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Adaptive RBF network control for robot manipulators

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Abstract
The uncertainty estimation and compensation are challenging problems for the robust control of robot manipulators which are complex systems. This paper presents a novel decentralized model-free robust controller for electrically driven robot manipulators. As a novelty, the proposed controller employs a simple Gaussian Radial-Basis-Function network (RBF network) as an uncertainty estimator. The proposed network includes a hidden layer with one node, two inputs and a single output. In comparison with other model-free estimators such as multilayer neural networks and fuzzy systems, the proposed estimator is simpler, less computational and more effective. The weights of the RBF network are tuned online using an adaptation law derived by stability analysis. Despite the majority of previous control approaches which are the torque-based control, the proposed control design is the voltage-based control. Simulations and comparisons with a robust neural network control approach show the efficiency of the proposed control approach applied on the articulated robot manipulator driven by permanent magnet DC motors.

Keywords: *Adaptive Uncertainty Estimator, RBF Network Control, Robust Control, Electrically Driven Robot Manipulators*.

1. Introduction

Torque Control Strategy (TCS) has attracted many research efforts in the field of robot control [1-3]. The robust torque-based control tries to overcome problems such as nonlinearity, coupling between inputs and outputs and uncertainty raised from manipulator dynamics. It is also assumed that the actuators can perfectly generate the proposed torque control laws for the joints. This assumption may not be satisfied due to the dynamics, saturation and some practical limitations associated with actuators. The problems associated with manipulator dynamics will be removed if a robust control approach can be free from manipulator model. Considering this fact, Voltage Control Strategy (VCS) [4-5] was presented for electrically driven robot manipulators. This control strategy is free from manipulator model but is dependent on actuator model. Nevertheless, the uncertainty estimation and compensation can be effective in VCS to improve the control performance [6]. Using the estimation of uncertainty, this paper presents a voltage-based robust neural-network control for electrically driven robot manipulators which is model-free from both manipulator and actuators. The proposed design has a simpler design compared with alternative valuable voltage-based robust control approaches such as fuzzy estimation-based control [7], observer-based control [8], adaptive fuzzy control [9], neural-network control [10], fuzzy-neural-network control [11] and intelligent control [12] were presented for electrically driven robot manipulators. The simplicity and efficiency of the proposed control approach is shown through a comparison with the robust neural network control approach given by [10].

In most conventional robust approaches such as sliding mode control, the uncertainty bound parameter should be known in advance or estimated. The tracking error and smoothness of the control input are significantly affected by this parameter. The switching control laws resulted from these robust control methods may cause the chattering problem which will excite the un-modeled dynamics and degrade the system performance. As a result, too high estimation of the bounds may cause saturation of input, higher frequency of chattering in the switching control laws, and thus a bad behavior of the whole system, while too low estimation of the bounds may cause a higher tracking error [13].

Generally, uncertainty estimation and compensation are essential in robust tracking control of robots and the control performance is entirely enhanced by these crucial tasks. Function approximation methods play an important role in this stage and various tools such as fuzzy logic, neural networks, optimization algorithms, trigonometric function and orthogonal functions series have been used. In the two past decades, fuzzy logic [14-17] and neural networks [18-20] and neuro-fuzzy control [21] have been frequently employed in control systems and different control objectives have been successfully fulfilled due to their powerful capability in function approximation [22]. As important criteria, the simplicity and efficiency of the estimator should be paid attention since complex estimators require excessive memory, computational burden and many parameters. Tuning or online adaptation of these parameters significantly influences the estimator performance and increases the computations, as well.

One of the effective tools to approximate a function is the Radial-Basis-Function (RBF) networks. Applications of RBF networks in the robust control of nonlinear systems can be classified into direct and indirect adaptive control [23-26]. In direct adaptive control, RBF networks are employed as controllers. The network parameters are tuned online using adaptation laws derived from stability analysis.

Indirect application of RBF networks consists of two stages. In the first stage, the system dynamics are estimated using RBF networks and in the second stage, the estimated functions are used to design the control laws.

The novelty of this paper is to propose a robust model-free control for electrically driven robot manipulators using a simple RBF network as an uncertainty estimator in the decentralized controller. The simplicity of estimator is for using RBF network which consists of a hidden layer with one node, two inputs and a single output. Compared with the conventional robust control, the proposed robust control requires neither the uncertainty bound parameter nor the bounding functions. In addition, it is free from the chattering problem.

The robust RBF network control is compared with a robust Neural Network control (robust NN control) given by [10]. The robust NN control has two interior loops. The inner loop is a voltage controller for motor using two-layer neural networks whereas the outer loop is a current controller using two-layer neural networks for providing the desired current. The robust RBF network control has a simpler design by using only one control loop and a RBF network.

The structure and design of the proposed Gaussian RBF network used as an adaptive uncertainty estimator in this paper is simpler than the fuzzy system used in [27] as an adaptive fuzzy controller [27]. These two designs have different structures. An interesting result is that fuzzy systems and neural networks can be designed somehow to perform the same behavior.

This paper is organized as follows. Section 2 explains modeling of the robotic system including the robot manipulator and motors. Section 3 develops the robust RBF network control approach. Section 4 describes the RBF network for estimation of the uncertainty. Section 5 presents the stability analysis. Section 6 illustrates the simulation results. Finally, section 7 concludes the paper.

2. Modeling

The robot manipulator consists of n links interconnected at n joints into an open kinematic chain. The mechanical system is assumed to be perfectly rigid. Each link is driven by a permanent magnet DC motor through the gears. The dynamics is described [28] as

$$\mathbf{D}(\mathbf{q})\ddot{\mathbf{q}} + \mathbf{C}(\mathbf{q},\dot{\mathbf{q}})\dot{\mathbf{q}} + \mathbf{g}(\mathbf{q}) = \boldsymbol{\tau}_\mathbf{r} - \boldsymbol{\tau}_\mathbf{f}(\dot{\mathbf{q}}) \qquad (1)$$

Where $\mathbf{q} \in R^n$ is the vector of joint positions, $\mathbf{D}(\mathbf{q})$ the $n \times n$ matrix of manipulator inertia, $\mathbf{C}(\mathbf{q},\dot{\mathbf{q}})\dot{\mathbf{q}} \in R^n$ the vector of centrifugal and Coriolis torques, $\mathbf{g}(\mathbf{q}) \in R^n$ the vector of gravitational torques, $\boldsymbol{\tau}_\mathbf{f}(\dot{\mathbf{q}}) \in R^n$ the vector of friction torques and $\boldsymbol{\tau}_\mathbf{r} \in R^n$ the joint torque vector of robot.

Note that vectors and matrices are represented in bold form for clarity. The electric motors provide the joint torque vector as follows [28]

$$\mathbf{J}\mathbf{r}^{-1}\ddot{\mathbf{q}} + \mathbf{B}\mathbf{r}^{-1}\dot{\mathbf{q}} + \mathbf{r}\boldsymbol{\tau}_\mathbf{r} = \boldsymbol{\tau}_\mathbf{m} \qquad (2)$$

Where $\boldsymbol{\tau}_\mathbf{m} \in R^n$ is the torque vector of motors, $\mathbf{J}$, $\mathbf{B}$ and $\mathbf{r}$ are the $n \times n$ diagonal matrices for motor coefficients namely the inertia, damping, and reduction gear, respectively. The joint velocity vector $\dot{\mathbf{q}}$ and the motor velocity vector $\dot{\mathbf{q}}_{\mathbf{m}} \in R^n$ are related through the gears to yield

$$\mathbf{r}\dot{\mathbf{q}}_{\mathbf{m}} = \dot{\mathbf{q}} \tag{3}$$

In order to obtain the motor voltages as the inputs of system, we consider the electrical equation of geared permanent magnet DC motors in the matrix form,

$$\mathbf{RI_a} + \mathbf{L}\dot{\mathbf{I}}_{\mathbf{a}} + \mathbf{K_b}\mathbf{r}^{-1}\dot{\mathbf{q}} + \boldsymbol{\varphi} = \mathbf{v} \tag{4}$$

Where $\mathbf{v} \in R^n$ is the vector of motor voltages, $\mathbf{I_a} \in R^n$ is the vector of motor currents and $\boldsymbol{\varphi} \in R^n$ is a vector of external disturbances. $\mathbf{R}$, $\mathbf{L}$ and $\mathbf{K_b}$ represent the $n \times n$ diagonal matrices for the coefficients of armature resistance, inductance, and back-emf constant, respectively.

The motor torque vector $\boldsymbol{\tau}_{\mathbf{m}}$ as the input for dynamic (2) is produced by the motor current vector,

$$\mathbf{K_m I_a} = \boldsymbol{\tau}_{\mathbf{m}} \tag{5}$$

Where $\mathbf{K_m}$ is a diagonal matrix of the torque constants. Using (1-5), obtains the state-space model

$$\dot{\mathbf{x}} = \mathbf{f}(\mathbf{x}) + \mathbf{bv} - \mathbf{b}\boldsymbol{\varphi} \tag{6}$$

Where $\mathbf{v}$ is considered as the inputs, $\mathbf{x}$ is the state vector and $\mathbf{f}(\mathbf{x})$ is of the form of

$$\mathbf{f}(\mathbf{x}) = \begin{bmatrix} \mathbf{x}_2 \\ \left(\mathbf{Jr}^{-1} + \mathbf{rD}(\mathbf{x}_1)\right)^{-1}. \\ \left(-\left(\mathbf{Br}^{-1} + \mathbf{rC}(\mathbf{x}_1,\mathbf{x}_2)\right)\mathbf{x}_2 - \mathbf{rg}(\mathbf{x}_1) + \mathbf{K_m x}_3 - \mathbf{r}\boldsymbol{\tau}_{\mathbf{f}}(\mathbf{x}_2)\right) \\ -\mathbf{L}^{-1}\left(\mathbf{K_b r}^{-1}\mathbf{x}_2 + \mathbf{Rx}_3\right) \end{bmatrix}$$

$$\mathbf{b} = \begin{bmatrix} \mathbf{0} \\ \mathbf{0} \\ \mathbf{L}^{-1} \end{bmatrix}, \quad \mathbf{x} = \begin{bmatrix} \mathbf{q} \\ \dot{\mathbf{q}} \\ \mathbf{I_a} \end{bmatrix} \tag{7}$$

The state-space (6) shows a highly coupled nonlinear system in a non-companion form. The complexity of model is a serious challenge for the control of the robot.

To avoid much more complexity, many works have ignored the motors' dynamics. However, considering the motors' dynamics is required in high-speed and high-accuracy applications.

3. Robust control design

By substituting (2), (3) and (5) into (4), the voltage equation of the i th motor in the scalar form can be expressed by

$$RK_m^{-1}Jr^{-1}\ddot{q} + (RK_m^{-1}Br^{-1} + K_b r^{-1})\,\dot{q} + RK_m^{-1}r\tau_r + L\dot{I}_a + \varphi = v \tag{8}$$

Where $\ddot{q}$, $\dot{q}$, τ_r, $\dot{I}_a$ and φ are the ith element of the vectors $\ddot{\boldsymbol{q}}$, $\dot{\boldsymbol{q}}$, $\boldsymbol{\tau_r}$, $\dot{\boldsymbol{I}}_{\boldsymbol{a}}$ and $\boldsymbol{\varphi}$, respectively.

Equation (8) can be rewritten as

$$\ddot{q} + F = v \tag{9}$$

Where F is referred to as the lumped uncertainty expressed by

$$F = (RK_m^{-1}Jr^{-1} - 1)\ddot{q} + L\dot{I}_a + \varphi + (RK_m^{-1}Br^{-1} + K_b r^{-1})\,\dot{q} + RK_m^{-1}r\tau_r \tag{10}$$

Let us define

$$u = \ddot{q}_d + k_d(\dot{q}_d - \dot{q}) + k_p(q_d - q) + \hat{F} \tag{11}$$

Where $\hat{F}$ is the estimate of F, q_d is the desired joint position, k_p and k_d are the control design parameters. In order to estimate F, this paper designs a simple RBF network as an uncertainty estimator. In order to protect the motor from over voltage, the motor voltage must be under a permitted value $v_{\max}$.

Therefore, a voltage limiter is used for each motor to hold the voltage under the value $v_{\max}$. Then, a robust control law is proposed as

$$v(t) = v_{\max} sat(u / v_{\max}) \tag{12}$$

Where

$$sat(u / v_{\max}) = \begin{cases} 1 & if \quad u > v_{\max} \\ u / v_{\max} & if \quad |u| \le v_{\max} \\ -1 & if \quad u < -v_{\max} \end{cases} \tag{13}$$

The control scheme is presented in figure1.

4. Adaptive uncertainty estimator

Applying control law (12) to the system (9) obtains the closed loop system

$$\ddot{q} + F = v_{\max} sat(u / v_{\max}) \tag{14}$$

In the case of $u > v_{\max}$, according to (13) we have

$$\ddot{q} + F = v_{\max} \tag{15}$$

Therefore, the estimator $\hat{F}$ is not effective in the closed loop system.

In the case of $u < -v_{\max}$, according to (13) we have

$$\ddot{q} + F = -v_{\max} \tag{16}$$

Therefore, the estimator $\hat{F}$ is not effective in the closed loop system.

In the case of $|u| \le v_{\max}$, according to (9), (11) and (13) we have

$$\ddot{q} + F = (\ddot{q}_d + k_d(\dot{q}_d - \dot{q}) + k_p(q_d - q)) + \hat{F} \tag{17}$$

Therefore, the closed loop system can be written as

$$\ddot{e} + k_d\dot{e} + k_p e = F - \hat{F} \tag{18}$$

Where e is the tracking error expressed by

$$e = q_d - q \quad (19)$$

This paper suggests a simple RBF estimator for every joint as

$$\hat{F} = \hat{p}\exp(-(e^2 + \dot{e}^2)) \quad (20)$$

Where $\hat{p}$ is an adaptive gain. One can easily represent (20) as

$$\hat{F} = \hat{p}\zeta \quad (21)$$

Where ζ is expressed as

$$\zeta = \exp(-(e^2 + \dot{e}^2)) \quad (22)$$

The estimator $\hat{F}$ defined by (21) can approximate F adaptively based on the universal approximation of RBF networks [22]. Thus,

$$|F - \hat{F}| \le \rho \quad (23)$$

Where ρ is a positive scalar. Suppose that F can be modeled as

$$F = p\zeta + \varepsilon$$

Where ε is the approximation error and vector p is constant. Assume that

$$|F - p\zeta| \le \beta \quad (25)$$

Considering (24) and (25) shows that $|\varepsilon| \le \beta$ in which β is the upper bound of approximation error. The dynamics of tracking error can be expressed by substituting (24) and (21) into (18) to have

$$\ddot{e} + k_d\dot{e} + k_p e = (p - \hat{p})\zeta + \varepsilon \quad (26)$$

The state space equation in the tracking space is obtained using (26) as

$$\dot{\boldsymbol{E}} = \boldsymbol{AE} + \boldsymbol{B}\omega \quad (27)$$

Where

$$\boldsymbol{A} = \begin{bmatrix} 0 & 1 \\ -k_p & -k_d \end{bmatrix},\ \boldsymbol{B} = \begin{bmatrix} 0 \\ 1 \end{bmatrix},\ \boldsymbol{E} = \begin{bmatrix} e \\ \dot{e} \end{bmatrix}$$

$$\omega = (p - \hat{p})\zeta + \varepsilon \quad (28)$$

Consider the following positive definite function [27]

$$V = 0.5\boldsymbol{E}^T\boldsymbol{SE} + \frac{1}{2\gamma}(p - \hat{p})^2 \quad (29)$$

Where γ is a positive scalar, $\boldsymbol{S}$ and $\boldsymbol{Q}$ are the unique symmetric positive definite matrices satisfying the matrix Lyapunov equation as

$$\boldsymbol{A}^T\boldsymbol{S} + \boldsymbol{SA} = -\boldsymbol{Q} \quad (30)$$

Taking the time derivative of V gives that

$$\dot{V} = 0.5\dot{\boldsymbol{E}}^T\boldsymbol{SE} + 0.5\boldsymbol{E}^T\boldsymbol{S}\dot{\boldsymbol{E}} - (p - \hat{p})\dot{\hat{p}}/\gamma \quad (31)$$

Substituting (27), (28) and (30) into (31) yields to

$$\dot{V} = (p - \hat{p})\left(\boldsymbol{E}^T\boldsymbol{S}_2\zeta - \frac{1}{\gamma}\dot{\hat{p}}\right) + \boldsymbol{E}^T\boldsymbol{S}_2\varepsilon - 0.5\boldsymbol{E}^T\boldsymbol{QE} \quad (32)$$

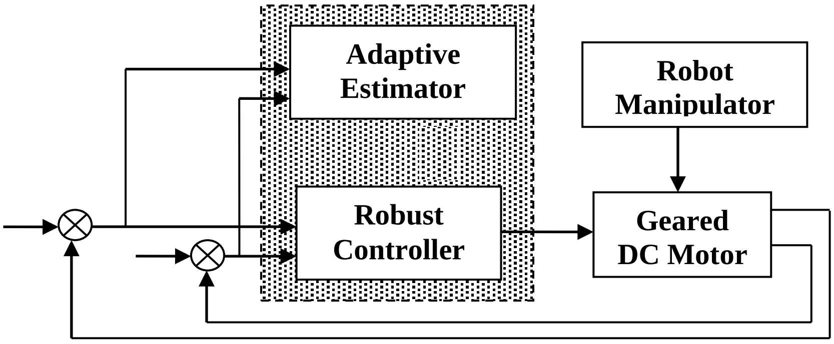

Figure 1. Proposed robust RBF network control.

Where $\boldsymbol{S}_2$ is the second column of $\boldsymbol{S}$. Since $-0.5\boldsymbol{E}^T\boldsymbol{QE} < 0$ for $\boldsymbol{E} \ne 0$, if the adaptation law is given by

$$\dot{\hat{p}} = \gamma\boldsymbol{E}^T\boldsymbol{S}_2\zeta \quad (33)$$

Then

$$\dot{V} = -0.5\boldsymbol{E}^T\boldsymbol{QE} + \boldsymbol{E}^T\boldsymbol{S}_2\varepsilon \quad (34)$$

The tracking error is reduced if $\dot{V} < 0$. Therefore, the convergence of $\boldsymbol{E}$ is guaranteed if

$$\boldsymbol{E}^T\boldsymbol{S}_2\varepsilon < 0.5\boldsymbol{E}^T\boldsymbol{QE}$$

Using the Cauchy–Schwartz inequality and $|\varepsilon| \le \beta$, we can obtain,

$$\boldsymbol{E}^T\boldsymbol{S}_2\varepsilon \le \|\boldsymbol{E}\|.\|\boldsymbol{S}_2\|.|\varepsilon| < \beta\|\boldsymbol{E}\|.\|\boldsymbol{S}_2\| \quad (36)$$

Since $\lambda_{\min}(\boldsymbol{Q})\|\boldsymbol{E}\|^2 \le \boldsymbol{E}^T\boldsymbol{QE} \le \lambda_{\max}(\boldsymbol{Q})\|\boldsymbol{E}\|^2$, in order to satisfy (35), it is sufficient that

$$\beta\|\boldsymbol{S}_2\| < 0.5\lambda_{\min}(\boldsymbol{Q})\|\boldsymbol{E}\| \quad \text{or} \quad (37)$$

$$2\beta\|\boldsymbol{S}_2\|/\lambda_{\min}(\boldsymbol{Q}) \square \delta_0 < \|\boldsymbol{E}\|$$

Where δ_0 is a positive constant, $\lambda_{\min}(\boldsymbol{Q})$ and $\lambda_{\max}(\boldsymbol{Q})$ are the minimum and maximum eigenvalues of $\boldsymbol{Q}$, respectively. Thus, we have $\dot{V} < 0$ as long as $\delta_0 < \|\boldsymbol{E}\|$. This means that the tracking error becomes smaller out of the ball with the radius of δ_0. As a result, the tracking error ultimately enters into the ball. On the other hand $\dot{V} > 0$ if $\delta_0 > \| \boldsymbol{E} \|$. This means that the tracking error does not converge to zero.

According to (33), the parameter of the RBF network estimator is calculated by

$$\hat{p}(t) = \hat{p}(0) + \int_0^t \gamma \boldsymbol{E}^T \boldsymbol{S}_2 \zeta d\tau \quad (38)$$

Where $\hat{p}(0)$ is the initial value.

Result 1: The tracking error e and its time derivatives $\dot{e}$ are bounded and ultimately enters into a ball with a radius of δ_0.

To evaluate the final size of error, it is worthy to note that it depends on the upper bound of approximation error, β, and the control design parameters k_p and k_d. Selecting large values for k_p and k_d, will provide a small size of tracking error. To evaluate the size of estimation error ρ in (23), one can substitute (24) into (23) to have

$$| p\zeta + \varepsilon - \hat{p}\zeta | \le | (p - \hat{p})\zeta | + | \varepsilon | \quad (39)$$

Thus, to satisfy (23), ρ can be given by

$$\rho = | (p - \hat{p})\zeta | + \beta \quad (40)$$

5. Stability analysis

A proof for the boundedness of the state variables $\boldsymbol{\theta}$, $\dot{\boldsymbol{\theta}}$ and $\mathbf{I_a}$ is given by stability analysis. In order to analyze the stability, the following assumptions are made:

Assumption 1 The desired trajectory q_d must be smooth in the sense that q_d and its derivatives up to a necessary order are available and all uniformly bounded [28].

As a necessary condition to design a robust control, the external disturbance must be bounded. Thus, the following assumption is made:

Assumption 2 The external disturbance φ is bounded as $|\varphi(t)| \le \varphi_{\max}$.

Control law (12) makes the following assumption.

Assumption 3 The motor voltage is bounded as $|v| \le v_{\max}$.

The motor should be sufficiently strong to drive the robot for tracking the desired joint velocity under the maximum permitted voltages. According to result1, $\mathbf{E} = [q_d - q \quad \dot{q}_d - \dot{q}]^T$ is bounded. Since q_d and $\dot{q}_d$ are bounded in assumption 1,

Result 2: The joint position q and joint velocity $\dot{q}$ are bounded.

From (4), we can write for every motor

$$RI_a + L\dot{I}_a + K_b r^{-1}\dot{q} + \varphi = v \quad (41)$$

Substituting control law (12) into (41) yields

$$RI_a + L\dot{I}_a + K_b r^{-1}\dot{q} + \varphi = v_{\max} sat(\frac{u}{v_{\max}}) \quad (42)$$

That is

$$RI_a + L\dot{I}_a = w \quad (43)$$

$$w = v_{\max} sat(u / v_{\max}) - k_b r^{-1}\dot{q} - \phi \quad (44)$$

The variables $\dot{q}$ and ϕ are bounded according to result 2 and assumption 2, respectively. Additionally, $|v_{\max} sat(u / v_{\max})| \le v_{\max}$.

Consequently, the input w in (43) is bounded. The linear differential (43) is a stable linear system based on the Routh-Hurwitz criterion. Since the input w is bounded, the output I_a is bounded.

Result 3: The current I_a is bounded.

As a result of this reasoning, for every joint, the joint position q, the joint velocity $\dot{q}$ and the motor current I_a are bounded. Therefore, the system states $\mathbf{q}$, $\dot{\mathbf{q}}$ and $\mathbf{I_a}$ are bounded and the stability of system is guaranteed.

6. Simulation results

The robust RBF network control is simulated using an articulated robot driven by permanent magnet DC motors.

The details of robot is given by [6]. The maximum voltage of each motor is set to $u_{\max} = 40$ V. The parameters of motors are given in table 1. The desired joint trajectory for all joints is shown in figure 1. The desired position for every joint is given by

$$\theta_d = 1 - \cos(\pi t / 5) \quad \text{for} \quad 0 \le t < 10 \quad (45)$$

Table 1. Specifications of DC motors.

$u_{\max}$ (V)	R (Ω)	K_b ($\frac{V.s}{rad}$)	L (H)	J_m ($\frac{Nm.s^2}{rad}$)	B_m ($\frac{Nm.s}{rad}$)	r
40	1.26	0.26	0.001	0.0002	0.001	0.01

The external disturbance φ in (8) for every joint is given by

$$\varphi = \begin{cases} 0 & 0 \le t \le 2 \text{ and } 4 \le t \le 6 \text{ and } 8 \le t \le 10 \\ 1 & 2 \le t \le 4 \text{ and } 6 \le t \le 8 \end{cases} \quad (46)$$

Tracking performance: The robust RBF network control in (12) is simulated with adaptive law (38) and the following parameters

$$\boldsymbol{A} = \begin{bmatrix} 0 & 1 \\ -100 & -20 \end{bmatrix}, S_2 = \begin{bmatrix} 50 \\ 6 \end{bmatrix},$$
$$\gamma = 5000, \ \hat{p}(0) = 0 \quad (47)$$

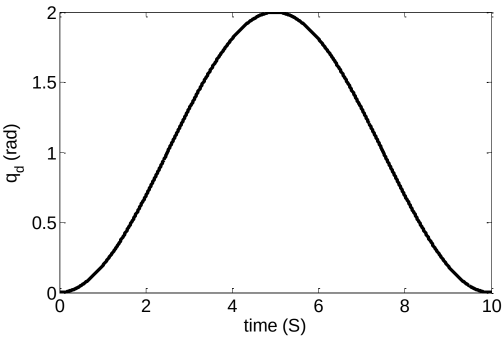

Figure 2. The desired joint trajectory.

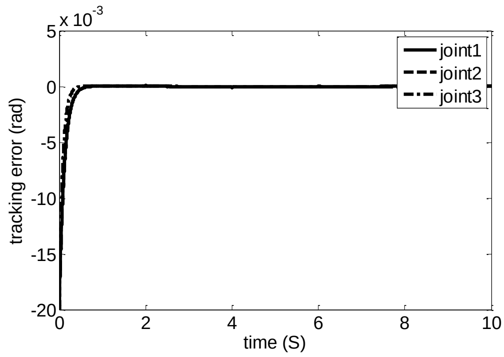

Figure 3. Performance of the proposed control.

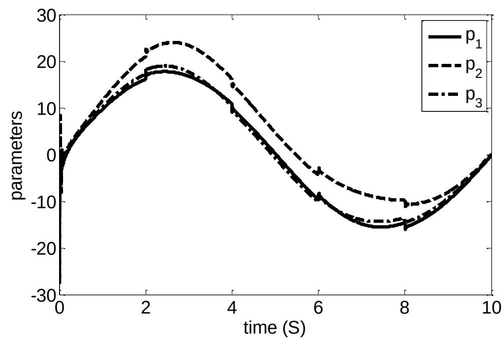

Figure 4. Adaptation of parameters.

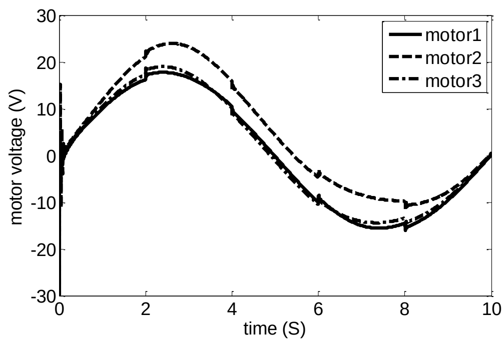

Figure 5. Control efforts of the proposed control.

The initial errors for all joints are given $0.02 rad$. The tacking performance is very good as shown in figure 3. All joint errors finally go under $4.2\times10^{-5} rad$ without overshoot.

The adaptation of parameters for all joints is shown in figure 4. All parameters are varied to cover all effects of higher order terms in RBF network estimators. Motors behave well under the permitted voltages as shown in figure 5.

The control efforts are increased when starting because of the initial tracking error. Simulation results confirm the effectiveness of the robust RBF network control.

A comparison: The robust RBF network control is compared with a robust Neural Network control (robust NN control) given by [10]. The control structure has two interior loops. The inner loop is a voltage controller for motor using two-layer neural networks whereas the outer loop is a current controller using two-layer neural networks for providing the desired current.

The control design is based on the stability analysis using Lyapunov theory. As a comparison it is noted that the robust RBF network control is much simpler since it has only one control loop using a RBF network.

The parameters of the robust NN control are set to $\Lambda=100$, $k_\tau=30$, $k_v=1$, $k_1=0.1$, $k_\omega=1$, $\Gamma=1000$, $\hat{W}_1(0)=0$ and $\hat{W}_2(0)=0$. The initial errors and external disturbances for all joints are the same as ones used in Simulation 1.

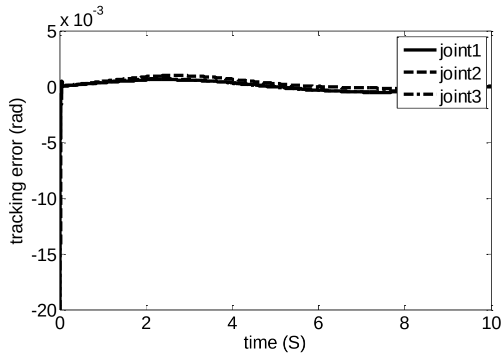

Figure 6. Performance of the robust NN control.

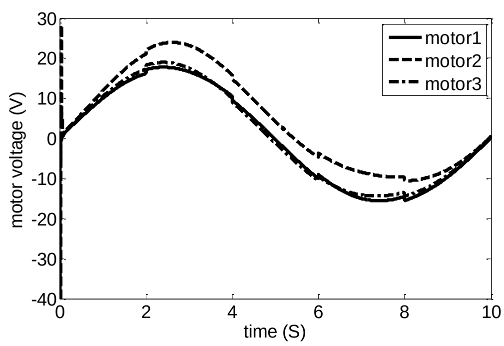

Figure 7. Control efforts of the robust NN control.

The control performance of [10] is shown in figure 6. Both control approaches are robust with a good tracking performance. Figure 8 shows voltages applied to the motors.

The control efforts in figure 7 are smooth and permitted. The robust RBF network control is much simpler, less computational, less number of design parameters and has better control performance. On the other hand, the tracking error of the robust NN control will be decreased by increasing the gains however the chattering phenomenon will be increased.

7. Conclusion

This paper has presented a novel robust model-free control approach for electrically driven robot manipulators. It has been found that the complex dynamics of the robotic system can be estimated by using a RBF network in a decentralized structure as an estimator of uncertainty. The robust controller has become model-free by using this estimator to compensate the uncertainty. The proposed adaptive mechanism has guaranteed the stability and provided a good tracking performance. The performance of the proposed estimator in the robust control system has been very good as shown by simulations. In order to have a simple design with easy implementation yet good performance it has been confirmed that using only the tracking error and its time derivatives is sufficient to form the estimator. A comparison with a robust NN control has shown that the proposed control approach is simpler in design, less computational and better control performance.

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نشریه هوش مصنوعی و داده کاوی

کنترل شبکه تابع-مبنا-شعاعی تطبیقی برای بازوهای رباتیک

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چکیده:

این مقاله به ارائه کنترل‌کننده جدید مقاوم و مستقل از مدل برای بازوهای رباتیک برقی می‌پردازد. به عنوان نوآوری، کنترل‌کننده پیشنهادی از شبکه تابع-مبنا-شعاعی گوسی به عنوان تخمینگر عدم قطعیت استفاده می‌نماید. شبکه پیشنهادی از یک لایه مخفی با یک گره، دو ورودی و یک خروجی تشکیل می‌شود. تخمینگر پیشنهادی در مقایسه با سایر تخمینگرهای مستقل از مدل مانند شبکه‌های عصبی چند لایه و سیستم‌های فازی، ساده‌تر با محاسبات کمتر و کارآمدتر است. وزن‌های شبکه تابع-مبنا-شعاعی با بکارگیری قانون تطبیقی مبتنی بر تحلیل پایداری تنظیم می‌گردد. بر خلاف اکثر روش‌های پیشین کنترل که مبتنی بر کنترل گشتاور هستند طراحی کنترل پیشنهادی بر مبنای کنترل ولتاژ است. کارآمدی روش کنترل پیشنهادی توسط شبیه‌سازی و مقایسه با روش کنترل عصبی مقاوم روی بازوی رباتیک هنرمند نشان داده می‌شود. این ربات توسط موتورهای جریان مستقیم مغناطیس دائم رانده می شود.

کلمات کلیدی: تخمینگر عدم قطعیت تطبیقی، کنترل شبکه تابع-مبنا-شعاعی، کنترل مقاوم، بازوهای رباتیک برقی.