NEUROFUZZY CONTROL STRUCTURE FOR A ROBOT MANIPULATOR

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Abstract

In this paper a neurofuzzy control structure is presented and used for controlling the two-link robot manipulator. A neurofuzzy networks are constructed for both the controller and for identification model of robot manipulator.

The performance of the proposed structure is studied by simulation. Different operating conditions are considered. Results of simulation show good performance for the proposed control structure .

السيطرة على معالجات الروبوت باستخدام الشبكات العصبية المضببة

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الـخلاصة :
فـي هـذا البحـث استخدمت تقنيـة الشبكات العصبية الضبابية للسيطرة علـى حركـة معالجـات الإنسـان الآلـي (الروبوت).تم تصميم شبكة عصبية ضبابية لكل من المسيطر و المعرف(Identifier).

تم دراسة أداء التركيب المقترح لمنظومة التحكم باستخدام الحاسبة بأخذ حالات عمل مختلفة.وقد لوحظ بان تلك المنظومة هي منظومة كفوئة للسيطرة على معالجات الإنسان الآلي.

1. Introduction:

The motion of the end-effector of robot manipulator is affected by nonlinearities in the dynamics, unknown load variations, and physical nonlinearities such as friction, backlash, and unknown of un-modeled parameter variations[1].Motion control of a robot manipulator requires a mapping between the Cartesian coordinates in which the robot manipulator is controlled[2].It is therefore necessary to design robust controller for a robot manipulator to ensure that its end-effector tracks a given trajectory in Cartesian space in the presence of such nonlinearities and un-modeled dynamics. To control the motion of the end-effector in Cartesian space ,it is necessary to obtain measurement of the end-effector motion.

Adaptive control techniques have been proposed to cope with dynamic uncertainty [1]. An advantage of this approach is that the controller performance improves with time, while, disadvantage it requires complicated structure, due to the complexity of the adaptation mechanism [3].

Another approach for the control of robot manipulator is the use of variable structure control (VSC) theory [4]. In [5] a two cascaded control loops, in the inner loop, internal model control (IMC) is adopted for perturbation rejection, for the outer loop, variable structure controller providing accurate tracking of motion trajectory.

In this paper, a neurofuzzy control structure is proposed for trajectory tracking of a two link robot manipulator .Two neurofuzzy network are designed, one for the forward model identifier, and the other for the controller. A simulation result illustrates that the proposed structure shows good performance under different operation condition.

2. Mathematical model of robot manipulator:

The dynamic equation of motion of robot derived manipulator from the Lagrangian equation [6]

$$L(q,\dot{q}) = T(q,\dot{q}) - G(q) \qquad ...(1)$$

where:

$T(q,\dot{q})$ is the kinetic energy of the manipulator structure , given as:

$$T(q,\dot{q}) = \frac{1}{2}\dot{q}^T M(q)\dot{q} \qquad ...(2)$$

and q is (nx1) vector of generalized joint coordinates , M(q) is the (nxn) inertial matrix , G(q) is the (nx1) vector of gravity forces .

$$\frac{d}{dt}\frac{\partial L}{\partial \dot{q}_i} - \frac{\partial L}{\partial q_i} = f_i \qquad i = 1,2,\dots,n \qquad ...(3)$$

Where n is number of rigid bodies, f_i the generalized force performing on q, $f=(u_1, u_2, \dots, u_n)^T$
and u_i denotes the external torque supplied by the motor at joint i.

Computing the derivative needed in (3) leads to the set of n second order nonlinear differential equation of the form

$$M(q)\ddot{q} + B(q,\dot{q})\dot{q} + G(q) = u \quad ...(4)$$

where $B(q,\dot{q})\dot{q}$ is (nx1) vector of coriolis and centrifugal forces terms.

$$B(q,\dot{q})\dot{q} = \dot{M}(q)\dot{q} - \frac{1}{2}\left(\frac{\partial}{\partial q}(\dot{q}^T H(q)\dot{q})\right)^T \quad ...(5)$$

The dynamic model of the manipulator in eq.(4) has the property that the inertial matrix M(q) is symmetric and positive definite [3].

In this paper, a neurofuzzy control structure is proposed for trajectory tracking of robot manipulator.

3.Neurofuzzy structure:

Fuzzy logic and neural networks have been combined in a variety of ways .In general, hybrid systems of fuzzy logic and neural networks are often referred to as neurofuzzy networks [7]. Neurofuzzy system have been widely used in control systems, pattern recognition, medicine, Expert systems ...etc. [8]. The best well known defuzzification method, is the center of area method which can be given as[7]:

$$y_k = \sum_{i=1}^{m}\left(\prod_{j=1}^{n} F_{ij}\right).w_{ik} \quad ...(6)$$

where :

y_k is the kth output

n is the number of inputs

m is the number of membership functions for each input

w_{ik} is the weight between node i and k

F_{ij} is the membership functions , terms

$F_{ij}=f(a_{ij},b_{ij})$.

The membership function is selected to be the gaussian function:

$$F_{ij} = Exp\left(-\frac{1}{2}\left(\frac{x_j - a_{ij}}{b_{ij}}\right)\right)^2 \quad ...(7)$$

Figure(1) shows the Gaussian function for different values for a_{ij} and b_{ij}=0.2.

Figure (2)shows the neurofuzzy structure.

4.Neurofuzzy control structure:

The neurofuzzy controller is a combination of a fuzzy logic controller and a neural network, which makes the controller self tuning and adaptive .The neurofuzzy controllers are attracting more and more interest since they are more efficient and powerful than either neural networks or fuzzy systems.

Figure (3) shows the plant with controller, where the controller generate a control signal that make the output of the plant tracking the desired trajectory, the controller will be trained and then it is connected to this structure.

4.1 Model Identification:

The problem of identification consists of setting up a suitably parameters to optimize performance function based on the error between the plant outputs and the identifier outputs .It will be trained by using back propagation algorithm. Training process stops when the error is sufficiently small.

Figure (4) shows the forward identifier structure . The equations that used to update the weights and parameters of

Gaussian function (i.e: a_{ij} and b_{ij}) are listed below:

$$w_{i1}(k+1) = w_{i1}(k) + \eta_{w1} e_1 u_i \quad ....(8)$$

$$w_{i2}(k+1) = w_{i2}(k) + \eta_{w2} e_2 u_i \quad ...(9)$$

$$a_{ij}(k+1) = a_{ij}(k) + \eta_{a1}(e_1 w_{i1}(k+1) + e_2 w_{i2}(k+1))u_i (x_j - a_{ij}(k))/(b_{ij}(k))^2 \quad ...(10)$$

$$b_{ij}(k+1) = b_{ij}(k) + \eta_{b1}(e_1 w_{i1}(k+1) + e_2 w_{i2}(k+1))u_i (x_j - a_{ij}(k+1))^2/(b_{ij}(k))^3 \quad ...(11)$$

where:

$e_1 = q_1 - p_1$

$e_2 = q_2 - p_2$

p_1 and p_2 are outputs of the forward identifier model, q_1 and q_2 are the outputs of plant,

$u_i = F_{i1}.F_{i2}. ... .F_{in}$

n is the number of input ,

$\eta_{w1}, \eta_{w2}, \eta_{a1}$ and η_{b1} are learning rates.

4.2.Neurofuzzy control structure for trajectory tracking of robot manipulator:

Since the robot manipulator compose of two link , so that the controller can be proposed as two controller one for each link(decoupled controller) or as one controller for both link (coupled controller) ,by experiment the coupled controller is best than decoupled controller.

Figure (5) shows the control structure for training of the coupled controller for robot manipulator . In this figure the purpose of the identifier is to be used as a path for the output error propagation to the neurofuzzy controller. This controller will be trained by using back propagation algorithm .The error between the outputs of plant (q) and desired trajectory (q_d) will be minimized during training phase.

The training process stops when the error is small.

The equations that were used to update the weights of controller and the parameter of Gaussian function are listed below:

$$w_{r1}(k+1) = w_{r1}(k) - \eta_{w3}(e_3 d_1 + e_4 d_2)u_r \quad ...(12)$$

$$w_{r2}(k+1) = w_{r2}(k) - \eta_{w4}(e_3 d_3 + e_4 d_4)u_r \quad ...(13)$$

$$a_{rs}(k+1) = a_{rs}(k) - \eta_{a2}(e_3(d_1 w_{r1}(k+1) + d_3 w_{r2}(k+1)) + e_4(d_2 w_{r1}(k+1) + d_4 w_{r2}(k+1))u_r (x_s - a_{rs}(k))/(b_{rs}(k))^2 \quad ...(14)$$

$$b_{rs}(k+1) = b_{rs}(k) - \eta_{b2}(e_3(d_1 w_{r1}(k+1) + d_3 w_{r2}(k+1)) + e_4(d_2 w_{r1}(k+1) + d_4 w_{r2}(k+1)) u_r (x_s - a_{rs}(k+1))^2/(b_{rs}(k))^3 \quad ...(15)$$

where:

$r=1,2,\ldots,v$; $s=1,2,\ldots,c$

c is the number of input of the controller ; v is the number of membership functions in the controller structure ,and $d_1=\partial q_1/\partial u_1$; $d_2=\partial q_2/\partial u_1$; $d_3=\partial q_1/\partial u_2$ and $d_4=\partial q_2/\partial u_2$

$u_r=F_{r1}.F_{r2}....F_{rc}$

$e_3=q_{1d}-q_1$; $e_4=q_{2d}-q_2$

$\eta_{w3}, \eta_{w4}, \eta_{a2}$ and η_{b2} are learning rates.

5.Simulation result:

A two-link manipulator is shown in fig.(5) . The dynamic is given by

$$\begin{bmatrix} M_{11} & M_{12} \\ M_{21} & M_{22} \end{bmatrix}\begin{bmatrix} \ddot{q}_1 \\ \ddot{q}_2 \end{bmatrix}+\begin{bmatrix} B_{11} & B_{12} \\ B_{21} & B_{22} \end{bmatrix}\begin{bmatrix} \dot{q}_1 \\ \dot{q}_2 \end{bmatrix}+\begin{bmatrix} G_1 \\ G_2 \end{bmatrix}=\begin{bmatrix} T_1 \\ T_2 \end{bmatrix} \quad ...(16)$$

$$\mathbf{M_{11} = (m_1 + m_2)l_1^2 + m_2 l_2^2 + 2m_2 l_1 l_2 \cos(q_2) + J_1}$$

$$\mathbf{M_{12} = M_{21} = m_2 l_2^2 + m_2 l_1 l_2 \cos(q_2)}$$

$$\mathbf{M_{22} = m_2 l_2^2 + J_2}$$

$$\mathbf{B_{11} = -2m_2 l_1 l_2 \dot{q}_2 \sin(q_2)}$$

$$\mathbf{B_{12} = -m_2 l_1 l_2 \dot{q}_2 \sin(q_2)}$$

$$\mathbf{B_{21} = m_2 l_1 l_2 \dot{q}_1 \sin(q_2)}$$

$$\mathbf{B_{22} = 0}$$

$$\mathbf{G_1 = ((m_1 + m_2)l_1 \cos(q_1) + m_2 l_2 \cos(q_1 + q_2))g}$$

$$\mathbf{G_2 = (m_2 l_2 \cos(q_1 + q_2))g}$$

The parameter values are

l_1=1m length of upper link.

l_2=0.8m length of lower link.

m_1=0.5kg mass of upper arm.

m_2=0.5kg mass of lower arm.

$\begin{bmatrix} J_1 & 0 \\ 0 & J_2 \end{bmatrix}=\begin{bmatrix} 5 & 0 \\ 0 & 5 \end{bmatrix}$, the inertia of the two joints.

The robot is idle at q_1=-1.57 rad and q_2=2.967 rad and it is required to track the trajectory ,for t≤2.5 sec

$$\mathbf{qd1(t) = -1.57 + 0.916(1 - \cos(1.26t))} \quad \mathbf{rad}$$

$$\mathbf{qd2(t) = 2.967 - 1.049(1 - \cos(1.26t))} \quad \mathbf{rad}$$

for t>2.5 sec

$$\mathbf{qd1(t) = 0.2618} \quad \mathbf{rad}$$

$$\mathbf{qd2(t) = 0.87269} \quad \mathbf{rad}$$

The simulation is conducted by means of the 4th order Runge-Kutta method. Neurofuzzy identification model is constructed as shown in fig.(4).It has six inputs(q_1(k-1),q_1(k-2),q_2(k-1), q_2(k-2),u_1(k-1),u_2(k-1)) and two outputs(p_1(k),p_2(k)) .Training is performed using back propagation method.

Figure (7) shows the output of plant and output of identifier for first and second iteration (where s denoted the number of iterations). Figure(8) shows the output of plant and output of identifier for last two iterations . Figure (9)shows the performance measure of error for both links(calculate from eq. (17) against the number of iteration. Figure(10) and Fig.(11) show the tracking error for first link and second link respectively against the time for various iterations.

Neurofuzzy controller is constructed as shown in Fig.(5) . It has six inputs (q_1(k-1),q_1(k-2),q_2(k-1),q_2(k-2),q_1d(k),q_2d(k)) and two outputs(u_1(k),u_2(k)).

Figs.(12,13)show the output of plant and the desired trajectory for various iterations . Figure (14) shows the performance measure of error for both links(calculate from eq. (17)) against the number of iteration .

Figure(15) and Fig.(16) show the tracking error for first link and second link respectively against the time for various iterations.

. Simulation is performed for different values of mass of lower arm (m_2). Table (1) shows the mean squared error (MSE) at changing the values of m_2. Performance measure MSE is evaluated by using

$$e_m = \frac{1}{N}\sum_{k=1}^{N} e_k^2 \quad ...(17)$$

where k denotes the step number of the numerical integration and N is the total number of steps.
From this table it was concluded that the proposed controller structure is robust, since it is not affected by changing of operating condition.

6.conclusion:

A neurofuzzy control structure for trajectory tracking of robot manipulator, is proposed .The designed structure is tested by simulation of a two link robot manipulator. Results of simulation reveals that the proposed structure has good tracking capabilities for different operating conditions.

7.References:

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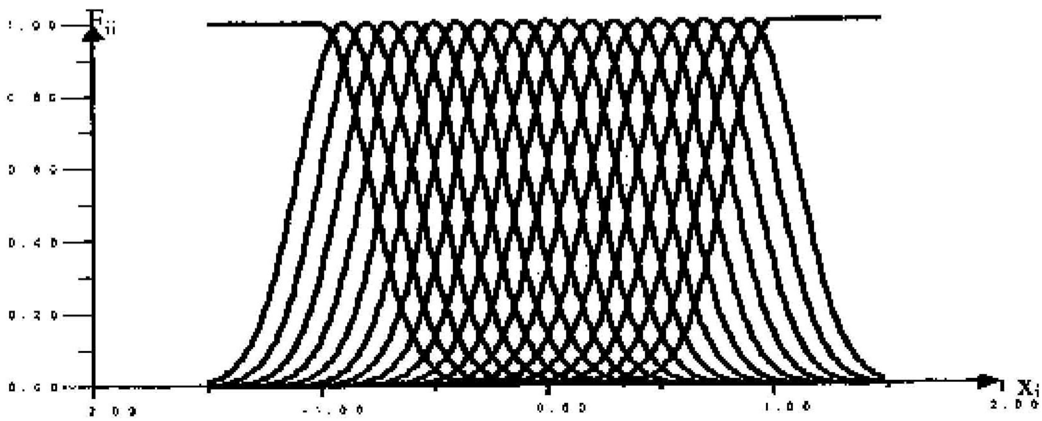


Fig.(1) Gaussian function for different values of a_{ij} at b_{ij}=0.2

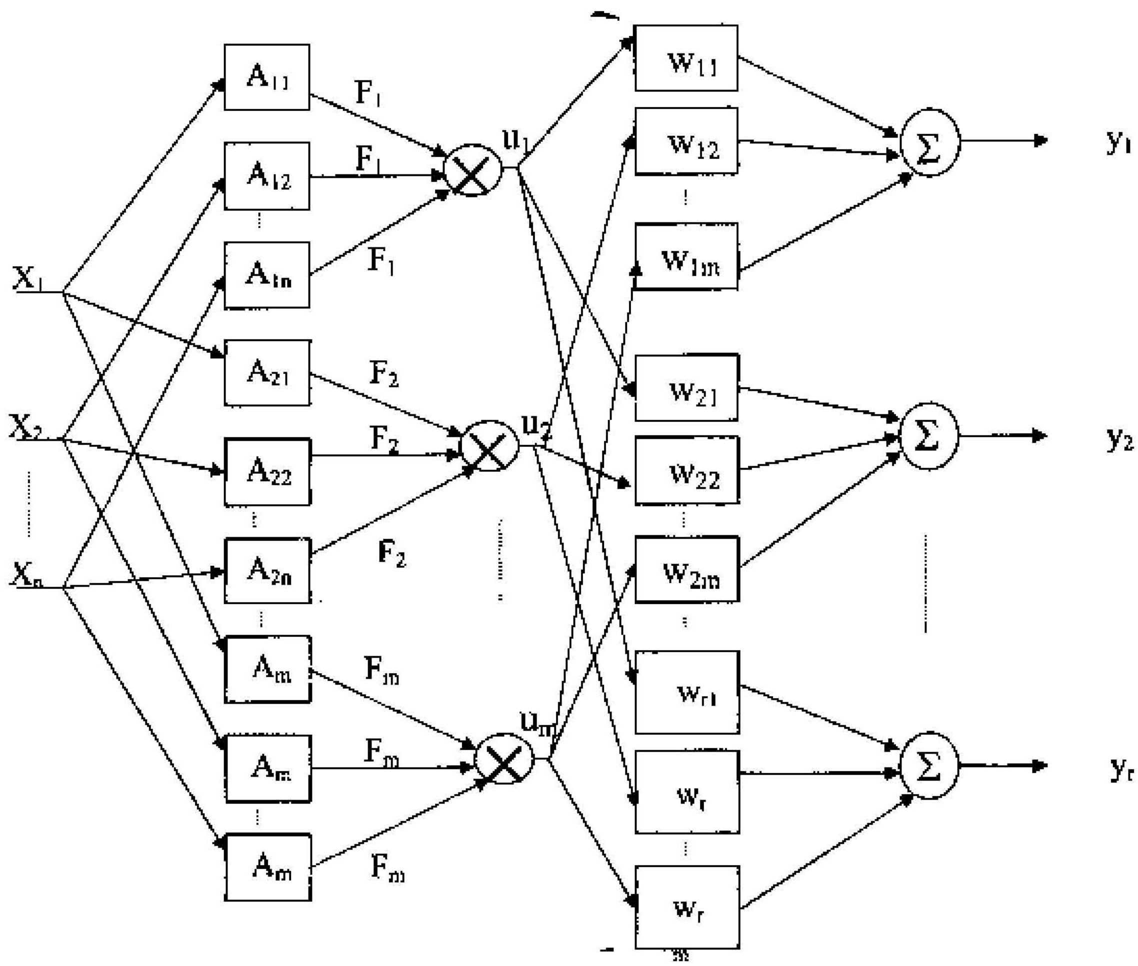


Fig.(2) The Structure of Neurofuzzy Network

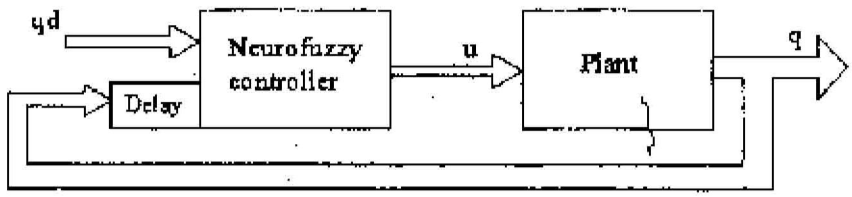


Fig.(3) plant with controller structure

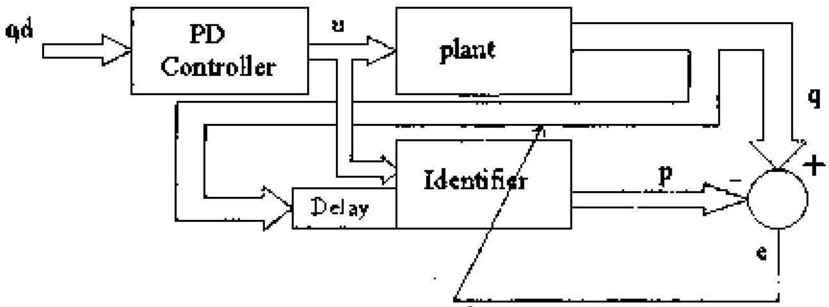


Fig.(4) Forward Identifier structure

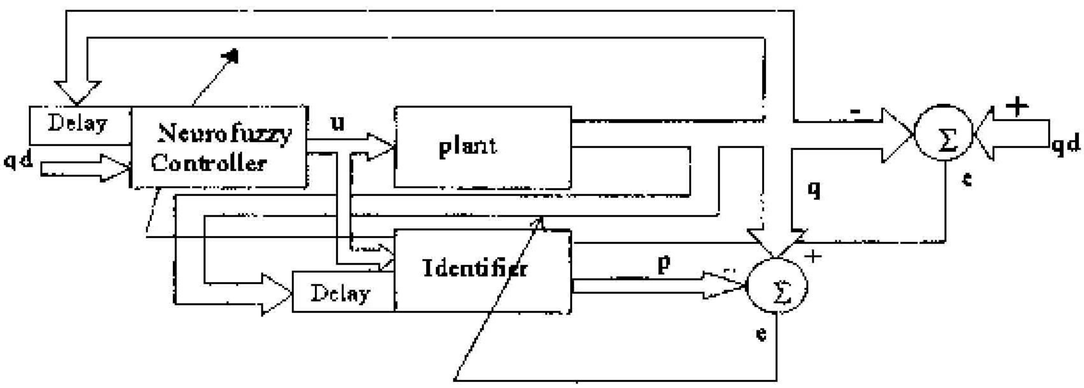


Fig.(5) The coupled controller structure

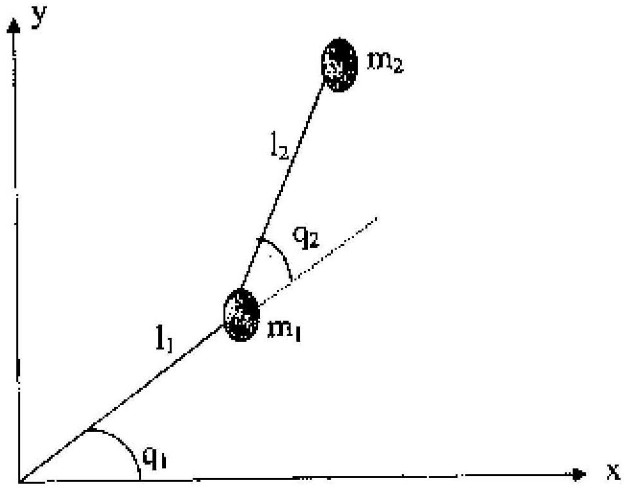
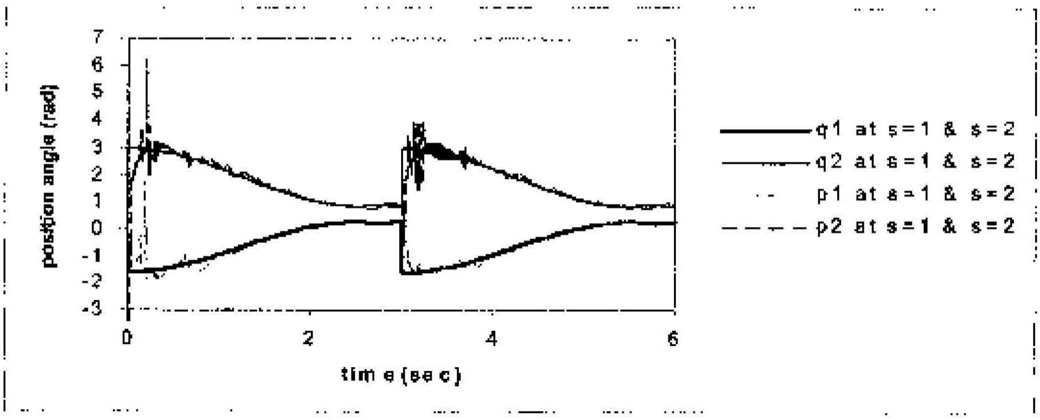


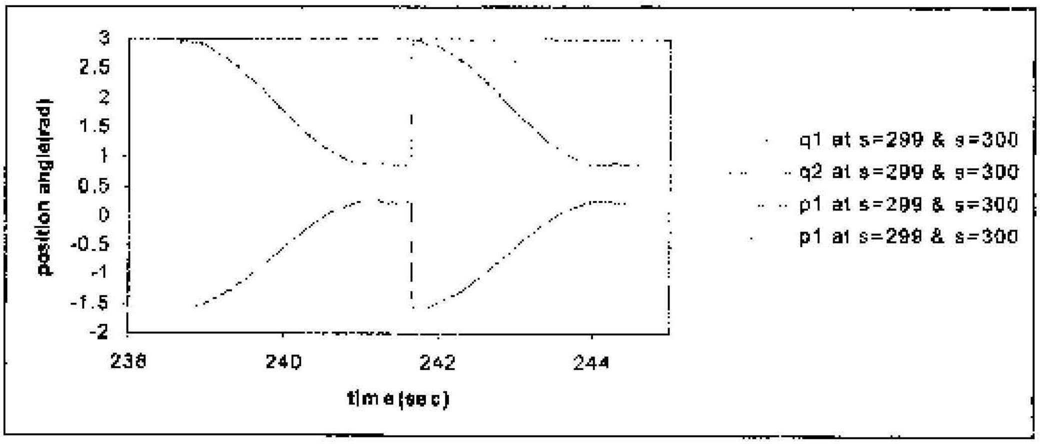
Fig.(6) A two-link robot manipulator

	m_2=0.5	m_2=2.5	m_2=4.5	m_2=6.5
First link	5.1×10^{-5}	1.6×10^{-4}	4.7×10^{-4}	6.6×10^{-4}
Second link	7.8×10^{-5}	1.7×10^{-4}	4.6×10^{-4}	6.9×10^{-4}

Table (1) Mean squared error for both link of robot manipulator



Fig(7) Output of plant and output of identifier for first and second



Fig(8) Output of plant and output of identifier for last two iteration

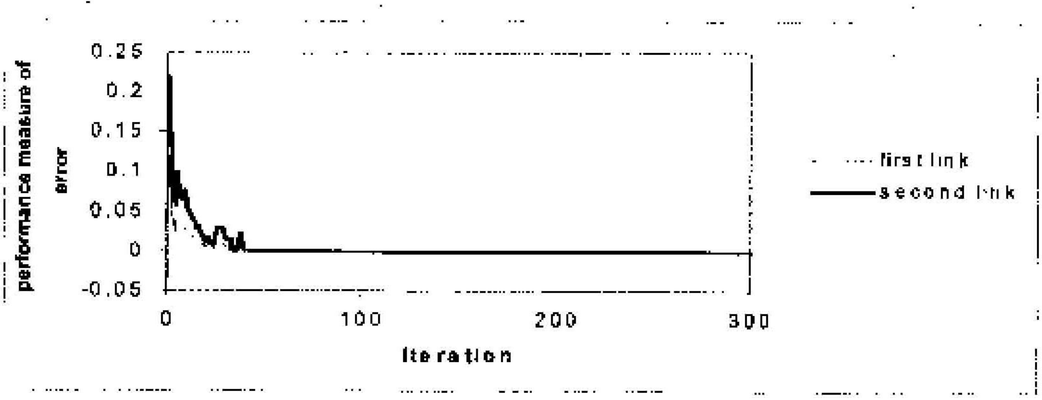


Fig.(9) performance measure of error for both links

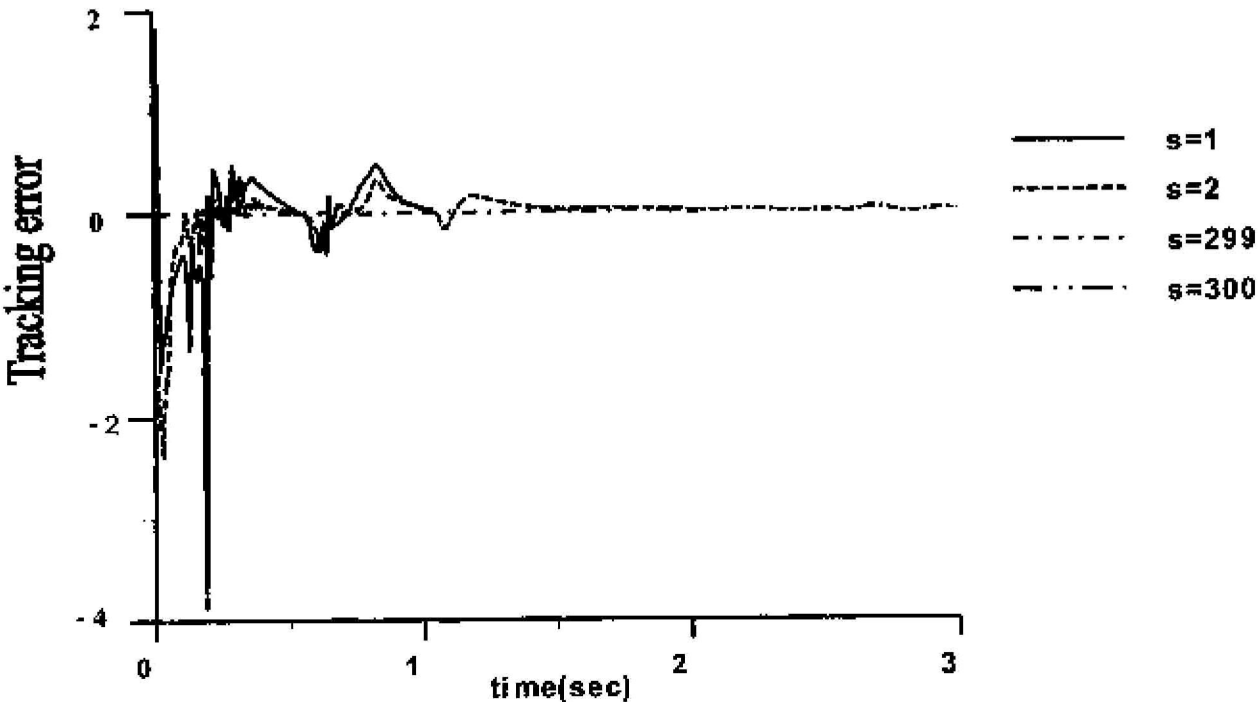


Fig.(10) Tracking error in identification for first link

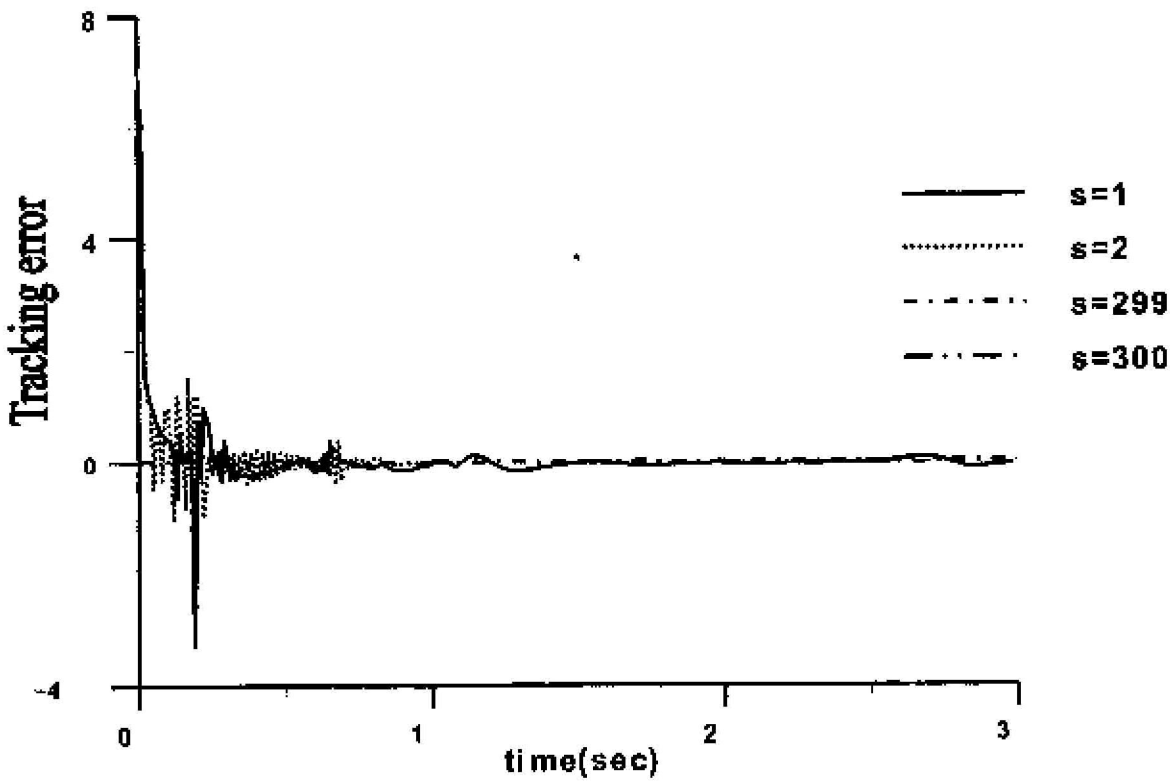


Fig.(11) Tracking error in identification for second link

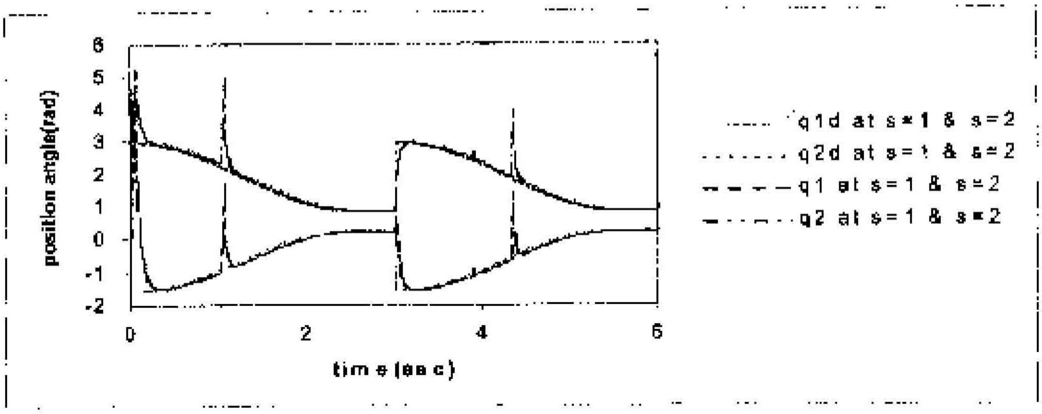


Fig.(12) Desired trajectory and output of plant for s=1 & s=2

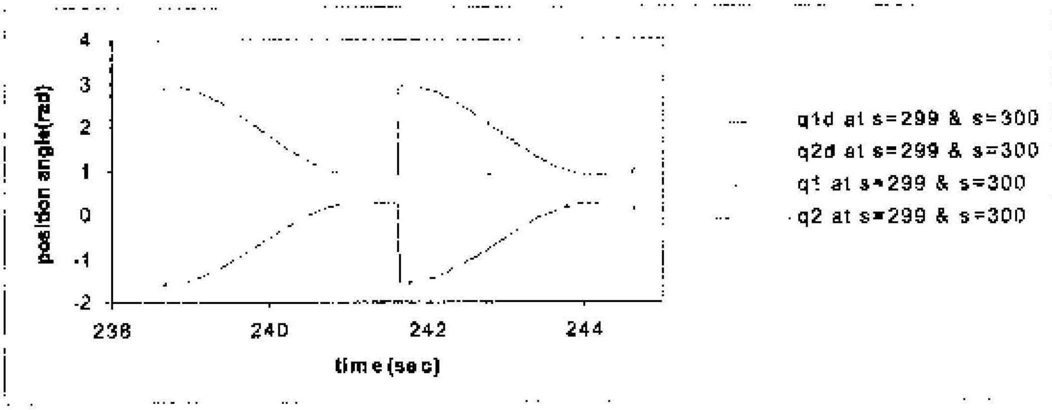


Fig.(13) Desired trajectory and output of plant for s=299 & s=300

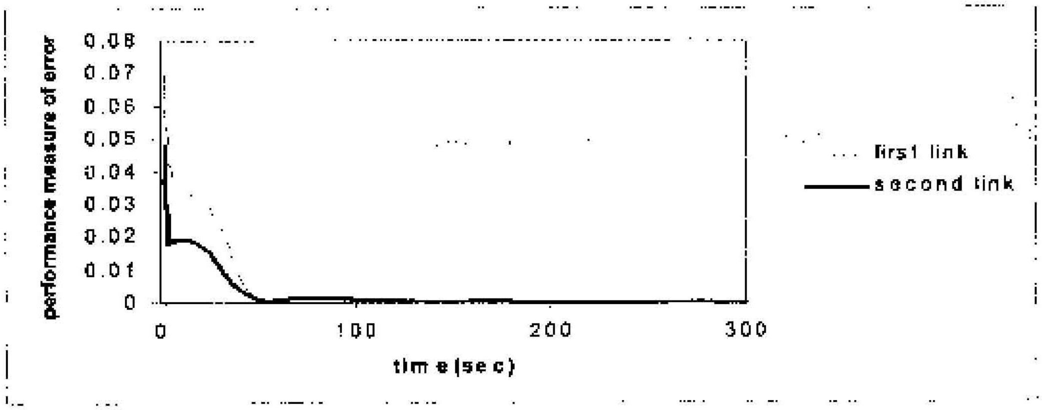
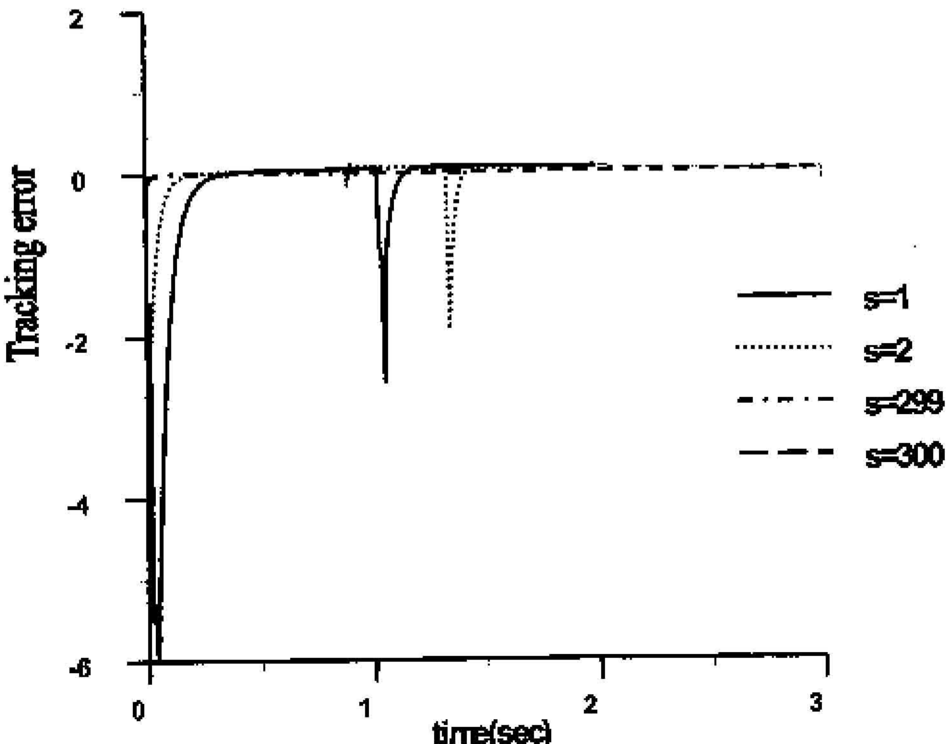


Fig.(14) Performance measure of error for both link



Fig(15) Tracking error for first link

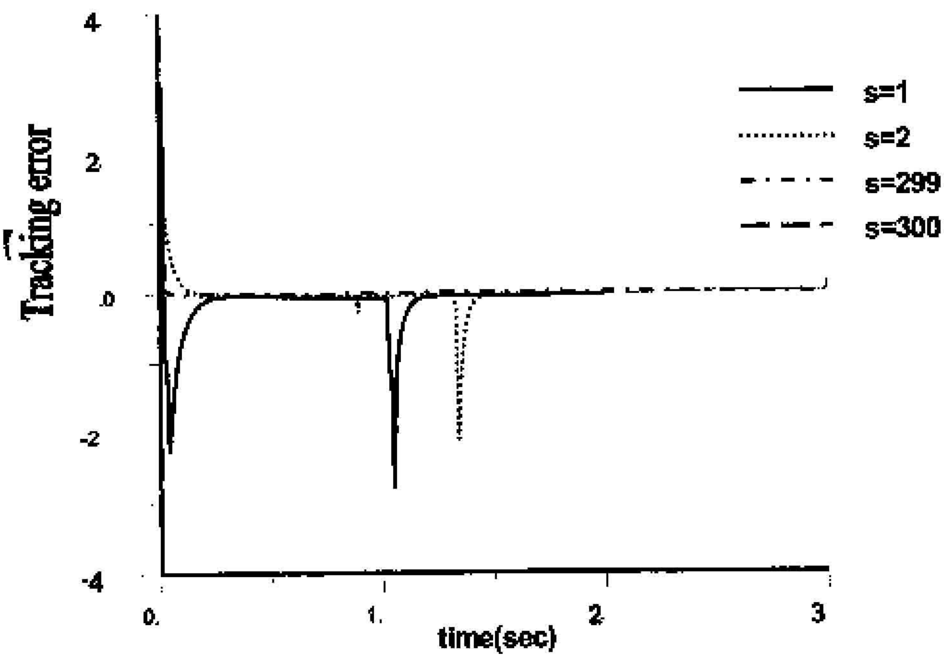


Fig.(16)Tracking error for second link