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MODEL-REFERENCE INTELLIGENT CONTROL SYSTEM

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This paper presents an intelligent controller based on a new type of model-reference adaptive control. The system state estimator of this controller is described by the differential equation of the reference model with the feedback speeding-up the estimator action during the tuning-up of the controller parameters and vanishing when the system performance approaches that of the reference model. The presented results of a simulation study demonstrate high effectiveness of the approach considered. The model dynamics, representing the required system performance, can be chosen within a wide range of speed with respect to the plant dynamics.

1. INTRODUCTION

This paper is concerned with model-reference intelligent control system shown in Fig. 1. In the analysis of the system performance the time-invariance of an unknown linear plant is assumed. However, due to the time-varying adaptive character-

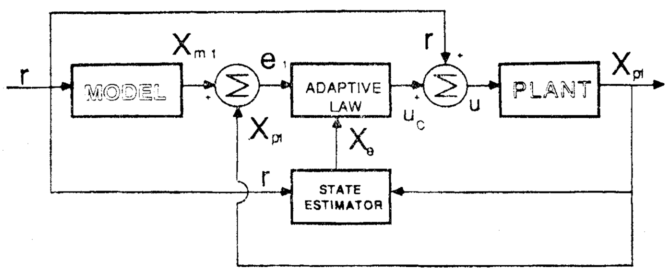


Fig. 1. Model-reference intelligent control system.

istics the controller compensates very well for the changes of the plant parameters. It was shown by the simulation study that the application of the proposed intelligent controller results in a system robust under extreme plant parameter variations, even if those variations lead to plant instability.

The intelligent controller considered contains a properly designed estimator to obtain the state vector estimate of a system which consists of an adaptive controller and an unknown plant. It is assumed that the system state estimator is described by the differential equation of the reference model with the proper feedback added. Due to this, during the tuning process of the controller, the estimator response is faster than that of the reference model. On the other hand, when as a result of the tuning process, the system dynamics approach that of the reference model, the feedback signal in the estimator approaches zero. In other words, both the system and its estimator approach the required dynamics of the reference model.

In the papers on adaptive observers [1–3], to mention just a few, a state vector which represents the dynamics of an unknown plant is produced by the observers that are required to be asymptotically stable and controllable. These very general specifications do not give any design guidelines to make a proper choice. On the contrary, a class of estimators, proposed in this paper, is well defined and well justified.

2. PERFORMANCE ANALYSIS OF AN INTELLIGENT CONTROLLER FOR A nTH-ORDER PLANT

Consider the system shown in Fig. 1 in which the plant is described by

$$\begin{aligned} \dot{x}_p &= A_p x_p + B_p u\,, \quad x_p \in \mathbb{R}^n\,, \quad u \in \mathbb{R} \\ y_p &= C_p x_p\,, \quad y_p \in \mathbb{R} \end{aligned} \tag{1}$$

the reference model is described by

$$\begin{aligned} \dot{x}_m &= A_m x_m + B_m r\,, \quad x_m \in \mathbb{R}^n\,, \quad r \in \mathbb{R} \\ y_m &= C_m x_m\,, \quad y_m \in \mathbb{R} \end{aligned} \tag{2}$$

the state estimator is described by

$$\begin{aligned} \dot{x}_e &= A_m x_e + B_m r + K e_2\,, \quad x_e \in \mathbb{R}^n \\ y_e &= C_e x_e\,, \quad y_e \in \mathbb{R} \end{aligned} \tag{3}$$

with $e_2' \triangleq y_p - y_e$, and the adaptive control law given by

$$u_c = \theta^T x_e\,, \quad u_c \in \mathbb{R} \tag{4}$$

$$\dot{\theta} = e_1 x_e\,, \quad \theta \in \mathbb{R}^n \tag{5}$$

with $e_1 \triangleq y_m - y_p$ and

$$u = u_c + r = \theta^T x_e + r\,. \tag{6}$$

It is assumed that $y_p = x_{p1}$, $y_m = y_{m1}$, and $y_e = x_{e1}$, or equivalently $C_p = C_m = C_e = C = [1, 0, \dots 0]$.

The model-reference intelligent controller, used to control an unknown plant (shown in Fig. 1), can be decomposed into the linear part shown in Fig. 2 and the

the nonlinear (adaptive) part shown in Fig. 3. The adaptive loop generates, constantly updated, parameter vector θ, which remains constant after $e_1 = 0$ is reached and the system from Fig. 1 reduces to the system from Fig. 2.

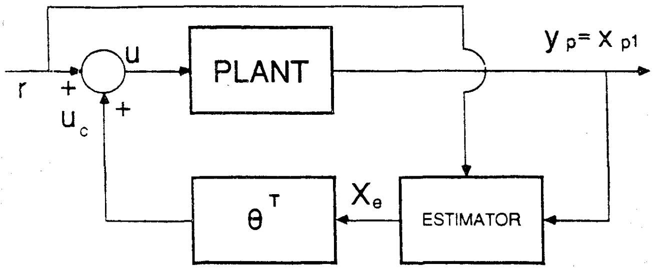


Fig. 2. Linear part of the controller.

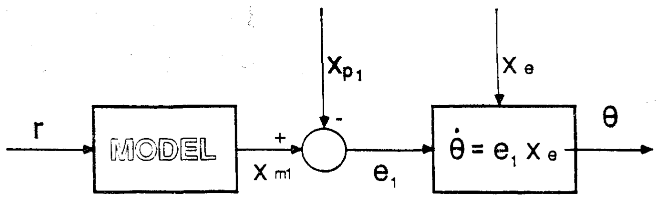


Fig. 3. Nonlinear part of the controller.

Consider now the system shown in Fig. 2. The estimator equation (3) can be written as follows:

$$\begin{aligned} \dot{x}_e &= (A_m - KC)\, x_e + B_m r + KCx_p \\ y_e &= Cx_e \end{aligned} \tag{7}$$

where

$$K = \begin{bmatrix} K_1 \\ K_2 \\ \cdots \\ \cdots \\ K_n \end{bmatrix} \tag{8}$$

The estimator poles are defined by the equation

$$\det [sI - A_m + KC] = 0 . \tag{9}$$

Since the estimator is implemented as a computer program or an electronic device, the increase of the feedback gain K, in order to increase the speed of response, is practically not limited. However, the bandwidth of the estimator becomes higher. This will cause the sensor noise to pass on to the control actuator. Therefore, the designer should try to get an acceptable transient response with a low enough bandwidth.

The design of the state feedback gain θ is performed automatically by the adaptive loop and according to the equation (5), assuming zero initial conditions,

$$\theta^{\mathrm{T}} = \int_0^t e_1 x_{\mathrm{e}}^{\mathrm{T}}\,\mathrm{d}\tau = \left[\int_0^t e_1 x_{\mathrm{e}1}\,\mathrm{d}\tau \int_0^t e_1 x_{\mathrm{e}2}\,\mathrm{d}\tau \ldots \int_0^t e_1 x_{\mathrm{e}n}\,\mathrm{d}\tau\right]. \tag{10}$$

As illustrated in Fig. 3 the state feedback gain vector θ is adjusted to get $e_1 = 0$, i.e. to make the plant output $y_{\mathrm{p}} = x_{\mathrm{p}1}$ to follow the model generated signal $y_{\mathrm{m}} = x_{\mathrm{m}1}$. In other words, the pole placement problem is continuously being solved by the adaptive loop.

Referring still to the system of Fig. 2 consider the closed-loop system zeros. The intelligent controller with the inputs $y_{\mathrm{p}} = x_{\mathrm{p}1}$ and r, and with the output u is described by the state equation (7) and by the output equation (6). One can see from (7) that B_{m} is not involved in the controller characteristic equation. Therefore, speaking in transfer function terms, B_{m} affects only the zeros of the transfer function from r to y_{p}. Before obtaining the equation for the closed-loop zeros, find out if there is any effect on closed-loop system zeros other than that of the reference model. Therefore, consider the system from Fig. 2 assuming that there is a state feedback and no estimation is involved. Then the equations of the closed-loop system are

$$\begin{aligned} \dot{x}_{\mathrm{p}} &= (A_{\mathrm{p}} + B_{\mathrm{p}}\theta^{\mathrm{T}})\,x_{\mathrm{p}} + B_{\mathrm{p}} r \\ y_{\mathrm{p}} &= C x_{\mathrm{p}} \end{aligned} \tag{11}$$

and the system zeros are the roots of the following equation:

$$\det \begin{bmatrix} sI - A_{\mathrm{p}} - B_{\mathrm{p}}\theta^{\mathrm{T}} & B_{\mathrm{p}} \\ -C & 0 \end{bmatrix} = 0 \tag{12}$$

which is equivalent to

$$\det \begin{bmatrix} sI - A_{\mathrm{p}} & B_{\mathrm{p}} \\ -C & 0 \end{bmatrix} = 0 \tag{13}$$

and this matrix is independent of the feedback gains θ^{T}. Therefore, the zeros of the closed-loop system are not affected by the state-variable feedback. Now, considering the controller equations (7) and (6), the equation for the zeros of the transfer function from r to u (letting $y_{\mathrm{p}} = x_{\mathrm{p}1} = 0$) is

$$\det \begin{bmatrix} sI - A_{\mathrm{m}} + KC & B_{\mathrm{m}} \\ -\theta^{\mathrm{T}} & 1 \end{bmatrix} = 0 \tag{14}$$

and this is equivalent to

$$\det\left[sI - A_{\mathrm{m}} + KC + B_{\mathrm{m}}\,\theta^{\mathrm{T}}\right] = 0\,. \tag{15}$$

This equation is in the form of equation (9) for the estimator poles which are placed at the desired locations by the proper selection of K. However, the closed-loop zeros due to the intelligent controller are additionally affected by the matrix $B_{\mathrm{m}}\theta^{\mathrm{T}}$.

Summarizing the above findings, one gets the following overall transfer function of the closed-loop system:

$$G(s) = \frac{Y_{\mathrm{p}}(s)}{R(s)} = \frac{K_{\mathrm{T}}\beta(s)\,b_{\mathrm{p}}(s)}{\alpha_{\mathrm{e}}(s)\,\alpha_{\mathrm{c}}(s)} \tag{16}$$

where K_T is the total system gain, $b_p(s)$ represents the plant zeros and

(17) $$\beta(s) = \det[sI - A_m + KC + B_m\theta^T]$$

(18) $$\alpha_e(s) = \det[sI - A_m + KC]$$

(19) $$\alpha_c(s) = \det[sI - A_p - B_p\theta^T]$$

3. ANALYSIS OF THE SECOND-ORDER SYSTEM

Assuming, as in the nth-order case, the phase variable canonical form of state equations, the plant matrices are:

(20) $$A_p = \begin{bmatrix} 0 & 1 \\ -a & -b \end{bmatrix}, \quad B_p = \begin{bmatrix} c \\ d \end{bmatrix}$$

that corresponds to the transfer function

(21) $$T_p(s) = \frac{c\left(s + b + \dfrac{d}{c}\right)}{s^2 + bs + a}$$

The model matrices are:

(22) $$A_m = \begin{bmatrix} 0 & 1 \\ -a_m & -b_m \end{bmatrix}, \quad B_m \begin{bmatrix} c_m \\ d_m \end{bmatrix}$$

that corresponds to the transfer function

(23) $$T_m(s) = \frac{c_m\left(s + b_m + \dfrac{d_m}{c_m}\right)}{s^2 + b_m s + a_m}$$

The estimator matrices are A_m, B_m and

(24) $$K = \begin{bmatrix} K_1 \\ K_2 \end{bmatrix}$$

Then, $\alpha_e(s)$, calculated from (18), is

(25) $$\alpha_e(s) = \begin{vmatrix} s + K_1 & -1 \\ a_m + K_2 & s + b_m \end{vmatrix} = s^2 + s(K_1 + b_m) + K_1 b_m + a_m + K_2 .$$

It can be expected that the estimator which, in each of the state equations, involves the feedback of the appropriate state variable error, instead of the output error, will perform much better. This idea, when the system state variables are approximated with appropriate output derivatives, leads to the following estimator equations in the second-order case:

$$\dot{x}_{e1} = x_2 + c_m r + K_1'(x_{p1} - x_{e1}),$$
$$\dot{x}_{e2} = -a_m x_{e1} - b_m x_{e2} + d_m r + K_2'(\dot{x}_{p1} - x_{e2})$$

These equations can be represented in the following form:

(26) $$\dot{x}_e = (A_m - IK')\,x_e + B_m r + K'Cx'_{p1}$$

where

(27) $$K' = \begin{bmatrix} K'_1 & 0 \\ 0 & K'_2 \end{bmatrix} \quad \text{and} \quad x'_{p1} = \begin{bmatrix} x_{p1} \\ \dot{x}_{p1} \end{bmatrix}$$

This results in the characteristic polynomial

(28)
$$\alpha'_e(s) = \begin{vmatrix} s + K'_1 & -1 \\ a_m & s + b_m + K'_2 \end{vmatrix} = s^2 + s(K'_1 + b_m + K'_2) + K'_1 b_m + a_m + K'_1 K'_2$$

Comparing $\alpha_e(s)$ and $\alpha'_e(s)$ one can see that the same damping ζ and natural frequency ω_n are achieved for $\alpha'_e(s)$ with smaller feedback gains K'. One can also say that if $K'_{1,2} = K_{1,2}$ then the poles of $\alpha'_e(s)$ will be faster. With this estimator the intelligent controller is described by the state equation (26) and the output equation (6). Therefore, the equation for the zeros of the transfer function from r to u (letting $x'_{p1} = 0$) is

(29) $$\beta'(s) = \det\left[sI - A_m + IK' + B_m\theta^T\right] = 0\,.$$

Assuming that $K' = K$, one can easily find out that the zeros defined by $\beta'(s)$ are faster than those defined by $\beta(s)$.

4. SIMULATION STUDY

The simulation was performed for the model with

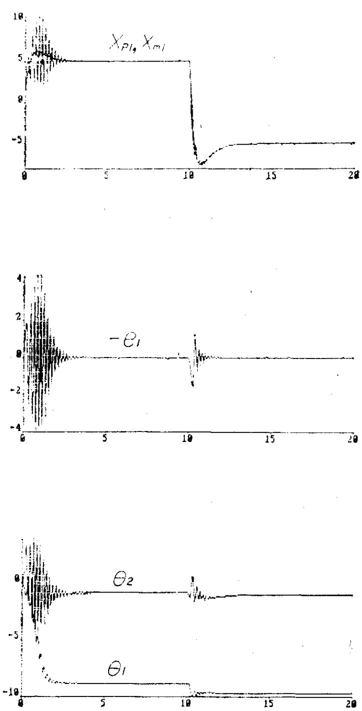
$$T_m(s) = \frac{s + 1}{(s + 2)(s + 3)} \quad \text{or} \quad A_m = \begin{bmatrix} 0 & 1 \\ -6 & -5 \end{bmatrix}, \quad B_m = \begin{bmatrix} 1 \\ -4 \end{bmatrix}$$

and the plant with

$$T_p(s) = \frac{s + 2}{(s - 1 + j\,2)(s - 1 - j\,2)} \quad \text{or} \quad A_m = \begin{bmatrix} 0 & 1 \\ -5 & 2 \end{bmatrix}, \quad B_p = \begin{bmatrix} 1 \\ 4 \end{bmatrix}$$

The results obtained for $K_1 = 100$, $K_2 = 0$ and the square wave input are shown in Fig. 4. The initial conditions at $t = 0$ were assumed to be zero. As a result of the controller action, certain values of the controller parameters θ_1 and θ_2 are reached during the first half of the square-wave period. Those values serve as the initial conditions for the second half-period of the input square-wave. It is clear from Fig. 4 that the control parameters θ_1 and θ_2 tend to stabilize and as a result of this the error $e_1 = x_{m1} - x_{p1}$ approaches zero.

The simulation results for the same system but with the modified estimator, defined by (26), with $K'_1 = 100$ and $K'_2 = 10$, are shown in Fig. 5. These results can be easily compared with the results from the previous simulation. The performace improvement is apparent.



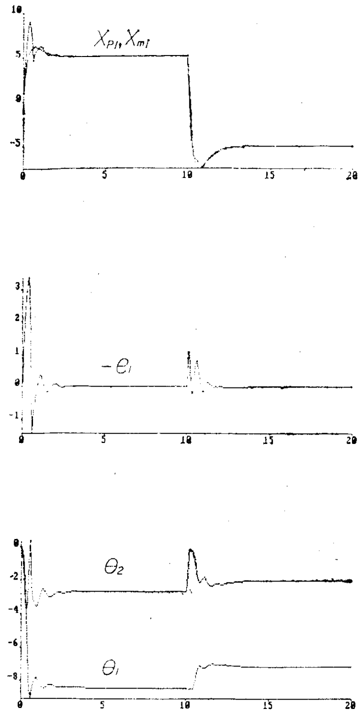


Fig. 4. System transients for the estimator with $K_1 = 100$ and $K_2 = 0$.

Fig. 5. System transients for a modified estimator with $K_1 = 100$ and $K_2 = 10$.

The proposed model-reference intelligent control system with the estimator defined by (26) was applied in a simulation study of the control of a laser communication mirror mounted on a space platform. The plant transfer function was

$$T_p(s) = \frac{25}{s^2 + 0{\cdot}57s + 800} \quad \text{or} \quad A_p = \begin{bmatrix} 0 & 1 \\ -800 & -0{\cdot}57 \end{bmatrix}, \quad B_p = \begin{bmatrix} 0 \\ 25 \end{bmatrix}$$

The step response of this system, shown in Fig. 6, is of course unacceptable.

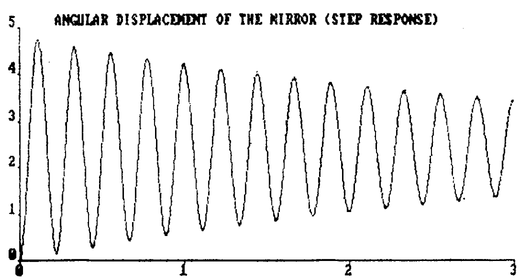


Fig. 6. Step response of a laser communications mirror.

For the system with the intelligent controller the reference model transfer function was

$$T_m(s) = \frac{25}{s^2 + 40s + 400} \quad \text{or} \quad A_m = \begin{bmatrix} 0 & 1 \\ -400 & -40 \end{bmatrix}, \quad B_m = \begin{bmatrix} 0 \\ -10 \end{bmatrix}$$

and the estimator feedback gains were $K_1' = 100$ and $K_2' = 40$. The step response of this system is given in Fig. 7. It is seen that due to the controller action the step

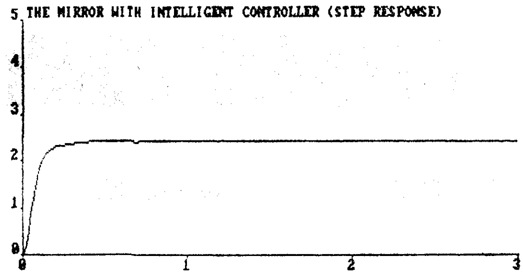


Fig. 7. Step response of a laser communication mirror controlled by the model-reference inteligent controller.

response of the compensated system has no oscillations. In this simulation the stabilized state feedback gain vector $\theta^T = [2{\cdot}2269, -2{\cdot}3334]$ was used as an initial condition.

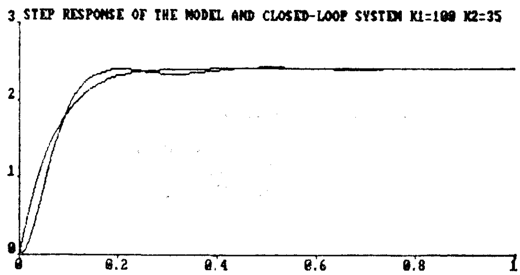


Fig. 8. Transients of the laser communication mirror control system.

In Fig. 8 the step responses of the same reference model and the closed-loop compensated system with $K_1' = 100$ and $K_2' = 35$ are shown to give the idea how well the system output follows the reference model. One can also see that the system response became slightly oscillatory as a result of decreasing K_2'.

5. CONCLUSION

The model-reference intelligent control system considered in this paper can be used to obtain the requested dynamics of the closed-loop system which can be chosen within a wide range of speed with respect to the dynamics of the plant.

Some of the results of the simulation study presented here show that the proposed controller can be used to control an unstable plant as well as to get a fast and well damped response of a plant with a very small damping ratio and relatively high undamped natural frequency. The proposed new approach to the estimation of the system state results in very fast estimator performance during the tuning process of the controller and in an estimation error approaching zero. This is due to the fact that the estimated system performance and the estimator performance both approach that of the reference model.

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REFERENCES

[1] K. S. Narendra and P. Kudva: Stable adaptive schemes for system identification and control — Parts I & II. IEEE Trans. Systems Man Cybernet. *SMC-4* (1974), 541—560.

[2] K. S. Narendra and A. M. Annaswamy: A new adaptive law for robust adaptation without persistent excitation. IEEE Trans. Automat. Control *AC-32* (1987), 134—145.

[3] K. S. Narendra and L. S. Valavani: Stable adaptive controller design-direct control. IEEE Trans. Automat. Control *AC-23* (1978), 570—583.

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