Online Identification and Internal Model Control for Regulating Hemodynamic Variables in Congestive Heart Failure Patient

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***Abstract*—This paper deals with one of the most challenging task of simultaneous control of two hemodynamic variables by the infusion of sensitive cardiac drugs in congestive heart failure (CHF) patients. A nonparametric internal model control (IMC) algorithm along with an integral control action has been proposed in this work for regulating two hemodynamic variables, the mean arterial pressure (MAP) and the cardiac output (CO) by simultaneous administration of two drugs – sodium nitroprusside (SNP) and dopamine (DPM). The two-input two-output physiological model of CHF patient is identified online by solving Volterra kernels from the input-output data of the physiological process. FFTs are taken on respective time domain kernels to obtain the Volterra transfer function (VTF) of the multivariable system. The internal model control algorithm is developed using this VTF. The integral control action has been combined with IMC for set-point tracking. Using this closed loop control algorithm MAP and CO reaches the steady state value within a very short time with the minimum infusion of highly sensitive cardiac drugs in presence of actuator and sensor noises.**

***Index Terms*—online identification, nonparametric model, Volterra kernel, internal model control, congestive heart failure.**

I. Introduction

The most common disorder in the cardiovascular system is congestive heart failure (CHF). The heart of the CHF patient fails to pump sufficient blood to the body's tissue and suffers from shortness of breath. High blood pressure damages the cardiac work and the blood vessels causing heart attack and heart failure. In intensive care unit or in operating theatre, certain hemodynamic variables of the patients suffered by a disturbance due to surgery or some sort of trauma are maintained at their desired value by the controlled infusion of drugs. In case of patients with congestive heart failure, mean arterial pressure (MAP) and cardiac output (CO) are simultaneously controlled at the safe level by intravenous infusion of two drugs – sodium nitroprusside (SNP) and dopamine (DPM) simultaneously. In clinical practice, these hemodynamic variables are kept at safe values using manual drug delivery by experienced physician. It is very difficult to determine the right infusion rates of the multiple drugs and maintain the variables at their safe value. An automatic drug delivery system is useful for close regulation of variables in the coupled process.

The model of cardiovascular system in congestive heart failure (CHF) patient with the responses of the hemodynamic variables and the infusion of two cardiac drugs SNP and DPM was initially developed by Yu *et al.* [1]. Efforts have been made from the last two decades in designing a closed loop control system that would be able to control the infusion rate of SNP and DPM [2]-[7]. Rao *et al.* [3], [4] developed a MPC strategy and tested on a nonlinear canine circulatory model for the regulation of MAP, CO, MPAP with the infusion of SNP, DPM, PNP and NTG under critical care conditions. Boldisor *et al.* [5] developed a fuzzy control strategy and Enbiya *et al.* [6] developed a multivariable model reference adaptive control (MRAC) algorithm to regulate the two variables MAP and CO by automatic infusion of two drugs SNP and DPM. But these controllers cannot regulate the hemodynamic variables online when the dynamics and parameters of the process vary widely with patient condition.

As the cardiovascular system is a complex nonlinear multivariable system and there are dynamic uncertainties from patient to patient, a dynamic model is required to be identified from the input-output data of the patient to predict the dynamic behavior of the patient. Various parametric and nonparametric identification methods have been developed by researchers to model complex systems [8]-[16]. But the main disadvantage of using parametric model is that the parametric model lack full information of nonlinearities in such a coupled system. A potential advantage of using nonparametric model is that it can yield nonlinear model based controller directly from the identified process [11]-[16].

This paper concentrates on the design of online nonparametric identification and internal model control algorithm that will automatically adjust the controller with the change in dynamics and parameters of the process. The two input two output patient hemodynamic model [6] described by a first order system with delays has been developed. The frequency domain Volterra kernels [11]-[14] of the virtual patient model are computed and used in nonparametric internal model

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control (IMC) to find the optimum drug dosage. The identification and the control of hemodynamic variables are made online by adaptive recursive least square (ARLS) algorithm [12]-[14]. As the problem of simultaneously controlling two vital hemodynamic variables MAP and CO by the intravenous infusion of cardiac drugs in a congestive heart failure patient is basically a set-point tracking problem, the control scheme is developed by combining IMC with an integral control action.

II. Congestive Heart Failure Patient Response Model

The patient hemodynamic model [6] is described by a 2-input-2-output first order system with delays.

$$\begin{bmatrix} MAP \\ CO \end{bmatrix} = \begin{bmatrix} \dfrac{K_{11}e^{-T_{11}s}}{\tau_{11}s+1} & \dfrac{K_{12}e^{-T_{12}s}}{\tau_{12}s+1} \\ \dfrac{K_{21}e^{-T_{21}s}}{\tau_{21}s+1} & \dfrac{K_{22}e^{-T_{22}s}}{\tau_{22}s+1} \end{bmatrix} \begin{bmatrix} SNP \\ DPM \end{bmatrix} \quad (1)$$

where, K_{ij} = Model gain

T_{ij} = Time delay (min) between the input and the system response.

τ_{ij} = Time constant (min)

The parameter values are taken from Enbiya *et al.* [6]. The infusion rate of the drugs used to control the variables MAP and CO are measured in (μg/kg/min). Cardiac output is measured in (ml/kg/min). Mean arterial pressure is measured in millimeters of mercury (mmHg).

III. Internal Model Control Framework

IMC generates control signals using parametric or nonparametric model of the process. In the present work, nonlinear control problem has been tried to solve by extending IMC to accommodate nonlinear nonparametric model identified online.

A. Patient Model Identification

Volterra equations have been solved online by adaptive recursive least square (ARLS) algorithm to compute the kernels of the patient model. For a MIMO system with x_i number of inputs, where i=1, 2, … m, the equation of the output $y(t)$ for a memory length M of generalized finite Volterra series up to second order kernel in time domain is as follows:

$$\begin{aligned} y(t) = & \sum_{\tau=0}^{M-1} g(\tau) + \sum_{i=1}^{m}\{\sum_{\tau=0}^{M-1} g_i^{(1)}(\tau)x_i(t-\tau)\} + \\ & \sum_{i=1}^{m}\{\sum_{\tau_1=0}^{M-1}\sum_{\tau_2=0}^{M-1} g_{ii}^{(2)}(\tau_1,\tau_2)x_i(t-\tau_1)x_i(t-\tau_2) \\ & + \sum_{j=i+1}^{m}\sum_{\tau_1=0}^{M-1}\sum_{\tau_2=0}^{M-1} g_{ij}^{(2)}(\tau_1,\tau_2)x_i(t-\tau_1)x_j(t-\tau_2)\} \end{aligned} \quad (2)$$

The self-kernels g_{ii} acting on a single input are symmetric and the cross-kernels g_{ij} acting on different inputs and they are asymmetric [8]-[10]. The required Volterra kernels are computed online in adaptive way using recursive least square (RLS) algorithm to select the filter coefficients [8]-[10] and update the same with new data set by minimizing a cost function:

$$J(t) = \sum_{\tau=0}^{t} \lambda^{t-\tau} e(\tau) = \sum_{\tau=0}^{t} \lambda^{t-\tau}(d(\tau) - y(\tau)) \quad (3)$$

where, $e(\tau)$ is the error signal and $d(\tau)$ is the desired signal. λ is a factor that controls the memory span of the adaptive filter.

The Volterra transfer function for the design of internal model control algorithm obtained from the frequency domain Volterra kernels can be written as:

$$G^{(k)}(f_1, f_2, ..., f_k) = \sum_{\tau_1=0}^{M-1}\sum_{\tau_2=0}^{M-1}.....\sum_{\tau_k=0}^{M-1} g^{(k)}(\tau_1,\tau_2,...,\tau_k)\prod_{q=0}^{k}\exp(-j2\pi f_q\tau_q) \quad (4)$$

The performance of the proposed identification algorithm for 15min simulation with the inputs SNP and DPM subjected to a step change from 0 to 1μg/kg/min and 0 to 4μg/kg/min respectively is shown in Fig. 1. The initial condition for MAP and CO is taken as 88mm*Hg* and 64ml/kg/min respectively.

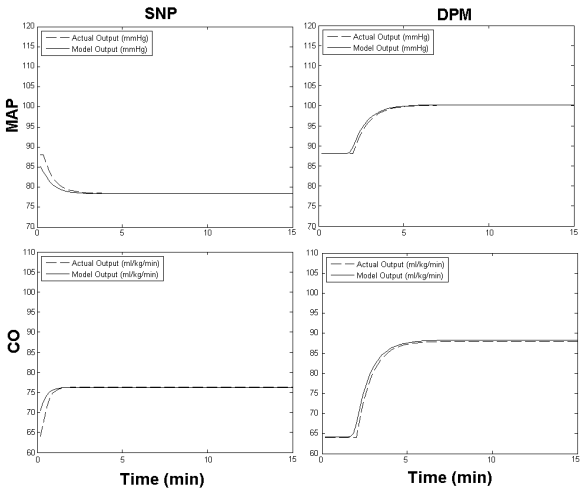

Figure 1. Performance of the proposed identification algorithm.

B. Design Objectives and Solution for IMC

A general model-based control structure is shown in Fig. 2. The nonlinear process *P* is modeled by *G*. An overall controller *H* is composed of a feed-forward path controller *Q* and the feedback model *G*. The feed-forward controller *Q* generates a control sequence *u* through observed plant output *y* and output predicted by *G* [15-16].

The design objective is to find $J:\Re\rightarrow\Re^{+}$ and to find a *Q* such that

$$J = \min_{u}\|e\| \quad (5)$$

where,

$$e = y_R - y \quad (6)$$

The IMC of Fig. 2 can be constructed using nonparametric model from analytical Volterra structure in frequency domain. The finite number of identified

frequency domain kernels of G, is denoted by g_i, with $i = 1,2,....N$. The model output can be written in compact form as:

$$y = y_M + n = \sum_{i=1}^{\infty} g_i * u + n = g * u + n \tag{7}$$

hence,

$$e = (\xi + n) - (y_M + n) = \xi - y_M = \xi - (g * q) * \xi \tag{8}$$

The objective of (5) is therefore strictly met if $(g * q) * \xi = \xi, \ \forall \xi$; i.e.

$$G * Q = I \text{ or, } Q = G^{-1} \tag{9}$$

Hence, an optimal solution of Q is found as G^{-1} i.e. inverse of the frequency domain kernel.

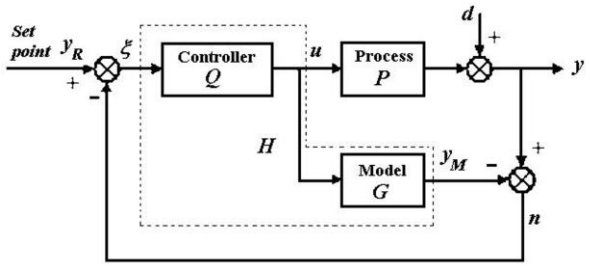

Figure 2. Structure of an IMC scheme.

C. Controller Synthesis Based on Volterra Model

Obtaining a strictly zero J of (5) would be impossible in practice. Thus the frequency domain Volterra kernels of the model G and the controller Q are decomposed into linear operator and a nonlinear one based on higher order Volterra kernels [16].

$$G = G_1 + (G_2 + G_3 + ...) \tag{10}$$

$$Q = Q_1 + (Q_2 + Q_3 + ...) \tag{11}$$

A problem arises if either the inverse of G_1 does not exist or it is unrealizable. Hence we revise the objective (5) as:

$$J_i = \min_{Q} \left\| e^{(i)} \right\|, \quad \forall i \tag{12}$$

where,

$$e = \sum_{i=1}^{\infty} e^{(i)} \tag{13}$$

$e^{(1)} = H_1[\xi] - \xi$ and $e^{(j)} = H_j[\xi]$, for $j = 2,3,...$

and $H = G * Q = H_1 + H_2 + ...$ (14)

If the Euclidian metric (or the L_2-norm) is used to measure revised objective (12), the optimization problem for the case $i = 1$ will have the solution:

$$u^{(1)} = G_1^{-L}[\xi] \tag{15}$$

i.e.

$$Q_1 = G_1^{-L} \tag{16}$$

Similarly, the higher-order solutions are derived as:

$$u^{(j)} = -G_1^{-L}\left[\xi^{(j)}\right], \text{ for } j = 2,3,..... \tag{17}$$

where $\xi^{(j)}$ is a quantity dependent upon known quantities up to step j. The block diagram of the overall online model identification and control process is shown in Fig. 3.

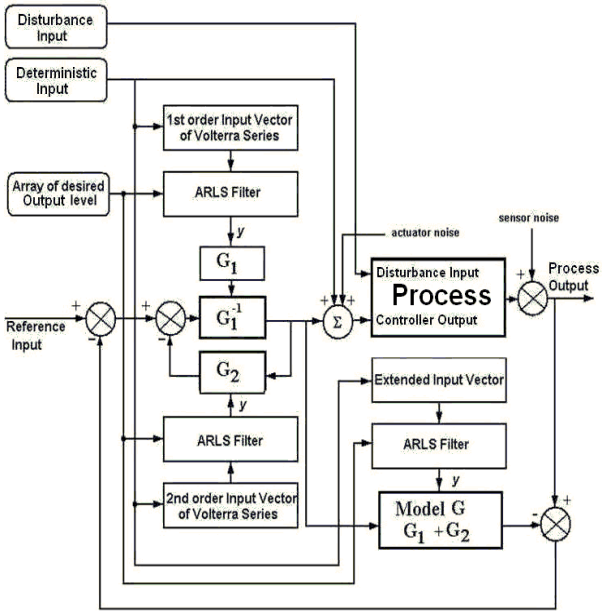

Figure 3. Block diagram of online internal model control scheme.

D. Set-point Tracking using Online Internal Model Controller

As the problem of simultaneously controlling of two vital hemodynamic variables MAP and CO by the intravenous infusion of cardiac drugs SNP and DPM in a congestive heart failure patient is basically a tracking problem, the control scheme is developed by combining IMC with an integral control action shown in Fig. 4. An integral control action is incorporated to the IMC that updates the controller based on the variability between the predicted output and the measured output and provide perfect set-point tracking.

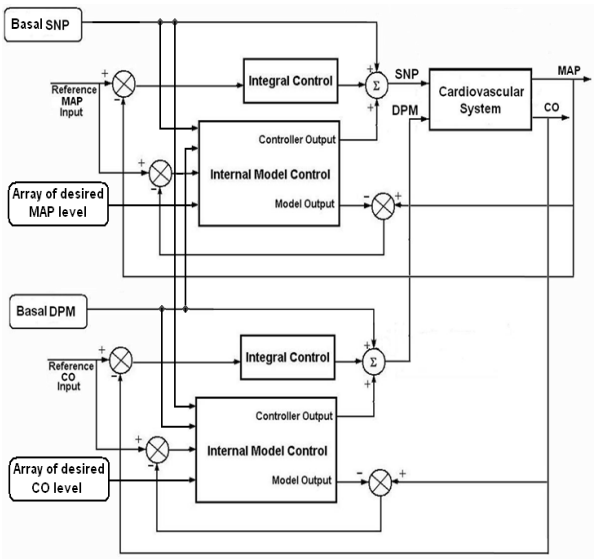

Figure 4. Block diagram of online internal model control with integral control action.

IV. Experiments and Verification of Results

The model is subjected to the basal SNP dose of 1μg/kg/min and basal DPM dose of 4μg/kg/min. The steady state value of this CHF patient is set at 97.5*mmHg* for MAP and 95ml/kg/min for CO [3]. The control objective is to maintain the variables MAP and CO within a range of values; they may not be exactly at the set-point. It is also desirable that the time required to reach the steady state should be very small. The performance of the IMC control scheme in addition with integral control action in controlling MAP and CO by the infusion of SNP and DPM without and with sensor and actuator noises are shown in Fig. 5 and Fig. 6 respectively. Here the time required to reach the steady state is only 8min and the required infusion of cardiac drug 'SNP' is only 0.5μg/kg/min and DPM is 4.1μg/kg/min. For regulating the hemodynamic variables, Rao *et al.* [3] has used the highly sensitive cardiac drug 'SNP' of value 4μg/kg/min which is required in our method is only 0.5μg/kg/min.

For robustness analysis, the parameters K_{11} (normal range -1 to -50) and K_{12} (normal range 0 to 9) [6] are responsible for the increase in MAP has been increased by +50% of the nominal value. Fig. 7 shows that the present control algorithm performs robustly for the congestive heart failure patient model tested with the variation of the parameters that has the maximum effect on MAP. Both the outputs MAP and CO are controlled by the infusion of more amount of the drugs SNP and DPM to the patient having parameter uncertainty than in the case of a nominal patient during the initial period.

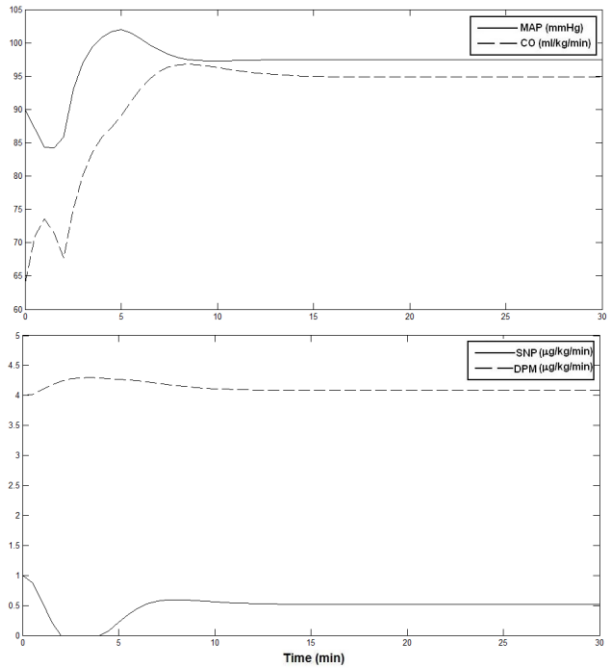

Figure 5. Response of MAP and CO and the corresponding infusion of SNP and DPM.

V. Comparison with Earlier Reported Results

The model is subjected to the same basal SNP dose and basal DPM dose and the steady state value of this CHF patient is set at 97.5mmHg for MAP and 95ml/min/kg for CO as in Rao *et al.* [3]. The settling time taken to reach the steady state value is same as obtained by Rao *et al.* [3], but the infusion of highly sensitive SNP dose needed to reach the steady state value in this proposed method is only 0.5g/kg/min which is very less than the value 4μg/kg/min as obtained by Rao *et al.* [3].

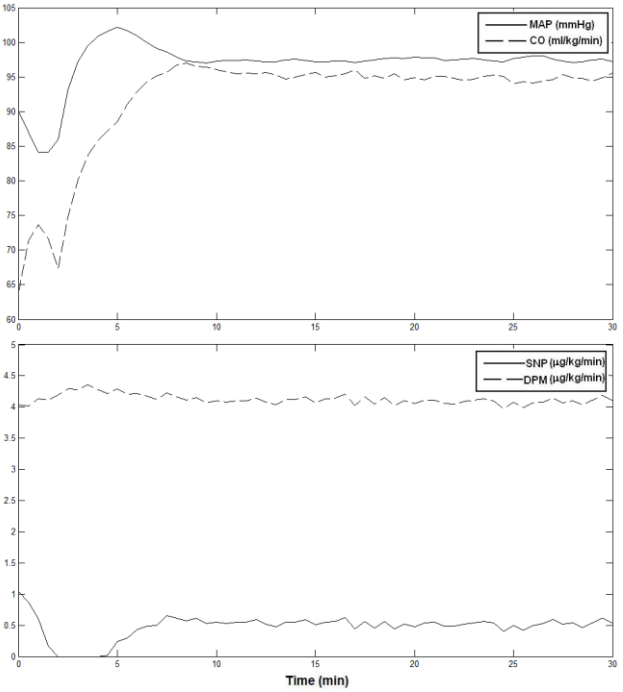

Figure 6. Response of MAP and CO and the corresponding infusion of SNP and DPM in presence of sensor and actuator noise.

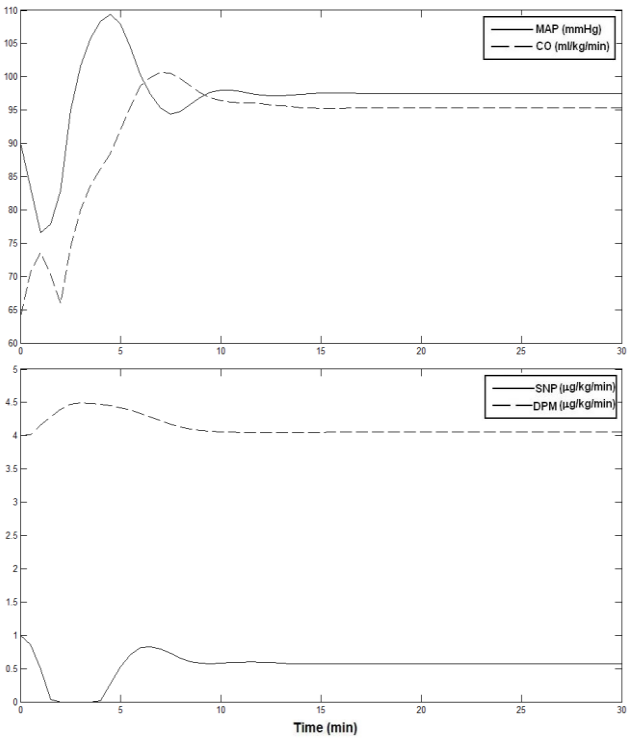

Figure 7. Response of MAP and CO and the corresponding infusion of SNP and DPM when K_{11} and K_{12} are increased by +50% of the nominal value.

VI. Conclusion

Model-based control requires a good model that closely represents the dynamics of the patient and design of a constrained controller. A data driven Volterra model for the nonlinear dynamic system of multivariable physiological process with multi drug infusion in a congestive heart failure patient with relatively short memory effects has been developed. The advantages of block-oriented model have been utilized with proper selection of Volterra kernels by ARLS algorithm and extended input vectors for the nonlinear process. Each frequency domain kernels, called the Volterra transfer function (VTF), is computed by taking the FFTs on respective time domain kernels for a specific length of extended input vector. An Internal Model Control algorithm has been developed by using the VTF. An integral control action has been added to provide perfect set-point tracking eliminating the steady state error. The performance of the proposed control algorithm has been tested on the congestive heart failure patient that yielded improved setting time with minimum intravenous infusion of sensitive cardiac drugs. The future research direction concerns in applying the present control algorithm in different patient conditions in critical care such as post-operative hypertension and sepsis shock.

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