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Adaptive Multilayer Neural Network Control of Blood Pressure

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Abstract:

In this paper we discuss a two model multilayer neural network controller for adaptive control of blood pressure using sodium nitroprusside. A model with auto-regressive moving average, represent the dynamics of the system and a modified backpropagation training algorithm are used to design the control system to meet specified objectives of design and clinical constraints. Controller simulation shows that it has acceptable settling time, it can be able to maintain the blood pressure within the desired set point. with a small variation in the steady state.

Keywords:
Multilayer Neural Network, Adaptive Control

1.Introduction

The maintenance of decreased level of arterial blood pressure(ABP) is of vital important in many clinical situations. Continuous infusion of drug such as sodium nitroprusside(SNP) rapidly decrease the blood pressure. Manual adjustment of the infusion rate of SNP to control ABP is often complicated by the variation of patient response to this pressure-controlling medication and by operation by inexperienced personnel. Lack of timely adjustment of infusion may yield undesirable oscillation.

Recognizing the need for automatic drug administration system to improve patient care, several closed-loop feedback systems to automatically control rates of infusion have attracted interest. Initially, nonadaptive methods such PD and PID controller were used to regulate arterial pressure about a set concentration. These controllers were not able to achieve satisfactory performance in the overall system because of the nonlinear nature of patient response and diverse patient sensitivities to the drug.. More complex adaptive and optimal controller need system parameters a priori. Neural networks appear to be powerful tools to learn static and dynamic nonlinear system. Several controllers based on multilayer neural network(MNN) with an algorithm for backpropagation of error serve to approximate the unknown nonlinear static function. So multilayer neural network control maybe powerful to control rate of drug infusion.

2.Plant Characteristics

A continuous-time deterministic model of the

ABP of a patient under the influence of SNP is represented in equations published by Slate:

$$P(t) = P_o + \Delta P(t) + P_d(t) + v(t)$$
$$\frac{\Delta P(t)}{u(t)} = -\frac{Ke^{-T_i s}(1 + ae^{-T_c s})}{(1 + T_1 s)} \quad (1)$$

where P is the ABP, P_0 is the initial blood press-
ure and ΔP is the variation of pressure due to infusion of SNP, v is stochastic background characteristic.

The ARMA model of a patient's ABP under the influence of SNP is

$$y(k) = P(K) - P_o$$
$$= -\frac{q^{-d}(b_o + b_m q^{-m})}{1 - a_1 q^{-1}} u(k) + \frac{c(q)}{1 - a_1 q^{-1}} w(k) \quad (2)$$

where $y(k)$ is the actual drop of blood pressure. $w(k)$ is a broadband random sequence and $c(q)$ is stable polynomial .

3.Design of control system

An overall schematic of controller is shown in Fig 1. P_C is the commanded pressure setpoint. A two-model three-layered neural network based on the backpropagation algorithm is used to construct a nonlinear controller to track the desired output. The weighting-determinant unit(WDU) is used to determine and to update the output weighting factors of the two parallel MNN controller.

For maximizing patient safety, a nonlinear unit was built into the system that limits the actual infusion rate, $u(k)$

$$u(k) = \begin{cases} u_i(k), & if \quad u_i(k) \le u_M \\ u_M, & if \quad u_i(k) \ge u_M \end{cases} \quad (3)$$

3.1.Design of Neural Network Controller

A neural network based controller is described as follows. A neural network with nonlinear elements offers distinct advantages over conventional linear adaptive controller to achieve the desired performance. Due to the slow learning speed of the neural network, it is necessary to have special consideration when employed in adaptive control for large dynamic range of parameter gains and time-varying plant. It is preferable to arrange two parallel MNN controllers to meet the clinical requirements of automated SNP infusion system. One MNN controller is to map the learned range of large-gain and the other is for range of small gain, function of the system characteristics .

The three-layered MNN architecture for system with SISO ,shown in Fig.2,is defined according to the basic nonlinear processing elements.

The inputs of this MNN controller, X_i ,are the system's desired drop of blood pressure ($y_C = P_C - P_O$) and tracking error $(e = y_C - y)$ that are all normalized by $|y_C|$ .According to (2),as the system output decreases as the control input increases , it is a negatively responded system. Because of interpatient and intrapatient variations in the response of the subject, it is necessary to adapt the weights of MNN controller online to track these variations .So the computation of each MNN controller for SISO system u_{Cl} is shown as follows:

1) The output of the HIDDEN layer: $H_j(k)$

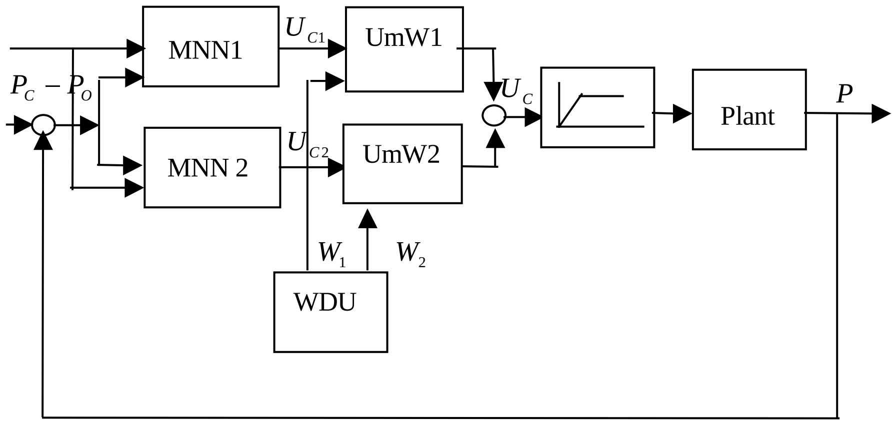

Fig1. Control System Diagram

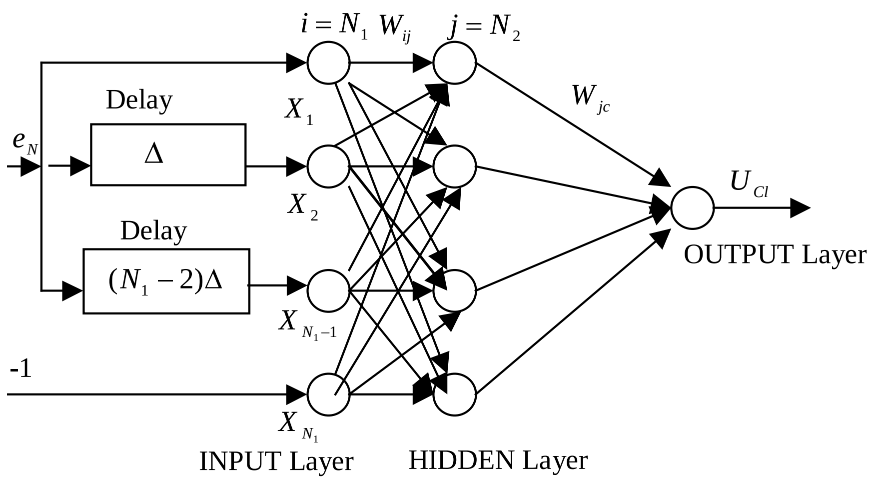

Fig2.Three-layered NN Controller(MNN)

$$H_j(k) = \frac{1}{1 + e^{\left(-O_j(k) - \theta_j(k)\right)}} \qquad O_j(k) = \sum_{i=1}^{N} W_{ij}(k) X_i(k) \tag{4}$$

2).The output layer $U_{cl}(k)$

$$U_{cl}(k) = \frac{1}{1 + e^{\left(-Q(k) - \phi(k)\right)}} \qquad Q(k) = \sum_{j=1}^{N_2} W_{jc}(k) H_j(k) \tag{5}$$

3).The weights are updated from HIDDEN to the OUTPUT layer; $W_{jc}(k+1)$

$$W_{jc}(k+1) = W_{jc}(k) + \Delta W_{jc}$$
$$\Delta W_{jc} = n^c \delta^c H_j(k) \quad (6)$$
$$\delta^c = -[-1 - y_N(k)]u_{cl}(k)[1 - u_{cl}(k)]$$

4).The weights are updated form the INPUT to the HIDDEN layered: $W_{ij}(k+1)$

$$W_{ij}(k+1) = W_{ij}(k) + \Delta W_{ij}$$
$$\Delta W_{ij}(k) = n^h \delta^h X_i(k) \quad (7)$$
$$\delta^h = \delta^c W_{jc}(k) H_j(k)[1 - H_j(k)]$$

5).The bias are updated at he OUTPUT and HIDDEN layer: $\phi(k+1), \theta_j(k+1)$

$$\phi(k+1) = \phi(k) + n_\phi^c \delta^c$$
$$\theta_j(k+1) = \theta_j(k) = n_\theta^h \delta_j^h \quad (8)$$

where

$\eta_\Phi^C > 0$ is gain factor of bias at OUTPUT layer

$\eta_\theta^h > 0$ is gain factor of bias at HIDDEN layer

3.2Design of Weighting-Determinant Unit

We select the same four inputs at the INPUT layer of each two model MNN controller, which are all the normalized values of desired blood pressure drop and tracking error: The number of HIDDEN nodes is also chosen to be four according to entensive computer simulation.

In order to determine each initial output weighting factor of the parallel two-model MNN controller, first, only the first MNN controller ($W_1 = 1, W_2 = 2$) is close to excite the system for k_{th} sampling periods. During this period, the WDU summed the measured ABP. At the sampling time k_{th} ,the WDU calculates the parameter ψ

$$\psi = (\sum_{k=1}^{k=k_{th}} (P(k-1) - P_{th}) / ((P_o - P_{th}) * k_{th}) \quad (9)$$

Thus, W_1, W_2 can be determined according to the parameter ψ and decision rule.

Rule 1.If $\psi < -2.0$,then set $W_1 = 0.8, W_2 = 0$

Rule 2.If $\psi \ge -2.0$ and $\psi < 0.5$,then set

$W_1 = 0.9, W_2 = 0$

Rule 3. If $\psi \ge -1.5$ and $\psi < -1.0$,then set

$W_1 = 1.0, W_2 = 0$

Rule 4. If $\psi \ge -1.0$ and $\psi < -0.5$,then set

$W_1 = 1.2, W_2 = 0$

Rule 5. If $\psi \ge -0.5$ and $\psi < -0.0$,then set

$W_1 = 0.9, W_2 = 0.1$

Rule 6. If $\psi \ge -0.0$ and $\psi < 0.2$,then set

$W_1 = 0.8, W_2 = 0.2$

Rule 7. If $\psi \ge 0.2$ and $\psi < 0.4$,then set

$W_1 = 0.7, W_2 = 0.3$

Rule 8. If $\psi \ge 0.4$ and $\psi < 0.6$,then set

$W_1 = 0.6, W_2 = 0.4$

Rule 9. If $\psi \ge 0.6$ and $\psi < 0.8$,then set

$W_1 = 0.4, W_2 = 0.6$

Rule 10. If $\psi \ge 0.8$ and $\psi < 0.9$,then set

$W_1 = 0.2, W_2 = 0.8$

Rule 11. If $\psi \geq 0.9$ .then set $W_1 = 0.0, W_2 = 1.0$

The total output of the two-model MNN controller u_c can be computed from the

$$u_c(k) = (u_{c1}(k) * W_1 + u_{c2}(k) * W_2) * u_M \qquad (10)$$

4.Conclusion

Simulation results indicate satisfactory performance and robustness of the proposed control in the presence of much noise and uncertainties and parameter variations.

The application of two-model MNN controller to update the nonlinear and time-varying nature of the patient response resented in this paper illustrates that a controller of this design has the capacity to provide clinically acceptable regulation of ABP using SNP drugs. Controller simulation shows that it has acceptable settling time, it can be able to maintain the blood pressure within the desired set point. with a small variation in the steady state.

The simulation indicate that a control system of this design has improve performance compared to other kinds controller in its robust performance, simple architecture and algorithm and no requirement of system parameters identification a priori. Now we need to test the system by experiment to verify its practical application.

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