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Adaptive Robust Control based on RBF Neural Networks for Duct Cleaning Robot

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Abstract: In this paper, a control strategy for duct cleaning robot in the presence of uncertainties and various disturbances is proposed which combines the advantages of neural network technique and advanced adaptive robust theory. First of all, the configuration of the duct cleaning robot is introduced and the dynamic model is obtained based on the practical duct cleaning robot. Second, the RBF neural network is used to identify the unstructured and dynamic uncertainties due to its strong ability to approximate any nonlinear function to arbitrary accuracy. Using the learning ability of neural network, the designed controller can coordinately control the mobile plant and cleaning arm of duct cleaning robot with different dynamics efficiently. The neural network weights are only tuned on-line without tedious and lengthy off-line learning. Then, an adaptive robust control scheme based on RBF neural network is proposed, which ensures that the trajectories are accurately tracked even in the presence of external disturbances and uncertainties. Finally, based on the Lyapunov stability theory, the stability of the whole closed-loop control system, and the uniformly ultimately boundedness of the tracking errors are all strictly guaranteed. Moreover, simulation and experiment results are given to demonstrate that the proposed control approach can guarantee the whole system converges to desired manifold with well performance.

Keywords: Adaptive robust control, duct cleaning robot, Lyapunov stability theory, RBF neural network, uncertainties.

1. INTRODUCTION

In the past decades, the central air-conditionings are widely used in many buildings, they furnish the comfortable environment of life and work for people, but simultaneously, a lot of ducts which locate the inside of the buildings mass a great deal of air pollution matters such as grain, dust, pathogen and so on after years used of ducts without cleaning, this is not desirable in the view point of public sanitation or health. Therefore, periodic cleaning of the duct is required. However, there exists a problem that the ducts of central air-conditioning are highly complicated, and the workers cannot enter the inside of the duct to clean. Recently, some duct cleaning robot products of central air-conditioning have been put on the market, such as Wintclean of Sweden, Hanlin of Korea (Shown in Fig. 1), Danduct of Denmark etc. are basically consist of mobile platform and cleaning arm with brush, only have a little distinctness. Moreover, these robots are telecontrolled by operator so that the robots lack of the ability of trajectory planning and tracking. In this paper, the duct cleaning robot with 3-DOF cleaning arm is designed and an adaptive robust control approach based on RBF neural network is presented for duct cleaning robot. The duct cleaning robot in this paper can be regards as a mobile manipulator with mobile platform and robotic manipulator which are mounted on the mobile platform.

Mobile manipulators have been received more and more attention over the last two decades due to their wide applicability in various fields and academic interest

(a) Wintclean of Sweden. (b) Hanlin of Korea.

Fig. 1. The products of duct cleaning robot.

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[1-5]. It is well known that the mobile manipulator combines the advantage of the mobile platform and robotic manipulator and reduce their drawbacks. Mobile manipulators have an infinite workspace almost; the mobile platforms extend the arm's workspace, whereas the arms offer much operational functionality. As far as we know, mobile manipulators have to encounter nonlinearities and various uncertainties in their dynamic models, such as friction, external disturbances, and load changing, specially relate to duct cleaning robot which works in unknown and complicated environment, additionally there exist coupling between mobile platform and manipulator, so that it is very difficult to reach excellent control performance. Thus, designing a robotic mobile manipulators controller is a challenging problem for engineers and researchers [6-10].

In the last decades, with the assumption of known dynamics, many researches have been carried out [11-15]. For example, in [12], nonlinear feedback control for the mobile manipulator was developed to compensate for the dynamic interaction between the mobile platform and the arm to achieve tracking performance; in [14], coordinate and control of mobile manipulators were presented by authors with two basic task-oriented controls: end-effectors task control and platform self-posture control. However, these researches ignore uncertainties and external disturbances which are inevitable and can affect the system stability and performance in the real application of robotic system. Furthermore, it is difficult to make the proposed schemes appropriate for realistic applications without dynamic model. To handle these difficulties, recently, several results about dynamic modeling were published [16,17] and there are have been tremendous progress in the development of controllers for robotics systems, such as feed forward and computed torque control, adaptive control, variable structure control, passivity-based control, fuzzy control and robust Lyapunov stability-based control [18-23], which provided the effective approaches to designing controller for duct cleaning robot that is subjected by nonholonomic constraints. A. A. Ata in [17] analyzes the dynamic performance and trajectory selection for mobile manipulator used to detect mines, the author derives the kinematic equation for the forward and inverse kinematics, and using Lagrange equation to obtain the dynamic model for mobile manipulator. In [19], the authors consider multiple mobile manipulators grasping a rigid object in contact with a deformable working surface, whose geometric and real physical parameter is unknown but the boundedness of physical parameter is known, they presented a neuro-adaptive robust force/motion tracking controller for coordinate mobile manipulators. An approach for adaptive sliding mode control of robotic manipulators is presented in [23]. Specially, robust and adaptive controls have been extensive investigated for robotic manipulators and dynamic nonholonomic systems. Robust controls assume the boundedness of uncertainties and external disturbances of systems are known. However, since this control strategy used max-min method to design the controller, it cannot yield the well transient performance. Nevertheless, adaptive controls could learn the unknown parameters of interest through adaptive tuning law, in this situation, the unknown nonlinear dynamics of robotic systems are always assumed to be linearly parameterisable, so there are some potential difficulties associated with this classical adaptive control design [24].

RBF neural network, one of the most popular intelligent computation approaches, has an inherent learning and can approximate any nonlinear continuous function to arbitrary accuracy. This property is crucial in controller design for complex model identifying and unstructured uncertainties compensating. To present, RBF neural network-based controls have been widely used in trajectory tracking by robot manipulators [25-30]. In [27], a neural network-based robust H_∞ control strategy is proposed for robot manipulators using the variable structure slide control approach. The authors address the robust trajectory tracking problem for a redundantly actuated omnidirectional mobile manipulator, the development of control algorithm is based on sliding mode control technique and neural network in [30]. However, the most of previous researches are applied to the symbolic 2-DOF manipulator mounted on the mobile platform, the duct cleaning robot which has more nonlinearization and stronger couples between robotic plant and the environment is not fully explored.

In this paper, an adaptive robust control scheme using RBF neural network is proposed for duct cleaning robot in the presence of uncertainties and external disturbances. The main contributions of this paper are listed as follows: 1) The proposed method can take advantage of strong robustness of adaptive control theory as well as self-learning and nonlinear mapping properties of RBF neural network to deal with both structured and unstructured uncertainties; 2) No preliminary learning knowledge is required for the RBF neural network weights, the neural network learning process is performed online; 3) the presented approach can coordinately control the mobile platform and mounted manipulator with different dynamics of duct cleaning robot effectively in the unconstructive and complex duct. The improved robust tracking performance of the whole system is verified by simulation and experiment.

The rest of this paper is organized as follows. The construction of duct cleaning robot is introduced, then the dynamic model of duct cleaning robot is derived, and some preliminaries are given in Section 2. The RBF networks approximation is presented in Section 3. The main results of control design and stability analysis are given in Section 4. In Section 5, Simulation and experiment results are given to demonstrate the effectiveness and superiority of proposed scheme. Concluding remarks are finally made in Section 6.

2. SYSTEM DESCRIPTIONS

The duct cleaning robot is a tracked mobile manipulator which consists of nonholonimic mobile platform

Fig. 2. The body of duct cleaning robot.

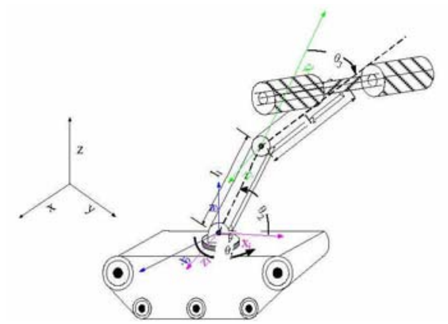


Fig. 3. Structure model of duct cleaning robot.

and holonomic robotic manipulator mounted on the mobile plant, as shown in Fig. 2. The robotic manipulator has 3 joints, one is rotational and the other two are planar joints, as shown in Fig. 3. Consider an n DOF manipulator mounted on nonholonomic mobile platform, the dynamic model of the mechanical system is derived by Lagrange theory and can be described with external disturbances by

$$\begin{aligned} &M(q)\ddot{q}+C(q,\dot{q})\dot{q}+G(q)+F(\dot{q})+d(t) \\ &\quad =B(q)\tau+A^T(q)\lambda, \end{aligned} \tag{1}$$

where $q\in R^n$ means the generalized coordinates of overall system, $M(q)\in R^{n\times n}$ is a symmetric positive define inertia matrix, $C(q,\dot{q})\dot{q}\in R^{n\times 1}$ represents a vector of centripetal and Coriolis force, $G(q)$ denotes gravitational torque vector. $F(\dot{q})\in R^n$ is the surface friction force, $B(q)\in R^{n\times n}$ is the input transformation matrix, $A(q)\in R^{m\times n}$ is the matrix associated with the constraints, and λ is the vector of constraint forces.

The kinematic constraints are considered independent of time t and can be expressed as

$$A(q)\dot{q}=0. \tag{2}$$

Let $S(q)$ be a full rank matrix $n-m$ formed by a set of smooth and linearly independent vector fields spanning the null apace of $A(q)$, i.e.,

$$S^T(q)A^T(q)=0. \tag{3}$$

According to (5) and (6), it is possible to define an auxiliary vector time function $\upsilon(t)\in R^{n-m}$ such that for all t

$$\dot{q}=S(q)\upsilon. \tag{4}$$

In order to reduce the complexity of the whole system, applying the projection of dynamic model into the null space of the constraints, we can obtain

$$\begin{aligned} &\upsilon(t)=\dot{q}_1, \qquad \dot{q}=S(q)\dot{q}_1, \\ &\bar{M}(q)\ddot{q}_1+\bar{C}(q,\dot{q})\dot{q}_1+\bar{G}(q)+\bar{F}(\dot{q})+\bar{d}(t)=\bar{B}(q)\tau, \end{aligned} \tag{5}$$

where

$$\begin{aligned} &\bar{M}(q)=S^T(q)M(q)S(q), \\ &\bar{C}(q,\dot{q})=S^T(q)[M(q)\dot{S}(q)+C(q,\dot{q})S(q)], \\ &\bar{G}=S^T(q)G(q), \quad \bar{F}(\dot{q})=S^T(q)F(\dot{q}), \\ &\bar{d}(t)=S^T(q)d(t), \quad \bar{B}(q)=S^T(q)B(q). \end{aligned}$$

It is well known that dynamic model (5) of robotic system has properties as follows.

Property 1: The matrix $\bar{M}(q)$ is symmetric and positive definite, and satisfies the following inequalities:

$$k_1\|x\|^2\le x^T\bar{M}(q)x\le k_2\|x\|^2,$$

where k_1, k_2 are known positive constants.

Property 2: The matrix $\dot{\bar{M}}(q)-2\bar{C}(q,\dot{q})$ is skew symmetric, means

$$\xi^T[\dot{\bar{M}}(q)-2\bar{C}(q,\dot{q})]\xi=0, \quad \forall\xi\in R^{n-m}.$$

Property 3: The unknown disturbances $\bar{d}(t)$ satisfy $\|\bar{d}(t)\|\le\beta$, where β is a known positive constant.

Property 1 is very important in generating a positive definite function to prove the stability of the closed-loop system, and property 2 will help in simplifying the controller, property 3 is essential to design robust controller.

According to the characteristics of crawler-type robot, the duct cleaning robot can equivalent to the form of differential type, as shown in Fig. 4. In Fig. 4, l_1, l_2, l_3 is the length of manipulator's link1, link2, link3, respectively; d is the distance between the center of drive axis O and manipulator F. Assume the centric of the mobile platform is at the center of drive axis, each link is homogeneous rigid body which the center of mass is in the geometric center. As a generalized coordinates of duct cleaning robot we take the vectors of variables $q=(x,y,\theta,\theta_1,\theta_2,\theta_3)^T$, $q_1=(\theta_L,\theta_R,\theta_1,\theta_2,\theta_3)^T$ where (x, y) denote Cartesian coordinates of the mass center of mobile platform relative the basic frame $X-Y-Z$, θ is

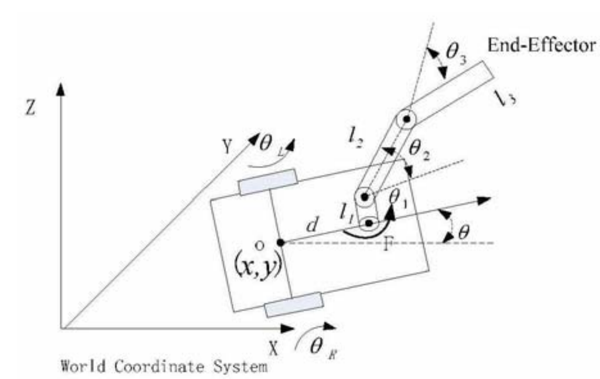


Fig. 4. Equivalent form of duct cleaning robot.

an orientation of platform, θ_1, θ_2, θ_3 is rotation angle of joint1, joint2, joint3 respectively, θ_L, θ_R is the rotation angle of left and right wheel of the equivalent model, respectively.

Moreover, $M(q) \in R^{6\times 6}$, $C(q,\dot{q}) \in R^{6\times 6}$, $G(q) \in R^{6\times 1}$. According to Lagrange equation of 3 DOF duct cleaning robot, $M(q)$, $C(q,\dot{q})$, $G(q)$ can be expressed as

$$M(q) = \begin{bmatrix} M_{11} & M_{12} & \cdots & M_{16} \\ M_{21} & M_{22} & \cdots & M_{26} \\ \vdots & \vdots & \ddots & \vdots \\ M_{61} & M_{62} & \cdots & M_{66} \end{bmatrix},$$

$$C(q,\dot{q}) = \begin{bmatrix} C_{11} & C_{12} & \cdots & C_{16} \\ C_{21} & C_{22} & \cdots & C_{26} \\ \vdots & \vdots & \ddots & \vdots \\ C_{61} & C_{62} & \cdots & C_{66} \end{bmatrix},$$

$$G(q) = (0, 0, 0, 0, G_1, G_2)^T.$$

where

$$G_1 = \frac{1}{2} m_2 g l_2 c_2 - m_3 g l_2 s_2 - \frac{1}{2} m_3 g l_3 s_{23},$$

$$G_2 = -\frac{1}{2} m_3 g l_3 s_{23}.$$

$$c_2 \equiv \cos\theta_2, \quad s_2 \equiv \sin\theta_2, \quad s_{23} \equiv \sin(\theta_2 + \theta_3).$$

Define the tracking error vector $e(t)$ and the auxiliary control vectors x_1, x_2 of duct cleaning robot as

$$\boldsymbol{e}(t) = q_{1d} - q_1, \tag{6}$$

$$x_1 = \boldsymbol{e}(t), \quad x_2 = \dot{\boldsymbol{e}}(t) + \alpha \boldsymbol{e}(t), \tag{7}$$

where q_{1d} denotes the desired duct cleaning robot trajectory vector and α is a positive constant.

Now, we introduce a control signal $\overline{\tau}$, which satisfies

$$\overline{M}(q)\ddot{q}_{1d} + \overline{C}(q,\dot{q})\dot{q}_{1d} + \overline{G}(q) + \overline{\tau} = \overline{B}(q)\tau \tag{8}$$

to compensate the system (5). Thus, the closed-loop control system of duct cleaning robot can be derived by substituting (5) into (8), means

$$\overline{M}(q)\ddot{e} + \overline{C}(q,\dot{q})\dot{e} + \overline{\tau} - \overline{F}(\dot{q}) - \overline{d}(t) = 0, \tag{9}$$

according to the formula (7), the system (9) can be written as

$$\begin{cases} \dot{x}_1 = x_2 - \alpha x_1 \\ \overline{M}(q)\dot{x}_2 = -\overline{C}(q,\dot{q})x_2 + f - d(t) - \overline{\tau}, \end{cases} \tag{10}$$

where $f = \overline{M}(q)\alpha\dot{e} + \overline{C}(q,\dot{q})\alpha e + \overline{F}(\dot{q})$.

We know, the function f is bounded (see Appendix A). However, we don't know the explicit details of it. It is well known, RBF neural network can approximate any nonlinear function to arbitrary accuracy. Therefore, in this paper, RBF neural network is directly used to identify the uncertain factors f of duct cleaning robot, rather than computes the regressor matrix or approximates the whole system dynamics.

3. CONSTRUCTION AND APPROXIMATION OF RBF NEURAL NETWORK

The neural network is one of most popular intelligent technique, and RBF neural network has becoming increasingly popular due to its simple structure, nonlinear mapping capability and training efficiency. In the front of this paper, we know that the function f is unknown but bounded. RBF neural network is used to estimate the uncertain function f in (10). The structure of a three layers RBF network is shown in Fig. 5. RBF neural network consists of the input layer, the hidden layer, and the output layer. Using u_i^l, o_i^l to denote the input and output of the ith node in the lth layer separately, to give a clear idea of signal propagation and the mathematical function in each layer, functions of RBF neural network are described layer by layer as follows.

Input layer: Each node in this layer, which corresponds to one input variable x_i, $(i = 1, 2, \cdots, m)$, only transmits input values to the next layer directly.

$$o_i^1 = u_i^1 = x_i, \quad i = 1, 2, \cdots, m.$$

Hidden layer: Each node in this layer, which corresponds to the input, is performed by

$$u_j^2 = \sum_{i=1}^{m} o_i^1 = \sum_{i=1}^{m} x_i, \quad j = 1, 2, \cdots, k.$$

The output is calculated by the nonlinear transfer function as follows

$$o_j^2 = \sigma_j = \frac{1}{1 + \mathrm{e}^{-u_j^2}}, \quad j = 1, \cdots, k.$$

Output layer: Each node in this layer corresponds to one output. The simple weighted sum is expressed as

$$y_h = o_h^3 = u_h^3 = \sum_{j=1}^{k} w_{hj} \cdot o_j^2 = \sum_{j=1}^{k} w_{hj} \cdot \sigma_j, \quad h = 1, \cdots, n.$$

For ease of notation, define adjustable parameter vectors W, σ and y collecting all parameters of RBF neural network as

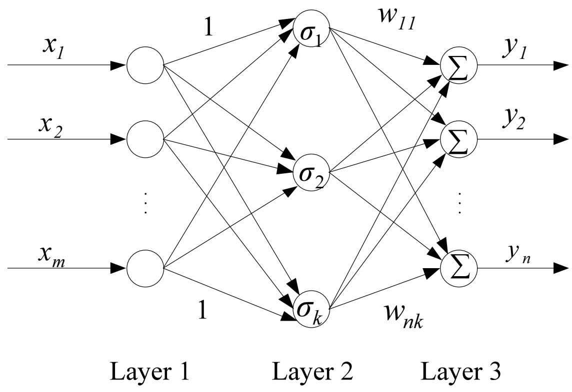


Fig. 5. The structure of RBF neural network.

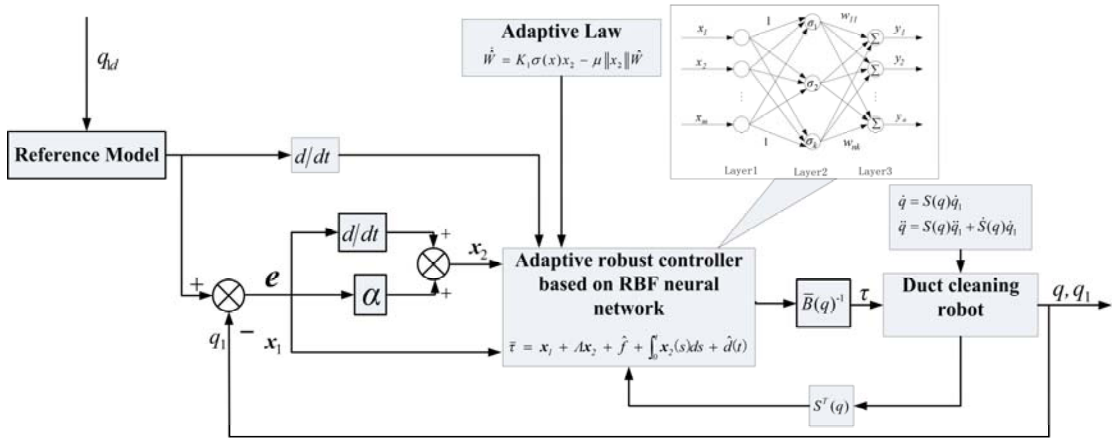


Fig. 6. Structure of adaptive robust controller of duct cleaning robot.

$$W = \begin{bmatrix} w_{11} & w_{12} & \cdots & w_{1k} \\ w_{21} & w_{22} & \cdots & w_{2k} \\ \vdots & \vdots & \ddots & \vdots \\ w_{n1} & w_{n2} & \cdots & w_{nk} \end{bmatrix}, \quad \sigma = \begin{bmatrix} \sigma_1 \\ \sigma_2 \\ \vdots \\ \sigma_k \end{bmatrix}, \quad y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix}.$$

Thus, the output of RBF neural network can be rewritten in the following vector form as

$$y = W^T \sigma. \tag{11}$$

According to the powerful approximation ability, there exist an optional neural network to learn the compound uncertain function f in (10) such that

$$f = W^T \sigma(x) + \varepsilon, \tag{12}$$

where $\| W \| \le b_w$, $\varepsilon \in R$ is a minimum approximation errors vector, which satisfies the following assumption:

Assumption 1: The RBF neural network approximation errors, uncertainties, and other unmolded dynamics are bounded, that is, there exist a positive constant, such that $\| \varepsilon \| \le \rho$ holds.

It is well known, the corresponding estimation $\hat{f}$ can be expressed as

$$\hat{f} = \hat{W}^T \sigma(x), \tag{13}$$

where $\hat{W}$ is the tuning parameter matrix of RBF neural network and it is adjusted in the learning process.

4. CONTROL LAW DESIGN

Now we consider the problem of adaptive robust controller design for system (1). First of all, some basic theorems will be reviewed.

Consider the following nonlinear system:

$$\dot{x} = f(t, x), \tag{14}$$

where x is a state vector with n dimensions, f is a nonlinear function with n dimensions, which structure is only relate to t.

Lasalle Theorem: Consider system (14), if f is locally Lipschitz stable for x, and uniformly continuous for all t, there exist a positive derivable function $V(t, x)$, which satisfies

$$\dot{V} = \frac{\partial V}{\partial x} f(t, x) \le -L(x) \le 0, \quad \forall t \ge 0,$$

where $L(x)$ is a continuous function, then the all solutions of system (14) are globally uniform boundedness, and satisfy

$$\lim_{t \to \infty} L(x) = 0.$$

Additionally, if $L(x)$ is positive definite, then the balance point of system (14) is globally uniform asymptotic stabilization.

From now on, we begin to design adaptive robust controller for duct cleaning robot. Fig. 6 shows the structure of this control strategy.

Define the control law as

$$\bar{\tau} = x_1 + \Lambda x_2 + \hat{f} + P \int_0^t x_2(s) ds + \hat{d}(t), \tag{15}$$

where Λ and P are positive definite, $\hat{d}(t)$ is the robustifying term to attenuate disturbances given by

$$\hat{d}(t) = \frac{K_d x_2}{\| x_2 \|}, \tag{16}$$

where K_d is positive matrix and $\| K_d \| \ge \beta$.

Then, substituting (12), (13), (15) into (10), we get the closed-loop dynamic as

$$\bar{M}(q)\dot{x}_2 = -\bar{C}(q, \dot{q})x_2 + W^T \sigma(x) + \varepsilon + \bar{d} - \bar{\tau}. \tag{17}$$

Theorem 1: Applying the control law (15) to duct cleaning robot system with the robustifying term (16). Let the weight tuning law of RBF network be

$$\dot{\hat{W}} = K_1 \sigma(x) x_2^T - \mu \| x_2 \| \hat{W}, \tag{18}$$

where K_1 is positive matrix and $\mu > 0$. Suppose that the desired trajectory $q_{1d}(t)$ is bounded. Then the following performance can be derived.

P1. With the suitable positive gain Λ and integration parameter matrix P, the tracking error $e(t)$ of the uncertain dynamic system will be uniformly ultimately bounded and converge to the neighborhood of zero.

P2. The proposed control law can guarantee the global stability and robustness of the duct cleaning robot system (10).

Proof: Consider system (10), define the following Lyapunov function:

$$V=\frac{1}{2}x_1^Tx_1+\frac{1}{2}x_2^T\bar{M}(q)x_2 +\frac{1}{2}\left(\int_0^t x_2(s)ds\right)^T P\int_0^t x_2(s)ds+\frac{1}{2}tr(\tilde{W}^T\tilde{W}),$$

with $\tilde{W}=W-\hat{W}$. Then the time derivative of V along the trajectory of (6) is

$$\dot{V}=x_1^T\dot{x}_1+x_2^T\bar{M}(q)\dot{x}_2+\frac{1}{2}x_2^T\dot{\bar{M}}(q)x_2 +x_2^TP\int_0^t x_2(s)ds+\frac{1}{2}tr(\tilde{W}^T\dot{\tilde{W}}),$$

according to (10), (17), above equation can be rewritten as

$$\begin{aligned}\dot{V}&=x_1^T(x_2-\alpha x_1)\\&\quad+x_2^T[-\bar{C}(q,\dot{q})x_2+W^T\sigma(x)+\varepsilon+\bar{d}-\bar{\tau}]\\&\quad+\frac{1}{2}x_2^T\dot{\bar{M}}(q)x_2+x_2^TP\int_0^t x_2(s)ds+tr(\tilde{W}^T\dot{\hat{W}})\\&=x_1^Tx_2-\alpha x_1^Tx_1+x_2^T\left[\frac{1}{2}\dot{\bar{M}}-\bar{C}(q,\dot{q})\right]x_2\\&\quad+x_2^T[\tilde{W}\sigma(x)+\varepsilon+\bar{d}(t)-x_1-\Lambda x_2-\hat{W}^T\sigma(x)\\&\quad-P\int_0^t x_2(s)ds-\hat{d}(t)]\\&\quad+x_2^TP\int_0^t x_2(s)ds+tr(\tilde{W}^T\dot{\hat{W}}),\end{aligned}$$

according to property 2, we can obtain

$$\begin{aligned}\dot{V}&=-\alpha x_1^Tx_1-x_2^T\Lambda x_2+x_2^T\tilde{W}\sigma(x)+x_2^T\varepsilon+x_2^T\bar{d}(t)\\&\quad-x_2^T\hat{W}^T\sigma(x)-x_2^T\hat{d}(t)-tr(\tilde{W}^T\dot{\hat{W}})\\&=-ax_1^Tx_1-x_2^T\Lambda x_2+x_2^T\tilde{W}\sigma(x)+x_2^T\varepsilon+x_2^T\bar{d}(t)\\&\quad-x_2^T\hat{d}(t)-tr(\tilde{W}^T\dot{\hat{W}})\\&\le-ax_1^Tx_1-x_2^T\Lambda x_2+x_2^T\tilde{W}\sigma(x)+x_2^T\varepsilon+x_2^T\bar{d}(t)\\&\quad-\frac{x_2^TK_dx_2}{\|x_2\|}-tr(\tilde{W}^T\dot{\hat{W}})\\&\le-ax_1^Tx_1-x_2^T\Lambda x_2+x_2^T\tilde{W}\sigma(x)+x_2^T\varepsilon+\beta\|x_2\|\\&\quad-\|K_d\|\|x_2\|-tr(\tilde{W}^T\dot{\hat{W}})\\&\le-ax_1^Tx_1-x_2^T\Lambda x_2+x_2^T\tilde{W}\sigma(x)+x_2^T\varepsilon-tr(\tilde{W}^T\dot{\hat{W}})\\&=-ax_1^Tx_1-x_2^T\Lambda x_2+x_2^T\tilde{W}\sigma(x)+x_2^T\varepsilon\\&\quad-tr(\tilde{W}^T[K_1\sigma(x)x_2^T-\mu\|x_2\|\hat{W}])\\&\le-ax_1^Tx_1-x_2^T\Lambda x_2+x_2^T\varepsilon+\mu tr(\tilde{W}^T\|x_2\|\hat{W}).\end{aligned}$$

According to the properties of matrix trace, inner product, and Frobenius norm theory, the following property holds:

$$\begin{aligned}tr(\tilde{W}\hat{W})&=tr(\tilde{W}(W-\tilde{W})),\\&=\langle\tilde{W},W\rangle-\|\tilde{W}\|^2\\&\le\|\tilde{W}\|\|W\|-\|\tilde{W}\|^2.\end{aligned}\tag{19}$$

Thus,

$$\begin{aligned}\dot{V}&\le-\alpha x_1^Tx_1-x_2^T\Lambda x_2+x_2^T\varepsilon-x_2^T\hat{d}(t)\\&\quad+\mu\|x_2\|(\|\tilde{W}\|\|W\|-\|\tilde{W}\|^2)\\&\le-\alpha x_1^Tx_1-\lambda_{\min}(\Lambda)\|x_2\|^2+\rho\|x_2\|\\&\quad-\beta\|x_2\|+\mu\|x_2\|(\|\tilde{W}\|b_w-\|\tilde{W}\|^2)\\&\le-\lambda_{\min}(\Lambda)\|x_2\|^2+\rho\|x_2\|-\beta\|x_2\|\\&\quad+\mu\|x_2\|(\|\tilde{W}\|b_w-\|\tilde{W}\|^2)\\&=-\|x_2\|\{\lambda_{\min}(\Lambda)\|x_2\|-\rho+\beta-\mu(\|\tilde{W}\|b_w-\|\tilde{W}\|^2)\}\\&=-\|x_2\|\{\lambda_{\min}(\Lambda)\|x_2\|-\rho+\beta+\mu(\|\tilde{W}\|^2-\|\tilde{W}\|b_w)\}\\&=-\|x_2\|\{\lambda_{\min}(\Lambda)\|x_2\|-\rho+\beta+\mu(\|\tilde{W}\|-\frac{b_w}{2})^2-\mu\frac{b_w^2}{4}\},\end{aligned}$$

where $\lambda_{\min}(\Lambda)$ is minimum singular value of Λ, let $\lambda_{\min}(\Lambda)=\varphi$. Therefore, $\dot{V}$ is negative when it satisfies the following inequalities:

$$\|x_2\|>\frac{\rho-\beta+\mu\frac{b_w^2}{4}}{\varphi}=\phi_s$$

or

$$\|\tilde{W}\|>\frac{b_w}{2}+\frac{1}{\mu}\sqrt{\rho-\beta+\mu\frac{b_w^2}{4}}=\phi_w.$$

Clearly, there exists a compact set

$$\Omega:\{\|x_2\|,\|\tilde{W}\|\mid 0\le\|x_2\|\le\phi_s,\ and\ \|\tilde{W}\|\le\phi_w\}.$$

Based on Lyapunov theorem and Lasalle theorem, for

$$x_2(t_0),\quad \tilde{W}(t_0)\in\Omega,$$

there exists $T(\phi_s,\phi_w,x_2(t_0),\tilde{W}(t_0))$ such that $0\le\|x_2\|\le\phi_s$ and $\|\tilde{W}\|\le\phi_w$ for all $t\ge t_0+T$. Means $\dot{V}$ is negative outside the compact set Ω. This completes the proof.

Remark 1: For the proposed control law (15), once the control parameters such as Λ, P, K_d are determined, the input torque $\bar{\tau}$ is bounded for all t. According to aforementioned proof, we can ensure the asymptotical stability of duct cleaning robot.

Remark 2: The proposed scheme is nonregressor based and requires no information about dynamic uncertainties and external disturbances of duct cleaning robot. Using the RBF neural network to approximate the uncertain term f and avoid using fixed large boundedness of robust controller to guarantee good performance, because large boundedness implies high noise amplification and high control cost.

Remark 3: The designed controller (15) consists of three components. The first component $x_1 + \Lambda x_2 + P\int_0^t x_2 ds$ is common PI control term which is used guarantee the stability of the system and achieve uniformly ultimately performance, and the second component $\hat{f}$ is the adaptive RBF neural network to approximate the uncertain term f, the third component $\hat{d}(t)$ is the robust term to attenuate disturbances.

Remark 4: As far as we know, all adaptive control methods should satisfy the persistent excitation condition due to the assumption that all the uncertainties in the system can be parameterized by the constant coefficient, but for the real systems, the assumption cannot be satisfied completely. Therefore, in our approach, we use the RBF neural network to deal with the uncertainties in the systems of the duct cleaning robot, and avert the complex computation. There will relax the requirement of persistent excitation condition, and only require that the weight of neural network is convergent, simultaneously, the x_2 is in a bounded set. In Appendix A, we have proof the e, $\dot{e}$ are bounded, so the x_2 is bounded. We assume that the $\| x_2 \| \le \phi$, according to the $\| x_2 \| > \varphi_x$, we can derive $\varphi_x < \| x_2 \| < \phi$. Through the proof of the Theorem 1, the designed tuning law of the weight of RBF neural network can converge, consequently, the proposed control approach don't require the persistent excitation condition.

5. SIMULATION AND EXPERIMENT

5.1. Simulation results

In this section, the proposed adaptive robust control strategy based on RBF neural network is applied to duct cleaning robot which shown in Fig. 2 to verify its feasibility and effectiveness. The parameters of the duct cleaning robot are shown in Table 1 list. Assuming that

Table 1. Parameters of mobile manipulator.

parameter	Value	Unit
Mass of platform	10	kg
Mass of link1	1	kg
Mass of link2	3	kg
Mass of link3	4	kg
Inertia of platform	0.1	kg·m^2
Inertia of link1	0.01	kg·m^2
Inertia of link2	0.02	kg·m^2
Inertia of link3	0.02	kg·m^2
Radial of the wheel r	0.05	m
Distance between the two driving wheel R	0.2	m
Length of link1	0.05	m
Length of link2	0.15	m
Length of link3	0.15	m

the mobile platform is pure rolling and non-slipping, the mobile manipulator is subjected to the following constraints:

$$\begin{aligned} &-\dot{x}\sin\theta + \dot{y}\cos\theta + R\theta_L = 0, \\ &\dot{x}\cos\theta + \dot{y}\sin\theta + R\theta_R = 0, \\ &\dot{x}\sin\theta - \dot{y}\cos\theta = 0, \end{aligned} \tag{20}$$

then the constraint matrix according to the formula (20) is:

$$A(q) = [\sin\theta \;\; \cos\theta \;\; 0 \;\; 0 \;\; 0 \;\; 0]^T.$$

Let $S(q)$ be one of the basis of the null space of $A(q)$:

$$S(q) = \begin{bmatrix} \frac{r}{2}\cos\theta + \frac{r}{R}\sin\theta & \frac{r}{2}\cos\theta - \frac{r}{R}\sin\theta & 0 & 0 & 0 \\ \frac{r}{2}\sin\theta - \frac{r}{R}\cos\theta & \frac{r}{2}\sin\theta + \frac{r}{R}\cos\theta & 0 & 0 & 0 \\ -\frac{r}{R} & \frac{r}{R} & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}.$$

Let

$$\begin{aligned} F(\dot{q}) = [&m_0 g\cos\dot{\theta},\, 0,\, m_1 g\sin\dot{\theta}_1, \\ &m_2\sin\dot{\theta}_2,\, 0,\, m_3 g\cos\dot{\theta}_3]^T. \end{aligned}$$

In the simulation, the external disturbances are chosen as

$$d(t) = \left[3\sin(t),\, 2\cos(t),\, \frac{4}{5}\sin(t),\, 0.7\cos(3t),\, 4\sin(4t)\right]^T.$$

Desired linear trajectory for overall system is given as:

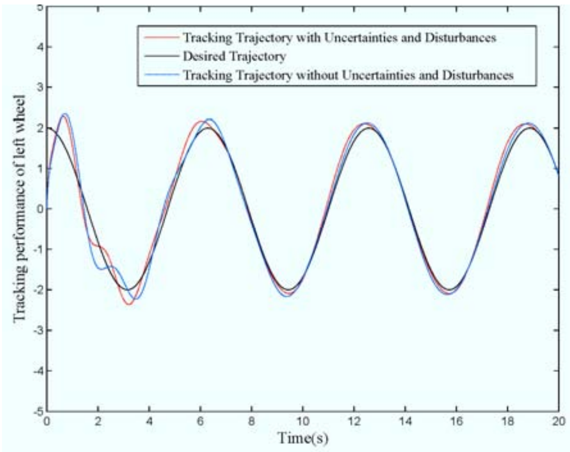
$$q_{1d} = [2\cos(t), 2\sin(t), \cos(2t), \sin(2t), -\cos(2t)]^T.$$

A RBF network was constructed, with 24 input neurons, 96 hidden layers, and 5 output neurons, to estimate on-line the unknown nonlinear dynamics f. The input pattern of the neural networks controller was chosen $(q, \dot{q}, q_{1d}, \dot{q}_{1d})$. The output of RBF network represents the compensation torques for nonlinear dynamics of all joints. The weights of RBF networks are simply initialized at zero and updated timely at each control cycle using proposed learning law (18).

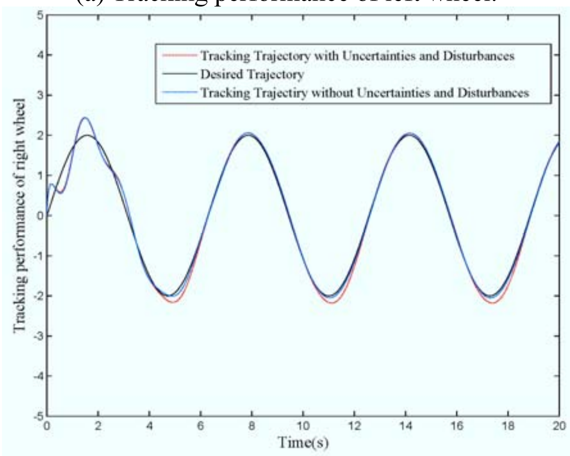
For the convenience of simulations, choose the parameters of the presented control strategy as

$$\begin{aligned} &\alpha = 13,\; \mu = 12,\; \Lambda = diag([1.5, 1.95, 3.18, 15, 27]), \\ &P = diag[2.6132, 3.6721, 7.5628, 15.7323, 30.12], \\ &K_1 = random('unif', 0, 0.5, 5, 15). \end{aligned}$$

Hence, by Theorem 1, we can conclude that the proposed approach can guarantee the global stability and get good tracking performance of duct cleaning

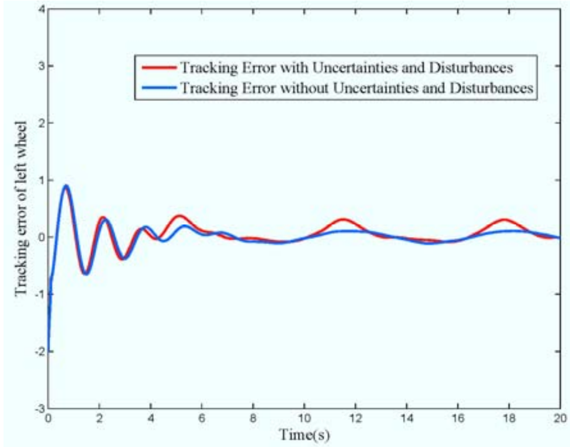


(a) Tracking performance of left wheel.

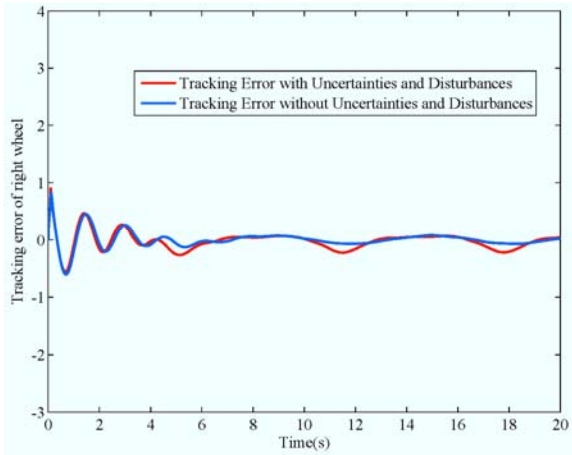


(b) Tracking performance of right wheel.

Fig. 7. Tracking performance of left wheel and left wheel.



(a) Tracking error of left wheel.



(b) Tracking error of right wheel.

Fig. 8. Tracking error of left wheel and right wheel.

robot. The presented adaptive robust control strategy based on RBF neural network is applied to the system which is shown in Fig. 2. At the same time, to demonstrate the proposed control approach has strong robustness performance to external disturbances, simulation experiment without external disturbances is given to compare with the proposed control strategy. The simulation results are shown in Figs. 7-10.

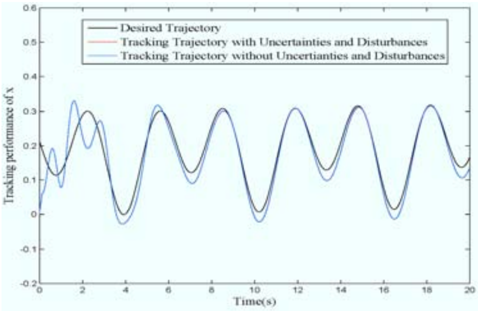
The tracking performances of the left wheel and right wheel are shown in Figs. 7-8, respectively. From above figures, it can be seen that the tracking results without external disturbances are a little better than the one with external disturbances. However, according to the formula (4) and $S(q)$, we can derive

$$\begin{bmatrix} \dot{x} \\ \dot{y} \\ \dot{\theta} \end{bmatrix} = \begin{bmatrix} \cos\theta & \sin\theta \\ \sin\theta & -\cos\theta \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \frac{r}{2} & \frac{r}{2} \\ -\frac{r}{R} & \frac{r}{R} \end{bmatrix} \begin{bmatrix} \dot{\theta}_L \\ \dot{\theta}_R \end{bmatrix}, \tag{21}$$

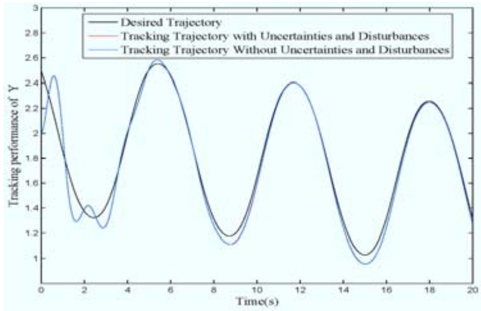
where $\dot{\theta}_L$, $\dot{\theta}_R$ represents the angular velocity of left wheel and right wheel, respectively. Hence, the tracking performances of $q=(x,y,\theta,\theta_1,\theta_2,\theta_3)^T$ are shown in Figs. 9(a)-(f), the tracking errors of q are given in Figs. 10(a)-(d).

Compare Figs. 7(a)-(b) with Figs. 9(a)-(c), we can see that the tracking trajectories with external disturbances coincide with the trajectories without external disturbances basically in Figs. 9(a)-(c), though the tracking trajectories of left wheel and right wheel are a little better in case of having no external disturbances. From the Figs. 9(d)-(f), the tracking trajectories with external disturbances show the good performance the same as the trajectories without external disturbances. Therefore, the proposed control approach has strong robustness performance to external disturbances.

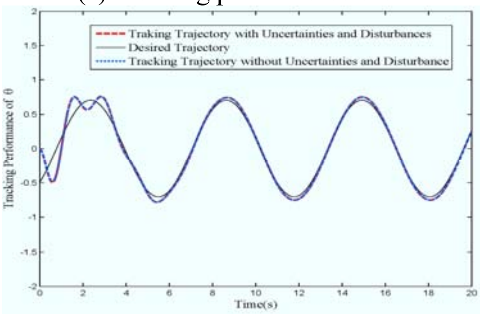
Remark 5: According to aforementioned simulation results, the proposed control approach can take advantages of strong robustness performance of adaptive robust control, nonlinear mapping properties and self-learning ability of RBF neural networks, to approximate the unmolded dynamics, structured uncertainties, unstructured uncertainties and external disturbance. The neural network can alleviate the chattering to some unknown errors and the learning process is online. The system dynamics identification and trajectory tracking performance are quite effective. Maybe, the proposed controller would be more perfect performance if some intelligent optimization approaches such as particle swarm algorithm, ant swarm algorithm to applied to determine the parameters of the controller.



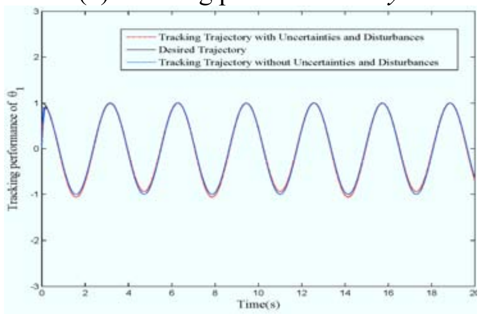
(a) Tracking performance of x.



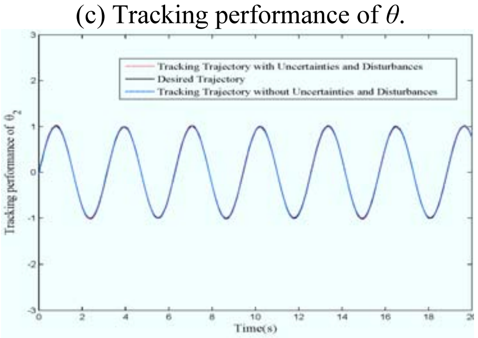
(b) Tracking performance of y.



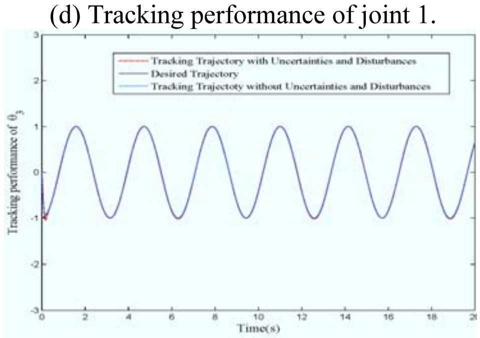
(c) Tracking performance of θ.



(d) Tracking performance of joint 1.

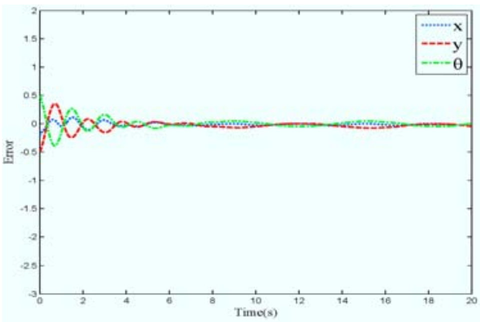


(e) Tracking performance of joint 2.

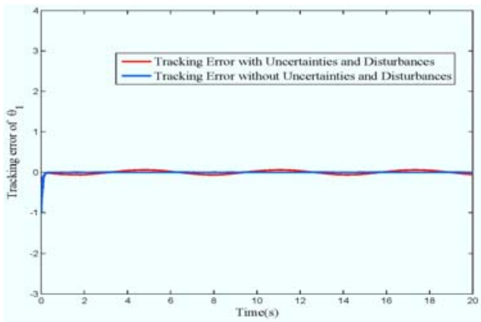


(f) Tracking performance of joint 3.

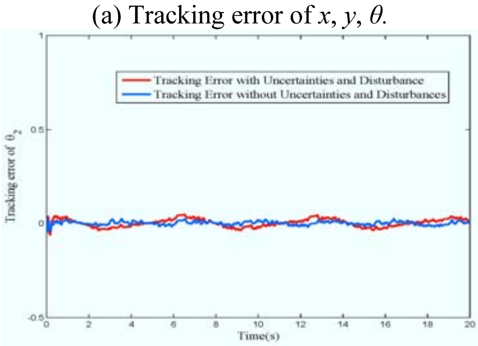
Fig. 9. Simulation results for tracking performance.



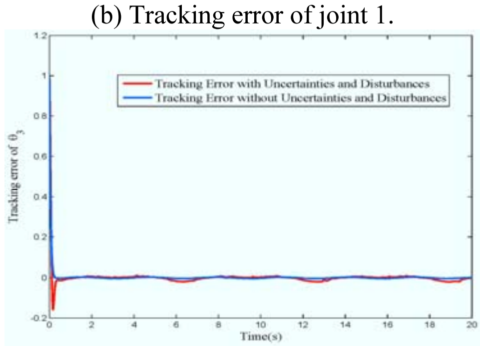
(a) Tracking error of x, y, θ.



(b) Tracking error of joint 1.



(c) Tracking error of joint 2.



(d) Tracking error of joint 3.

Fig. 10. Simulation results for tracking errors.

5.2. Experiment results

In this part, an experimental for real system of duct cleaning robot is described. Because the above simulation results well illustrate the effectiveness of the proposed control strategy merely relate to the equivalent model of duct cleaning robot, but it is well known that good simulation performance of a control approach does not guarantee its effectiveness in real system and true environment due to friction and backlash between joints, coupling between mobile platform and robotic manipulator, unexpected disturbances in the measurement and other limitations. The most previous researches about controller design for robotic system are only given the simulation results to demonstrate the proposed control law can guarantee the whole system stability and have good performance; only a small set has been verified by experiments in real systems. Therefore, in this paper, the experiment results are given to demonstrate that the proposed control strategy is effective for real duct cleaning robot which is shown in Fig. 2. The experiment environment is given in the Fig. 11. Table 1 explains the experimental and the duct cleaning robot parameters that were utilized for experiment and their values. The other parameters such as α, μ, Λ, P, K_1 and K_d are given as

$$\alpha = 18.76, \quad \mu = 15,$$
$$\Lambda = diag[(2.79, 1.95, 3.56, 16.78, 29.23)],$$
$$P = diag[(2.851, 3.676, 8.785, 15.49, 30.25)],$$
$$K_1 = random('unif', 0, 0.5, 5, 10),$$
$$K_d = diag[(5, 6.5, 10.7, 17, 30)].$$

Experiment results are shown in Figs. 12-13. Figs. 12(a) shows the tracking performance of mobile platform of duct cleaning robot; Figs. 12(b)-(d) reveal the tracking performance of joints of manipulator, respectively. Figs. 13(a)-(b) show the tracking errors which are uniformly ultimately bounded and converge to a small neighborhood of zero, and Figs. 14(a)-(b) show that the control torque inputs are very smooth.

Compare the simulation results and experiment results, we can obtain that the simulation results have better tracking performance than experiment results, and the tracking errors of simulation strictly converge to zero, rather than the tracking errors of experiment converge to the neighborhood of zero, this is because in real duct cleaning robot, there exists more uncertainties and unknown disturbances to effect the tracking performance, make the tracking errors in a small bound nearby zero

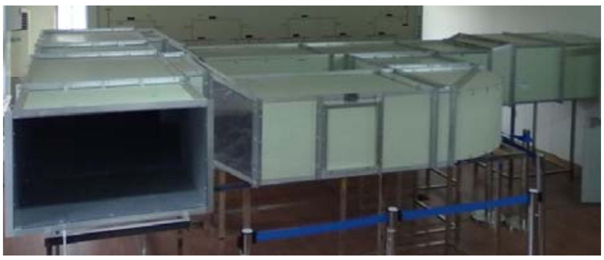
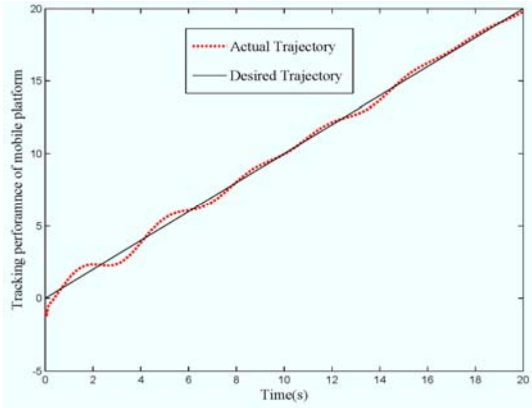
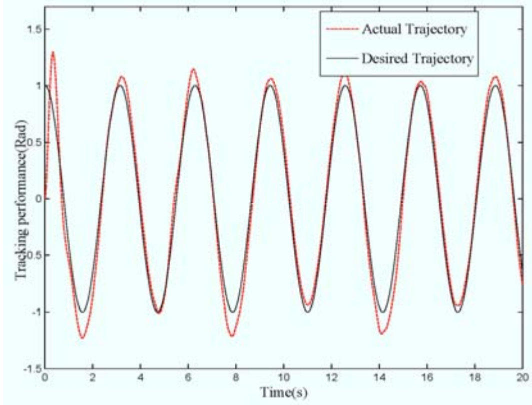


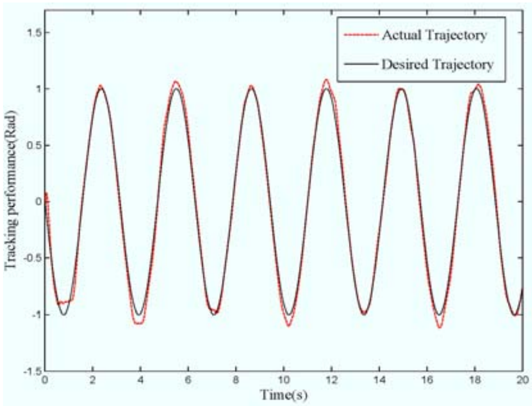
Fig. 11. Simulation environment of duct cleaning robot.



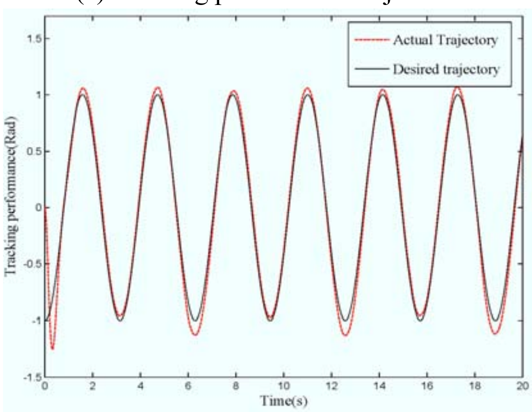
(a) Tracking performance of mobile platform.



(b) Tracking performance of joint 1.

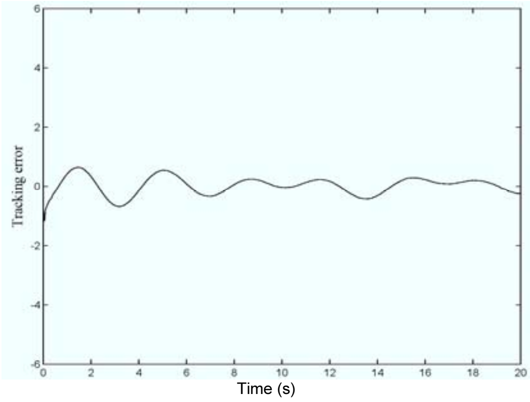


(c) Tracking performance of joint 2.

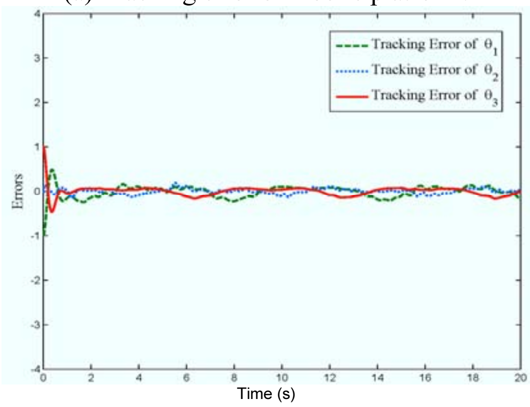


(d) Tracking performance of joint 3.

Fig. 12. Experiment results for tracking performance by the proposed approach.

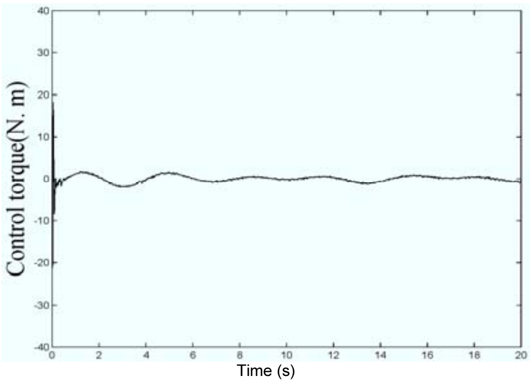


(a) Tracking error of mobile platform.

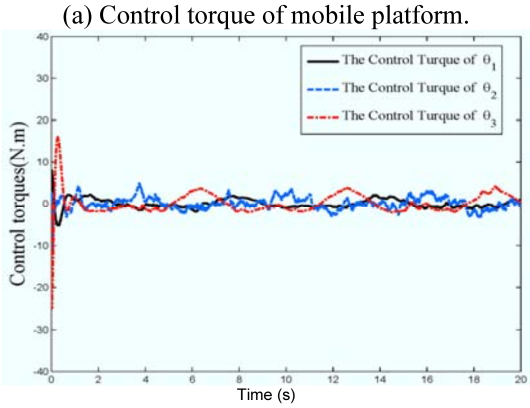


(b) Tracking errors of joints.

Fig. 13. Experiment results of tracking errors by the proposed approach.



(a) Control torque of mobile platform.



(b) Control torques of joints.

Fig. 14. Experiment results of control torque by the proposed approach.

means that the proposed control scheme can guarantee the whole system of duct cleaning robot stability in real application. In a word, the simulation and experiment results reveal that the proposed control strategy is effective for duct cleaning robot in the presence of uncertainties and external disturbances.

6. CONCLUSIONS

In this paper, the approach which combines the advantages of RBF neural network and effective adaptive robust trajectory tracking control strategy is presented systematically for real duct cleaning robot in the presence of uncertainties and external disturbances. Based on Lyapunov stability theory, the proposed control scheme can guarantee the stability, the uniformly ultimately bonded of the closed-system and the tracking performance of duct cleaning robot system. Through simulation and experiment, the proposed controller is verified that it is robust not only to external disturbances but also to the parameter and unparameter uncertainties. RBF neural network is used to approximate the structured and unstructured system uncertainties directly. In the traditional neural network control approach, the convergence of weights for neural network can't be guaranteed when the persistent excitation condition isn't satisfied. The proposed approach uses the adaptive tuning law to guarantee the weights of neural network are converging quickly without satisfying the persistent excitation. Simulation and experiment results show the effective control performance of the proposed control strategy.

APPENDIX A

In this Appendix, we give the proof that the function f is bounded. First of all, a lemma is given as follows.

Lemma 1: Consider system (17), if there exists a positive derivable function $V(\boldsymbol{x}, t)$, which satisfies [22]

$$k_1\|\boldsymbol{x}\|^2 \le V(\boldsymbol{x},t) \le k_2\|\boldsymbol{x}\|^2, \quad \forall \boldsymbol{x}, \quad \forall t > 0, \tag{A.1}$$

$$\dot{V}(\boldsymbol{x},t) \le -k_3\|\boldsymbol{x}\|^2 + \varepsilon, \quad \forall \boldsymbol{x}, \quad \forall t > 0, \tag{A.2}$$

where $k_1 > 0,\ k_2 > 0,\ k_3 > 0,\ \varepsilon > 0$ are given positive constants, then for any initial state $\boldsymbol{x}(0)$, the following formulation is found:

$$\|\boldsymbol{x}\| \le \left\{\frac{k_1}{k_2}\|\boldsymbol{x}(0)\|^2 e^{-kt} + \frac{\varepsilon}{k_1 k_2}(1-e^{-kt})\right\}^{\frac{1}{2}}, \tag{A.3}$$

where $k = \dfrac{k_3}{k_2}$.

According to Theorem 1 and Lemma 1, transform the formula (7) into the following form

$$\dot{\boldsymbol{e}} + \alpha\boldsymbol{e} - x_2 = 0, \tag{A.4}$$

solve this one-order linear differential equation to derive

$$\boldsymbol{e}(t) = \boldsymbol{e}(0)e^{-at} + \int_0^t e^{-a(t-s)}x_2(s)ds.$$

Define each component of $\boldsymbol{e}(t)$ as

$$\boldsymbol{e}_i(t)=\boldsymbol{e}_i(0)e^{-at}+\int_0^t e^{-a(t-s)}x_{2i}(s)ds,\quad (i=1,\cdots,5)$$

then we know that

$$|\boldsymbol{e}_i(t)|\le|\boldsymbol{e}_i(0)|e^{-at}+\int_0^t e^{-a(t-s)}|x_{2i}(s)|ds,$$

sum the each component

$$\sum_{i=1}^5|e_i(t)|\le\sum_{i=1}^5|e_i(0)|e^{-at}+\int_0^t e^{-a(t-s)}\sum_{i=1}^5|x_{2i}|ds.$$

Ultimate the inequalities as follows

$$\|\boldsymbol{e}(t)\|\le\sum_{i=1}^5|\boldsymbol{e}_i(t)|,\quad |\boldsymbol{e}_i(t)|\le\|\boldsymbol{e}(t)\|,\quad |x_{2i}(t)|\le\|x_2\|,$$

$$\|\boldsymbol{e}(t)\|\le 5\|\boldsymbol{e}(0)\|e^{-at}+5\int_0^t e^{-a(t-s)}\|x_2(s)\|ds. \tag{A.5}$$

Let $E=\frac{\varepsilon}{k_1k}$, $F=\frac{k_3}{k_2}\|x_2(0)\|^2-\frac{\varepsilon}{k_1k}$, the according to the formula (A.3), we can derive

$$\|x_2(t)\|^2\le E+Fe^{-kt},\quad \|x_2(t)\|\le\sqrt{E}+\sqrt{F}e^{\frac{kt}{2}}. \tag{A.6}$$

Substituting (A.6) into (A.5), obtains

$$\begin{aligned}\|x_2(t)\|&\le 5\|\boldsymbol{e}(0)\|e^{-at}+5\int_0^t e^{-a(t-s)}(\sqrt{E}+\sqrt{F}e^{-\frac{ks}{2}})ds\\
&=5\|\boldsymbol{e}(0)\|e^{-at}+5\sqrt{E}\int_0^t e^{-a(t-s)}ds+5\sqrt{F}\int_0^t e^{-a(t-s)}e^{-\frac{ks}{2}}ds\\
&=5\|\boldsymbol{e}(0)\|e^{-at}+\frac{5\sqrt{E}}{a}(1-e^{-at})+\frac{5\sqrt{F}}{2k-a}(e^{-\frac{kt}{2}}-e^{-at})\\
&=\left[5\|\boldsymbol{e}(0)\|-\frac{5\sqrt{E}}{a}-\frac{5\sqrt{F}}{2k-a}\right]e^{-at}+\frac{5\sqrt{F}}{2k-a}e^{-\frac{kt}{2}}+\frac{5\sqrt{E}}{a},\end{aligned}$$

means

$$\|e(t)\|\le Ae(0)e^{-at}+Be^{-\frac{kt}{2}}+C, \tag{A.7}$$

where

$$A=5\|\boldsymbol{e}(0)\|-\frac{5\sqrt{E}}{a}-\frac{5\sqrt{F}}{2k-a},\qquad B=\frac{5\sqrt{F}}{2k-a},$$
$$C=\frac{5\sqrt{E}}{a}=\frac{5}{a}\sqrt{\frac{\varepsilon}{k_1k}}.$$

According to the formula (A.7), the tracking error $\boldsymbol{e}$ is bounded. $\dot{\boldsymbol{e}}$ is bounded. Thanks to

$$f=\bar{M}(q)\alpha\dot{\boldsymbol{e}}+\bar{C}(q,\dot{q})\alpha\boldsymbol{e}+\bar{F}(\dot{q}),$$

according to the property of dynamic model (5) that the $\|\bar{M}(q)\|\le M$, $\|\bar{C}(q,\dot{q})\|\le C$, $\|\bar{F}(\dot{q})\|\le F$, are bounded, so f is bounded. Proof is over.

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