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New MIT Control Strategy Combined with Iterative Learning Control

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Abstract: As the pioneer of model reference adaptive control (MRAC) method, MIT control strategy is still used in various practical applications. In this paper, MIT is applied to the speed control of ultrasonic motor, trying to use a relatively simple control method to obtain good control performance. However, MIT control strategy only adjusts the gain, so it is difficult to achieve a large correction of the system's dynamic characteristics, which limits the actual performance. To solve this problem, two improved MIT control strategies based on iterative learning are proposed in this paper to enhance the control performance. Both methods adopt the P-type iterative learning control (P-ILC) strategy with simplest structure. One is to connect the P-ILC controller with the MIT controller in series to adjust the given value of the MIT controller in real time. The other is to use the P-ILC controller to adjust the adaptive gain of the MIT controller in real time, so as to enhance its control freedom and adaptive ability to deal with complex objects. The experimental results show that the proposed control strategies have their own advantages and can significantly improve the control performance after finite iterative learning processes.

Keywords: Iterative learning control, MIT, model reference adaptive control, ultrasonic motor.

1. INTRODUCTION

As the earliest model reference adaptive control (MRAC) method, MIT control strategy is still used in various practical applications [1–6]. MIT based control scheme is proposed in [3] as a solution to control problem of continuous stirred tank reactor (CSTR). Artificial Bee Colony (ABC) based controller parameter tuning technique is applied to get the optimal performance of the controller. Simulation studies show that ABC-MIT based control scheme can improve the transient and steady state response. In [5], MIT control strategy is used to enhance the adaptivity for dynamic changes resulting from load uncertainties. A standard integral resonant controller (IRC) is first designed using an analytical approach, assuming that a second-order system model is obtained in advance. Afterwards, the designed closed-loop is utilized as a reference model for systems with model uncertainties. The adaptive laws of the controller gains are determined according to the well-known MIT rules. An offline trial-and-error operation is conducted for adaption gains' tuning.

The outstanding advantages of MIT control strategy are the simple principle and easy implementation. However, it also has some problems. The adaptive law designed by the local parameter optimization method cannot guarantee the stability of the closed-loop system, so the stability of the system should be checked. In MIT controller, only the value of the gain can be adjusted. This limits the adjustment of the dynamic characteristics of the system. So it is difficult to achieve large correction of the system's dynamic characteristics, which limits the application range of the MIT model reference adaptive control strategy [2,4]. The adaptive law of MIT controller which is designed based on Lyapunov stability theory, replacing the output of the reference model with a given value, can ensure the closed-loop stability of the designed control system [4–6]. However, because MIT strategy only adjusts the gain, the degree of improvement of the system's dynamic performance is restricted, which is still a problem.

The direct way to solve this problem is to increase the adjustment freedom of MIT controller, which will certainly lead to the increase of the complexity of the control strategy. It is expected to solve this problem with a lower cost of design and implementation complexity, in exchange for a significant improvement in the performance of MIT control strategy. From this point of view, it may be a feasible way to adopt the idea of iterative learning control (ILC).

Since Arimoto S. put forward the basic idea of ILC in 1984 [7], ILC has been developed for more than thirty years, and its application fields have been continuously expanded [8,9]. The theoretical studies on learning convergence and stability have also matured increasingly [10–12]. The outstanding advantage of ILC strategy is its effective and simple iterative learning idea, which makes it possible to learn the control experience and continuously

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improve the control performance in the repeated operation processes [13]. However, there is a disadvantage of the ILC such as the delay of response process in case of non-repetitive disturbances. For example, in the case of sudden change of given value, there will be steady-state error.

To solve this problem, the effective solution is to include closed-loop control method in the iterative learning control system. There are many ways to integrate the closed-loop control method into the iterative learning control system. One of these methods is the indirect ILC [14]. There are two independent parts of closed-loop controller and ILC in an indirect ILC system. In such a system, the closed-loop controller is usually the main part, which directly generates the control quantity used to control the state of the controlled object. ILC is used as an auxiliary part to improve the control performance. Such a kind of structure is derived from actual application requirements. In fact, the demand for performance improvement due to dissatisfaction with the existing control performance often exists. Moreover, in order to reduce costs, it is often undesirable to make a significant change to the original system. In this case, it is a feasible choice to enhance the control performance of the closed-loop controller in the original system by adding a relatively simple ILC.

Both of the MIT control strategy and iterative learning control strategy have advantages and disadvantages, and these advantages and disadvantages are complementary to each other to a certain extent. On the one hand, in order to improve the robustness against non repetitive disturbances, iterative learning control needs to be combined with closed-loop control method, and MIT control strategy is an ideal closed-loop control strategy. On the other hand, with the help of the online learning ability of iterative learning control, the adjustment freedom and the dynamic performance of MIT controller may be improved. The crux of this problem lies in how to integrate MIT and ILC, so that we can use their respective advantages to overcome their disadvantages.

Two control schemes are proposed in this paper to solve this problem. The main contributions of the paper are elaborated below.

1) Control scheme 1. Using the idea of indirect ILC, an iterative learning controller with simple structure is proposed to adjust the given value of existing MIT controller.
2) Control scheme 2. Iterative learning method is proposed to adjust the value of adaptive gain of existing MIT controller online, instead of changing the given value of the controller.
3) The proposed control schemes can not only maintain the independence of the design of MIT controller and the stability of the system, but also can significantly improve the dynamic performance of the system, so as to achieve greater correction of the dynamic characteristics of the system.
4) Using ultrasonic motor as the controlled object, the control performance and applicability of the two control schemes have been substantiated by comparative experiments. Even if a first-order model which is different from the high-order object is used in the design of MIT controller, the proposed ILC control schemes can still overcome the influence of this model error, and make the dynamic response of the system tend to the desired characteristic after finite iterations.

2. INDIRECT ITERATIVE LEARNING MIT CONTROL STRATEGY

2.1. System structure

The indirect iterative learning MIT speed control system for ultrasonic motor is designed as shown in Fig. 1. The part inside the dot-and-dash frame is a standard MIT model reference adaptive controller. The adaptive law of MIT designed based on Lyapunov stability theory is adopted, that is

$$\dot{K}_{\mathrm{c}} = \mu y_{\mathrm{Tr}k} e_k, \tag{1}$$

where K_c is the adjustable gain of MIT controller, coefficient μ is the adaptive gain, $y_{\mathrm{Tr}k}$ and e_k are the given value of MIT controller and output error in the k-th iterative control process, respectively.

In Fig. 1, the output of the iterative learning controller, Δy_{rk}, is added to the value of given speed y_{rk} to obtain the given value of the MIT controller $y_{\mathrm{Tr}k}$. Iterative learning controller adopts simple P-type structure (P-ILC)

$$\Delta y_{\mathrm{r}k}(i) = \Delta y_{\mathrm{r}(k-1)}(i) + \lambda_{\mathrm{P}} e_{\mathrm{m}(k-1)}(i+1), \tag{2}$$

where coefficient λ_P is the proportional learning gain, $\Delta y_{\mathrm{r}(k-1)}(i)$ and $e_{\mathrm{m}(k-1)}(i+1)$ are the increment of given value at the i-th moment and the input error of the iterative learning controller at the time $i+1$ in the $(k-1)$-th iterative control process, respectively. The dashed line in Fig. 1 represents the previous control information stored in the memory.

As can be seen from Fig. 1,

$$u_k(i) = K_{\mathrm{c}}(i) y_{\mathrm{Tr}k}(i), \tag{3}$$
$$y_{\mathrm{Tr}k}(i) = y_{\mathrm{r}k}(i) + \Delta y_{\mathrm{r}k}(i), \tag{4}$$
$$e_k(i) = y_{\mathrm{m}k}(i) - y_k(i), \tag{5}$$
$$K_{\mathrm{c}}(i) = \mu \sum \left[y_{\mathrm{Tr}k}(i) e_k(i) \right]. \tag{6}$$

The reference model I, which is located at the front end of ILC controller, is used to express the desired and achievable control performance, so that the iterative learning process may converge to a stable state under various given signals (such as step signals). In Fig. 1, the reference model I and the reference model II are the same.

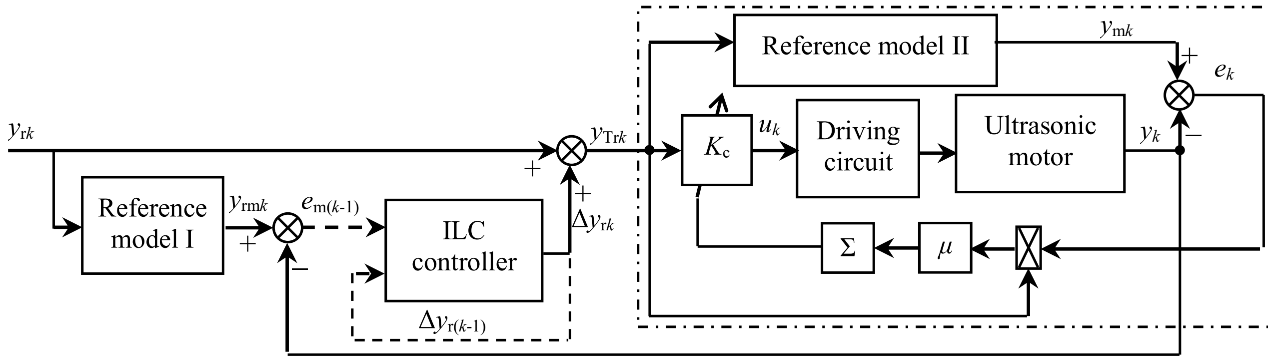


Fig. 1. Structure block diagram of indirect iterative learning MIT speed control system for ultrasonic motor.

The mathematical model of ultrasonic motor is needed for the design of reference model of MIT controller. Generally, a third-order identification model can better describe the dynamic characteristics of traveling wave ultrasonic motor [16–18]. In order to verify the control performance of the proposed control strategy in the case of large model error, and to show that the control strategy can greatly correct the dynamic performance of the system, the first-order inertial model shown in (7) is used to identify the model of ultrasonic motor. The selected first-order model also meets the desired performance requirement.

$$G(s) = \frac{k_p}{\tau s + 1}, \tag{7}$$

where k_p is the gain of motor model, τ is the first-order inertial time constant.

Take the reference model II of MIT controller as

$$G_m(s) = \frac{1}{\tau s + 1}. \tag{8}$$

Obviously, (8) is only different in gain from (7), which is consistent with the design premise of the MIT controller. For the convenience of programming, the above formula is transformed into difference form,

$$y_{mk}(i) = e^{-T_s/\tau} y_{mk}(i-1) + \left(1 - e^{-T_s/\tau}\right) y_{Trk}(i), \tag{9}$$

where T_s is the sampling time, $y_{mk}(i)$, $y_{mk}(i-1)$ and $y_{Trk}(i)$ are the output of reference model at time i, $i-1$, and the given value of MIT controller at time i in the k-th iterative control process, respectively. The values of the parameters in (7) can be determined by the identification of motor model based on the experimental data, and then the reference model II can be obtained as

$$y_{mk}(i) = 0.72 y_{mk}(i-1) + 0.28 y_{Trk}(i). \tag{10}$$

The reference model I in Fig. 1 are the same as the above formula, except that the input and output variables are different.

The system's structure shown in Fig. 1 contains two reference models. In the following, according to the system's structure, the role of these two reference models is investigated. The reference model I is located at the input of the iterative learning controller, and its output is subtracted from the motor speed to obtain the input error of the iterative learning controller $e_{mk}(i)$. In the P-type iterative learning controller given in (2), when $e_{mk}(i)$ is always 0, that is, the speed response process of the motor is the same as the output of the reference model I, the output of the controller will maintain the current status and is no longer updated. That is, the learning convergence state is reached. Correspondingly, the speed response curve also remains unchanged. It can be seen that the reference model I determines the convergence state of the iterative learning process, that is to say, the end point of learning, and also determines the expected state of the speed response.

Reference model II is a necessary part of MIT model reference adaptive control system, which is used to reflect the desired output state. But in the system described in this paper, the given value of the MIT controller $y_{Trk}(i)$ is no longer the given value of motor speed $y_{r(k-1)}(i)$ which is the input of the whole system, but is constantly changing under the adjustment of ILC controller. The following experimental results show that there is a big difference between $y_{Trk}(i)$ and $y_{r(k-1)}(i)$ in the dynamic response process. Therefore, the reference model II with $y_{Trk}(i)$ as the input signal also loses its original function and significance. In other words, it no longer determines the expected output state of the system.

2.1.1 Experimental research and improvement of the control strategy

The ultrasonic motor used in the experiment is USR60 traveling wave ultrasonic motor produced by Shinsei Company. The specifications of the motor are shown in Table 1. The speed adjustable range of the experimental motor is 0 r/min to 120 r/min. The structure of the experimental test rig is shown in Fig. 2, and the photo of the experimental test bench is shown in Fig. 3. The main struc-

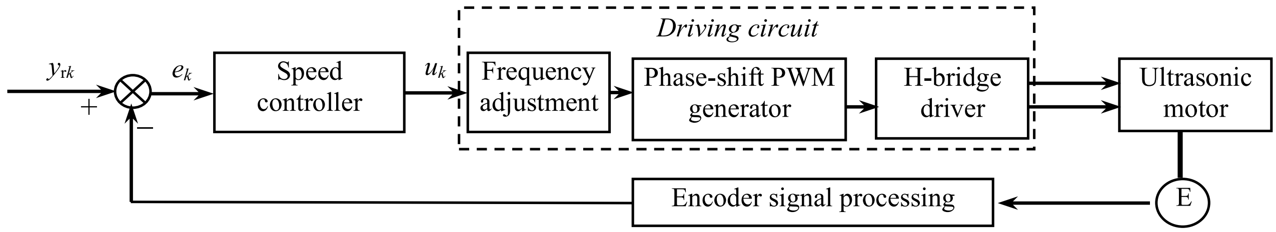
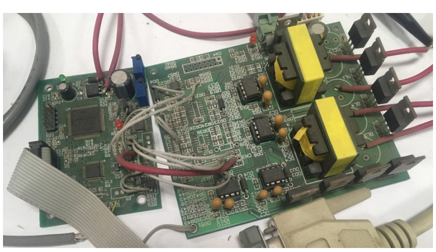


Fig. 2. Structure of the experimental test rig for the ultrasonic motor's speed control system.

Table 1. The specifications of USR60 ultrasonic motor.

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



(a)

(b)

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

ture of its driving circuit is H-bridge, and the phase-shift PWM method is adopted to adjust the amplitude, phase angle and frequency of the driving voltage. In Fig. 2, y_{rk} is the given value of speed. 'E' is a photoelectric encoder, HEDM-5540, used to measure the motor speed. The output of the controller is the frequency of driving voltage, and the motor speed can be controlled by adjusting the frequency.

The DSP chip is programmed to realize the controller shown in Fig. 1, and the speed control experiment of ultrasonic motor is carried out to study the control effect of the controller. Six consecutive step response experiments are carried out to study the effect of iterative learning. In order to provide initial learning information for the subsequent iterative learning control process, the iterative learning controller is not used for the first step response control process, only the MIT controller in the dot-and-dash box of Fig. 1 is used during the first control process. So the experimental result of the first step response is the experimental result of the MIT controller. The second to sixth control processes adopt the control structure shown in Fig. 1 to gradually improve the control performance by iterative learning. Set the initial value of the adjustable gain K_c to 3, the adaptive gain μ is set to be 0.002 and the proportional learning gain λ_P is 0.3. The step given value of motor speed is 30 r/min. Six consecutive iterative learning control experiments are carried out, and the experimental results are shown in Fig. 4.

The curve of the increment of MIT controller's given value is shown in Fig. 4(c), which is the output value of P-ILC (2). This value plus the given value of 30 r/min equals the given value of MIT controller. Fig. 4(c) shows that due to the successive accumulation of (2), the increment of the given value increases continuously. For the MIT controller, the increase of the given value means that the output of the controller is more and more large, which will speed up the response speed of the motor, as shown in Fig. 4(a) that the rise time of the step response curve is decreasing. Fig. 4 shows that the proposed ILC is effective, and the system response gradually approaches the expected performance expressed by the reference model through iterations.

What's not good enough is that the step response shown in Fig. 4(a) has overshoot. And as the number of iterations increases, the amount of overshoot gradually increases. It does not meet the expectation of no overshoot. In order to suppress the overshoot, the P-ILC control law (2) can be adjusted to

$$\Delta y_{rk}(i) = \begin{cases} \Delta y_{r(k-1)}(i) + \lambda_P e_{m(k-1)}(i+1), & |y_k(i)| < |y_{rk}(i)|, \\ 0, & |y_k(i)| \geq |y_{rk}(i)|. \end{cases} \quad (11)$$

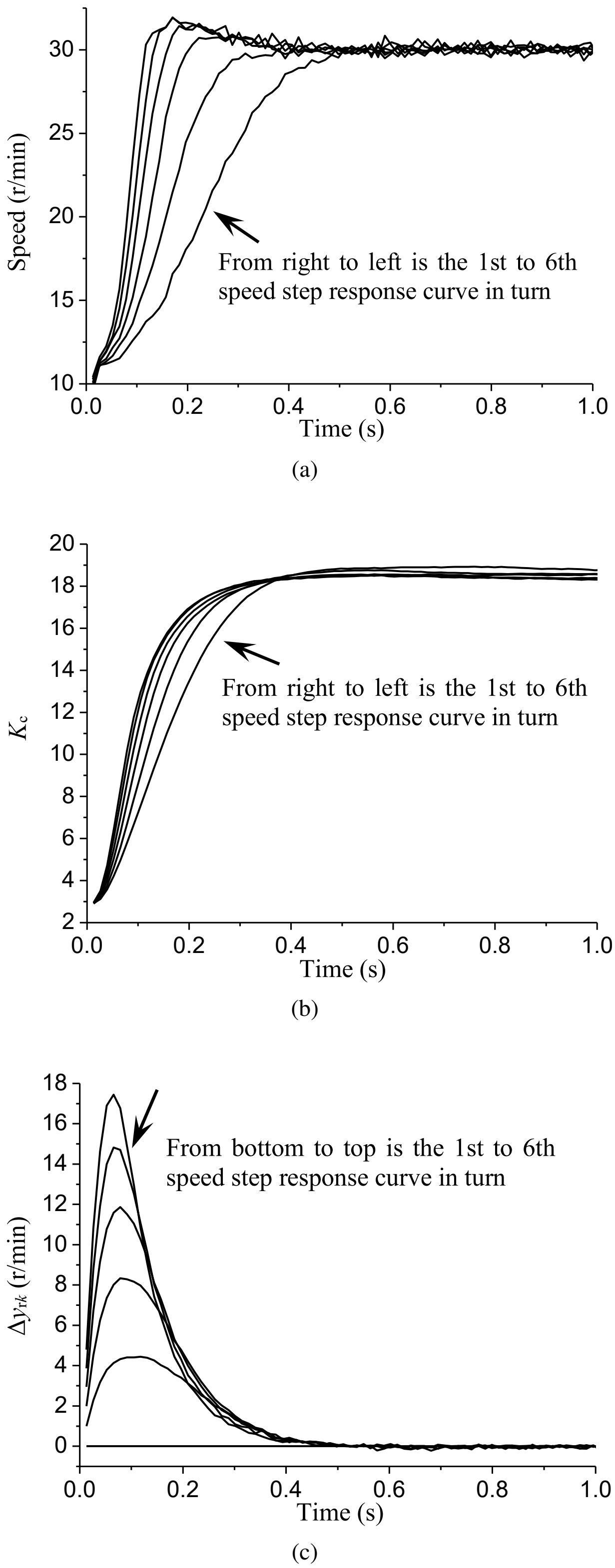


Fig. 4. Experimental results of indirect iterative learning MIT speed control (P-ILC, $\lambda_P = 0.3$). (a) Curve of speed step response. (b) Changing curve of the value of controller's gain K_c. (c) The increment of MIT controller's given value.

That is, after the motor speed reaches the given value y_{rk}, the iterative learning controller is no longer used. The control system shown in Fig. 1 becomes a MIT control system. When Δy_{rk} is set to 0 according to (11) at the ith moment, the control quantity $u_k(i-1)$ at the previous moment is

$$u_k(i-1) = (y_{rk}(i-1) + \Delta y_{rk}(i-1))\,K_c(i-1). \tag{12}$$

The control quantity $u_k(i)$ at the current moment is

$$u_k(i) = (y_{rk}(i) + \Delta y_{rk}(i))\,K_c(i) = y_{rk}(i)K_c(i). \tag{13}$$

To avoid sudden change of control quantity, let $u_k(i) = u_k(i-1)$. At the same time, $y_{rk}(i)$=$y_{rk}(i-1)$ for the reference signal is step signal. Therefore, K_c can be adjusted as follows according to Δy_{rk} and y_{rk} value at the previous moment to avoid sudden change of control quantity.

$$K_c(i) = \left(1 + \frac{\Delta y_{rk}(i-1)}{y_{rk}(i-1)}\right) K_c(i-1), \tag{14}$$

where $K_c(i)$ and $K_c(i-1)$ are the K_c values at time i and time $i-1$ in the current control process, respectively.

In addition, the response curve shown in Fig. 4(a) shows obvious speed fluctuation in the steady-state region, and the fluctuation amplitude increases with the increase of the number of iterations. In the structure of the control system shown in Fig. 1, the output of the iterative learning controller changes the given value of MIT, and directly leads to the change of the control quantity u_k through the gain K_c, thus affecting the speed of the motor. But this is not the only influence way of Δy_{rk} on the speed. Fig. 1 also shows that Δy_{rk} directly changes the input of reference model II, and makes the output y_{mk} and output error e_k of reference model change by the same order of magnitude. The MIT adaptive law given in (1) contains the product term of y_{mk} and e_k, so the change of Δy_{rk} will also cause the change of gain K_c in the same direction, and the change amount and Δy_{rk} are approximately square relations. The change of K_c will also affect the value of the control quantity, which in turn changes the motor speed. That is to say, the relationship between motor speed and Δy_{rk} is approximately cubic. This cubic relationship can also be derived by using mathematical expressions. From (5) and (10), the expression of e_k can be obtained. Then, the expression of K_c can be obtained by substituting the expression of e_k into (6). Substituting the expression of K_c into (3), the cubic relationship can be derived. In the actual motor control system, there must be noise and random error in the process of speed measurement. These random errors and noises are amplified by this cubic relation, which makes the response curve of motor speed fluctuate obviously. The ILC law accumulates Δy_{rk} successively in the iterative process, which makes the speed fluctuation become larger, as shown in Fig. 4(a).

The improvement measures given in (11) and (14) are for the control process after the speed reaches the given value. In order to suppress the influence of the above cubic relation on the dynamic process before the speed reaches the given value, the following low-pass filter is introduced into the output of P-ILC to filter the Δy_{rk} signal.

$$\Delta y_{\mathrm{r}k}(i) = 0.52\Delta y_{\mathrm{r}k}(i-1) + 0.48\Delta\tilde{y}_{\mathrm{r}k}(i), \tag{15}$$

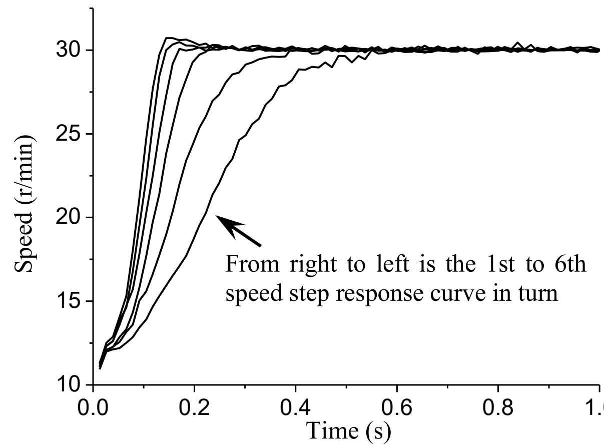
where $\Delta y_{\mathrm{r}k}(i)$ and $\Delta y_{\mathrm{r}k}(i-1)$ are the values of $\Delta y_{\mathrm{r}k}$ at time i and time $i-1$ in the current control process, respectively, $\Delta\tilde{y}_{\mathrm{r}k}(i)$ is the value of $\Delta y_{\mathrm{r}k}$ at time i calculated according to (2). The time constant of the first-order low-pass filter given in the above formula is designed to be 1/2 of the inertia time constant of the reference model in (10), so as to reduce the impact on the dynamic response of the system.

The speed control experiment of ultrasonic motor is carried out by using (11), (14) and (15). The experimental results are shown in Fig. 5. The control parameters used in the experiment are the same as those in Fig. 4. With the increase of the number of iterations, the speed response curve quickly approaches the desired state, and the obvious fluctuation of the speed disappears. The rising section of the speed response is smoother, especially in the area close to the given value. The speed fluctuation is also reduced. Due to the existence of system inertia and various disturbances, the value of K_c given by (14) will not be completely accurate. But it must be close to the accurate value, which can be adjusted to the accurate value by MIT adaptive law. In the case given in Fig. 5(b), the calculated value of (14) is slightly larger, and then it gradually tends to and stabilizes at a steady value under the action of MIT adaptive law. The adjustment time of the sixth response process shown in Fig. 5(a) is reduced to 0.1310 s, as shown in Table 2.

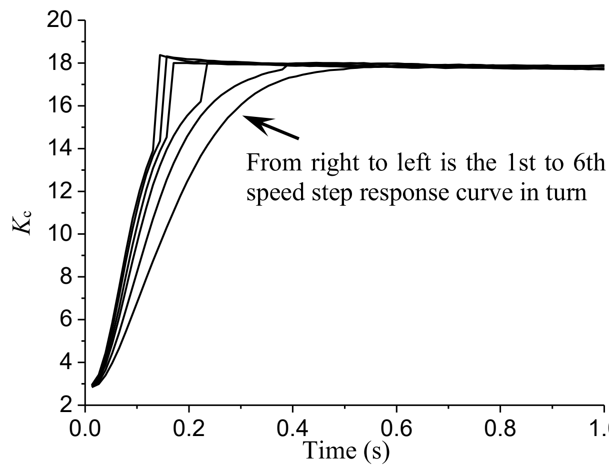
If the vlue of λ_P is increased to 0.6, the response speed will be faster, as shown in Table 2. It can be seen that due to overshoot, the adjustment time of the response curve shown in Fig. 4(a) is longer, and the adjustment time does not decrease monotonically as the number of iterations increases. Because the low-pass filter is also added, the curves corresponding to $\lambda_P = 0.6$ and the curves shown in Fig. 5(a) have the same characteristics. Because the value of learning gain increases, the response speed is accelerated, and the adjustment time of each step response corresponding to $\lambda_P = 0.6$ is less than that of Fig. 5(a).

Table 2. The adjustment time of step response shown in Figs. 4 and 5.

Cycle	Adjustment time (s)		
	Fig. 4(a)	Fig. 5(a)	$\lambda_P = 0.6$
1	0.3930	0.4061	0.4192
2	0.2620	0.2751	0.1703
3	0.1834	0.1965	0.1310
4	0.2358	0.1572	0.1179
5	0.2227	0.1441	0.1048
6	0.1965	0.1310	0.1048



(a)



(b)

Fig. 5. Experimental results of indirect iterative learning MIT speed control ((11), (14) and (15), $\lambda_P = 0.3$). (a) Curve of speed step response. (b) Changing curve of the value of controller gain K_c.

In this section, a P-ILC controller is connected in series with MIT model reference adaptive controller to form an indirect iterative learning control system. The P-ILC controller is used to adjust the given value of MIT controller in real time. Since only the given value of MIT adaptive controller is changed, the structure of MIT controller and its adaptive law designed based on Lyapunov stability theory are still retained, so the improved system still has Lyapunov stability. Experiments show that the proposed control method significantly improves the performance of MIT control system. It should be noted that, in order to investigate the performance of the proposed indirect iterative learning control system, a reduced-order model is deliberately used to design the MIT controller, which increases the model error. The experimental results show that the proposed control method can obtain good control performance even if there is a large model error.

3. ADAPTIVE MIT CONTROL OF ULTRASONIC MOTOR

In the case of adopting the control system structure shown in Fig. 1, the speed response of ultrasonic motor has overshoot, as shown in Fig. 4. In order to eliminate overshoot, the measures shown in (11) and (14) are adopted in the previous section, which increases the complexity of the control system.

In the structure diagram of the control system shown in Fig. 1, the control variable applied to the ultrasonic motor and its driving circuit is the product of the adjustable gain K_c and the given value y_{Trk}. The value of K_c is directly related to the value of the control variable. Therefore, in the control process of the step response shown in Fig. 4, the value of K_c must reach and stabilize at a certain value corresponding to the given value of the speed, so that the speed response determined by the control variable can reach the stable state. In other words, the value of K_c reaching the steady state is the prerequisite for the step response to reach the steady state.

Based on this conclusion, the experimental results given in Fig. 4 can be analyzed again. Due to the role of iterative learning controller, the value of y_{Trk} is constantly improved, which makes the rise time of speed response shorter and shorter. However, under the action of fixed adaptive gain μ, the curve of K_c shown in Fig. 4(b) does not change synchronously with the speed response shown in Fig. 4(a). The rising rate of K_c is obviously slower than that of the response curve, resulting in the consequence that when the motor's speed has risen to the given value, the value of K_c has not reached the required value, and K_c will still rising. Therefore, it is impossible for the motor's speed to stabilize at the given value when it reaching the given value. It is necessary to go through a process to increase the value of K_c to the desired value, and then the response process can reach a steady state. This is the cause of the speed overshoot.

Therefore, in order to eliminate the speed overshoot, how to make the adjustment curve of K_c change synchronously with the accelerating speed response curve should be considered. That is, to speed up the response by increasing the rising rate of the adjustment curve of K_c. It can be seen from (1) that in order to adjust the changing rate of K_c, it is a feasible way to change the adaptive gain μ online. Therefore, the structure of the control system given in Fig. 1 is changed to make the iterative learning controller no longer used to change the given value of the MIT controller, but to adjust the value of μ online. The new control method is shown in Fig. 6. In this section, the

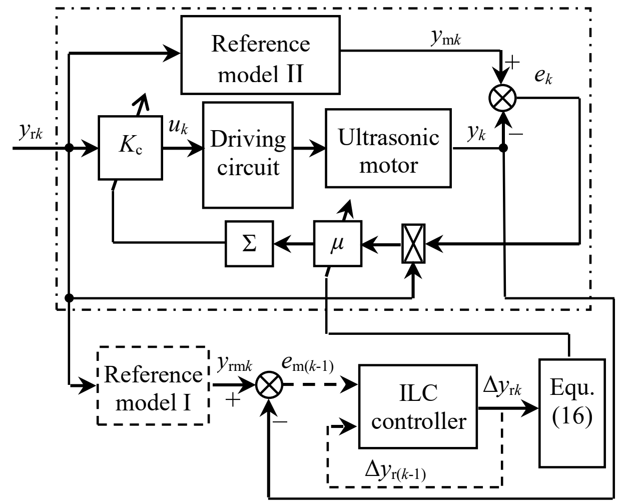


Fig. 6. Structure block diagram of adaptive MIT speed control system for ultrasonic motor.

control strategy shown in Fig. 6 refers to as adaptive MIT control strategy.

The part inside the dot-dash line frame in Fig. 6 is a standard MIT controller. Different from the system structure shown in Fig. 1, the given signal of the MIT controller is the given value of speed, the output of the iterative learning controller is no longer used to change the input given signal of the MIT controller, but to realize online adaptive adjustment of the adaptive gain μ. The value of μ determines the adjustment range of MIT adaptive law (1) to gain K_c. By changing μ from a fixed value to an online non-linear adjustable value, the control freedom of the system can be increased, and the correction ability of the controller to complex object can be improved. The motor speed is fed back to the input terminal of the iterative learning controller to adjust the value of μ for the purpose of making the speed tracking error equal to zero, ensuring the effectiveness of this adaptive adjustment process.

The reference model I in the dotted box in Fig. 6 is optional. The iterative learning controller in Fig. 6 is designed as the P-type ILC (P-ILC) shown in (2). The reference model I and reference model II are as (10), and the MIT adaptive law is as (1). The definition of each variable is the same as before. According to the output of the iterative learning controller, that is Δy_{rk}, the following formula is proposed to adjust the value of μ.

$$\mu_k(i) = \left(1 + \frac{\Delta y_{rk}(i)}{y_{rk}(i)}\right)\mu_0, \tag{16}$$

where μ_0 is the initial value of adaptive gain, $\mu_k(i)$, $\Delta y_{rk}(i)$ and $y_{rk}(i)$ are the adaptive gain, the output of the iterative learning controller and the given value at time i in the k-th iterative control process, respectively.

The DSP chip is programmed to realize the speed control strategy of ultrasonic motor shown in Fig. 6, and the experiment is carried out to study the control performance of the controller. The value of λ_P is 2, the initial value of K_c is 3, μ_0 is set to 0.002. The given value of step response is set as 30 r/min. Six consecutive iterative learning control experiments are carried out, and the experimental results are shown in Fig. 7. The dotted line in Fig. 7(a) is the output signal of reference model in the case of step input. Fig. 7(b) shows that, the value of μ changes continuously during the step response with the action of adaptive law (16). As the iterative learning process progresses, the value of μ continues to increase, resulting in the rising rate of the changing curve of K_c shown in Fig. 7(c) being successively accelerated. Therefore, the rising rate of the response curve shown in Fig. 7(a) being successively accelerated. As a result, the adjustment time being shortened. For example, the adjustment time of the sixth step response is 0.1572 s, it gradually approaches the output of the reference model. The experimental results show that the system structure shown in Fig. 6 and the adaptive adjustment law (16) are effective, and the speed of dynamic response is accelerated by increasing the rising rate of the adjustment curve of K_c.

Fig. 7(a) shows that, as the iterative learning process goes on, the step-by-step improvement of the speed response is getting smaller and smaller. The difference between the 5th and 6th step responses is very small, which indicates that the system is close to learning convergence state. However, there is still some gap between the sixth response curve and the output of the reference model. The gap between the actual response curve and the output of the reference model is first determined by the MIT model reference adaptive control strategy itself. It can be seen from the MIT adaptive law shown in (1) that the adjustment amount of the MIT controller's gain K_c is proportional to the error of motor speed, e_k. It means that the value of K_c may only change if the speed error is not zero. Fig. 7(c) shows that the initial value of K_c is often inconsistent with its steady-state value. Therefore, it is necessary to adjust the adaptive law to achieve the steady-state value in order to eliminate the steady-state error of the speed. It can be seen that non-zero error is the prerequisite for MIT adaptive control. In other words, the adaptive law of MIT determines that the output of the MIT control system cannot fully track the output of reference model. There must be a difference between the actual response and the output of reference model.

Increasing the value of λ_P will increase the amplitude of the changing curve of μ shown in Fig. 7(b) and accelerate the rising rate of the curve of K_c shown in Fig. 7(c). As a result, the gap between the learning convergence state and the output of reference model can be narrowed. For example, increasing λ_P to 4, the speed of response will be further accelerated. It can be seen from Table 3 that the adjustment time of the sixth step response is reduced to 0.1441 s, and the gap between the sixth step response and

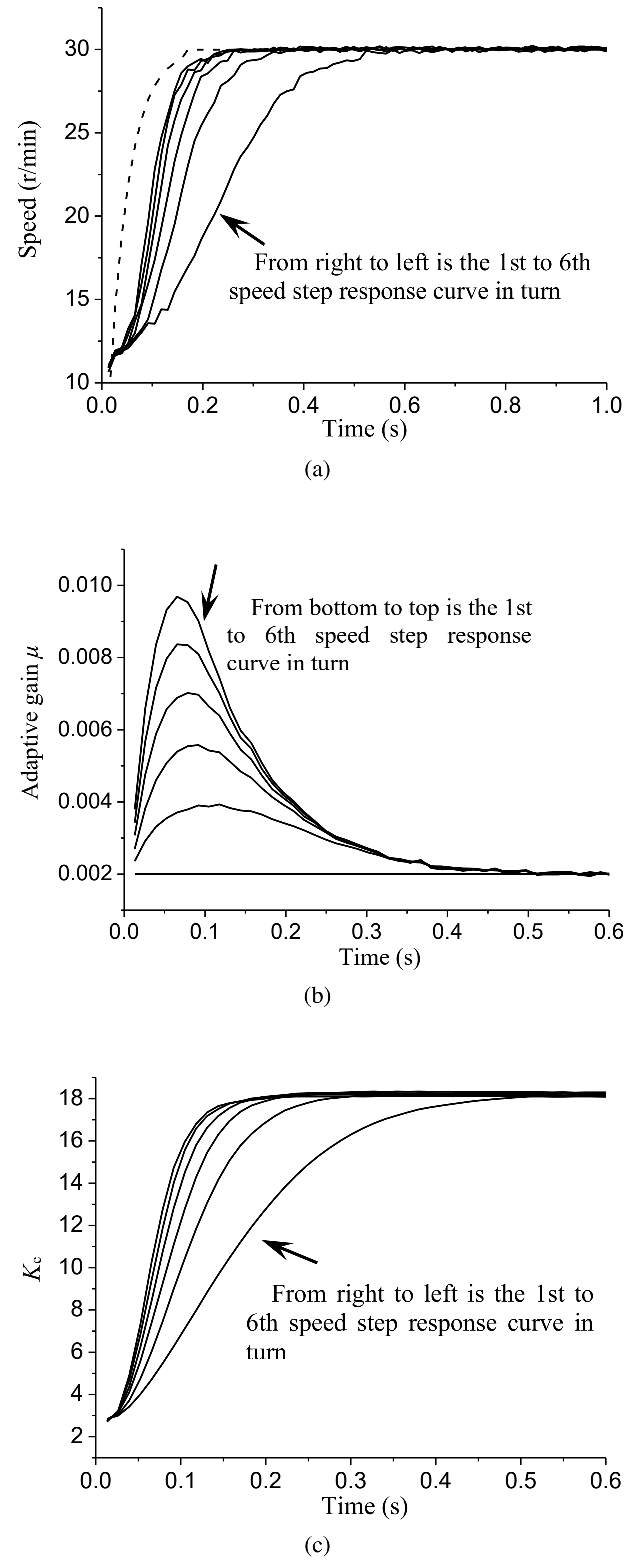


Fig. 7. Experimental results of indirect adaptive MIT speed control (P-ILC, $\lambda_P = 2$). (a) Curve of speed step response. (b) Changing curve of the value of adaptive gain μ. (c) Changing curve of the value of controller gain K_c.

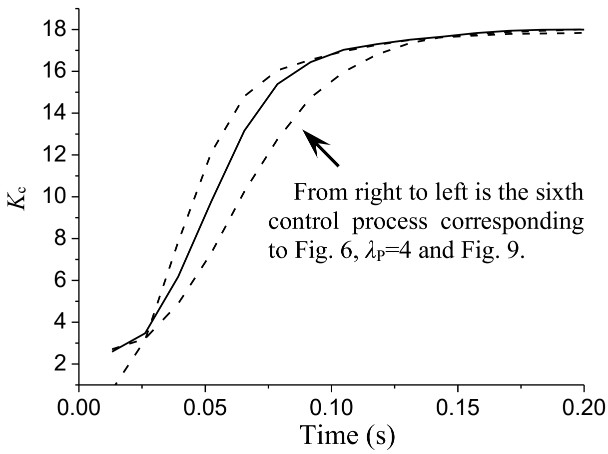
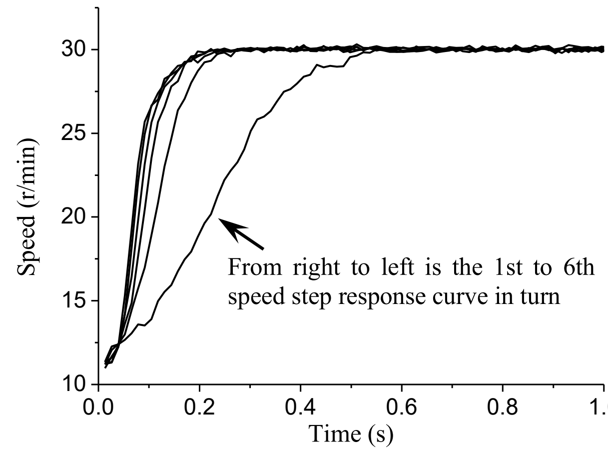
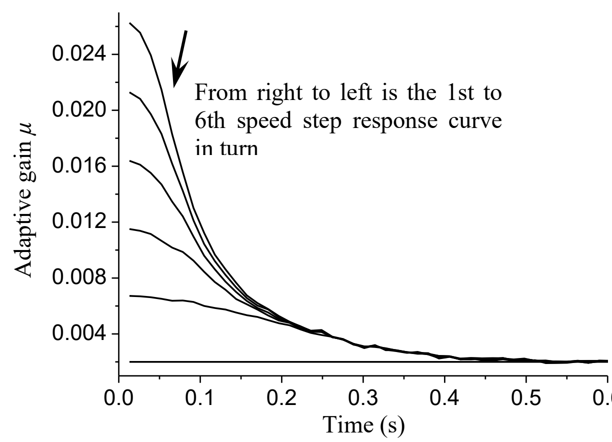


Fig. 8. Changing curve of the value of controller gain, K_c.



(a)



(b)

Fig. 9. Experimental results of adaptive MIT speed control (P-ILC, without reference model I, $\lambda_P = 4$). (a) Curve of speed step response. (b) Changing curve of the value of adaptive gain μ.

the output of the reference model is further narrowed.

The comparison of the changing curves of K_c under different conditions is shown in Fig. 8. The three curves in Fig. 8 correspond to the sixth step response process in three cases. In Fig. 8, the dotted line on the right side corresponds to the control result of P-ILC shown in Fig. 7, and the solid line corresponds to $\lambda_P = 4$. Obviously, when λ_P is set to 4, the rising rate of the changing curve of K_c is significantly faster than the curve of K_c corresponding to Fig. 7.

The above experiments are carried out with the control structure shown in Fig. 6, that is, the "reference model I" part is included. Next, we delete the part of the reference model I. The speed control experiment of ultrasonic motor is carried out with the same control parameter value as the case where $\lambda_P = 4$. The experimental results are shown in Fig. 9. The corresponding data of adjustment time is shown in Table 3.

Because the reference model I is deleted, the input error of the iterative learning controller, that is $e_{mk}(i)$, is no longer the difference between the output of the reference model I and the speed, but the difference between the step given value $y_{rk}(i)$ and the actual speed. Since the aforementioned reference model is taken as the first-order inertial, deleting this model will lead to the change of $e_{mk}(i)$, especially at the beginning section of the curve of $e_{mk}(i)$. Therefore, the changing curve of μ given in Fig. 9(b) is obviously different from that in Fig. 7(b). The value of μ in the beginning section increases obviously, and the decreasing section is basically the same. This change is reflected in the curve of K_c shown in Fig. 8 (the dotted line on the left is the changing curve of K_c in the sixth step response process of Fig. 9(a)). The value of K_c in the beginning section is significantly higher than that of $\lambda_P = 4$, which makes the rising rate of the starting section of the speed response shown in Fig. 9(a) faster. However, whether the reference model I is added at the front of the iterative learning controller has no significant effect on the adjustment time of the step response. Table 3 shows that, the adjustment time of the responses shown in Fig. 9(a) is the same as the case where $\lambda_P = 4$.

Table 3. The adjustment times of the step responses shown in Figs. 7-9.

Cycle	Adjustment time (s)		
	Fig. 7(a)	$\lambda_P = 4$	Fig. 9(a)
1	0.4061	0.4192	0.4192
2	0.2751	0.1965	0.1965
3	0.2096	0.1703	0.1703
4	0.1834	0.1572	0.1572
5	0.1703	0.1572	0.1572
6	0.1572	0.1441	0.1441

The above experiments are carried out with the step

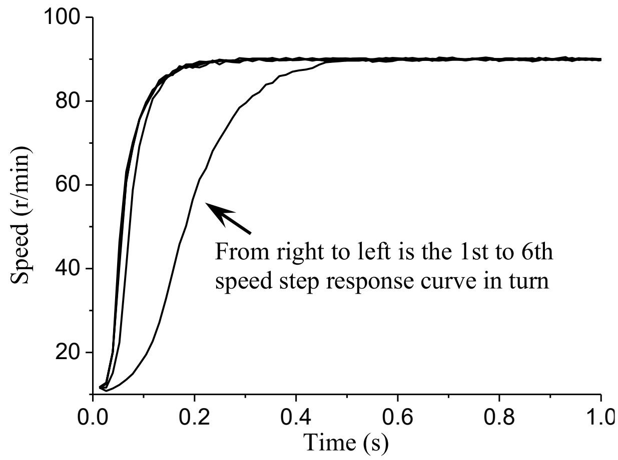


Fig. 10. Experimental results of adaptive MIT speed control (P-ILC, without reference model I, $\lambda_P = 4$).

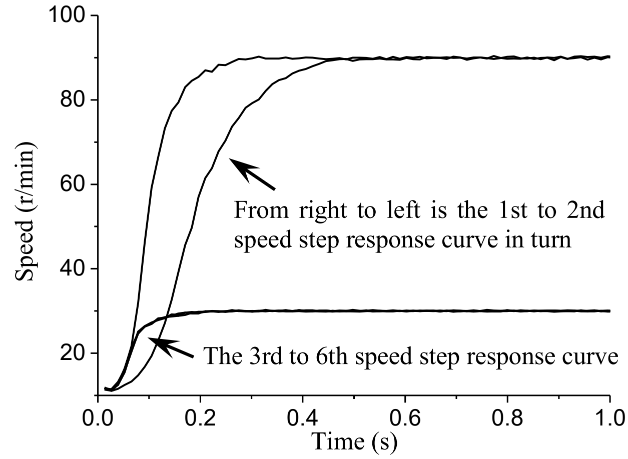


Fig. 11. Experimental results of adaptive MIT speed control (P-ILC, without reference model I, $\lambda_P = 2$).

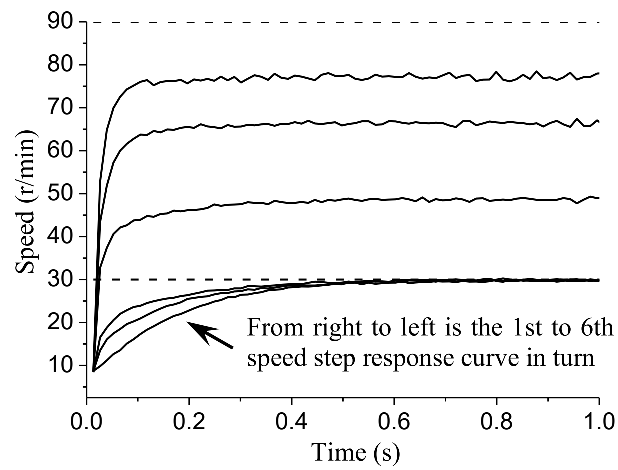


Fig. 12. Experimental results of traditional iterative learning controller.

given value of motor's speed is 30 r/min. In order to verify the adaptability of the proposed control strategy to different given values, change the value of step reference to 90 r/min, and take λ_P as 4. The experimental results shown in Fig. 10 can be obtained. It can be seen that the control performance is still good, and there is no obvious difference from the control performance when y_{rk} is 30 r/min. In Fig. 10, the second step response is close to the expected control performance. And the third to sixth step response curves coincide approximately, reach and stabilize in the convergence state.

In Fig. 11, the step given value of the first and second step response is 90 r/min, and then, the given value changes to 30 r/min at the third iteration. The responses shown in Fig. 11 shows that the proposed control strategy can well adapt to the sudden change of the given value and maintain good control performance. Moreover, the iterative learning process before and after the change have an inheritance relationship. Although the mutation of given value occurred in the third step response, the third response reached the learning convergence state on the basis of the previous learning cumulative memory. The subsequent several responses are maintained in this state, and the response curve no longer changes.

For traditional ILC strategies (such as P-ILC), the repeatability of control conditions and environment is the basis of its analysis and application. The experiment corresponding to Fig. 11 is no longer repeatable. If the traditional ILC strategy is used for this kind of experiment, there will be a steady-state error as shown in Fig. 12. After changing the given value of speed from 30 to 90 r/min in the third control process, the traditional ILC failed to make corresponding changes immediately. The steady-state speed of the third response is still 30 r/min. As shown in Fig. 12, the steady-state error will gradually decrease with the increase of the number of iterations. That is to say, the response of traditional ILC to the disturbance of the given value has a significant delay. Therefore, compared with the traditional ILC controller, the proposed control strategy is more robust and can make a timely and effective response to disturbance.

A new MIT control strategy is proposed in this section, which is used to improve the performance of the MIT controller and enhance the ability of the MIT control strategy to correct the dynamic performance of the controlled object. In this control strategy, a simple P-type iterative learning controller is used to adjust the gain μ on-line adaptively according to the previous control error. The proposed method increases the degree of freedom of the MIT control strategy, and improves the ability to adapt to complex controlled objects. The experimental results show the effectiveness of the proposed control strategy.

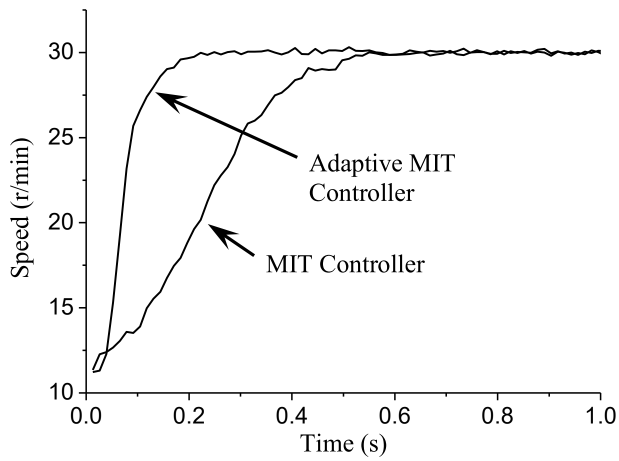


Fig. 13. Experimental results of MIT controller and adaptive MIT controller.

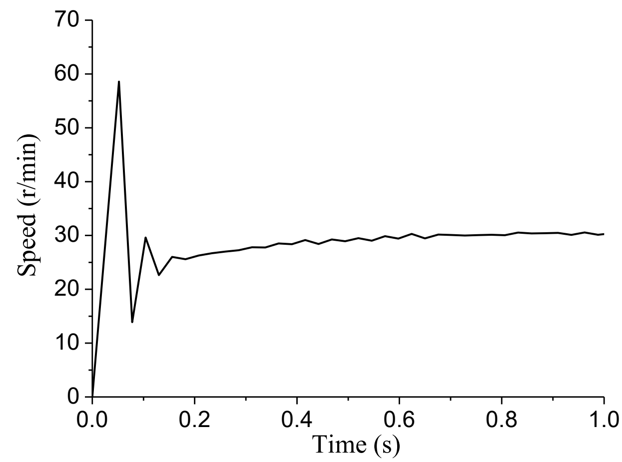


Fig. 14. Experimental result of MIT controller with larger value of adaptive gain μ.

4. COMPARISON WITH MIT CONTROL STRATEGY

The comparative experiment is provied in this section to verify the control performance of the proposed control strategy. In order to compare the control performance of the MIT controller and the adaptive MIT controller, Fig. 13 shows the experimental result of MIT controller and the result of adaptive MIT controller after six iterations. Here, the initial parameter value of the adaptive MIT controller is the same as the MIT controller. It can be seen from Fig. 13 that the response speed of adaptive MIT controller is faster than that of MIT controller. Therefore, the proposed control method can greatly improve the control performance of MIT controller by the learning ability.

As we know, the value of adaptive gain, μ, of MIT controller may be increased to accelerate the response speed. However, although increasing the parameter value can speed up the response speed, it often leads to large overshoot as shown in Fig. 14. Different from the MIT controller with fixed value of μ, the parameter value of the proposed controller are variable, as shown in Fig. 9(b). Therefore, the parameter value is automatically reduced to avoid overshoot when approaching the given value. At the same time, the parameter value is automatically increased to get faster response speed during the initial stage of response.

5. CONCLUSION

In this paper, two improved MIT control strategies are proposed, which make it possible to use MIT control strategy to achieve large-scale correction of system's dynamic characteristics, and expand the application scope of MIT model reference adaptive control strategy. The first method is to design a P-type iterative learning controller to adjust the given value of MIT controller to form an indirect iterative learning control system. Using this method, the response of the system depends on the reference model on the front-end of the iterative learning controller, and it has the ability to achieve the desired performance expressed by the reference model.

Compared with the indirect iterative learning method, the adaptive MIT strategy no longer takes adjusting the given value of MIT controller as a means to improve the system performance. The approximate cubic relationship between the output of the system and the iterative learning controller is avoided. Therefore, it is no longer necessary to add a low-pass filter at the output of iterative learning controller to suppress the influence of noise, nor to adopt a compulsory measure to suppress the fluctuation of speed.

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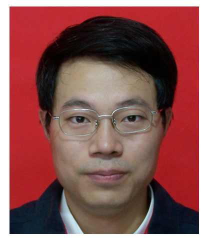

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