Foundations of Generic Optimization

Volume 2: Applications of Fuzzy Control, Genetic Algorithms and Neural Networks

Edited by

R. Lowen
University of Antwerp, Belgium

and

A. Verschoren
University of Antwerp, Belgium

Springer

Robert Lowen
University of Antwerp
Belgium

Alain Verschoren
University of Antwerp
Belgium

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Stable Anti-Swing Control for an Overhead Crane with Velocity Estimation and Fuzzy Compensation

Wen Yu, Xiaoou Li, and George W. Irwin

Abstract This chapter proposes a novel anti-swing control strategy for an overhead crane. The controller includes both position regulation and anti-swing control. Since the crane model is not exactly known, fuzzy rules are used to compensate friction, gravity as well as the coupling between position and anti-swing control. A high-gain observer is introduced to estimate the joint velocities to realize PD control. Using a Lyapunov method and an input-to-state stability technique, the controller is proven to be robustly stable with bounded uncertainties, if the membership functions are changed by certain learning rules and the observer is fast enough. Real-time experiments are presented comparing this new stable anti-swing PD control strategy with regular crane controllers.

Keywords: Lyapunov stability; PD controller; Motion control

1 Introduction

Although cranes are very important systems for handling heavy goods, automatic cranes are comparatively rare in industrial practice [24], because of high investment costs. The need for faster cargo handling requires control of the crane motion so that

Wen Yu
Department of Automatic Control

Xiaoou Li
Department of Computer Science
Center for Research and Advanced Studies of the National Polytechnic Institute (CINVESTAV-IPN)
A.P. 14-740, Av.IPN 2508, México D.F., 07360, México, e-mail: yuw@ctrl.cinvestav.mx

George W. Irwin
School of Electronics, Electrical Engineering and Computer Science
Queen's University Belfast, Ashby Building, Stranmillis Road, Belfast, BT9 5AH, UK

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its dynamic performance is optimized. Specifically, the control of overhead crane systems aims to achieve both position regulation and anti-swing control. Several authors have looked at this including [3], time-optimal control was considered using boundary conditions, an idea which was further developed in [2] and [25]. Unfortunately, to increase robustness, some time optimization requirements, like zero angular velocity at the target point [21], have to be given up. Gain scheduling has been proposed as a practicable method [6] to increase tracking accuracy, while observer-based feedback control was presented in [24].

Many attempts, such as planar operation [6] and assuming the absence of friction [21], have been made to introduce simplified models for application of model-based control [24]. Thus, a self-tuning controller with a multilayer perceptron model for an overhead crane system was proposed [19] while in reference [5], the controller consists of a combined position servo control and a fuzzy-logic anti-swing controller.

Classical proportional and derivative (PD) control has the advantage of not requiring an overhead crane model but because of friction, gravitational forces and the other uncertainties, it cannot guarantee a zero steady-state error. While PID control can remove this error, it lacks global asymptotic stability [14]. Several efforts have therefore been made to improve the performance of PD controllers. Global asymptotically stable PD control was realized by pulsing gravity compensation in [27] while in [15], a PD controller for a vertical crane-winch system was developed, which only requires the measurement of angles and their derivatives rather than a cable angle measurement. In [9], a passivity-based controller was combined with a PD control law. Here, asymptotic regulation of the gantry and payload position was proven, but unfortunately both controllers again require a crane model to compensate for the uncertainties.

There are two main weaknesses in applying PD control to this application: (a) The PD controller requires suitable sensors to provide measurements of both position and velocity. Position can be obtained very accurately by means of an encoder, while velocity is usually measured by a tachometer, which can be expensive and is often contaminated by noise [12]; (b) Due to the existence of friction and gravitational forces, the steady-state error is not guaranteed to be zero [13]. It is therefore important to be able to realize PD control using only position measurement. One possible approach is to use a velocity observer, which can be either model-based or model-free. Model-based observers assume that the dynamics of the overhead crane are either completely or partially known. For example, the variable structure observer in [7] needed information about the inertia matrix to calculate the sliding mode gain. In contrast model-free observers do not require such exact knowledge about the overhead cranes. The most popular model-free observers are high-gain ones which can estimate the derivative of the output [22]. Recently, an observer was presented in reference [12], where the non-linearity of the manipulator was estimated by a static neural network.

In this chapter, a new modified algorithm is proposed which overcomes both these limitations of PD control at the same time. Firstly, a high-gain observer which can achieve stability is added to regular PD control. A fuzzy system is then used to estimate both friction and gravity. Unlike other work which used the singular perturbation method [22], a new proof of stability is presented using Lyapunov analysis. This proof explains the relation between the observer error and the observer gain.

Since the swing of the payload depends on the acceleration of the trolley, minimizing both the operation time and the payload swing produces partially conflicting requirements. The anti-swing control problem involves reducing the swing of the payload while moving it to the desired position as fast as possible [1]. One particular feedforward approach is input shaping [26], which is an especially practical and effective method of reducing vibrations in flexible systems. In [20] the anti-swing motion-planning problem is solved using the kinematic model in [17]. Here, anti-swing control for a three-dimensional overhead crane is proposed, which addresses the suppression of load swing. Non-linear anti-swing control based on the singular perturbation method is presented in [30]. Unfortunately, all of these anti-swing controllers are model-based.

In this chapter, a PID law is used for anti-swing control which, being model-free, will affect the position control. The same fuzzy compensator used for friction and gravity is applied to handle the position error. The required online learning rule is obtained from the tracking error analysis and there is no requirement for off-line learning. The overall closed-loop system with the high-gain observer and the fuzzy compensator is shown to be stable if the membership functions have certain learning rules and the observer is fast enough. Finally, results from experimental tests carried out to validate the controller are presented.

2 Preliminaries

The overhead crane system described schematically in Figure 1 (a) has the system structure shown in Figure 1 (b). Here α is the payload angle with respect to the vertical and β is the payload projection angle along the X-coordinate axis. The dynamics of the overhead crane are given by [28]:

$$M(x)\ddot{x}+C(x,\dot{x})\dot{x}+G(x)+F=\tau \tag{1}$$

where $x=[x_w,y_w,\alpha,\beta,R]^T$, (x_w,y_w,R) is position of the payload, $\tau=[F_x,F_y,0,0,F_R]^T$, F_x, F_y and F_R represent the control forces acting on the cart and rail and along the lift-line, $F=[\mu_x,\mu_y,0,0,\mu_R]^T\dot{x}$, μ_x, μ_y and μ_R are frictions factors, $G(x)$ is gravitational force, $C(x,\dot{x})$ is the Coriolis matrix and $M(x)$ is the dynamic matrix of the crane.

In (1), there are some differences from other crane models in the literature. The length of the lift-line is not considered in [9], so the dimension of M is 4×4, while in [20], which also addresses anti-swing control and position control, the dimension of M is 3×3. In [16], the dimension of M is 5×5 as in this chapter. However, some uncertainties such as friction and anti-swing control coupling are not included. This overhead crane system shares one important property with robot systems: the

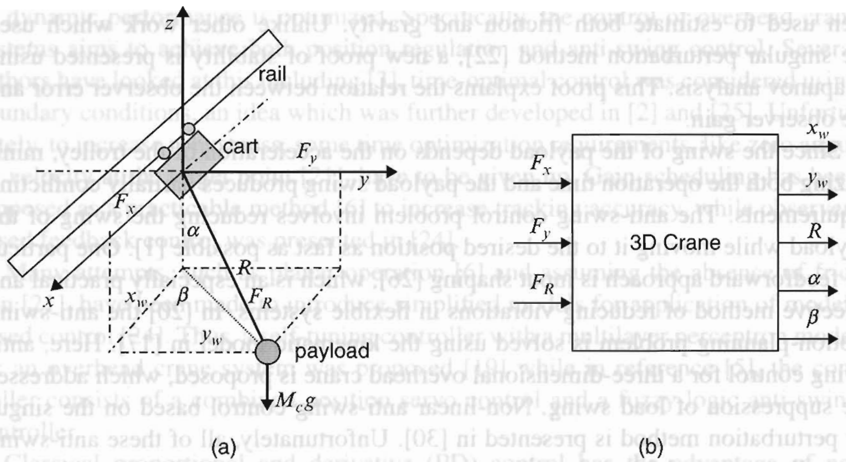

Fig. 1 Overhead crane

Coriolis matrix $C(x,\dot{x})$ is skew-symmetric, i.e., it satisfies the following relationship [9]

$$x^T\left[M(x) - 2C(x,\dot{x})\right]x = 0 \tag{2}$$

A normal PD control law has the following from

$$\tau = -K_p(x - x^d) - K_d(\dot{x} - \dot{x}^d)$$

where K_p and K_d are positive definite, symmetric and constant matrices, which correspond to the proportional and derivative coefficients, $x^d \in \Re^5$ is the desired position, and $\dot{x}^d \in \Re^5$ is the desired joint velocity. Here the regulation problem is discussed, so $\dot{x}^d = 0$.

Input-to-state stability (ISS) is another elegant approach for stability analysis besides the Lyapunov method. It can lead to general conclusions on stability using the input and state characteristics. Thus, consider a class of non-linear systems described by

$$\dot{x}_t = f(x_t, u_t) \tag{3}$$

where $x_t \in \Re^n$ is the state vector, $u_t \in \Re^m$ is the input vector, $y_t \in \Re^m$ is the output vector. $f : \Re^n \times \Re^m \to \Re^n$ is locally Lipschitz. Some passivity properties, as well as some stability properties of passive systems are now recalled [4].

Definition 1. *A system (3) is said to be globally input-to-state stability if there exists a $\mathcal{K}$-function $\gamma(s)$ (continuous and strictly increasing $\gamma(0) = 0$) and a $\mathcal{KL}$-function $\beta(s,t)$ ($\mathcal{K}$-function and for each fixed $s_0 \geq 0$, $\lim_{t\to\infty} \beta(s_0,t) = 0$), such that, for each $u_t \in L_\infty$ ($\|u(t)\|_\infty < \infty$) and each initial state $x^0 \in R^n$, the following holds*

$$\left\|x(t,x^0,u_t)\right\| \leq \beta\left(\left\|x^0\right\|,t\right) + \gamma\left(\|u_t\|_\infty\right)$$

for each $t \geq 0$.

This definition implies that if a system has input-to-state stability, its behaviour should remain bounded when its inputs are bounded.

3 Anti-Swing Control for the Overhead Crane

The control problem is to move the rail in such a way that the actual position of the payload reaches the desired one. The three control inputs $[F_x, F_y, F_R]$ can force the crane to the position $[x_w, y_w, R]$, but the swing angles $[\alpha, \beta]$ cannot be controlled using the dynamic model (1) directly. In order to design an anti-swing control, linearization models for $[\alpha, \beta]$ are analyzed. Because the acceleration of the crane is much smaller than the gravitational acceleration, the rope length is kept slowly varying and the swing is not big, giving

$$|\ddot{x}_w| \ll g, \quad |\ddot{y}_w| \ll g, \quad |\ddot{R}| \ll g$$
$$|\dot{R}| \ll R, \quad |\dot{\alpha}| \ll 1, \quad |\dot{\beta}| \ll 1$$
$$s_1 = \sin\alpha \approx \alpha, \quad c_1 = \cos\alpha \approx 1,$$

The approximated dynamics of $[\alpha, \beta]$ are then

$$\ddot{\alpha} + \ddot{x}_w + g\alpha = 0, \quad \ddot{\beta} + \ddot{y}_w + g\beta = 0$$

Since $\ddot{x}_w = \frac{F_x}{M_r}$, $\ddot{y}_w = \frac{F_y}{M_m}$, the dynamics of the swing angles are

$$\ddot{\alpha} + g\alpha = -\frac{F_x}{M_r}, \quad \ddot{\beta} + g\beta = -\frac{F_y}{M_m} \tag{4}$$

The control forces F_x and F_y are assumed to have the following form

$$\begin{aligned} F_x &= A_1(x_w, \dot{x}_w) + A_2(\alpha, \dot{\alpha}) \\ F_y &= B_1(y_w, \dot{y}_w) + B_2\left(\beta, \dot{\beta}\right) \end{aligned} \tag{5}$$

where $A_1(x_w, \dot{x}_w)$ and $B_1(y_w, \dot{y}_w)$ are position controllers, and $A_2(\alpha, \dot{\alpha})$ and $B_2(\beta, \dot{\beta})$ are anti-swing controllers. Substituting (5) into (4), produces the anti-swing control model

$$\ddot{\alpha} + g\alpha + \frac{A_1}{M_r} = -\frac{A_2}{M_r}, \quad \ddot{\beta} + g\beta + \frac{B_1}{M_m} = -\frac{B_2}{M_m} \tag{6}$$

Now if $\frac{A_1}{M_r}$ and $\frac{B_1}{M_r}$ are regarded as disturbance, $\frac{A_2}{M_r}$ and $\frac{B_2}{M_m}$ as control inputs, then (6) is a second-order linear system with disturbances. Standard PID control can now be applied to regulate α and β thereby producing the anti-swing controllers

$$A_2(\alpha,\dot{\alpha}) = k_{pa2}\alpha + k_{da2}\dot{\alpha} + k_{ia2}\int_0^1 \alpha dt$$
$$B_2\left(\beta,\dot{\beta}\right) = k_{pb2}\beta + k_{db2}\dot{\beta} + k_{ib2}\int_0^1 \beta dt \tag{7}$$

where k_{pa2}, k_{da2} and k_{ia2} are positive constants corresponding to proportional, derivative and integral gains.

Substituting (5) into (1), produces the position control model

$$M(x)\ddot{x} + V(x,\dot{x})\dot{x} + G(x) + T\dot{x} + D = u_1 \tag{8}$$

where $D = [A_2, B_2, 0, 0, 0]^T$, $u_1 = [A_1, B_1, 0, 0, F_R]^T$. Using this model, a position controller will be designed in Section 4.

4 Position Control with Fuzzy Compensation

A generic fuzzy model for friction and gravity is provided by a collection of l fuzzy rules (Mamdani fuzzy model [18])

$$\begin{array}{c} \mathrm{R}^i\text{: IF } (x_w \text{ is } A_{1i}) \text{ and } (y_w \text{ is } A_{2i}) \text{ and } (\alpha \text{ is } A) \text{ and } (\beta \text{ is } A_{4i}) \\ \text{and } (R \text{ is } A_{5i}) \text{ THEN } \left(\widehat{f}_x \text{ is } B_{1i}\right) \text{ and } \left(\widehat{f}_y \text{ is } B_{2i}\right) \text{ and } \left(\widehat{f}_z \text{ is } B_{3i}\right) \end{array} \tag{9}$$

Here $\widehat{f}_x$, $\widehat{f}_y$ and $\widehat{f}_z$ are the uncertainties (friction, gravity and coupling errors) along the X, Y, Z -coordinate axis. $i = 1, 2 \cdots l$. A total of fuzzy IF-THEN rules are used to perform the mapping from the input vector $x = [x_w, y_w, \alpha, \beta, R]^T \in \Re^5$ to the output vector $\widehat{y}(k) = \left[\widehat{f}_1, \widehat{f}_2, \widehat{f}_3\right]^T = [\widehat{y}_1, \widehat{y}_2, \widehat{y}_3] \in R^3$. Here $A_{1i}, \cdots A_{ni}$ and $B_{1i}, \cdots B_{mi}$ are standard fuzzy sets. In this chapter, some on-line learning algorithms are introduced for the membership functions B_{ji} such that the PD controller is stable.

By using product inference, centre-average defuzzification and a singleton fuzzifier, the pth output of the fuzzy logic system can be expressed as [29]

$$\widehat{y}_p = \left(\sum_{i=1}^{l} w_{pi}\left[\prod_{j=1}^{5}\mu_{A_{ji}}\right]\right) / \left(\sum_{i=1}^{l}\left[\prod_{j=1}^{5}\mu_{A_{ji}}\right]\right) = \sum_{i=1}^{l} w_{pi}\phi_i \tag{10}$$

where $p = 1, 2, 3$, $\mu_{A_{ji}}$ is the membership functions of the fuzzy sets A_{ji}, and w_{pi} is the point at which $\mu_{B_{pi}} = 1$. Defining

$$\phi_i = \prod_{j=1}^{n}\mu_{A_{ji}} / \sum_{i=1}^{l}\prod_{j=1}^{n}\mu_{A_{ji}} \tag{11}$$

then (10) can be expressed in matrix form

$$\widehat{y} = \hat{W}_t \Phi(x) \tag{12}$$

where the parameter matrix $\hat{W}(k) = \begin{bmatrix} w_{11} & & w_{1l} \\ w_{21} & \cdots & w_{2l} \\ w_{31} & & w_{3l} \end{bmatrix} \in R^{3\times l}$, and the data vector $\Phi[x] = [\phi_1 \cdots \phi_l]^T \in R^{l\times 1}$. The position controllers have a PD form with a fuzzy compensator

$$u_1 = [A_1(x_w, \dot{x}_w), B_1(y_w, \dot{y}_w), 0, 0, F_R]^T = -K_{p1}\left(x - x^d\right) - K_{d1}\left(\dot{x} - \dot{x}^d\right) + \hat{W}_t\Phi(x) \tag{13}$$

where $x = [x_w, y_w, \alpha, \beta, R]^T$, $x^d = \left[x_w^d, y_w^d, 0, 0, R^d\right]^T$, and x_w^d, y_w^d and R^d are the desired positions. In the regulation case $\dot{x}_w^d = \dot{y}_w^d = \dot{R}^d = 0$. Further, $K_{p1} = diag\left[k_{pa1}, k_{pb1}, 0, 0, k_{pr}\right]$, $K_{d1} = diag\left[k_{da1}, k_{db1}, 0, 0, k_{dr}\right]$. The time-varying weight matrix $\hat{W}_t$ is determined by the fuzzy learning law. According to the Stone–Weierstrass theorem [8], a general non-linear smooth function can be written as

$$f(x) = W^*\Phi(x) + \mu(t) \tag{14}$$

where W^* is optimal weight matrix, and $\mu(t)$ is the modeling error. In this chapter we use the fuzzy compensator (12) to approximate the unknown non-linearity (gravity, friction and coupling of anti-swing control) as

$$\hat{W}_t\Phi(x) = G(x) + T\dot{x} + D + \mu(t) \tag{15}$$

When the velocity $\dot{x}$ is not available, a velocity observer is needed. Section 6.5 describes how to incorporate a model-free observer to PD control for the overhead crane.

5 PD Control with a Velocity Observer

The overhead crane dynamics (1) can be rewritten in state-space form as [22]

$$\begin{aligned} \dot{x}_1 &= x_2 \\ \dot{x}_2 &= H_1(X, u) \\ y &= x_1 \end{aligned} \tag{16}$$

where $x_1 = x = [x_w, y_w, \alpha, \beta, R]^T$ is the position vector, x_2 is the velocity vector, $X = [x_1^T, x_2^T]^T$, and $u = \tau$ is the control input. The output is a position measurement,

$$H_1(X, u) = -M(x_1)^{-1}\left[C(x_1, x_2)\dot{x}_1 + G(x_1) + F\dot{x}_1 + u\right] \tag{17}$$

If the velocity vector x_2 is not measurable and the dynamics of manipulator are unknown, a high-gain observer can be used to estimate x_2 [22]

$$\frac{d}{dt}\hat{x}_1 = \hat{x}_2 + \frac{1}{\varepsilon}K_1(x_1 - \hat{x}_1)$$
$$\frac{d}{dt}\hat{x}_2 = \frac{1}{\varepsilon^2}K_2(x_1 - \hat{x}_1) \tag{18}$$

where $\hat{x}_1 \in \Re^5$, $\hat{x}_2 \in \Re^5$ denotes the estimated values of x_1, x_2 respectively; ε is a small positive parameter, and K_1 and K_2 are positive definite matrices chosen such that the matrix $\begin{bmatrix} -K_1 & I \\ -K_2 & 0 \end{bmatrix}$ is stable. Defining the observer error as

$$\tilde{x} = x - \hat{x}, \quad \tilde{z}_1 = \tilde{x}_1, \quad \tilde{z}_2 = \varepsilon\tilde{x}_2 \tag{19}$$

where $\hat{x} = [\hat{x}_1^T, \hat{x}_2^T]^T$, the observer error equation can then be formed from (16) and (18)

$$\varepsilon\frac{d}{dt}\tilde{z}_1 = \tilde{z}_2 - K_1\tilde{z}_1$$
$$\varepsilon\frac{d}{dt}\tilde{z}_2 = -K_2\tilde{z}_1 + \varepsilon^2 H_1 \tag{20}$$

or in the matrix form:

$$\varepsilon\frac{d}{dt}\tilde{z} = A\tilde{z} + \varepsilon^2 BH_1 \tag{21}$$

where $A = \begin{bmatrix} -K_1 & I \\ -K_2 & 0 \end{bmatrix}$, $B = \begin{bmatrix} 0 \\ I \end{bmatrix}$. The structure of the velocity observer is the same as in [22], but a new theorem is proposed here in order to integrate the observer and the fuzzy compensator .

Theorem 2. *If the high gain observer (18) is used to estimate the velocity of the overhead crane (16), the observer error $\tilde{x}$ will converge to the following residual set*

$$D_\varepsilon = \{\tilde{x} \mid \|\tilde{x}\| \le \bar{K}(\varepsilon)\}$$

where $\bar{K}(\varepsilon) = 2\varepsilon^2 \sup_{t\in[0,T]} \|BH_1\|^T \|P\|$, P is the solution of Lyapunov equation:

$$A^T P + PA = -I \tag{22}$$

See appendix for the proof of Theorem 1.

Reference [22] gave the proof of stability under the assumption of $\varepsilon \to 0$. Here ε can be any positive constant. Since $\sup_{t\in[0,T]} \|BH_1\|^T \|P\|$ is bounded, ε can be selected arbitrary small to make $\bar{K}(\varepsilon)$ small enough. Hence the observer error $\tilde{x}$ becomes arbitrary small as $\varepsilon \to 0$. However, a large observer gain $\left(\frac{1}{\varepsilon}\right)$ will enlarge the observer noise, so ε should be selected to be as large as possible if the observer accuracy $\bar{K}(\varepsilon)$ is within tolerance.

The PD control law in combination with the state estimate from a high-gain observer is then given by

$$\tau = -K_p(x_1 - x_1^d) - K_d(\hat{x}_2 - x_2^d) \tag{23}$$

where $x_1^d \in \Re^5$ is the desired position, $x_2^d \in \Re^5$ is the desired velocity. In the regulation case $x_2^d = 0$, and $\hat{x}_2$ is of course the velocity approximation from the high-gain observer.

The coupling between anti-swing control and position control can be explained as follows. For the anti-swing control (6), the position control A_1 and B_1 are disturbances, which can be decreased by the integral action in PID control. The anti-swing model (6) is an approximator, but the anti-swing control (7) does not in fact use this, as it is model-free. Hence while the anti-swing control law (7) cannot suppress the swing completely, it can minimize any consequent vibration.

For the position control (8), the anti-swing control lies in the term $D = [A_2, B_2, 0, 0, 0]^T$, which can also be regarded as a disturbance. The coupling due to anti-swing control can be compensated by the fuzzy system. Consequently, the PD control with the fuzzy compensation can be expressed as

$$\tau = -K_p(x_1 - x_1^d) - K_d x_2 + \hat{W}_t \Phi(x) \tag{24}$$

If neither the velocity x_2 nor the friction and gravity are known, the normal PD control needs to be combined with velocity estimation and fuzzy compensation to give

$$\tau = -K_p(x_1 - x_1^d) - K_d(\hat{x}_2 - x_2^d) + \hat{W}_t \Phi(s) \tag{25}$$

where $s = \left(x_1^T, \hat{x}_2^T\right)^T$, $x_2^d = 0$. The stability of this controller is analysed next.

6 Stability Analysis

Equation (14) can be rewritten as

$$G(x) + F(x) = W^* \Phi(x) + \eta_g \tag{26}$$

where $x = \left[q^T, \dot{q}^T\right]^T$, W^* is fixed bounded matrix, and η_g is the approximation error whose magnitude also depends on the value of W^*. Now, η_g is assumed to be quadratic bounded such that

$$\eta_g^T \Lambda_g \eta_g \leq \bar{\eta}_g \tag{27}$$

where $\bar{\eta}_g$ is a positive constant. Friction and gravity can be estimated according to

$$G(x) + F(x) \approx \hat{W}_t \Phi(s) \tag{28}$$

where $\hat{W}_t$ is a time-varying weight matrix for the fuzzy system. The following relation holds

$$W^* \Phi(x) - \hat{W}_t \Phi(x) = \tilde{W}_t \Phi(s) \tag{29}$$

where $\tilde{W}_t = W^* - \hat{W}_t$. From Theorem 1 it is known that the high gain observer (18) can make $(\hat{x}_2 - x_2)$ converge to a residual set and it is possible to write $x_2 = \hat{x}_2 + \delta$, where δ is bounded such that $\delta^T \Lambda_\delta \delta \leq \bar{\eta}_\delta$. Now defining the tracking error as $(x_2^d = 0), \bar{x}_1 = x_1 - x_1^d$:

$$\tilde{x}_2 = \hat{x}_2 = \bar{x}_2 - \delta \tag{30}$$

the following theorem holds.

Theorem 3. *If the updating laws for the membership functions in (28) are*

$$\frac{d}{dt}\hat{W}_t = -K_w \Phi(s) \tilde{x}_2^T \tag{31}$$

where K_w, K_v and Λ_3 are positive definite matrices, and K_d satisfies

$$K_d > \Lambda_g^{-1} + \Lambda_\delta^{-1} \tag{32}$$

then the PD control law with fuzzy compensation in (25) can make the tracking error stable. In fact, the average tracking error $\bar{x}_2$ converges to

$$\limsup_{T \to \infty} \frac{1}{T} \int_0^T \|\bar{x}_2\|_{Q_1}^2 \, dt \leq \bar{\eta}_g + 2\bar{\eta}_\delta \tag{33}$$

where $Q_1 = K_d - \left(\Lambda_g^{-1} + \Lambda_\delta^{-1}\right)$.

The proof of Theorem 2 is contained in the Appendix.

7 Experimental Comparisons

The proposed anti-swing control for overhead crane systems has been implemented on a InTeCo [10] overhead crane test-bed, see Figure 2. The rail is 150 cm long., and the physical parameters for the system are as follows:

$$M_r = 6.5kg, \quad M_c = 0.8kg, \quad M_m = 1.3kg, \quad I = 0.01kg \cdot m^2$$

Here interfacing is based on a Xilinx FPGA microprocessor, comprising a multi-function analog and digital I/O board dedicated to real-time data acquisition and control in the Windows XP environment, mounted in a PC Pentium-III 500 MHz host. Because the Xilinx FPGA chip supports real-time operations without introducing latencies caused by the Windows default timing system, the control program operated in Windows XP with Matlab 6.5/Simulink. All of the controllers employed a sampling frequency of 1 kHz.

The anti-swing control is discussed first. There are two inputs in the anti-swing model (6), A_1 and A_2 with A_1 from the position controller and A_2 from the anti-swing controller. When the anti-swing control A_2 is designed by (6), A_1 is regarded as a disturbance. The chosen parameters of the PID (7) control law were

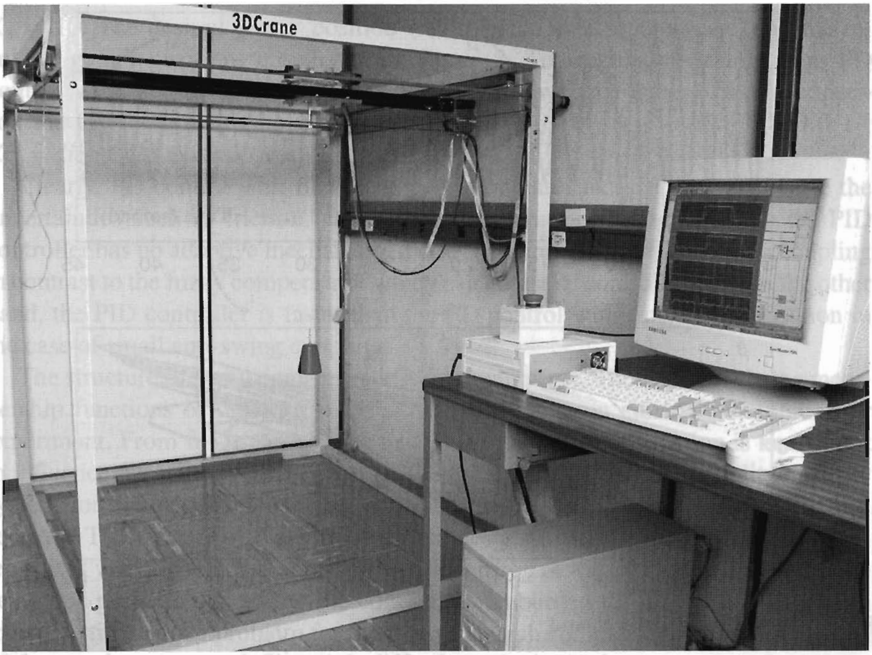

Fig. 2 Real-time control for an overhead crane

$$k_{pa2} = 2.5, \quad k_{da2} = 18, \quad k_{ia2} = 0.01$$
$$k_{pb2} = 15, \quad k_{db2} = 10, \quad k_{ib2} = 0.6$$

The resulting angles are shown in Figure 3 for the position control without anti-swing, and in Figure 4 for the position control with anti-swing. It can be seen that the swing angles α and β are decreased a lot with the anti-swing controller.

The position control law in equation (13) is discussed next. In this case there are two types of input to the position model (8), $D = [A_2, \ldots]^T$, $u_1 = [A_1, \ldots]^T$. When the position control A_1 is designed by (25) with $u_1 = \tau$, the anti-swing control A_2 in (8) is regarded as a disturbance which will be compensated for the fuzzy system (12). Theorem 2 implies that to assure stability, K_d should be large enough such that $K_d > \Lambda_g^{-1} + \Lambda_\delta^{-1}$. Since these upper bounds are not known, $K_{d1} = diag[80, 80, 0, 0, 10]$ is selected. The position feedback gain does not effect the stability, but it should be positive, and was chosen as $K_{p1} = diag[5, 5, 0, 0, 1]$.

A total of 20 fuzzy rules were used to compensate the friction, gravity and the coupling from anti-swing control. The membership function for A_{ji} was chosen to be the Gaussian function

$$A_{ji} = \exp\left\{-(x_j - m_{ji})^2 / 100\right\}, \quad j = 1 \cdots 5, \quad i = 1 \cdots 20$$

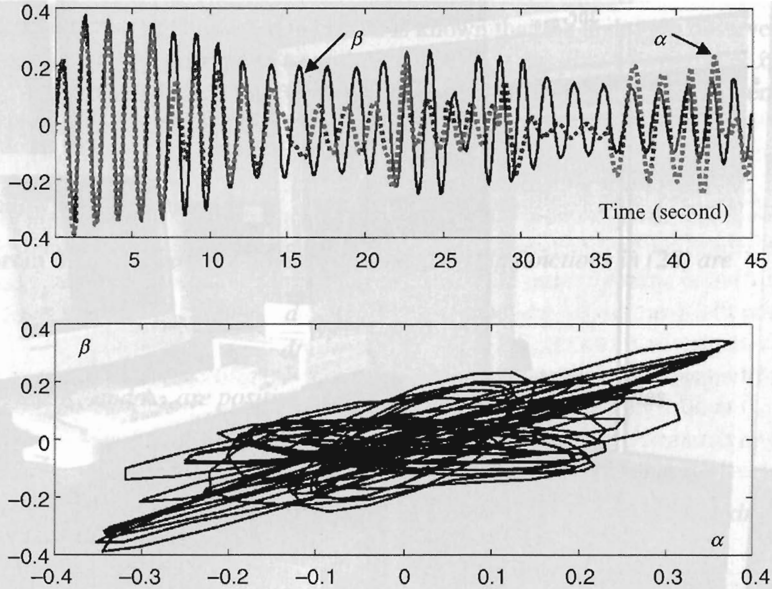

Fig. 3 Without swing angles control

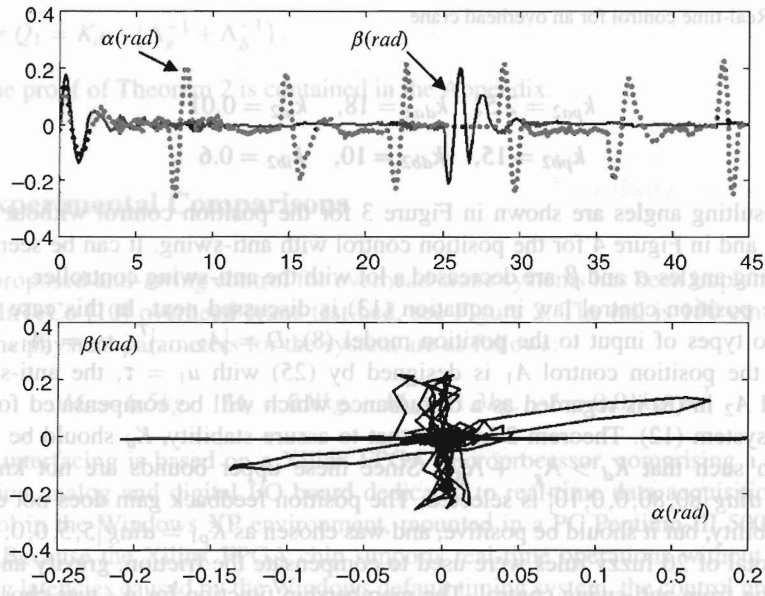

Fig. 4 With swing angles control

where the centres m_{ji} were selected randomly to lie in the interval $(0, 1)$. Hence, $\hat{W}_t \in R^{5\times 20}$, $\Phi(x) = [\sigma_1 \cdots \sigma_{20}]^T$. The learning law took the form in (31) with

$K_w = 10$. The desired gantry position was selected as a square wave, and the resulting gantry positions are shown in Figure 5. The regulation results from PD control without fuzzy compensation [15] are shown in Figure 6. For comparison the PID control results ($K_{d1} = diag[80,80,0,0,10]$, $K_{p1} = diag[5,5,0,0,1]$, $K_{i1} = diag[0.25,0.25,0,0,0.1]$) are shown in Figure 7.

Clearly, PD control with fuzzy compensation can successfully compensate the uncertainties such as friction, gravity and anti-swing coupling. Because the PID controller has no adaptive mechanism, it does not work well for anti-swing coupling in contrast to the fuzzy compensator which can adjust its control action. On the other hand, the PID controller is faster than the PD control with fuzzy compensation in the case of small anti-swing coupling.

The structure of fuzzy compensator is very important. The constants in the membership functions of the fuzzy system have to be chosen either by simulation or experiment. From fuzzy theory the form of the membership function is known not to influence the stability of the fuzzy control, but the approximation ability of fuzzy system for a particular non-linear process depends on the membership functions selected. The number of fuzzy rules constitutes a structural problem for fuzzy systems. It is well known that increasing the dimension of the fuzzy rules can cause the "overlap" problem and add to the computational burden [29]. The best dimension to use is still an open problem for the fuzzy research community. In this application 20 fuzzy rules were used. Since it is difficult to obtain the fuzzy structure from prior knowledge, several fuzzy identifiers can be put in parallel and the best one selected by a switching algorithm. The learning gain K_w will influence the learning speed, so a very large gain can cause unstable learning, while a very small gain produce slow learning process.

8 Conclusion

In this chapter, the disadvantages of the popular PD control for overhead crane are overcome in the following two ways: (1) a high-gain observer is proposed for the estimation of the velocities of the joints; (2) a fuzzy compensator is used to compensate for gravity and friction. Using Lyapunov-like analysis, the stability of the closed-loop system with velocity estimation and fuzzy compensation was proven. Real-time experiments were presented comparing our stable anti-swing PD control strategy with regular crane controllers. These showed that the PD control law with the anti-swing and fuzzy compensations is effective for the crane system.

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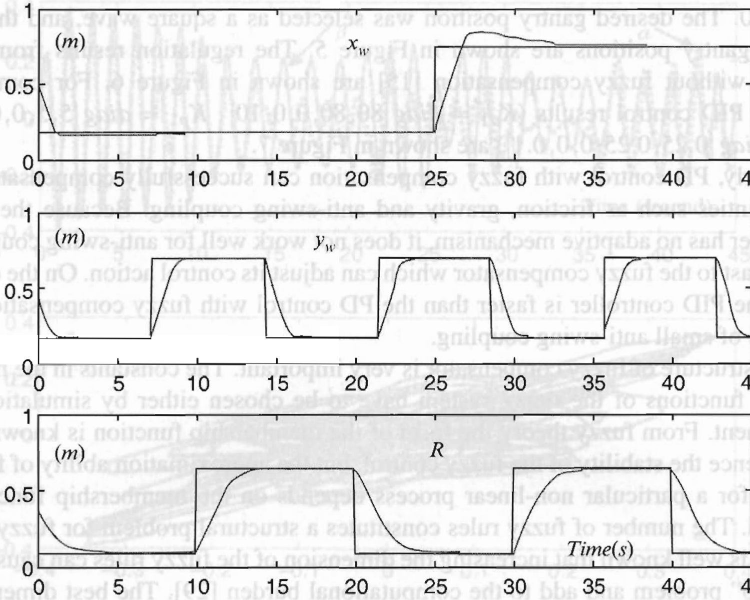

Fig. 5 PD control with fuzzy compensation

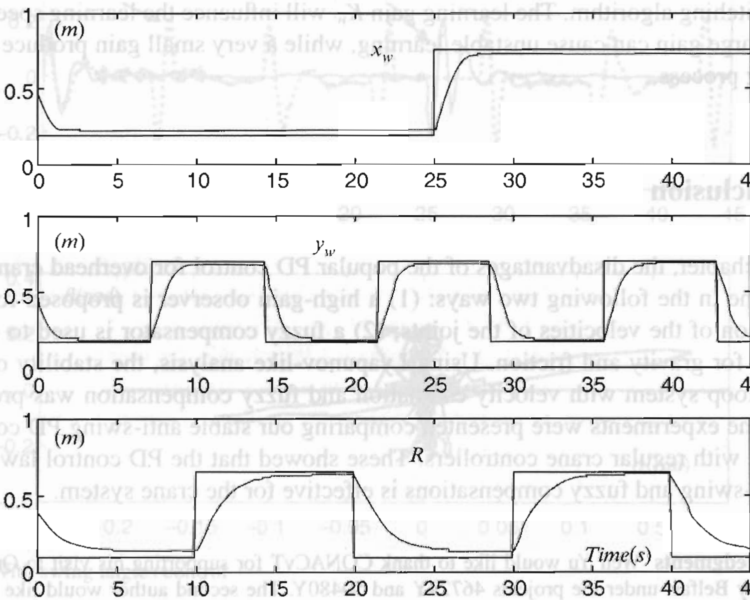

Fig. 6 PD control without compensation

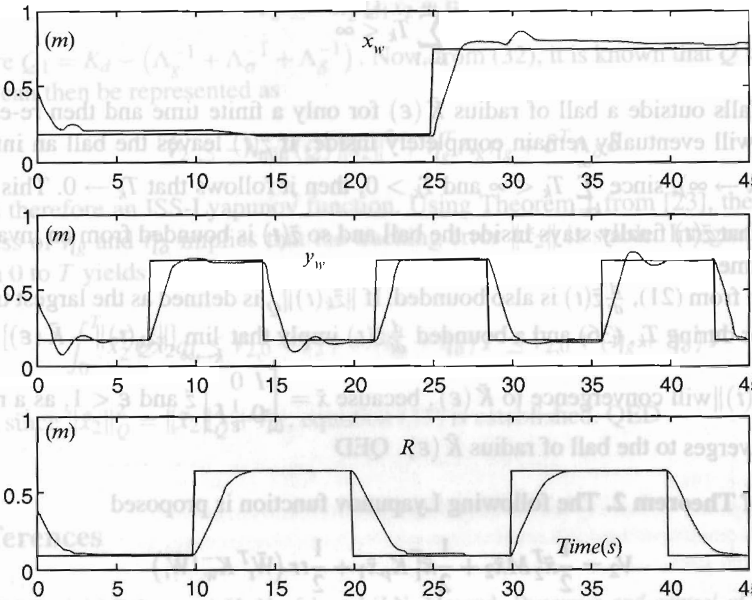

Fig. 7 PID

9 Appendix

Proof of Theorem 1. Since the spectra of K_1 and K_2 are in the left half plane, (22) has a positive definite solution P. Consider the following candidate Lyapunov function:$V_0(\tilde{z}) = \varepsilon \tilde{z}^T P \tilde{z}$. The derivative of this along the solutions of (20) is:

$$\begin{aligned} \dot{V}_0 &= \varepsilon \frac{d}{dt}\tilde{z}^T P \tilde{z} + \varepsilon \tilde{z}^T P \frac{d}{dt}\tilde{z} \\ &= \tilde{z}^T \left(A^T P + PA\right)\tilde{z} + 2\varepsilon^2 \left(BH_1\right)^T P \tilde{z} \qquad (34) \\ &\leq -\left\|\tilde{z}\right\|^2 + 2\varepsilon^2 \left\|BH_1\right\| \left\|P\right\| \left|\tilde{z}\right| \end{aligned}$$

Since (16) has a solution for any $t \in [0,T]$, $\|H_1\|$ is bounded for any finite time T. It can be therefore concluded that $\|BH_1\| \|P\|$ is bounded.

$$\dot{V} \leq -\|\tilde{z}\|^2 + \bar{K}(\varepsilon)\|\tilde{z}\|$$

where $\bar{K}(\varepsilon) = 2\varepsilon^2 \sup_{t\in[0,T]} \|BH_1\| \|P\|$. Note that if

$$\|\tilde{z}(t)\| > \bar{K}(\varepsilon) \qquad (35)$$

Now, let T_k denote the time interval during which $\|\tilde{z}(t)\| > \bar{K}(\varepsilon)$. Then $\dot{V}_0 < 0$, $\forall t \in [0,T]$ means the total time during which $\|\tilde{z}(t)\| > \bar{K}(\varepsilon)$ is finite

$$\sum_{k=1}^{\infty} T_k < \infty \tag{36}$$

If $\tilde{z}(t)$ falls outside a ball of radius $\bar{K}(\varepsilon)$ for only a finite time and then re-enters it, $\tilde{z}(t)$ will eventually remain completely inside. If $\tilde{z}(t)$ leaves the ball an infinite times $(k \to \infty)$, since $\sum_{k=1}^{\infty} T_k < \infty$ and $T_k > 0$, then it follows that $T_k \to 0$. This then means that $\tilde{z}(t)$ finally stays inside the ball and so $\tilde{z}(t)$ is bounded from an invariant set argument.

Now, from (21), $\frac{d}{dt}\tilde{z}(t)$ is also bounded. If $\|\tilde{z}_k(t)\|_Q$ is defined as the largest tracking error during T_k, (36) and a bounded $\frac{d}{dt}\tilde{z}(t)$ imply that $\lim_{k\to\infty} [\|\tilde{z}_k(t)\| - \bar{K}(\varepsilon)] = 0$, and $\|\tilde{z}_k(t)\|$will convergence to $\bar{K}(\varepsilon)$, because $\tilde{x} = \begin{bmatrix} I & 0 \\ 0 & \frac{1}{\varepsilon}I \end{bmatrix} \tilde{z}$ and $\varepsilon < 1$, as a result $\|\tilde{x}\|$ converges to the ball of radius $\bar{K}(\varepsilon)$. QED ■

Proof of Theorem 2. The following Lyapunov function is proposed

$$V_2 = \frac{1}{2}\tilde{x}_2^T M \tilde{x}_2 + \frac{1}{2}\tilde{x}_1^T K_p \tilde{x}_1 + \frac{1}{2} tr\left(\tilde{W}_t^T K_w^{-1} \tilde{W}_t\right) \tag{37}$$

where K_w and K_v are any positive definite matrices. Using (1), (25) and (26), the closed-loop system is given by

$$M\dot{x}_2 = -Cx_2 - K_p\tilde{x}_1 - K_d\tilde{x}_2 + \hat{W}_t\Phi(s) - W^*\Phi(s) - \eta_g \tag{38}$$

Now the derivative of (37) is

$$\dot{V}_2 = \tilde{x}_2^T M\dot{\tilde{x}}_2 + \frac{1}{2}\tilde{x}_2^T \dot{M}\tilde{x}_2 + \tilde{x}_2^T K_p \dot{\tilde{x}}_1 + tr\left(\dot{\tilde{W}}_t^T K_w^{-1} \tilde{W}_t\right) \tag{39}$$

and from (38) and (29) it follows that

$$\tilde{x}_2^T M\dot{\tilde{x}}_2 = -\tilde{x}_2^T M\dot{x}_2^d - \tilde{x}_2^T C\tilde{x}_2 - \tilde{x}_2^T Cx_2^d - \tilde{x}_2^T K_p\tilde{x}_1 - \tilde{x}_2^T K_d\tilde{x}_2 - \tilde{x}_2^T\left[\tilde{W}_t\Phi(s) + \eta_g\right]$$

Using (2) and (39), this then can be written as

$$\begin{aligned}\dot{V}_2 = &-\tilde{x}_2^T M\dot{x}_2^d - \tilde{x}_2^T Cx_2^d - \tilde{x}_2^T K_d\tilde{x}_2^T - \tilde{x}_2^T\left[v_\sigma + \eta_g\right] \\ &+ \tilde{x}_2^T\delta + tr\left[\left(K_w^{-1}\frac{d}{dt}\tilde{W}_t - \Phi(s)\tilde{x}_2^T\right)\tilde{W}\right]\end{aligned} \tag{40}$$

In view of the matrix inequality,

$$X^TY + \left(X^TY\right)^T \le X^T\Lambda^{-1}X + Y^T\Lambda Y \tag{41}$$

which is valid for any $X, Y \in \Re^{n\times k}$ and for any positive definite matrix $0 < \Lambda = \Lambda^T \in \Re^{n\times n}$, it follows that if $X = \tilde{x}_2$, and $Y = \delta$, then $\tilde{x}_2^T\delta \le \tilde{x}_2^T\Lambda_\delta^{-1}\tilde{x}_2 + \bar{\eta}_\delta$. Since $x_2^d = \dot{x}_2^d = 0$, and using the learning law (31) and the skew-symmetric (2), then (40) becomes

$$\dot{V}_2 \le -\tilde{x}_2^T Q_1 \tilde{x}_2 + \bar{\eta}_g + \bar{\eta}_\delta \qquad (42)$$

where $Q_1 = K_d - \left(\Lambda_g^{-1} + \Lambda_\sigma^{-1} + \Lambda_\delta^{-1}\right)$. Now, from (32), it is known that $Q > 0$, and (42) can then be represented as

$$\dot{V}_2 \le -\lambda_{\min}(Q) \|\tilde{x}_2\|^2 + \eta_g^T \Lambda_g \eta_g + \delta^T \Lambda_\delta \delta$$

V_2 is therefore an ISS-Lyapunov function. Using Theorem 1 from [23], the boundedness of η_g and $\bar{\eta}_\delta$ implies that the tracking error $\|\tilde{x}_2\|$ is stable. Integrating (42) from 0 to T yields

$$\int_0^T \tilde{x}_2^T Q \tilde{x}_2 dt \le V_{2,0} - V_{2,T} + (\bar{\eta}_g + \bar{\eta}_\delta) T \le V_{2,0} + (\bar{\eta}_g + \bar{\eta}_\delta) T$$

and, since $\|\tilde{x}_2\|_Q^2 = \|\tilde{x}_2\|_Q^2 + \bar{\eta}_\delta$, equation (33) is established. QED ■

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