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Improved Indirect Iterative Learning MIT Control Method for Ultrasonic Motor

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ABSTRACT MIT control strategy is a kind of model reference adaptive control method with the simplest structure. The reason why the structure is simple is that only the gain of the controlled object is adaptively adjusted. Because only the gain is adjusted, the ability of MIT control strategy to change the characteristics of the controlled object is limited. This also limits its application. In this paper, the simple idea of iterative learning control is introduced into MIT controller to increase the controller's ability to adjust the characteristics of the controlled object, and make it suitable for complex control objects. In the proposed control method, the output of the iterative learning controller is used to adjust the adaptive law of the MIT controller. The proposed control method is applied to the speed control system of ultrasonic motor. Experiments show that although only the gain of MIT controller can be adjusted, the learning process based on memory increases the degree of control freedom. Therefore, the dynamic characteristics of the system can be greatly changed, and the control performance can be significantly improved. Moreover, the proposed method only needs to add a simple P-type iterative learning controller to the MIT controller, and the increase of online calculation amount is small.

INDEX TERMS Ultrasonic motor, iterative learning control (ILC), MIT control.

I. INTRODUCTION

As the earliest proposed model reference adaptive control (MRAC) method, MIT control strategy is still used in various practical applications [1]–[6]. 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 verification of stability is needed [3]. Only adjusting the gain has limited effect on the dynamic characteristics of the system, so it is difficult to achieve large correction of the system's dynamic characteristics, which limits the application area of MIT control strategy [2], [4].

No matter from the aspects of design, debugging or system maintenance, the structure of the control system is expected to be simpler. It is for this reason that the MIT adaptive control strategy with simple structure has always been concerned, and its improvement measures have also been continuously proposed. The adaptive law of MIT designed based on Lyapunov stability theory, replacing the output of the reference model with the given value, can ensure that the designed adaptive control system has closed-loop stability [4]–[6]. However, because the MIT strategy only adjusts the gain, the degree of improvement of the system's dynamic performance is restricted, which is still a problem.

Since only adjusting the gain is the reason of this problem, the direct way to solve the problem is to increase the adjustment freedom of the controller, which may 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 control performance. From this point of view, it may be a feasible way to design an iterative learning controller (ILC) [7]–[10] with a simple structure to adjust the given value of the MIT controller by using the idea of indirect iterative learning control (indirect ILC). The work in this paper shows that this method can not only keep the independence of MIT controller design and system stability, but also improve the dynamic performance of the system obviously. For example, even if the first-order model is deliberately used

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to express the originally high-order controlled object, and the first-order model is used in the design of the MIT controller, the control strategy proposed in this paper can still make the dynamic response tends to the expected performance.

Since Arimoto S. put forward the basic idea of ILC in 1984, ILC has been developed for more than thirty years, and its application fields have been continuously expanded. The iterative learning control problem is investigated for the distributed building automatic temperature system in [8], and a kind of mixed PD-type ILC algorithm is proposed to make the tracking error of parabolic singular distributed parameter systems converge to any tracking accuracy. In [9], a time-varying control method based on norm optimal cross-coupling iterative learning is proposed to improve the control precision of multi-axis motion control system. And a neural network-based error-track iterative learning control scheme is proposed in [10] to tackle trajectory tracking problem for tank gun control systems.

The indirect ILC method is to connect the iterative learning controller and the closed-loop controller in series to form a control structure similar to the double closed-loop system. The closed loop controller constitutes the inner loop, and the iterative learning controller is in the outer loop. The output of ILC is used to change the given value of the closed-loop controller [11]–[15]. This control structure is first proposed in [11]. The proposed scheme iteratively changes the control signal by adjusting the given value. The control method proposed in [11] has been applied to batch processes with time varying uncertainties [12], [13]. And in [14], the same method is extended to multi-input multi-output systems. Although the generalized predictive controller (GPC) [15] is used as the inner loop controller in some literatures, most of the researches in literatures are focused on the case that the inner loop is a PID controller [11]–[14].

Some literatures have studied indirect ILC, but from the perspective of practical application, there are still some deficiencies. For example, the control performance in time domain is still obviously insufficient, and there are obvious overshoots in the response process. The work of this paper shows that there is also obvious overshoot when using iterative learning controller to adjust the given value of MIT controller (see section II). Overshoot is not allowed in many industrial applications, such as most of the motion control fields. How to use the idea of ILC to solve the problem of MIT control strategy, improve the performance of MIT control system, and keep good control performance in the iterative learning process to meet the needs of industrial application is the main problem that this paper attempts to solve.

The main contributions of the paper are elaborated below.

1) The traditional indirect ILC proposed in [11]–[15] is used to improve the performance of MRAC system. Experimental results show that, the step response of the system has a large overshoot. The control performance is not so good.
2) Aiming at the problem of obvious overshoot, a new indirect ILC method different from that in [11]–[15] is proposed. In this control method, the simple P-type iterative learning controller is no longer used to change the given value of the MIT controller, but is used to adjust the adaptive law of the MIT controller online.
3) Using ultrasonic motor as the controlled object, the control performance and applicability of the proposed control strategy is 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 scheme can still overcome the influence of this model error, and make the dynamic response of the system tends to the desired characteristic after finite iterations. Experimental results show that this new control method can not only significantly improve the performance of the MIT control system, but also maintain good time-domain performance during the iterative learning process.

The rest of the paper is organized as follows. In Section II, In order to show the limitation of the indirect ILC method described in [11]–[15], this method is applied to the MIT control system of ultrasonic motor, and experimental research is carried out. In Section III, an improved indirect iterative learning MIT control method is given. Afterwards, comparative experiments are provided to verify the feasibility of the proposed strategy in Section IV. Finally, Section V concludes this paper.

II. STRUCTURE OF INDIRECT ITERATIVE LEARNING MIT CONTROLLER AND EXPERIMENTAL RESULTS

A. INDIRECT ITERATIVE LEARNING MIT CONTROLLER

Using the indirect ILC method described in [11]–[15], the indirect iterative learning MIT control system shown in Fig. 1 is designed. Fig. 1 shows the speed control system of ultrasonic motor. The dashed line in Fig. 1 represents the previous control information stored in the memory. 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 [1]

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

where, K_{c} is the adjustable gain of MIT controller, coefficient μ is 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. The output error, e_k, is the difference between the output of the reference model and the actual output of the system, that is

$$e_k = y_{\mathrm{m}k} - y_k \tag{2}$$

where, $y_{\mathrm{m}k}$ is the output of the reference model, y_k is the actual output of the system.

In Fig. 1, the output of the iterative learning controller, $\Delta y_{\mathrm{r}k}$, is added to the given value $y_{\mathrm{r}k}$ to obtain the given value of the MIT controller, $y_{\mathrm{Tr}k}$. Iterative learning controller

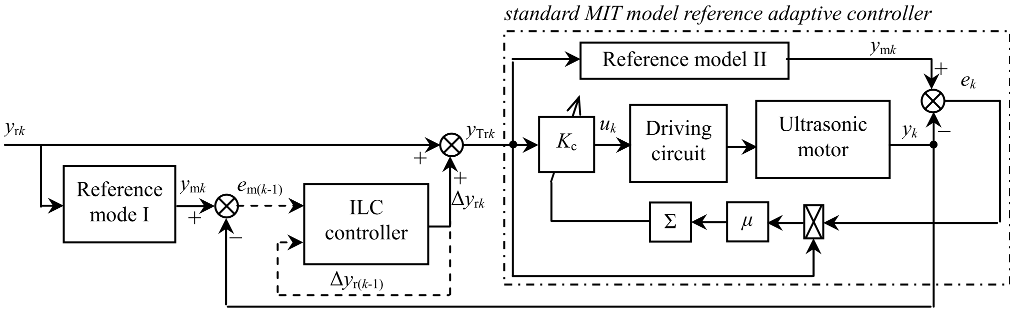

FIGURE 1. Structure diagram of indirect iterative learning MIT speed control system for ultrasonic motor.

adopts simple P-type structure (P-ILC)

$$\Delta y_{rk}(i) = \Delta y_{r(k-1)}(i) + \lambda_P e_{m(k-1)}(i+1) \tag{3}$$

where, coefficient λ_P is proportional learning gain, $\Delta y_{r(k-1)}(i)$ and $e_{m(k-1)}(i+1)$ are the increment of given value at the time i and the value of input error of iterative learning controller at the time $i+1$ in the $(k-1)$-th iterative control process, respectively.

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. In Fig.1, the reference model I and the reference model II are the same.

The mathematical model of ultrasonic motor is needed for the design of MIT controller in Fig. 1. Generally, the third or fourth order model can better describe the dynamic characteristics of ultrasonic motor [16]. 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 better correct the dynamic performance of the system, the first-order inertial model shown in (4) is used to identify the model of ultrasonic motor. The first-order model also meets the desired system performance requirements, such as no overshoot.

$$G(s) = \frac{k_P}{\tau s + 1} \tag{4}$$

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

Take the reference model II of MIT controller as

$$G_m(s) = \frac{1}{\tau s + 1} \tag{5}$$

Obviously, equation (5) is only different in gain from (4), which is consistent with the design premise of MIT controller. For the convenience of programming, the above formula is transformed into difference form

$$y_{mk}(i) = e^{-T_s/\tau} y_{mk}(i-1) + \left(1 - e^{-T_s/\tau}\right) y_{Trk}(i) \tag{6}$$

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 value of the parameters in (4) can be determined by the identification of motor's model based on the experimental data, and then the reference model II can be obtained as

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

$$y_{mk}(i) = 0.72 y_{mk}(i-1) + 0.28 y_{Trk}(i) \tag{7}$$

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

B. EXPERIMENTAL RESULTS

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 performance of the controller. The ultrasonic motor used in the experiment is USR60 traveling wave ultrasonic motor of Shinsei Company. The specifications of the motor are shown in Table 1. In the experimental platform, a permanent magnet DC motor is rigidly connected with the ultrasonic motor to provide load torque.

The adjustable range of the experimental motor's speed is 0r/min to 120r/min. The photo of the experimental test bench is shown in Fig. 2. The main structure of the motor's 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's speed. The output of the controller is the frequency of driving voltage, and the speed can be controlled by adjusting the frequency.

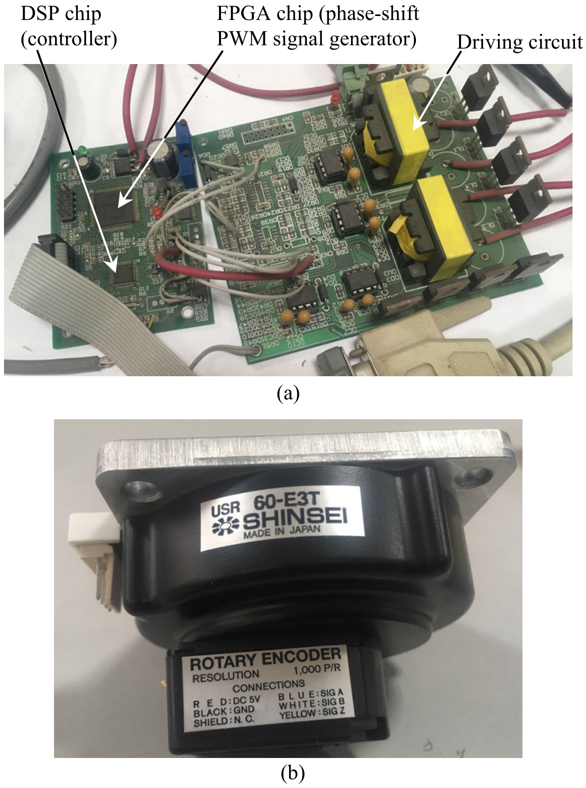

FIGURE 2. Photo of the experimental test bench. (a) Driving and control circuits. (b) Ultrasonic motor.

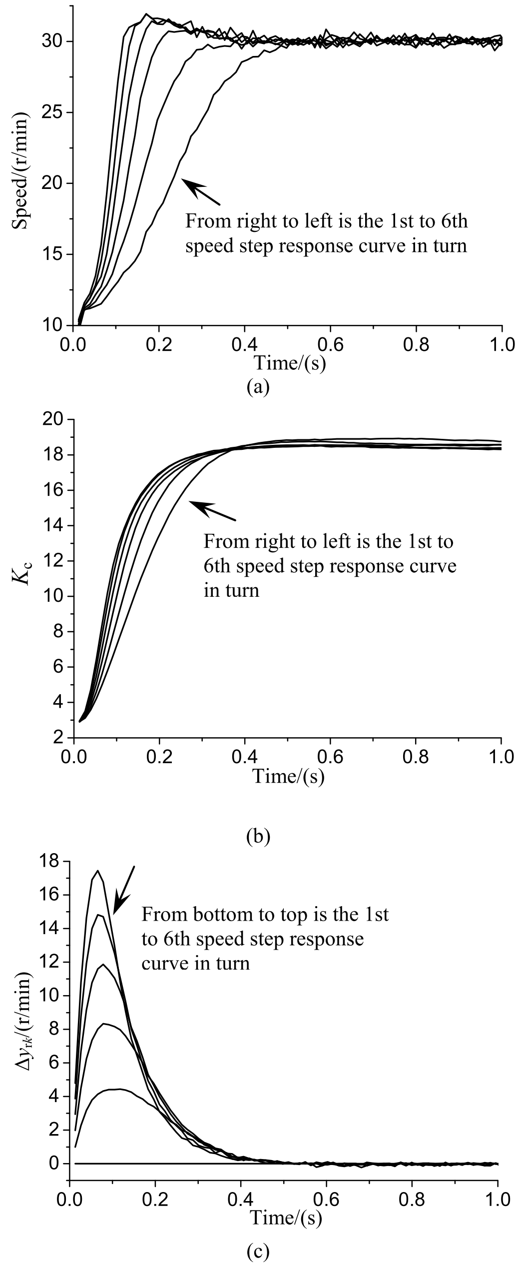

FIGURE 3. Experimental results of indirect iterative learning MIT speed control ($\lambda_P = 0.3$). (a) Curve of speed step response. (b) Changing curve of the value of controller gain K_c. (c) Incremental curve of the given value of MIT controller.

Set the initial value of the adjustable gain K_c to 3. Set the adaptive gain μ to 0.002 and the proportional learning gain λ_P to 0.3. The step given value of speed is set as 30 r/min. Six consecutive iterative learning control experiments are carried out, and the experimental results are shown in Fig. 3.

The incremental curve of the given value of MIT controller is shown in Fig. 3(c), which is the output of P-ILC formula (3). This value plus the given value of 30 r/min is the given value of MIT controller. Fig. 3(c) shows that due to the successive accumulation of (3), 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. That is to say, the rise time of the step response curve shown in Fig. 3(a) is decreasing. Corresponding to Fig. 3(c), mainly due to the continuous increase of the value of y_{Trk}, the changing rate of the gain K_c is also gradually accelerated under the effect of the adaptive law (1), as shown in Fig. 3(b). Fig. 3 shows that ILC is effective, and the system's response gradually approaches the expected performance expressed by the reference model through iterations.

However, there are obvious overshoots in the experimental results shown in Fig. 3, which limits the application range of the indirect ILC method described in [11]–[15], because overshoot is not allowed in many applications. It should be pointed out that this overshoot is not caused by the use of a special object such as ultrasonic motor. In fact, the simulation or experiment conducted on different objects in [11]–[15] also shows obvious overshoot. This indicates that the indirect ILC method described in [11]–[15] is the main cause of the overshoot. In the following section, we will consider how to improve the control method to avoid overshoot.

III. IMPROVED INDIRECT ITERATIVE LEARNING MIT CONTROL METHOD

In Fig. 3, the adjustment time of the step response obtained in the first experiment with the MIT controller is longer

TABLE 2. Comparison of speed control performance of improved indirect iterative learning MIT.

Cycle	Adjustment time (s)			Steady state value of K_c		
	Fig. 5(a)	Fig. 8(a)	Fig. 9(a)	Fig. 5(c)	Fig. 8(b)	Fig. 9(b)
1	0.4716	0.4323	0.4716	17.77	19.86	18.12
2	0.2358	0.2227	0.2227	17.94	19.89	19.26
3	0.1834	0.1572	0.1965	17.75	19.43	18.15
4	0.1834	0.1572	0.1572	17.90	19.67	19.42
5	0.1703	0.1572	0.1572	17.76	19.47	18.09
6	0.1572	0.1572	0.1572	17.78	19.53	18.26

than the expected adjustment time. As shown in Fig. 3(c), in order to accelerate the response speed to make the control performance approach the expectation, the increment of the given value (output of the iterative learning controller) is getting larger and larger. The value of control quantity and response speed are enhanced by increasing the given value of MIT controller. Comparing Fig. 3(a) and Fig. 3(c), it can be seen that when the speed response curve has reached the actual step given value, the increment of the given value output by the iterative learning controller is still greater than zero. And its value is relatively large. Therefore, in the process of MIT controller trying to reach the given value by adjusting the control quantity, overshoot will inevitably occur.

In the control system shown in Fig. 1, the iterative learning controller is used to adjust the given value of the MIT controller. In the initial stage of step response, increasing the given value is beneficial to accelerate the response speed, so as to make the control performance gradually approach the expected state. But the given value of the MIT controller is still large while the actual speed reaches the given value, which causes overshoot. In order to make the overshoot zero, it is necessary to avoid inappropriate changes to the given value of MIT controller, and use the closed-loop control ability of the MIT controller to suppress the overshoot.

In the control method described in Fig. 1, the given value $y_{\mathrm{Tr}k}$ adjusted by the iterative learning controller affects the operating process of MIT controller in several different ways. Firstly, the control quantity u_k is the product of K_c and $y_{\mathrm{Tr}k}$. So, changing $y_{\mathrm{Tr}k}$ will directly change the control quantity output by MIT controller. Secondly, $y_{\mathrm{Tr}k}$ is also the input signal of the reference model (reference model II in Fig. 1) in MIT controller. In MIT control strategy, the reference model is used to reflect the expected control state. So, the output signal of the reference model directly determines the control target of the controller. Changing $y_{\mathrm{Tr}k}$ changes the output signal of the reference model. Such a change can be used to adjust the dynamic response of the system, but it also makes the control target of the system deviate from the direction specified by the actual given value $y_{\mathrm{r}k}$. Thirdly, changing $y_{\mathrm{Tr}k}$ also affects the adaptive law of K_c through (1). Increasing $y_{\mathrm{Tr}k}$ will increase the rate of change of K_c, thereby changing the dynamic response process. As mentioned above, in order to make the overshoot zero, it is necessary to avoid inappropriate changes to the given value of MIT controller. Based on this point of view, the control method is modified as shown in Fig. 4. The iterative learning controller is still used to adjust the given value of the system, but the adjustment result is no longer used as given value to act on the MIT controller. It is only used in the adaptive law of K_c. The dynamic performance of the system is adjusted by changing the adaptive rate of K_c. In such a control method, the given value of MIT controller equal to the actual given value of speed. Therefore, the closed-loop control advantages of the MIT controller can be used to suppress overshoot and maintain a good response process. In addition, the learning ability of ILC is used to enhance the adaptive ability and robustness of the system, so that the control performance of the system meets expectation, so as to achieve complementary advantages, foster strengths and circumvent weaknesses.

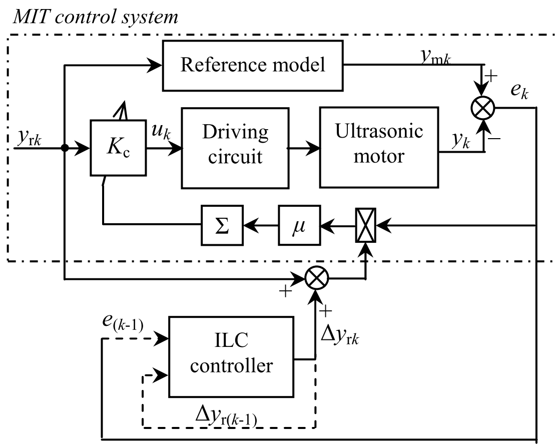

FIGURE 4. Structure diagram of improved indirect iterative learning MIT speed control system for ultrasonic motor.

The dashed line in Fig. 4 represents the previous control information stored in the memory. In the control method shown in Fig. 4, the adaptive law of gain K_c is

$$\dot{K}_c = \mu\left(y_{\mathrm{r}k} + \Delta y_{\mathrm{r}k}\right) e_k \tag{8}$$

Iterative learning controller still adopts P-type structure.

$$\Delta y_{\mathrm{r}k}(i) = \Delta y_{\mathrm{r}(k-1)}(i) + \lambda_{\mathrm{P}} e_{(k-1)}(i+1) \tag{9}$$

The form of the reference model is still the same as (7), but the input variable is changed from $y_{\mathrm{Tr}k}$ to $y_{\mathrm{r}k}$, that is

$$y_{\mathrm{m}k}(i) = 0.72 y_{\mathrm{m}k}(i-1) + 0.28 y_{\mathrm{r}k}(i) \tag{10}$$

IV. EXPERIMENTAL VERIFICATION

The DSP chip is programmed to realize the speed controller of ultrasonic motor shown in Fig. 4. Experiments are carried out to investigate the effectiveness of the proposed control method. Set the initial value of K_c to 3. Set the adaptive gain μ to 0.002 and the proportional learning gain λ_P to 4. The given value of speed's 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. 5. Obviously, the overshoot of rotating speed is 0. Table 2 shows the index data of control performance.

It can be seen from Fig. 5(b) that since the response speed of the motor's speed is slower than the output signal of the reference model, the output error e_k is positive. So, the amplitude of the output signal Δy_{rk} of the iterative learning controller gradually increases. Because the curve of speed response gradually approaches the output signal of reference model during the iterative learning process, and the amplitude of e_k gradually decreases, so the increase of Δy_{rk} between two adjacent response processes gradually decreases. It shows that the learning process converges gradually. The step response curves given in Fig. 5(a) show this convergence process more clearly. The fifth and sixth step response curves are basically coincident, and they are close to and stabilized in the expected state. According to (8), the gradually increasing Δy_{rk} causes the rate of change of K_c to gradually increase. Comparing Fig. 5(c) with Fig. 3(b), the steady-state values of the two are close. However, the rising rate of the curve shown in Fig. 5(c) is significantly faster than that of Fig. 3(b). And with the progress of iterative learning, the rising rate becomes faster and faster, and the amount of change in the rising rate gradually reduced. The curves of K_c corresponding to the fifth and sixth response processes are nearly coincident and tend to the learning convergence state. The change rule of the curve shown in Fig. 5(c) and Fig. 5(a) is the same. The curves of K_c shown in Fig. 5(c) is the result of the adjustment of iterative learning controller, which is the cause of the step responses shown in Fig. 5(a).

The experimental results shown in Fig. 5 indicate that the proposed control method is effective. It not only avoids overshoot, but also effectively improves the performance of MIT control system, so that it can better adapt to the constantly changing object. In the design process of the controller shown in Fig. 4, it is no longer like the design process of the MIT controller that a compromise between stability and dynamic performance is needed to determine an appropriate value of adaptive gain. Here, the value of μ only needs to be set to a smaller value that can guarantee the steady-state stability. The iterative learning controller can adjust the rate of change of the gain K_c according to actual needs through online learning.

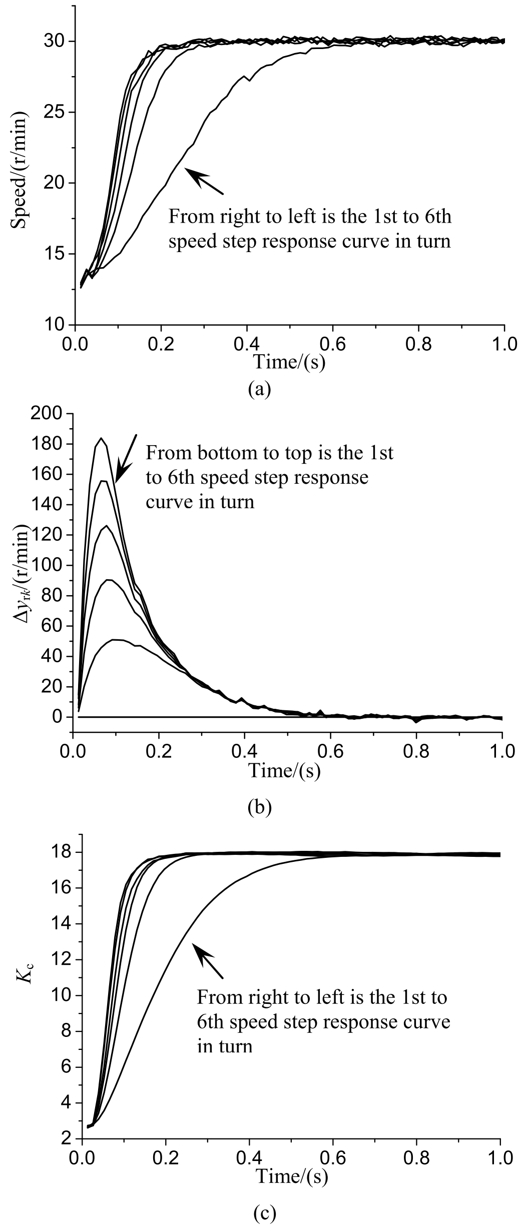

FIGURE 5. Experimental results of improved indirect iterative learning MIT speed control ($\lambda_P = 4$). (a) Curve of speed step response. (b) Output of the ILC controller. (c) Changing curve of the value of controller gain K_c.

A. EXPERIMENTS UNDER DIFFERENT GIVEN VALUE OF SPEED

In the following experiments, the step given value of speed is changed to investigate the adaptability of the proposed control method under different speed conditions. The given value of speed is set as 60r/min. The P-type iterative learning control law is still adopted and the same reference model as the previous experiment is also used. Set the initial value of K_c to 0.5. Set the adaptive gain μ to 0.0004 and λ_P to 3. The experimental results are shown in Fig. 6. Table 3 shows the corresponding adjustment time.

Obviously, the control performance of motor's speed is gradually improved during the iterative learning process. The speed of learning convergence is fast, and the control method is effective. In Fig. 6(a), the third to sixth curves are nearly coincident. Its adjustment time is 0.1572s, which has approached and stabilized in the expected control state.

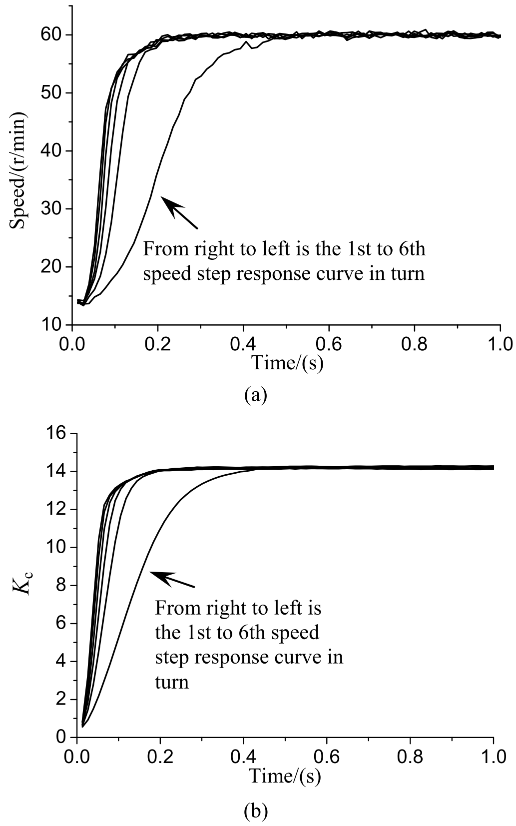

FIGURE 6. **Experimental results of improved indirect iterative learning MIT speed control ($\lambda_P = 3$, 60r/min). (a) Curve of speed step response. (b) Changing curve of the value of controller gain K_c.**

TABLE 3. **Comparison of speed control performance under different speed.**

Cycle	Adjustment time (s)	
	Fig. 6(a)	Fig. 7
1	0.3799	0.3668
2	0.1703	0.1834
3	0.1572	0.1572
4	0.1572	0.1572
5	0.1572	0.1572
6	0.1572	0.1572

Only the rising section of the four response curves is slightly different. The response speed of the four response curves is gradually accelerating, and moving closer to the output signal of the reference model. Compared with the experimental results in Fig. 5, which also uses P-ILC but with a given value of 30r/min, the trend of the curves is the same, and the adjustment time of the sixth step response is also the same. The difference is that due to the increase of speed, the amplitude of the output signal of iterative learning controller is significantly increased to obtain the expected response speed. In addition, the steady-state value of K_c is reduced from 17.78 in Fig. 5(c) to 14.15 in Fig. 6(b), which indicates that the steady-state gain of the ultrasonic motor is different at different speeds. It also shows that the proposed control method has an adaptive ability to the difference of object

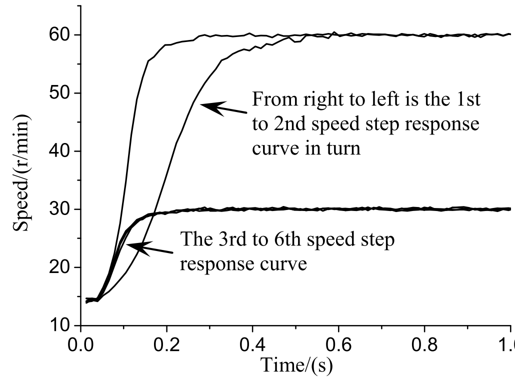

FIGURE 7. **Experimental results under the condition of given value mutation ($\lambda_P = 3$).**

characteristics caused by the change of speed. In other words, the robustness of the control strategy is better.

The process of the experiment is further modified. In six successive step response experiments, the given value of the first and second step response is 60r/min, the given value of the third and subsequent step response changes to 30r/min. This is to add non-repetitive disturbances in the iterative learning process by changing the given value. The experimental results shown in Fig. 7 are obtained by using the same reference model and control parameters as in Fig. 6.

As can be seen from Fig. 7, the speed response is still fast and stable. During the process of iterative learning, the control performance gradually approaches and finally stabilizes to the desired state. The sudden change of the given value does not slow down the process of learning convergence and the speed of convergence. The adjustment time corresponding to Fig. 7 is shown in Table 3. Compared with Table 2, it can be found that the adjustment time of the sixth step response is the same 0.1572s no matter in Fig. 5 and Fig. 6 under the condition of 30r/min and 60r/min, or in Fig. 7 under the mutation of given value. This shows that the proposed control method has good robustness and can effectively deal with non-repetitive disturbance in the learning process.

There are three parameters in the proposed control method. They are adaptive gain μ, the initial value of adjustable gain K_c, and learning gain λ_P. Their values will affect the control performance.

Adaptive gain is a parameter of the standard MIT control strategy. In MIT control strategy, the value of the adaptive gain μ determines the adaptive adjustment rate of K_c. However, the method to determine the specific value of μ is not given in the MIT control strategy [1], [2], [4]. The value of μ is usually designed by trial and error according to the simulation and/or experimental results. The larger the value of μ is, the faster the response speed will be. But too large value will lead to instability. In the proposed control method, the control performance of the system after finite iterations is mainly guaranteed by the iterative learning controller. The influence of the specific value of μ on control performance is weakened. Therefore, μ can be set as a smaller value without too much consideration of the response speed, thus simplifying the process of determining its value.

In the experiments shown in Fig. 5 and Fig. 6, μ is set as different values to adapt to different given values of speed. Fig. 4 shows that y_{rk} directly changes the input of reference model, and makes y_{mk} and output error e_k change by the same order of magnitude. The MIT adaptive law given in (1) and (8) contains the product term of y_{rk} and e_k, so the change of y_{rk} will also cause the change of gain K_c in the same direction, the change amount of K_c and y_{rk} are approximately square relation. The change of K_c will also affect the value of the control quantity u_k which is the product of y_{rk} and K_c. That is to say, the relationship between u_k and y_{rk} is approximately cubic. Therefore, the value of μ can be inversely proportional to the cubic approximation of the given value of speed. In this way, the performance of MIT controller in the proposed control method can be approximately the same under different given values of speed.

Since the value of K_c is automatically adjusted by the iterative learning controller in the proposed control method, the initial value of K_c is not important. However, the initial value of K_c will affect the adjustment time of the first response process when the value of μ is determined. In the experiments with different given values of speed shown in Fig. 5 and Fig. 6, the initial value of K_c is different. The purpose of this is to make the adjustment time of the first response process similar in different experiments, so as to facilitate the comparison of the experimental results.

The value of learning gain λ_P directly affects the learning convergence rate of ILC. In practice,the learning gain is tuned to achieve a tradeoff between the rate of ILC convergence and the robustness of the controller to measurement noise [18]. The ILC control law given in (9) contains the product term of λ_P and e_k. As mentioned earlier, different given values of speed can result in different magnitude of e_k. Therefore, it is a reasonable experience to reduce the value of λ_P with the increase of the given value of speed.

B. EXPERIMENTS UNDER DIFFERENT LOAD CONDITIONS

The above experimental results are carried out under the condition of no-load. In order to further verify the control performance of the proposed control method under load disturbance, loading experiments are carried out. The P-ILC is still adopted. A load torque of 0.5Nm is continuously applied to the motor, six consecutive iterative learning control experiments are carried out. The experimental results are shown in Fig. 8.

In the six consecutive iterative learning control experiments, a load torque of 0.5Nm is only applied during the second and fourth control process, and the other four are no-load. The experimental results are shown in Fig. 9. Comparing Fig. 8(a), Fig. 9(a) and no-load experimental results Fig. 5(a), it can be seen that the loading condition has no obvious effect on the speed response curves, the speed control process still

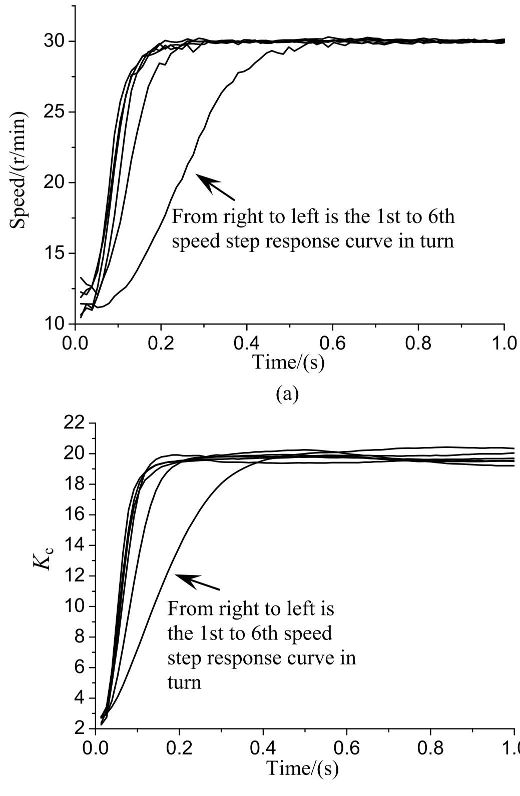

FIGURE 8. Experimental results of improved indirect iterative learning MIT speed control ($\lambda_P = 4$, loading 0.5Nm). (a) Curve of speed step response. (b) Changing curve of the value of controller gain K_c.

has good performance. The learning convergence is still fast and can be stable in the desired state. The adjustment time given in Table 2 also shows that the adjustment times of the sixth step response under no-load and different loading modes are the same 0.1572s. It shows that the proposed control method has good robustness to load disturbance.

It should be pointed out that for the traditional ILC, the intermittent loading of the experiment shown in Fig. 9 belongs to non-repetitive disturbance, which does not meet the repeatability premise required by ILC. So the control performance will become worse. If the traditional ILC is used alone to carry out the experiment shown in Fig. 9, the resulting step response curves will have obvious steady-state errors. It can be seen that the control method described in this paper can not only effectively improve the performance of MIT controller, but also can deal with non-repetitive disturbances, and its robustness is better than that of ILC.

In the case of loading, in order to resist the influence of load and maintain the control performance, the control quantity output by the controller should have a corresponding change. In the system shown in Fig. 4, the control quantity applied to the motor is proportional to the gain K_c. From the changing curves of K_c shown in Fig. 8(b) and Fig. 9(b), we can see the effort made by the controller to resist the load torque. Table 2 also shows the steady-state data of K_c. Compared

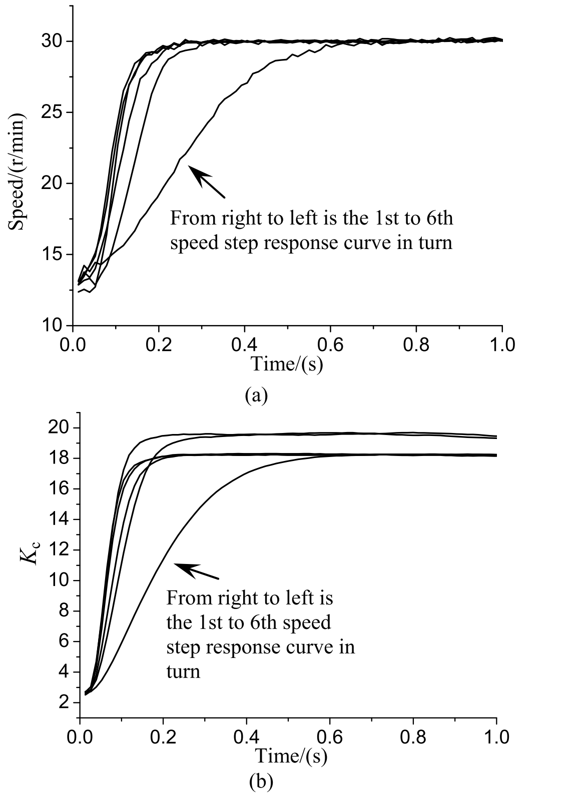

FIGURE 9. Experimental results of improved indirect iterative learning MIT speed control ($\lambda_P = 4$, loading 0.5Nm during the second and fourth step response). (a) Curve of speed step response. (b) Changing curve of the value of controller gain K_c.

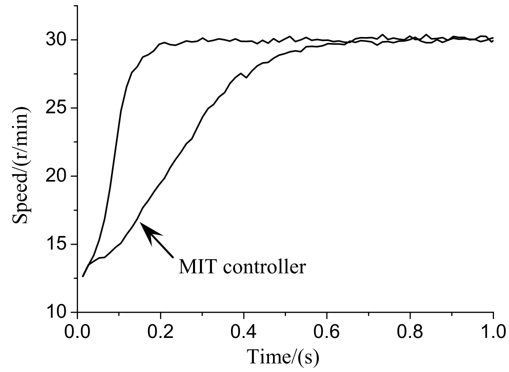

FIGURE 10. Comparison of experimental result between improved indirect iterative learning MIT controller and MIT controller.

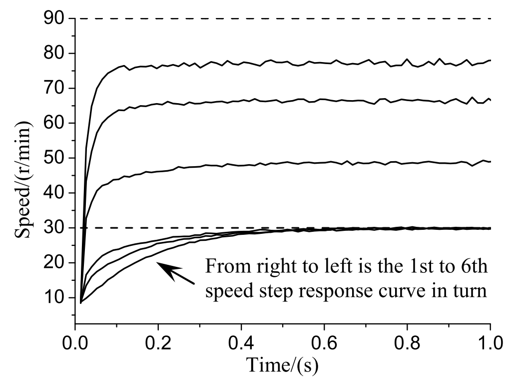

FIGURE 11. Experimental results under the condition of sudden change of given value (traditional ILC).

with Fig. 5(c) under no-load condition, the steady-state value of K_c corresponding to each step response under continuous loading condition is obviously increased, so as to strengthen the control effect to resist the influence of load. In the case of intermittent loading, the steady-state value of K_c of the second and fourth experimental results under load is obviously greater than that of the other four, which also shows the adaptive ability of the controller.

It can be seen from the data in Table 2 that the four steady-state values of Kc under no-load condition in Fig. 9 is 18.16 (average value), which is greater than the 17.82 (average value) corresponding to the same no-load experiment in Fig. 5. The reason for this difference is that the temperature of the motor body is different when these two sets of experiments are carried out. Ultrasonic motor transmits mechanical energy through the friction between the stator and rotor, and frictional heating causes the temperature of the motor to change continuously during operation [17]. The temperature of the motor body during the experiment in Fig. 5 is 29.0°C, and the temperature of the motor during the experiment in Fig. 9 is 30.3°C. The dynamic characteristics of ultrasonic motor are directly related to the temperature. The characteristics of motor are different when the temperature of motor is different, so the difference in the steady state value of K_c appears. In fact, all the above experiments are carried out under different temperature conditions. These experimental results also show that the proposed control method is robust to temperature changes.

C. COMPARATIVE EXPERIMENTS

In order to compare the control performance of improved indirect iterative learning MIT controller and standard MIT controller, Fig. 10 shows the experimental result of improved indirect iterative learning MIT controller after six iterations and the experimental result of MIT controller. The initial value of parameter of the improved indirect iterative learning MIT controller is the same as that of the MIT controller. It can be seen that, the response speed of improved indirect iterative learning MIT controller is faster than that of MIT controller. Therefore, compared with MIT controller, the proposed control strategy can improve the control performance by learning.

Fig. 7 shows the experimental results obtained by using the improved indirect iterative learning MIT controller under the condition of given value's mutation. As a contrast, Fig. 11 shows the experimental results of the traditional P-type iterative learning controller. In Fig. 11, the given value of the first and second step responses is 30r/min. And then, from the third time on, the given value suddenly changes to 90r/min. Here, the P-type ILC control law is specified as

$$u_k(i) = u_{k-1}(i) + 0.4e_{k-1}(i) \tag{11}$$

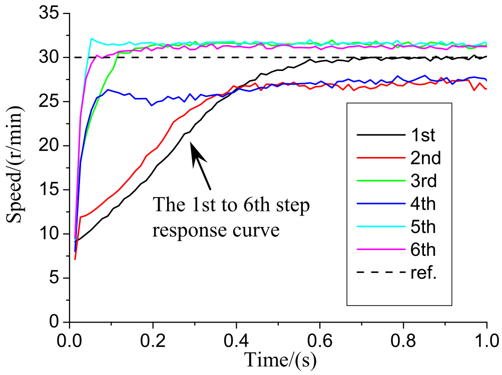

FIGURE 12. Experimental results of traditional ILC (loading 0.5Nm during the second and fourth step response).

TABLE 4. Comparison of steady-state error with different control methods.

Cycle	Steady-state error (r/min)		Steady-state error (r/min)	
	Fig. 7	Fig. 11	Fig. 9(a)	Fig. 12
1	0	0	0	0
2	0	0	0	3.35
3	0	60.18	0	-1.50
4	0	41.21	0	2.85
5	0	23.70	0	-1.48
6	0	12.92	0	-1.23

After changing the given speed to 90r/min in the third response process, the traditional ILC failed to make corresponding changes immediately. In the third response process, the motor's speed under steady-state is still 30r/min, rather than the expected 90r/min. In the following several response processes, the steady-state error still exists, but the value of error is decreasing as shown in Table 4. That is to say, the response of traditional ILC to this disturbance 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 the non-repetitive disturbance.

Fig. 9 shows the experimental results obtained by using the improved indirect iterative learning MIT controller under the condition of intermittent load. As a contrast, Fig.12 shows the experimental results of the traditional P-type ILC. The experimental conditions are the same as those in Fig. 9. It can be seen from Fig. 12 that in the case of traditional ILC, there are steady-state errors in the second and fourth step responses. The values of steady-state error are given in Table 4. Therefore, compared with the traditional ILC controller, the proposed control strategy is more robust.

V. CONCLUSION

Adding the iterative learning method to the MIT model reference adaptive control system is a simple and effective way to enhance the robustness and adaptive ability of the system and improve the control performance. However, using an iterative learning controller to adjust the given value of the MIT controller will cause a significant overshoot in the response process.

Aiming at the overshoot problem caused by the indirect iterative learning control method that modifies the given value, an improved indirect iterative learning MIT control method is presented in this paper. In this control strategy, the output of the iterative learning controller is still the increment of the given value, and this increment is added to the actual given value to get a new given value. However, this new given value no longer acts on the input of the MIT controller, and is only used to adjust the adaptive law of gain K_c.

The experimental results under no-load and different loading modes show the effectiveness of the proposed control method. The control performance of motor's rotating speed is improved by adjusting the changing rate of K_c. By using the learning ability of ILC, the adaptive ability of the original MIT controller is enhanced, the control performance is significantly improved. It also has good robustness to disturbances such as load and temperature. Compared with the traditional ILC, the robustness to deal with non-repetitive disturbances is significantly improved.

The values of control parameters will affect the control performance of the proposed control strategy. A detailed discussion on how to determine the values of control parameters is also provided in this paper.

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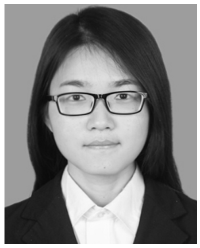

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