

Hybrid Controller Design for Wing Rock Systems via CMAC Approach

Chih-Min Lin
Dept. of Electrical Engineering
Yuan-Ze University
Chung-Li, Tao-Yuan, 320
Taiwan, Republic of China

Chun-Fei Hsu
Dept. of Electrical and Control Engineering
National Chiao-Tung University
Hsinchu, 300
Taiwan, Republic of China

Yuan-Ze University
Dept. of Electrical Engineering
Chung-Li, Tao-Yuan, 320
Taiwan, Republic of China

Abstract: - A wing rock system is manifested by a limit cycle oscillation predominantly as an aircraft operating at subsonic speeds and high angles of attack. The dynamic characteristic of the wing rock is nonlinear and the precise dynamic model of the wing rock is difficult to obtain, so that a model-free design method referred to as hybrid control system is developed in this paper. The design of the hybrid control system contains three parts: an adaptive indirect controller (AIC), an adaptive direct controller (ADC) and a robust controller. A weighting factor, which can be adjusted by the tradeoff between plant knowledge and control knowledge, is adopted to sum together from the AIC and the ADC. Moreover, the robust controller is designed to compensate the approximation error caused by the AIC and the ADC. Finally, simulation results demonstrate that the proposed hybrid control system can achieve a favorable tracking performance for unknown the dynamics of the wing rock systems.

Key-Words: - Adaptive control, approximation theorem, CMAC, wing rock system

1 Introduction

Most current techniques for designing control systems are based on a good understanding of the plant dynamics and even its working environment. However, in a number of instances, the controlled plant is too complex and the basic physical processes in it are not fully understood. To tackle this problem, adaptive control techniques are developed to control these kinds of dynamic systems [1]. It is a model-free approach based on the idea of on-line estimating the plant parameters or the controller parameters using on the measured system signals. If the adaptive algorithm is used to estimate the model of the plant, it is referred to as the adaptive indirect control (AIC). If the adaptive algorithm is used to estimate the controller of the plant, it is referred to as the adaptive direct control (ADC).

Besides the adaptive control techniques, the neural network control approaches are other model-free design methods for control of unknown dynamic systems [2]-[4]. The success key element is the neural network can capable of approximating mapping through choosing adequately learning method. Because of this property, many neural network controllers have been developed for the compensation for the effects of nonlinearities and system uncertainties in control system so that the system performance such as the stability, convergence, and robustness can be improved. Recently, the cerebellar model articulation control (CMAC) have been adopted widely for the control of complex dynamical systems owing to its fast learning property, good generalization capability, and simple

computation compared with the neural network [5], [6]

Some combat aircraft often require operating at subsonic speeds and high angles of attack. At sufficiently high angles of attack, these aircraft become unstable due to oscillation, mainly a rolling motion known as wing rock [7]. This wing rock is a concern because it may have adverse effects on maneuverability, tracking accuracy, and operational safety. Because the modern combat aircraft is difficult to isolate the various flow phenomena created by the forebody, strake, wing and their relationship to the wing rock, the behavior of the wing rock system is not clearly understood. Recently, several theoretical and experimental studies have been performed to understand the dynamics of the wing rock and to predict the amplitude and frequency of limit cycle oscillation.

A series of papers have considered the control of the wing rock system based on output feedback linearization theory and adaptive control technique [8]-[10]. In the feedback linearization design approaches, the feedback control gain should be pre-selected to achieve the design performance by trial-and-error procedure; however, this tuning procedure is time-consuming [8]. In the adaptive control techniques, controller requires the knowledge of the structure of the aerodynamic functions; however, this structure is difficult to obtain [9], [10]. In addition, neural network control approaches also have been proposed to control the wing rock system [9]. However, the structure of the neural network must be selected with a sufficiently large number of

neurons in the hidden layer, which consumes a large amount of learning processing time.

In this paper, a hybrid control system is developed for the wing rock system. The hybrid control system is comprised of an AIC, an ADC, and a robust controller. In the AIC design, a CMAC neural network is used to approximate the plane dynamics, and in the ADC design, the CMAC neural network is used to approximate the controller behavior. A weighting factor is adjusted by the tradeoff between the plant knowledge and the control knowledge from the AIC and the ADC. In the robust controller design, the robust controller is designed to compensate the approximation error caused by the AIC and the ADC. Moreover, an error estimation mechanism is investigated to estimate the bound of approximation error so that the chattering phenomenon of the control effort can be reduced. Additionally, the parameters of the hybrid control can be on-line tuned in the sense of the Lyapunov stability theorem; thus the stability of the control system can be guaranteed. Finally, the simulation results demonstrate that the proposed hybrid control system can achieve favorable tracking performances for unknown the wing rock dynamics.

2 Problem Statement

The delta wing for a wing rock system is represented schematically in Fig. 1. This wing has one degree of freedom, and the dynamical system includes the wing (a flat uniform plate) and the parts of the sting that rotate with it. The differential equation describing the wing rock is given by [7]

$$\ddot{\phi} = (pU_{\infty}^2 Sb / 2I_{xx})C_l + u \quad (1)$$

where ϕ is the roll angle, an over-dot denotes a derivative with respect to time, u is the control effort, p is the density of air, U_{∞} is the freestream velocity, S is the wing reference area, b is the chord, I_{xx} is the mass moment of inertia, and C_l is the roll moment coefficient written as

$$C_l = c_0 + c_1\phi + c_2\dot{\phi} + c_3|\phi|\dot{\phi} + c_4|\dot{\phi}|\dot{\phi} + c_5\phi^3. \quad (2)$$

The aerodynamic parameters c_i , $i=0,1,\dots,5$ are nonlinear functions of the angle of attack. The numerical values of the parameters have been provided for different values of angle of attack. By defining the state vector $\boldsymbol{\phi} = [\phi, \dot{\phi}]^T$ and substituting (2) into (1), the dynamic equation can be rewritten in a state variable form as

$$\ddot{\phi} = f(\boldsymbol{\phi}) + u \quad (3)$$

where

$$f(\boldsymbol{\phi}) = b_0 + b_1\phi + b_2\dot{\phi} + b_3|\phi|\dot{\phi} + b_4|\dot{\phi}|\dot{\phi} + b_5\phi^3 \quad (4)$$

and the parameters b_i , $i=0,1,\dots,5$ are given by

$$b_i = (pU_{\infty}^2 Sb / 2I_{xx})c_i. \quad (5)$$

For observing the qualitative natural behavior of the wing rock system, the open-loop system time response with $u=0$ was simulated for two initial conditions: a small initial condition ($\phi(0) = 6 \text{ deg}$, $\dot{\phi}(0) = 3 \text{ deg/sec}$) and a large initial condition ($\phi(0) = 30 \text{ deg}$, $\dot{\phi}(0) = 10 \text{ deg/sec}$ shown is Fig. 2. For the small initial condition, a limit cycle is obtained; and for the large initial condition, the roll angle is divergent. Thus, it is shown that the uncontrolled wing rock system will be unstable for some initial conditions.

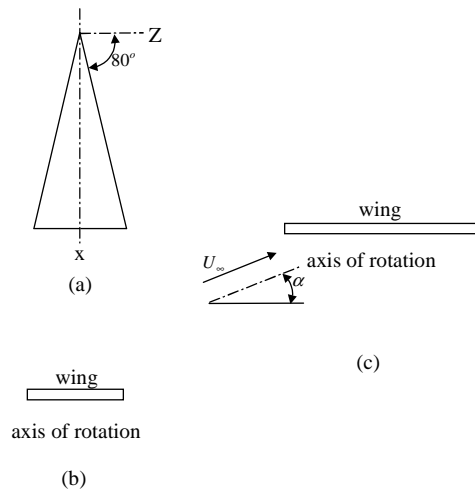


Fig. 1. Scheme of the delta wing: (a) plan view; (b) end view; (c) side view.

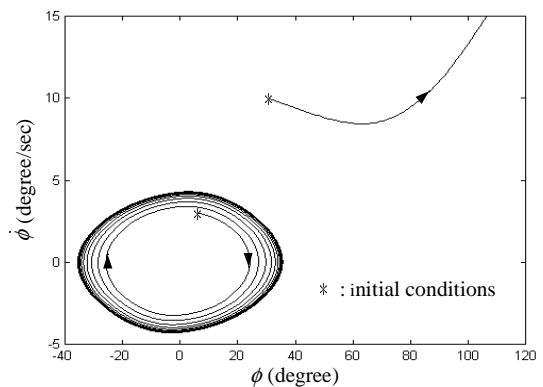


Fig. 2. Phase-plane portraits of the uncontrolled wing rock system.

3 Description of CMAC

A cerebellar model articulation controller (CMAC) is depicted in Fig. 3 which can be considered as "1"-layer feedforward neural network with input

preprocessing element [5]. If $\sigma(\cdot)$ is a continuous discriminant function, the CMAC output performs the mapping according to

$$y = \sum_{i=1}^N w_i \sigma_i(p_i) \quad (6)$$

where w_i are the output layer weight values, p_i are the network input to the i th neuron, $\sigma(\cdot): R \rightarrow R$ is the activation function, and N is the number of units (also called nodes and neurons) in the hidden layer. Note that the activation functions $\sigma(\cdot)$ for each neuron are not necessarily the same. For ease of notation, the CMAC equation (6) can be expressed in a compact vector form as

$$y = \mathbf{w}^T \boldsymbol{\sigma} \quad (7)$$

where $\mathbf{w} = [w_1, w_2, \dots, w_N]^T$ and $\boldsymbol{\sigma} = [\sigma_1, \sigma_2, \dots, \sigma_N]^T$. It has been proven that there exists an approximator in (7) such that it can uniformly approximate any nonlinear even time-varying function Ω [5]. By the universal approximation theorem, there exists an ideal approximator y^* such that

$$\Omega = y^* + \varepsilon = \mathbf{w}^{*T} \boldsymbol{\sigma} + \varepsilon \quad (8)$$

where \mathbf{w}^* is the optimal vector of \mathbf{w} and ε denotes the approximation error. In fact, the optimal vector that is needed to best approximate a given nonlinear function Ω is difficult to determine and might not even be unique. Thus, an estimator is defined as

$$\hat{y} = \hat{\mathbf{w}}^T \boldsymbol{\sigma} \quad (9)$$

where $\hat{\mathbf{w}} = [\hat{w}_1, \hat{w}_2, \dots, \hat{w}_N]^T$ is the estimated vector of \mathbf{w}^* . Define the estimated error \tilde{y} as

$$\tilde{y} = \Omega - \hat{y} = y^* - \hat{y} + \varepsilon = \tilde{\mathbf{w}}^T \boldsymbol{\sigma} + \varepsilon \quad (10)$$

where $\tilde{\mathbf{w}} = \mathbf{w}^* - \hat{\mathbf{w}}$. In the followings, an update law will be derived to on-line tune the estimated vector to achieve favorable estimation.

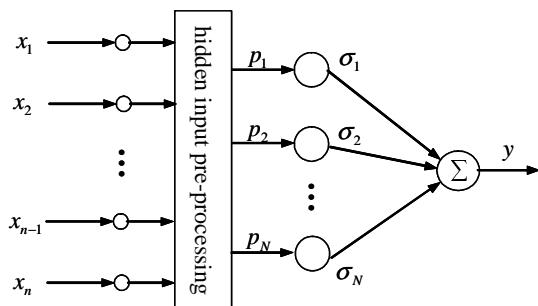


Fig. 3. Network structure of a CMAC neural network.

4 Hybrid Control Design

The control objective of the wing rock system is to find a control law so that the roll angle ϕ can track a desired command ϕ_m . Define the tracking error as

$$e = \phi_m - \phi. \quad (11)$$

If the system parameters in (3) are well known, an ideal controller can be obtained [11]

$$u^* = -f(\boldsymbol{\varphi}) + \ddot{\phi}_m + k_1 \dot{e} + k_2 e. \quad (12)$$

Substituting (12) into (3) gives

$$\ddot{e} + k_1 \dot{e} + k_2 e = 0. \quad (13)$$

If k_1 and k_2 are chosen to correspond to the coefficients of a Hurwitz polynomial, it implies that $\lim_{t \rightarrow \infty} e(t) = 0$. However, the system dynamics $f(\boldsymbol{\varphi})$ in (3) is a nonlinear time-varying function and it cannot be exactly obtained, so the ideal controller u^* cannot be implemented.

To overcome this drawback, the block diagram of the design concept of the hybrid controller for the wing rock system is shown in Fig. 4. The control law is designed as

$$u_{hc} = \alpha u_{AI} + (1 - \alpha) u_{AD} + u_{RC} \quad (14)$$

where u_{AI} is the adaptive indirect controller (AIC), u_{AD} is the adaptive direct controller (ADC), u_{RC} is a robust controller, and $\alpha \in [0, 1]$ is a weighting factor chosen by a control designer based on the understanding level of the plant knowledge and control knowledge. From the adaptive control approach, the CMAC neural network is used as modeling of the plant in the AIC, and the CMAC neural network is used as a controller in the ADC. Thus, the AIC can be defined as

$$u_{AI} = -\hat{f}(\hat{\mathbf{w}}_f) + \ddot{\phi}_m + k_1 \dot{e} + k_2 e \quad (15)$$

where the system dynamic estimator is chosen as

$$\hat{f} = \hat{\mathbf{w}}_f^T \boldsymbol{\Theta}_f \quad (16)$$

with $\hat{\mathbf{w}}_f$ is the estimated vector and $\boldsymbol{\Theta}_f$ is the regressive vector of the modeling, respectively. Similarly, the ADC is defined as

$$u_{AD}(\hat{\mathbf{w}}_u) = \hat{\mathbf{w}}_u^T \boldsymbol{\Theta}_u \quad (17)$$

where $\hat{\mathbf{w}}_u$ is the estimator vector and $\boldsymbol{\Theta}_u$ is the regressive vector of the controller, respectively. Then, applying (12), (14), (15), (16) and (17) into (3) and after some simple manipulations, the error dynamic equation can be obtained as

$$\ddot{e} = -k_1 \dot{e} - k_2 e - \alpha \tilde{f} + (1 - \alpha) \tilde{u} - u_{RC}. \quad (18)$$

where

$$\tilde{f} = f - \hat{f} = \tilde{\mathbf{w}}_f^T \boldsymbol{\Theta}_f + \varepsilon_f \quad (19)$$

$$\tilde{u} = u^* - u_D = \tilde{\mathbf{w}}_u^T \boldsymbol{\Theta}_u + \varepsilon_u \quad (20)$$

with $\tilde{\mathbf{w}}_f = \mathbf{w}_f^* - \hat{\mathbf{w}}_f$, $\tilde{\mathbf{w}}_u = \mathbf{w}_u^* - \hat{\mathbf{w}}_u$, and ε_f and ε_u are the approximator errors. By defining the tracking error vector $\mathbf{e} = [e, \dot{e}]^T$, equation (18) can be rewritten in the vector form as

$$\dot{\mathbf{e}} = \mathbf{A}_m \mathbf{e} + \mathbf{b}_m [-\alpha \tilde{\mathbf{w}}_f^T \Theta_f + (1-\alpha) \tilde{\mathbf{w}}_u^T \Theta_u + \varepsilon - u_{RC}] \quad (21)$$

where $\mathbf{A}_m = \begin{bmatrix} 0 & 1 \\ -k_2 & -k_1 \end{bmatrix}$, $\mathbf{b}_m = [0, 1]^T$, and the

lumped approximation error $\varepsilon = -\alpha \varepsilon_f + (1-\alpha) \varepsilon_u$ with the assumption $|\varepsilon| \leq E$, in which E is a given positive constant. However, the bound of lumped approximation error, E , is difficult to measure in practical applications. To relax the bound of lumped approximation error, an error estimation mechanism is investigated to estimate the bound, where \hat{E} is the estimation bound value of the lumped approximation error. Then the estimation error is defined as

$$\tilde{E} = E - \hat{E}. \quad (22)$$

Since \mathbf{A}_m is a Hurwitz matrix, given a positive definite symmetric matrix \mathbf{Q} (denoted as $\mathbf{Q} > 0$), there exists a matrix $\mathbf{P} > 0$ such that a Lyapunov equation

$$\mathbf{A}_m^T \mathbf{P} + \mathbf{P} \mathbf{A}_m = -\mathbf{Q} \quad (23)$$

is satisfied. Thus, the stability theorem of the hybrid control system can be obtained as follow.

Theorem: Consider the wing rock system presented in (3). The hybrid control is designed as in (14), in which the adaptive indirect controller u_{AI} is given in (15), the adaptive direct controller u_{AD} is given in (17) and the robust controller u_{RC} is given in (25) with the adaptive laws given in (23), (24) and (26)

$$\dot{\tilde{\mathbf{w}}}_f = -\dot{\tilde{\mathbf{w}}}_f = -\eta_1 \mathbf{e}^T \mathbf{P} \mathbf{b}_m \Theta_f \quad (23)$$

$$\dot{\tilde{\mathbf{w}}}_u = -\dot{\tilde{\mathbf{w}}}_u = \eta_2 \mathbf{e}^T \mathbf{P} \mathbf{b}_m \Theta_u \quad (24)$$

$$u_{RC} = \hat{E} \operatorname{sgn}(\mathbf{e}^T \mathbf{P} \mathbf{b}_m) \quad (25)$$

$$\dot{\hat{E}} = -\dot{\hat{E}} = \eta_3 |\mathbf{e}^T \mathbf{P} \mathbf{b}_m| \quad (26)$$

where η_1 , η_2 and η_3 are the learning rates with positive constants.

Proof: Define a Lyapunov function as

$$V = \frac{1}{2} \mathbf{e}^T \mathbf{P} \mathbf{e} + \frac{\alpha}{2\eta_1} \tilde{\mathbf{w}}_f^T \tilde{\mathbf{w}}_f + \frac{(1-\alpha)}{2\eta_2} \tilde{\mathbf{w}}_u^T \tilde{\mathbf{w}}_u + \frac{\tilde{E}^2}{2\eta_3}. \quad (27)$$

Differentiating (27) with respect to time and using (21), (23) ~ (26), it is obtained that

$$\dot{V} = \frac{1}{2} \mathbf{e}^T \mathbf{P} \dot{\mathbf{e}} + \frac{1}{2} \dot{\mathbf{e}}^T \mathbf{P} \mathbf{e} + \frac{\alpha \tilde{\mathbf{w}}_f^T \dot{\tilde{\mathbf{w}}}_f}{\eta_1} + \frac{(1-\alpha) \tilde{\mathbf{w}}_u^T \dot{\tilde{\mathbf{w}}}_u}{\eta_2} + \frac{\tilde{E} \dot{\tilde{E}}}{\eta_3}$$

$$= \frac{1}{2} \mathbf{e}^T (\mathbf{A}_m^T \mathbf{P} + \mathbf{P} \mathbf{A}_m) \mathbf{e} + \alpha \tilde{\mathbf{w}}_f^T (-\mathbf{e}^T \mathbf{P} \mathbf{b}_m \Theta_f + \frac{\dot{\tilde{\mathbf{w}}}_f}{\eta_1})$$

$$+ (1-\alpha) \tilde{\mathbf{w}}_u^T (\mathbf{e}^T \mathbf{P} \mathbf{b}_m \Theta_u + \frac{\dot{\tilde{\mathbf{w}}}_u}{\eta_2}) + \mathbf{e}^T \mathbf{P} \mathbf{b}_m (\varepsilon - u_{RC}) + \frac{\tilde{E} \dot{\tilde{E}}}{\eta_3}$$

$$\begin{aligned} &= \frac{-1}{2} \mathbf{e}^T \mathbf{Q} \mathbf{e} + \alpha \mathbf{e}^T \mathbf{P} \mathbf{b}_m - E |\mathbf{e}^T \mathbf{P} \mathbf{b}_m| \\ &\leq \frac{-1}{2} \mathbf{e}^T \mathbf{Q} \mathbf{e} - (E - |\varepsilon|) |\mathbf{e}^T \mathbf{P} \mathbf{b}_m| \\ &\leq 0 \end{aligned} \quad (28)$$

Since \dot{V} is negative semi-definite, that is $V(t) \leq V(0)$, it implies that \mathbf{e} , $\tilde{\mathbf{w}}_f$, $\tilde{\mathbf{w}}_u$ and \tilde{E} are bounded. Let function $\Xi(t) \equiv (E - |\varepsilon|) |\mathbf{e}^T \mathbf{P} \mathbf{b}_m| \leq -\dot{V}_2$, and integrate $\Xi(t)$ with respect to time, then it is obtained that

$$\int_0^t \Xi(\tau) d\tau \leq V(0) - V(t). \quad (29)$$

Because $V(0)$ is bounded, and $V(t)$ is nonincreasing and bounded, the following result can be obtained:

$$\lim_{t \rightarrow \infty} \int_0^t \Xi(\tau) d\tau < \infty \quad (30)$$

Also, $\dot{\Xi}(t)$ is bounded, so by Barbalat's Lemma [11], it can be shown that $\lim_{t \rightarrow \infty} \Xi(t) = 0$. That is, $\mathbf{e} \rightarrow 0$ as $t \rightarrow \infty$. As a result, the hybrid control system is asymptotically stable. Thus the proof of Theorem is complete.

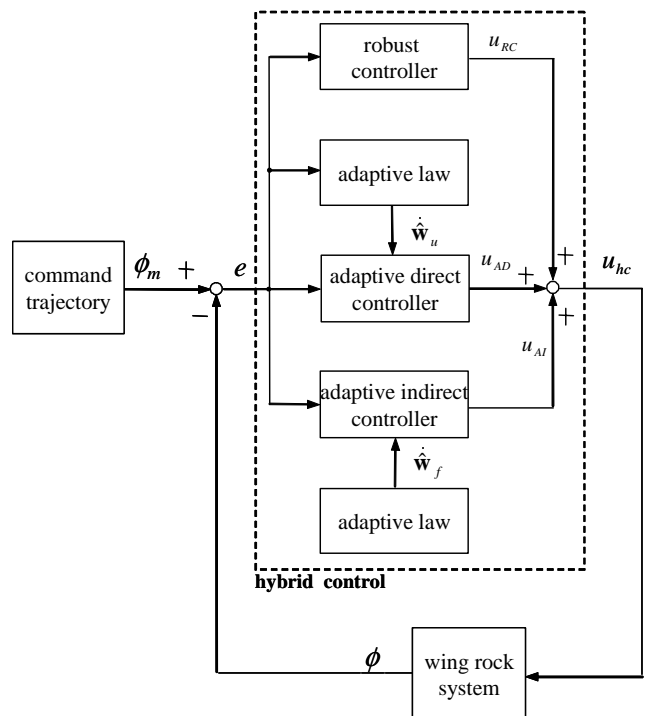


Fig. 4. Hybrid control wing rock system.

5 Simulation Results

The aerodynamic parameters of the delta wing for a 25 deg angle of attack are used for simulation. It is assumed that $U_\infty = 15 \text{ m/sec}$ and $b = 0.429 \text{ m}$. The

b_i parameters for the model in (4) are given by $b_0 = 0$, $b_1 = -0.01859521$, $b_2 = 0.015162375$, $b_3 = -0.06245153$, $b_4 = 0.00954708$, and $b_5 = 0.02145291$. It should be emphasized that the derivation of the hybrid control system does not need to use the aerodynamic parameters and the structure of the aerodynamic functions. The aerodynamic parameters are utilized only for simulations. The CMAC neural network with 7 hidden layer neurons in the AIC and the ADC is utilized, respectively. For simulations, two initial conditions (a small initial condition and a large initial condition) are examined to illustrate the effectiveness of the proposed hybrid control. The learning rates are selected as $\eta_1 = \eta_2 = 30$ and $\eta_3 = 0.1$. Let $\alpha = 1.0$ if pure AIC is required and $\alpha = 0.0$ when pure ADC is chosen. For comparing the flexibility of the developed hybrid control system, three cases are chosen to simulate as $\alpha = 1.0$, $\alpha = 1.0$ and $\alpha = 0.5$. The simulation results of the hybrid control system with $\alpha = 0.0$ for small and large initial conditions are shown in Fig. 5. The state responses are shown in Figs. 5(a) and 5(c); the associated control efforts are shown in Figs. 5(b) and 5(d), respectively. The simulation results of the hybrid control system with $\alpha = 1.0$ for small and large initial conditions are shown in Fig. 6. The state responses are shown in Figs. 6(a) and 6(c); the associated control efforts are shown in Figs. 6(b) and 6(d), respectively. The simulation results of the hybrid control system with $\alpha = 0.5$ for small and large initial conditions are shown in Fig. 7. The state responses are shown in Figs. 7(a) and 7(c); the associated control efforts are shown in Figs. 7(b) and 7(d), respectively. Simulation results show that the robust tracking performance of the hybrid control system has been achieved for the different initial conditions. The weighting factor α can be tuned by a controller designer based on the understanding level of the plant knowledge and control knowledge.

6 Conclusions

In this paper, a hybrid control system is developed to control a wing rock system. The hybrid control system is comprised of an adaptive indirect controller (AIC), an adaptive direct control (ADC), and a robust controller. A weighting factor is a tradeoff between plant knowledge and control knowledge to sum together the control efforts from the AIC and the ADC. The robust controller is designed to compensate the approximation error caused by the AIC and the ADC. The adaptive laws based on the Lyapunov stability theorem can automatically adjust the parameters of the hybrid control, thus the system

stability can be guaranteed. Simulation results have demonstrated that the developed hybrid control can achieve the desired control performance for the wing rock system. The major contributions of this paper are (1) the successful development of the bridge between the adaptive indirect control and adaptive direct control using a weighting factor; and (2) the successful application of the proposed hybrid control system to control the wing rock system.

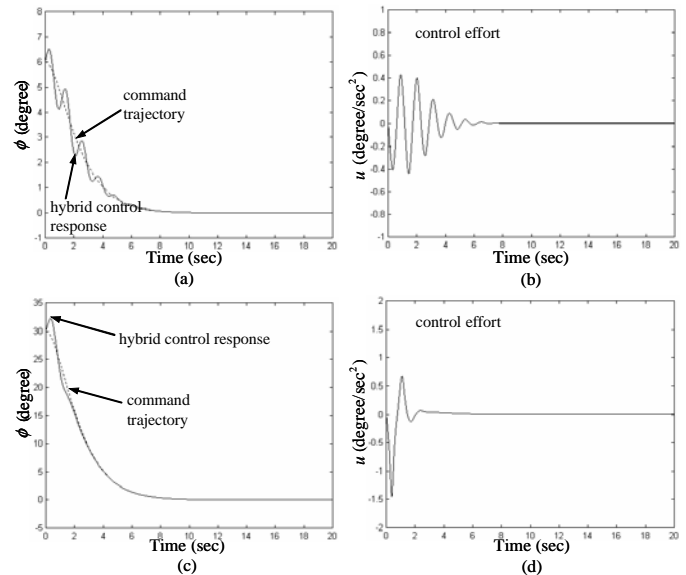


Fig. 5 Simulation results with $\alpha = 0.0$.

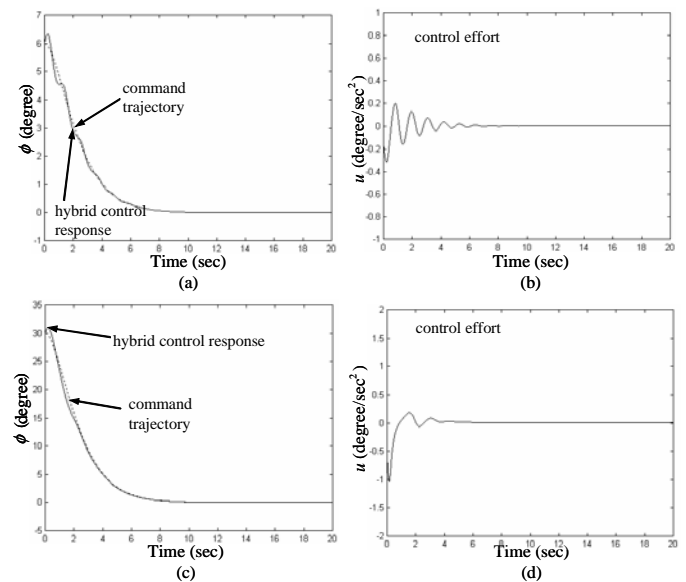


Fig. 6 Simulation results with $\alpha = 1.0$.

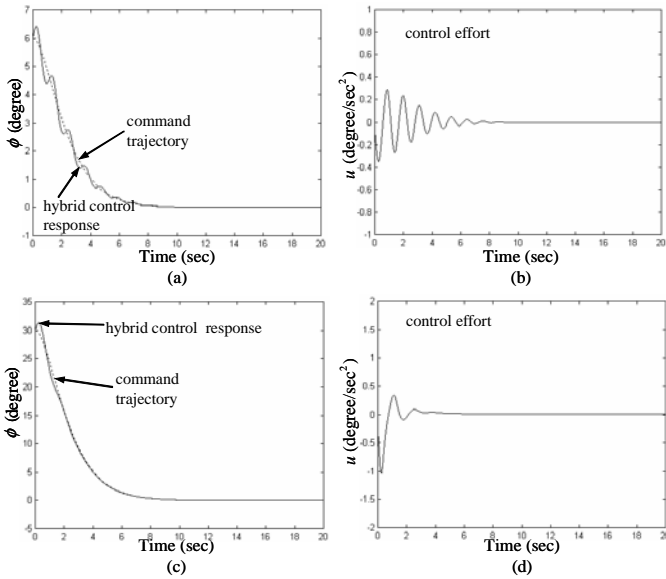


Fig. 7 Simulation results with $\alpha = 0.5$.

7 Acknowledgment

This paper is supported by the National Science Council of Republic of China under grant NSC 90-2213-E-155-016.

References:

- [1] S. Sastry and M. Bodson, *Adaptive Control – Stability, Convergence, and Robustness*, Prentice-Hall, Englewood Cliffs, New Jersey, 1989.
- [2] M. M. Polycarpou, “Stable adaptive neural control scheme for nonlinear systems,” *IEEE Trans. Automat. Contr.*, Vol. 41, No. 2, 1996, pp. 447-451.
- [3] F. J. Lin, R. J. Wai, and H. P. Chen, “A PM synchronous servo motor drive with an on-line trained fuzzy neural network controller,” *IEEE Trans. Energy Conversion*, Vol. 13, No. 6, 1998, pp. 319-325.
- [4] C. M. Lin and C. F. Hsu, “Neural network hybrid control for antilock braking systems,” *IEEE Trans. Neural Network*, Vol. 14, No. 2, 2003, pp. 351-359.
- [5] C. M. Lin and Y. F. Peng, “Adaptive CMAC-based supervisory control for uncertain nonlinear systems,” *IEEE Trans. Systems, Man, and Cybernetics Part B*, Vol.34, No.2, 2004, pp.1248-1260.
- [6] C. M. Lin and Y. F. Peng, “Missile guidance law design using adaptive cerebellar model articulation controller,” *IEEE Trans. Neural Networks*, Vol. 16, No. 3, 2005, pp. 636-644.
- [7] A. H. Nayfeh, J. M. Elzebdia, and D. T. Mook, “Analytical study of the subsonic wing-rock

phenomenon for slender delta wings,” *J. Aircraft*, Vol. 26, 1989, pp. 805-809.

- [8] S. P. Shue and R. K. Agarwal, “Nonlinear H_∞ method for control of wing rock motions,” *Journal of Guidance, Control, and Dynamics*, Vol. 23, 2000, pp. 60-68.
- [9] S. N. Singh, W. Yim, and W. R. Wells, “Direct adaptive and neural control of wing-rock motion of slender delta wings,” *Journal of Guidance, Control, and Dynamics*, Vol. 18, 1995, pp. 25-30.
- [10] C. M. Lin and C. F. Hsu, “Recurrent neural network adaptive control of wing rock motion,” *J. Guidance, Control, and Dynamics*, vol. 25, 2002, pp. 1163-1165.
- [11] J. J. E. Slotine and W. P. Li, *Applied Nonlinear Control*, Prentice-Hall, Englewood Cliffs, NJ, 1991.