Chapter 4
Stable Adaptive Compensation with Fuzzy Cerebellar Model Articulation Controller for Overhead Cranes

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Abstract This chapter proposes a novel control strategy for overhead cranes. The controller includes both position regulation and anti-swing control. Since the crane model is not exactly known, fuzzy cerebellar model articulation controller (CMAC) is used to compensate friction, and gravity, as well as the coupling between position and anti-swing control. Using a Lyapunov method and an input-to-state stability technique, the controller is proven to be robustly stable with bounded uncertainties. Real-time experiments are presented comparing this new stable control strategy with regular crane controllers.

4.1 Introduction

Although cranes are very important systems for handling heavy goods, automatic cranes are comparatively rare in industrial practice [5] [28], because of high investment costs. The need for faster cargo handling requires control of the crane motion so that its dynamic performance is optimized. Specifically, the control of overhead crane systems aims to achieve both position regulation and anti-swing control [11]. Several authors have looked at this including [4], time-optimal control was considered using boundary conditions, an idea which was further developed in [3] and [29]. Unfortunately, to increase robustness, some time optimization requirements, like zero angular velocity at the target point [23], have to be given up. Gain scheduling has been proposed as a practical method [12] to increase tracking accuracy, while observer-based feedback control was presented in [28].

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Many attempts, such as planar operation [12] and assuming the absence of friction [23], have been made to introduce simplified models for application of model-based control [28]. Thus, a self-tuning controller with a multilayer perceptron model for an overhead crane system was proposed [21], while in [10], 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 a proportional integral derivative (PID) control can remove this error, it lacks global asymptotic stability [17]. 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 [31] while in [18], 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 [14], 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 is one weakness in applying PD control to this application: due to the existence of friction and gravitational forces, the steady-state error is not guaranteed to be zero [16].

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 [2]. One particular feedforward approach is input shaping [30], which is an especially practical and effective method of reducing vibrations in flexible systems. In [22] the anti-swing motion-planning problem is solved using the kinematic model in [20]. Here, anti-swing control for a three-dimensional (3D) overhead crane is proposed, which addresses the suppression of load swing. Nonlinear anti-swing control based on the singular perturbation method is presented in [35]. Unfortunately, all of these anti-swing controllers are model-based. In this paper, a PID law is used for anti-swing control which, being model-free, will affect the position control.

Therefore, there are three uncertain factors influencing the PD control for the overhead crane: friction, gravity, and errors coming from the PID anti-swing controllers. A model-free compensator is needed to reduce steady-state error. Two popular models can be used: neural networks and fuzzy systems. While neural networks are black-box models, which use input/output data to train their weights, fuzzy systems are based on fuzzy rules, which are constructed from prior knowledge [9]. Sometimes, fuzzy systems are regarded as gray-box models.

CMAC proposed by Albus [1] is an auto-associative memory feedforward neural network, it is a simplified mode of cerebellar based on the neurophysiological theory. A very important property of CMAC is that it has better convergence speed than feedforward neural networks. Many practical applications have been presented in recent literature [7], [8].

Since the data in CMAC is quantized, linguistic information cannot be dealt with. FCMAC uses fuzzy sets (fuzzy labels) as input clusters instead of crisp sets [8].

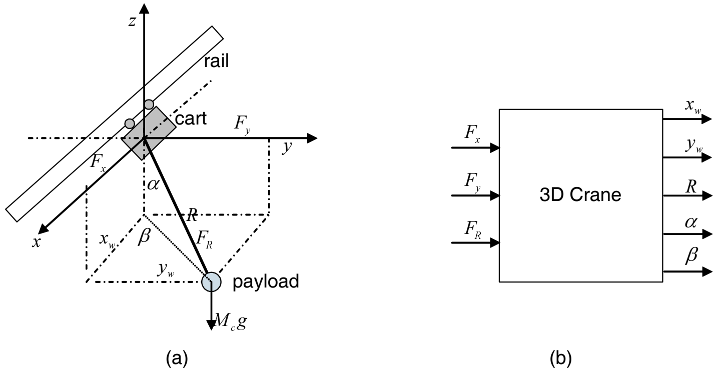

Fig. 4.1 Overhead crane

Compared with the normal CMAC, FCMAC can not only model linguistic variables based on fuzzy rules, but also is simple and highly intuitive [7]. Many ideas were realized on FCMAC extension and application. Bayesian Ying–Yang learning was introduced to determine the optimal FCMAC [24]. The Yager inference scheme was subsequently mapped onto FCMAC by [25]. In [26], a credit assignment idea was used to provide fast learning for FCMAC. Adaptation mechanisms were proposed for FCMAC learning in [34].

In this chapter, a FCMAC is used to estimate the above uncertainties. The required on-line 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 FCMAC compensator is shown to be stable. Finally, results from experimental tests carried out to validate the controller are presented.

4.2 Preliminaries

The overhead crane system described schematically in Figure 4.1(a) has the system structure shown in Figure 4.1(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 [32]:

$$M(x)\ddot{x} + C(x,\dot{x})\dot{x} + G(x) + F = \tau \quad (4.1)$$

where $x = [x_w, y_w, \alpha, \beta, R]^T$, $\tau = [F_x, F_y, 0, 0, F_R]^T$, F_x, F_y and F_R represent the control forces acting on the cart and rail and along the lift-line, (x_w, y_w, R) is position of the payload, $F = [\mu_x, \mu_y, 0, 0, \mu_R]^T \dot{x}$, 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.

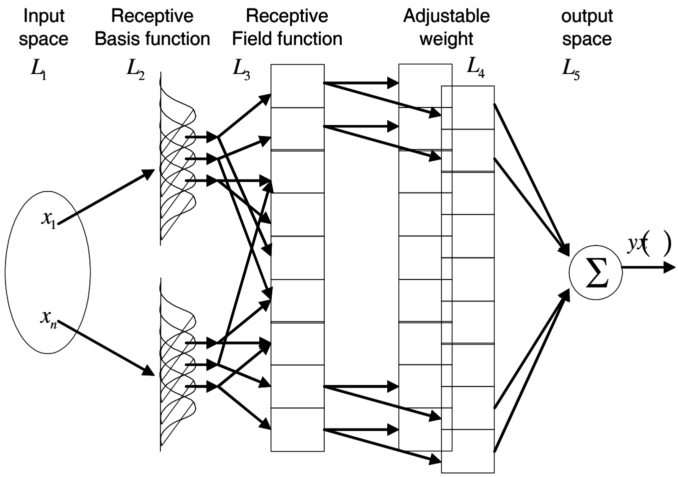

Fig. 4.2 The architecture of CMAC

In (4.1), there are some differences from other crane models in the literature. The length of the lift-line is not considered in [14], so the dimension of M is 4×4, while in [22], which also addresses anti-swing control and position control, the dimension of M is 3×3. In [19], 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 Coriolis matrix $C(x,\dot{x})$ is skew-symmetric, *i.e.,* it satisfies the following relationship [14]

$$x^T \left[\dot{M}(x) - 2C(x,\dot{x})\right] x = 0. \tag{4.2}$$

A general FCMAC (see Figure 4.2) has five layers: input layer (L_1), fuzzified layer (L_2), fuzzy association layer (L_3), fuzzy post-association layer (L_4), and output layer (L_5).

Each input variable x_i in the $n-$dimension input space L_1 is quantized into m discrete regions (or elements) according to a resolution definition. Several elements in L_1 can be accumulated as a block. CMAC requires that the block number p is bigger than 2. By shifting an element in each input variable, different pieces are obtained. Each piece performs a basis function, which can be formulated as rectangular, triangular, Gaussian, or any continuously bounded function. If an input falls in $q-$th receptive-field, this field is active. Its neighborhoods are also activated, so it produces similar outputs near $q-$th receptive-field. This FCMAC property is called local generalization. The total shifting times is defined as l.

A fuzzified layer L_2 is also called association memory space. Each function at the fuzzified layer L_2 corresponds to a linguistic variable which is expressed by a membership functions ϕ_j^i $i = 1 \cdots n$, $j = 1 \cdots l$. The dimension of this layer is l^n. L_2 can be regarded as a fuzzification of input variables.

Fuzzy association layer L_3 is also called receptive-field space. The areas formed by the shifting units are called receptive-fields. Each location corresponds to a fuzzy association. A fuzzified layer connects and accomplishes the matching of the precondition of fuzzy logic rule. Each node at this layer completes fuzzy implication operation to obtain firing strength which is defined as α_k which is defined as

$$\alpha_j = \prod_{i=1}^{n} \lambda_q \left(\phi_j^i (x_i) \right), \quad q = 1 \cdots l, j = 1 \cdots l$$

where q is association time, l is the association number (or total shifting times), λ is the selection vector of the association memory which is defined as

$$\lambda_q \left(\phi_j^i (x_i) \right) = \phi_j^i (x_i) = [0, 0 \cdots 1, 0 \cdots] \begin{bmatrix} \phi_1^i \\ \vdots \\ \phi_l^i \end{bmatrix}.$$

Fuzzy post association layer L_4 is also called weight memory space, which calculates the normalization of firing strength and prepares for fuzzy inference

$$\begin{aligned} \varphi_q &= \alpha_q / \sum_{j=1}^{l} \alpha_j \\ &= \left(\prod_{i=1}^{n} \lambda_k \left(\phi_q^i (x_i) \right) \right) / \left(\sum_{j=1}^{l} \prod_{i=1}^{n} \lambda_j \left(\phi_j^i (x_i) \right) \right). \end{aligned}$$

In the output layer L_5, Takagi fuzzy inference is used, that is, the consequence of each fuzzy rule is defined as a function of input variables

$$R^j : If\ x_1\ is\ A_j^1 \cdots and\ x_n\ is\ A_j^n\ Then\ \hat{y}\ is\ f(X) \tag{4.3}$$

where $X = [x_1, \cdots, x_n]^T$. The output of the FCMAC can be expressed as

$$\hat{y} = \sum_{j=1}^{l} w_j \varphi_{kj} \tag{4.4}$$

where w_j denotes the connecting weight of $j-$th receptive-field. In matrix form it is

$$\hat{y} = W \varphi (X) \tag{4.5}$$

where $W = [w_1, \cdots w_l]$, $\varphi (x) = [\varphi_1, \cdots \varphi_l]^T$.

4.3 Control of an 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 (4.1) 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

$$\begin{array}{c}|\ddot{x}_w| \ll g, \quad |\ddot{y}_w| \ll g, \quad \left|\ddot{R}\right| \ll g,\\ \left|\dot{R}\right| \ll R, \quad |\dot{\alpha}| \ll 1, \quad \left|\dot{\beta}\right| \ll 1,\\ s_1 = \sin\alpha \approx \alpha, \quad c_1 = \cos\alpha \approx 1.\end{array}$$

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

$$\ddot{\alpha} + g\alpha = -\frac{F_x}{M_r}, \quad \ddot{\beta} + g\beta = -\frac{F_y}{M_m}. \tag{4.6}$$

Only F_x and F_y participate the anti-swing control, F_R does not affect the swing angles α, β. The control forces F_x and F_y are assumed to have the following form

$$\begin{array}{l}F_x = A_1(x_w, \dot{x}_w) + A_2(\alpha, \dot{\alpha}),\\ F_y = B_1(y_w, \dot{y}_w) + B_2\left(\beta, \dot{\beta}\right)\end{array} \tag{4.7}$$

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 (4.7) into (4.6), produces the anti-swing control model

$$\begin{array}{l}\ddot{\alpha} + g\alpha + \frac{A_1}{M_r} = -\frac{A_2}{M_r},\\ \ddot{\beta} + g\beta + \frac{B_1}{M_m} = -\frac{B_2}{M_m}.\end{array} \tag{4.8}$$

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 (4.8) 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

$$\begin{array}{l}A_2(\alpha, \dot{\alpha}) = k_{pa2}\alpha + k_{da2}\dot{\alpha} + k_{ia2}\int_0^t \alpha(\tau)\, d\tau,\\ B_2\left(\beta, \dot{\beta}\right) = k_{pb2}\beta + k_{db2}\dot{\beta} + k_{ib2}\int_0^t \beta(\tau)\, d\tau\end{array} \tag{4.9}$$

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

Substituting (4.7) into (4.1), produces the position control model

$$M(x)\ddot{x} + C(x,\dot{x})\dot{x} + G(x) + T\dot{x} + D = \tau \tag{4.10}$$

where $D = [A_2, B_2, 0, 0, 0]^T$, $\tau = [A_1, B_1, 0, 0, F_R]^T$. Using this model, a position controller will be designed in the next section.

4.4 Position Regulation with FCMAC Compensation

A PD type controller is used for position regulation, which has the following form

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

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 $\dot{x}^d = 0$.

A filtered regulation error is defined as

$$r = (\dot{x} - \dot{x}^d) + \Lambda(x - x^d) = \tilde{x}_2 + \Lambda\tilde{x}_1$$

where $\tilde{x}_1 = (x - x^d)$,$\tilde{x}_2 = (\dot{x} - \dot{x}^d)$, $\cdot\tilde{x}_1 = \tilde{x}_2$,$\Lambda = \Lambda^T > 0$. Using (4.10) and $\dot{x}^d = \ddot{x}^d = 0$,

$$\begin{aligned} M\dot{r} &= M\dot{\tilde{x}}_2 + M\Lambda\dot{\widetilde{x}}_1 \\ &= M\ddot{x} - M\ddot{x}^d + M\Lambda\dot{\widetilde{x}}_1 \\ &= \tau - C\dot{x} - G - T\dot{x} - D + M\Lambda\dot{\widetilde{x}}_1 + C\Lambda\widetilde{x}_1 - C\Lambda\widetilde{x}_1 \\ &= \tau - Cr + f \end{aligned} \tag{4.11}$$

where

$$f(s) = M\Lambda\dot{x} + C\Lambda\widetilde{x}_1 - G - T\dot{x} - D$$

where $s = \left[x^T, \dot{x}^T, \tilde{x}_1^T\right]^T$.

Because $f\left(x, \dot{x}, \tilde{x}_1\right) = [f_x, f_y, f_z]^T$ is unknown, a FCMAC (4.5) is used to approximate it. The fuzzy rule (4.3) has the following form

$$\begin{aligned}
&\mathrm{R}^i\text{: IF } \left(x_w \text{ is } A^1_{1i}\right) \text{ and } \left(\alpha \text{ is } A^1_{2i}\right) \text{ and } \left(\dot{x}_w \text{ is } A^1_{3i}\right)\\
&\text{and } \left(\dot{\alpha} \text{ is } A^1_{4i}\right) \text{ and } \left(\tilde{x}_w \text{ is } A^1_{5i}\right) \text{THEN } \widehat{f_x} \text{ is } B_{1i}\\
&\text{IF } \left(y_w \text{ is } A^2_{1i}\right) \text{ and } \left(\beta \text{ is } A^2_{2i}\right) \text{ and } \left(\dot{y}_w \text{ is } A^2_{3i}\right)\\
&\text{and } \left(\dot{\beta} \text{ is } A^2_{4i}\right) \text{ and } \left(\widetilde{y}_w \text{ is } A^2_{5i}\right) \text{THEN } \widehat{f_y} \text{ is } B_{2i}\\
&\text{IF } \left(R \text{ is } A^3_{1i}\right) \text{ and } \left(\dot{R} \text{ is } A^3_{2i}\right)\\
&\text{and } \left(\widetilde{R} \text{ is } A^3_{3i}\right) \text{THEN } \widehat{f_z} \text{ is } B_{3i}.
\end{aligned} \tag{4.12}$$

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 paper, some on-line learning algorithms are introduced for the membership functions A_{ji} and B_{ji} such that the PD controller with the fuzzy compensator is stable. (4.5) can be expressed as

$$\widehat{f} = \hat{W}_t \Phi(s) \tag{4.13}$$

where the parameter matrix $\hat{W} = diag\left[\hat{W}_1, \hat{W}_2, \hat{W}_3\right]$, and the data vector $\Phi(x) = [\Phi_1, \Phi_2, \Phi_3]^T$, $\hat{W}_p = \left[w_{p1} \cdots w_{pl}\right]$, $\Phi_p = \left[\phi^p_1 \cdots \phi^p_l\right]^T$.

The position controller have a PD form with a fuzzy compensator

$$\begin{aligned}
\tau &= [A_1(x_w, \dot{x}_w), B_1(y_w, \dot{y}_w), 0, 0, F_R]^T = -Kr - \widehat{f}\\
&= -K\Lambda\left(x - x^d\right) - K\left(\dot{x} - \dot{x}^d\right) - \hat{W}_t \Phi(s)
\end{aligned} \tag{4.14}$$

where $x = [x_w, y_w, \alpha, \beta, R]^T$, $x^d = \left[x^d_w, y^d_w, 0, 0, R^d\right]^T$, and x^d_w, y^d_w and R^d are the desired positions, $K = K^T_{p1} > 0$.

According to the Stone-Weierstrass theorem [13], a general nonlinear smooth function can be written as

$$f(s) = M\Lambda\dot{x} + C\Lambda\widetilde{x}_1 - G - T\dot{x} - D = W^*\Phi(s) + \mu(t) \tag{4.15}$$

where W^* is the optimal weight matrix, and $\mu(t)$ is the modeling error. In this chapter the fuzzy compensator (4.13) is used to approximate the unknown nonlinearity (the gravity, friction, and coupling of anti-swing control).

The coupling between anti-swing control and position control can be explained as follows. For the anti-swing control (4.8), the position control A_1 and B_1 are disturbances, which can be decreased by the integral action in PID control. Although the anti-swing model (4.8) is an approximator, the anti-swing control (4.9) does not in fact use this, as it is model-free. Hence while the anti-swing control law (4.9) cannot suppress the swing completely, it can minimize any consequent vibration.

For the position control (4.10), 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. For example, in order to decrease the swing, we should increase A_2 and B_2, this means increase the disturbances of the crane, so τ should be increased.

4.5 FCMAC Training and Stability Analysis

(4.15) can be rewritten as

$$M\Lambda\dot{\widehat{x}} + C\Lambda\widetilde{x}_1 - G - T\dot{x} - D = W^0\Phi(s) + \eta_g \tag{4.16}$$

where $s_1 = \left[x^T, x_2^T, \tilde{x}_1^T\right]^T$, W^0 is a fixed bounded matrix, and η_g is the approximation error whose magnitude also depends on the value of W^0. Now, η_g is assumed to be quadratic bounded such that

$$\eta_g^T \Lambda_g \eta_g \leq \overline{\eta}_g \tag{4.17}$$

where $\overline{\eta}_g$ is a positive constant. In this paper, we use Gaussian functions in the receptive-field ϕ_i^j, which is expressed as

$$\phi_i^j = \exp\left[-\left(\frac{s_j - c_{i,j}}{\sigma_{i,j}}\right)^2\right] \tag{4.18}$$

where ϕ_i^j presents the $i-$th rule of the $j-$th input x_j, c_j^i is the mean, σ_j^i is the variance, $\Phi(x) = [\Phi_1, \Phi_2, \Phi_3]^T$, $\Phi_p = \left[\phi_1^p \cdots \phi_l^p\right]^T$.

Firstly, we assume the Gaussian functions in the receptive-field are given by prior knowledge, i.e., we only train $\hat{W}_t$. Now defining $\tilde{W}_t = W^0 - \hat{W}_t$, for the filtered regulation error $r = (\dot{x} - \dot{x}^d) + \Lambda(x - x^d)$, the following theorem holds.

Theorem 4.1. *If the updating laws for the membership functions in (4.13) are*

$$\frac{d}{dt}\hat{W}_t = K_w\Phi(s)r^T \tag{4.19}$$

where K_w is a positive definite matrix, and K_d satisfies

$$K > \frac{1}{2}\Lambda_g^{-1}, \tag{4.20}$$

then the PD control law with FCMAC compensation in (4.14) can make the tracking error r stable. In fact, the average tracking error r_1 converges to

$$\limsup_{T\to\infty} \frac{1}{T}\int_0^T \|r\|_{Q_1}^2 \, dt \leq \overline{\eta}_g \tag{4.21}$$

where $Q_1 = 2K - \Lambda_g^{-1}$.

Proof. The following Lyapunov function is proposed

$$V = r^T M r + tr\left(\widetilde{W}_t^T K_w^{-1} \widetilde{W}_t\right) \tag{4.22}$$

where K_w is a positive definite matrix. Using (4.11) and (4.14), the closed-loop system is given by

$$M\dot{r} = \tau - Cr + f = -Kr - \widetilde{W}_t \Phi(s_1) - Cr + \eta_g. \tag{4.23}$$

Now the derivative of (4.22) is

$$\dot{V} = -2r^T Kr - 2r^T Cr + 2r^T \eta_g + r^T \dot{M} r - 2r^T \widetilde{W}_t \Phi(s) + 2tr\left(\widetilde{W}_t^T K_w^{-1} \dot{\widetilde{W}}_t\right). \tag{4.24}$$

In view of the matrix inequality,

$$X^T Y + \left(X^T Y\right)^T \leq X^T \Lambda^{-1} X + Y^T \Lambda Y \tag{4.25}$$

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 $X = r$, and $Y = \eta_g$, from (4.17)

$$2r^T \eta_g \leq r^T \Lambda_g^{-1} r + \eta_g^T \Lambda_g \eta_g \leq r^T \Lambda_g^{-1} r + \overline{\eta}_g. \tag{4.26}$$

Using (4.2) and (4.24), this then can be written as

$$\dot{V} \leq -r^T \left(2K - \Lambda_g^{-1}\right) r + 2tr\left[\left(K_w^{-1} \frac{d}{dt} \tilde{W}_t - \Phi(s) r^T\right) \tilde{W}\right] + \overline{\eta}_g. \tag{4.27}$$

Since $x_2^d = \dot{x}_2^d = 0$, and using the learning law (4.19), then (4.27) becomes

$$\dot{V} \leq -r^T Q r + \overline{\eta}_g \tag{4.28}$$

where $Q_1 = 2K - \Lambda_g^{-1}$. Now, from (4.20), it is known that $Q_1 > 0$, and (4.28) can then be represented as

$$\dot{V} \leq -\lambda_{\min}(Q_1) \|r\|^2 + \eta_g^T \Lambda_g \eta_g.$$

V is therefore an input-to-state stability (ISS)-Lyapunov function. Using Theorem 1 from [27], the boundedness of η_g and $\overline{\eta}_\delta$ implies that the tracking error $\|r\|$ is stable, so x and $\widehat{x}$ are bounded.

Integrating (4.28) from 0 to T yields

$$\int_0^T r^T Q_1 r dt \leq V_0 - V_T + \overline{\eta}_g T \leq V_0 + \overline{\eta}_g T.$$

(4.21) is established. □

Secondly, neither the receptive-field function nor $\hat{W}_t$ are known. pth output of the FCMAC compensator can be expressed as $\hat{W}_p \Phi_p(s),\ p = 1,2,3$. Using the Taylor series,

$$\begin{aligned}
&\hat{W}_p \Phi_p(s) - f(s) + \mu_p \\
&= \sum_{i=1}^{l} \left(w_{pi}^{*} - \hat{w}_{pi} \right) z_i^p / b_p + \sum_{i=1}^{l} \sum_{j=1}^{n_p} \frac{\partial}{\partial c_{ji}^p} \left(\frac{a_p}{b_p} \right) \left(c_{ji}^{p*} - c_{ji}^p \right) \\
&+ \sum_{i=1}^{l} \sum_{j=1}^{n_p} \frac{\partial}{\partial \sigma_{ji}^p} \left(\frac{a_p}{b_p} \right) \left(\sigma_{ji}^{p*} - \sigma_{ji}^p \right) - R_{1p}
\end{aligned} \tag{4.29}$$

where R_{1p} is second order approximation error of the Taylor series, and

$$z_i^p = \prod_{i=1}^{n} \lambda_k \left(\phi_j^i \right), \quad a_p = \sum_{k=1}^{l} w_p z_p, \quad b_p = \sum_{k=1}^{l} z_p.$$

Using the chain rule, we get

$$\begin{aligned}
&\frac{\partial}{\partial c_{ji}^p} \left(\frac{a_p}{b_p} \right) = \frac{\partial}{\partial z_i^p} \left(\frac{a_p}{b_p} \right) \frac{\partial z_i^p}{\partial c_{ji}^p} \\
&= \left(\frac{1}{b_p} \frac{\partial a_p}{\partial z_i^p} + \frac{\partial}{\partial z_i^p} \left(\frac{1}{b_p} \right) a_p \right) \left(2 z_i^p \frac{s_j - c_{ji}^p}{\left[\sigma_{ji}^p \right]^2} \right) \\
&= \left(\frac{w_{pi}}{b_p} - \frac{a_p}{[b^p]^2} \right) \left(2 z_i^p \frac{s_j - c_{ji}^p}{\left[\sigma_{ji}^p \right]^2} \right) \\
&= 2 z_i^p \frac{w_{pi} - \widehat{y}_p}{b_p} \frac{s_j - c_{ji}^p}{\left[\sigma_{ji}^p \right]^2}
\end{aligned}$$

and

$$\begin{aligned}
&\frac{\partial}{\partial \sigma_{ji}^p} \left(\frac{a_p}{b_p} \right) = \frac{\partial}{\partial z_i^p} \left(\frac{a_p}{b_p} \right) \frac{\partial z_i^p}{\partial \sigma_{ji}^p} \\
&= 2 z_i^p \frac{w_{pi} - \widehat{y}_p}{b_p} \frac{\left(s_j - c_{ji}^p \right)^2}{\left[\sigma_{ji}^p \right]^3}.
\end{aligned}$$

There are three subsystems, for each one

$$\hat{W}_p \Phi_p(s) - f(s)_p = Z_p \widetilde{W}_p + \Psi_p \tilde{C}_p I + \Psi_p \tilde{B}_p I - \zeta_p \tag{4.30}$$

where $\zeta_p = \mu_p + R_{1p}$

$$
\begin{aligned}
&Z_p = \left[z_1^p/b \cdots z_l^p/b\right]^T, \quad \widetilde{W}_p = \hat{W}_p - W_p^*, \quad W_p = \left[\hat{w}_{p1} \cdots \hat{w}_{pl}\right], \\
&\Psi_p = \left[2z_1^p \frac{\hat{w}_{p1} - \widehat{y}_p}{b_p}, \cdots, 2z_l^p \frac{\hat{w}_{pl} - \widehat{y}_p}{b_p}\right], \quad I = [1, \cdots 1]^T, \\
&\tilde{C}_p = \begin{bmatrix} \frac{s_1 - c_{11}^p}{\left[\sigma_{11}^p\right]^2}\left(c_{11}^p - c_{11}^{p*}\right) & & \frac{s_n - c_{n1}}{\left[\sigma_{n1}^p\right]^2}\left(c_{n1}^p - c_{n1}^{p*}\right) \\ & \ddots & \\ \frac{s_1 - c_{1l}^p}{\left[\sigma_{1l}^p\right]^2}\left(c_{1l}^p - c_{1l}^{p*}\right) & & \frac{s_n - c_{nl}}{\sigma_{nl}^{p2}}\left(c_{nl}^p - c_{nl}^{p*}\right) \end{bmatrix} \\
&\tilde{B}_p = \begin{bmatrix} \frac{\left(s_1 - c_{11}^{p2}\right)^2}{\sigma_{11}^{p3}}\left(\sigma_{11}^p - \sigma_{11}^{p*}\right) & & \frac{\left(s_n - c_{n1}\right)^2}{\sigma_{n1}^{p3}}\left(\sigma_{n1}^p - \sigma_{n1}^{p*}\right) \\ & \ddots & \\ \frac{\left(s_1 - c_{1l}^p\right)^2}{\sigma_{1l}^{3p}}\left(\sigma_{1l}^p - \sigma_{1l}^{p*}\right) & & \frac{\left(s_n - c_{nl}\right)^2}{\sigma_{nl}^{3p}}\left(\sigma_{nl}^p - \sigma_{nl}^{p*}\right) \end{bmatrix}.
\end{aligned}
$$

In vector form

$$
\hat{W}_t \Phi(s_1) - f_1(s_1) = Z\widetilde{W} + \Psi\tilde{C}I + \Psi\tilde{B}I - \zeta. \tag{4.31}
$$

Now, ζ is assumed to be quadratic bounded such that

$$
\zeta^T \Lambda_\zeta \zeta \leq \overline{\zeta}.
$$

For the filtered regulation error r, the following theorem holds.

Theorem 4.2. *If the updating laws for the membership functions in (4.13) are*

$$
\begin{aligned}
&\frac{d}{dt}\hat{W}_p = -K_w Z_p r^T, \\
&\frac{d}{dt}c_{ji}^p = -2k_c z_i^p \frac{\hat{w}_{pi} - \widehat{y}_p}{b_p} \frac{s_j - c_{ji}^p}{\left[\sigma_{ji}^p\right]^2} r^T, \\
&\frac{d}{dt}\sigma_{ji}^p = -2k_b z_i^p \frac{\hat{w}_{pi} - \widehat{y}_p}{b_p} \frac{\left(s_j - c_{ji}^p\right)^2}{\left[\sigma_{ji}^p\right]^3} r^T
\end{aligned} \tag{4.32}
$$

where K_w is definite matrix, k_c and k_b are positive constant, and K satisfies

$$
K > \frac{1}{2}\left(\Lambda_\zeta^{-1} + \Lambda_g^{-1}\right),
$$

then the PD control law with fuzzy compensation in (4.14) can make the tracking error stable. The average tracking error r converges to

$$
\limsup_{T \to \infty} \frac{1}{T} \int_0^T \|r\|_{Q_2}^2 \, dt \leq \overline{\eta}_g + \overline{\zeta}
$$

where $Q_2 = 2K - \left(\Lambda_\zeta^{-1} + \Lambda_g^{-1}\right)$.

Proof. Let use define $\widetilde{c}_{ji} = \hat{c}_{ji} - c_{ji}^*$, $\widetilde{b}_{ji}(k) = \tilde{\sigma}_{ji}(k) - \sigma^*(k)$, the element of $\widetilde{C}$ is expressed as $\widetilde{c}_{ji} = \left[\widetilde{C}\right]$. We selected a positive defined scalar V_3 as

$$V_1 = r^T M r_1 + tr\left(\tilde{W}_t^T K_w^{-1} \tilde{W}_t\right) + tr\left(\widetilde{C}_t^T K_c^{-1} \widetilde{C}_t\right) + tr\left(\widetilde{B}_t^T K_b^{-1} \widetilde{B}_t\right) \tag{4.33}$$

where K_p, K_w K_c and K_b are any positive definite matrices. Using (4.30),

$$M\dot{r} = \tau - Cr + f = -Kr - \widetilde{W}_t \Phi(s) - Cr + \eta_g \tag{4.34}$$

$$M\dot{x}_2 = -Cx_2 - K_p \bar{x}_1 - K_d \tilde{x}_2 + \hat{W}_t \Phi(s) - (G(x) + F(x) + D).$$

So

$$\begin{array}{l} r^T M\dot{r} = -r^T K r - r^T \widetilde{W}_t \Phi(s) - r^T C r \\ +r^T \eta_g - r^T \left[Z\widetilde{W} + \Psi \tilde{C} I + \Psi \tilde{B} I - \zeta\right]. \end{array}$$

Similar as to Theorem 4.1

$$2r^T \zeta \leq r^T \Lambda_\zeta^{-1} r + \zeta^T \Lambda_\zeta \zeta \leq r^T \Lambda_g^{-1} r + \overline{\zeta},$$

$$\begin{array}{l} \dot{V}_1 = -r^T \left(2K - \Lambda_g^{-1} - \Lambda_\zeta^{-1}\right) r + \overline{\eta}_g + \overline{\zeta} + 2tr\left[\left(K_w^{-1} \frac{d}{dt} \tilde{W}_t - Z r^T\right) \tilde{W}\right] \\ +2tr\left[\left(K_c^{-1} \frac{d}{dt} \tilde{C}_t - \Psi r^T\right) \tilde{C}_t\right] + 2tr\left[\left(K_b^{-1} \frac{d}{dt} \tilde{B}_t - \Psi r^T\right) \tilde{B}_t\right], \end{array} \tag{4.35}$$

using the learning law (4.32), then (4.35) becomes

$$\dot{V}_1 \leq -r^T Q_2 r + \overline{\eta}_g + \overline{\zeta}.$$

The rest of the proof is the same as the proof for Theorem 4.1. □

4.6 Experimental Comparisons

The proposed anti-swing control for overhead crane systems has been implemented on a InTeCo [15] overhead crane test-bed, see Figure 4.3. The rail is 150cm long, and the physical parameters for the system are as follows: the mass of rail is $M_r = 6.5kg$, the mass of cart is $M_c = 0.8kg$, the mass of payload is $M_m = 1.3kg$, see Figure 4.3. Here interfacing is based on a microprocessor, comprising a multifunction analog and digital I/O board dedicated to the real-time data acquisition and control in the Windows® XP environment, mounted in a PC Pentium®-III 500MHz host. Because the 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®.

There are two inputs in the anti-swing model (4.14), 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 (4.8), A_1 is regarded as a disturbance. The chosen parameters of the PID (4.9) control law were

$$\begin{array}{lll} k_{pa2} = 2.5, & k_{da2} = 18, & k_{ia2} = 0.01, \\ k_{pb2} = 15, & k_{db2} = 10, & k_{ib2} = 0.6. \end{array}$$

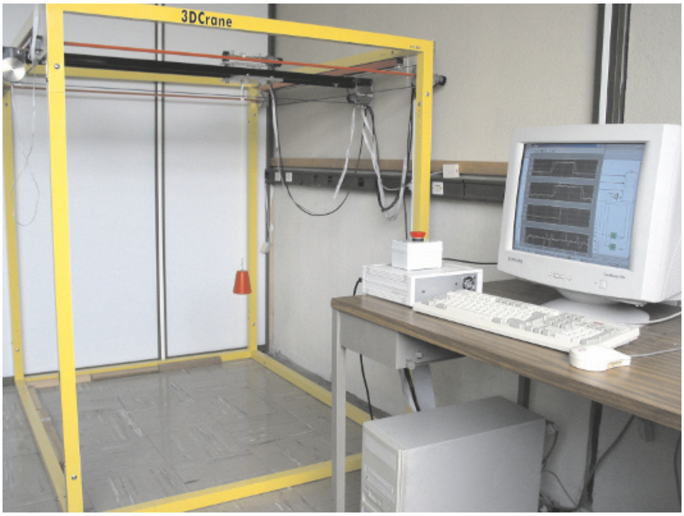

Fig. 4.3 Real-time control for an overhead crane

The position control law in (4.14) is discussed next. In this case there are two types of input to the position model (4.10), $D = [A_2, B_2, 0, 0, 0]^T$, $\tau = [A_1, B_1, 0, 0, F_R]^T$. When the position control A_1 is designed by (4.14), the anti-swing control A_2 in (4.10) is regarded as a disturbance which will be compensated for the fuzzy system (4.13). Theorem 4.2 implies that to assure stability, K_d should be large enough such that $K_d > \Lambda_g^{-1}$. 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 in the receptive-field were used to compensate for the friction, gravity and the coupling from anti-swing control. The membership function for A_{ji} was chosen to be the Gaussian function

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

where m_{ji} and σ_{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 (4.32) with $K_w = 10$. The desired gantry position was selected as a circle with $x_w^d = 0.5\sin(0.2t)$, $y_w^d = 0.5\cos(0.2t)$. The resulting gantry positions and angles are shown in Figure 4.4 and Figure 4.5. The control inputs are shown in Figure 4.6.

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 in Figure 4.7 and Figure 4.8.

It can be seen that the swing angles α and β are decreased a lot with the anti-swing controller. From Figure 4.6 and Figure 4.8 we see that the the improvement is

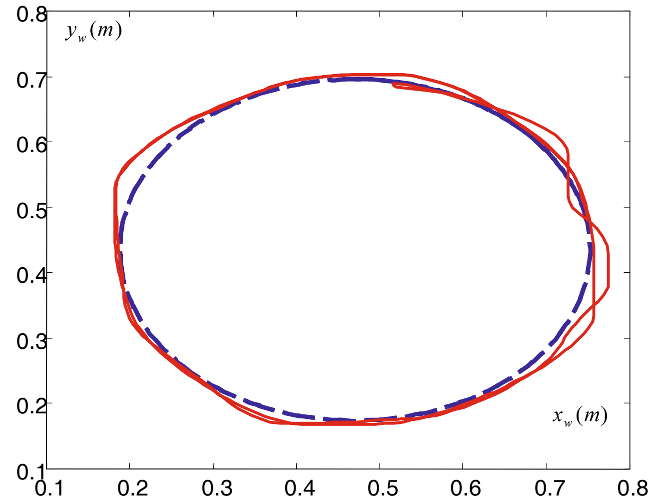

Fig. 4.4 Positions control with FCMAC compensation

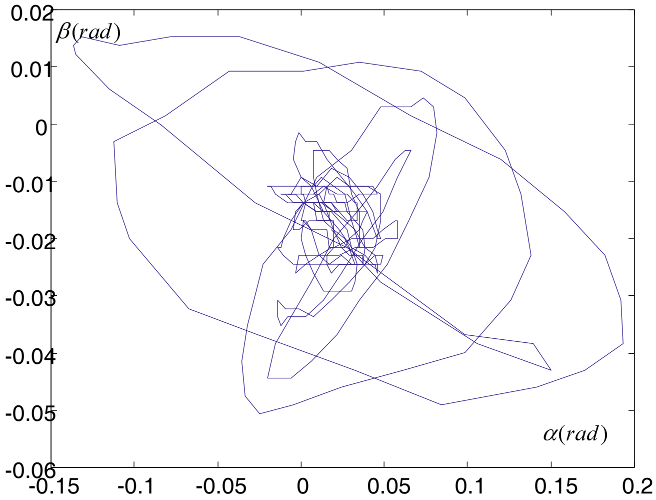

Fig. 4.5 Angles of PD control with FCMAC compensation

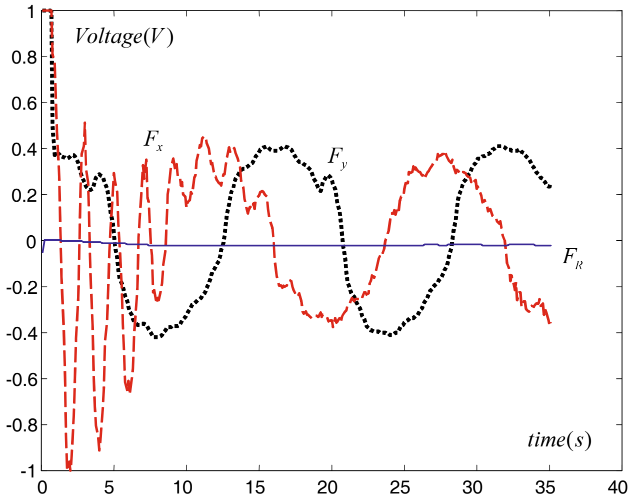

Fig. 4.6 Control inputs

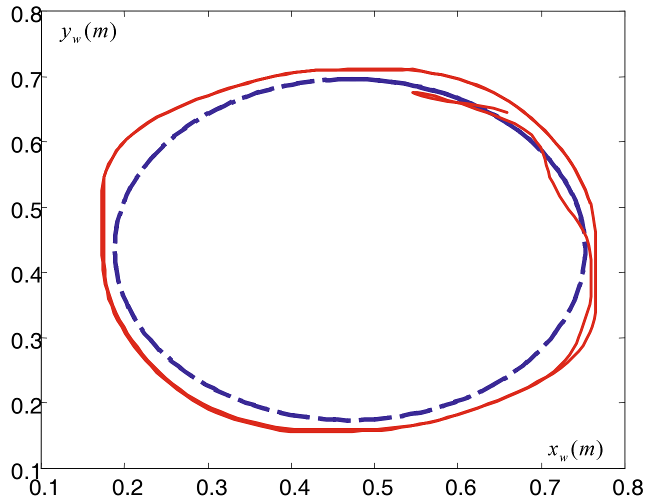

Fig. 4.7 PID position control with anti-swing control

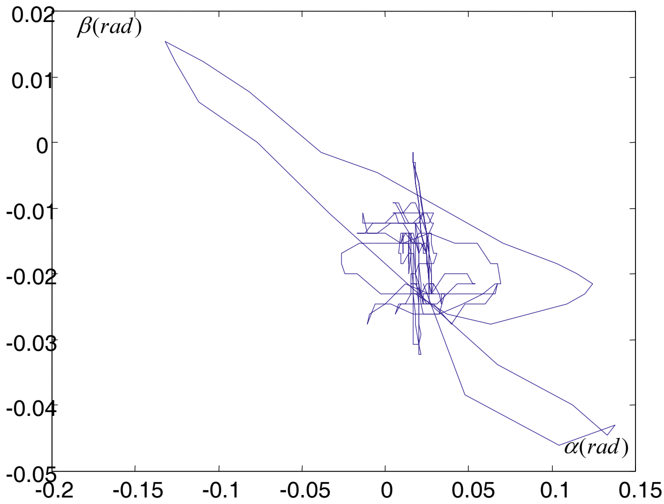

Fig. 4.8 Angles of PID position control with anti-swing control

not so good in α direction, because in this direction the inertia comes from the rail, its mass M_r is bigger than the cart M_c (β direction).

Clearly, PD control with FCMAC 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. 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 nonlinear process depends on the membership functions selected. The number of fuzzy rules in receptive-field constitutes a structural problem. It is well known that increasing the dimension of the fuzzy rules can cause the ”overlap” problem and add to the computational burden [33]. The best dimension of CMAC to use is still an open problem. 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 produces a slow learning process.

4.7 Conclusions

In this chapter, a FCMAC compensator is used to compensate for gravity and friction. Using Lyapunov-like analysis, the stability of the closed-loop system with the FCMAC 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 FCMAC compensations is effective for the overhead crane system.

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