Multiple Model SPGPC for Blood Pressure Control

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Abstract: Multiple model adaptive control procedures have been considered for a computer-based feedback system, which regulates the infusion rate of a drug (nitroprusside) in order to maintain the blood pressure as close as possible to the desirable value. Transfer function parameters can differ significantly between patients, and also time-dependent, so the development of a suitable algorithm becomes required not only for maintaining steady-state but also the transient specifications. In this paper, based on computer simulations, a multiple model adaptive control procedures show to be successfully applied to blood pressure control, despite the uncertainty related with delays, time constant and gains associated.

1 INTRODUCTION

Arterial hypertension is an important risk factor responsible to cause cardiovascular diseases, begin responsible for 40% of the deaths caused by coronary arterial disease. Twenty-nine percent (29%) of the world's population has arterial hypertension with Brazil contributing to 22% to 44%, depending on the region (Mion et al., 2010). These numbers become very important as high blood pressure is directly associated to cerebrovascular events, coronary arterial disease and mortality (Kochar and Woods, 1990).

Postsurgical complications of hypertension can occur, or to be aggravated, in cardiac patients. To decrease the probability of complications it is necessary to reduce, at the earliest stage possible, the elevated blood pressure. A way to reach this objective is to use a continuous infusion of vasodilator drugs, such as sodium nitroprusside (SNP), that can quickly lower the blood pressure in most patients, bearing in mind that an overdose of nitride could cause toxic side effects.

It is known that each patient has a different SNP sensibility, and therefore it can also be time-dependent. So, it is necessary to establish an appropriate control of the infusion rate of SNP to accomplish the desired blood pressure. To maintain the desired blood pressure, a constant monitoring of arterial blood pressure is required and a frequently adjust on drug infusion rate. Manual control of arterial blood pressure by clinical personnel it is very demanding and time consuming, usually leading to a poor control quality of the hypertension.

The objective of this paper is to develop an adaptive method control for a blood pressure management for any patient without changing the controller. Blood pressure control of a patient under the influence of SNP, that is a vasodilator, is modelled through an uncertain model (Slate, 1980; Maitelli and Yoneyama, 1997). A multi-model approach is used in order to control the blood pressure under the influence of this drug. Multi-model approaches are commonly applied to control non-linear systems that operates in long ranges (Cavalcanti et al., 2007; Cavalcanti et al., 2009; Silva et al. 2010; Silva, 2010). The basic idea of multi-model approach consists in decompose the system's operating range into a number of operating regimes that completely cover the chosen trajectory (Cavalcanti et al., 2009). There are, basically, two approaches for multi-model. The first one consists of designing a set of suitable controllers (one for each operating regime) and to calculate weighting factors to them as showed by the study by Cavalcanti et al. (2009). The global control signal is a weighting sum of the contributions of each controller. The second

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one consists of building a global model as a weighting sum of each local model as showed in (Cavalcanti et al., 2009). In both cases, a way to measure distances between models is defined.

In this work, a multi-model is used to control the blood pressure control. A set of models is chosen and a Smith Predictor Generalized based Predictive Control (SPGPC) is designed for each chosen model. A validity function is defined in order to calculate the weight of each controller. The weight factor selected considers the residual error between the output of a given model and the plant (patient) output.

2 PROBLEM FORMULATION

A model of the mean arterial pressure (MAP) of a patient under the influence of sodium nitroprusside can be represented, as in Slate (1980), by:

$$MAP(t) = P_0 - \Delta P(t) + v(t) \quad (1)$$

where MAP is the mean arterial pressure, P_o is the initial blood pressure, also called a background pressure, $\Delta P(t)$ is the pressure differential due to infusion of Nipride, and $v(t)$ is a stochastic background noise. In this paper it is assumed that P_o is constant. A continuous-time deterministic model describing the relationship between the change in the blood pressure and drug infusion rate (Slate, 1980) is as follows:

$$\Delta P(s) = \frac{Ke^{-T_i s}(1+\alpha e^{-T_c s})}{1+\tau s} I(s) \quad (2)$$

where $\Delta P(s)$ is the blood pressure variation, $I(s)$ is the infusion rate, K is drug sensitivity, α is the recirculation constant, T_i is the initial transport delay, T_c is the recirculation time delay, and τ is a time constant.

The corresponding discrete-time deterministic model for this process can be given as follows:

$$\Delta P(t) = \frac{q^{-d}(b_o + b_m q^{-m})}{1 - a_1 q^{-1}} I(t); b_o > 0 \quad (3)$$

where q^{-1} denotes a unit delay operator. The parameters b_o, b_m, a_1, d, and m are obtained from the sampled version of the continuous-time model given in (2).

A range of typical values for the parameters of the model (2) for different patients is given by Slate (1980). Values for the parameters in the model (3) for the case with the sampling time 15 *s* are found in Table 1.

Table 1: Range of values for parameters of the discrete-time deterministic plant model for sampling time of 15 *s*.

Parameter	Minimum	Maximum	Nominal
b_o	0.053	3.546	0.187
b_m	0	1.418	0.075
a_1	0.606	0.779	0.741
d	2	5	3
m	2	5	3

It can be seen that there is a considerable difference in the parameter values, including the pure time delay, for different patients. For a given patient, time delays are unknown, but are assumed to be constant over a long period of time. The parameters b_0, b_m and a_1, however, change during the infusion procedure. In this work, it is assumed that the parameters change in an exponential manner. The change of parameters is modeled as follows (Pajunen et al., 1990):

$$par(t) = par(0)(2 - e^{-t/\gamma}) \quad (4)$$

for increase and decrease in the parameter value, respectively, where $par(t)$ represents the parameter of the continuous-time model and γ is the change time constant. Thus, the controller when turned for a particular patient, should be able to handle time-varying parameters and initially unknown time delays. An automated drug SNP infusion system for blood pressure control should produce good response characteristics, such as pressure undershoot (i.e., maximum excursion below commanded level) less than 10 *mmHg*, 20 percent settling time of 5-10 *min*, steady-state error within *+5 mmHg*, and also satisfy the following clinical conditions (Slate, 1980), where:

- U_M = maximum infusion rate (*ml/hr*);
- W_p = patient weight (*kg*);
- i_M = maximum recommended dose ($10\mu g.kg^{-1}\min^{-1}$);
- C_S = drug concentration ($\mu g / ml$).

For patient safety, the infusion rate should be reduced under hypotension, i.e., when there is a drop in excess of *20 mmHg* from the set point.

3 SMITH PREDICTOR BASED GENERALIZED PREDICTIVE CONTROL (SPGPC)

The Smith Predictor (SP) was the first control system proposed in the literature that introduces a

delay compensator (Smith, 1957). The SP improves the performance of a system with a delay compared to other techniques, such as PID, especially when the delay is dominant (greater than twice the dominant time constant of the system).

The idea of using a Smith predictor instead of an optimal predictor in generalized predictive controllers for stable plants was presented in Normey-Rico and Camacho (1996). The advantages in the use of this control strategy instead of the standard Generalized Predictive Control (GPC) in real applications was also shown in Normey-Rico et al. (1998). This has great interest in the case of time-delay systems. These authors have shown that, by modifying the GPC algorithm, it is possible to improve the robustness of the closed-loop system while maintaining the nominal performance. The basic idea of the Smith predictor based generalized predictive control (SPGPC) is to use a Smith predictor structure to compute the predictions of the output of the plant and to calculate a sequence of future control signals in order to minimize a multistage cost function defined over a control horizon, as follows:

$$J(N_1,N_2)=\sum_{j=N_1}^{N_2}\delta(j)[\hat{y}(t+j\mid t)-w(t+j)]^2+\sum_{j=1}^{N_2-d}\lambda(j)[\Delta u(t+j-1)]^2 \quad (5)$$

where N_1 and N_2 are the minimum and maximum costing horizons, respectively, d is the delay of the process model, $\delta(j)$ and $\lambda(j)$ are weighting sequences, $w(t+j)$ is a future set-point or reference sequence, $\Delta u(t)$ is the incremental control action ($\Delta u(t) = u(t)-u(t-1)$) and $\hat{y}(t+j|t)$ is the j-step ahead prediction of the system output on data up to time t computed using the following model of the plant:

$$A(z^{-1})y(t)=z^{-d}B(z^{-1})u(t-1) \quad (6)$$

where

$$A(z^{-1})=1+a_1z^{-1}+a_2z^{-2}+\cdots+a_{na}z^{-na}$$
$$B(z^{-1})=b_0+b_1z^{-1}+b_2z^{-2}+\cdots+b_{nb}z^{-nb} \quad (7)$$

Using this procedure, the final control law can be written as:

$$\Delta u(t)=ly_1\hat{y}(t+d\mid t)+ly_2\hat{y}(t+d-1\mid 1)+\cdots+ly_{na+1}\hat{y}(t+d-1-na\mid t)+lu_1\Delta u(t-1)+lu_2\Delta u(t-2)+\cdots+lu_{nb}\Delta u(t-nb)+\sum_{i=1}^{N}f_iw(t+d+i) \quad (8)$$

where ly_i, lu_i and f_i are constants and the prediction of the output of the plant is computed using the prediction of the output using the open loop model of the plant given in (6). Moreover, a correct prediction in each open loop can be used, by adding the mismatch between the output and the prediction:

$$\hat{y}(t+d-i\mid t)\leftarrow\hat{y}(t+d-i\mid t)+y(t-i)-\hat{y}(t-i) \quad (9)$$

To compute the coefficients of the control law in (8), the same procedure as in the GPC is used. First, consider that the horizons N_1 and N_2 are computed as $N_1=d+1$ and $N_2=N+d$ where d is the dead time of the plant model. Then, using these horizons, the prediction of the output of the plant is computed using an incremental model of the process (Camacho, 2003).

4 MULTIPLE MODEL SPGPC METHOD

The Multiple Model SPGPC (MMSPGPC) procedure, shown in Figure 1, is based upon the assumption that the plant can be represented by a finite number of models and, for each model a controller can be priori designed.

An adaptive mechanism is then need to decide which controller should be dominant for a given plant. One procedure for solving this problem is to considered a weighted sum of all the controller outputs, where the weighting factors are determined by the relative residuals between the plant response and the model responses (Silva et al., 2010).

In Figure 1, since the plant gain is negative, the system error is expressed as:

$$e(k)=p(k)-p_c \quad (10)$$

where k is the sampling time and p_c, is the commanded or set-point pressure level.

4.1 Model Bank Design

The model bank consists of a number of models with constant parameters characterizing the individual plant subspace (He et al., 1986). Since these models should have the same structure as the plant, the following discrete model will describe them:

$$\Delta P_{mj}(k)=\frac{q^{-d}(b_{0j}+b_{mj}q^{-m})}{1-a_{1j}q^{-1}}u(k);b_{oj}>0 \quad (11)$$

$(j=1, \ldots, N)$

where the output pressure from model j is:

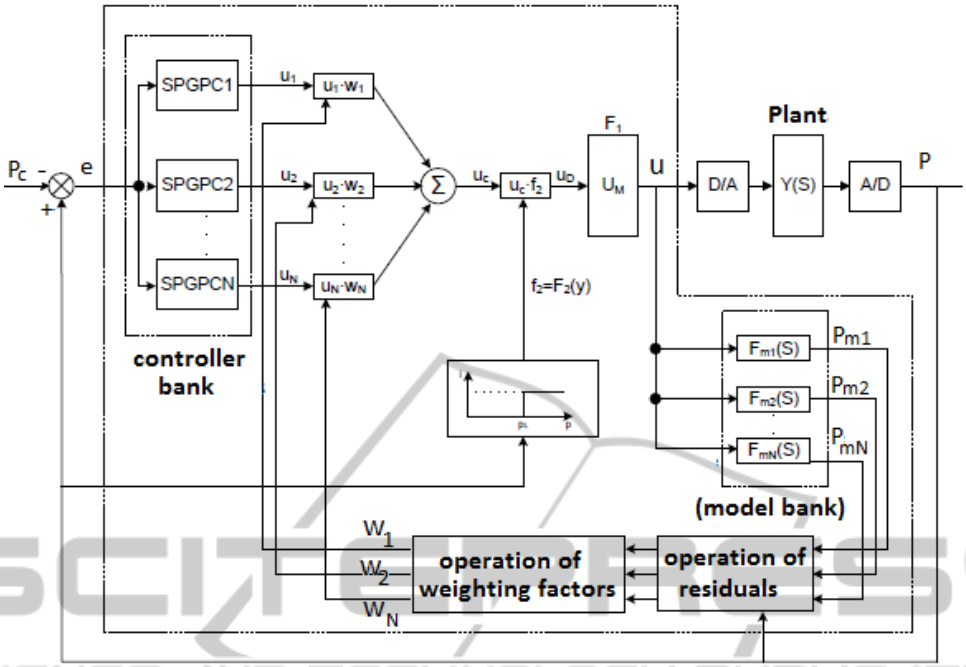

Figure 1: Multi-model SPGPC schema.

$$P_{mj}(k) = \Delta P_{mj}(k) + P_0 \ (j=1,\ldots,N) \tag{12}$$

where $\Delta P_{mj}(k)$is the change in the *jth* model output, $u(k)$ is the model input, P_0 is the initial value of each model's output and equals the initial plant output.

The relative residual $R_j^2(k)$ will be defined as the normalized squared error between plant and model, i.e., as follows:

$$R_j^2(k) = \{[P_{mj}(k) - P(k)]/(P_0 - P_c)\}^2 \quad (j=1,\ldots,N) \tag{13}$$

At each sample time k, the model that has the smallest residual is defined as the matching model, which is used to represent the plant characteristics.

4.2 Control Algorithm

To reach desirable system performance and to guarantee patient safety, the control algorithm should converge quickly to the optimal values and should react to time varying plant characteristics, as well as ensure a reasonable rate of blood pressure change. Thus, the control was computed as a weighted sum of controller bank signals, and represented by the following equation:

$$u_c(k) = \sum_{j=1}^{N} W_i(k) u_j(k) \tag{14}$$

where N is the number of models, $u_c(k)$ is the control variable, $u_j(k)$ are the individual controller outputs and $W_j(k)$ are the weighting factors. The weights were selected as follows:

1. Recursive update

$$W_j'(k) = \frac{\exp[-R_j^2 / 2V^2] W_j(k-1)}{\sum_{i=1}^{N} \exp[-R_i^2 / 2V^2] W_i(k-1)} \tag{15}$$

2. Bounding away from zero

$$W_j(k) = \begin{cases} W_j'(k) & W_j'(k) > \delta \\ \delta & W_j'(k) \le \delta \end{cases} \tag{16}$$

3. Normalization

$$W_j(k) = \frac{[W_j(k)]^2}{\sum_{i=1}^{N} [W_i(k)]^2} \tag{17}$$

where $R_j(k)$ are the residuals and defined in (13), V is a parameter controlling the convergence rate of $W'j(k)$ with $R_j(k)$ and δ is a threshold to limit the importance of past information.

Equations (14) and (15) express the basic relationship between the control, the weighting factors, and the relative residuals. Equation (16) is used to delimit the importance of past information enabling the adaptive mechanism quickly react to the new information about the plant characteristics.

Equation (17) is used to normalize the weighting factors so that their square sum is equal to unity.

5 SIMULATION RESULTS

Computer simulations were used to evaluate the response of the system design (Section 4) over a representative plant parameter envelope. Of interest were the response to step command in the presence of plant background noise, the adaptation of the algorithm to time-varying plant parameter.

The regime blood pressure considered was *150 mmHg* and the multi-model controller deviation reference of *-50 mmHg*. The plant background noise *v(t)* was simulated as a white Gaussian noise sequence with standard deviation of *2 mmHg*. Figure 2 shows the blood pressure of a given simulated patient, with time varying parameters, calculated by the Equation (4). Figure 3 shows the deviation in infusion rate.

Simulations results have shown the convergence process of the weighting factors $W_j(k)$, in Figure 4, such as the global control effort is calculated to the closest model (less residual error). Figure 2 shows that the schema leads the blood pressure of the chosen patient to the given reference. Thus, the drug infusion rate and the blood pressure both change in a smooth manner. These responses also show that the MMSPGPC algorithm is robust even in the presence of the plant background noise.

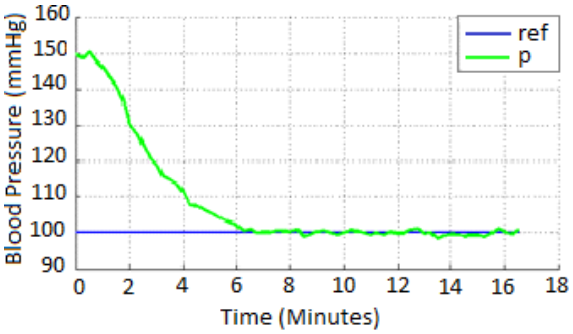

Figure 2: blood pressure (mmHg).

6 FINAL REMARKS

The results showed that this multi-model schema MMSPGPC presented has a great potential of application in uncertain systems. Even in presence of representative noise background, the presented approach has shown a reasonable result and could be applied, as first approach, in tests with animals. Others basic controllers, in order to attenuate the delay effect, may be considered.

The results also show that the controller using GPCs with Smith predictor, in the controllers bank, provides a faster control (in the order of 6 *min*) and with a reasonable rate of infusion, compared to the results obtained in Cavalcanti et al. (2009), that used only GPCs in the controllers bank, with an obtained response times of 20 *min*.

In the future, robustness tests can be implemented with the submission of the system to a larger range of disturbances and parameters. Comparative studies with other control algorithms, as adaptive control, they would also be important to accomplish.

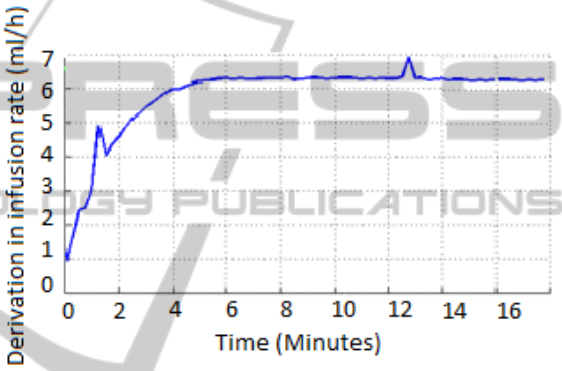

Figure 3: deviation in infusion rate.

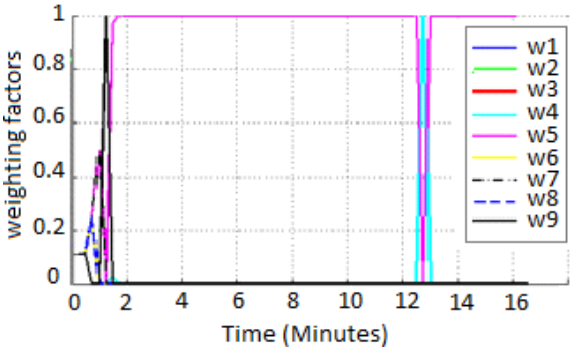

Figure 4: weighting factors.

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