

DSP-Based Cross-Coupled Synchronous Control for Dual Linear Motors via Functional Link Radial Basis Function Network

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Abstract—A digital signal processor (DSP)-based cross-coupled functional link radial basis function network (FLRBFN) control is proposed in this study for the synchronous control of a dual linear motors servo system which is installed in a gantry position stage. The dual linear motors servo system comprises two parallel permanent magnet linear synchronous motors (PMLSMs). First, the dynamics of the field-oriented control PMLSM servo drive with a lumped uncertainty, which contains parameter variations, external disturbance and friction force, is introduced. Then, to achieve accurate trajectory tracking performance with robustness, an intelligent control approach using FLRBFN is proposed for the field-oriented control PMLSM servo drive system. The proposed FLRBFN is a radial basis function network (RBFN) embedded with a functional link neural network (FLNN). The network structure and its on-line learning algorithms for connective weights, means and standard derivations are described in detail. Moreover, since a cross-coupled technology is incorporated into the proposed intelligent control scheme for the gantry position stage, both of the position tracking errors and synchronous errors of dual linear motors will converge to zero, simultaneously. Finally, some experimental results are illustrated to depict the validity of the proposed control approach.

Keywords- Dual linear motors servo system, gantry position stage, functional link neural network, radial basis function network, cross-coupled technology.

I. INTRODUCTION

The high precision motion control of gantry position stages has found numerous applications in the manufacturing industries including microelectronics, aerospace, solar cell, and flat panel manufacturing and inspection [1]. In the configuration of gantry position stage, two motors are mounted on two parallel linear guides to drive a moving stage. For the machining centers with heavy type high-speed gantry position stage, though the pillars of the two side of the gantry have the same drive mechanisms, the synchronous error between the two motors is unavoidable due to non-balanced forces adding to the cross gantry and other moving parts, mechanism assembly variations and various uncertainty disturbances during the working process. The synchronous error will influence the quality of the work-pieces and even lead to stop

the working process due to the over current protection. Hence, the control of the synchronous error in the gantry configuration has become a challenge with increasing demands for high-speed and high accuracy manufacture and inspection.

Over the past decade, the cross-coupled technology was majorly used in machine tools and multiple axes motion applications for the reducing of contour tracking errors [2-3]. Recently, the cross-coupled technology was incorporated into some well-know adaptive control approaches to solve the synchronous control problem and improve the control performance [2-3]. In [3], an adaptive coupling control approach had been developed for the synchronous control of multiple motion axes systems. This approach was developed to stabilize the position tracking of each axis while synchronizing its motion with the motions of the other axes. However, a linear sliding mode control (SMC) has been adopted in this synchronous strategy.

In general, intelligent control approaches such as neural and fuzzy mechanisms are dynamic model-free control techniques [4]. Therefore, many studies on neuro-fuzzy approaches for controller developments and for describing the dynamic behaviors of complex systems have been published [5]. In these approaches, the RBFN method, which took local receptive field to perform function mappings, was investigated in [6]. Because the RBFN has a simple structure, the convergence speed of the RBFN is faster than a multilayer perceptron (MLP) network. Moreover, the RBFN has similar features in the following as the fuzzy system: (i) The output value is obtained by using a weighted sum method; (ii) The number of nodes in hidden layer in the RBFN is identical to the number of if-then rules in the fuzzy system; (iii) The receptive field functions in RBFN are similar to the membership functions of the premise part in the fuzzy system. As a result, the RBFN is one of the powerful tools for the systems control development [6].

The basic idea behind an FLNN is the use of the functional links. These functional links generate nonlinear transformations of the original input space before they are fed to the network which constructs the output layer. In other words, the input

variables can be enhanced and linear separability can be achieved in the extended space using the FLNN [7]. Moreover, the FLNN can capture nonlinear input-output relationship by the adequate set of polynomial inputs since the high order effects are incorporated in the input variables to increase the dimension of the input space. Thus, FLNN is suitable to be applied in system identifications or control applications [7].

II. MODELING OF DUAL LINEAR MOTORS SERVO SYSTEM

The dual linear motors servo system adopted in this study is composed of two 220V 5.0A 330N PMLSMs. The detailed machine model of the PMLSM, described in the synchronously rotating reference frame, can be found in [22, 23]. With the implementation of the field-oriented control, the electromagnetic force can be simplified as follows [23]:

$$F_{ei} = K_{fi} i_{qi}^* \quad (1)$$

$$K_{fi} = 3\pi n_{pi} \lambda_{PMi} / (2\tau_i) \quad (2)$$

where K_{fi} is the thrust coefficient; i_{qi}^* is the thrust current command; λ_{PMi} is the permanent magnet flux linkage; n_{pi} , which is 1, is the number of primary pole pairs; τ_i , which is 32mm, is the pole pitch; $i = y1, y2$ is to represent the y1-axis and y2-axis of the dual linear motors servo system.

The mover dynamic equation using the electromagnetic force shown in (1) is

$$F_{ei} = M_i \dot{v}_i + D_i v_i + F_{Li} + f_i(v) \quad (3)$$

where v_i is the linear velocity of the mover; M_i is the total mass of the mover; D_i is the viscous friction and iron-loss coefficient; F_{Li} is the external disturbances term; $f_i(v)$ is the friction force. Considering Coulomb friction, viscous friction and Stribeck effect, the friction force can be formulated as follows [24]:

$$f_i(v) = F_{Ci} \operatorname{sgn}(v_i) + (F_{Si} - F_{Ci}) e^{-(v_i/v_{Si})^2} \operatorname{sgn}(v_i) + K_{vi} v_i \quad (4)$$

where F_{Ci} is the Coulomb friction; F_{Si} is the static friction; v_{Si} is the Stribeck velocity parameter; K_{vi} is the coefficient of viscous friction; $\operatorname{sgn}(\cdot)$ is a sign function. All the parameters in (4) are time-varying.

Curve-fitting technique based on step response of the mover position is applied here to find the model of the motor drive system. For the convenience of the controller design, the position and speed signals in the control loop are set at $1V=0.04963m$ and $1V=0.04963m/sec$, respectively. The major system parameters are:

$$\begin{aligned} \bar{K}_{fi1} &= 195 \text{ N/A}, \bar{M}_{y1} = 6.32\text{kg} = 0.4023 \text{ Nsec/V}, \\ \bar{D}_{y1} &= 819.4069 \text{ kg/sec} = 52.165 \text{ N/V} \end{aligned} \quad (5)$$

$$\begin{aligned} \bar{K}_{fi2} &= 195 \text{ N/A}, \bar{M}_{y2} = 6.33\text{kg} = 0.4123 \text{ Nsec/V}, \\ \bar{D}_{y2} &= 821.4103 \text{ kg/sec} = 53.261 \text{ N/V} \end{aligned} \quad (6)$$

The overbar symbol represents the system parameter in the nominal condition. Though the electromagnetic force can be simplified as (1) via the field-oriented control mechanism, however, considering the variations of system parameters, external disturbances and friction force, the dual linear motors servo system is a nonlinear time-varying system in practical applications.

III. PROPOSED CROSS-COUPLED FLRBFN CONTROL SYSTEM

A. Strategy of Cross-Coupled Synchronous Control

Assuming that the system parameter variations, external disturbances and friction force are absent, each field-oriented control PMLSM servo drive can be formulated by rewriting (1) and (3) as follows:

$$\ddot{d}_i(t) = -\frac{\bar{D}_i}{\bar{M}_i} \dot{d}_i(t) + \frac{K_{fi}}{\bar{M}_i} i_{qi}^*(t) \triangleq A_{mi} \dot{d}_i(t) + B_{mi} u_i \quad (7)$$

where $d_i(t)$ is the position of the mover $A_{mi} = -\bar{D}_i/\bar{M}_i$; $B_{mi} = K_{fi}/\bar{M}_i > 0$; u_i is the control effort, i.e., the thrust current command. Now, considering the existence of parameter variations, external force disturbances and friction force for the single-axis field-oriented control PMLSM servo drive system, then (7) becomes

$$\begin{aligned} \ddot{d}_i(t) &= (A_{mi} + \Delta A_i) \dot{d}_i(t) + (B_{mi} + \Delta B_i) u_i + (C_{mi} + \Delta C_i)[F_{Li} \\ &+ f_i(v)] = A_{mi} \dot{d}_i(t) + B_{mi} u_i + H_i \end{aligned} \quad (8)$$

where $C_{mi} = -1/\bar{M}_i$; ΔA_i , ΔB_i and ΔC_i denote the uncertainties introduced by system parameters M_i and D_i ; H_i is named the lumped uncertainty and defined by

$$H_i \triangleq \Delta A_i \dot{d}_i(t) + \Delta B_i u_i + (C_{mi} + \Delta C_i)[F_{Li} + f_i(v)] \quad (9)$$

Here, the lumped uncertainty is assumed to be bounded

$$|H_i| \leq \rho_i \quad (10)$$

where ρ_i is a given positive constant.

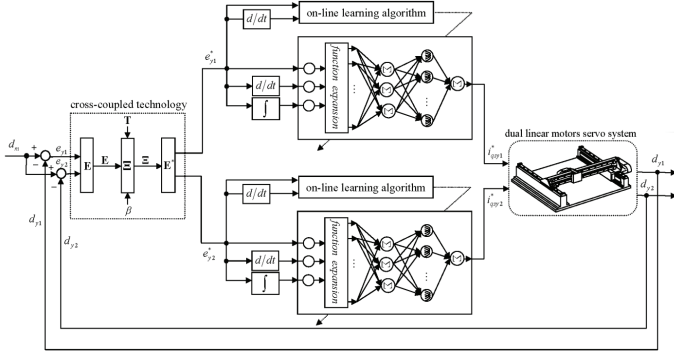


Figure 1. Configuration of cross-coupled FLRBFN control system.

In the proposed control approach, besides the position tracking of each axis, the position synchronization of two axes is considered simultaneously. First, define the position tracking error as

$$e_i = d_m - d_i \quad (11)$$

where d_m denotes the desired command. Then, the synchronous errors are defined as

$$\varepsilon_{y1} = e_{y1} - e_{y2}, \quad \varepsilon_{y2} = e_{y2} - e_{y1} \quad (12)$$

where ε_{y1} and ε_{y2} denote the synchronous errors of dual linear motors, respectively. If the synchronous errors show in (12) are zero, the goal of synchronous control, i.e., $e_{y1} = e_{y2}$, is achieved [3]. Rewrite (12) in the matrix form as

$$\Xi = \mathbf{T}\mathbf{E} \quad (13)$$

where $\Xi = [\varepsilon_{y1} \quad \varepsilon_{y2}]^T$, $\mathbf{E} = [e_{y1} \quad e_{y2}]^T$, and $\mathbf{T} = \begin{bmatrix} 1 & -1 \\ -1 & 1 \end{bmatrix}$ denotes the synchronous transformation matrix. Then, a cross-coupled position tracking error is defined as

$$\mathbf{E}^* = \mathbf{E} + \beta \Xi \quad (14)$$

where $\mathbf{E}^* = [e_{y1}^* \quad e_{y2}^*]^T$ and β is a positive coupled parameter. Substituting (13) into (14) yields

$$\mathbf{E}^* = (\mathbf{I} + \beta \mathbf{T})\mathbf{E} \quad (15)$$

where $\mathbf{I}$ is a unit matrix and $(\mathbf{I} + \beta \mathbf{T})$ is a positive defined matrix. In (15), $\mathbf{E} = \mathbf{0}$ if and only if $\mathbf{E}^* = \mathbf{0}$. It also implies that $\Xi = \mathbf{0}$ [3]. Therefore, the control objective is to design a controller to guarantee the convergence of both the position tracking error e_i and the synchronous error ε_i to zero, simultaneously.

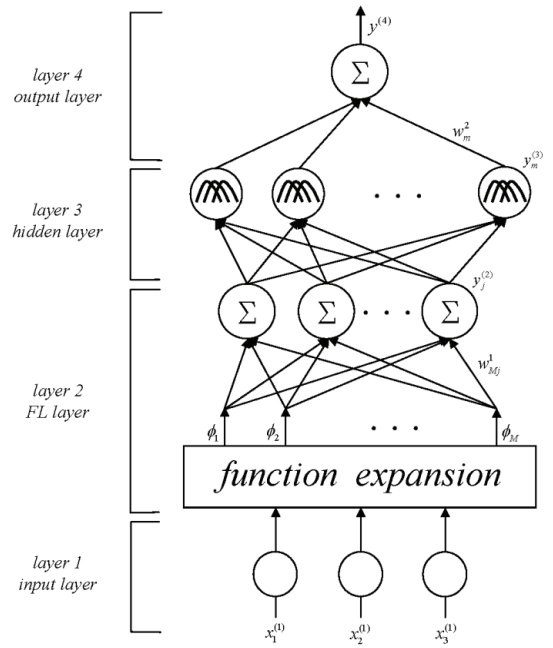


Figure 2. Structure of FLRBFN.

B. Proposed Cross-Coupled FLRBFN Control System

Not only to eliminate the synchronous error of the dual linear motors but also to guarantee the precision position tracking requirement in single axis motor, a cross-coupled FLRBFN control system shown in Fig. 1 is proposed. The four-layer neural network structure of the FLRBFN is shown in Fig. 2. Moreover, since the motions of the y1-axis and y2-axis are controlled separately, all the subscripts i are removed for simplicity in the following description.

1) Functional link neural network

To improve the accuracy of the function approximation, an FLNN is adopted to implement the function expansion for the proposed FLRBFN. In the function expansion of the FLNN, the basis functions such as trigonometric, Gaussian or other orthogonal polynomials are feasible. In this study, the trigonometric function is adopted since it forms a more compact representation than Gaussian function, and the sine and cosine functions can be computed more quickly. Therefore, for an input vector $\mathbf{X} = [x_1, x_2, x_3]^T$, the input variables can be separated in the enhanced space as $\Phi = [\phi_1, \phi_2, \dots, \phi_M]^T = [x_1, \cos(\pi x_1), \sin(\pi x_1), x_2, \cos(\pi x_2), \sin(\pi x_2), x_3, \cos(\pi x_3), \sin(\pi x_3)]^T$. Moreover, the output of the FLNN is given by a linear sum of the j th node as:

$$\hat{f}_j = \sum_M w_{Mj}^1 \phi_M(\mathbf{X}), \quad M = 1, 2, \dots, 9 \quad j = 1, 2, \dots, k \quad (16)$$

where k is the number of the output nodes of the FLNN; $\hat{f}_j$ is the output of the FLNN; w_{Mj}^1 is the connective weight; ϕ_M is the output of function expansion.

2) Structure of FLRBFN

The structure of the FLRBFN is a three-layer RBFN embedded with an FLNN, including the input layer (layer 1), the functional link (FL) layer (layer 2), the hidden layer (layer 3) and the output layer (layer 4). To give a clear understanding, the signal propagation and the basic function of each layer are introduced in the following:

Layer 1 (input layer):

In this layer, the node output is represented as

$$y_l^{(1)} = x_l^{(1)}, \quad l = 1, 2, 3 \quad (17)$$

where $x_l^{(1)}$ and $y_l^{(1)}$ are the input and output of the l th node in this layer. In this study, $x_1^{(1)}$, $x_2^{(1)}$ and $x_3^{(1)}$ are the cross-coupled position tracking error e^* , its integral $\int e^* d\tau$ and its derivative $\dot{e}^*$, respectively.

Layer 2 (FL layer):

In this layer, each node represents the outputs of the FLNN. The FLNN is designed to increase the dimensionality of the input variables and provide greater discrimination capability in the input variables space [7]. For the j th node

$$y_j^{(2)} = \hat{f}_j(y_l^{(1)}) \quad j = 1, 2, \dots, k \quad (18)$$

where $y_j^{(2)}$ is the output of the layer 2.

Layer 3 (hidden layer):

In this layer, the Gaussian function [8] is adopted as the receptive field function. The mathematical function of each node is

$$\Gamma_{jm}(y_j^{(2)}) = \exp\left[\frac{-(y_j^{(2)} - c_{jm})^2}{\sigma_{jm}^2}\right], \quad m = 1, 2, \dots, f \quad (19)$$

where f is the number of the hidden nodes; c_{jm} and σ_{jm} are the mean and standard derivation of the Gaussian function, respectively; $\Gamma_{jm}(y_j^{(2)})$ is the output of the receptive field function. Then, in this layer, the node output is represented as

$$y_m^{(3)} = \prod_{j=1}^k \Gamma_{jm}(y_j^{(2)}), \quad j = 1, 2, \dots, k, \quad m = 1, 2, \dots, f \quad (20)$$

where $y_m^{(3)}$ is the output of the layer 3.

Layer 4 (output layer):

In the output layer, the weighted sum method is used to calculate the output of the FLRBFN. Then, the node output becomes

$$y^{(4)} = i_q = \sum_{m=1}^f y_m^{(3)} w_m^2 \quad m = 1, 2, \dots, f \quad (21)$$

where w_m^2 is the connective weight between the hidden layer and the output layer; $y^{(4)}$ is the output of the FLRBFN as the trust command current.

3) On-line learning algorithms

To describe the on-line learning algorithms of the FLRBFN using gradient decent method, first the energy function E is defined as

$$E = \frac{1}{2} e^{*2} \quad (22)$$

Then, the learning algorithms of connective weights, means and standard derivations are described as follows:

Layer 4:

The error term to be propagated is given by

$$\delta^{(4)} = -\frac{\partial E}{\partial y^{(4)}} = -\frac{\partial E}{\partial d} \frac{\partial d}{\partial y^{(4)}} \quad (23)$$

and the connective weight is updated by the amount

$$\Delta w_m^2 = -\eta_1 \frac{\partial E}{\partial w_m^2} = -\eta_1 \frac{\partial E}{\partial y^{(4)}} \frac{\partial y^{(4)}}{\partial w_m^2} = \eta_1 \delta^{(4)} y_m^{(3)} \quad (24)$$

The connective weight w_m^2 is updated according to the following equation:

$$w_m^2(n+1) = w_m^2(n) + \Delta w_m^2 \quad (25)$$

where the factor η_1 is the learning rate of the connective weight.

Layer 3:

The error term propagated in this layer is derived as

$$\delta_m^{(3)} = -\frac{\partial E}{\partial y_m^{(3)}} = -\frac{\partial E}{\partial y^{(4)}} \frac{\partial y^{(4)}}{\partial y_m^{(3)}} = \delta^{(4)} w_m^2 \quad (26)$$

and the update law of c_{jm} is

$$\begin{aligned} \Delta c_{jm} &= -\eta_m \frac{\partial E}{\partial c_{jm}} = -\eta_m \frac{\partial E}{\partial y^{(4)}} \frac{\partial y^{(4)}}{\partial y_m^{(3)}} \frac{\partial y_m^{(3)}}{\partial c_{jm}} \\ &= 2\eta_m \delta_m^{(3)} \frac{(y_j^{(2)} - c_{jm})}{\sigma_{jm}^2} \prod_{j=1}^k \exp\left[\frac{-(y_j^{(2)} - c_{jm})^2}{\sigma_{jm}^2}\right] \end{aligned} \quad (27)$$

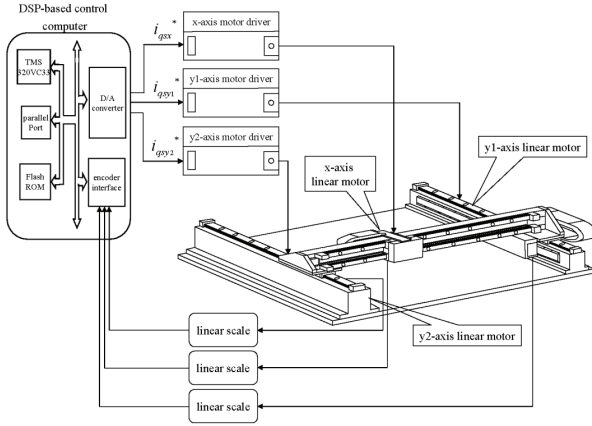


Figure 3. Block diagram of DSP-based control system.

where the factor η_m is the learning rate of the mean. The update law of σ_{jm} is

$$\begin{aligned} \Delta \sigma_{jm} &= -\eta_\sigma \frac{\partial E}{\partial c_{jm}} = -\eta_\sigma \frac{\partial E}{\partial y_j^{(4)}} \frac{\partial y_j^{(4)}}{\partial y_m^{(3)}} \frac{\partial y_m^{(3)}}{\partial \sigma_{jm}} \\ &= 2\eta_\sigma \delta_m^{(3)} \frac{(y_j^{(2)} - c_{jm})^2}{\sigma_{jm}^3} \prod_{j=1}^k \exp \left[\frac{-(y_j^{(2)} - c_{jm})^2}{\sigma_{jm}^2} \right] \end{aligned} \quad (28)$$

where the factor η_σ is the learning rate of the standard derivation. The mean c_{jm} and the standard derivation σ_{jm} of the Gaussian function are updated as follows:

$$c_{jm}(n+1) = c_{jm}(n) + \Delta c_{jm} \quad (29)$$

$$\sigma_{jm}(n+1) = \sigma_{jm}(n) + \Delta \sigma_{jm} \quad (30)$$

Layer 2:

The error term propagated in this layer is derived as

$$\begin{aligned} \delta_j^{(2)} &= -\frac{\partial E}{\partial y_j^{(2)}} = -\frac{\partial E}{\partial y_j^{(4)}} \frac{\partial y_j^{(4)}}{\partial y_m^{(3)}} \frac{\partial y_m^{(3)}}{\partial y_j^{(2)}} \\ &= \delta_m^{(3)} \frac{(-2)(y_j^{(2)} - c_{jm})^2}{\sigma_{jm}^2} \prod_{j=1}^k \exp \left[\frac{-(y_j^{(2)} - c_{jm})^2}{\sigma_{jm}^2} \right] \end{aligned} \quad (31)$$

According to (31), the connective weight is updated by the amount

$$\Delta w_{Mj}^1 = -\eta_2 \frac{\partial E}{\partial w_{Mj}^1} = -\eta_2 \frac{\partial E}{\partial y_j^{(4)}} \frac{\partial y_j^{(4)}}{\partial y_m^{(3)}} \frac{\partial y_m^{(3)}}{\partial y_j^{(2)}} \frac{\partial y_j^{(2)}}{\partial w_{Mj}^1} = \eta_2 \delta_j^{(2)} \phi_M \quad (32)$$

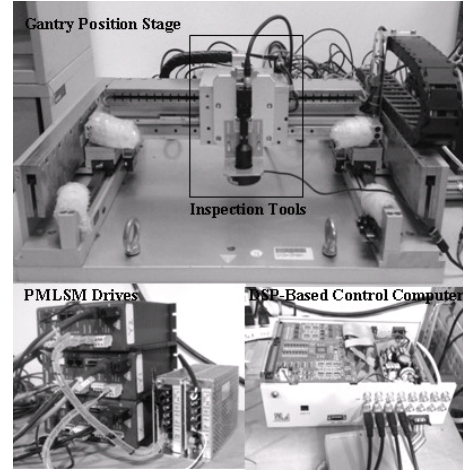


Figure 4. Photos of experimental setup.

TABLE I. EXPERIMENTAL CASES.

	reference trajectories				loads (add iron disk on the moving table)
	sinusoid		trapezoid		
	frequency	stroke	frequency	stroke	
Case 1	0.2Hz	$\pm 4mm$	0.2Hz	4mm	0kg
Case 2	0.6Hz	$\pm 6mm$	0.6Hz	6mm	7.32kg
Case 3	1Hz	$\pm 10mm$	1Hz	10mm	10kg

where the factor η_2 is the learning rate of the connective weight in layer 2. The connective weight w_{Mj}^1 is updated according to the following equation:

$$w_{Mj}^1(n+1) = w_{Mj}^1(n) + \Delta w_{Mj}^1 \quad (33)$$

The exact calculation of the Jacobian of the system, $\partial d / \partial y^{(4)}$, is difficult to be determined due to the unknown dynamics of the PMLSM servo drive system. In this study, a linear combination of the cross-coupled position tracking error and its first derivative is adopted to approximate the Jacobian of the system in order to simplify the on-line adaption laws of the FLRBFN in practical applications as follows:

$$\delta^{(4)} \cong e^* + \dot{e}^* \quad (34)$$

IV. EXPERIMENTAL RESULTS

The block diagram of the DSP-based computer control dual linear motors servo system is shown in Fig. 3. A TMS320VC33 floating-point DSP is the core of the control computer. The photos of the experimental setup including the dual linear motors servo system installed in the gantry position stage, the motor drives and the control computer using DSP are shown in Fig. 4. To investigate the effectiveness of the proposed DSP-based control system with different test signals, strokes and load conditions, three cases as shown in Table I are

considered. The experimental results of the tracking response, control effort and tracking error of the three test conditions are shown in Fig. 5 and Fig. 6, respectively. From the results, the excellent control performance of the proposed cross-coupled FLRBFN control system under the occurrence of parameter variations and different trajectories are obvious owing to on-line learning.

V. CONCLUSIONS

The major contributions of this study are: (i) the successful development of an on-line trained FLRBFN which combines the merits of FLNN and RBFN; (ii) the successful implementation the intelligent control approach and the cross-coupled technology in a control computer which is based on a 32-bit floating-point DSP, TMS320VC33; (iii) the successful application of the cross-coupled FLRBFN control system to dual linear motors servo system to track different reference trajectories with robust control performance.

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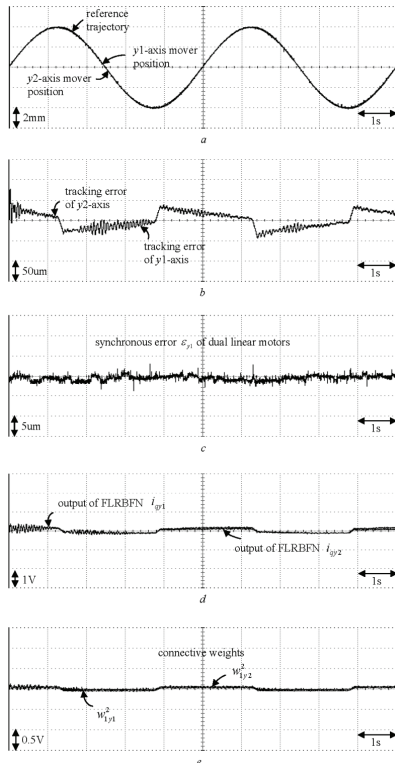


Figure 5. Experimental results of cross-coupled FLRBFN controller with for periodical sinusoidal reference trajectory: (a) Tracking responses of y1-axis and y2-axis at Case 1. (b) Tracking errors of y1-axis and y2-axis at Case 1. (c) Synchronous error of dual linear motors at Case 1. (d) Outputs of two FLRBFNs at Case 1. (e) Connective weights of two FLRBFNs at Case 1.

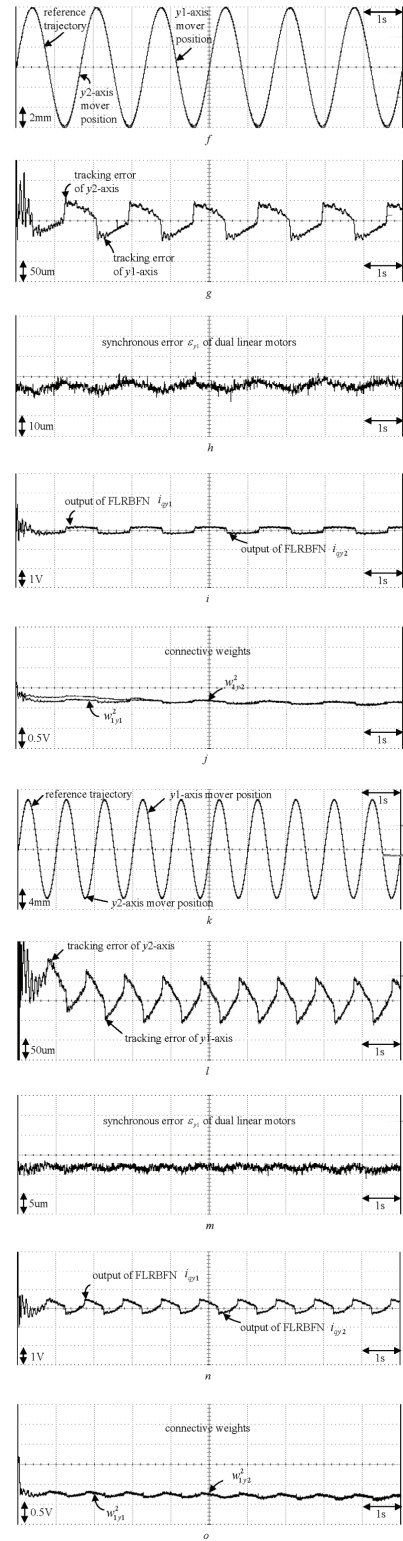


Figure 5. (Cont.) Experimental results of cross-coupled FLRBFN controller with for periodical sinusoidal reference trajectory: (f) Tracking responses of y1-axis and y2-axis at Case 2. (g) Tracking errors of y1-axis and y2-axis at Case 2. (h) Synchronous error of dual linear motors at Case 2. (i) Outputs of two FLRBFNs at Case 2. (j) Connective weights of two FLRBFNs at Case 2. (k) Tracking responses of y1-axis and y2-axis at Case 3. (l) Tracking errors of y1-axis and y2-axis at Case 3. (m) Synchronous error of dual linear motors at Case 3. (n) Outputs of two FLRBFNs at Case 3. (o) Connective weights of two FLRBFNs at Case 3.

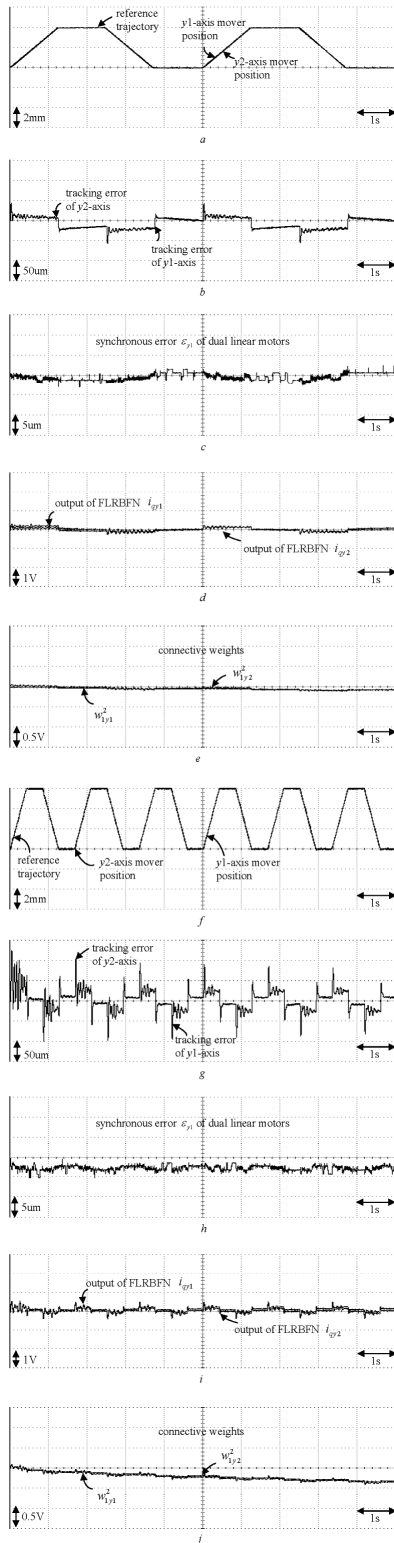


Figure 6. Experimental results of cross-coupled FLRBFN controller with for periodical trapezoidal reference trajectory: (a) Tracking responses of y1-axis and y2-axis at Case 1. (b) Tracking errors of y1-axis and y2-axis at Case 1. (c) Synchronous error of dual linear motors at Case 1. (d) Outputs of two FLRBFNs at Case 1. (e) Connective weights of two FLRBFNs at Case 1. (f) Tracking responses of y1-axis and y2-axis at Case 2. (g) Tracking errors of y1-axis and y2-axis at Case 2. (h) Synchronous error of dual linear motors at Case 2. (i) Outputs of two FLRBFNs at Case 2. (j) Connective weights of two FLRBFNs at Case 2.

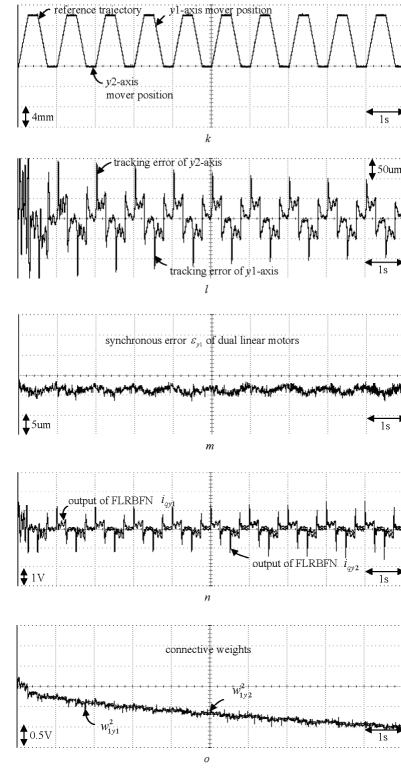


Figure 6. (Cont.) Experimental results of cross-coupled FLRBFN controller with for periodical trapezoidal reference trajectory: (k) Tracking responses of y1-axis and y2-axis at Case 3. (l) Tracking errors of y1-axis and y2-axis at Case 3. (m) Synchronous error of dual linear motors at Case 3. (n) Outputs of two FLRBFNs at Case 3. (o) Connective weights of two FLRBFNs at Case 3.

REFERENCES

- [1] O. Sawodnya, H. Aschemannb, and S. Lahres, "An automated gantry crane as a large workspace robot," *Control Engineering Practice*, vol. 10, pp. 1323-1338, 2002.
- [2] M. T. Yan, M. H. Lee, and P. L. Yen, "Theory and application of a combined self-tuning adaptive control and cross coupling control in a retrofit milling machine," *IEEE/ASME Trans. Mechatronics*, vol. 15, no. 2, pp. 193-211, 2005.
- [3] D. Sun, "Position synchronization of multiple motion axes with adaptive coupling control," *Automatica*, vol. 39, no. 3, pp. 997-1005, 2003.
- [4] T. L. Chien, C. C. Chen, Y. C. Huang, and W. J. Lin, "Stability and almost disturbance decoupling analysis of nonlinear system subject to feedback linearization and feedforward neural network controller," *IEEE Trans. Neural Networks*, vol. 19, no. 7, pp. 1220-1230, 2008.
- [5] J. S. R. Jang, C. T. Sun, and E. Mizutani, *Neuro-fuzzy and soft computing: a computational approach to learning and machine intelligence*, Prentice-Hall, NJ, 1997.
- [6] X. Hong, "Modified radial basis function neural network using output transformation," *IET Control Theory and Applications*, vol. 1, no. 1, pp. 1-8, 2007.
- [7] J. C. Patra and A. C. Kot, "Nonlinear dynamic system identification using Chebyshev functional link artificial neural networks," *IEEE Trans. Syst., Man, and Cybern. B*, vol. 32, no. 4, pp. 505-511, 2002.
- [8] F. J. Lin, P. H. Shen, P. H. Chou, and S. L. Yang, "TSK-type recurrent fuzzy network for DSP-based permanent magnet linear synchronous motor servo drive," *IEE Proc. Electric Power Application*, vol. 153, no. 6, pp. 921-931, 2006.