Non linear control of glycaemia in type 1 diabetic patients

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A fuzzy controller for the closed loop control, by insulin infusion of glycaemia in type 1 diabetic patients is proposed. The controller uses type-2 fuzzy sets. The controller was tested in simulation using a complex nonlinear model of the glucose metabolism. Simulation results confirm the effectiveness and the robustness of the type-2 fuzzy logic controller. The design of the controller uses an optimization method based on genetic algorithms. This makes the type-2 fuzzy controller more efficient and faster than a fuzzy controller with type-1 fuzzy sets, allowing a more accurate control of the glucose in the blood.

1. Introduction

Diabetes mellitus is one of the most serious and diffuse metabolic diseases and represents a growing problem around the world. The most common forms of diabetes are the so called type 1 and type 2 diabetes. The control problem afforded in this paper is concerned with type-1 diabetes. The main characteristic of type 1 diabetes is that the pancreatic beta-cells fail to produce the insulin needed for the body's glucidic metabolism requiring that patients inject themselves, several times a day, with external insulin for their survival. The insulin therapy simulates in a dicrete way the pancreas activity. The diabetes has to be kept under control, because abnormal low or high blood glucose levels may lead respectively to cardiovascular problems or to fainting and also to diabetic coma.

The development of a completely automatic system, a sort of "artificial pancreas", that is able to determine and to inject the insulin required by the body's metabolism on the basis of the measured glucose level in the blood, has been the objective of many researches in the last decades. All the elements that should constitute the closed control loop have been considered: from the sensor of insulin to the infusion system, from the knowledge of all metabolic processes and their mathematical modeling to the more suitable control techniques. The process to be controlled is very complex and in some respects not yet well known. An idea of the problem complexity can be achieved looking at the mathematical models that have been proposed, highly non linear and with parameters that are difficult to determine but in all case strongly affected by uncertainty. In this study the attention is focused on the control technique. Mainly PID and model predictive controllers have been applied to the closed loop control of glucose. Recently a fuzzy controller that makes use of type-2 fuzzy sets has been proposed (Singh et al., 2007). In this paper a type-2 fuzzy logic controller optimized by genetic algorithms is

presented. The controller is tested by simulation using one of the most complex models of glucose metabolism that have been proposed (Sorensen, 1985).
The choice of using a type-2 fuzzy controller is justified by the non linearity of the metabolic processes and the parameter uncertainty, also present in the model used for the simulation. It is well known in fact that fuzzy controllers are a suitable solution for non linear processes and it has been demonstrated that type-2 fuzzy controllers can handle all kinds of uncertainties better than traditional type-1 fuzzy controllers, due to the larger number of freedom degrees that can be used in their design (Mendel, 2001).

2. Control problem

2.1 Metabolic process model

In Fig. 1 (Sorensen, 1985) the behavioral difference among diabetic and normal patients for the blood glucose concentration (Fig. 1a) and the plasma free insulin concentration (Fig. 1b), when a meal is taken, is shown.

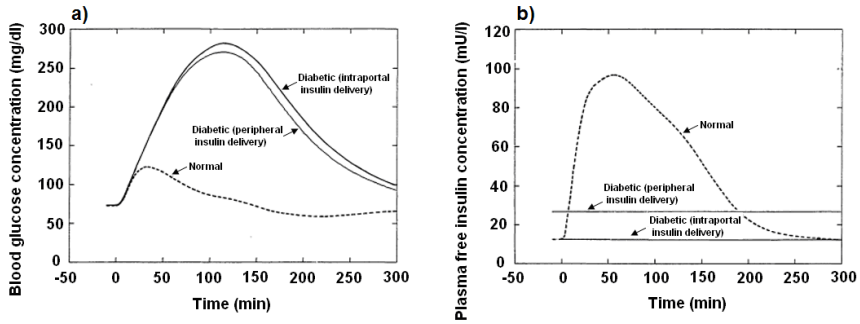

Fig. 1: a) Blood glucose concentration and b) Plasma free insulin concentration for normal and diabetic persons (peripheral and intraportal insulin delivery).

This very big difference can be compensated only by the use of an efficient closed-loop insulin delivery system.
The model used in this study is a multi-compartment model constituted by 19 differential equations where glucose and insulin are transferred into the compartments with a convective transport by the blood plasma. A detailed analysis of the model can be found in Sorensen (1985). The output of the system, used for the control proposed in this study, is the peripheral interstitial blood glucose concentration Gpi (set-point value = 80.7 mg/dl). Two inputs are considered: the intravenous release of insulin to the patient that represents the manipulation variable and the meal that instead represents the disturbance to the system. The Sorensen model does not include a module for the meal metabolism and considers as input the rate of gut oral glucose absorption determined by the assumption of a standard amountò (100 g) of glucose, as shown in Fig. 2 (Sorensen, 1985).

The control target is to obtain for a diabetic patient a glucose concentration, after a meal, comparable to that of a healthy person.

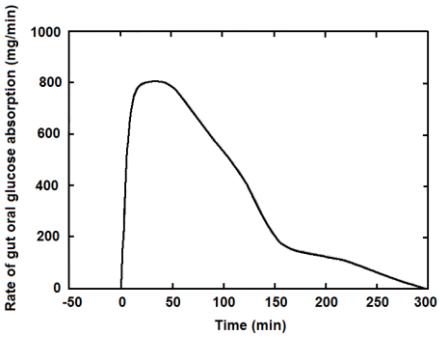

Fig. 2: Rate of gut oral glucose absorption vs time.

3. Interval type-2 fuzzy sets

The traditional fuzzy logic (type-1 fuzzy logic) offers a way of representing and modelling uncertainty and imprecision. In a type-1 fuzzy system uncertainty is modelled by a membership function that can assume a value between zero and one. When systems are characterized by a high degree of fuzziness, some difficulties can arise also in using a membership grade as a crisp number in [0 1]. Therefore in these cases fuzzy sets with a higher degree can be used, for instance type-2 fuzzy sets (Mendel and Liang, 1999). The use of type-2 fuzzy sets and in particular of interval type-2 fuzzy sets, subsets of type-2 fuzzy sets, but computationally simpler to handle, may be a valid alternative to type-1 fuzzy sets, especially in all those circumstances where systems are characterized by a high degree of uncertainty. Let us imagine blurring the type-1 Gaussian membership function depicted in Fig. 3 (a), by shifting the points on the Gaussian membership function either to the left or to the right, not necessarily by the same amount. We obtain a type-2 Gaussian membership function characterized by a shaded region (Fig. 3 (b)) called the Footprint of Uncertainty (FOU) (Mendel, 2001).
A type-2 fuzzy controller has the same structure of a type-1 FLC but uses type-2 fuzzy sets.

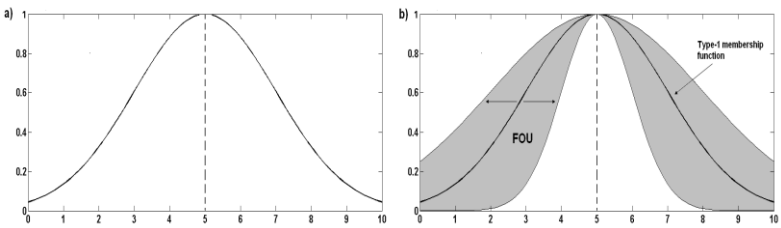

Fig. 3. (a) Type-1 Gaussian membership function. (b) Type-2 Gaussian membership function

4. Design of fuzzy controllers

4.1 Type-1 and type-2 fuzzy fogic fontrollers

Each fuzzy controller is characterized by two inputs (the error between desired and actual glucose concentration and the derivative of the error), one output (the insulin manipulation variable), a zero order Sugeno inference, a rule base constituted by 9 rules and Gaussian membership functions. The center of the Gaussian membership functions is the same for type-2 FLC (type-2 Gmfs) and type-1 FLC (type-1 Gmfs), while the amplitude value of type-1 Gmf is the average of the corresponding amplitude values of type-2 lower and upper Gmfs (Galluzzo and Cosenza, 2009).

4.2 Optimization of the type-2 FLC by a genetic algorithm

A genetic algorithm (GA) is an optimization algorithm (Holland, 1992) that takes inspiration from natural population genetics and aims to find evolutive solutions to complex problems. In this case study the GA is applied to optimize the parameters of the type-2 FLC. There are two approaches for selecting the parameters of a type-2 fuzzy logic controller: the *partially dependent approach* and the *totally independent approach* (Wu and Tan, 2006). In the first case the parameters of a type-1 fuzzy logic controller are used to initialize the parameters of a type-2 fuzzy logic controller. The main advantages of this method are a small search space for each variable and a smaller number of parameters to be tuned. In the second case all parameters of the type-2 fuzzy logic controller are tuned, without the aid of an existing type-1 fuzzy controller. It is evident that the computational load needed to implement the GA is lower in the partially dependent approach than in the totally independent approach, but the last one allows to avoid local minima and to assure maximum design flexibility. In Fig. 4 the rule surfaces for the type-2 FLC (Fig. 4 (a)) and for the type-2 FLC optimized with genetic algorithms (type-2 FLC-GA) (Fig. 4 (b)) are shown.

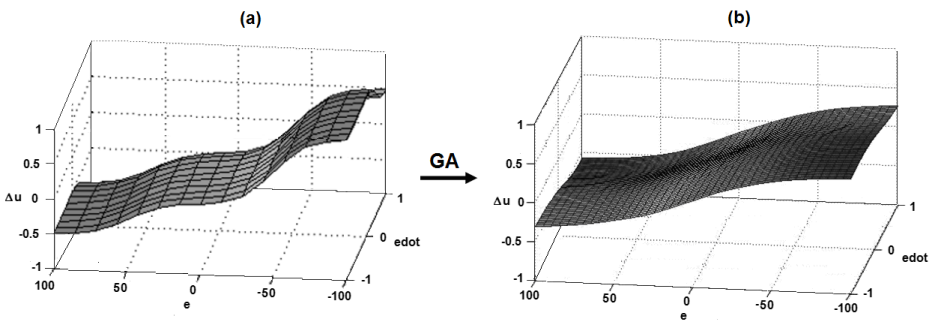

Fig. 4. Rule surface for a) the type FLC b) the type-2 FLC optimized with genetic algorithms.

5. Results and discussion

In Fig. 5 the responses to the disturbance of Fig. 2 of the system controlled by the type-1 FLC and by the type-2 FLC are shown. It is evident the better result of the type-2 FLC over its type-1 counterpart in terms of decrease of the G_{pi} peak-value.

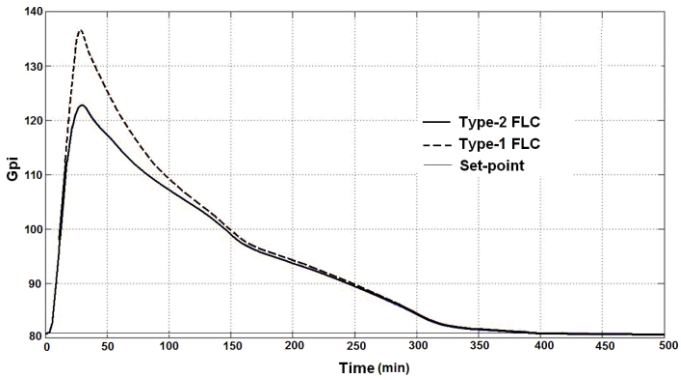

Fig. 5: Responses to the disturbance (rate of gut oral glucose absorption) shown in Fig. 2 of the system controlled by the type-1 and type-2 FLCs.

In Fig. 6 the behaviour of the system controlled by the type-2 FLC and by the type-2 FLC-GA for the same disturbance is instead shown. The G_{pi} peak-value further decreases and the set-point value is more quickly reached.

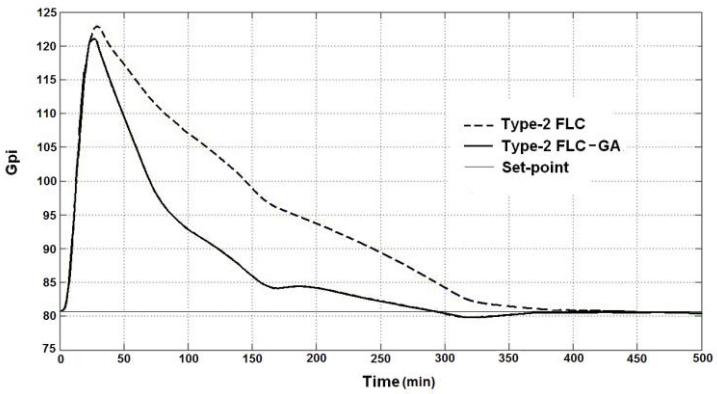

Fig. 6. Responses to the disturbance (rate of gut oral glucose absorption) shown in Fig. 2 of the system controlled by the type-1 FLC and the type-2 FLC-GA.

In Fig.7 the performances of all three fuzzy controllers (type-1 FLC, type-2 FLC and type-2 FLC-GA) are shown when a disturbance starting at t=100 min and with a slope of -0.001, 0.004 and -0.015 was introduced respectively for V_L^I, Q_{ga} and τ_x in addition to the same disturbance. Although any fuzzy controller is able to reach the set-point value, the type-2 FLC-GA is the only fuzzy controller able to reduce the off-set drastically, keeping the Gpi value close to the set-point value.

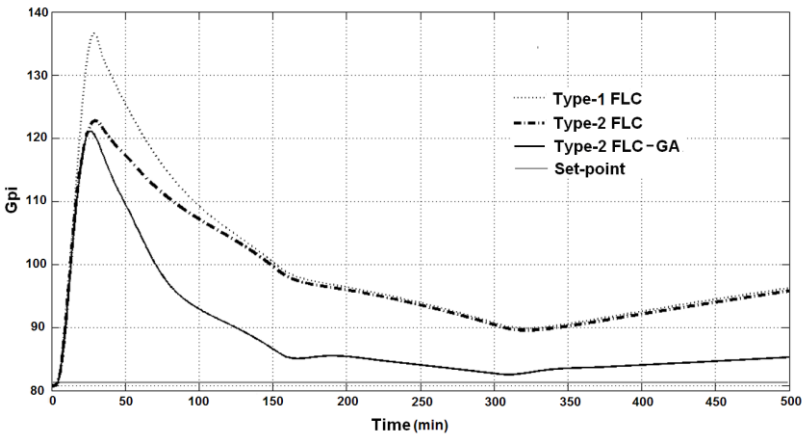

Fig. 7. Responses of the system controlled by type-1 FLC, type-2 FLC and type-2 FLC-GA to a rate of gut oral glucose absorption disturbance shown in Fig. 2 and a ramp variation of three model parameters.

The simulation results confirm a faster and more robust control action of the type-2 FLC-GA over the simple type-2 FC. The use of a type-2 fuzzy logic controller optimized by a method based on genetic algorithms may represent a solution for a difficult control problem like the control of glucose metabolism.

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