Neuro-Fuzzy Network Based Adaptive Tracking Controller for a Nonlinear System

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***Abstract*- In this paper, a neuro-fuzzy network-based adaptive tracking controller is suggested for controlling a type of nonlinear system. Where two neuro-fuzzy networks have been used to learn the system dynamics uncertainty bounds by using Lyapunov method. Then the output of these two networks are used to build a sliding mode controller. The stability of the control system is proved and stable neuro-fuzzy controller parameters adjustment laws are selected using Lyapunov theory. Simulation case study shows that the controlled system tracking the reference model effectively with smooth control effort and robust performance has been achieved.**

Index Terms- Neuro-Fuzzy network, Adaptive Control, Model Reference Control, Uncertain Dynamics, sliding mode controller.

I. Introduction

Neuro-fuzzy network presents a newly emerged class of hybrid intelligent system combining the important features of artificial neural network with main features of the fuzzy logic system. It is known that neither fuzzy reasoning nor neural network by themselves capable of solving problems involving at the same time the numerical and linguistic info together [1]. In many situation a problem can be solved more efficiently by using a combination of fuzzy logic and neural network rather than exclusively [2].

In the industrial application most of the mechanical system are subjected to structure or unstructured uncertainties. The structured uncertainty is due to the uncertainty in the dynamical model, while unstructured uncertainty is a related to the un-modeled dynamics. The neuro-fuzzy network ability to approximate the system dynamics through learning are widely used nowadays. However, stability and the error convergence have not proved totally for the off-learning [3].

An online learning ANFIS Based on RBF is suggested in [1], and an RBF neural network is used to indirectly learn the uncertain bounds of the system has been suggested in [4]. G. Mester [5] proposed a new form of neuro-fuzzy genetic controller to control rigid link flexible joint robot. J. K. Liu and F.C. Sun [6] proposed a global fuzzy logic sliding mode controller where the fuzzy controller are used to learn the unknown dynamics of the system then used to linearized the closed loop system.

In this paper, we suggested a neuro-fuzzy adaptive tracking control for a type of nonlinear system. Where combining the two technologies will have important capacities not found in each of them separately. Two neuro-fuzzy networks are designed to learn the upper and lower bounds of the dynamics uncertainty of the system through a compact set, then the outputs of these two networks are used to adaptively construct the sliding mode control law. Lyapunov theory used to derive the network learning laws and prove the system error convergence. To reduce the chattering (ringing) phenomena associated with the sliding mode control a modified control law is proposed and applied with significant results.

This paper is organized as follows. In Section II the mathematical model considered is described in details, then in Section III the neuro-fuzzy adaptive controller is developed together with a complete control structure and the learning algorithms for the parameters adaptation are selected. Section IV shows a simulation case study. Finally the features of the proposed controller are summarized and concluded in Section V.

II. System General Dynamics

A neuro-fuzzy network based robust adaptive tracking controller scheme will be designed for the following type of nonlinear system. The dynamic equation of the system can be described by:

$$x^{(n)}(t) = -f\left(x(t), \dot{x}(t), \dots\dots, x^{(n-1)}(t)\right) + b\left(x(t), \dot{x}(t), \dots\dots, x^{(n-1)}(t)\right)u(t) \qquad (1)$$

Where $x(t)$ is the output variable, and the superscript n on $x(t)$ signifies the order of differentiation, $u(t)$ is the system input. $f\left(x(t), \dot{x}(t), \dots\dots, x^{(n-1)}(t)\right)$ and $b\left(x(t), \dot{x}(t), \dots\dots, x^{(n-1)}(t)\right)$ are unknown nonlinear components of the system.

Equation (1) can be re-written as below:

$$\dot{\boldsymbol{x}} = A\boldsymbol{x} + Bu + F \qquad (2)$$

where

$$\boldsymbol{x} = \left[x(t), \dot{x}(t), \dots\dots, x^{(n-1)}(t)\right]^T$$

$$A = \begin{bmatrix} 0 \ 1 \ 0 \dots\dots 0 \\ \cdot \\ \quad \cdot \\ \quad\quad \cdot \\ \quad\quad\quad 1 \\ 0 \ 0 \dots\dots \quad 0 \end{bmatrix}$$

$$B = [0, \dots, b(\boldsymbol{x})]^T$$
$$F = [0, \dots, -f(\boldsymbol{x})]^T.$$

The reference model desired for the plant to follow is expressed by:

$$\dot{x}_r = A_r x_r + B_r\, r(t) \qquad (3)$$

where

$$x_r = [x_r(t), \dot{x}_r(t), \dots \dots, x_r^{(n-1)}(t)]^T$$

A_r and B_r are known constant matrices and $r(t)$ is the model reference input. The tracking error can be defined by

$$e(t) = x - x_r = [\varepsilon, \dot{\varepsilon}, \dots, \varepsilon^{(n-1)}]^T \qquad (4)$$

where

$$\varepsilon^{(j)} = x^{(j)} - x_r^{(j)}, \quad (j = 0, 1, \dots \dots (n-1))$$

Then the dynamics equation of the error can be written as:

$$\dot{e} = Ae + (A - A_r)\, x_r + F - B_r\, r + B\, u \qquad (5)$$

If we define the switching plan variable as [7]:

$$s = \Lambda\, e \qquad (6)$$

where $\Lambda = [\lambda_1, \lambda_2, \dots \dots \lambda_n]$ with Λ is chosen such that the eigenvalues of the switching plan polynomial are in the left half of the complex plan. Usually, $\Lambda\, e$ is called the sliding mode control variable [7].

III. Neuro-Fuzzy Network Controller Design

If we define $b_l(x)$ as a positive lower bound of $b(x)$ and $f_u(x)$ as a positive upper bound of $f(x)$ and both of them are unknown nonlinear functions then, we will use neuro-fuzzy networks to approximate their behavior. Then:

$$g_1(x) = 1/b_l(x) \qquad (7)$$

$$g_2(x) = f_u(x) \qquad (8)$$

And the following NF networks are used to approximate these bounds $g_1(x)$ and $g_2(x)$

$$\bar{g}_1(x, \hat{w}_1) = \hat{w}_1^T\, \phi(x) \qquad (9)$$

$$\bar{g}_2(x, \hat{w}_2) = \hat{w}_2^T\, \psi(x) \qquad (10)$$

With $\hat{w}_1 \in R^{N_1}$ and $\hat{w}_2 \in R^{N_2}$ are the interconnection weights vectors from rule to output layer, where N_1 and N_2 are number of the neurons in the rule layer of the first and second neuro-fuzzy networks respectively. $\phi(x) \in R^{N_1}$ and $\psi(x) \in R^{N_2}$ are the Gaussian type basis function defined by:

$$\phi_i(x) = \Pi_{j=1}^{M_1} \exp\left(\frac{(x_j - c_{1ij})^2}{2\sigma_{1ij}^2}\right) \qquad (11)$$

Where $i = 1,2 \dots N_1$ and $j = 1,2 \dots M_1$, with M_1 is number of inputs to the first neuro-fuzzy network.

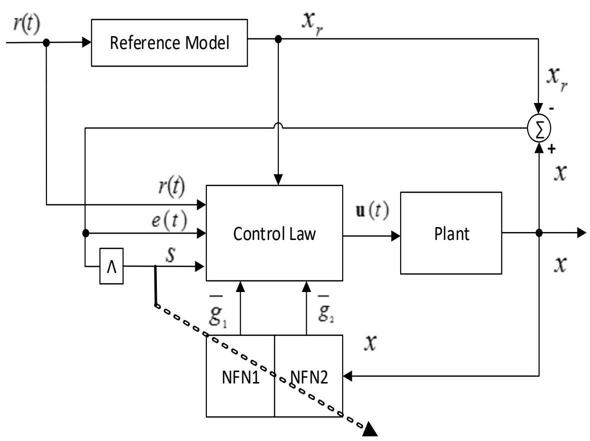

Fig. 1 Proposed Neuro-Fuzzy Based Adaptive Tracking Controller

$$\psi_i(x) = \Pi_{j=1}^{M_2} \exp\left(\frac{(x_j - c_{2ij})^2}{2\sigma_{2ij}^2}\right) \qquad (12)$$

Where $i = 1,2 \dots N_1$ and $j = 1,2 \dots \dots . n2$, with M_2 is number of inputs to the second neuro-fuzzy network.

Where c_1 and c_2 is the mean and σ_1 and σ_2 is the standard deviation of the Gaussian basis functions. The theoretical analysis of the Gaussian networks usually assumes that the basis function are evenly distributed on an n-dimensional lattice with the mean of a basis function located at every point on the lattice. In practical application there are many methods can be used to select the appropriate parameter of the basis function. One of them the unsupervised competitive clustering algorithm [8] which used for on-line adjustment of the mean and deviation of the Gaussian network.

The control input u and the learning equation of the neuro-fuzzy weight are selected using Lyapunov method to insure the error dynamics (5) asymptotically converge to zero, as below:

$$u = -\frac{sgn(s)}{\lambda_n}\left(\hat{w}_1^T\ \phi(x)\right)^2 [|CAe| + |C(A - A_r)x_r| + |CB_r r|] - sgn(s)\left(\hat{w}_1^T\ \phi(x)\, \hat{w}_2^T\ \psi(x)\right)$$
(13)

$$\dot{\hat{w}}_1 = \Gamma_1\, sgn(s)\, s\, \phi(x)\, [|CAe| + |C(A - A_r)x_r| + |CB_r r|]$$
(14)

$$\dot{\hat{w}}_2 = \Gamma_2\, sgn(s)\, s\, \lambda_n\, \psi(x) \qquad (15)$$

where

$$sgn(s) = \begin{cases} +1 & if\ s(t) \geq 0 \\ -1 & if\ s(t) < 0 \end{cases} \qquad (16)$$

The whole system is shown in Fig. 1. The learning rate Γ_1 and Γ_2 should be > 0. To prove the selected equations above the following Lyapunov function is defined as below [4]:

$$L = \frac{1}{2}s^2 + \frac{1}{2}\Gamma_1^{-1}\, \tilde{w}_1^T \tilde{w}_1 + \frac{1}{2}\Gamma_2^{-1}\, \tilde{w}_2^T \tilde{w}_2 \qquad (17)$$

where

$$\tilde{w}_1 = w_1^* - \hat{w}_1 \qquad (18)$$
$$\tilde{w}_2 = w_2^* - \hat{w}_2 \qquad (19)$$

where w_1^* and w_2^* are the optimal weights vectors. By differentiating Lyapunov function (17) with respect to time and using the suggested control law (13):

$$\begin{aligned} \dot{L} &= s\,\dot{s} - \Gamma_1^{-1}\,\tilde{w}_1^T \dot{\hat{w}}_1 - \Gamma_2^{-1}\,\tilde{w}_2^T \dot{\hat{w}}_2 \\ &= s[\,CAe + C(A - A_r)x_r + CF - CB_r r + CBu] \\ &\quad -\Gamma_1^{-1}\,\tilde{w}_1^T \dot{\hat{w}}_1 - \Gamma_2^{-1}\,\tilde{w}_2^T \dot{\hat{w}}_2 \\ &= -sgn(s)\ \ s\,b(x)\,[|CAe| + |C(A - A_r)x_r| + |CB_r r|] \\ &(\hat{w}_1^T\ \phi(x))^2 + sgn(s)\,s\,[|CAe| + |C(A-A_r)x_r| + |CB_r r|]\,\hat{w}_1^T\ \phi(x) \\ &\quad - sgn(s)\,s\,\lambda_n[b(x)\hat{w}_1^T\ \phi(x)\,\hat{w}_2^T\ \psi(x) - \hat{w}_2^T\ \psi(x)] + (s\,CAe + s\,C(A-A_r)x_r - s\,CB_r r) \\ &\quad - sgn(s)\,s\,[|CAe| + |C(A-A_r)x_r| + |CB_r r|]\,w_1^{*T}\ \phi(x) - [s\,\lambda_n\,f(x) + sgn(s)\,s\,\lambda_n\,w_2^{*T}\ \psi(x)] \end{aligned} \qquad (20)$$

For further analysis, it is assumed that for the two continuous functions $g_1(x)$ and $g_2(x)$ defined in (7) and (8) on a compact set, there exist two optimal weight vectors w_1^* and w_2^* such that:

$$|\varepsilon_1(x)| = |\bar{g}_1(x, w_1^*) - g_1(x)| < \delta_1 \qquad (21)$$
$$|\varepsilon_2(x)| = |\bar{g}_2(x, w_2^*) - g_2(x)| < \delta_2 \qquad (22)$$

Then, if we assume that the uncertainty bounds $b_l(x)$ and $f_u(x)$ meet the following inequalities on the compact set:

$$0 < b_l(x) < \frac{1}{1-\delta_1} \qquad (23)$$
$$f_u(x) - |f(x)| > \delta_2 \qquad (24)$$

Then (20) can be written as:

$$\begin{aligned} \dot{L} &= -b_l(x)\,|s|\,[(\hat{w}_1^T(0) - w_1^{*T})\,\phi(x) \\ &+ \Gamma_1\Big(\int_0^t (|CAe| + |C(A-A_r)x_r| + |CB_r\psi_r|)\,|s|\ \phi(x))\,dt\Big)\,\phi(x) - \delta_1][|CAe| + |C(A-A_r)x_r| + |CB_r r|]\,\hat{w}_1^T\ \phi(x) \\ &\quad - |s|(-b(x)\,\hat{w}_1^T\ \phi(x) + 1)\,|s|\ \lambda_n \hat{w}_2^T\ \psi(x) \\ &\quad - |s|\big(b_l^{-1}(x) - (1+\delta_1)\big)[|CAe| + |C(A-A_r)x_r| + |CB_r r|] - |s|\ \lambda_n[\varepsilon_2(x) + \delta_2] \end{aligned} \qquad (25)$$

So $\dot{L} < 0$ according to Lyapunov stability theory (25) means that the error metric equation $s = \Lambda\,e$ converge to zero in finite time.

IV. Simulation Case Study

To show the effectiveness of the proposed neuro-fuzzy network controller, a single link rigid robot arm is used in the simulation. The dynamic model of the arm can be written as below:

$$m\,l^2\,\ddot{q} + d\,\dot{q} + m\,l\,g\cos q = u \qquad (26)$$

Where l is the link length, m is the mass, q is the angular position. (26) can be written in matrix form as

$$\dot{x} = Ax + Bu + F$$

where

$$x = [q \ \ \dot{q}]^T$$

$$A = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}$$

$$B = \begin{bmatrix} 0 \\ (m\,l)^{-1} \end{bmatrix}$$

$$F = \begin{bmatrix} 0 \\ -(m\,l)^2 d\,\dot{q} - \ l^{-1} g\cos q \end{bmatrix}$$

The reference model will be selected such that

$$\ddot{q}_r + 8\,\dot{q}_r + 16\,q_r = r(t) \qquad (27)$$

The error metric vector $\Lambda = [10 \ \ 1]$

The initial output weight vectors:

$\hat{w}_1(0) = \hat{w}_2(0) = 0.5$

Five Gaussian membership functions are evenly distributed with the following parameters for the neuro-fuzzy networks:

$c_1 = c_2 = [i\,, i]^T$ where $i = -2\ -1\ 0\ 1\ 2$

$\sigma_1 = \sigma_2 = 0.77$

The selected learning rate $\Gamma_1 = \Gamma_2 = 0.1$

All the initial values of the system and the reference model are set to zero.

Simulation result for the system with the proposed controller are as follows where Fig. (2) (a) – (c) show a good result for angular position tracking a sinusoidal input, the tracking error and the control input generated by the controller respectively, while Fig. 3 (a) – (c) show the results for a square wave input. It can be seen that the control input is not smooth due to chattering because of the existence of the sign function in the control law. Many approaches are suggested to reduce the chattering [9] proposes chattering reduction by low-pass filtering the control signal, while [10] suggests a sliding mode controller using uncertainty and disturbance estimator to reduce the chattering. In this paper a boundary layer around the switching surface is used, where a continuous control is applied within the boundary [11] [12], the chattering in the control input can be removed by replacing the $sgn(s)$ term in the control law by $sat(s, \mu)$ where

$$sat(s,\mu) = \begin{cases} \frac{s(t)}{\mu} & if\ |s(t)| < \mu \\ s(t) & otherwise \end{cases} \qquad (28)$$

where μ is the boundary layer thickness which is a positive number.

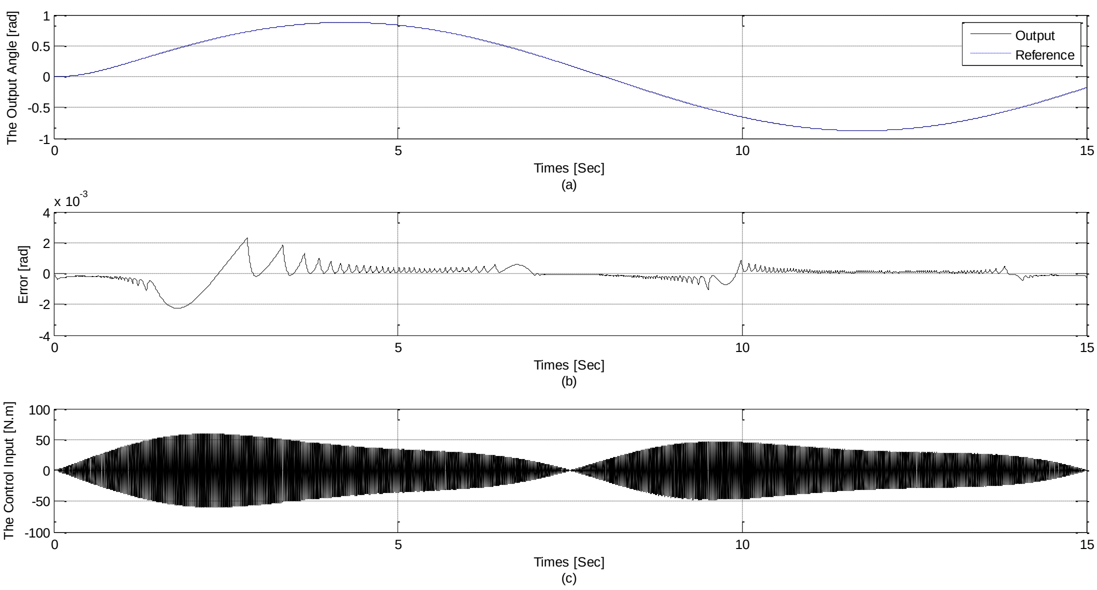

Fig. (2) (a) The angular position of the robot manipulator. (b) The output tracking error. (c) The control input signal.

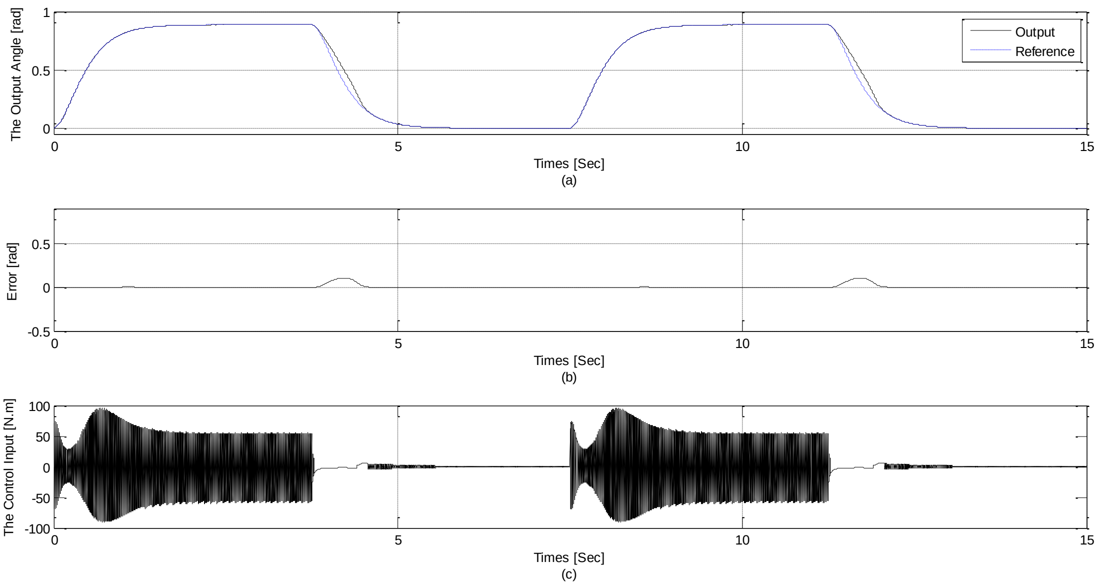

Fig. (3) (a) The angular position of the robot manipulator. (b) The output tracking error. (c) The control input signal.

Fig. 4 (a) – (c) and Fig. 5 (a) – (c) show the result of the simulation after using the boundary layer technique around the switching surface to reduce the chattering in the controller output, which is successfully smoothed the control signal.

III. Conclusion

The neuro-fuzzy networks based adaptive tracking controller designed in this paper has been simulated for a rigid robot manipulator and shown a good performance for different tracking signals. Two neuro-fuzzy networks successfully designed and learned the uncertainty bound in the system and then adaptively change the controller output. Including Lyapunov stability theory in the design of neuro-fuzzy networks learning algorithms enables the use of the proposed control law to ensure stability and robustness of the controlled system. To reduce the chattering in the control signal a modified control law based on boundary layer technique has been used and good ringing free control signal are gotten.

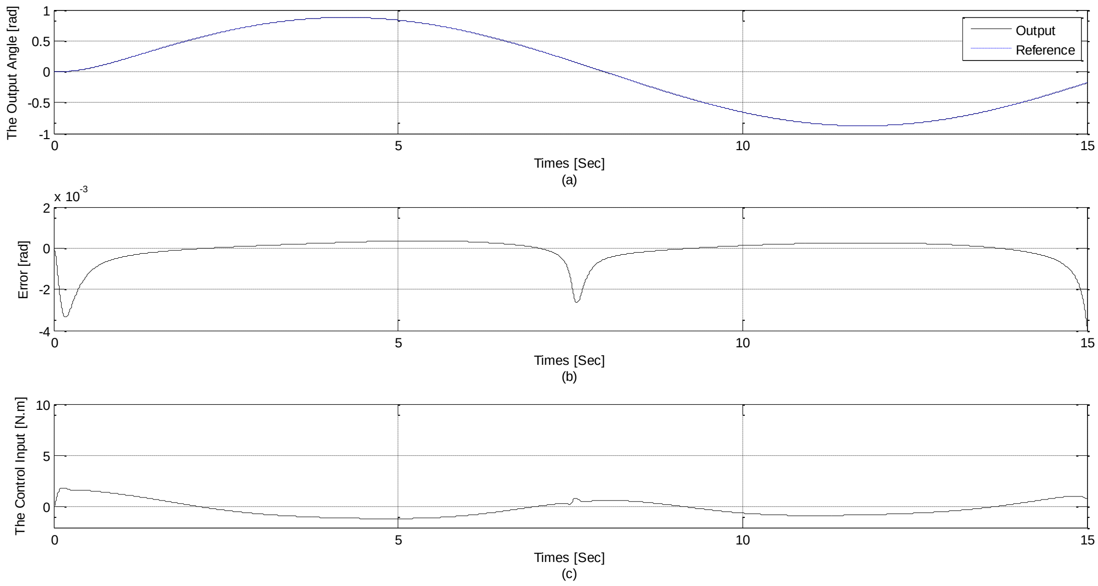

Fig. (4) (a) The angular position of the robot manipulator. (b) The output tracking error. (c) The control input signal.

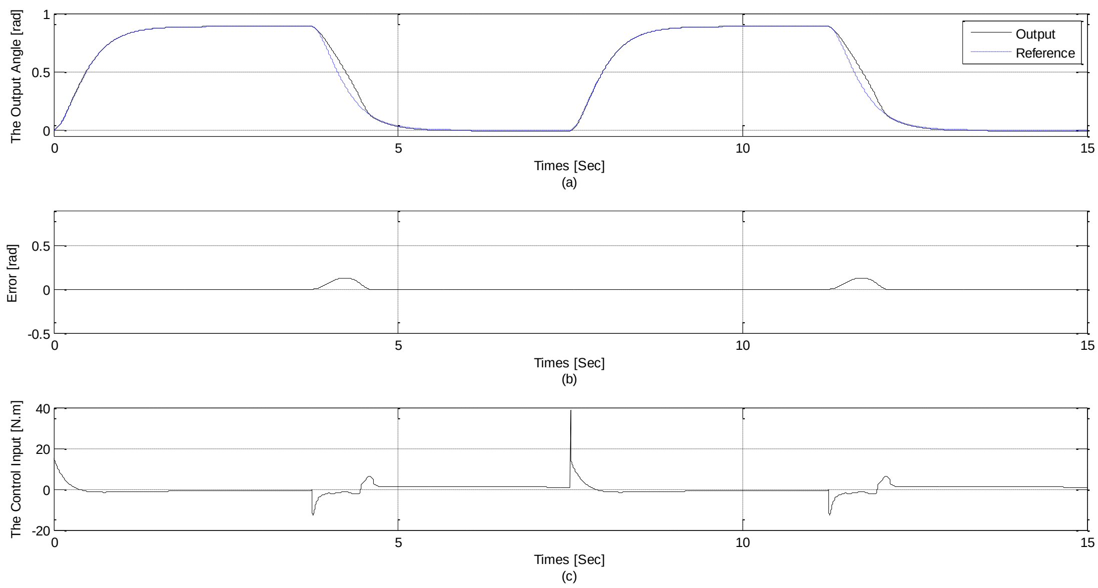

Fig. (5) (a) The angular position of the robot manipulator. (b) The output tracking error. (c) The control input signal.

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