ROBUST ADAPTIVE CONTROL FOR ROBOT MANIPULATORS TRAJECTORY TRACKING BASED ON ITERATIVE LEARNING OBSERVER WITH TIME-DELAY

Fu Xingjian, He Jiahui

Received on December 19, 2021
Presented by Ch. Roumenin, Member of BAS, on February 24, 2022

Abstract

For the trajectory tracking of the robot manipulators, the robust adaptive control based on iterative learning observer is designed. The robot manipulators model is given, and an iterable dynamic equation is obtained by linearizing the model. An iterative learning observer is designed, so that the output state of the observer can converge to the actual state of the system and the convergence analysis of the observer is also given. Based on Lyapunov stability theory, the robust adaptive controller is given to ensure that the trajectory tracking error of the robot manipulators gradually approaches zero. Finally, the double joint robot manipulators systems are simulated, and the results verify the effectiveness of the method.

Key words: iterative learning, observer, robust adaptive control, robot manipulators

1. Introduction. With the development and in-depth research in the industrial field, the complexity of the controlled objects is getting higher and higher, and the requirements for control accuracy are getting higher and higher. Therefore, intelligent control methods are widely used in industrial control.

This work is supported by National Natural Science Foundation of China under Grant 61973041.
DOI:10.7546/CRABS.2022.06.10

861
Modern intelligent control is different from the traditional classic control that relies on precise mathematical models. It uses data-driven theory to optimize the control method. At present, many intelligent methods have been developed, such as fuzzy control, neural network control, genetic algorithm control, learning control [1–3], and so on. Learning control has been proposed since 1970. It is characterized by its own learning thinking function to understand the control object and adjust its own performance according to the external environment [4,5]. That is, it can imitate the learning process of human beings, and has some judgment, memory and decision-making capabilities. In the application, through multiple training, learn from experience and continuously adjust yourself to achieve a certain performance index.

In 1978, Japanese scholar Uchiyama [6] proposed the concept of Iterative Learning Control (ILC) for the first time in the literature in order to solve the high-speed robot manipulators system in industry. In 1984, Arimoto and others perfected Uchiyama’s idea, established a practical algorithm, and theoretically proved the feasibility of the algorithm. Iterative learning control is a branch of intelligent control. It mainly uses the error between the dynamic process of the controlled object and the desired ideal trajectory to adjust and correct, and gradually completes the controlled object’s approach to the desired operation in the iteration direction. Its characteristic is to make full use of the information and experience of repeated trajectories, so that the system continuously improves performance during operation. Applications of iterative learning control can be systems with repetitive motion characteristics such as robot manipulators, XY platforms, robots, and CNC machine tools [7,8].

Many scholars have combined traditional iterative learning strategies with other theories to explore new combination algorithms. At present, many new iterative learning control methods have appeared, such as adaptive iterative learning control [9,10], robust iterative learning control, and optimal iterative learning control. The idea of adaptive iterative learning control is to make full use of system experience to perform adaptive iterative learning for uncertain parameters in the system and unknown controller gain [11,12]. Both iterative learning control and adaptive control have learning correction function. The former is mainly for the correction of control input. The latter is mainly to modify control parameters or system parameters. In [11], some adaptive iterative learning control (ILC) schemes were proposed for trajectory tracking of rigid robot manipulators, with unknown parameters, performing repetitive tasks. In [12], on the basis of the nonlinear iterative learning, a double iterative compensation learning control is proposed. It can be seen that the adaptive control is introduced in the iterative learning, which can learn and modify the prior knowledge, and can make full use of adaptive control to handle the uncertainty. In this way, the optimization of dynamic response in adaptive control is achieved.

The robot manipulators control system is a highly complex, highly coupled
and typically uncertain nonlinear system. The trajectory tracking of the robot manipulators has always been one of the important topics in nonlinear control research [13–15]. The difficulty in its controller design is its highly nonlinear and inherently unknown dynamics. Because the control tasks are repetitive, iterative learning control has been widely used in robot manipulators control systems. Scholars at home and abroad have conducted a lot of researches on iterative learning applied to robot manipulators [16–18].

At present, most research methods of iterative learning control are based on the assumption that the states of the controlled object are easy to measure or obtain. However, in the actual control system, as the internal variables of the system, sometimes it is impossible to measure all, and sometimes it is limited in terms of economics and applicability, which makes the physical implementation of state feedback difficult. This formed a more complicated contradiction. The solution to this contradiction is to design an observer, and use the observer to approximate the state of the system, so as to obtain the output control based on the state observer. In this paper, for the robot manipulators control system, a robust adaptive control based on an iterative learning observer with time-delay is designed to accurately track the trajectory of the angular and angular speed states of the robot manipulators. Finally, the double joint robot manipulators system is simulated, and the results verify the effectiveness of the method.

2. Robot manipulators system model. The structure of the double-joint robot manipulators is shown in Fig. 1, where \( l_j, l_j^G, I_j \) and \( m_j (j = 1, 2) \), respectively, represent the length of the connecting rod, the distance from the centre to the axis, moment of inertia and the mass of the rod. Trajectory tracking is an important issue in robot control. If the two-dimensional manipulator is a rigid arm, its dynamic equation can be obtained by using Lagrange equation. Considering a non-linear robot manipulators system with rotating joints of two degrees of freedom within a finite time interval \([0, T]\), for the existing uncertainty, the dynamic equation of the robot manipulators system with two degrees of freedom including non-repeating disturbance is

\[
D(q_k(t)) \ddot{q}_k(t) + C(q_k(t), \dot{q}_k(t)) \dot{q}_k(t) + G(q_k(t), \dot{q}_k(t)) + \omega_k(t) = u_k(t),
\]

where \( k \) is the number of iterations, \( t \in [0, t_f] \). \( q_k(t) \in \mathbb{R}^n \), \( \dot{q}_k(t) \in \mathbb{R}^n \) and \( \ddot{q}_k(t) \in \mathbb{R}^n \) are the joint angle, angular speed, and angular acceleration, respectively. \( D(q_k(t)) \in \mathbb{R}^{n \times n} \) is the inertia term, \( C(q_k(t), \dot{q}_k(t)) \) \( \dot{q}_k(t) \in \mathbb{R}^n \) is the centrifugal force and Coriolis force, \( G(q_k(t), \dot{q}_k(t)) \in \mathbb{R}^n \) is the gravity and friction terms, \( \omega_k(t) \in \mathbb{R}^n \) is the unknown disturbance, and \( u_k(t) \in \mathbb{R}^n \) is the control input. The dynamic equation of the robot manipulators satisfies the following characteristics:

1) \( D(q_k(t)) \) is a symmetric positive definite bounded matrix;
2) $\dot{D}(q_k(t)) - 2C(q_k(t), \dot{q}_k(t))$ is an obliquely symmetric matrix, satisfying

\[
x^T \left( \dot{D}(q_k(t)) - 2C(q_k(t), \dot{q}_k(t)) \right) x = 0.
\]

The dynamic equation of the robot manipulators satisfies the following assumptions:

1) The expected trajectory $q_d(t)$ is third-order derivable within $t \in [0, t_f]$.
2) The iterative process satisfies the initial conditions, i.e.

\[
q_d(0) - q_k(0) = 0, \quad \dot{q}_d(0) - \dot{q}_k(0) = 0, \quad \forall k \in \mathbb{N}.
\]

Let $x_1(t) = q(t), x_2(t) = \dot{q}(t)$. The equation of state can be obtained as follows:

\[
\dot{x}(t) = \begin{bmatrix} \dot{x}_1(t) \\ \dot{x}_2(t) \end{bmatrix} = \begin{bmatrix} \dot{q}(t) \\ \ddot{q}(t) \end{bmatrix} = f(x(t), t) + B(t)u(t).
\]

Taking the joint angular displacement and angular velocity as output variables, the output equation is

\[
y(t) = C_1(t) x(t),
\]

where $f(x(t), t) = \begin{bmatrix} \dot{q}(t) \\ -M^{-1}(q(t))[C(q(t), \dot{q}(t)) + G(q(t))] \end{bmatrix}$,

\[
B(t) = \begin{bmatrix} 0 \\ M^{-1}(q) \end{bmatrix}, \quad C_1(t) = I.
\]

3. Design of iterative learning observer with time-delay. In robot manipulators control systems, time-delay also exists. The existence of time-delay makes the analysis and synthesis of the system more complicated and difficult. At the same time, the existence of time-delay is often the source of system instability.
Combined with the model of the robot manipulators, the model with time-delay is established as

\[
\begin{align*}
  x_k(t+1) &= A_1 x_k(t) + A_2 x_k(t-d) + Bu(t) + H \omega(t) \\
  y_k(t) &= C_2 x_k(t),
\end{align*}
\]

where \( x_k(t) \in \mathbb{R}^n \) is the state vector, \( y_k(t) \in \mathbb{R}^n \) is the output vector, \( u(t) \in \mathbb{R}^q \) is the control input of the system, \( \omega(t) \) is an unknown repeated disturbance, \( d \) is the time-delay, \( A_1, A_2, C_2 \) and \( H \) are constant matrix with appropriate dimensions. The subscript \( k \) indicates the number of iterations.

Iterative learning observers are used to observe the state of the system in real time. Design the observer as

\[
\begin{align*}
  \dot{\hat{x}}_k(t+1) &= A_1 \hat{x}_k(t) + A_2 \hat{x}_k(t-d) + \hat{B} u_k(t) + L(y_k - \hat{y}_k) \\
  \hat{y}_k(t) &= C_2 \hat{x}_k(t)
\end{align*}
\]

\[
\gamma_k = x - \hat{x}_k
\]

\[
\hat{g}(k+1) = \hat{g}_k + k_p \gamma_k + k_d \dot{\gamma}_k
\]

\[
|y_k(t) - \hat{y}_k(t)|_\infty \leq \varepsilon.
\]

Here \( \hat{g}(t) \) is a PD-type iteration of the state estimation error, \( L \) is the gain value of the known observer, \( \gamma_k \) is the error comparing the actual state with the output of the observer, \( k_p \) and \( k_d \) are normal numbers.

**Assumption 1.** The initial value of equation (5) is known, \( x(0) \) and \( y(0) \) are known.

**Assumption 2.** The system control coefficients are bounded, that is, \( |g| < \varepsilon \) and \( |u| < \xi \), where \( \varepsilon \) and \( \xi \) are normal numbers.

**Assumption 3.** The coefficient estimation error in equation (14) is bounded, that is \( ||\hat{B}\| \leq \beta_1 ||x_k - \hat{x}_k|| \), where \( \beta_1 \) is a normal number.

**Lemma** (Barbalat Theorem [19]). Let \( x : [0, \infty) \rightarrow \mathbb{R} \) be first-order continuously differentiable and have a limit when \( t \rightarrow \infty \), if \( \dot{x}(t) \), \( t \in [0, \infty) \) exists and is bounded, then \( \lim_{t \rightarrow \infty} \dot{x}(t) = 0 \).

**Theorem 1.** For system (5), the iterative learning observer (6) is designed. In a limited time, if the initial conditions of the iteration satisfy \( \hat{x}_k(0) = x(0) \). When \( k \rightarrow \infty \), it can not only make the iterative learning observer states \( \hat{x}_k \) infinitely approximate the actual states \( x_k \) of the system under the \( \lambda \) norm, but also ensure that the output \( \hat{y}_k \) of the tracking observer converges to the actual system output \( y \). So we get \( \lim_{k \rightarrow \infty} ||x(t) - \hat{x}_k(t)||_\lambda = 0 \), \( \lim_{k \rightarrow \infty} ||y(t) - \hat{y}_k(t)||_\lambda = 0 \).
Proof. In \([0, t_0] \), \(\dot{x}_k(0) = x(0), \dot{y}_k(0) = y(0)\)

\[
\|x_k - \hat{x}_k\| = \left\| x_k(0) - \hat{x}_k(0) + \int_0^t \left[ A_1 x_k(s) + A_2 x_k(s - d) + B u(s) + H g(s) \right] ds \\
- \int_0^t \left[ A_1 \dot{x}_k(t) + A_2 \dot{x}_k(t - d) + \dot{B} u_k(t) + \dot{H} \dot{g}(t) + L (y_k - \hat{y}_k) \right] ds \right\|
\]

\[
\leq \int_0^t \|A_1 - L C_2\| \|x_k(s) - \hat{x}_k(s)\| ds \\
+ \int_0^t \|A_2 - L C_2\| \|x_k(s - d) - \hat{x}_k(s - d)\| ds \\
+ \int_0^t \|\dot{H}\| \|g_k(s) - \dot{g}(s)\| ds + \int_0^t \|\dot{B} u(s) + B g_k(s)\| ds.
\]

Let \(a_1 = \|A_1 - L C_2\|, a_2 = \|A_2 - L C_2\|, b = \|\dot{H}\|, a_1, a_2\) and \(b\) are normal numbers.

\[
\|x_k - \hat{x}_k\| \leq \int_0^t \left[ a_1 + \beta_1(\eta + \delta) \right] \|x_k(s) - \hat{x}_k(s)\| ds \\
+ \int_0^t a_2 \|x_k(s - d) - \hat{x}_k(s - d)\| ds + \int_0^t b \|g_k(s) - \dot{g}_k(s)\| ds
\]

\[
= \int_0^t a_3 \|x_k(s) - \hat{x}_k(s)\| ds + \int_0^t b \|g_k(s) - \dot{g}_k(s)\| ds \\
+ \int_0^t a_2 \|x_k(s - d) - \hat{x}_k(s - d)\| ds
\]

where \(a_3 = a_1 + \beta_1(\eta + \delta), a_3, \eta, \delta\) are normal numbers.

From the Grönwall–Bellman (\([20]\)) integral inequality, we get

\[
\|x_k - \hat{x}_k\| \leq b \int_0^t (e^{a_3(t-s)} + e^{a_2(t-s)}) \|g_k(s) - \dot{g}_k(s)\| ds.
\]

Let

\[
\Lambda(t) = b \int_0^t (e^{a_3(t-s)} + e^{a_2(t-s)}) \|g_k(s) - \dot{g}_k(s)\| ds.
\]

We have

\[
\| x_k - \hat{x}_k \| \leq \Lambda(t).
\]

From (7), \(g_k + \dot{g}_{(k+1)} - g_{(k+1)} - \dot{g}_k = k_p \gamma_k + k_d \dot{\gamma}_k\). Let

\[
\dot{\epsilon}_k = \dot{B} u_k + B g - \dot{B} \dot{g}_k - L (y_k - \dot{y}_k).
\]

Then

\[
\dot{g}_{(k+1)} = (I - k_d C_2 H) \dot{B} k + [k_p C_2 + k_d C_2([A - L C_2])] \int_0^t \dot{B} u_k du + k_d C_2 \dot{B} u_k.
\]

F. Xingjian, H. Jiahui
Take the norm on both sides of (15) to get
\[
\begin{align*}
|| \hat{g}_{k+1} || & \leq a_4 || \hat{g}_k || + a_5 \int_0^t || \hat{g} || du + a_5 \int_0^t \hat{B} u_k du + a_6 \hat{B} u_k. \\
\end{align*}
\]
Let \( a_4 = (I - k_d C_2 H) \), where \( I \) is an identity matrix of appropriate dimensions. \( a_5 = \| k_p C_2 + k_d C_2 (A - LC_2) \|, a_6 = \| k_d C_2 \|, a_4, a_5 \) and \( a_6 \) are normal numbers. This is
\[
\begin{align*}
|| \hat{g}_{k+1} || & \leq a_4 || \hat{g}_k || + a_5 \int_0^t || \hat{g} || du + a_5 (\beta_1 \eta) \int_0^t \| x_k (u) - \hat{x}_k (u) \| du + a_6 (\beta_1 \eta) \| x_k (u) - \hat{x}_k (u) \|, \\
& = a_4 || \hat{g}_k || + a_5 \int_0^t || \hat{g} || du + a_5 a_7 \int_0^t \| x_k (u) - \hat{x}_k (u) \| du \\
& \quad + a_6 a_7 \| x_k (u) - \hat{x}_k (u) \|
\end{align*}
\]
where \( a_7 = \beta_1 \eta, a_7 \) is a normal number. Then
\[
\begin{align*}
|| \hat{g}_{k+1} || & \leq a_4 || \hat{g}_k || + a_5 \int_0^t || \hat{g} || du + a_5 a_7 \int_0^t \Lambda (u) du + a_6 a_7 \Lambda (t) \\
& \leq a_4 || \hat{g}_k || + a_5 \int_0^t || \hat{g} || du + a_5 a_7 t_n \Lambda (t) + a_6 a_7 \Lambda (t) = a_4 || \hat{g}_k || \\
& \quad + a_5 \int_0^t || \hat{g} || du + (a_5 a_7 t_n + a_6 a_7) \int_0^t (e^{a_3 (t-s)} + e^{a_2 (t-s)}) \| g_k (s) - \hat{g}_k (s) || ds
\end{align*}
\]
Choosing \( a_8 = \max \{ a_5 a_7 t_n + a_6 a_7, a_4 \} \), \( a_8 \) is a normal number. Take the \( \lambda \) norm on both sides of (18) to get
\[
\begin{align*}
|| \hat{g}_{k+1} || \leq a_4 || \hat{g}_k || + a_5 \int_0^t || \hat{g} || du + a_5 a_7 \int_0^t \lambda (u) du + a_6 a_7 \lambda (t) \\
& = [a_4 + a_5 \frac{1 - e^{-\lambda t_n}}{\lambda} + a_8 \frac{1 - e^{(a_{10} - \lambda) t_n}}{\lambda - a_{10}}] || \hat{g}_k ||
\end{align*}
\]
By choosing a sufficiently large value of \( \lambda \) such that
\[
\begin{align*}
a_4 + a_5 \frac{1 - e^{-\lambda t_n}}{\lambda} + a_8 \frac{1 - e^{(a_{10} - \lambda) t_n}}{\lambda - a_{10}} < 1
\end{align*}
\]
we have \( \lim_{k \to \infty} || g(t) - \hat{g}_k (t) ||_\lambda = 0 \). Then
\[
\begin{align*}
\lim_{k \to \infty} || x(t) - \hat{x}_k (t) ||_\lambda = 0, \quad \lim_{k \to \infty} || g(t) - \hat{g}_k (t) ||_\lambda = 0.
\end{align*}
\]
The proof is completed. This indicates when \( k \to \infty \), the iterative learning observer states approximate the actual states of the system under the \( \lambda \) norm, and the output of the tracking observer converges to the actual system output.
4. Robust adaptive controller design. Let $e_i = x_i - y_{id}$, $s_i = \dot{e}_i + m_i e_i$, then

$$
\dot{s}_i = \ddot{e}_i + m_i \dot{e}_i = \ddot{x}_i - \ddot{y}_{id} + m_i \dot{e}_i = \dot{B} u_k + \dot{H} \dot{y} + L(y_i - \dot{y}_i) - \ddot{y}_{id} + m_i \dot{e}_i,
$$

where $e_i$ is the error between the state vector and the output vector of the controlled system, $m_i$ is the normal number. The control law can be selected as

$$
u_k = \frac{1}{B} [-L(y_i - \dot{y}_i) + \ddot{y}_{id} - m_i \dot{e}_i] - \dot{H} \dot{y}.
$$

The parameter adaptive rate is taken as

$$
\dot{\tilde{\xi}}_i = \tilde{\xi}_i s_i, \quad \dot{\tilde{\eta}}_i = \tilde{\xi}_i \tilde{\eta}_i u_k, \quad \dot{\tilde{w}}_i = \tilde{\xi}_i \tilde{\eta}_i \eta_i h_i
$$

$\tilde{\xi}_i$, $\tilde{\eta}_i$, $\eta_i h_i$ and $\eta_i$ are normal numbers. Let

$$
\dot{s}_i = -k_i s_i + \tilde{w}_i^T \eta_i \eta_i u_i + \tilde{\omega}_i f \eta_i f + \tilde{\omega}_i h \eta_i h_i.
$$

Theorem 2 considers the model of the robotic arm.

**Theorem 2.** Based on Theorem 1, applying the above control law (23) and parameter adaptive law (24) can ensure that the trajectory tracking error of the robot manipulators system will gradually approach zero.

**Proof.** The Lyapunov function is defined as

$$
V = \sum_{i=1}^{n} V_i,
$$

where $V_i = \left( \frac{1}{2} s_i^2 + \frac{1}{2} w_i^T \dot{w}_i + \frac{1}{2} \tilde{\omega}_i f \dot{\tilde{\omega}}_i + \frac{1}{2} \tilde{\omega}_i h \dot{\tilde{\omega}}_i \right)$. Then $\dot{V} = \sum_{i=1}^{n} \dot{V}_i$, where

$$
\dot{V}_i = s_i \dot{s}_i - \frac{1}{\tilde{\xi}_i} \tilde{w}_i f \dot{\tilde{w}}_i f - \frac{1}{\tilde{\xi}_i} \tilde{\omega}_i \dot{\tilde{\omega}}_i \dot{\tilde{\omega}}_i - \frac{1}{\tilde{\xi}_i} \tilde{\omega}_i h \dot{\tilde{\omega}}_i h_i
$$

$$
= s_i \left( -k_i s_i + \tilde{w}_i f \eta_i u_i + \tilde{\omega}_i f \eta_i f + \tilde{\omega}_i h \eta_i h_i \right)
$$

$$
- \frac{1}{\tilde{\xi}_i} \tilde{w}_i f \dot{\tilde{w}}_i f - \frac{1}{\tilde{\xi}_i} \tilde{\omega}_i \dot{\tilde{\omega}}_i \dot{\tilde{\omega}}_i - \frac{1}{\tilde{\xi}_i} \tilde{\omega}_i h \dot{\tilde{\omega}}_i h_i \leq -k_i s_i^2
$$

According to Barbalat theorem, $\lim_{t \to \infty} s_i(t) = \dot{s}_i = 0$ can be obtained, that is, the trajectory tracking error $e_i = \dot{y}_{id} - y_{id}$ will also gradually approach 0.

5. Simulations application. The dynamic equation (1) of the double joint robot manipulators is simulated. Each parameter in the equation is taken

$$
D(q) = \begin{bmatrix}
    m_1 I_1^G + m_2 (l_1^G l_2^G + l_1^G l_2^G \cos q_2) + I_1 + I_2 & m_2 (l_1^G l_2^G + l_1^G l_2^G \cos q_2) + I_2 \\
    m_2 (l_1^G l_2^G + l_1^G l_2^G \cos (q_1 + q_2)) & m_2 I_2^G + I_2
\end{bmatrix}
$$

F. Xingjian, H. Jiahu
\[
C(q, \dot{q}) = \begin{bmatrix}
-m_2l_2l_1 \dot{q}_1 \sin q_2 & -m_2l_2l_1 (\dot{q}_1 + \dot{q}_2) \sin q_2 \\
m_2l_2l_1 \dot{q}_1 \sin q_2 & 0
\end{bmatrix}
\]

\[
G(q) = \begin{bmatrix}
\left( m_1 l_1^G + m_2 l_1 \right) g \cos \theta_1 & + m_2 l_2^G g \cos (\theta_1 + \theta_2) \\
m_2 l_2^G g \cos (\theta_1 + \theta_2)
\end{bmatrix}
\]

The disturbance \( \omega(t) = 0.3 \sin t \). System parameters are \( m_1 = 5 \text{ kg}, m_2 = 5 \text{ kg}, l_1 = l_2 = 0.5 \text{ m}, l_1^G = l_2^G = 0.25 \text{ m}, I_1 = 1 \text{ kg.m}^2, I_2 = 0.8 \text{ kg.m}^2, g = 9.8 \text{ m/s}^2 \). Expected trajectory \( q_1 = \sin 2t \) and \( q_2 = 0.5 \cos 2t \). Adaptive parameters are \( \xi_{11} = 3, \xi_{22} = 0.05, \xi_{32} = 0.5, \eta_{1f} = 0.2, \eta_{2f} = 0.02, \eta_{3f} = 0.1 \). The initial state of the robot manipulators is \( x = [2 \ 2 \ 2 \ 2]^T \).

The observer gain is \( L = \begin{bmatrix} 10 & 0 \\ 0 & 20 \end{bmatrix} \), \( A_2 = \begin{bmatrix} 0.1 & 0.1 \\ 0 & 0.2 \end{bmatrix} \), \( H = \begin{bmatrix} 0.1 & 0 \\ 0 & 0.2 \end{bmatrix} \).

After the number of iterations is 10, the angle state curves of iterative learning observer of joint 1 and joint 2 for robot manipulators and expected trajectory curves are shown in Fig. 2.

![Fig. 2. Angle tracking curves](image)

After the number of iterations is 10, the angle speed state curves of iterative learning observer for robot manipulators and expected trajectory curves are shown in Fig. 3.

Angle error convergence curves after 10 iterations are shown in Fig. 4(a). Angle speed error convergence curves after 10 iterations are shown in Fig. 4(b).

It can be seen from the simulation results of the angle and angular velocity trajectory that the manipulator state trajectory gradually moves closer to the desired trajectory, the system error gradually decreases, and converges to zero, achieving a good tracking effect. After 10 iterations of learning, the angle and angular speed of the double-joint robot manipulators can achieve the ideal tracking effect, which can meet the performance of the actual system.

C. R. Acad. Bulg. Sci., 75, No 6, 2022, 869
6. Conclusion. Aiming at the robot manipulators control system, a trajectory tracking robust adaptive control based on iterative learning observer is designed in this paper. The iterative learning observer is used to observe the angle and angular speed states of the robot manipulators system, and the states tracking of the dual-joint robot manipulators are realized. Based on the Lyapunov stability theory, the robust adaptive controller design is given to ensure that the trajectory tracking error of the robot manipulators system gradually approaches zero. The trajectory tracking control of the dual-joint robot manipulators system model was verified by simulation. It can be seen that the method designed in this paper has a good tracking effect, and this method is feasible and practical.
REFERENCES


School of Automation
Beijing Information Science and Technology University
No. 12 Xiaoying East Road
Qinghe, Haidian District
Beijing, 100192, China
e-mail: fxj@bistu.edu.cn
647811515@qq.com