)^2]\, dt \quad (3)$$

Where G_{target} is the target glucose level, set to 100 mg/dL. The weighting factors Q and R were set as follows:

- *Q (q1)*: Weighting factor for glucose error, set to 100. (This value was selected to ensure strong and rapid correction of glucose deviation) 10.
- *R (q2)*: Weighting factor for insulin infusion rate, set to 0.01.

For numerical solution, the continuous integral was approximated by a discrete sum over the time steps *dt*.

2.3 Neural Network Controller

A feedforward neural network with a single input (current glucose level *G(t)*) and a single output (optimal insulin infusion rate *u(t)*) was used. The network architecture consists of a hidden layer with 10 neurons, trained using MATLAB's train function [8, 9,10].

2.4 Training Data Generation

Training data is generated by numerically solving the optimal control problem using MATLAB's fmincon function (MATLAB 2014) , a nonlinear optimization solver [11]. For a range of initial glucose levels (G_0, ranging from 50 to 200 *mg/dL* in increments of 5), fmincon is used to find the optimal control input u that minimizes the cost function over a finite time horizon (T_{opt} = 20 minutes with $dt = 1$ minute). The initial glucose levels and the corresponding optimal insulin infusion rates at the first-time step are used as input-target pairs for training. This approach uses the first control action of the optimal trajectory as the target, simplifying the training process while still capturing the essence of the optimal control policy.

2.5 Simulation

The performance of the trained neural network controller is evaluated through simulation over a time horizon of 50 minutes. A meal disturbance ($D = 50$ *mg/dL/min* for 5 minutes) is introduced at $t = 10$ minutes to simulate a postprandial glucose rise. The glucose and insulin trajectories under the neural network control are compared with those obtained using the directly calculated optimal control at each time step. The simulation uses a discrete-time approximation of the continuous-time system model.

3. RESULTS

Figure (1) illustrates the glucose response to the simulated meal disturbance and the performance of both the neural network (NN) and optimal controllers. Before the meal at $t = 10$ minutes, both controllers maintain glucose levels close to the target of 100 mg/dL. The meal disturbance causes a rapid increase in glucose concentration. The optimal controller reacts quickly with a sharp increase in insulin infusion Figure (2), limiting the peak glucose excursion to approximately 115 mg/dL at $t = 12$ minutes. The neural network controller also increases insulin delivery, but with a slightly less aggressive initial bolus, resulting in a slightly higher peak glucose level of 120 mg/dL at $t = 13$ minutes. This represents a difference of approximately 4.3% in the peak glucose excursion between the two controllers. After the peak, both controllers effectively bring the glucose level back to the target range within approximately $10 - 15$ minutes. The meal disturbance D is also shown, having a duration of 5 minutes.

Figure (2) depicts the insulin infusion rates delivered by both controllers. The optimal controller exhibits a more pronounced initial bolus in response to the meal, reaching a peak of approximately 8 mU/min, followed by a rapid decrease. The neural network controller's insulin profile is smoother, with a less pronounced peak of approximately 6 mU/min and a more gradual decline.

Figure (3) presents two distinct, fast-acting bolus profiles that start at the same time. While the Optimal Controller delivering a sharp pulse around 8 minutes, and the NN Controller delivering a smoother pulse that peaks slightly later.

Figure (4) shows the training data used to train the neural network. It depicts the learned relationship between the initial glucose levels and the corresponding optimal insulin infusion rates at the first-time step. The data exhibits a clear trend: higher initial glucose levels correspond to higher initial insulin boluses, as expected.

4. Discussion

The results demonstrate the feasibility of using neural networks to approximate optimal control strategies for glucose regulation in a simplified model. The neural network controller achieves performance reasonably comparable to the directly calculated optimal control, suggesting that this approach could be effective for personalized glucose management. The small differences observed between the NN and the optimal controller, particularly in the peak glucose excursion and the initial insulin bolus, are likely due to several factors:

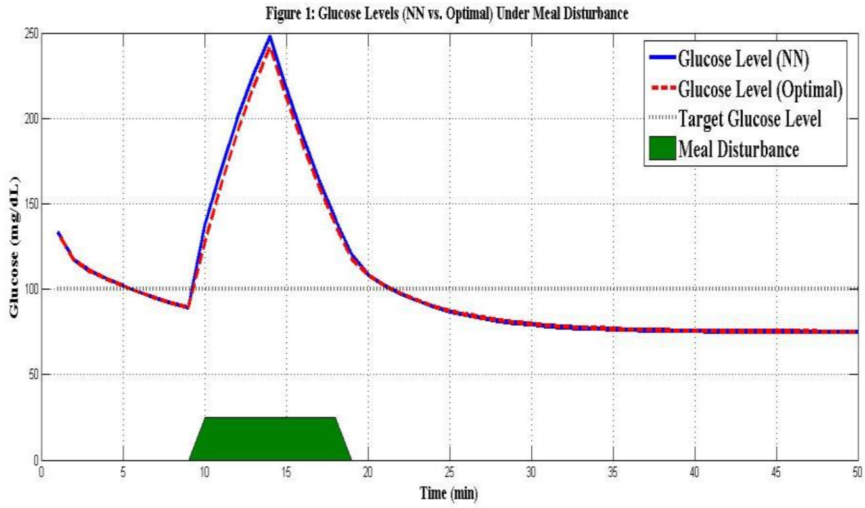

Fig 1. Glucose levels over time for both the neural network controller and the optimal controller, along with the target glucose level and the meal disturbance.

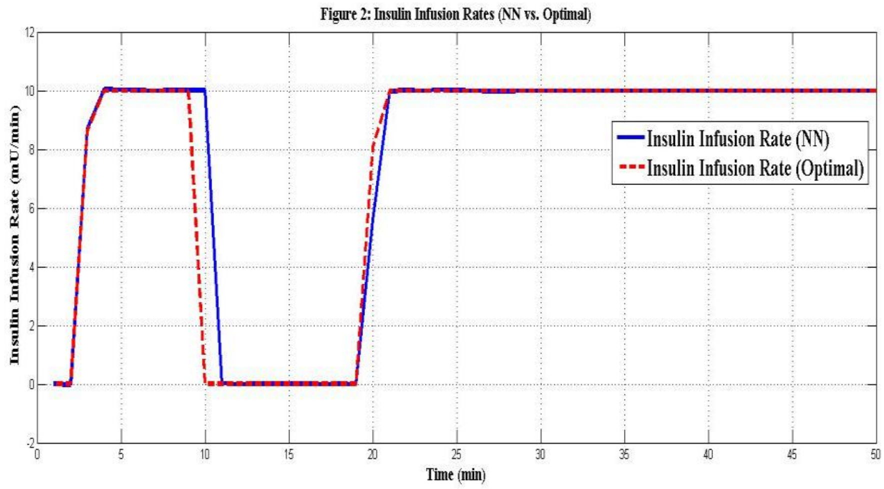

Fig 2. Insulin infusion rates over time for both controllers.

- **Simplified NN Architecture:** The use of a single hidden layer feedforward network with only 5 neurons limits the network's capacity to perfectly capture the complex nonlinear relationship between glucose, insulin, and control actions.
- **Training Data:** Training the NN solely on the first control action of the optimal

trajectory simplifies the training process but may not fully capture the dynamic nature of the optimal control policy over the entire time horizon.

- **Linear Model Limitations:** The linear model used in this study is a simplification of the complex physiological processes involved in glucose-insulin regulation. Nonlinear models, such as the Bergman minimal model [7], are known to better represent the actual physiological dynamics, including saturation effects and time delays.

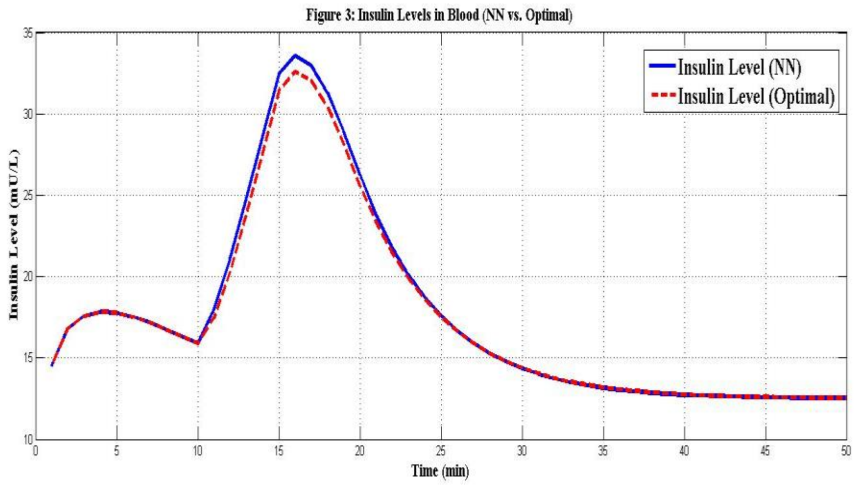

Fig 3. Insulin levels over time for both controllers.

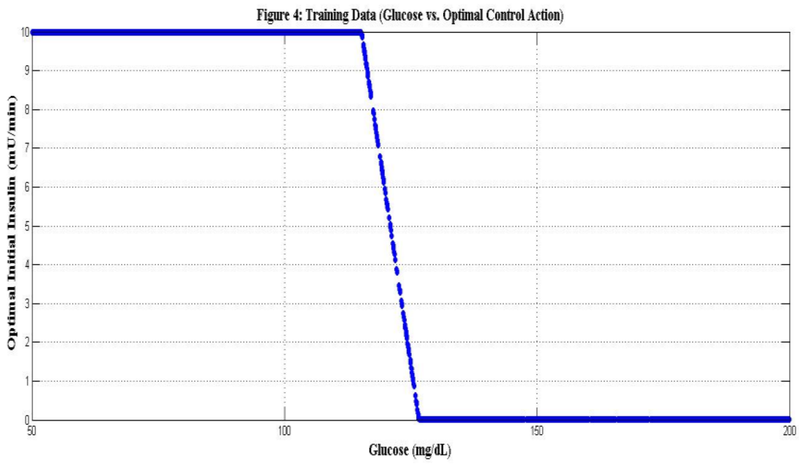

Fig 4. Training data used for the neural network.

Despite these limitations, the NN controller demonstrates a promising ability to approximate the optimal control strategy. The inclusion of the meal disturbance in the simulation provides a more realistic test case and highlights the controller's ability to respond to rapid changes in glucose levels. The comparison of insulin levels as in Figure (3) provides further insight into the system's dynamics and the controllers' behaviour.

5. CONCLUSION

This study presents a preliminary investigation into the use of neural networks for optimal glucose control. The results suggest that neural networks can effectively learn to approximate optimal control policies for glucose regulation in a simplified setting. Moving forward, future work will focus on addressing the limitations of this study by using more complex nonlinear models, such as the well-established Bergman Minimal Model, which provides a more detailed representation of glucose-insulin dynamics.

Furthermore, to effectively capture the time-dependent nature of glucose regulation, more advanced architectures like Recurrent Neural Networks (RNNs) and LSTMs will be utilized, as they are designed to process sequential data and remember information over longer periods. The research will also explore Reinforcement Learning techniques to eliminate the need for pre-calculated optimal control data by enabling the neural network to learn through interaction and receive real-time feedback, thus supporting online adaptation to individual patients. Finally, to handle model uncertainties and disturbances more effectively, robust control techniques such as H-infinity control or Model Predictive Control (MPC) with robustness considerations will be incorporated, ensuring the system remains stable and effective in the presence of unpredictable factors.

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