RESEARCH

Evolution of blood pressure control identification in lieu of post-surgery diabetic patients: a review

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Abstract

The blood pressure disparity is the major problem in post-operative surgery especially diabetic patients, because there is substantial interrelation between diabetic and hypertension and this abnormality creates complicated problems and needs to be controlled by continuous monitoring based on the severity. To overcome this problem, implementation of automatic drug infusion is required for critical patients, by which workload of the clinical staffs are reduced. Most commonly the sodium nitroprusside (SNP) is used to reduce the blood pressure in fast action based on the prescribed level. In this paper three different types of estimation techniques (PID, IMC and MPC) are used to identify the valuation. The strength of the projected controller performance is evaluated under different types of patients such as sensitive, and normal along with insensitive patients. Therefore, this paper reviews the validation results based on the optimized SNP infusion rate for persistent blood pressure control compared then the reviewed methods. The MATLAB simulation is used to evaluate the efficiency of the proposed work and obtain the results based on the projected values.

Keywords: Blood pressure regulation, Diabetes and hypertension relation, Optimization techniques

Introduction

The post-operative hypertension is a well-known complications in surgery patients especially in cardiac surgery patients. In this condition most of the patients need continuous drug administration in order to keep their mean arterial pressure within safe limits. In such patients the blood pressure should monitor and control continuously to infuse sodium nitroprusside (SNP) drug as necessary. SNP is used to control the pressure is that the precision of the amount and of the rate of the administered level of infusion [1].

Sodium nitroprusside is often considered a drug of choice for hypersensitive emergencies and it has immediate onset of action within two minutes time. Nitroprusside is a very potent agent to control the blood pressure and it will decrease the cerebral blood flow while increasing the intracranial pressure and based on the severity

the level of infusion to be controlled. The dose is starting initially 0.5 µg/kg/min and it can increase maximum of 0.5 µg/kg/min. As a result, the goals of safety, reducing costs and human effort are met more rapidly and naturally.

As per the research literature the hypertension and diabetes are major risk factor for major chronic disease and these two are interrelated with the substantial overlap between them [2, 3]. As per the medical studies the insulin resistance variation is also an route cause for elevation of hypertension, indeed the hypertension and diabetes shares [4–9] the common conduits like oxidative stress, inflammation, insulin resistance and mental stress, based on the studies the hypertension need to be maintain in a prescribed way especially for diabetic patients.

Based on the importance to keep stable hypertension has researchers developed automatic SNP drug delivery system and it would calculate the necessary drug delivery ratio to keep the blood pressure level in a stable range as per the physician advice with its patient interactive performance [10]. In this paper three different types (PID,

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IMC and MPC) of control strategies used to identify the optimal infusion performance of the drug delivery and the optimal delivery can be identified with these controllers. Based on the output the difficulty in PID controller is the large delay of the subcutaneous sensing and actuation and this time delay and precision output can be achieved with the help of IMC controller, also IMC controller having time delay in settling the desired level and it has main drawbacks of combining conjunctive or disjunctive clauses. In this case the Model Predictive control can be used to archive the desired results with minimum time delay, Also this would be acceptable if Model Predictive Controllers always driven, but the evidence is that they require significant resources to install and maintain, can be difficult to operate, and often display poor performance. The purpose of this work is to compare existing work results for regulate the Blood Pressure level and the case study propose a new dual control strategy to improve and steady the performance of Hypertension Monitoring [11] and SNP dosage prediction controller. The key idea of this assessment is to identify the proper design the controller for drug evaluation that provides more stability and high performance guarantees.

The infusion system is an integrated system contains of injection materials as per the medical standards, which will sensing the blood pressure level and calculate the desired amount of SNP required and deliver the desired amount to the human body with the help of automatic pump. Figure 1 shows the basic architecture of the closed loop infusion control system, in which the controller regulates the details between the sensor input and desired SNP range [12].

The control algorithm is used based on the optimal requirement and the controller input given to drug delivery driver with the help of syntactic micro needle to the human body. In this paper the proposed closed loop control strategy will produce the output equal to the desired

blood pressure level and this research is keen to develop the system which will produce the optimal infusion to the critically ill patients.

System model

The control modeling of drug delivery problems is a very complex task in biomedical engineering and it is an challenging work, similar to the system model has developed [13] the patient model with dynamic model of SNP infusion with the help of correlation analysis. The behavior of the SNP of Blood pressure is modelled as

$$G_{BP}(s) = \frac{\Delta Pd(s)}{I_i(s)} = \frac{ke^{-T_i s}(1 + \alpha e^{-T_c s})}{\tau s + 1} \quad (1)$$

where the descriptions as follows; $\Delta Pd(s)$ is the change in Pressure (mmHg), $I_i(s)$ is the infusion rate of SNP (ml h⁻¹), k gives the patient's sensitivity (a high value of k → sensitive patient), α is a recirculation index, τ is a time constant, T_i is the initial transport delay and T_c is the recirculation time.

All the time constant of the model will be measure in seconds and the model is classified basically in three categories like normal, sensitive and insensitive, The below table shows the parameters [14] of the models and these values are approximated on will vary person to person. In the meantime the real time patient responses will differ based on the linear characteristics as well as non-linear disturbances, also the physical activities influenced the respiratory effects and reflex Responses due to drop in blood pressure, based on the observations the patient model parameters as per the below Table 1.

Controllers design and simulation

In this review various types of control algorithms for blood pressure control have been reported and some of the algorithms include: PID control [13], and IMC control [14] and Model predictive Control [15]. However,

Table 1 Patient model parameters

Parameter	Sensitive	Normal	Insensitive
k	− 9	− 0.714	− 0.179
α	0	0.4	0.4
τ	20	30	60
T _i	30	45	75
T _c	30	40	60

our studies have focused on using the successfully captured Blood pressure dynamics combined model presented in introduction section with SNP reaction. Which has been used before for control purposes of drug infusion and compared three control algorithms the PID, IMC and MPC controllers using MatLab/Simulink. The target SNP infusion range that the controllers were supposed to attain and maintain is similar to healthy blood pressure levels. The proposed blood pressure range is between 120/80.

PID controller

The most traditional of all controllers is probably the proportional integral derivative (PID) controller. A PID controller uses a proportional term, an integral term, and a derivative term, each with a coefficient that provides a weight for that term. In many processes, especially industrial, PID controllers are used to keep some kind of a steady state. The controller takes a measurement from a plant process (mathematical model) and compares it with a set-point (reference) value of BP concentration based on the concentration the SNP will infuse to the human body [16]. The difference (or “error” signal) is then used

to adjust the input to the plant in order to bring the measured value back to its desired set-point. PID controller can adjust process outputs based on the history and rate of change of the error signal. The schematic diagram of the PID controller used with the composite model is shown in Fig. 2.

The general equation of the PID error controller is given as:

$$U_{bp}(t) = k_p * e(t) + k_i \int_0^t e(t) d\tau + k_d \frac{d}{dt} e(t) \quad (2)$$

where K_p is the Proportional gain, K_i is the integral gain, K_d is the Derivative gain, e: Error is the set point measured value, t is the time, τ is the variable of integration.

The timing constraints of integral systems is find using Routh array method. Based on the simulation the transfer function modeling of hypertension patient is designed and the artificial designed pancreas model produces the insulin result as like real patient. To estimate percentage of insufficient insulin to the patient body this output is connected with PI controller. For the case study the P and I value is obtained from reference paper [17–20]. From the pi controller output and necessary constant to get the result value of insulin required for blood pressure patient.

Internal model control

The internal model control (IMC) is an advanced control strategy commonly used in industrial application and controller algorithm is simple and robust to handle the nonlinear and inaccuracies in the process The IMC controller is contain the specific locating process of the controller performance also the controller is taking the specific control track of the process for an set point of the

Fig. 2 Simulation diagram for PID controller

process, also the IMC controller is contain the explicit filter technique to reject the disturbance for the steady state processes [21]. The Internal Model Control system structure shown in Fig. 3 with three different positions. The main part of the controller is used to forecast the process output [22–25] of the system. The following is the internal loop which is used to differentiate the process output and the internal model output. To end, the third position of the controller can be used to control the error to compute the upcoming values of the process outputs [26–29].

The difference between the output of the internal model and the process output is fed back to produce the error, used by the controller. This helps to reduce the effect of disturbances on the system [30–33]. In this model the IMC developed by Garcia and his co-authors [35] on the patient model proposed by Slate and his co-authors [34]. The IMC has been applied to control of blood pressure in [35–37]. The conventional IMC parameter G_p is the plant to be controlled and G_m is a plant model of the process, C is the controller based on model control and $x(t)$ is the system output and D is the external disturbance of the system.

Based on the parameters the formulae evaluated as follows,

$$K_{cp} = \frac{2\tau + \tau_d}{2(\lambda + \tau_d)} \quad (3)$$

where

$$\tau_d = \frac{\tau \tau_d}{2\tau + \tau_d} \quad (4)$$

Model predictive controller

Model predictive controller (MPC) is an advanced controller used in process control filed since 1980. The MPC controller provides various advanced actions such as fast response, accurate model prediction and provide multiple input/output processes in a logical mode, The controlled optimal set point will depend on dynamic process and dynamic principles of the mode of control also these controllers are used in bio control field [38–41] to control and provide the optimal response.

MPC can handle the limitations of the process and it may control the constraints of the process variables, in the meantime the controller can manipulate the variables in a systematic manner naturally in its structural stochastics. Also it is a controller to tune easily based on the requirement [42], also this controller is totally open methodology based on particular principles and procedures which allow for future extensions [43–46]. The controller schemes depends on working process methods and the process output is to be responsible on the predictions of the values in future condition. The MPC controller calculations are depends on predefined system variables in the present condition which contains the sequence of regulated changes. The output changes has been manipulated in the prediction level and it will move the set point in an optimal manner and the control technique is shown in Fig. 4.

If the process is in nonlinear and it may probably accurate with the dynamic model of the system and the current measurements can be used to predict the values of the process output. The MPC is can be implemented

Fig. 3 Simulation diagram of IMC controller

based on discrete time nonlinear process model and the mathematical description can be represented as

$$x_{k+1} = f(x_k, u_k) \quad (5)$$

The MPC control problem is as follows with the knowledge of current output y_k

$$J = \phi(y_k + N_k) + \sum_{j=0}^{N-1} L(y_k + j|k, u_k + j|k, \Delta u_k + j|k) \quad (6)$$

The process inflow is varies depends on the movement of variable N and it is the control sequence of the process and it minimizes the objectives and the measurement is available the parameters of the problem. This recurrent optimization is using to obtain the function and modified through the entire process feedback of MPC to control the variables and optimal output.

Hypertension and diabetes mellitus relationship

In recent research and emerging evidence states an important relationship between hypertension and insulin resistance. Both are associated with substantial overlap and disease mechanisms. Besides that the genetic aspects and environmental factors and the variation of the insulin resistance (Hyperinsulinemia, hyperglycemia and dyslipidemia) develop the hypertension (Fig. 5). The recent studies realized that the insulin resistance develops the type2 diabetes, also has a role to develop the hypertension [47], indeed both hypertension and diabetic share common pathways such as insulin resistance, stress, oxidative stress and inflammation.

The pathways interact and influence each other and may create spiteful cycle, in addition to that the genetic.

Predispositions, cellular abnormalities in insulin signaling and associated homodynamic and metabolic derangements appear to predispose to the development of hypertension. In reality the diabetic mellitus and hypertension having the consequence of the interaction of multiple adaptive pathways that involve vascular and endothelial dysfunction, sodium retention, increased sympathetic nervous system activity, and an overactive tissue renin-angiotensin-aldosterone system. More of the human body, hyperinsulinemia and insulin resistance variation are elevate the intracellular calcium concentration, thus leading to vasoconstriction, as well as the

Fig. 6 PID controller based patient's response

Table 2 Controller performance of sensitive patient model

Parameter	PID	IMC	MPC
Settling Time (sec)	1024	738	526
Overshoot (mmHg)	0.429	0	0

Table 3 Controller performance of normal patient model

Parameter	PID	IMC	MPC
Settling time (s)	948	738	706
Overshoot (mmHg)	0	0	0

proliferation of vascular smooth muscle cells, with resulting Hypertension and Concomitant Diseases [47–49].

Based on the study the hypertension will vary based on the insulin resistance and need to control the hypertension in appropriate way, the same etiology will follow the diabetic mellitus vice versa for the control of insulin.

Discussion and conclusion

In the observation the results of all three different controllers were analyzed with their response. Tables 2, 3, and 4 shows the time it takes the responses to reach -30 mmHg (settling time) in the SNP infusion status along with the overshoot.

Modeling and control of blood pressure regulation for diabetic patients in post-surgery patients are studied. The

Table 4 Controller performance of insensitive patient model

Parameter	PID	IMC	MPC
Settling time (s)	858	820	816
Overshoot (mmHg)	0	0	0

detailed and realistic model for blood pressure regulation is developed by including the drug response model of Slate et al. and in addition to the random disturbance. The results shows that the performance criteria of the controllers are satisfied for PID, IMC and MPC controller. However, the response time for the PID control of all three patients responses are higher than with IMC and

Fig. 7 IMC controller based patient's response

Fig. 8 MPC controller based patient's response

Fig. 9 Drug (SNP) infusion rate

MPC controller because of slow response in nature, especially the sensitive patient's response which has a delay in settling time of offered by the other controllers. The overshoot of the controllers achieved zero except a small amount in the sensitive patient's response with PID Control [50–53]. Figures 6, 7, 8 and 9 show the infusion rate for all three types of patients and it is observed the infusion rate better with IMC and MPC controllers compare with PID controller for the normal and insensitve patient the infusion rate is obtained with PID control is more or less the same as with IMC and MPC controllers.

Based on the observation the maximum value of the infusion rate does not exceed 300 ml/h even for the “insensitve patient” as reported [53]. As per the expected the infusion rate for the sensitive patient is low, around 8 ml/h. The main focus of this paper was to compare and review the performance of three control strategies; PID control and IMC to control blood pressure using three types of patient's models and the results analyzed and the results found that the IMC and MPC controller offered

much better results and achieve the optimal insulin drug infusion.

Future scope

Based on the review the relationship between hypertension and Diabetes are proved in medical terms, also the findings builds the chance to develop a complex control system to control both hypertension and diabetic mellitus simultaneously based on the measured values and obtain the optimal drug delivery through auto infusion.

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