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Original Research Article

In silico testing of optimized Fuzzy P + D controller for artificial pancreas

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ABSTRACT

Background and objectives: Despite therapeutic advances, a complete cure has not been found yet for patients with type 1 diabetes (T1D). Artificial pancreas (AP) is a promising approach to cope with this disease. The controller part of the AP can compute the insulin infusion rate that keeps blood glucose concentration (BGC) in normoglycemic ranges. Most controllers rely on model-based controllers and use manual meal announcements or meal detection algorithms. For a fully automated AP, a controller only using the patient's BGC data is needed.
Methods: An optimized Mamdani-type hybrid Fuzzy P + D controller was proposed. Using the University of Virginia/Padova Simulator, a 36 h scenario was tested in nine virtual adult patients. To take into account the effect of continuous glucose monitor noise, the scenario was repeated 25 times for each adult. The main outcomes were the percentage of time BGC levels are in the euglycemic range and blood glucose risk index (BGRI), respectively.
Results: The obtained BGC values were found to be in the euglycemic range for 82.6% of the time. Moreover, the BGC values were below 50 mg/dl, below 70 mg/dl and above 250 mg/dl for 0%, 0.35% and 0.74% of the time, respectively. The BGRI, low blood glucose index (LBGI), and high blood glucose index (HBGI) were also found as 3.75, 0.34 and 3.41, respectively. The proposed controller both increases the time the BGC levels are in the euglycemic range and causes less hypoglycemia and hyperglycemia relative to the published techniques studied in a similar scenario and population.

1. Introduction

Diabetes, a disorder of the glucose-insulin metabolism, is characterized by chronic hyperglycemia that results from the failure of the pancreas in insulin secretion, insulin action, or both. According to the International Diabetes Federation, in 2014 there were almost 387 million people suffering from diabetes and by 2035, the number of patients is expected to reach 592 million [1]. Type 1 diabetes (T1D), which is most

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common in children and adolescents, results from the autoimmune destruction of pancreatic beta cells. T1D patients are unable to produce insulin; therefore exogenous insulin needs to infused at an appropriate rate in order to keep blood glucose concentration (BGC) in a euglycemic range (70–180 mg/dl) for patients with T1D [2,3]. The artificial pancreas (AP), also known as the closed-loop control system, is a promising approach that may reduce the number of hypoglycemia or hyperglycemia events by computing the optimal amounts of insulin. The AP consists of a CGM, a controller, and an insulin pump. The CGM signals are transmitted to the controller. The controller uses a control algorithm to send the data relating to the proper insulin dose to the insulin pump. In the literature, many control designs have been tested for the controller part of the AP (proportional-integral-derivative (PID) control [4–6], model predictive control (MPC) [7–11], generalized predictive control (GPC) [12], H∞ control [13,14]). Two fundamental challenges must be considered in the light of these studies. Firstly, these controllers are mostly model-based. In other words, a control model of the glucose-insulin regulation system is required in these controllers. However, it is difficult to incorporate uncertain and varying parameters into such complex biomedical models. The fuzzy logic controller (FLC) is a promising approach to cope with such nonlinear and complex control problems. The FLC is insensitive to changeable physiological parameters and robust to measurement uncertainties stemming from sensor noise. It is based only on the glucose management parameters using their nonlinear linguistic mapping between inputs and outputs [15,16]. On the other hand, many studies have shown that a better control system can be achieved by designing a hybrid control system which combines the conventional PID controller and the FLC [16–19]. Another issue that needs to be addressed is the design of a fully automated AP. Many studies in the literature use manual meal announcements. To be a fully automated AP, no meal announcement should be used [20,21].

Considering these two challenges, an optimized Mamdani-type hybrid Fuzzy P + D controller is proposed in this paper. The optimization process was executed by a swarm-based global optimization algorithm, namely the particle swarm optimization (PSO) algorithm. Fuzzy P + D strategy was proposed to improve the performance yield of the conventional proportional-derivative (PD) controller with the Fuzzy P part. Only the errror and error rate of change of the patient's BGC values were used as inputs for the Fuzzy P + D controller. In this study, the aim was to design a fully automated AP without any meal announcement or meal detection algorithm.

This paper is structured as follows. We begin with a brief explanation of the PSO algorithm and the University of Virginia/Padova (UVa/Padova) [22] metabolic simulator of patients with T1D. We then detail the description of the optimized hybrid Fuzzy P + D controller. Afterwards, we demonstrate the outstanding performance of our controller on the UVa/Padova Simulator against the published results of an extended model predictive controller (EMPC) [8] and proportional-integral-derivative with double phased lead (PIDD) [6] controller. Validation of the controller on another common nonlinear model developed by Hovorka et al. [23] and usage of the controller as an individual patient controller are also given in this section. Then, all the results obtained are discussed and conclusions are provided.

2. Materials

2.1. PSO algorithm

The PSO, which was introduced by Kennedy and Eberhart [24], is a modern population-based heuristic algorithm that is inspired by behaviors in nature such as birds flocking and fish schooling. The PSO is widely used because of its simple and flexible structure. In the PSO, each particle serves as a candidate solution to the problem and has a position and a velocity. The best values for the particles and swarm are kept by the algorithm to be used when needed. The best previous position is kept and called Pbest (P_b). The best particle among all particles in the population is called the overall best value, and its position is called Gbest (G_b). The position and the velocity of each particle are updated according to Eqs. (1) and (2).

$$V_i^{(k+1)} = w_i \cdot V_i^{(k)} + c_1 \cdot r_1 \cdot \left(P_b - X_i^{(k)}\right) + c_2 \cdot r_2 \cdot \left(G_b - X_i^{(k)}\right) \quad (1)$$

$$X_i^{(k+1)} = X_i^{(k)} + V_i^{(k+1)} \quad (2)$$

where $X_i^{(k)}$ is the kth position of the particle i; $V_i^{(k)}$ is the kth velocity of the particle i; c_1 and c_2 are cognitive and social constants; r_1 and r_2 are uniformly distributed random numbers in [0 1], and w is the inertia weight. The inertia weight is used to achieve a balance in the exploration and exploitation of the search space. In this paper, we used a linearly decreasing inertia weight [25] that demonstrates its superiority in the computational complexity, success rate, and solution quality as follows:

$$w_i = w_{\min} + \frac{iter_{\max} - iter}{iter_{\max}} \cdot (w_{\max} - w_{\min}) \quad (3)$$

where w_i is the inertia weight of i. iteration, $iter_{\max}$ is the maximum number of iterations, and $iter$ is the i. iteration. The PSO control parameter values used are given in Table 1.

Table 1 – Control parameter values of the PSO algorithm.

Parameters	Value
Maximum Iteration	30
Size of the swarm	50
Cognitive parameter c_1	2
Social parameter c_2	2
Inertia weight [w_{max}–w_{min}]	[0.9–0.4]

2.2. UVa/Padova metabolic simulator

The UVa/Padova T1D metabolic simulator [22,26] was approved by the Food and Drug Administration (FDA) as a

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