당뇨I 유형환자에 대한 PID제어기 설계

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PID control for Type I diabetic patients

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Introduction

Many control algorithms have been developed to deliver insulin in IDDM type I(insulin dependent diabetic mellitus)(Sorensen, 1985; Ollerton, 1989; Fisher, 1991; Parker et al., 1999a). Although those control algorithms show good performance, they are too difficult to use a practical insulin pump because of their own complexity and needs of computation devices. Proportional-integral-derivative (PID) control is inherently simple algorithm and it is composed of more simple devices than the other control algorithms(MPC, Robust control, etc.).

A physiological model of diabetes patients was developed with mathematical analysis of insulin-glucose interactions (Bolie, 1961; Ackerman et al, 1965). It has 19 states differential equations, which is composed of 11 states for the glucose dynamics, 7 states for the insulin dynamics, and one state for the glucagons dynamics. This model is a nonlinear system. Although it is well established, practical patients have various uncertainties. Uncertainty causes differences between an actual patient and the diabetic patient model. Through the parameter sensitivity analysis, most sensitive metabolic parameters were found to affect the glucose and insulin dynamics(Parker et al., 1998).

We apply the appropriate PID control algorithm to the diabetic patient model with uncertainties. This paper suggests that the PID controller guarantees the robust performance in the allowable region with uncertainty and proposes the topic which is how to estimate the PID control parameters.

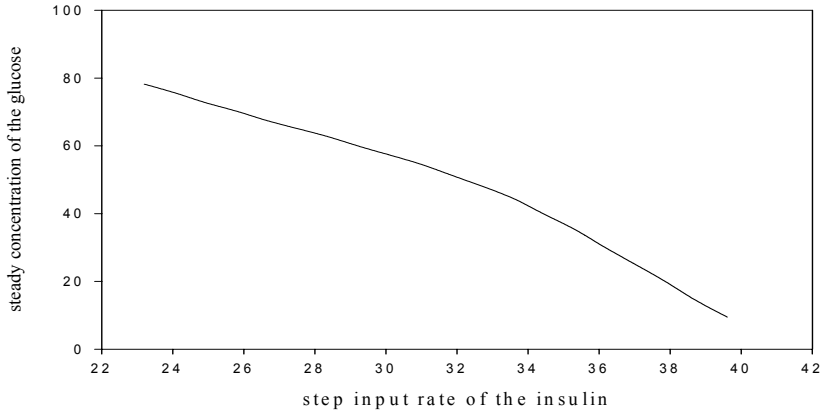


Figure 1. The step input responses versus the step input changes.

Application of the PID control algorithm

Although the diabetic patient model is a nonlinear model, insulin-glucose dynamics of this model is similar to the behavior of a linear system. It can be observable from various step input responses

which is shown in Figure 1. Since the PID control algorithm was developed in a linear system, this fact allows applying the PID control algorithm to this nonlinear system. We estimated the PID tuning parameters which minimized the time weighted integral of the square error, by using the Levenberg-Marquardt optimization method. However, the traditional ideal PID controller has a somewhat dangerous problem. It is the derivative kick caused by the ideal derivative controller. To prevent such phenomenon, we recommend the anti-derivative kick PID controller which is expressed the following equation,

$$u(t) = k_c e(t) + \frac{k_c}{\tau_i}\int e(t)dt - k_c\tau_d \frac{dy(t)}{dt}$$

where *u(t)* and *y(t)* denote the process input and the process output, respectively, and *kc*, *τi*, and *τd* are the controller gain, integral time, and derivative time, respectively. Here is another problem with the constraint of the input insulin delivery rate. It is caused by the mechanical or the physiological constraint and it is the cause of the integral windup. Therefore, we used the anti-windup optimal PID controller. This phenomenon does not exist in the course of tuning parameter estimation for the proposed diabetic patient model. However, when we consider the model uncertainty, the anti-windup optimal PID controller tuning strategy must be adopted. The diabetic patient model has one input disturbance, the meal. This disturbance shape is proposed by Lehmann and Deutsh et al.(1992). Figure 2 is shown that the PID controller rejects the 50g meal disturbance.

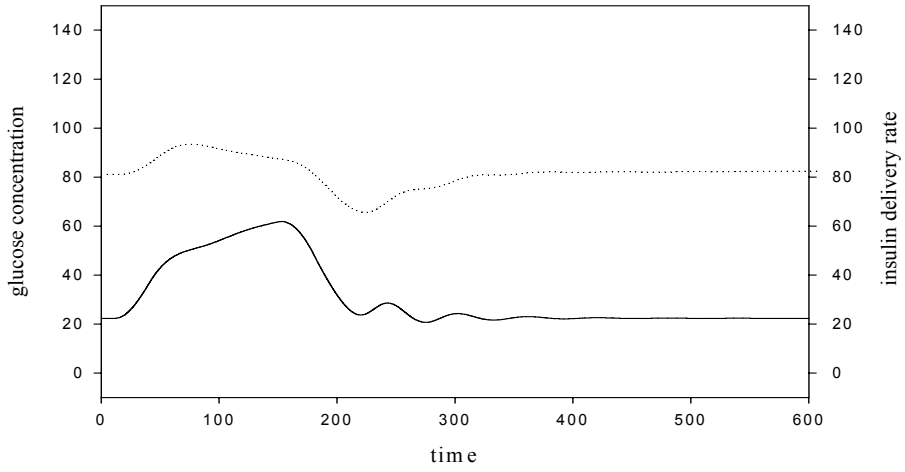


Figure 2. The control performance of the disturbance rejection

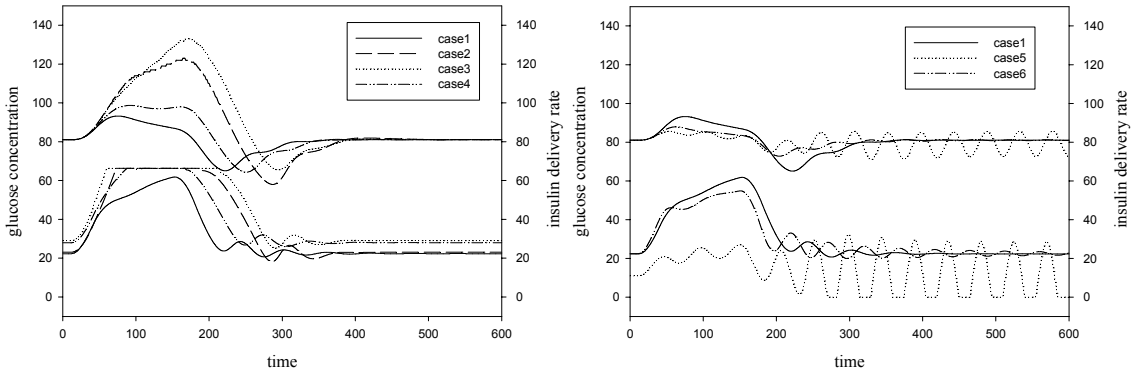
Uncertainty Characterization

Although optimal PID tuning parameters for the patient model can be estimated by computation, we cannot pass over the difference between practical patients and patient model. Glucose metabolism is mathematically described by threshold function with the following structure

$$\Gamma_e = E_\Gamma\{A_\Gamma - B_\Gamma \tanh[C_\Gamma(x_i + D_\Gamma)]\}$$

Uncertainty of the physiological model is great influenced by the effect of glucose on hepatic glucose uptake(EGHGU), the effect of insulin on peripheral glucose uptake(EIPGU), and the fractional of hepatic insulin clearance(FHIC)(Parker et al., 2000). Parker et al. proposed that it was assumed that

±40% parameter variability in each parameter except the FHIC which was limited to ±20% to guarantee nonnegative glucose concentration. Figure 3 indicates that the 5 cases of the uncertainty model were simulated.



Case 1	EIPGU-DΓ×100%	EGHGU-DΓ×100%	FHIC×100%
Case 2	EIPGU-DΓ×60%	EGHGU-DΓ×60%	FHIC×90%
Case 3	EIPGU-DΓ×60%	EGHGU-DΓ×60%	FHIC×110%
Case 4	EIPGU-EΓ×60%	EGHGU-EΓ×60%	EGHGP-EΓ×140%
Case 5	EIPGU-DΓ×140%	EGHGU-DΓ×140%	FHIC×80%
Case 6	EIPGU-DΓ×60%	EGHGU-DΓ×140%	FHIC×120%

Figure 3. The control performance of the disturbance rejection for the diabetic patient model with uncertainties

The model of case 1 indicates the nominal diabetic patient model. The model of case 2~4 are well tuned using the PID parameters which is estimated from nominal model. However, the model of case 5 and case 6 are not well tuned. The reason can be inferred from the parameters of the second order plus time delay(SOPTD) model through the system identification. The models of case 5 and case 6 have lower damping factor and time constant than other models. That is, if a model with uncertainties lies in the allowable region, we can suggest that the tuning parameters estimated from the nominal model guarantees the satisfactory control performance.

Conclusion

In fact, the PID control is not easy to obtain the better performance than the MPC or the robust H-infinite control(Parker et al., 2000). However, such advanced control algorithms are strongly required for complex computation. From the result(Figure 1), we can define that the diabetic patient model is nearly a linear system. Therefore, the PID control can apply the diabetic patient model and the PID controller guarantees the robust performance in the allowable region for the model with uncertainty. If the diabetic patient model is similar to the practical patients, we can suggest simpler tuning rule using the system identification (SOPTD).

Acknowlegement

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