Adaptive Fuzzy Controller of the Overhead Cranes With Nonlinear Disturbance

Cheng-Yuan Chang

Abstract—**Overhead cranes are common industrial structures that are used in many factories and harbors. They are usually operated manually or by some conventional control methods, such as the optimal and PLC-based methods. The theme of this paper is to provide an effective all-purpose adaptive fuzzy controller for the crane. This proposed method does not need the complex dynamic model of the crane system, but it uses trolley position and swing angle information instead to design the fuzzy controller. An adaptive algorithm is provided to tune the free parameters in the crane control system. The ways to speed the transportation and reduce the computational efforts are also given. Therefore, the designing procedure of the proposed controller will be very easy. External disturbance, such as the wind and the hit, which always deteriorates the control performance, is also discussed in this paper to verify the robustness of the proposed adaptive fuzzy algorithm. At last, several experimental results with different wire length and payload weight compare the feasibility and effectiveness of the proposed scheme with conventional methods.**

Index Terms—**Adaptive, crane, disturbance, fuzzy, position, swing.**

I. Introduction

OVERHEAD cranes are widely used in many factories and harbors for moving heavy cargos. Most cranes are operated manually. One operator moves the trolley slowly to take care of the loads, and another operator monitors the motion of the crane system on the ground. However, it is not efficient. The trolley travel always accompanies the load swing. When the trolley accelerates, the resulting backward swing can be expected, and the deceleration of the crane leads to the forward swing. These phenomena can be explained by the inertia theorem. To improve the efficiency of cargo handling with cranes, it is necessary to control the crane so that the swing angle of heavy loads, the position error of trolley, and the control power are all minimized.

Several papers have investigated the control of the overhead crane system. Generally speaking, the dynamic equations of a crane are nonlinear and time-varying differential equations. Corriga *et al.* applied an implicit gain-scheduling method to control the crane [1]. Auernig and Troger used minimal time control to minimize the load swing [19]. Agostini *et al.* applied the generating swing-suppressed maneuvers with rate saturation method to control the crane [12]. Moustafa and Ebied used a nonlinear modeling and anti-swing control method for the overhead cranes [21]. Based on the linearized theory and optimal control approaches, many researches designed their control according to the linearized crane model [4], [6], [10]. However, the linearized method cannot provide the sufficient accuracy of information about position error and load swing. Besides, the uncertain nonlinear factors such as the wind, the hit, and the friction of track will also reduce the performance of linearized crane control systems. Several studies applied nonlinear theory to control the crane [2], [3], [9]. Those approaches designed the control systems based on the mathematic model of the crane, but it is not easy for an engineer to design an industrial crane controller because the dynamics of the practical crane system is hard to know. Moreover, Matsuo *et al.* used the $\mathrm{PID}+\mathrm{Q}$-based controller to anti-sway the crane [22]. Takagi and Mishimura developed a centralized control system with coupling between the up-and-down and rotation directions to restrain the swing of a jib-type crane [23]. The input shaping method was also addressed [11]. The algorithm worked by taking a desired command and convolving it with a series of impulses. The vibration induced by the first impulse is desired to be canceled by the second impulse. However, these studies focused on control of the suppression of load swing but did not solve the problem of position error during crane motion. Besides, the time period between the impulses of the input shaping method was also hard to obtain.

For many years, the fuzzy-based method has been considered as a concise solution to nonlinear systems. It is well known that fuzzy set theory is arisen from the desire of linguistic description for complex system, and it can be utilized to formulate and translate the human experience to proper control strategies [7]. Some fuzzy-based methods were also proposed to control the crane [8], [17], [20], [24]. Unfortunately, such fuzzy controllers cannot provide the desired performance for the crane system, due to the uncertainty and large disturbances of the fuzzy system, reducing the working efficiency.

In this paper, one examines the trolley position and load swing control problem of the overhead crane by the adaptive fuzzy control law. Compared with the conventional control methods, the proposed adaptive fuzzy control method can deal easily with the external disturbance such as wind and hit in crane control. Besides, the proposed control law does not need any complex plant information of crane to design the controller. The all-purpose adaptive fuzzy controller can tune the free parameters adaptively to control the position error and swing angle of load very well. So, the computational complexity is hence reduced, and the crane control algorithm can be easily realized. Experimental results under the situations of external disturbance

Manuscript received May 30, 2006; revised August 23, 2006; resubmitted December 6, 2006; revised February 23, 2007. This work was supported by the National Science Council of the Republic of China under Grant NSC-93-2622-E-231-030-CC3. Paper no. TII-06-12-0155.R1.

The author is with the Department of Electronic Engineering, Ching Yun University, Jhongli 320, Taiwan, R.O.C. (e-mail: cychang@cyu.edu.tw).

Color versions of one or more of the figures in this paper are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/TII.2007.898433

and variations of wire length and payload weight are also given to illustrate the robustness of the proposed adaptive fuzzy controller.

This paper is organized as follows. The modeling of the crane system and some conventional control methods are addressed in Section II. In Section III, the proposed adaptive fuzzy law is illustrated. The ways to design an effective fuzzy controller, including the rules, inference method, fuzzified and defuzzifed methods, and adaptive algorithm, are also depicted. Simulations and experimental results demonstrate the improvements of the proposed method in Sections IV and V. This paper concludes with a summary in Section VI.

II. System Modeling and Conventional Control Methods

Basically, an overhead crane is made up of a trolley moving along a horizontal axis with a load hung from a flexible wire, as shown in Fig. 1, where m_c is the trolley mass, l is the wire length, m_L is the payload mass, x_1 is the trolley position $r(t)$, x_3 is the swing angle $\theta(t)$, and u is the control power applied to the trolley. After assigning $\dot{x}_1 = x_2 = \dot{r}$, and $\dot{x}_3 = x_4 = \dot{\theta}$, we have the state vector $x = [x_1, x_2, x_3, x_4]^t = [r, \dot{r}, \theta, \dot{\theta}]^t$. By Lagrange equations, we have

$$\begin{aligned}&(m_L+m_c)\ddot{x}_1 + m_L l\left(\ddot{x}_3\cos x_3 - \dot{x}_3^2\sin x_3\right) +\\ &\quad m_L\sin x_3\ddot{l} + 2m_L\cos x_3\dot{l}\dot{x}_3 + w_1(x,t) = u \qquad (1)\\ &m_L l\ddot{x}_1\cos x_3 + m_L l^2\ddot{x}_3 + 2m_L l\dot{l}\dot{x}_3 +\\ &\quad w_2(x,t) = -m_L g l\sin x_3 \qquad (2)\end{aligned}$$

where g is the gravitational acceleration, and $w_1(x,t)$ and $w_2(x,t)$ represent the external disturbance functions to the crane model. Some assumptions, including the dynamics and nonlinearity of driving motor, are neglected, and the mass and elasticity of the wire are ignored. Thus, the plant of crane system can be simplified [10]. Moreover, one lets $\ddot{x}_1 = \dot{x}_2$ and $\ddot{x}_3 = \dot{x}_4$, and then, the model can be linearized by setting $\dot{l} = 0$, $\cos x_3 \cong 1$, $\sin x_3 \cong x_3$, $x_3^2 \cong 0$. Thus, the plant model of the crane will be

$$\dot{x} = Ax + Bu + d \qquad (3)$$

where

$$A = \begin{bmatrix} 0 & 1 & 0 & 0\\ 0 & 0 & \frac{m_L}{m_c}g & 0\\ 0 & 0 & 0 & 1\\ 0 & 0 & -\frac{(m_L+m_c)g}{m_c l} & 0\end{bmatrix},\ B = \begin{bmatrix} 0\\ \frac{1}{m_c}\\ 0\\ -\frac{1}{m_c l}\end{bmatrix}$$

$$d = \begin{bmatrix} 0\\ \frac{-w_1 l + w_2}{m_c l}\\ 0\\ \frac{w_1 l - 2w_2}{m_c l^2}\end{bmatrix} = \begin{bmatrix}0\\ d_1\\ 0\\ d_2\end{bmatrix}. \qquad (4)$$

The total disturbance vector, $d \in R^{4X1}$, includes the external disturbance functions such as wind, hit, and friction effects on the crane model [18]. Based on the dynamic (1)–(4), several control methods were presented.

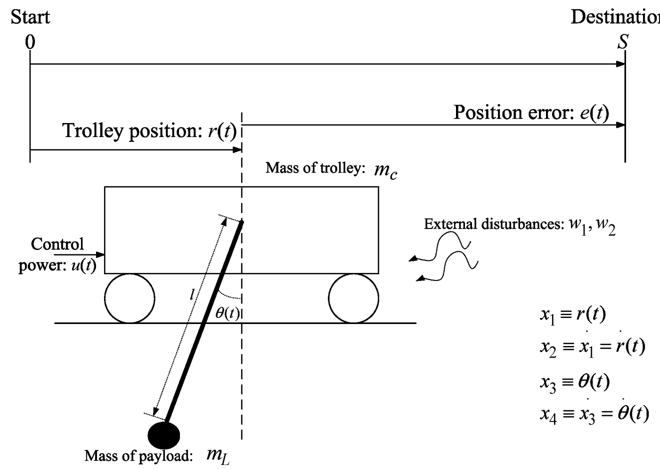

Fig. 1. Overhead crane system.

A. Linear Quadratic Method

In these years, optimal control-based methods have become the main stream of the topic of the crane system. The quadratic performance index, used in most optimal control-based methods to be minimized, can be shown in the following form [13]:

$$J = \frac{1}{2}x^t(T)K(T)x(T) + \frac{1}{2}\int_0^T \left(x^t Q(t)x + uR(t)u\right)dt \quad (5)$$

where the time interval over which we are interested is $[0, T]$. The weighting matrix $K(T)$ and $Q(t)$ are symmetric and positive semi-definite, while $R(t)$ is symmetric and positive definite for all $t \in [0, T]$. The Hamiltonian is

$$H = \frac{1}{2}(x^t Qx + u^t Ru) + \lambda^t(Ax + Bu) \qquad (6)$$

where $\lambda \in R^{4X1}$ is the Lagrange multiplier. The state, costate, and stationary equations are $\dot{x} = H_\lambda = \partial H/\partial\lambda = Ax + Bu$, $-\dot{\lambda} = H_x = \partial H/\partial x = Qx + A^T\lambda$, and $0 = H_u = \partial H/\partial u = Ru + B^T\lambda$, respectively. Thus, according to the optimal control theory, there exists an optimal control

$$u(t) = -R^{-1}B^t\lambda. \qquad (7)$$

Since the final state of the crane control system is fixed, it is not necessary to include a final state weighting in the performance index, so in (5), $K(T) = 0$. Furthermore, one focused the motion of trolley and payload at the destination, so the weighting matrix Q is also 0 in this paper. Hence, the cost function will become $J = (1/2)\int_0^T u^t Rudt$, and R is chosen one for all t in this paper. The state and costate equations will be $\dot{x} = Ax - BR^{-1}B^T\lambda$ and $\dot{\lambda} = -A^T\lambda$, respectively; hence, one has

$\lambda(t) = e^{A^T(T-t)}\lambda(T)$. Using this expression in the state equation yields $\dot{x} = Ax - BR^{-1}B^T e^{A^T(T-t)}\lambda(T)$, whose solution is

$$x(t) = e^{At}x(0) - \int_0^t e^{A(t-\tau)}\left[BR^{-1}B^T e^{A^T(T-\tau)}\lambda(T)\right]d\tau. \tag{8}$$

To find $\lambda(T)$, evaluate (8) at $t = T$ to get

$$x(T) = e^{AT}x(0) - G(0,T)\lambda(T) \tag{9}$$

where the weighted continuous reachability gramian is

$$G(0,T) = \int_0^T e^{A(T-\tau)}BR^{-1}B^T e^{A^T(T-\tau)}d\tau \tag{10}$$

then

$$\begin{aligned}\lambda(T) &= -G^{-1}(0,T)\left[x(T) - e^{AT}x(0)\right], \quad \text{and}\\ \lambda(t) &= e^{A^T(T-t)}\lambda(T).\end{aligned} \tag{11}$$

The optimal control can be written as

$$u(t) = R^{-1}B^T e^{A^T(T-t)}G^{-1}(0,T)\left[x(T) - e^{AT}x(0)\right]. \tag{12}$$

B. Conventional Fuzzy Method

Several authors also proposed the nonlinear fuzzy controller to control the crane [17], [20], [24]. In these papers, the error and the differential of error were applied to be the antecedent parts of the fuzzy controller. The dynamic and knowledge of experienced crane operator were used to design the fuzzy rules. Suppose that the swing angle, swing angular velocity, position error, and position velocity were all divided into five fuzzy linguistic sets, and then, it needed 5^4 rules to fulfill a fuzzy controller, reducing the efficiency. Some papers also divided the crane controller into two parts—swing controller and position controller [24]. However, the rule number was still big. Besides, the uncertainty and external disturbance problems also deteriorated the performance of these conventional fuzzy methods.

III. Adaptive Fuzzy Crane Control Method

Most proposed methods are very complex and hard to realize in crane control. In order to transfer the load efficiently and smoothly, this paper develops an adaptive fuzzy method to be an alternative. Only the position error $e(t) = S - r(t)$ and swing angle of load $\theta(t)$ are used to be the antecedent variables of the fuzzy controller. The output power $u'(t)$ is applied to be the consequent. The notation "S" is the distance to the destination from the start, and $r(t)$ represents the trolley position at time t.

The basic configuration of a fuzzy system includes fuzzifier, defuzzifier, inference engine, and rule base. The fuzzier is a mapping from a real-valued point to a fuzzy set. In a fuzzy inference engine, fuzzy logic principles are used to combine the

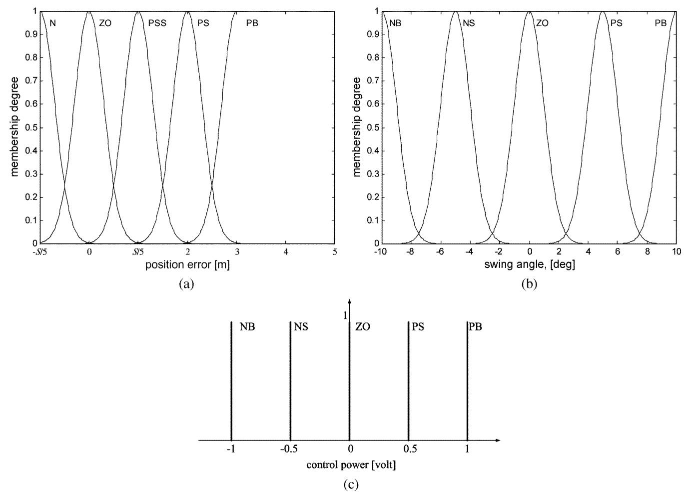

Fig. 2. Linguistic terms and membership function of the fuzzy antecedents and consequent variables (a) $e(t)$ (b) $\theta(t)$, and (c) $u'(t)$.

fuzzy IF-THEN rules in the fuzzy rule base into a mapping from the domain of input variables to the domain of output variables. Defuzzification is the process of converting a fuzzy demand of output variables into a crisp demand. After fuzzification, inference, and defuzzification procedures, the fuzzy controller will derive a proper output power $u(t)$, according to the fuzzy inputs, to control the crane. The design process of the fuzzy crane controller is shown below.

The dynamic ranges of all the input and output ranges of proposed fuzzy controller are $[-S/5, S]$, $[-10°, 10°]$, and $[-1, 1]$ for $e(t)$, $\theta(t)$, and $u'(t)$, respectively. Five fuzzy sets with Gaussian membership functions, N, ZO, PSS, PS, and PB, with the means $\bar{e}_i$, and standard deviations $\sigma_{ri}, i = 1, \cdots, 5$ are used for the input variable $e(t)$. When $e(t) \geq 3S/5$, the membership function of the fuzzy set PB is 1 for rapid transporting. The other mean values of Gaussian-type membership functions are equally distributed over their dynamic ranges. All the standard deviations are 0.3 at first, shown in Fig. 2(a). Besides, the linguistic terms NB, NS, ZO, PS, PB, with the means $\overline{\theta}_i$, and standard deviations $\sigma_{\theta i}$, $i = 1, \cdots, 5$ are used for the other input factor $\theta(t)$. The fuzzy consequent part, $u'(t)$, is represented by the singleton functions, NB, NS, ZO, PS, PB, with the value $\overline{u'_i}$, $i = 1, \cdots, 5$. All the mean values of Gaussian membership functions of $\theta(t)$ and singleton values of $u'(t)$ are also equally distributed over their respective dynamic ranges initially. The standard deviations of $\theta(t)$ are 1 at first. Fig. 2(b)–(c) shows these functions. The fuzzy rules are shown in the following:

$$R^{(n)}: \text{ If } (e(t) \text{ is } A^n) \text{ and } (\theta(t) \text{ is } B^n), \text{ then } (u'(t) \text{ is } C^n) \tag{13}$$

where A^n, B^n, and C^n are fuzzy sets of $e(t)$, $\theta(t)$, and $u'(t)$, respectively; $n = 1, \ldots, k$ represents the rule number. Since two fuzzy antecedents are used in the rules, each is divided into five fuzzy sets, so $k = 5^2 = 25$ fuzzy rules are determined. The membership functions of fuzzy sets A^n, B^n, and C^n in these rules will change during the adaptation procedures shown below; therefore, the rules constructed in (13) are initial rules of the adaptive fuzzy controller.

Following the fuzzy sliding-mode control concept, a diagonal rule table is adopted and tabulated in Table I [15]. It is because

TABLE I
FUZZY RULE MAP

Consequent: Control power		Antecedent: Position error				
		PB	PS	PSS	ZO	N
Antecedent: Swing angle	PB	PB	PB	PS	PS	ZO
	PS	PB	PS	PS	ZO	NS
	ZO	PS	PS	ZO	NS	NS
	NS	PS	ZO	PS	NS	NB
	NB	ZO	PS	NS	NS	NB

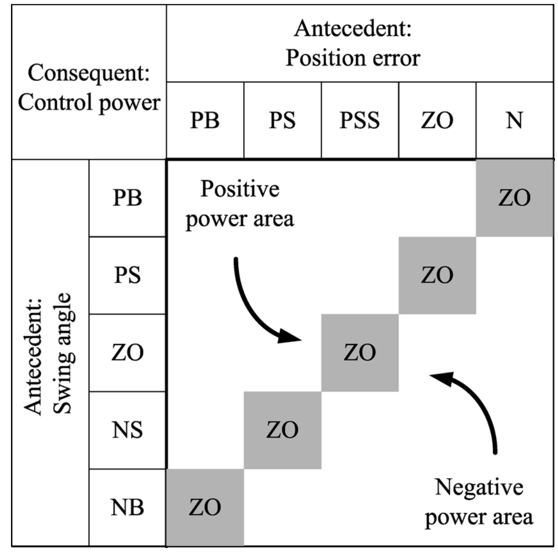

Fig. 3. Phase trajectories of fuzzy logic controller.

an alternative way of considering the rule table as a phase trajectory is shown in Fig. 3, where the arrows indicate the direction of reinforcement. From Fig. 3, the arrows push the control power to "ZO," and the area constructed by ZO can be a switching surface. So, fuzzy logic control is similar to sliding-mode control with boundary layer. The control power drives state trajectories toward a sliding surface (in fact, the ZO area in this application) and to maintain the state trajectories sliding on the sliding surface until stable equilibrium state is reached. In the crane application case, the author chooses the sliding surfaces for efficient and anti-swing control, defined as $e(t)$ and $\theta(t)$. For example, the crane is fixed at first and far away from the destination, that is, $e(t)$ is PB and $\theta(t)$ is ZO. In this case, the crane has to speed up to decrease $e(t)$. The control power $u'(t)$ is PS instead of PB to avoid severe swing. On the other hand, suppose $e(t)$ is ZO and $\theta(t)$ is NB, which presents the crane as very close to the destination with the load lagged behind the trolley. We must back the trolley in order to wait for the load and restrain the swing. Hence, a negative control power is given. We can conclude that if $e(t)$ is close to the sliding area, the control power is smaller than those that are far from the area.

The proposed method uses a minimum inference engine and a centroid defuzzifier to convert the conclusions obtained from the fired fuzzy rules to a single real number. The centroid method computes the center of gravity of the entire fuzzy command. The resulting real number, in some sense, summarizes the elastic constraint imposed on the possible value of the output variables by the fuzzy sets. Thus, the actual control power $u(t)$, which sums up all the consequents part $u'(t)$ of the fuzzy rules, is given by

$$u(t) = \frac{\sum_{n=1}^{25} p^n \left(\min \mu_{A^n}(e), \mu_{B^n}(\theta)\right)}{\sum_{n=1}^{25} \left(\min \mu_{A^n}(e), \mu_{B^n}(\theta)\right)} \tag{14}$$

where $\mu_{A^n}(e)$ and $\mu_{B^n}(\theta)$ are the Gaussian membership function, and $p^n \in R$ represents the greatest value of linguistic terms in C^n. Because we choose the membership functions $\mu_{A^n}(e)$ and $\mu_{B^n}(\theta)$ to be Gaussian functions that are nonzero for any $e(t)$ and $\theta(t)$, the denominator of (14) is nonzero for any antecedent part of (13); therefore, the fuzzy controller is well defined.

However, the crane system is a highly nonlinear plant system that is difficult to control well by a basic fuzzy controller. Besides, the uncertain disturbance such as wind, hit, and friction of track always degrades the control performance of the crane system. An adaptive algorithm is especially well known to deal with the information that is not known completely. Therefore, this work develops an adaptive algorithm to tune the means and standard deviations of the fuzzy sets A^n, B^n, and C^n of (13), respectively. By this way, the proposed control law will be more efficient and robust than usual. So, one can easily design the crane controller to control the position error and swing angle of the load well. The adaptive algorithm for the means is represented by

$$\overline{e_i}(t+\Delta t) = \overline{e_i}(t) + \lambda_c \cdot e(t) \cdot \gamma_i(t) \cdot \frac{e(t) - \overline{e_i}(t)}{\sigma_{ei}^2(t)} \tag{15}$$

$$\overline{\theta_i}(t+\Delta t) = \overline{\theta_i}(t) + \lambda_c \cdot \theta(t) \cdot \gamma_i(t) \cdot \frac{\theta(t) - \overline{\theta_i}(t)}{\sigma_{\theta i}^2(t)} \tag{16}$$

$$\overline{u_i'}(t+\Delta t) = \overline{u_i'}(t) + \lambda_c \cdot u(t) \cdot \frac{p_i(t)}{q(t)} \tag{17}$$

where $\overline{e_i}$ and $\overline{\theta_i}$ represent the means of Gaussian functions of fuzzy antecedent parts, $\overline{u_i'}$ is the mean value of fuzzy singleton of the consequent part, $i = 1, \ldots, 5$, and λ_c is a small positive constant 0.1. The adaptations of standard deviations of Gaussian functions are

$$\sigma_{ei}(t+\Delta t) = \sigma_{ei}(t) + \xi \cdot e(t) \cdot \gamma_i(t) \frac{\left(e(t) - \overline{e_i}(t)\right)^2}{\sigma_{ei}^3(t)} \tag{18}$$

$$\sigma_{\theta i}(t+\Delta t) = \sigma_{\theta i}(t) + \xi \cdot \theta(t) \cdot \gamma_i(t) \frac{\left(\theta(t) - \overline{\theta_i}(t)\right)^2}{\sigma_{\theta i}^3(t)} \tag{19}$$

where

$$p_i(t) = \min\left(\exp\left[-\frac{1}{2}\left(\frac{e(t)-\overline{e_i}(t)}{\sigma_{ei}}\right)^2\right] \cdot \exp\left[-\frac{1}{2}\left(\frac{\theta(t)-\overline{\theta_i}(t)}{\sigma_{\theta i}}\right)^2\right]\right) \quad (20)$$

$$q(t) = \sum_{i=1}^{5} p_i(t) \quad (21)$$

$$\gamma_i(t) = \frac{\overline{u_i'}(t)+u(t)}{q(t)} p_i(t) \quad (22)$$

ξ is a small positive constant 0.1 [5], [14]. Thus, the proposed fuzzy controller can be tuned adaptively.

Some comments on this adaptive fuzzy controller are now in order.

Remark 1: One can find the fuzzy sets overlap at a small level in Fig. 2(a)–(b). This condition may affect the resolution of the fuzzy controller; moreover, a smaller overlap region will also lead to the fewer activated rules in a fuzzy control power. However, no matter how many rules are activated, the fuzzification and defuzzification processes will derive the right control power when the fuzzy sets are sensible. The adaptive algorithm provided in this paper will also tune the shape and overlap region of membership function automatically. So, the overlap region of fuzzy sets will not impact the performance of the controller in this paper [16].

Remark 2: The reasons to determine the membership functions in this paper are as follows.

1) The Gaussian-type membership functions, which make the denominator of fuzzy controller (14) always greater than zero, help to keep the system stable during the adaptive process.
2) The membership function of "PB" of position error is 1, when $e(t) \geq 3s/5$. This way helps to speed the transporting.
3) The fuzzy singleton function is chosen to save the computational effort for the real time control.
4) The adaptive algorithm will tune the fuzzy membership functions automatically according to (15)–(22). So, one can easily design the membership functions at the start. The design process of the nonlinear fuzzy controller is simplified.

Remark 3: The advantages of proposed method are presented in the following.

1) A lot of adaptive fuzzy controllers, such as in [5] and [14], still need plant information to design the controller for some special purposes. This paper uses the position error and swing angle only to fulfill the proposed adaptive fuzzy crane controller without any plant information. Thus, an all-purpose controller is derived and can be applied to the other crane system directly.
2) In general, fuzzy crane controller uses four variables, including position error $e(t)$, swing angle $\theta(t)$, and their differentiations $\dot{e}(t)$ and $\dot{\theta}(t)$, to be the fuzzy antecedents [24]. The proposed method uses only two variables—position error and swing angle—to derive the fuzzy crane controller. The adaptive algorithm shown in this paper will help to improve the system performance. Using two fuzzy antecedents only also helps to reduce the rule number of the fuzzy controller, reducing the computing effort in real-time control.
3) The different control situations, including the variation of length of wire and weight of payload, help to verify the robustness of the proposed controller. The experimental results of crane control under external disturbance also prove the robustness of the proposed controller.

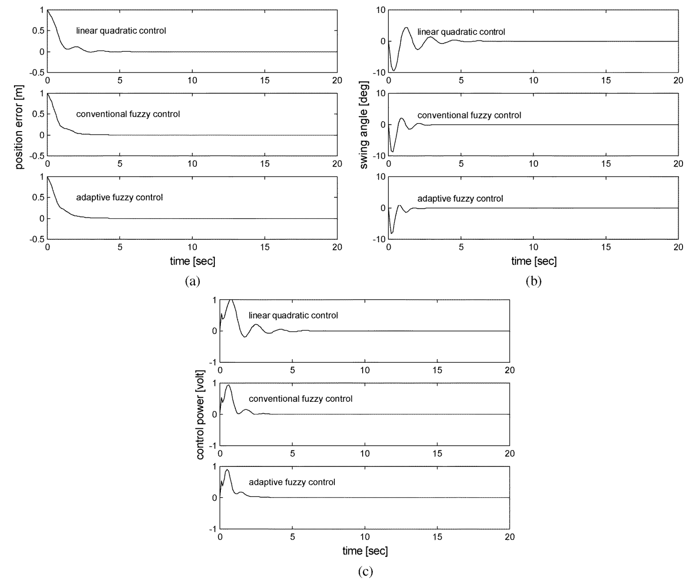

Fig. 4. Simulation results: (a) position error, (b) swing angle, and (c) control power.

IV. Simulation Results

The author verifies the performance of linear quadratic, conventional fuzzy method [24], and proposed adaptive fuzzy method by two simulations. The initial state $x(0)$ and the constrained final state $x(T)$ of linear control are

$$x(0) = [0,0,0,0], \quad x(T) = [1,0,0,0]. \quad (23)$$

The constants of the crane model are

$$m_c = 24\text{ kg}, \quad m_L = 5\text{ kg}, \quad l = 1\text{ m}, \quad g = 9.8\frac{m}{\sec^2}$$
$$d_1 = 0.2\cos t, \quad d_2 = 0.2\sin t. \quad (24)$$

The disturbances are set to be sine and cosine waves in the simulations.

In the first simulation, one can find the linear quadratic method has to drive the trolley back and forth to restrain the swing, but the conventional fuzzy method and adaptive fuzzy method perform well, shown in Fig. 4(a)–(b). Fig. 4(c) shows the control power of all the presented methods. One can find that the control powers of both the fuzzy-based methods are also more efficient than the linear quadratic one.

In order to verify the robustness of the proposed adaptive fuzzy method, the second simulation depicts the performance of the crane control system with disturbance. The performances of linear quadratic, conventional fuzzy, and adaptive fuzzy approaches are demonstrated in Fig. 5(a)–(c), respectively. It is clear that the position error and swing angle of linear quadratic

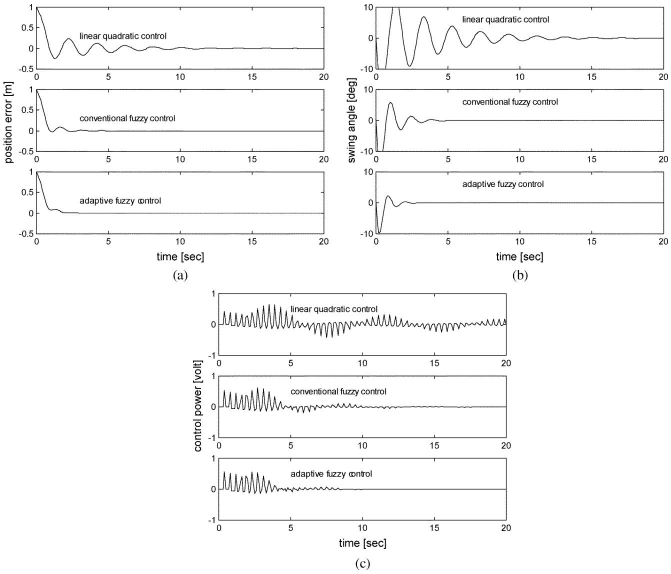

Fig. 5. Simulation results, with disturbance: (a) position error, (b) swing angle, and (c) control power.

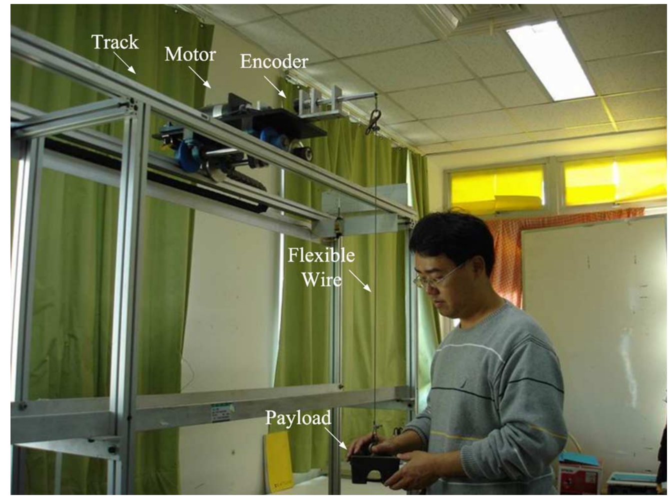

Fig. 6. Physical apparatus of the overhead crane system.

and conventional fuzzy methods become worse than those in the pervious simulation, and the proposed adaptive fuzzy approach still controls very well, shown in Fig. 5(a)–(b). The control power of the proposed adaptive fuzzy method is still more economic, shown in Fig. 5(c). So, according to these simulations, one can find the proposed adaptive fuzzy method not only controls the crane well but also provides the ability to control the crane under the situation of external disturbance. Besides, the error signals of the adaptive fuzzy control algorithm, including position error and swing angle, both converge to zero, shown in Figs. 4(a)–(b) and 5(a)–(b). These results also confirm the convergence of the adaptive algorithm.

V. Experimental Results

A prototype overhead crane, 5 m long and 2 m high, is shown in Fig. 6 to verify the effectiveness of the proposed control law. This crane is driven by a 65 watt, 24 V dc motor with ± 1 V velocity mode servo controller. A flexible wire, with 1 meter long $(l = 1)$, is tied to the load. The mass of trolley m_c is 24 kg, and the load m_L is 5 kg. Two 2000 pulse-per-round (PPR) encoders, position sensor, and angular sensor were included for accurate measurements of the trolley position $r(t)$ and the load swing $\theta(t)$. So, the resolution of encoder of swing angle is 360/2000 degrees and of position is about 1/130 meters according to radius of trolley wheels. The trolley motion always accompanies with undesired load swing $\theta(t)$. In this paper, the load swings backward is defined as negative swing, and swings forward is defined as positive swing. The destination S was 1 meter away from the initial position.

The initial values of the membership functions in the adaptive fuzzy controller are depicted as follows. The mean values of these linguistic terms are equally distributed over their dynamic range initially, i.e., $\overline{e_i}(0) = -0.2$, 0, 0.2, 0.4, 0.6, for $i = 1, \cdots, 5$, with respect to the fuzzy linguistic variables N, ZO, PSS, PS, and PB, and $\overline{\theta_i}(0) = -10$, -5, 0, 5, 10, for $i = 1, \cdots, 5$, with respect to the fuzzy linguistic variables NB, NS, ZO, PS, and PB, and $\overline{u_i'}(0) = -1$, -0.5, 0, 0.5, 1, for $i = 1, \cdots, 5$. The standard deviations of $\sigma_{ei}(0)$ and $\sigma_{\theta i}(0)$ are 0.3 and 1 at first, for $i = 1, \cdots, 5$. The external disturbance of wind is generated by an electric fan with a diameter of 380 mm, 60 watt ac motor, and a 58 $\mathrm{m}^3/\mathrm{min}$ wind directly blowing on the payload. This kind of disturbance, which is like the random noise, will lead to additional sway of payload about $\pm 3^\circ$. Additional 10° swing angle, which is made by hand at the start, is like a hit in crane control. The author uses this hit to be another external disturbance to increase the control nonlinearity and verify the performance of proposed controllers.

Fig. 7(a)–(c) shows the performances of the linear quadratic method. The trolley position, swing angle, and control power are shown in Fig. 7(a)–(c), respectively. One can find the linear quadratic control method can stop the trolley at the destination, that is, the position error is near zero. It takes about 8 s. However, this method has to drive the trolley back and forth to restrain the crane, reducing the efficiency. Besides, the swing of load by the linear quadratic method is more severe than both the fuzzy-based methods during the first few seconds' transportation, shown in Fig. 7(b). The residual swing error is also exists. The main reasons are that the viscous of damping of load and the track friction of trolley are not taken into consideration in the design of the linear quadratic scheme. The linearized processes also degrade the performance. Fig. 7(c) shows the respective control power.

In Fig. 8, the disturbance is applied to verify the robustness of lthe inear quadratic controller. One can find that the performance become worse, shown in Fig. 8(a)–(b). The respective control power is shown in Fig. 8(c).

Fig. 9(a)–(c) shows the performances of the conventional fuzzy method [24]. Four variables, including position error, swing angle, and their differentiations, are used to be the fuzzy antecedents. The trolley position, swing angle of payload, and control power are shown in Fig. 9(a)–(c), respectively. One can find the conventional fuzzy control method still can stop the trolley at the destination, that is, the position error is near zero. However, this fuzzy-based method does not have to drive the trolley back and forth to restrain the crane, improving the efficiency. However, the swing angle is still not good enough. The main reasons are that the disturbances, including the friction

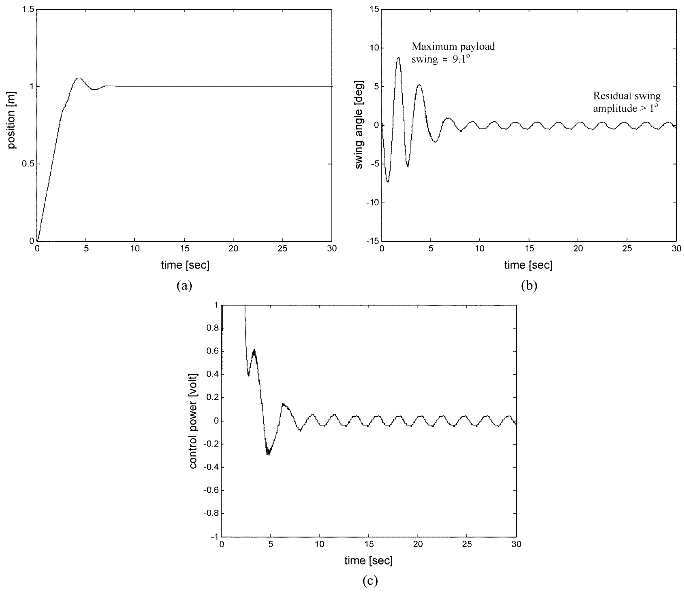

Fig. 7. Experimental results of linear quadratic control, rope length: 1 m, and payload: 5 kg, (a) position, (b) swing angle, and (c) control power.

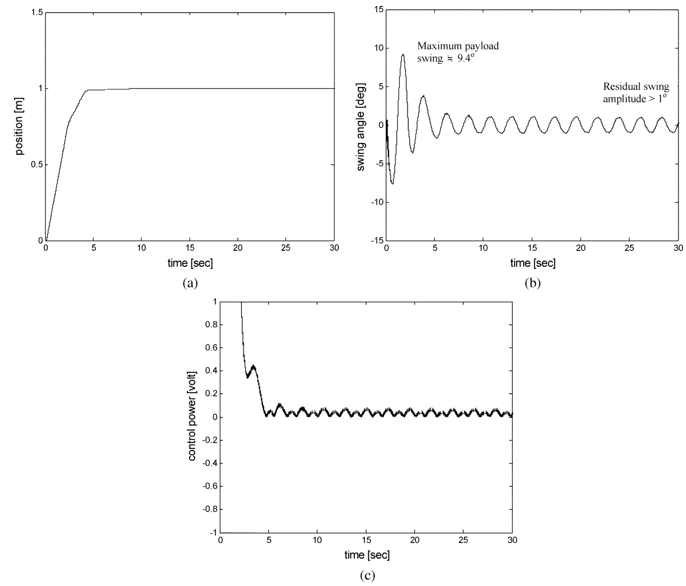

Fig. 9. Experimental results of conventional fuzzy method, rope length: 1 m and payload: 5 kg, (a) position, (b) swing angle (c), and control power.

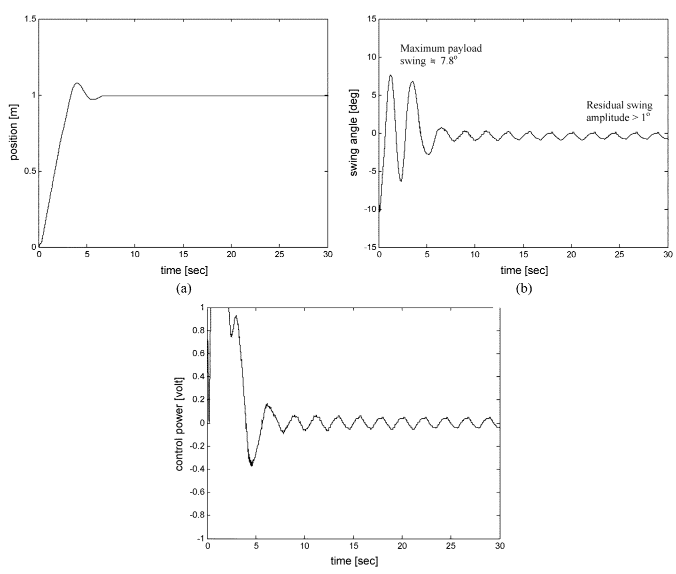

Fig. 8. Experimental results of linear quadratic control, rope length: 1 m and payload: 5 kg, with external disturbance (a) position, (b) swing angle, and (c) control power.

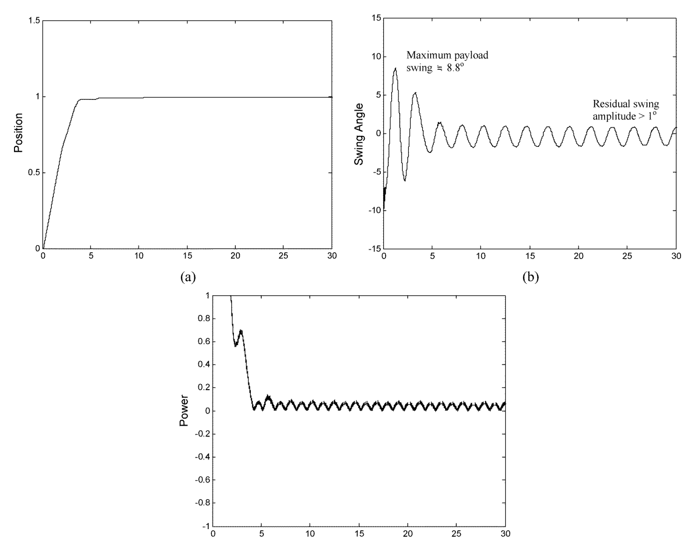

Fig. 10. Experimental results of conventional fuzzy method, rope length: 1 m and payload: 5 kg, with external disturbance, (a) position, (b) swing angle, and (c) control power.

of track and deadzone, etc., are not taken into consideration in the design. Fig. 9(c) shows the respective control power. The conventional fuzzy strategy also takes about 8 s to stop the trolley and reach the destination.

In Fig. 10, the external disturbance is applied to verify the robustness of the conventional fuzzy controller. One can find the performance of trolley position and swing angle are still not good enough, shown in Fig. 10(a)–(b). The respective control power is shown in Fig. 10(c).

Fig. 11(a)–(c) shows the performances of the proposed adaptive fuzzy method. The trolley position, swing angle, and control power are shown in Fig. 11(a)–(c), respectively. One can find the adaptive fuzzy control method can not only stop the trolley at the destination but also restrain the swing angle of load very well, shown in Fig. 11(a) and (b). The time to the destination is also about 8 s, and the maximum swing angle is only about 4°. Compared with linear quadratic and conventional fuzzy methods, the proposed adaptive fuzzy law especially has the good capability to restrain the swing. Fig. 11(c) shows the respective control power. It is evident that the control power is more efficient and economic than those of the linear quadratic and conventional fuzzy methods.

The experimental results under different control conditions, including the joining of external disturbance, increasing of payload weight, and wire length to compare with Fig. 11, are shown in Figs. 12–14, respectively. In Fig. 12, the external disturbance is applied to verify the robustness of adaptive fuzzy controller. The external disturbance includes the wind and the hit of the payload. One can find the performance of trolley position and

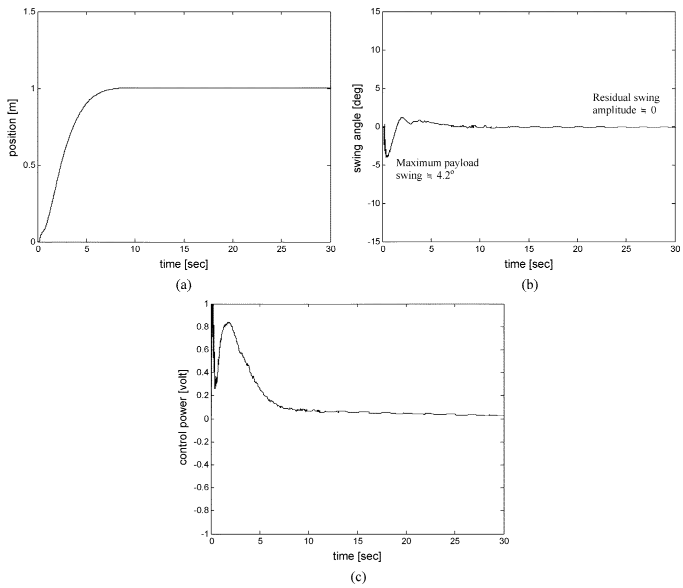

Fig. 11. Experimental results of adaptive fuzzy method, rope length: 1 m and payload: 5 kg: (a) position, (b) swing angle, and (c) control power.

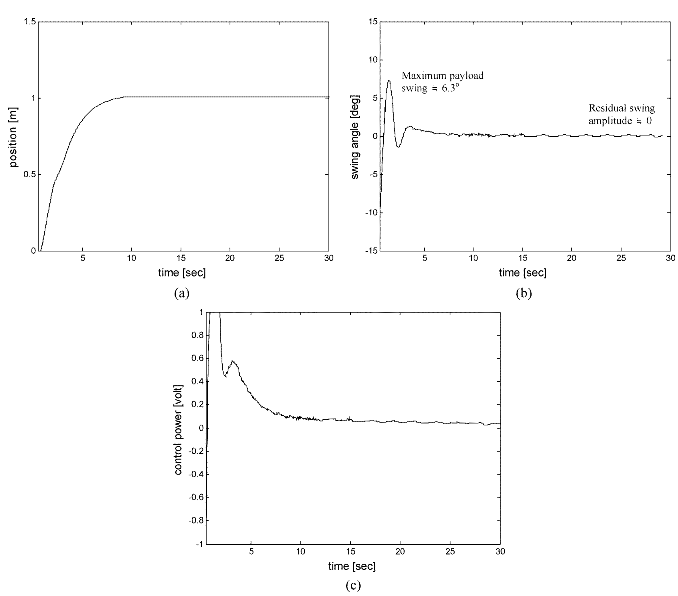

Fig. 12. Experimental results of adaptive fuzzy method, rope length: 1 m and payload: 5 kg, with external disturbance, (a) position, (b) swing angle, and (c) control power.

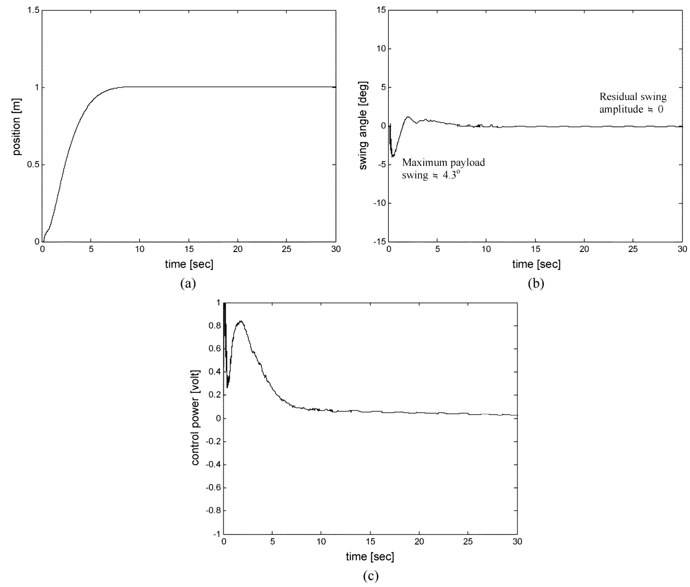

Fig. 13. Experimental results of adaptive fuzzy method, rope length: 1 m and payload: 7 kg, (a) position, (b) swing angle, and (c) control power.

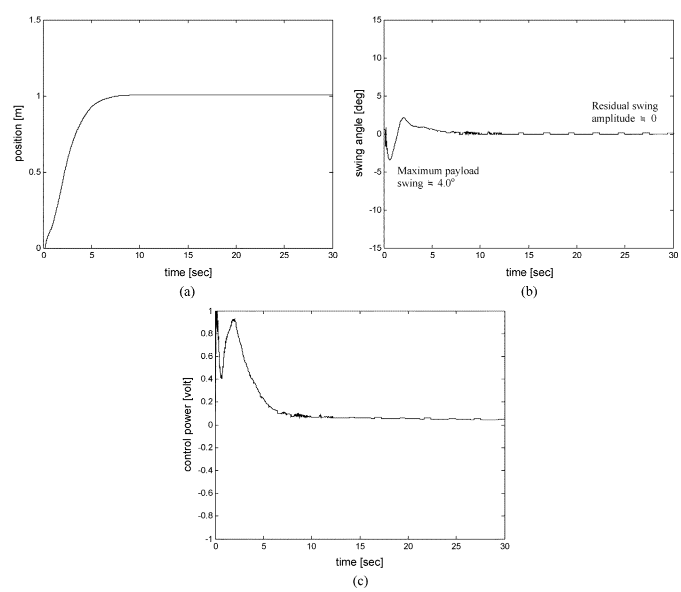

Fig. 14. Experimental results of adaptive fuzzy method, rope length: 1.5 m, and payload: 5 kg, (a) position, (b) swing angle, and (c) control power.

swing angle still performs well, shown in Fig. 12(a)–(c). The hit is made by hand at the beginning (about 10°) to increase the nonlinearity of control. The proposed adaptive fuzzy controller shows the ability to overcome the external disturbance effects.

In Fig. 13, the wire length is 1m, and the weight of payload increases to 7 kg. One can find that the performance of the position error is still good. Besides, the control power is larger than the other cases to reach the destination at 8 s, but the swing angle is also good.

In Fig. 14, the weight of payload is also 5 kg, and the wire length will increase to 1.5 m to compare the results with Fig. 11. The experiment results are still very good.

By these experiments, one can find that the proposed adaptive fuzzy method not only improves the precise position control but also helps to restrain the swing very well. One can also conclude that the proposed adaptive fuzzy law controls the crane system very well, under the bounding limits of experimental setup. When compared with quadratic control and conventional fuzzy methods, the proposed adaptive fuzzy method greatly enhances the maximum payload swing and residual swing amplitude and shortens the time to restrain the swing. These results are shown in Table II. Experiments also show that the adaptive fuzzy method provides smoother control power to drive the trolley. Since the major influence of control power is on the operating speed of the trolley, the differentiation-acceleration of trolley plays an important role in payload swing, such as in (1). There is no doubt that the adaptive fuzzy-based method provides the better and more efficient control than linear quadratic and conventional fuzzy methods. The experiments also verify

TABLE II
COMPARISON OF PAYLOAD SWING

Control Methods	Maximum Payload Swing	Residual Swing Amplitude	Time to Restrain the Swing
Linear quadratic control	9.1°	> 1°	> 30s
Linear quadratic control with external disturbance	7.8°	> 1°	> 30s
Conventional fuzzy	9.4°	> 1°	> 30s
Conventional fuzzy with external disturbance	8.8°	> 1°	> 30s
Proposed method	4.2°	Almost zero	< 6s
Proposed method with external disturbance	6.3°	Almost zero	< 6s

the robustness of the proposed control law with external disturbance.

VI. CONCLUSION

In this paper, one designs an adaptive fuzzy control law for the overhead crane and shows the effectiveness of the proposed control law by experiments in a prototype crane. The proposed method does not need to analyze the dynamics of crane system but uses position and swing errors only to formulate the control output. Experimental results show that the proposed control law is capable of having the accurate position control and fast damping of load swing despite the mass of load, length of flexible wire, and external disturbance of the crane. The nonlinearity of disturbance is also increased to verify the effectiveness of the developed technique on a realistic system. So, one expects that the proposed adaptive fuzzy control law will be applied very effectively in control of real cranes. The proposed adaptive fuzzy method can be also used for many other applications.

REFERENCES

[1] G. Corriga, A. Giua, and G. Usai, "An implicit gain-scheduling controller for cranes," *IEEE Trans. Control Syst. Technol.*, vol. 6, no. 1, pp. 15–20, Jan. 1998.

[2] C. Chun and J. Hauser, "Nonlinear control of a swinging pendulum," *Automatica*, vol. 31, no. 6, pp. 851–862, 1995.

[3] Y. Fang, W. E. Dixon, D. M. Dawson, and E. Zergeroglu, "Nonlinear coupling control laws for an underactuated overhead crane systems," *IEEE/ASME Trans. Mechatron.*, vol. 8, no. 3, pp. 418–423, Sep. 2003.

[4] A. N. Goritov and A. M. Korikov, "Optimality in robot design and control," *Autom. Remote Control*, vol. 62, no. 7, pp. 1097–1103, 2001.

[5] L. X. Wang and J. M. Mendel, "Fuzzy adaptive filter, with application to nonlinear channel equalization," *IEEE Trans. Fuzzy Syst.*, vol. 1, no. 3, pp. 161–170, Aug. 1993.

[6] J. J. Hamalainen, A. Marttinen, L. Baharova, and J. Virkkunen, "Optimal path planning for a trolley crane: Fast and smooth transfer of load," *Proc. Inst. Elect. Eng., Control Theory Appl.*, vol. 142, no. 1, pp. 51–57, 1995.

[7] G. J. Klir and B. Yuan, *Fuzzy Sets and Fuzzy Logic, Theory and Applications*. Englewood Cliffs, NJ: Prentice-Hall, 1995.

[8] C. Li and C. Y. Lee, "Fuzzy motion control of an auto-warehousing crane system," *IEEE Trans. Ind. Electron.*, vol. 48, no. 5, pp. 983–994, Oct. 2001.

[9] H. H. Lee, "A new motion-planning scheme for overhead cranes with high-speed hoisting," *ASME Trans. Dynam. Syst., Meas., Control*, vol. 126, no. 2, pp. 359–364, 2004.

[10] A. Piazzi and A. Visioli, "Optimal dynamic-inversion-based control of an overhead crane," *Proc. Inst. Elect. Eng., Control Theory Appl.*, vol. 149, no. 5, pp. 405–411, 2002.

[11] W. Singhose, L. Porter, M. Kenison, and E. Kriikku, "Effects of hoisting on the input shaping control of gantry cranes," *Control Eng. Pract.*, vol. 8, no. 10, pp. 1159–1165, 2000.

[12] M. J. Agostini, G. G. Parker, H. Schaub, K. Groom, and R. D. Robinett, III, "Generating swing-suppressed maneuvers for crane systems with rate saturation," *IEEE Trans. Control Syst. Technol.*, vol. 11, no. 4, pp. 471–481, Jul. 2003.

[13] F. L. Lewis and V. L. Syrmos, *Optimal Control*, 2nd ed. New York: Wiley, 1995.

[14] K. K. Shyu, C. Y. Chang, and M. C. Kuo, "Self-tuning controller with fuzzy filtered-X algorithm," *Electron. Lett.*, vol. 36, no. 2, pp. 182–184, 2000.

[15] T.-H. S. Li, S. J. Chang, and W. Tong, "Fuzzy target tracking control of autonomous mobile robots by using infrared sensors," *IEEE Trans. Fuzzy Syst.*, vol. 12, no. 4, pp. 491–501, Aug. 2004.

[16] J. R. Boston, "Effects of membership function parameters on the performance of a fuzzy signal detector," *IEEE Trans. Fuzzy Syst.*, vol. 5, no. 2, pp. 249–255, Oct. 1997.

[17] S. K. Cho and H. H. Lee, "A fuzzy-logic antiswing controller for three-dimensional overhead cranes," *ISA Trans.*, vol. 41, no. 2, pp. 235–243, 2002.

[18] E. Kim, "A fuzzy disturbance observer and its application to control," *IEEE Trans. Fuzzy Syst.*, vol. 10, no. 1, pp. 77–84, Feb. 2002.

[19] J. W. Auernig and H. Troger, "Time optimal control of overhead cranes with hoisting of the load," *Automatica*, vol. 23, pp. 437–447, 1987.

[20] Y. C. Liang and K. K. Koh, "Concise anti-swing approach for fuzzy crane control," *Electron. Lett.*, vol. 3, no. 2, pp. 167–168, 1997.

[21] K. A. F. Moustafa and A. M. Ebeid, "Nonlinear modeling and control of an overhead crane load sway," *ASME Trans. Dynam. Syst., Meas., Control*, vol. 110, no. 3, pp. 266–271, 1988.

[22] T. Matsuo, R. Yoshino, H. Suemitsu, and K. Nakano, "Nominal performance recovery by PID+Q controller and its application to antisway control of crane lifter with visual feedback," *IEEE Trans. Control Syst. Technol.*, vol. 12, no. 1, pp. 156–166, Jan. 2004.

[23] K. Takagi and H. Mishimura, "Control of a jib-type crane mounted on a flexible structure," *IEEE Trans. Control Syst. Technol.*, vol. 11, no. 1, pp. 32–42, Jan. 2003.

[24] C. Y. Chang, "The switching algorithm for the control of overhead crane," *Neural Comput. Appl.*, vol. 15, no. 3–4, pp. 350–358, 2006.

Cheng-Yuan Chang was born in Taiwan, R.O.C., in 1968. He received the B.S. and M.S. degrees in electrical and control engineering from National Chiao-Tung University, Hsinchu, Taiwan, R.O.C., in 1990 and 1994, respectively, and the Ph.D. degree in electrical engineering from National Central University, Taiwan, R.O.C., in 2000.

He is currently an Associate Professor in the Department of Electronic Engineering, Ching Yun University, Jhongli, Taiwan. His current research interests are in the area of intelligent control applications.