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Model Reference Adaptive Iterative Learning Speed Control for Ultrasonic Motor

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ABSTRACT In the design process of the controller, the adaptive gain of model reference adaptive control (MRAC) often requires a tradeoff between the adaptive ability, robustness and stability of the control system. The tradeoff of adaptive gain leads to poor control performance and increase design difficulty. Aiming at this problem, the iterative learning idea is introduced into the model reference adaptive control strategy. The control parameter adaptive law based on the parameters of the previous control process is designed. For scalar systems, a new control strategy is constructed, which is the combination of MRAC and iterative learning control (ILC). The adaptive ability of the model reference adaptive controller is improved by using learning ability of ILC. An appropriate composite energy function is designed to prove the uniform convergence of the proposed control strategy and the boundedness of the control quantity. The proposed control strategy is applied to the ultrasonic motor. The effectiveness of the proposed control strategy is verified by experiments and simulations. The controller is designed by using the first-order model that is large different from the actual object. It verifies that the control strategy has strong robustness to model deviation and online time-varying characteristics.

INDEX TERMS Ultrasonic motor, iterative learning control, model reference control, composite energy function

I. INTRODUCTION

Since the model reference adaptive control (MRAC) strategy was proposed, it has been widely used in various practical control systems due to its adaptive ability to changing controlled objects and the stability guaranteed by the design process based on the Lyapunov function[1]-[6]. In particular, MIT control strategy with the simplest form [7]-[8] and MRAC strategy based on input and output variables [9] are widely used. In more and more practical applications, researchers and users are aware of the benefits of applying MRAC strategy, but also more clearly aware of its shortcomings. In MRAC strategy, the adaptive gain (matrix) is usually the only control parameter to be set. A larger value of the adaptive gain can accelerate the adaptive rate and make the dynamic process of the system closer to the expected state specified by the reference model. However, it also reduces the robustness to random disturbances such as noise, resulting in overshoot and oscillation convergence process. Excessive adaptive gain also causes the system to lose stability. Therefore, the value of the adaptive gain often requires a tradeoff between the adaptive ability, robustness and stability of the control system. The more obvious the change of the controlled object during operation, the more this compromise choice tends to maintain the stability of the system. It is necessary to select a sufficiently small adaptive gain value to sacrifice system control performance to maintain stability and the necessary degree of robustness. In this case, the adaptive ability of MRAC strategy is weakened. So, the system performance is more dependent on the initial parameters. The fluctuation amplitude of control performance caused by the change of object also increases. How to keep the adaptive ability of the MRAC strategy in this case, and how to avoid the influence of the tradeoff of the adaptive gain on the control performance of the MRAC controller. This is a fundamental problem that must be solved in order to improve the practical application performance and reduce the design complexity of MRAC strategy.

In order to meet application requirements, MRAC is improved in some literatures [10]-[13]. In [10], it is shown that under the same MRAC design conditions without the knowledge of the plant parameters, an MRAC system ensures that the tracking error has the stronger higher order

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convergence property. Such a new MRAC system property leads to several new results of adaptive stabilization and tracking control using either state feedback or output feedback. In [11], a novel result for adaptive asymptotic tracking control of uncertain switched linear systems is established. The result exploits stability condition for switched systems. A time-varying positive definite Lyapunov function is used to develop a novel piecewise continuous model-reference adaptive law and a dwell-time switching law. In [12], piecewise linear reference model systems are used for generating desired state trajectories and their stability properties are studied. Adaptive state feedback control schemes are developed.

Iterative learning control (ILC) [14]-[17] is a completely different control method from model reference adaptive control. Based on previous information, ILC adopts the iterative method to gradually improve control performance. ILC introduces simple learning ideas into the control system. Moreover, the learning goal is the control signal rather than the structure or parameters of the object model, which makes it essential different from the classical control methods such as model reference adaptive control.

In this paper, the iterative learning control (ILC) idea is introduced into the MRAC strategy. A new control strategy is constructed, which is the combination of MRAC and ILC. This control strategy is used for scalar systems. The learning ability of ILC is used to improve the adaptive ability of model reference adaptive controller. Improve and maintain system control performance in line with expectations through online self-learning. Compared with the MRAC strategy, the online computation of the new control strategy increases little, but the control performance is significantly improved. By means of the composite energy function [18]-[21], the uniform convergence of the proposed control strategy is proved. The control strategy is applied to the speed control system of ultrasonic motor. A first-order ultrasonic motor model that is large different from the actual object is used for controller design, so as to verify the robustness of the control method to model deviations. The simulation and experimental research are carried out. Simulation and experimental results indicate the effectiveness of the proposed control strategy. The experimental results show that we only need to set the adaptive gain of model reference adaptive controller to a small value which can ensure the stability of the system. The subsequent iterative learning control process can improve the control performance and make it gradually approach the desired control state specified by the reference model. Therefore, the influence of the tradeoff of adaptive gain on the control performance is avoided. A simple and effective method is provided to improve the practical application performance of MRAC.

This article is organized as follows. In Section II, the model reference adaptive iterative learning control algorithm is presented. In Section III, the convergence of model reference adaptive iterative learning control algorithm is analyzed. In Section IV and Section V, the proposed algorithm is applied to speed control for ultrasonic motor. The simulation results and the experiment results are given in Section IV and Section V respectively.

II. MODEL REFERENCE ADAPTIVE ITERATIVE LEARNING CONTROL ALGORITHM

Assuming that the controlled object can be described by differential equation as

$$\dot{y}_{\mathrm{p}}(k,i) = -a_{\mathrm{p}}(i)y_{\mathrm{p}}(k,i) + k_{\mathrm{p}}u(k,i) \tag{1}$$

Where, $y_{\mathrm{p}}(k,i)$ and $u(k,i)$ are the output and input of the controlled object at time i in the kth cycle respectively, $a_{\mathrm{p}}(i)$ is unknown bounded time-varying parameter, k_{p} is unknown bounded constant parameter. It is assumed that $k_{\mathrm{p}}>0$.

It is assumed that the reference model to be tracked is a linear time-invariant system with the same structure as the controlled object, that is

$$\dot{y}_{\mathrm{m}}(k,i) = -a_{\mathrm{m}}y_{\mathrm{m}}(k,i) + k_{\mathrm{m}}y_{\mathrm{r}}(k,i) \tag{2}$$

Where, $y_{\mathrm{m}}(k,i)$ and $y_{\mathrm{r}}(k,i)$ are the output and bounded given input of the reference model respectively, a_{m} and k_{p} are constants greater than 0.

The tracking error of the kth iterative learning control is defined as

$$e(k,i) \triangleq y_{\mathrm{p}}(k,i) - y_{\mathrm{m}}(k,i) \tag{3}$$

It is assumed that the controlled system satisfies the same initial conditions under the condition of repeatable operation. That is to say, for $\forall k \geq 1$, the following equation is satisfied.

$$e(k,0) = 0 \tag{4}$$

The control goal is to obtain the appropriate control input $u(k,i)$ to adapt to the unknown time-varying inertial parameters by using the model reference adaptive iterative learning control (MRAILC) algorithm, so that the output $y_{\mathrm{p}}(k,i)$ can converge uniformly to the reference model output $y_{\mathrm{m}}(k,i)$ when the number of iterations approaches to infinity, that is $\lim_{k\to\infty} \sup_{i\in[0,T]} e(k,i) = 0$. In addition, ensure that all signals in the controlled system are bounded in each iteration process. In order to achieve the above control goals, the model reference adaptive control and iterative learning control are combined. The control law is designed as

$$u(k,i) = \hat{a}(k,i)y_{\mathrm{p}}(k,i) + \hat{b}(k,i)y_{\mathrm{r}}(k,i) \tag{5}$$

Where, $\hat{a}(k,i)$ and $\hat{b}(k,i)$ are adjustable parameters in the kth cycle. It is updated by the parameter iterative learning adaptive law shown in (6).

$$\hat{\theta}(k,i) = \hat{\theta}(k-1,i) - \Gamma w(k,i)e(k,i) \tag{6}$$

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Where, $\hat{\theta}(k,i) \triangleq \left[\hat{a}(k,i) \quad \hat{b}(k,i)\right]^{\mathrm{T}}$ is parameter estimation vector, $w(k,i) \triangleq \left[y_{\mathrm{p}}(k,i) \quad y_{\mathrm{r}}(k,i)\right]^{\mathrm{T}}$ is regression vector, Γ is constant positive definite symmetric matrix. The initial value of parameter $\hat{\theta}(0,i)$ is bounded for $\forall i \in [0,T]$. It can be seen that the form of the control law (5) is the same as the commonly used form of the control law in the MRAC strategy.

Taking the derivation on both sides of (3), the tracking error equation of the kth iterative learning control can be obtained as follows.

$$\begin{aligned}
\dot{e}(k,i) &= \dot{y}_{\mathrm{p}}(k,i) - \dot{y}_{\mathrm{m}}(k,i) \\
&= -a_{\mathrm{p}}(i)y_{\mathrm{p}}(k,i) + k_{\mathrm{p}}u(k,i) + a_{\mathrm{m}}y_{\mathrm{m}}(k,i) - k_{\mathrm{m}}y_{\mathrm{r}}(k,i) \\
&= -a_{\mathrm{p}}(i)y_{\mathrm{p}}(k,i) + k_{\mathrm{p}}\left[\hat{a}(k,i)y_{\mathrm{p}}(k,i) + \hat{b}(k,i)y_{\mathrm{r}}(k,i)\right] \\
&\quad + a_{\mathrm{m}}y_{\mathrm{m}}(k,i) - k_{\mathrm{m}}y_{\mathrm{r}}(k,i) \\
&= -a_{\mathrm{m}}e(k,i) + k_{\mathrm{p}}[(\hat{a}(k,i) - \frac{a_{\mathrm{p}}(i) - a_{\mathrm{m}}}{k_{\mathrm{p}}})y_{\mathrm{p}}(k,i) \\
&\quad + (\hat{b}(k,i) - \frac{k_{\mathrm{m}}}{k_{\mathrm{p}}})]
\end{aligned} \tag{7}$$

Defined that $\theta^*(i) \triangleq \left[a^*(i) \quad b^*(i)\right]$, where, $a^*(i) \triangleq (a_{\mathrm{p}}(i) - a_{\mathrm{m}})/k_{\mathrm{p}}$, $b^*(i) \triangleq k_{\mathrm{m}}/k_{\mathrm{p}}$. The parameter error vector is defined as $\tilde{\theta}(k,i) \triangleq \left[\tilde{a}(k,i) \quad \tilde{b}(k,i)\right]^{\mathrm{T}}$, where, $\tilde{a}(k,i) \triangleq \hat{a}(k,i) - a^*(i)$, $\tilde{b}(k,i) \triangleq \hat{b}(k,i) - b^*(i)$. Then the tracking error equation can be rewritten as

$$\dot{e}(k,i) = -a_{\mathrm{m}}e(k,i) + k_{\mathrm{p}}(\tilde{\theta}(k,i))^{\mathrm{T}}w(k,i) \tag{8}$$

III.CONVERGENCE ANALYSIS OF MODEL REFERENCE ADAPTIVE ITERATIVE LEARNING CONTROL ALGORITHM

For controlled object (1) and reference model (2), for $k \in \mathbf{Z}_+$, the reference input $r(k,i)$ is continuously bounded over the finite time interval $i \in [0,T]$. The identical initial condition (4) is satisfied. The control law is designed as (5) and (6). The following conclusions are satisfied.

1) The tracking error $e(k,i)$ is bounded and satisfies $\lim_{k\to\infty} \sup_{i\in[0,T]} e(k,i) = 0$ for $i \in [0,T]$ and $k \geq 1$;
2) The parameter estimation vector $\hat{\theta}(k,i)$ is bounded for $i \in [0,T]$ and $k \geq 1$. $\hat{\theta}(k,i)$ converges to bounded vector $\theta(\infty,i)$ pointwisely along the cycle index, that is $\lim_{k\to\infty}\hat{\theta}(k,i) = \theta(\infty,i)$.
3) The control quantity $u(k,i)$ is bounded for $i \in [0,T]$ and $k \geq 1$.

Proof:

The composite energy function (CEF) is designed as

$$E(k,i) = \frac{1}{2k_{\mathrm{p}}}e^2(k,i) + \frac{1}{2}\int_0^t \tilde{\theta}^{\mathrm{T}}(k,\tau)\Gamma^{-1}\tilde{\theta}(k,\tau)d\tau \tag{9}$$

First, derive the difference of CEF between two adjacent iterations. In order to make the expression more concise, the time variable i of the function is omitted in the following proof process without affecting the readability.

Define the difference of $E(k,i)$ at the kth iteration as

$$\begin{aligned}
\Delta E(k,i) &= E(k,i) - E(k-1,i) \\
&= \frac{1}{2k_{\mathrm{p}}}e^2(k) - \frac{1}{2k_{\mathrm{p}}}e^2(k-1) \\
&\quad + \frac{1}{2}\int_0^t\left[\tilde{\theta}^{\mathrm{T}}(k)\Gamma^{-1}\tilde{\theta}(k) - \tilde{\theta}^{\mathrm{T}}(k-1)\Gamma^{-1}\tilde{\theta}(k-1)\right]d\tau
\end{aligned} \tag{10}$$

Where

$$\begin{aligned}
\frac{1}{2k_{\mathrm{p}}}e^2(k) &= \int_0^t \frac{1}{k_{\mathrm{p}}}e(k)\dot{e}(k)d\tau - \frac{1}{2k_{\mathrm{p}}}e^2(k,0) \\
&= \int_0^t \frac{1}{k_{\mathrm{p}}}e(k)\left[-a_{\mathrm{m}}e(k) + k_{\mathrm{p}}(\tilde{\theta}(k))^{\mathrm{T}}w(k)\right]d\tau \\
&= -a_{\mathrm{m}}\int_0^t \frac{1}{k_{\mathrm{p}}}e^2(k)d\tau + \int_0^t(\tilde{\theta}(k))^{\mathrm{T}}w(k)e(k)d\tau
\end{aligned} \tag{11}$$

$$\begin{aligned}
&\frac{1}{2}\int_0^t\left[\tilde{\theta}^{\mathrm{T}}(k)\Gamma^{-1}\tilde{\theta}(k) - \tilde{\theta}^{\mathrm{T}}(k-1)\Gamma^{-1}\tilde{\theta}(k-1)\right]d\tau \\
&= \frac{1}{2}\int_0^t \begin{bmatrix}\tilde{\theta}^{\mathrm{T}}(k)\Gamma^{-1}\tilde{\theta}(k) - (\tilde{\theta}(k) + \Gamma w(k)e(k))^{\mathrm{T}}\Gamma^{-1}(\tilde{\theta}(k) \\ +\Gamma w(k)e(k))\end{bmatrix} d\tau \\
&= \frac{1}{2}\int_0^t \begin{bmatrix}\tilde{\theta}^{\mathrm{T}}(k)\Gamma^{-1}\tilde{\theta}(k) - \tilde{\theta}^{\mathrm{T}}(k)\Gamma^{-1}\tilde{\theta}(k) - w^{\mathrm{T}}(k)\tilde{\theta}(k)e(k) \\ -\tilde{\theta}^{\mathrm{T}}(k)w(k)e(k) - w^{\mathrm{T}}(k)\Gamma w(k)e^2(k)\end{bmatrix} d\tau \\
&= -\int_0^t\left[\tilde{\theta}^{\mathrm{T}}(k)w(k)e(k)\right]d\tau - \frac{1}{2}\int_0^t\left[w^{\mathrm{T}}(k)\Gamma w(k)e^2(k)\right]d\tau
\end{aligned} \tag{12}$$

Substituting (11) and (12) into (10) yields

$$\begin{aligned}
\Delta E(k,i) &= -a_m\int_0^t \frac{1}{k_{\mathrm{p}}}e^2(k)d\tau + \int_0^t \tilde{\theta}(k))^{\mathrm{T}}w(k)e(k)d\tau \\
&\quad - \frac{1}{2k_{\mathrm{p}}}e^2(k-1) - \int_0^t\left[\tilde{\theta}^{\mathrm{T}}(k)w(k)e(k)\right]d\tau \\
&\quad - \frac{1}{2}\int_0^t\left[w^{\mathrm{T}}(k)\Gamma w(k)e^2(k)\right]d\tau
\end{aligned}$$

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$$
\begin{aligned}
&= -a_m \int_0^t \frac{1}{k_{\mathrm{p}}} e^2(k) d\tau - \frac{1}{2}\int_0^t \left[w^{\mathrm{T}}(k) \Gamma w(k) e^2(k) \right] d\tau \\
&- \frac{1}{2k_{\mathrm{p}}} e^2(k-1) \\
&\le -\frac{1}{2k_{\mathrm{p}}} e^2(k-1) \\
&\le 0
\end{aligned} \tag{13}
$$

Because $\Delta E(k,i) \le 0$, so as long as $E(1,i)$ is bounded, for all $k \ge 1$ and $\forall i \in [0,T]$, $E(k,i)$ is bounded. In the following, it is further proved that the parameter adaptive learning law (6) can guarantee $E(1,i)$ bounded.

$$
E(1,i) = \frac{1}{2k_{\mathrm{p}}} e^2(1) + \frac{1}{2}\int_0^t \tilde{\theta}^{\mathrm{T}}(1) \Gamma^{-1} \tilde{\theta}(1) d\tau \tag{14}
$$

Derivation of both sides of (14) with respect to time can be obtained.

$$
\begin{aligned}
\dot{E}(1,i) &= \frac{1}{k_{\mathrm{p}}} e(1)\dot{e}(1) + \frac{1}{2}\tilde{\theta}^{\mathrm{T}}(1)\Gamma^{-1}\tilde{\theta}(1) \\
&= \frac{1}{k_{\mathrm{p}}} e(1)\left[-a_m e(1) + k_{\mathrm{p}} \tilde{\theta}^{\mathrm{T}}(1) w(1) \right] \\
&+ \frac{1}{2}(\tilde{\theta}(0) - \Gamma w(1)e(1))^{\mathrm{T}} \Gamma^{-1} (\tilde{\theta}(0) - \Gamma w(1) e(1)) \\
&= -\frac{a_{\mathrm{m}}}{k_{\mathrm{p}}} e^2(1) + (\tilde{\theta}(0) - \Gamma w(1)e(1))^{\mathrm{T}} w(1)e(1) \\
&+ \frac{1}{2}\tilde{\theta}^{\mathrm{T}}(0)\Gamma^{-1}\tilde{\theta}(0) - \frac{1}{2} w^{\mathrm{T}}(1)\tilde{\theta}(0)e(1) \\
&- \frac{1}{2}\tilde{\theta}^{\mathrm{T}}(0) w(1) e(1) + \frac{1}{2} w^{\mathrm{T}}(1)\Gamma w(1) e^2(1) \\
&= -\frac{a_{\mathrm{m}}}{k_{\mathrm{p}}} e^2(1) - \frac{1}{2} w^{\mathrm{T}}(1)\Gamma w(1) e^2(1) + \frac{1}{2}\tilde{\theta}^{\mathrm{T}}(0)\Gamma^{-1}\tilde{\theta}(0) \\
&\le \frac{1}{2}\tilde{\theta}^{\mathrm{T}}(0)\Gamma^{-1}\tilde{\theta}(0)
\end{aligned} \tag{15}
$$

Because $\tilde{\theta}(0,i) \triangleq \hat{\theta}(0,i) - \theta^*(i)$, $\hat{\theta}(0,i)$ is bounded, so $\tilde{\theta}(0,i)$ is bounded. Therefore there exists a finite constant $M_0 = \max\limits_{i \in [0,T]} \left[\frac{1}{2}\tilde{\theta}^{\mathrm{T}}(0,i)\Gamma^{-1}\tilde{\theta}(0,i) \right]$ greater than 0, so that $\frac{1}{2}\tilde{\theta}^{\mathrm{T}}(0,i)\Gamma^{-1}\tilde{\theta}(0,i) \le M_0$ and $\dot{E}(1,i) \le M_0$. From the definition and the assumption of the same initial conditions, we can see that $E(1,0) = 0$. Therefore, for $i \in [0,T]$, it is satisfied that $E(1,i) \le M_0 T$, that is, $E(1,i)$ is bounded. Hence, for all $i \in [0,T]$ and $k \in \mathbf{Z}_+$, $E(k,i)$ is bounded.

Second, prove the uniform convergence of tracking error $e(k,i)$ along cycle index, that is $\lim\limits_{k\to\infty} \sup\limits_{i \in [0,T]} e(k,i) = 0$, and the parameter error $\tilde{\theta}(k,i)$ converges to bounded vector pointwisely along the cycle index.

According that for all $i \in [0,T]$ and $k \in \mathbf{Z}_+$, $E(k,i)$ is bounded, it can be derived that each item of $E(k,i)$ is bounded on $i \in [0,T]$, hence $e(k,i)$ is bounded on $i \in [0,T]$. According to (13), the following CEF at the kth iteration can be obtained.

$$
\begin{aligned}
E(k,i) &= E(1,i) + \sum_{j=2}^{k} \Delta E(j,i) \\
&\le E(1,i) - \sum_{j=2}^{k} \frac{1}{2k_{\mathrm{p}}} e^2(j-1,i)
\end{aligned} \tag{16}
$$

Because $\lim\limits_{k\to\infty} E(k,i) + \lim\limits_{k\to\infty} \sum\limits_{j=1}^{k-1} \frac{1}{2k_{\mathrm{p}}} e^2(j,i) \le E(1,i)$ and $E(1,i)$ and $\lim\limits_{k\to\infty} E(k,i)$ is bounded, so $\lim\limits_{k\to\infty} \sum\limits_{j=1}^{k-1} \frac{1}{2k_{\mathrm{p}}} e^2(j,i)$ is bounded. It can be obtained from Barbalat's lemma that for $i \in [0,T]$, $\lim\limits_{k\to\infty} \frac{1}{k_{\mathrm{p}}} e^2(k,i) = 0$. Because $k_{\mathrm{p}} > 0$, it can be derived that

$$
\lim_{k\to\infty} e(k,i) = 0, i \in [0,T] \tag{17}
$$

Equation (17) indicates that the tracking error $e(k,i)$ converges to zero pointwisely when the iteration number approaches to infinity.

It can be known from assumption that $y_{\mathrm{r}}(k,i)$ is bounded, so $y_{\mathrm{m}}(k,i)$ is bounded. Knowing that for all $i \in [0,T]$ and $k \in \mathbf{Z}_+$, $e(k,i)$ is bounded, then because $y_{\mathrm{p}}(k,i) = y_{\mathrm{m}}(k,i) + e(k,i)$, $y_{\mathrm{p}}(k,i)$ is bounded. Therefore, the regression vector $w(k,i)$ is bounded. The terms on the right side of (8) are bounded. For all $i \in [0,T]$ and $k \in \mathbf{Z}_+$, $\dot{e}(k,i)$ is bounded. So the sequence $e(k,i)$ is equicontinuous. According to (17), it can be obtained that $\lim\limits_{k\to\infty} \sup\limits_{i \in [0,T]} e(k,i) = 0$, that is, the tracking error uniform converges to zero over $i \in [0,T]$ when the iteration number approaches to infinity.

According to (6), it can be derived that for $i \in [0,T]$, $\lim\limits_{k\to\infty} \hat{\theta}(k,i) = \lim\limits_{k\to\infty} \left[\hat{\theta}(k-1,i) - \Gamma w(k,i) e(k,i) \right]$. Substituting (17) into it, the following can be obtained.

$$
\lim_{k\to\infty} \hat{\theta}(k,i) = \lim_{k\to\infty} \hat{\theta}(k-1,i) \triangleq \theta(\infty,i) \tag{18}
$$

Because $\lim\limits_{k\to\infty} E(k,i)$ is bounded, so $\theta(\infty,i)$ is bounded vector. For $i \in [0,T]$ and $k \ge 1$, the parameter estimation

$\hat{\theta}(k,i)$ is bounded and converges to $\theta(\infty,i)$ pointwisely along cycle index.

Third, prove the control quantity $u(k,i)$ is bounded over $i\in[0,T]$.

It can be obtained from (5) that $u(k,i)=w^T(k,i)\hat{\theta}(k,i)$. For $i\in[0,T]$ and $k\in\mathbf{Z}_+$, $w(k,i)$, $\hat{\theta}(k,i)$ and $e(k,i)$ are bounded, so $u(k,i)$ is bounded.

IV. SIMULATION STUDY ON MODEL REFERENCE ADAPTIVE ITERATIVE LEARNING SPEED CONTROL OF ULTRASONIC MOTOR

In this section, the control law (5) and the parameter iterative learning adaptive law (6) are applied to the speed control of ultrasonic motor. The control parameters are designed by simulation analysis. Using the identification modeling method based on differential evolution algorithm [22], the first-order Hammerstein model of the ultrasonic motor is established, which is consistent with the object model (1) given above. It should be pointed out that the dynamic characteristic of ultrasonic motor is relatively complex. Its dynamic model is usually third-order or fourth-order [22-24]. Because the proposed controller is designed based on the object model, so reducing the order of the ultrasonic motor model to the first order can significantly reduce the complexity of the controller. It can also greatly reduce the amount of online computation, and thus reduce the implementation cost. However, if low-order models are used to simulate high-order objects, the difference between the model and the actual ultrasonic motor will inevitably increase. This is a challenge to the proposed control strategy. From another point of view, it can also better demonstrate the controller's online adaptive capability and robustness by using a model which is big different from the actual object to design a controller.

The model reference adaptive iterative learning controller is designed by simulation analysis method. The linear dynamic part of Hammerstein model of ultrasonic motor system is as follow.

$$\dot{y}_{\mathrm{p}}(k,i)=-148.7y_{\mathrm{p}}(k,i)+155.1u(k,i) \qquad (19)$$

As a commonly used form of nonlinear model, the Hammerstein model consists of two parts: a nonlinear part and a linear dynamic part, which are connected in series. This model structure makes the nonlinear part of the model be used to express the nonlinearly changing object gain. Therefore, in the case of using the Hammerstein model to describe the ultrasonic motor, because the change of the gain is expressed by the nonlinear part, so the gain of the linear dynamic part of the model can be considered as fixed. That is to say, the coefficient 155.1 in (19) is a fixed value, which is consistent with the assumptions made in the previous proof process.

$$G_{\mathrm{m}}(s)=\frac{1}{\tau_{\mathrm{m}}s+1} \qquad (20)$$

Where, τ_{m} is the first-order inertial time constant. Take the time constant τ_{m} of the reference model as 0.04s. The step response of the reference model has no overshoot, and the adjustment time is about 0.12s.

Transforming (20) into (2) form, the following can be obtained:

$$\dot{y}_m(k,i)=-25y_m(k,i)+25y_{\mathrm{r}}(k,i) \qquad (21)$$

In order to be used in digital control system, the reference model (21) is transformed into a recursive calculation formula.

$$y_{\mathrm{m}}(k,i)=0.72y_{\mathrm{m}}(k,i-1)+0.28y_{\mathrm{r}}(k,i) \qquad (22)$$

According to the performance of the speed step response obtained by the simulation, the appropriate value of Γ and initial value of $\hat{a}$ and $\hat{b}$ are determined. In the simulation process, the number of continuous iterative learning is six. In order to provide initial learning information for the subsequent iterative learning control process, the MRAC controller is used for the first step response control. The initial value of control quantity is set to 10.5328. It is consistent with the initial value of the control quantity in the actual ultrasonic motor control system. The control law and parameter update law of the model reference adaptive controller used for the first control are shown in (23) and (24), respectively.

$$u(k,i)=\hat{a}(k,i)y_{\mathrm{p}}(k,i)+\hat{b}(k,i)y_{\mathrm{r}}(k,i) \qquad (23)$$

$$\hat{\theta}(k,i)=\hat{\theta}(k,i-1)-\Gamma_1 w(k,i)e(k,i) \qquad (24)$$

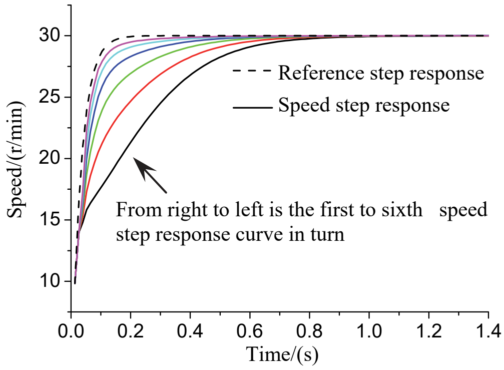
Take Γ_1 as the following positive definite diagonal matrix.

$$\Gamma_1=\begin{bmatrix} r_1 & 0 \\ 0 & r_1 \end{bmatrix} \qquad (25)$$

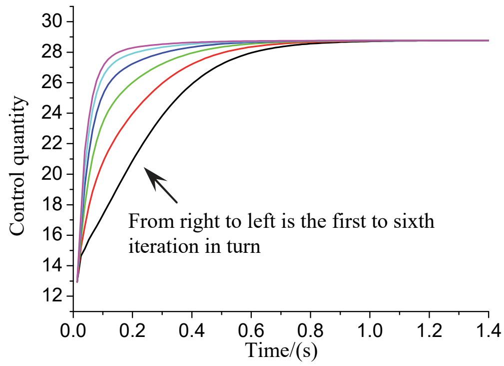
Where, the adaptive gain r_1 is a positive real number and a constant.

In the following, it attempts to select different values of $\hat{a}$ and $\hat{b}$. According to simulation results, the initial values of $\hat{a}$ and $\hat{b}$ are set to 0.4 and 0.3, respectively. Parameter iterative learning adaptive law (6) Γ takes the positive definite diagonal matrix in the form of (25). According to (5) and (6), the value of matrix Γ determines the adaptive adjustment rate of controller parameters $\hat{a}$ and $\hat{b}$. The larger the value of Γ, the larger the parameter adjustment amount. The control quantity given by the control law can adapt to the unknown time-varying inertia parameters faster. The larger the value of Γ, the larger the adjustment range relative to the previous iteration, which helps to reach the learning convergence faster. Conversely, the smaller the value of Γ, the smaller the parameter adjustment amount, and the smaller the adjustment range relative to the previous iteration. The learning effect is not obvious. The speed of learning convergence is slower. The number of iterations required to track the reference trajectory is larger. It can be seen that the value of Γ directly affects the control performance and iterative learning effect of the system. By comparing the simulation results under different values, the value of Γ can be determined according to the expected control performance.

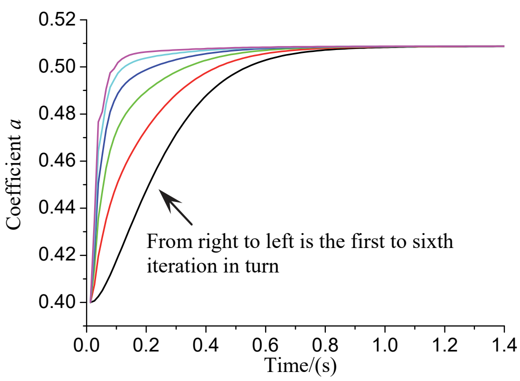
The given value of speed step response is set as 30r/min.The control parameter values are r_1=0.00002 and r=0.0002. The corresponding simulation result is shown in Fig. 1.



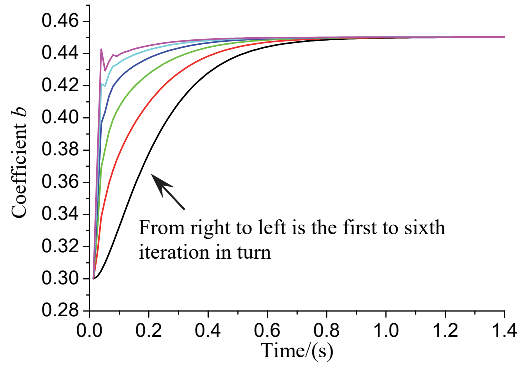
(a)



(b)



(c)



(d)

FIGURE 1. Simulation results of MRAILC speed control (r_1=0.00002, r=0.0002, 30r/min). (a) Curve of speed step response. (b) Changing curve of control quantity. (c) Changing curve of the value of coefficient *a*. (d) Changing curve of the value of coefficient *b*.

The adjustment time of step response obtained by using MRAC is 0.5240s, which is significantly longer than the adjustment time of the reference model 0.12s. Comparing the step response curve obtained from the six iterations, it can be seen that as the iteration progresses, the step response curve gets closer and closer to the curve of reference step response output by the reference model. The adjustment time is gradually reduced, and the step response has no overshoot. The results show that the proposed MRAILC strategy is effective.

The changing curve of control quantity corresponding to Fig. 1(a) is shown in Fig. 1(b). It can be seen that the change trend of the control quantity is consistent with the speed step response curve. With the increase of the number of iterations, the change rate of the control quantity is accelerated, so that the step response speed is accelerated. According to (5) and (6), it can be seen that the acceleration of the change rate of the control quantity must be related to the change of the coefficients a and b. The corresponding changing curve of a and b are shown in Fig. 1(c) and Fig. 1(d), respectively. The change trend of a and b are consistent with the speed step response curve. It can be seen from (6) that based on the previous iteration, the values of coefficients a and b are updated according to the values of $y_m(k,i)$, $r(k,i)$ and $e(k,i)$. As the number of iterations increases, the value of $e(k,i)$ decreases, and the increase amount of coefficients a and b relative to the previous iteration decrease. After reaching the steady state, the value of $e(k,i)$ is zero. The values of coefficients a and b are also stable at a certain fixed value, so that the control quantity no longer changes.

V. EXPERIMENTAL STUDY ON MODEL REFERENCE ADAPTIVE ITERATIVE LEARNING SPEED CONTROL OF ULTRASONIC MOTOR

Experiments are conducted for the control strategy proposed in the previous section. The ultrasonic motor used in the experiment is USR60 two-phase traveling wave ultrasonic motor produced by Shinsei Company. The specifications of the motor are shown in Table I. The speed adjustable range

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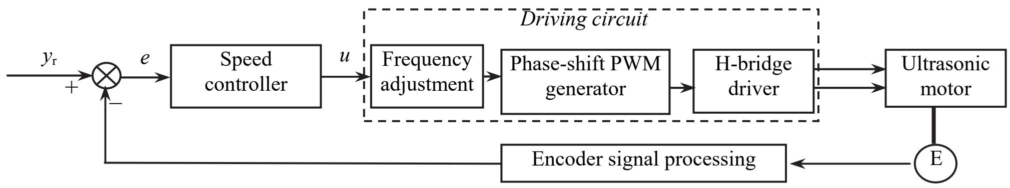
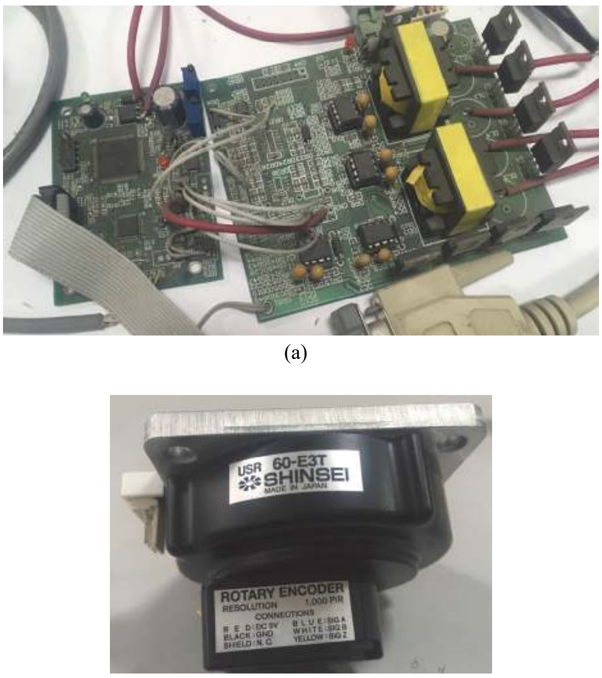


FIGURE 2. Structure of the experimental test rig for the ultrasonic motor's speed control system

of the experimental motor is 0r/min to 120r/min. The structure of the experimental test rig is shown in Fig. 2. The photo of the experimental test bench is shown in Fig. 3. The main structure of its driving circuit is H-bridge. Phase-shift PWM method is adopted to adjust the amplitude1, phase angle and frequency of the driving voltage. In Fig. 2, y_r is the given value of speed. 'E' is a photoelectric encoder, HEDM-5540, used to measure the motor speed to form the closed-loop control. The speed controller is programmed by DSP chip. The output of the controller is the frequency of driving voltage, and the motor speed can be controlled by adjusting the frequency.

TABLE 1
THE SPECIFICATIONS OF USR60 ULTRASONIC MOTOR

Definition	Value/Units
Driving frequency	About 40kHz
Driving voltage	About 130Vrms
Rated torque	0.5Nm
Rated output	5W
Rated speed	100r/min
Maximum torque	1Nm
Retention torque	1Nm
Temperature range	-10℃-55℃
Weight	275g

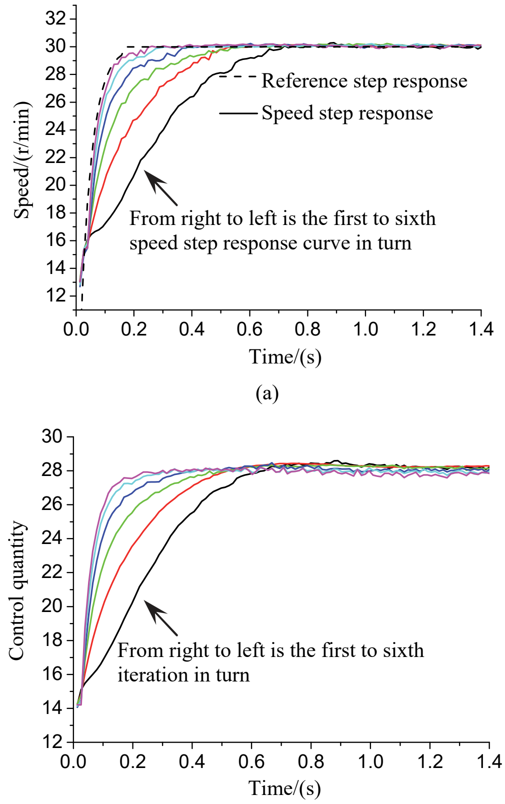


(a)

(b)

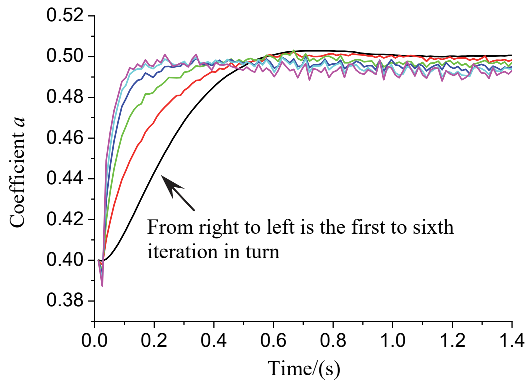
FIGURE 3. Photo of the experimental test bench. (a) Driving and control circuits. (b) Ultrasonic motor.

Six consecutive speed step response experiments are carried out to study the effect of iterative learning. The experimental results of the first step response are the experimental results of the MRAC controller. It can be used to compare with the control strategy proposed in this paper to show its control performance. The second to sixth step response process adopts MRAILC controller to gradually improve the control performance by iterative learning. The given value of speed step response is set as 30r/min, and the control parameters are the same as the parameters designed by simulation above. The experimental results are shown in Fig. 4. For comparison, the experimental results corresponding to r=0.0003 and r=0.0004 are shown in Fig. 5 and Fig. 6, respectively.

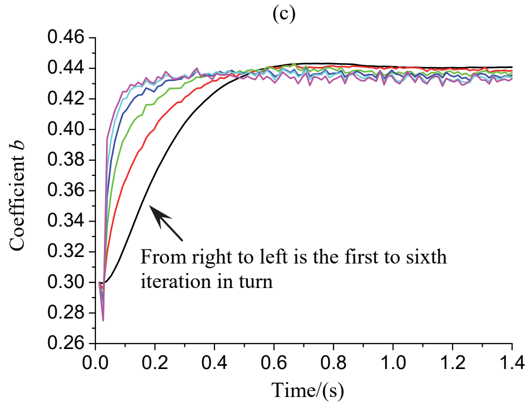


(a)

(b)



(c)



(d)

FIGURE 4. Experiment results of MRAILC speed control (r_1=0.00002, r=0.0002, 30r/min). (a) Curve of speed step response. (b) Changing curve of control quantity. (c) Changing curve of the value of coefficient *a*. (d) Changing curve of the value of coefficient *b*

As can be seen from Fig. 4, the speed step response curve gradually approaches the curve of the reference model output without overshoot. With the progress of iterative learning, the adjustment time decreased from 0.5502s to 0.1310s, with a decrement of 76.19%. The adjustment time of six step responses is shown in Table II. It indicates that the proposed control strategy is effective, and the method of designing control parameters according to simulation is also effective. Comparing Fig. 4 to Fig. 6 and Table II, it can be seen that the increase of r can accelerate the learning convergence speed. Fig. 6 has reached the state of convergence at the fifth iteration, and the learning effect is obvious. However, the step response shown in Fig. 6 shows a small amplitude oscillation, and the absolute average of steady-state fluctuations of the fifth and sixth speed step responses are significantly larger than those in Fig. 4(a) and Fig. 5.

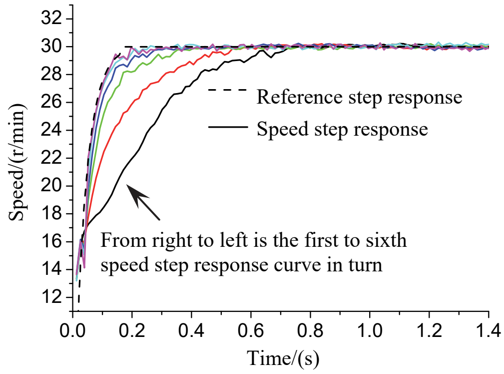


FIGURE 5. Curve of speed step response (r_1=0.00002, r=0.0003)

The changing curves of *a* and *b* shown in Fig. 4(c) and Fig. 4(d) are consistent with the speed step response curve, and the steady-state values are close to the simulation results. However, there is a little difference in the steady-state values of *a* and *b* in each iteration in Fig. 4(c) and Fig. 4(d), while the steady-state values of *a* and *b* in each iteration are the same in the simulation results. The reason is that ultrasonic motor is controlled objects with obvious time-varying characteristics. As the iteration progresses and time goes by, its characteristics will change. Therefore, the value of *a* and *b* corresponding to the given speed also have differences. It reflects the adaptability of the controller. In simulation, the time-varying characteristics of the ultrasonic motor are not considered, so the steady-state values of *a* and *b* are the same.

TABLE II

THE INDEX VALUES OF CONTROL PERFORMANCE FOR THE STEP RESPONSES UNDER DIFFERENT VALUES OF Γ (EXPERIMENTAL RESULTS)

Cycle	Fig. 4(a)		Fig. 5		Fig. 6	
	Adjustment time (5%, s)	The absolute average of the steady speed fluctuation (r/min)	Adjustment time (5%, s)	The absolute average of the steady speed fluctuation (r/min)	Adjustment time (5%, s)	The absolute average of the steady speed fluctuation (r/min)
1	0.5502	0.21740	0.4978	0.31195	0.4716	0.35152
2	0.3930	0.27541	0.3668	0.27241	0.3275	0.31678
3	0.3144	0.36989	0.2227	0.26918	0.1965	0.23440
4	0.2096	0.37768	0.1572	0.29524	0.1441	0.23846
5	0.1572	0.25330	0.1441	0.26962	0.1310	0.31095
6	0.1310	0.30981	0.1310	0.28838	0.1310	0.52267

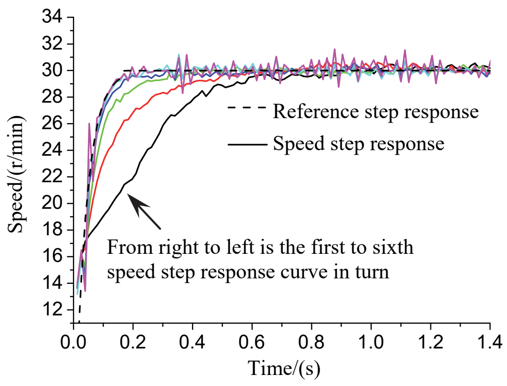


FIGURE 6. **Curve of speed step response (r_1=0.00002, r=0.0004)**

The loading experiment is carried out, and the speed step response is obtained as shown in Fig. 7. The adjustment time of the first to sixth step responses in Fig. 7 are 0.4061s, 0.3799s, 0.3275s, 0.3013s, 0.2882s, and 0.2227s, respectively. With the progress of iterative learning, the adjustment time continues to decrease, with a decrement of 45.16%. It shows that the proposed iterative learning control strategy has strong robustness.

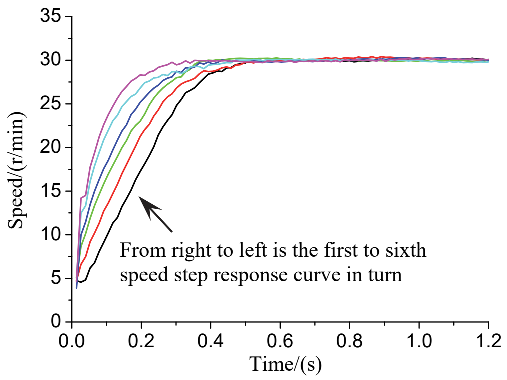


FIGURE 7. **Curve of speed step response (r_1=0.00006, r=0.0002, load 0.2Nm)**

The given value of speed step response is changed to 60r/min, and the experimental result is obtained as shown in Fig. 8. The speed step response curve also gradually approaches to the curve of the given value with no overshoot. The adjustment time of the first to sixth step responses in Fig. 8 are 0.2751s, 0.2358s, 0.1965s, 0.1572s, 0.1441s, and 0.1310s, respectively. With the progress of iterative learning, the adjustment time continues to decrease, with a decrement of 52.38%. It shows that the proposed iterative learning control strategy is applicable to different speeds.

In [25], predictive iterative learning speed control strategy with on-line identification for ultrasonic motor is presented. Six consecutive speed step response experiments are carried out using the control strategy in [25]. The adjustment time of the first to sixth step responses are 0.3799s, 0.2358s, 0.2096s, 0.1834s, 0.1703s, and 0.1572s, respectively. The adjustment time of the first step response is less than that of Fig. 4(a), but the adjustment time of the sixth step response is longer than that of Fig. 4(a). The comparison of their sixth step response is shown in Fig. 9. It shows that after six iterations, the adjustment time reduction rate of the control strategy proposed in this paper is larger, and the improvement of control performance is greater. It further demonstrates the effectiveness of the proposed control algorithm.

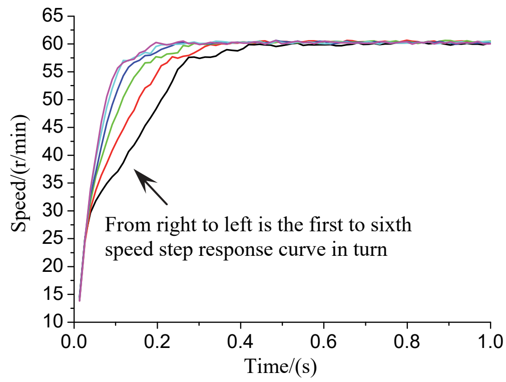


FIGURE 8. **Curve of speed step response (r_1=0.00002, r=0.00005, 60r/min)**

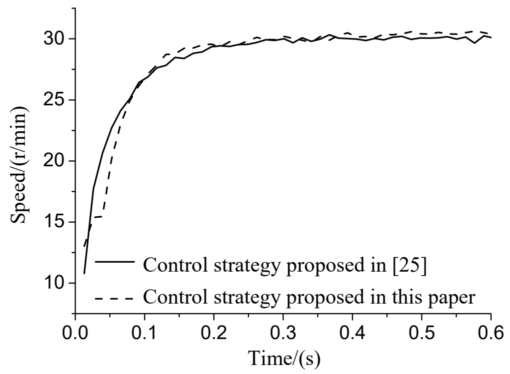


FIGURE 9. Curve of the sixth speed step response

VI. CONCLUSION

In MRAC, the tradeoff of adaptive gain leads to poor control performance and increase design difficulty. Aiming at this problem, the iterative learning idea is introduced into MRAC. The control parameter adaptive law based on the parameters of the previous control process is constructed. It attempts to use iterative learning method to improve the adaptive ability of the model reference adaptive controller and enhance the robustness of the control object under time-varying conditions. An appropriate composite energy function is designed to prove the uniform convergence of the proposed control strategy and the boundedness of the control quantity.

The control strategy is applied to speed control of ultrasonic motor. The experimental results under different speed conditions show that the speed response process is fast, smooth and steady without overshoot. The iterative learning item introduced in the parameter adaptive law enables the control system to inherit the control experience from the previous process in the continuous control process. The speed control performance of motor is improved effectively. It is able to achieve the desired control state. The controller design based on low order model has no effect on the system performance, and the speed control performance is good. It indicates that the proposed control strategy has strong robustness to model deviation and online time-varying characteristics.

In the future, further work will be done to extend this idea beyond scalar systems.

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