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Identification and Control of Insulin Glucose Regulation in Type 1 Diabetes

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ABSTRACT:The control of diabetes has always been a significant field of research due to the increasing number of diabetics and the lack of ideal control strategies to counter it. Although many control strategies have been developed, they are however limited by the complexity of glucose homeostasis. In this work the authors employ Model Reference Adaptive Control (MRAC) strategy to control blood glucose regulation and account for parameter uncertainties. The crux of the paper lies in developing a new closed loop reference model for blood glucose regulation using system identification techniques. The developed controller and reference model is then tested on the Bergman's model which closely resembles the human insulin glucose regulation. The controller parameters are computed using least squares tuning rules. The results obtained show that the MRAC with the developed closed loop reference model provides better blood glucose control than existing conventional controllers like proportional integral (PI).

KEYWORDS: Insulin-Glucose regulation, Bergman's Model, Model Reference Adaptive Control.

I.INTRODUCTION

Diabetes is a universal metabolic disorder resulting in chronic hyperglycaemia which in turn effects micro-vascular and macro-vascular complications [1, 2].These complications range from limb loss, blindness, ischemic heart disease to end stage renal disease. Diabetes is broadly classified into two types, type 1 diabetes and type 2 diabetes. Both are born out of complex interactions between genes and their environment, however their pathogenesis is distinct. Type 1 diabetes is characterized by the mediated destruction of the beta-cells in the islets of Langerhans which is the site of insulin secretion and production. Type 1 diabetes occurs in childhood and adolescence (although it can occur at all ages) and is characterized by absolute insulin deficiency. Consequently, affected individuals require insulin therapy to control hyperglycaemia and sustain life.

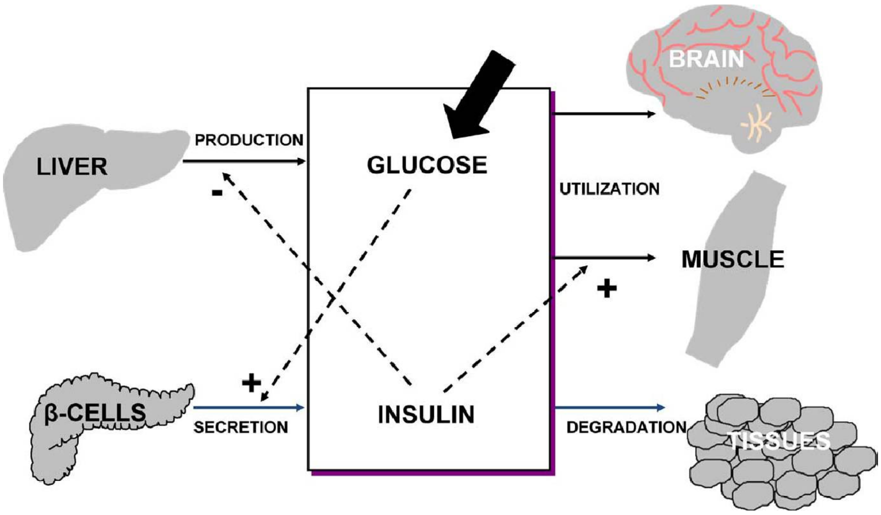

Figure 1INSULIN GLUCOSE CONTROL SYSTEM [9]

Glucose concentration is tightly regulated in humans by a complex neuro-hormonal control system [1, 2]. Insulin is the primary regulator of glucose homeostasis, i.e., it promotes glucose utilization and inhibits glucose production.

One of the best treatments currently available is functional insulin therapy (FIT). FIT consists of a number of daily insulin injections depending on the measurements of blood glucose(BG) and carbohydrate food intake, with the purpose of maintaining normal glycaemic (range: 70–120 mg/dl). However most of the patients have difficulties in computing the correct amount of insulin to be injected due to incorrect estimates of carbohydrate food in-take[3]. The incidence of physical activity or stress can also to lead to variability in the patient's insulin [4]. Therefore, patients with type 1 diabetes often face disorders such as hypo- (BG <70 mg/dl) and hyperglycaemia (BG >180 mg/dl) due to too large or too small insulin doses. The fully automated artificial pancreas could significantly reduce the hypoglycaemia and hyperglycaemia events and, thus, the risk of complications for T1DM patients. However a model of insulin and glucose dynamics is required to design a model-based controller. Many glucose–insulin models have been developed [5-9], with varying complexity. The Minimal model developed by Bergman in 1981[10], enabled the estimation of the insulin sensitivity index for healthy subjects and type 1 diabetic patients. This nonlinear model became very popular and some modified versions are still used in applications for the artificial pancreas. The obtained model requires an apt controller for optimising the model dynamics.

A Proportional Integral Derivative controller for blood glucose regulation in Type I Diabetic patients was introduced by Y. Ramprasad et al [11] and also by Chang Kyu Lee et al [12].Unfortunately, most of these models feature apparent equilibria in fasting periods so that, for each BG value, a different insulin infusion rate is needed to maintain constant BG level. In [3] the authors have developed a Model Predictive Controller for Type 1 diabetic system. The conventional controller, which gives good set point tracking, may not give good disturbance rejection due to model mismatch.

In this paper the authors have developed a MRAC for maintaining glucose homeostasis in the human body. MRAC is a direct adaptive strategy with some adjustable controller parameters and an adjusting mechanism to adjust them.MRAC comprises of, a plant containing unknown parameters, a reference model for compactly specifying the desired output of the control system, a feedback control law containing adjustable parameters. The MRAC strategy works on the principle of adjusting the controller parameters so that the output of the actual plant tracks the output of a reference model having the same reference input. As compared to the well-known and simple structured fixed gain PID controllers, adaptive controllers are very effective in handling the unknown parameter variations and changes in operating conditions.

The reference model parameters for the MRAC is obtained by applying the non-linear least squares technique on the data obtained from the simulation of the Bergman's model in MATLAB. The output error (OE) model thus obtained provides a second order transfer function which can be discretised for implementing in the reference model of the MRAC. The output error model as the name suggests, assumes that the white noise directly affects the output. The authors have opted for an OE model as it also gives the best deterministic model in open loop conditions.

II.BERGMAN'S MODEL

The Bergman'sminimal model is a three compartment model, meaning that the body is described as a compartment/tank with a basal concentration of glucose and insulin.Bergman and colleagues successfully quantified the pancreatic responsiveness and insulin sensitivity of a diabetic patient using a three-compartmental mathematical model [10], as shown in Figure 2.

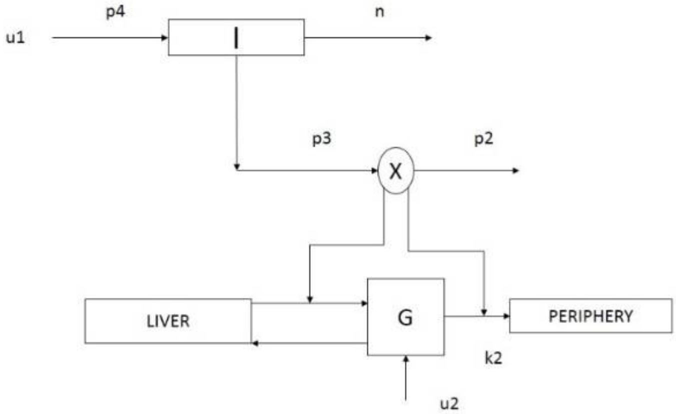

Figure 2 SCHEMATIC REPRESENTATION OF BERGMAN' MODEL

Compartments I, X, and G represent plasma insulin (μU/ml), remote insulin (μU/ml), and plasma glucose (mg/dl) concentrations, respectively. The model as written assumes that all the necessary insulin is infused exogenously ($u1$), thereby modelling the insulin-dependent diabetic patient.

The Bergman's model can be mathematically described as

$$\frac{di}{dt} = -nI(t) + p_4 u1(t)$$

$$\frac{dX}{dt} = -p_2 X(t) + p_3[I(t) - I_b]$$

$$\frac{dG}{dt} = -p_1 G(t) - X(t)G(t) + p_1 G_b + u_2(t)/vol_G$$

Where,

$$I(0) = I_b = \left(\frac{p_4}{n}\right)u_{1b}$$

$$x(0) = 0$$

$$G(0) = G_b$$

Table 1 Bergman’s model parameters [10]

p_1	0.035
p_2	0.05
p_3	0.000028
p_4	0.098
N	0.142
Vol_G	117.0

This set of equations was implemented in MATLAB and the corresponding step response without delay to a step change of 5 was obtained as shown in figure 3.

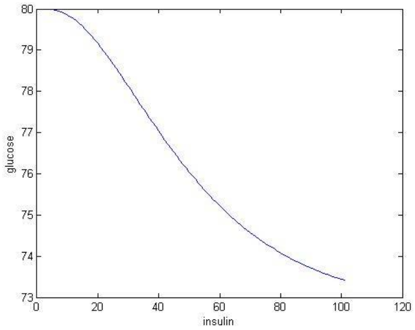

Figure 3 STEP RESPONSE OF THE BERGMAN’S MODEL

The Bergman’s model step response shown in figure 3 represents the human body in MRAC. The corresponding section deals with MRAC.

III.MODEL REFERENCE ADAPTIVE CONTROLLER

The field of adaptive control has focused on problems where the parameters in the system are uncertain. Typically, system dynamics, which are invariably nonlinear, are often linearized to derive the requisite linear controller. The resulting linear model and its parameters vary with the operating condition. In such a scenario, a controller is called for that provides a uniformly satisfactory performance in the presence of parametric uncertainties and variations. The adaptive approach to this problem is to design a controller with varying parameters, which are adjusted in such a way that they adapt to and accommodate the uncertainties and variation in the process to be controlled.

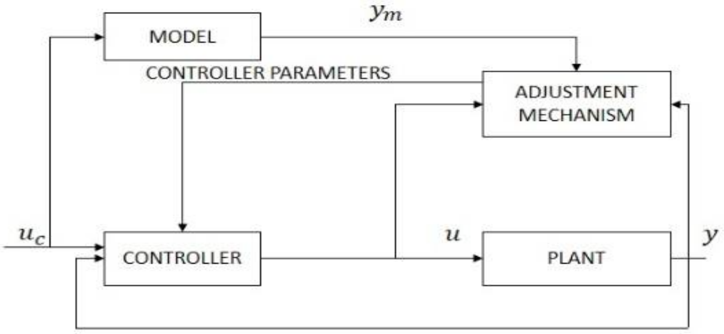

Figure 4 MRAC BLOCK SCHEMATIC

The MRAC is an adaptive servo system in which the desired performance is expressed in terms of a reference model, which gives desired response to a reference signal. MRAC comprises of, a plant containing unknown parameters, a reference model for compactly specifying the desired output of the control system, a feedback control law containing adjustable parameters. The ordinary feedback loop is called inner loop and the parameter adjustment loop is called outer loop. The plant is assumed to have a known structure although the parameters are unknown. The reference model is used to specify the ideal response of the adaptive control system to the external input. The reference model should reflect the performance specification in the control tasks, such as rise time, settling time, overshoot or equivalent frequency domain characteristics, and, specify an ideal behaviour that can be achieved by the adaptive control system. The controller is usually parameterized by a number of adjustable parameters which implies that there exists different sets of controller values for which the desired control task is achievable. The adaptation mechanism is used to adjust the parameters in the control law by driving the tracking error to zero. The adaptation mechanism is designed using the MIT rule[13]. In this rule a cost function is defined as,

$$J(\theta) = e^2/2$$

where e is the error between outputs of the plant and model and θ is the adjustable parameter.
In this paper, the authors have developed a closed loop MRAC for the given process and the reference model has been obtained by applying standard system identification techniques to obtain an output error model.
The OE model as the name suggests, assumes that the white noise directly affects the output. Figure 3 provides a schematic representation of the same.

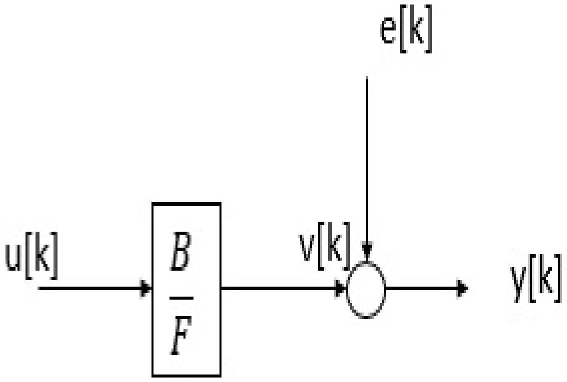

Figure 5SCHEMATICREPRESENTATIONOF AN OE MODEL[14]

The OE model can be mathematically represented as follows;

$$y[k] = \left(\left(\frac{B(q^{-1})}{(F(q^{-1}))}\right)u[k]\right) + e[k]$$

The parameters of an OE model can be estimated in a number of ways and in this paper the authors have used non-linear least squares method to estimate the same. The state parameters of the obtained discrete output error model are converted to continuous form and updated in the reference block of the MRAC.

IV.RESULTS AND DISCUSSION

The MRAC was simulated in MATLAB as shown in figure 6.

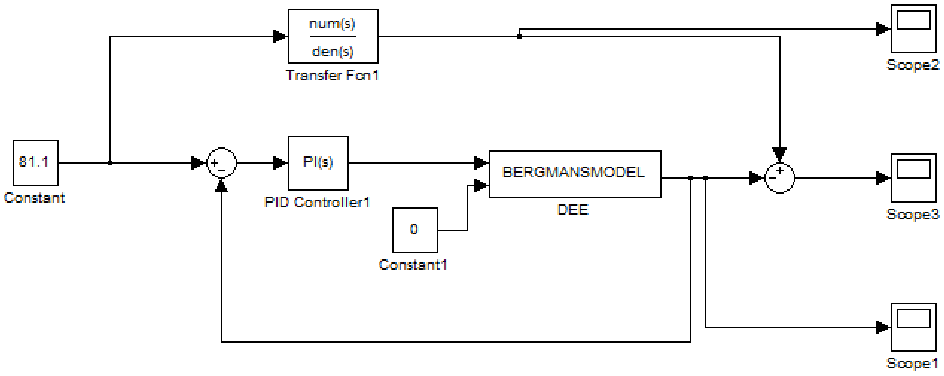

Figure 6 MRAC BLOCK SCHEMATIC IN MATLAB

The parameters of this controller are identified using MIT tuning rules. The plot of the obtained parameters for different time instants is shown in figure 7.

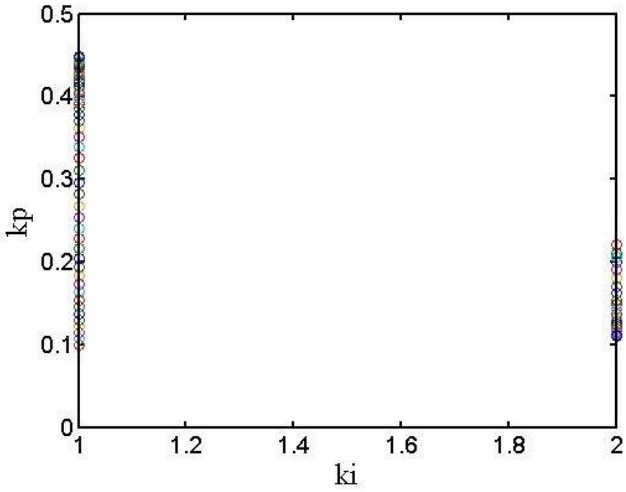

Figure 7 PLOT FOR MRAC PARAMETERS

As discussed in previous sections the authors chose an OE model which was obtained in its discrete form using non-linear least squares technique as shown below.

$$\left(\frac{B(q)}{F(q)}\right) = \left(\frac{0.1955 - \left(0.1452(q^{-1})\right)}{1 - 1.825(q^{-1}) + 0.8535(q^{-2})}\right)$$

The discrete OE model was converted to continuous form which is shown below.

$$\left(\frac{B(s)}{F(s)}\right) = \left(\frac{0.1955(s^2) + 0.2359(s) + 0.05445}{(s^2) + 0.1584(s) + 0.03119}\right)$$

The servo response of the MRAC system is given in figure 8.

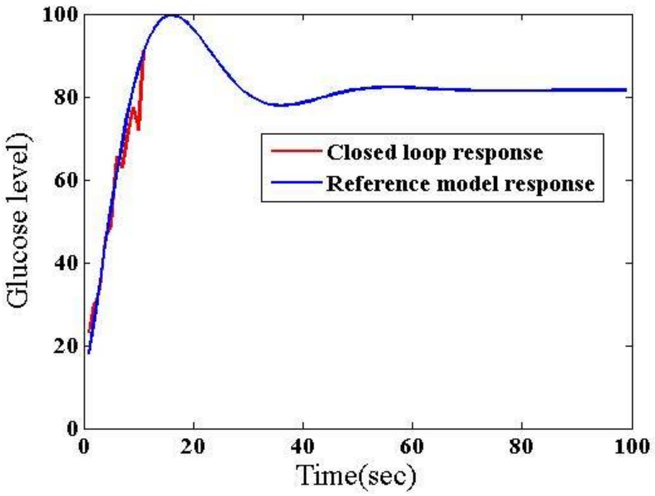

Figure 8 SERVO RESPONSE OF MRAC

From figure 8 it is evident that MRAC controller performance was satisfactory. The mismatch in the reference model response and closed loop response is minimal. For performance comparison purposes, a PI controller was developed for the same process and its response is shown I figure 9.

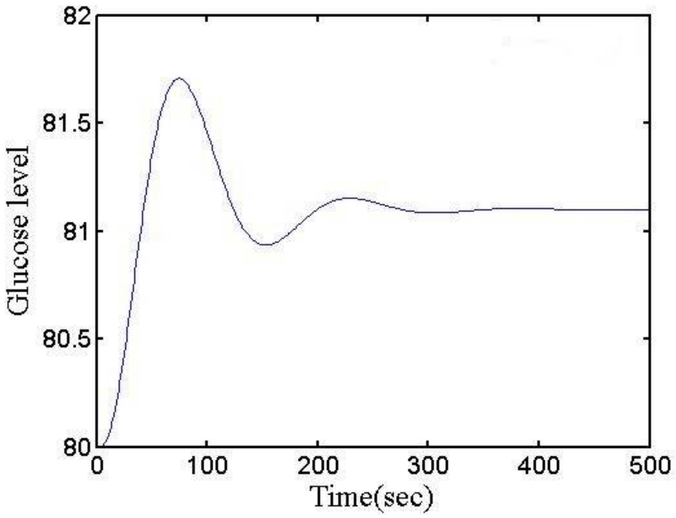

Figure 9 PI CONTROL RESPONSE CURVE

Upon comparing figures 8 and 9 it is evident that for the given system MRAC provides better control than PI. As the MRAC tracks the reference model the mismatch is minimised in comparison with PI controller. From the PI response it is clear that the PI controller takes a lot more time to reach the given set point in comparison with the MRAC. Also the MRAC provides better control over a wide range of operating conditions unlike the PI controller which does not track any particular reference model.

V.CONCLUSION

In this work the authors employed Model Reference Adaptive Control (MRAC) strategy to control the blood glucose regulation in type 1 diabetes and account for parameter uncertainties. A new closed loop reference model for blood glucose regulation was developed using least square system identification techniques. The OE model thus obtained proved to be highly deterministic and apt for modelling the reference model on. The developed controller and reference model were then tested on the Bergman's model which closely resembles the human insulin glucose regulation. The results obtained showed that the MRAC with the developed closed loop reference model provided better blood glucose control than existing conventional controllers like proportional integral (PI) for the same system.

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