International Journal of Engineering and Advanced Technology (IJEAT)
ISSN: 2249-8958 (Online), Volume-11 Issue-2, December 2021

A New Neural Network Based Sliding Mode Adaptive Controller for Tracking Control of Robot Manipulator

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Abstract: In this paper a New RBF Neural Network based Sliding Mode Adaptive Controller (NNNSMAC) for Robot Manipulator trajectory tracking in the presence of uncertainties and disturbances is introduced. The research offers a learning with minimal parameter (LMP) technique for robotic manipulator trajectory tracking. The technique decreases the online adaptive parameters number in the RBF Neural Network to only one, lowering computational costs and boosting real-time performance. The RBFNN analyses the system's hidden non-linearities, and its weight value parameters are updated online using adaptive laws to control the nonlinear system's output to track a specific trajectory. The RBF model is used to create a Lyapunov function-based adaptive control law. The effectiveness of the designed NNNSMAC is demonstrated by simulation results of trajectory tracking control of a 2 dof Robotic Manipulator. The chattering effect has been significantly reduced.

Keywords: Neural Network, Sliding Mode Control, Robot manipulator, Trajectory Tracking.

I. INTRODUCTION

In recent years, robot manipulators have become increasingly important in scientific study and engineering applications. Manipulators are increasingly being used in industry to save labour and improve accuracy. Neural networks, which offer high-speed parallel distributed processing and can be easily implemented by hardware, have been widely used in many control systems as a potent tool for real-time processing[6].Using neural networks(NN) to control robot manipulators, in particular, has gotten a lot of attention, and several relevant schemes and methods have been developed and researched[1,4,5,9].

To handle systems with nonlinearities and uncertainties Sliding Mode Control(SMC) is one of the most robust and powerful control approach.It has appealing characteristics such as rapid dynamic reaction, insensitivity to variations in plant parameters, and resistance to external disturbance. But the presence of mismatched uncertainty in the manipulator and the high frequency chattering imposes a restriction on the use of the conventional SMC in the robot manipulator.

Manuscript received on November 10, 2021.
Revised Manuscript received on November 15, 2021.
Manuscript published on December 30, 2021.

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Robotic manipulators have been widely used in a variety of fields due to their ability to perform a wide range of automated activities. To complete the jobs, high-performance trajectory tracking control of robot manipulators is usually required, which is still a challenging task. Strong nonlinearities, huge couplings, and unknown dynamics are the key challenges[16-18]. RBF neural network (RBFNN) control for nonlinear systems has been the subject of extensive research. It is commonly known that a neural network can accurately approximate any nonlinear function.Many adaptive neural network control strategies have been devised to tackle the significant nonlinearity of robotic manipulator tracking control based on the universal approximation property of multi-layer neural networks.[1,4-6,8] This research offers a NNNSMAC technique for robotic manipulator trajectory tracking that integrates the benefits of both NN and SMC. It is motivated by published work. The lumped uncertainty of the system, which incorporates unknown dynamics, parameter fluctuations, and external disturbances, is extremely difficult to determine in real applications due to the nonlinear and complicated dynamics of a robotic manipulator. Because of its capacity to globally estimate any unknown continuous function to arbitrary accuracy, the RBFNN is used to approximate the lump uncertainties of the robotic manipulator to deal with this problem. [1]. Furthermore, during approximation processing, an adaptive rule is employed to change the NN weight . As a result, the suggested control strategy not only benefits from SMC's resiliency, but also fully utilises NN's precise approximation of the robotic manipulator's dynamics uncertainty. The Neural Network-based sliding-mode adaptive control learning with minimal parameter (LMP) technique is presented in this research. LMP reduces the number of online adaptive parameters in the RBFNN to just one, lowering computational costs and boosting real-time performance.[4]. The structure of this paper is as follows. In Section II,some preliminaries including the system model, its properties and some assumption are introduced. The control law design and stability analysis are presented in Section III and IV. In Section V, the control law is validated via a simulation on a 2 DOF robot. Finally, a conclusion is included in Section VI.

II. PROBLEM DESCRIPTION

Consider the dynamics of n link robot manipulators as

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$$M(q)\ddot{q} + C(q,\dot{q})\dot{q} + G(q) + F(\dot{q}) + \tau_d = \tau \qquad (1)$$

where $q, \dot{q}$ and $\ddot{q} \in R^n$ are vectors of angular position, angular velocity and angular acceleration of the joints respectively. $M(q) \in R^{n\times n}$ is the inertia matrix, $G(q) \in R^n$ is the gravitational vector, and $C(q,\dot{q})\dot{q} \in R^n$ is the centrifugal Coriolis torque vector. $F(\dot{q})$ is friction, $\tau \in R^n$ is joint torque vector and τ_d is unknown disturbance.

The dynamics of robotic manipulator given in (1) has the following properties.

Property I :

The inertial matrix $M(q)$ is a positive definite symmetric matrix for all $q \in R^n$ i.e, $M(q) = M(q)^T$ and $M(q) > 0$ and is upper and lower bounded i.e.,

$$\mu_1 I \le M(q) \le \mu_2 I$$

$$m_1 \le \|M(q)\| \le m_2 \qquad (2)$$

where μ_1 and μ_2 are scalars which can be computed for a given arm. And the inverse of inertia matrix is bounded since

$$\frac{1}{\mu_2} I \le M(q)^{-1} \le \frac{1}{\mu_1} I \qquad (3)$$

Property II :

$\dot{M}(q) - 2C(q,\dot{q})$ is skew symmetric matrix. i.e.,

$$x^T \left[\frac{1}{2}\dot{M}(q) - C(q,\dot{q})\right] x = 0, \quad \forall x \ne 0 \qquad (4)$$

Assumption 1: All joints of the manipulator are revolute. This makes Property 1 valid.

Assumption 2: The reference trajectory $q_d(t) \in R^n$ and its time derivatives $\dot{q}_d$ and $\ddot{q}_d$ are bounded and continuous.

III. NNNSMAC DESIGN

In this section the design of RBF neural network based adaptive sliding mode controller is discussed. The goal of trajectory tracking control is to provide a control torque τ so that for a desired trajectory q_d, the tracking error $e = q_d - q$ converged to zero in finite time. Let us define the sliding surface as follows

$$s = \dot{e} + \lambda e \qquad (5)$$

Where $\lambda = \lambda^T > 0$ Therefore,

$$\dot{q} = -s + \dot{q}_d + \lambda e$$

$$M\dot{s} = M(\ddot{q}_d - \ddot{q} + \lambda\dot{e})$$

$$= M(\ddot{q}_d + \lambda\dot{e}) - M\ddot{q}$$

$$= M(\ddot{q}_d + \lambda\dot{e}) + C\dot{q} + G + F + \tau_d - \tau$$

$$= M(\ddot{q}_d + \lambda\dot{e}) - Cs + C(\dot{q}_d + \lambda e) + G + F + \tau_d - \tau$$

$$= -Cs - \tau + f + \tau_d \qquad (6)$$

Where

$$f = M(\ddot{q}_d + \lambda\dot{e}) + C(\dot{q}_d + \lambda e) + G + F \qquad (7)$$

To approximate eq. (7) the RBFNN learning with minimal parameter (LMP) is used .

For the i th joint, The RBFNN algorithm is

$$p_{ij} = \exp\left(\|x_i - c_{ij}\|^2 / \sigma_{ij}^2\right) \quad , \quad j=1,2,......,m$$

$$f_i = w_i^T p_i + \varepsilon_i \qquad (8)$$

Where $x_i = [e_i \quad \dot{e}_i \quad q_{di} \quad \dot{q}_{di} \quad \ddot{q}_{di}]$ are input of RBFNN, $p_i = [p_{i1} \quad p_{i2} \dots\dots\dots \; p_{im}]^T$, ε_i is approximation error and w_i is ideal weight value.

The inputs of RBFNN are chosen as

$$X = [e \quad \dot{e} \quad q_d \quad \dot{q}_d \quad \ddot{q}_d]$$

Then

$$f = [f_1 \dots\dots f_i \dots\dots f_n]^T = \begin{bmatrix} w_1^T p_1 + \varepsilon_1 \\ \vdots \\ w_i^T p_i + \varepsilon_i \\ \vdots \\ w_n^T p_n + \varepsilon_n \end{bmatrix} = \begin{bmatrix} w_1^T p_1 \\ \vdots \\ w_i^T p_i \\ \vdots \\ w_n^T p_n \end{bmatrix} + \varepsilon$$

Where $\varepsilon = [\varepsilon_1 \dots\dots \varepsilon_i \dots\dots \varepsilon_n]^T$, $\|\varepsilon\| \le \varepsilon_N$. Now, Let us define $\hat{w}_i$ as an approximation of w_i , then $\tilde{w}_i = w_i - \hat{w}_i$, $\|w_i\|_F \le w_{imax}$. Let us define the minimum parameter(MP) as $\phi = max_1 \le i \le n\|w_i\|^2$ where $\phi > 0$ is a constant term, and $\hat{\phi}$ is an estimation of ϕ, $\tilde{\phi} = \hat{\phi} - \phi$

Define

$$W = \begin{bmatrix} w_1 \\ \vdots \\ w_n \end{bmatrix}, \quad P = \begin{bmatrix} p_1 \\ \vdots \\ p_n \end{bmatrix}, \quad \widetilde{W} = W - \widehat{W}$$

according to the GL operator, we have

$$W^{\circ}P = \begin{bmatrix} w_1^T p_1 \\ \vdots \\ w_n^T p_n \end{bmatrix}, \quad s^{\circ}s = \begin{bmatrix} s_1^T s_1 \\ \vdots \\ s_n^T s_n \end{bmatrix}, \quad P^{\circ}P = \begin{bmatrix} p_1^T p_1 \\ \vdots \\ p_n^T p_n \end{bmatrix}$$

And expression of f is

$$f = W^{\circ}P + \varepsilon$$

The controller is designed as

$$\tau = \frac{1}{2}\hat{\phi} so(PoP) + Ks - \nu \qquad (9)$$

where ν is the robust term to eliminate error approximation ε.

The design of ν is given as

$$\nu = -(\varepsilon_N + b_d) sgn(s) \qquad (10)$$

Where $\|\tau_d\| \le b_d$.

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Substituting eq (9) into eq (6) we have

$$M\dot{s} = -(K+C)s - \frac{1}{2}\hat{\phi}so(PoP) + (f+\tau_d) + v \quad (11)$$

IV. STABILITY ANALYSIS

The Lyapunov function is define as

$$V = \frac{1}{2}s^T M s + \frac{1}{2\gamma}\tilde{\phi}^2$$
$$\dot{V} = s^T M\dot{s} + \frac{1}{2}s^T\dot{M}s + \frac{1}{\gamma}\tilde{\phi}\dot{\hat{\phi}}$$
$$= s^T\left[-(K+C)s - \frac{1}{2}\hat{\phi}so(PoP) + (f+\tau_d) + v\right] + \frac{1}{2}s^T\dot{M}s + \frac{1}{\gamma}\tilde{\phi}\dot{\hat{\phi}}$$
$$= s^T\left[-Ks - \frac{1}{2}\hat{\phi}so(PoP) + WoP + (\varepsilon + \tau_d + v)\right] - \frac{1}{2}s^T(\dot{M}-2C)s + \frac{1}{\gamma}\tilde{\phi}\dot{\hat{\phi}}$$
$$= s^T\left[-\frac{1}{2}\hat{\phi}so(PoP) + WoP\right] - s^T Ks + s^T(\varepsilon + \tau_d + v) + \frac{1}{\gamma}\tilde{\phi}\dot{\hat{\phi}} \quad (12)$$

Now

$$s^T(\dot{M}-2C)s = 0$$
$$s^T(\varepsilon + \tau_d + v) = s^T(\varepsilon + \tau_d(\varepsilon_N + b_d)sgn(s)) \le 0$$
$$s^T[WoP] = [s_1 \dots\dots\dots s_n]\begin{bmatrix} w_1^T h_1 \\ \cdot \\ \cdot \\ \cdot \\ w_n^T h_n \end{bmatrix} =$$
$$s_1 w_1^T p_1 + \cdots \dots\dots\dots + s_n w_n^T p_n = \sum_{i=1}^{n}(s_i w_i^T p_i)$$
$$s_i^2 \phi p_i^T p_i + 1 \ge s_i^2\|w_i\|^2\|p_i\|^2 + 1 \ge 2s_i w_i^T p_i$$

Which is

$$s_i w_i^T p_i \le \frac{1}{2}s_i^2\phi p_i^T p_i + \frac{1}{2}$$
$$s^T[WoP] \le \frac{1}{2}\phi\sum_{i=1}^{n} s_i^2 p_i^T p_i + \frac{n}{2}$$
$$s^T\left[-\frac{1}{2}\hat{\phi}so(PoP)\right] = -\frac{1}{2}\hat{\phi}[s_1 \dots\dots s_n]\left(\begin{bmatrix} s_1 \\ \cdot \\ \cdot \\ s_n \end{bmatrix} o \begin{bmatrix} p_1^T p_1 \\ \cdot \\ \cdot \\ p_n^T p_n \end{bmatrix}\right)$$
$$= -\frac{1}{2}\hat{\phi}[s_1 \dots\dots s_n]\begin{bmatrix} s_1 p_1^T p_1 \\ \cdot \\ \cdot \\ \cdot \\ s_n p_n^T p_n \end{bmatrix}$$
$$= -\frac{1}{2}\hat{\phi}(s_1^2\|p_1\|^2 + \cdots \dots\dots + s_n^2\|p_n\|^2) = -\frac{1}{2}\hat{\phi}\sum_{i=1}^{n}(s_i^2\|p_i\|^2)$$

where n is the number of joints of the manipulator. Now

$$\dot{V} \le -\frac{1}{2}\hat{\phi}\sum_{i=1}^{n}(s_i^2\|p_i\|^2) + \frac{1}{2}\phi\sum_{i=1}^{n}s_i^2 p_i^T p_i + \frac{n}{2} + \frac{1}{\gamma}\tilde{\phi}\dot{\hat{\phi}} - s^T Ks$$
$$= -\frac{1}{2}\tilde{\phi}\sum_{i=1}^{n}(s_i^2\|p_i\|^2) + \frac{n}{2} + \frac{1}{\gamma}\tilde{\phi}\dot{\hat{\phi}} - s^T Ks$$
$$= \tilde{\phi}\left(-\frac{1}{2}\sum_{i=1}^{n}s_i^2\|p_i\|^2 + \frac{1}{\gamma}\dot{\hat{\phi}}\right) + \frac{n}{2} - s^T Ks \quad (13)$$

The adaptive law is

$$\dot{\hat{\phi}} = \frac{\gamma}{2}\sum_{i=1}^{n}(s_i^2\|p_i\|^2) \quad (14)$$

Then

$$\dot{V} \le \frac{n}{2} - s^T Ks \quad (15)$$

To guarantee $\dot{V} \le 0$, we must ensure $\frac{n}{2} \le s^T Ks$, then we have

$$\|s\| \le \sqrt{\frac{n}{2K}} \quad (16)$$

V. SIMULATION RESULTS

Consider the dynamic model of a two-link manipulator as follows:

$$M(q)\ddot{q} + C(q,\dot{q})\dot{q} + G(q) + F(\dot{q}) + \tau_d = \tau \quad (17)$$

$$M(q) = \begin{bmatrix} m_1 + m_2 + 2m_3 cosq_2 & m_2 + m_3 cosq_2 \\ m_2 + m_3 cosq_2 & m_2 \end{bmatrix} \quad (18)$$

$$C(q,\dot{q}) = \begin{bmatrix} -m_3\dot{q}_2 sinq_2 & -m_3(\dot{q}_1 + \dot{q}_2)sinq_2 \\ m_3\dot{q}_1 sinq_2 & 0 \end{bmatrix} \quad (19)$$

$$G(q) = \begin{bmatrix} m_4 gcosq_1 + m_5 gcos(q_1+q_2) \\ m_5 gcos(q_1+q_2) \end{bmatrix} \quad (20)$$

Let the disturbance $\tau_d = [0.2\sin(t) \quad 0.2\sin(t)]^T$ is added to the system. The frictional force is given as $F(\dot{q}) = 0.2sgn(\dot{q})$

Simulations are done for initial state [1,0,1,0]. Let $m = [m_1, m_2, m_3, m_4, m_5] = [2.9, 0.76, 0.87, 3.04, 0.87]$. Reference trajectory as given below are considered to study effectiveness of the controller.

$$q_{d1} = 5/4 - 7/5e^{-t} + 7/20\, e^{-4t}$$
$$q_{d2} = 5/4 + e^{-t} - 1/4e^{-4t} \quad (21)$$

Based on *f(x)* ,in the RBFNN design the inputs are selected as follows: $z = [e \quad \dot{e} \quad q_d \quad \dot{q}_d \quad \ddot{q}_d]$.
Based on the input range ,we can choose .

$$c = 0.1 \times \begin{bmatrix} -1 & 0.5 & 0 & 0.5 & 1 \\ -1 & 0.5 & 0 & 0.5 & 1 \\ -1 & 0.5 & 0 & 0.5 & 1 \\ -1 & 0.5 & 0 & 0.5 & 1 \\ -1 & 0.5 & 0 & 0.5 & 1 \end{bmatrix}, b_i = 0.50, \quad i = 0,1,\dots\dots 5. \quad (22)$$

and the initial weight values are chosen as zero.
The control law is (9) and adaptive law is (14) , the parameters are chosen as : $K = diag\{150,150\}$ $\Lambda = diag\{50,50\}$, $\varepsilon_N = 0.55$, $b_d = 0.21$, $\gamma = 550$ and $\Delta = 0.01$. The saturation function is used instead of switching function to reduce chattering action. The simulation results are shown in figures 1,2,3 and 4. The transient and steady state behaviours of tracking for each joint are shown in figures 1 and 2. Figures 3 and 4 shows the input torques of each joints. Convergence is satisfactory in presence of uncertainities.

VI. CONCLUSION

A New RBF Neural Network based Sliding Mode Adaptive Controller (NNNSMAC) for Robotic Manipulator trajectory tracking is presented in this work.

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The simulation results of a 2dof robot manipulator in presence of uncertainties and external disturbances shows the satisfactory implementation of the controller. The RBF model is used to construct an adaptive control law based on the Lyapunov function. Faster convergence for different trajectories guarantees the effectiveness of the control approach. The chattering action is satisfactorily reduced.

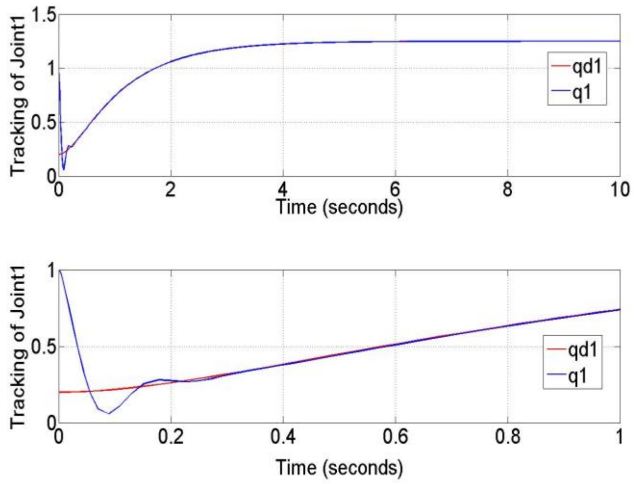

Fig. 1. Trajectory tracking of Joint1

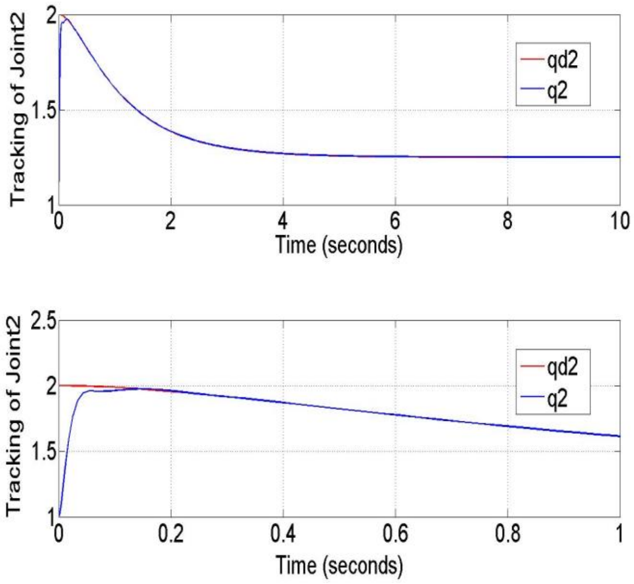

Fig. 2. Trajectory tracking of Joint2

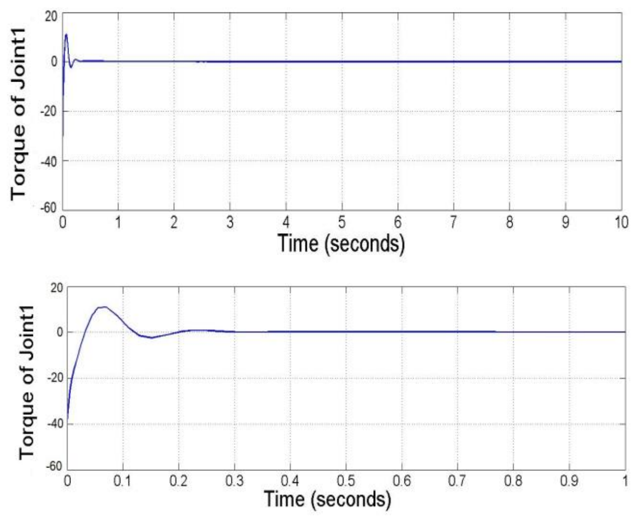

Fig. 3. Torque of Joint1

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Retrieval Number: 100.1/ijeat.B32171211221
DOI: 10.35940/ijeat.B3217.1211221
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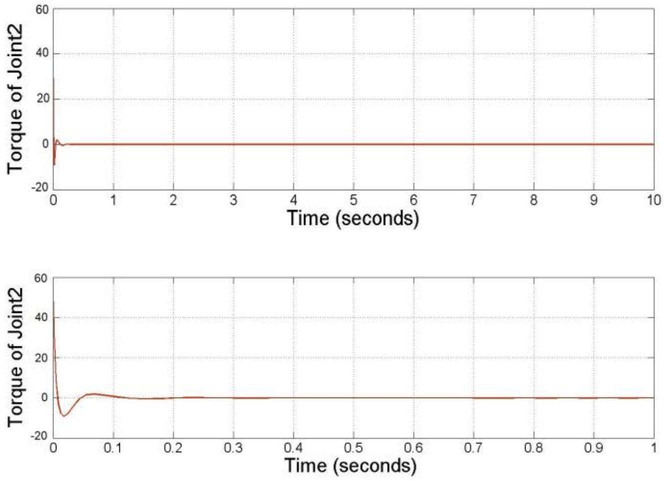

Fig. 4. Torque of Joint2

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