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Fuzzy PD-type Iterative Learning Control of A Single Pneumatic Muscle Actuator

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Abstract. Pneumatic muscles actuator (PMA) is widely used in the field of rehabilitation robot for its good flexibility, light weight and high power/mass ratio as compared to traditional actuator. In this paper, a fuzzy logic-based PD-type iterative learning controller (ILC) is proposed to control the PMA to track a predefined trajectory more precisely during repetitive movements. In order to optimize the parameters of the learning law, fuzzy logic control is introduced into ILC to achieve smaller errors and faster convergence. A simulation experiment was first conducted by taking the PMA model fitted by support vector machine (SVM) as controlled target, which showed that the proposed method achieved a better tracking performance than traditional PD-type ILC. A satisfactory control effect was also obtained when fuzzy PD-type ILC was applied to actual PMA control experiment. Result showed that it takes 25 iterations for the maximum error of trajectory converges to a minimum of about 0.2.

Keywords: Iterative learning control, Pneumatic muscle actuator, Fuzzy logic.

1 Introduction

Robot-assisted rehabilitation and therapy has been used to help the elderly and the disabled or movement disorders patients to perform exercise and training [1]. As a compliant actuator, pneumatic muscle actuator (PMA) is widely used in rehabilitation robot for its "force - shrink" characteristics, which is very similar to human muscle. And it has many advantages such as low price, good flexibility, high ratio of output power and weight and so on [2]. However, the strong non-linearity of the PMA, coupled with the non-linear effect of the aerodynamic dynamics and the pressure proportional valve in pneumatic control system, making the PMA difficult to be controlled with high precision. Traditional model-based control method is not suitable for PMA due to its difficulties in modeling. Therefore, it is particularly important to find a model-free and high-precision control algorithm for PMA.

Iterative learning control (ILC) algorithm is a kind of non-model-dependent control method which is suitable for the object with repetitive motion characteristics. It was proposed by Arimoto et al in 1984 and has been applied to various fields of control theory and engineering recently. It focuses on the problems where the interaction between different durations is normally zero but the repetition of tracking the same trajectory creates a possibility of improving tracking performance [3]. When ILC was first proposed, only differential item of the error was used to correct the last input, i.e. D-type ILC [4]. After that, some other scholars take proportional and integral items into account using PID control for reference, and propose ILC methods of PI-type, PD-type and PID-type. With the development of intelligent control method in recent years, fuzzy control [5], neural network [6], adaptive control [7] and other methods have been introduced into ILC.

The application of ILC algorithm to PMA control has several prominent advantages. Meng et al. proposed a robust iterative feedback tuning (IFT) technique for repetitive training control of a PMAs driven compliant parallel ankle rehabilitation robot, which achieves a better and better tracking performance during the robot repetitive control [8]. Schindele et al. studied a lot on ILC for PMA. First, they studied a fast linear axis driven by PMA [9-10] and proposed a model free PID-type ILC and a model-based norm-optimal ILC for PMA control. Both methods have achieved good tracking results. Then, they designed a 2-DOF PMA-driven parallel robot and proposed a P-type ILC with leading phase compensation to iteratively compensate the uncertainties of remaining model, which makes the desired trajectories for the end-effector position to be tracked with high accuracy [11]. Balasubramanian et al. designed a 4-DOF upper limb repetitive therapy wearable robot named “RUPERT” driven by PMA, using for the shoulder, elbow and wrist rehabilitation training [12]. On the basis of RUPERT, the adaptive control strategy was designed. Using the closed-loop control method, the PID feedback controller and the ILC were combined, and fuzzy controller was introduced, leading to strong robustness of RUPERT [13-14].

In this paper, a fuzzy logic-based PD-type ILC method is proposed to control a PMA to track the desired trajectories precisely after several iterations. Support vector machine (SVM) is used to fit the relationship between shrinkage and air pressure of PMA. Comparative experiments between general PD-type ILC algorithm and fuzzy PD-type ILC algorithm are carried out. Results show the latter is proved to be better than the former in controlling the fitted model above. A good control effect is achieved when fuzzy PD-type ILC applied in the actual PMA control experiment.

2 Fuzzy logic-based ILC

2.1 Iterative Learning Control

A non-linear system is described as follows:

$$\begin{cases} \dot{x}(t) = f(x(t), u(t), t) \\ y(t) = g(x(t), u(t), t) \end{cases} \tag{1}$$

where $u(t) \in R^{n_u}$, $x(t) \in R^{n_x}$, $y(t) \in R^{n_y}$ are the control input, the state and the output of the system respectively, and $f(\cdot)$ and $g(\cdot)$ are the state functions and output functions of the system, whose structure and parameters are unknown. If $k = 1,2,3 \cdots$

and $t \in [0, T]$ represents the number of iterations and the sampling time points respectively, ILC can be described as: in the finite time interval $t \in [0, T]$, the expected response $y_d(t)$ and the corresponding expected initial state $x_d(0)$ of the controlled object are known, seeking for a control quantity $u_k(t)$ that makes $y_k(t)$ to be improved when compared to $y_{k-1}(t)$. If $k \to \infty$, $y_k(t) \to y_d(t)$, i.e.:

$$\lim_{k\to\infty} y_k(t) = y_d(t) \tag{2}$$

ILC method updates the input for the next iteration by the current iteration input $u_k(t)$ and the error $e_k(t)$. This method is reflected by the iterative learning law. The general form of learning law is PID-type:

$$u_{k+1}(t) = u_k(t) + Le_k(t) + \Gamma \dot{e}_k(t) + \Psi \int_0^t e_k(\tau) d\tau \tag{3}$$

where L, Γ, Ψ are the gain matrix. Different choices for Γ and Ψ will lead to P-type, PD-type or PI-type learning law. The algorithm flowchart is shown in Fig. 1.

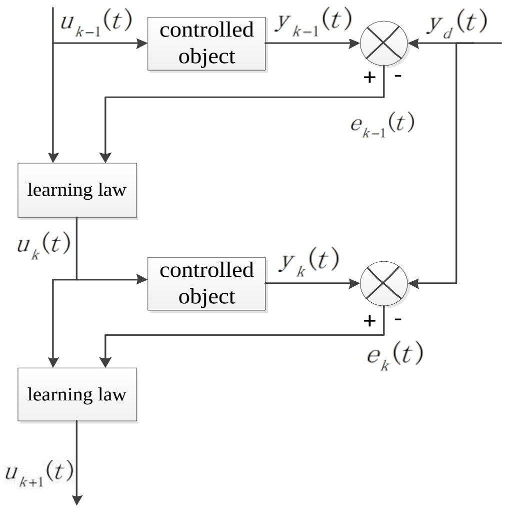


Fig. 1. ILC algorithm flow

2.2 Fuzzy logic-based Iterative Learning Control

Fuzzy logic control has been proved effective for complex, non-linear systems which are difficult to define. Moreover, it is used in various industrial applications nowadays because of prominent performance [15]. Fuzzy set theory is the basis of fuzzy logic control. In the theory, accurate quantity is described as fuzzy variables such as big, medium, small, etc. Linguistic variables and defined rules are utilized in fuzzy inference mechanism.

The choice of parameters in learning law has an important effect on the convergence of the algorithm. Inappropriate parameters often lead to the rise of controller input and output errors, even the situation in which the system does not converge. The introduction of fuzzy logic to avoid the blindness in selecting the parameters, the fuzzification of the input quantity can reduce the effect caused by special value and improve the convergence speed of the algorithm. A basic fuzzy controller mainly includes the following three procedures:

a). Fuzzification: Convert the precise error e and the error change ratio ec into fuzzy quantity E and EC;

b). Fuzzy reasoning: Define fuzzy rules in the form of "if-then", for example, if E is NB and EC is NM, then U is PB (NB, NM, PB are fuzzy level);

c). Defuzzification: Convert the results of fuzzy reasoning into the precise quantity that can be used for actual control.

In fuzzy logic ILC algorithm, after appropriate membership functions and fuzzy rules determined, output error e and the differential of error ec are set to be the input of the fuzzy controller and the output is the corrected value of gain matrix. In the case of large output deviation, the fuzzy corrected value is used to increase the ILC convergence speed; In the case of small output deviation, the fuzzy compensation is used to ensure the stability of the system, achieving the effect of rapid convergence. Fuzzy logic iterative learning law is described as follows:

$$u_{k+1}(t) = u_k(t) + f(e_k(t), \dot{e}_k(t)) + g(e_k(t), \dot{e}_k(t)) \tag{4}$$

where $f(\cdot)$ is the proportion, integral, and differential item of error in traditional iterative learning law, $g(\cdot)$ is fuzzy controller. Fuzzy ILC algorithm flowchart is shown in Fig. 2.

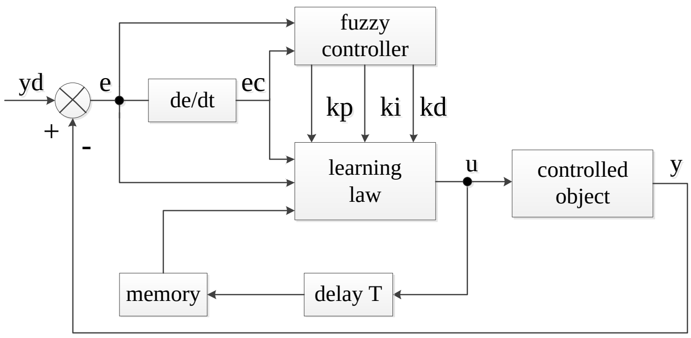


Fig. 2. Fuzzy ILC algorithm flow

3 Experiments

3.1 Simulation

The control object is a PMA. Many researchers have investigated different modeling method of PMAs [16]. Among them, Yao took its internal friction and non-ideal cylinder and other characteristics caused by the hysteresis phenomenon into account, regarding it as the ideal model, hysteresis item, elastic item in parallel, where the hysteresis item consists of the position-dependent hysteresis and the velocity-dependent hysteresis [17]. The model with high precision and simple form reflects the physical properties of PMA. According to this model, the relationship between PMA pressure and shrinkage can be described as follows:

$$P = \frac{F}{a(1-\varepsilon)^2 - b)} + P_{hys} + P_{vis} + P_e \quad (5)$$

where the first item is the ideal model (F is external load, a and b are parameters related to PMA diameter and braided mesh angle, ε is shrinkage), P_{hys} is the position-dependent hysteresis and P_{vis} is the velocity-dependent hysteresis, P_e is the elastic item. Equation (5) describes air pressure as a function of shrinkage. However, in the simulation process, a description of shrinkage by air pressure is more expected, i.e.:

$$\varepsilon = f(P, F) \quad (6)$$

Therefore, support vector machine (SVM) is used in re-fitting the above model in order to obtain the relationship between shrinkage and air pressure when external load is fixed. SVM is a supervised learning method, which presents many unique advantages in solving small sample, nonlinear and high dimensional pattern recognition, and can be applied to other machine learning problems such as function fitting. Fig. 3 shows the result of real PMA and SVM method (external load F=200N), where the red line indicates that the shrinkage increases linearly by 0.01 as the air pressure increases in real PMA and the blue line indicates the shrinkage predicted by SVM under the same pressure. It shows that SVM method has a good effect on fitting the relationship between shrinkage and air pressure of PMA and the predict accuracy is 99.86% when the error is allowed.

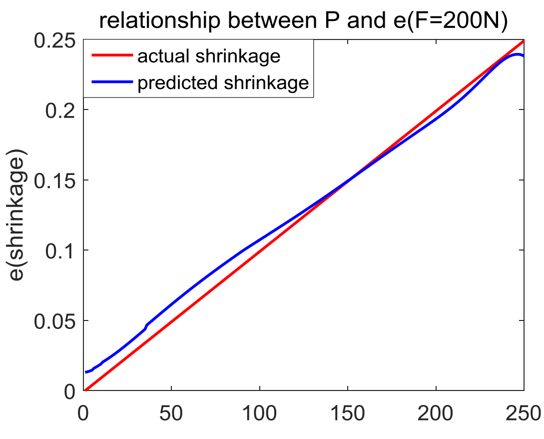


Fig. 3. Actual value and predict value of shrinkage

The experimental method was designed and shown in Fig. 4. A PMA was fixed on the Y axis, whose bottom coincides with the origin and the top was the free movement end. The length was 1m in the case of non-inflated. Inflate the PMA and make the top move in cosine trajectory between 0.76 and 0.96, i.e. make the shrinkage change between 0.04 and 0.24. Therefore, the desired trajectory is $y_d = 0.86 + 0.1 * \cos(\pi t)$ and the actual trajectory is $y = 1 - \varepsilon$, where ε is shrinkage.

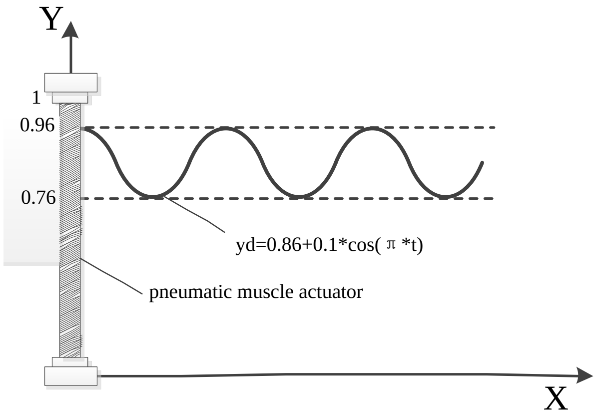


Fig. 4. Experimental method

Fig. 5 shows that the output trajectory of PMA after iterations of 2, 5, 8, 15 times when general PD-type iterative learning law was used. It can be obviously seen that with the number of iterations grows, the actual trajectory is approaching the desired trajectory gradually.

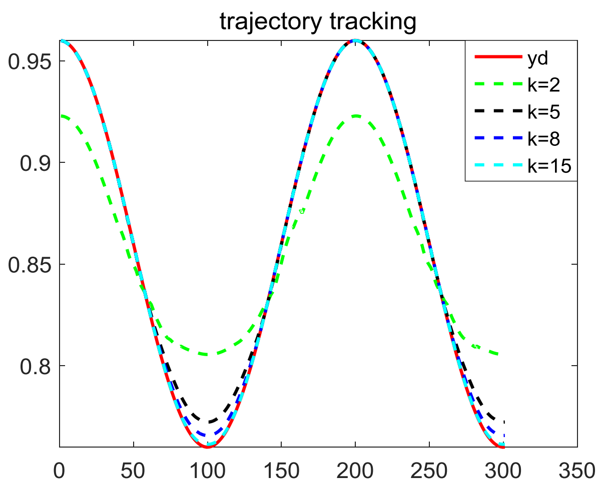
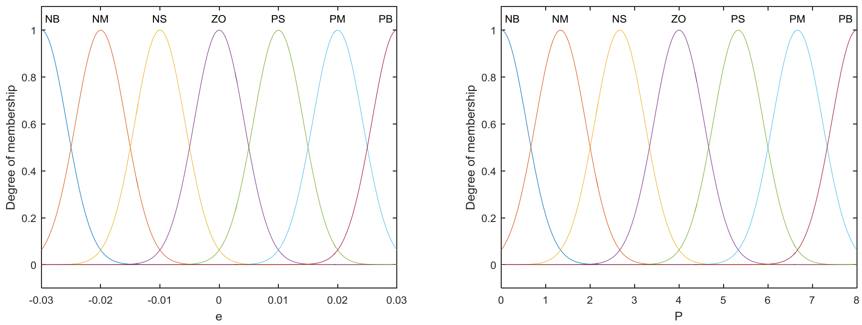


Fig. 5. Trajectories of different iterations

In order to improve the convergence rate of the algorithm and the performance of the algorithm, fuzzy logic control was introduced. Fuzzy PD controller was designed as follow steps: the domain of input error e and differential of error ec was [-0.3, 0.3], outputs were corrected value Δp and Δd, whose domain was [0, 8]. Membership functions (MFs) of each variable was Gaussian-type shown in Fig. 6. Fuzzy levels of each variable were divided into seven grades: NB, NM, NS, ZO, PS, PM, PB. Fuzzy rules are shown in Table 1.



a(MFs of *e* and *ec*) b(MFs of p and *d*)

Fig. 6. Membership function curve of variables

Table 1. Fuzzy rules of Δp and Δd

$\Delta p,\Delta d$		*e*						
		NB	NM	NS	ZO	PS	PM	PB
ec	NB	PB,NS	PM,NS	NB,NS	PB,PB	NS,PS	PM,NB	ZO,NS
	NM	PB,NS	PM,NS	NB,NM	PM,PM	NS,PS	PM,NB	PS,NS
	NS	PM,NS	PS,NM	NM,NM	PM,PM	NS,ZO	PS,NM	PS,NS
	ZO	PM,NS	PS,NM	NM,ZO	PM,PS	NM,ZO	PS,NM	PM,NS
	PS	PS,NS	PS,NM	NS,ZO	PM,ZO	NM,NM	PS,NM	PM,NS
	PM	PS,NS	PS,NB	NS,PS	PM,PS	NB,NM	PM,NS	PB,NS

And iterative learning law is described as follows:

$$u_{k+1}(t) = u_k(t) + (p + \Delta p)e_k(t) + (d + \Delta d)\dot{e}_k(t) \tag{7}$$

Fig. 7 shows the comparison results of general PD-type ILC and fuzzy PD-type ILC. In Fig. 7(a), three trajectory tracking effects at the 5^{th} iteration are compared. It can be seen that compared to the general method, fuzzy PD-type ILC achieves a closer trajectory to the desired one. In Fig. 7(b), the error convergence curve are compared, where the blue line indicates that the maximum error varies with the number of iterations when fuzzy controller was not used, and the red line indicates the result after adding fuzzy controller. It can be seen that the error convergence is obviously accelerated in fuzzy PD-type ILC. The validity and superiority of the algorithm are proved.

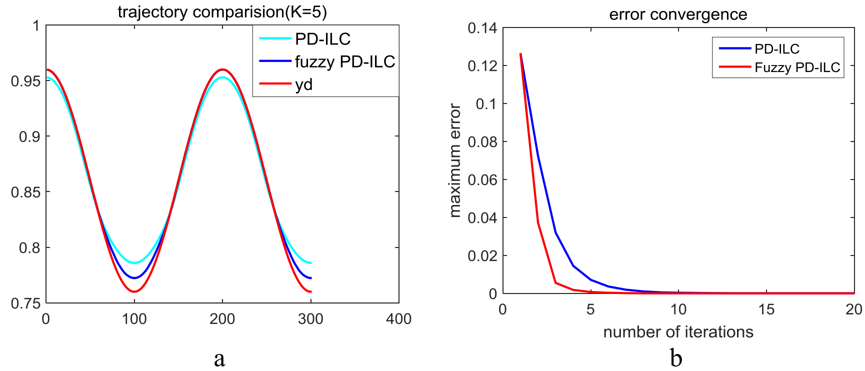


Fig. 7. Results Comparison

3.2 PMA Control Experiment

The proposed algorithm was applied to a single PMA control in actual experiment. The experimental setup is shown in Fig. 8. A PMA is suspended on a stable stent, the control quantity send by the control program is converted to voltage by NIroboRIO to the proportional valve which can be used to control the air intake of the PMA. The displacement is measured by the positional transducer fixed at the bottom of the PMA and send to the control program via NI roboRIO.

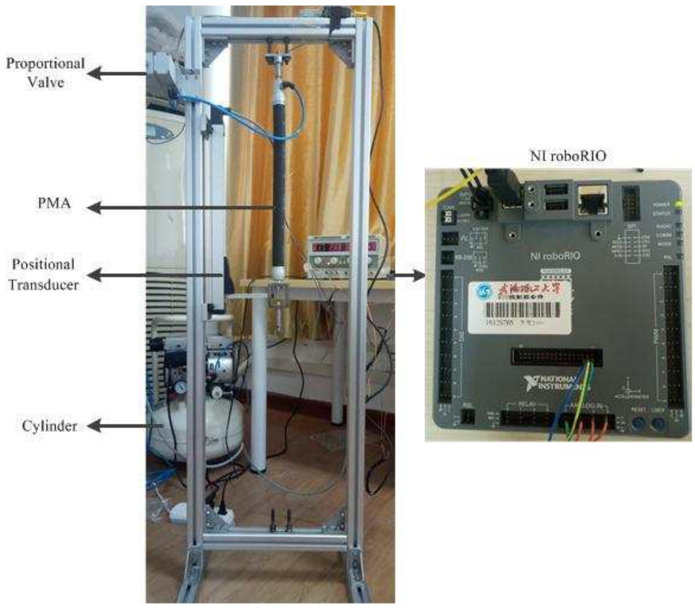


Fig. 8. Experiment Setup

The control program was built by LibVIEW, where the desired trajectory is $y_d = 0.85 * \sin(0.02 * \pi * t) + 2$ and the number of iterations was 40. Experimental trajectories of different iteration are shown in Fig. 9, where the red line indicates the desired trajectory and the blue line indicates the experimental trajectory. It can be seen that the experimental trajectory is getting closer to the desired trajectory with the number of iterations increasing. Fig. 10 shows the comparison of PD-ILC and fuzzy PD-ILC in trajectory tracking and error convergence. It is easily observed in Fig. 10(a) that the actual trajectory is closer to the desired trajectory when fuzzy PD-ILC is applied in the same iteration (K=25). Error convergence rate is shown in Fig. 10(b), fuzzy PD-ILC presents a faster convergence rate and a smaller error. The experiment shows that the application of the proposed algorithm has a good effect in PMA control.

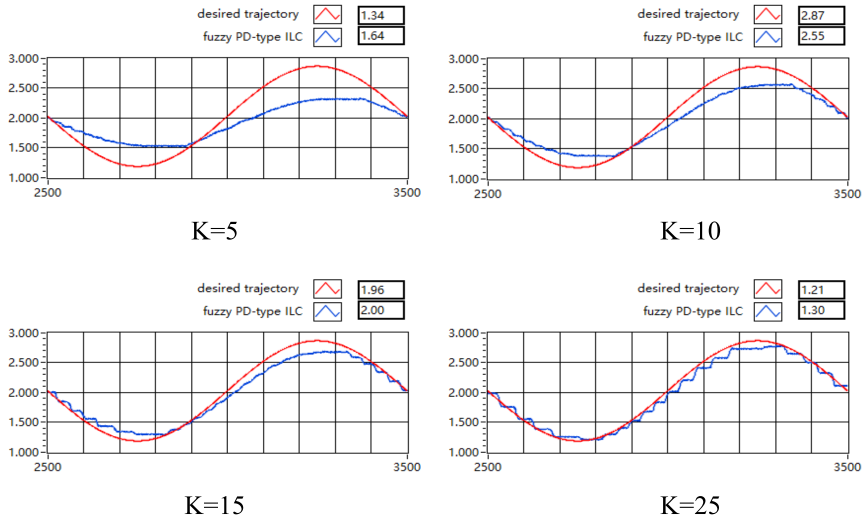


Fig. 9. Experimental trajectory of different iteration

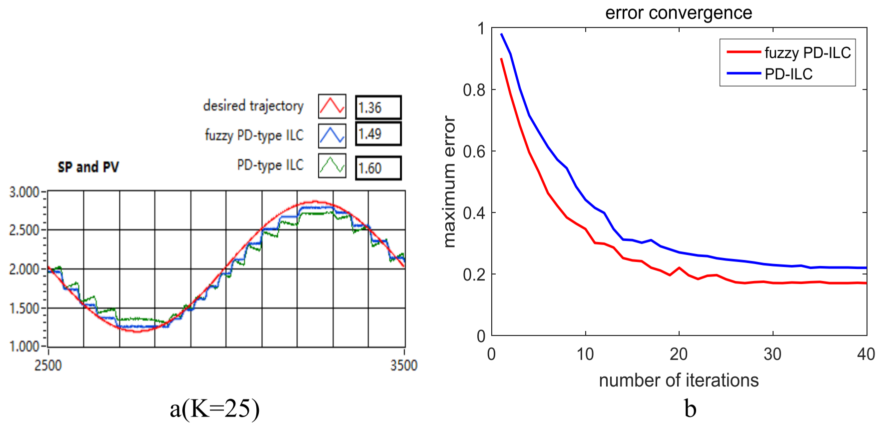


Fig. 10. Comparisons of PD-ILC and fuzzy PD-ILC

The results of the simulation and the actual control experiment indicate that fuzzy PD-type ILC is an effective method for trajectory tracking in PMA repetitive movements. The fitting of PMA model by SVM makes simulation availabel so that the theoretical basis of the proposed method can be obtained. The introduction of fuzzy logic contributes a better tracking effect for the desired trajectory and a higher convergence rate. In the future work, the method to reduce the jitter of PMA during the iterative process will be studied in depth.

4 Conclusion

In this paper, a PD-type ILC algorithm based on fuzzy logic for PMA is proposed. A simulation experiment is carried out on computer. The controlled object is the model fitted by SVM and the result shows that the accuracy is 99.86%. General PD-type ILC performs well in controlling the model and the actual trajectory can almost completely track the desired trajectory after 10 iterations. Fuzzy logic controller is introduced into ILC algorithm in order to improve the convergence rate. Compared with the general PD-type ILC, fuzzy PD-type ILC can significantly reduce the number of iterations required for algorithm convergence. In actual PMA control experiment, the maximum error converges to about 0.2cm after 25 iterations. Therefore, fuzzy ILC is an effective method of controlling the PMA.

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