Predictive Iterative Learning Speed Control With On-Line Identification for Ultrasonic Motor

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This work was supported by the National Natural Science Foundation of China under Grant U1304501.

ABSTRACT

Aiming at the needs of ultrasonic motor motion control, a new two-dimensional (2D) predictive control objective function is proposed. Different from the existing methods, the objective function consists of three terms, including the product of the control quantity and the error of the previous control process. Based on the objective function, the predictive iterative learning control (ILC) law is derived by using the design method of generalized predictive control (GPC) without specifying ILC law form in advance. An on-line identification method for model parameters is given to realize effective identification under a small amount of data circumstances, and therefore, the parameters of controller are adjusted adaptively according to the identification results. The proposed control method is validated both in simulation and experiment. The experimental results show that the proposed predictive iterative learning control strategy can obtain better control effect than GPC, and has more obvious characteristics of iterative learning control. It can maintain the expected performance under the condition of intermittent loading and replacing the motor. It presents strong robustness.

INDEX TERMS

Ultrasonic motor, iterative learning control, generalized predictive control, on-line identification.

I. INTRODUCTION

As a new type of actuator, ultrasonic motor has obvious nonlinear characteristics, and it is not easy to obtain good control performance [1], [2]. In the repeated operation process, based on previous information, iterative learning control (ILC) adopts the iterative method to make the change process of the control quantity gradually approach the expected change process [3]–[5]. ILC has been applied in many different control fields [1], [6]–[9]. The conventional iterative learning control strategy was adopted to control the piezoelectric actuators in [1], results showed that it is superior to pure proportional-integral (PI) controller. A combination of model predictive control and iterative learning control was proposed in [9] to not only speed up the response time of the system but also effectively reduce the speed ripples. In order to solve different application problems, ILC is combined with other methods, and some new control methods are proposed. In [10], a high-order optimal terminal iterative learning control (OTILC) is proposed via a data-driven approach. The controller design does not use any explicit model information of the controlled plant except for the measured input/output (I/O) data. The learning gain is iteratively updated by using the I/O data, which enhances the flexibility of the proposed controller for modifications and expansions. A two-step iterative learning algorithm is proposed in [11] by introducing a combination of ILC and optimal path tracking for robotic manipulators within the framework of a two-step algorithm, which compensates for such model-plant mismatch and finds the time-optimal motion, improving tracking performance and ensuring feasibility. In [12], a model-free trajectory tracking of multiple-input multiple-output (MIMO) systems is proposed by the combination of ILC and primitives. It guarantees that the optimal performance with respect to a new trajectory to be tracked is theoretically predicted, without executing the trajectory and without learning by repetition. The new model-free primitive-based ILC approach is capable of planning, reasoning, and learning.

In [13]–[15], the ILC strategy is applied to the speed control of ultrasonic motor, which shows that the ILC strategy is suitable for ultrasonic motor control. Traditional ILC is a control strategy that combines closed-loop learning control along the cycle index with a time-wise open-loop feed-forward control. In order to simultaneously guarantee the learning
convergence along the cycle index and the control stability along the time index, it can be consider that combining ILC with the feedback control method along the time index.

Generalized predictive control (GPC) proposed by Clarke et al. [16], [17] is a kind of model predictive control. Different from general predictive control methods, GPC is a predictive control technology with adaptive function, which emphasizes more on-line adaptation to changes in the characteristics of the controlled object. For systems with variable parameter, variable delay, and variable order, as long as the input and output data are sufficient and proper system identification can be performed, stable control results can be obtained by using GPC. The output prediction of GPC includes both zero-input prediction and zero-state prediction. It optimizes the effect of future multi-step control according to a certain objective function, and only implements the control of the nearest step. From the whole control process of the system, the control quantity given in each control period may not be global optimum, but it must be the best control quantity that can be given in this period. These characteristics make GPC not only suitable for stable open-loop system, but also for pure time delay system, non-minimum phase system and open-loop unstable system. GPC has been widely used in the field of industrial control. Therefore, GPC is selected to integrate with ILC in order to simultaneously obtain good control performance in time domain and iterative domain.

GPC is a feedback control strategy along the time index. In some literatures, the combination of GPC and ILC has been studied in order to obtain better control performance [18], [19]. The application shows that the combination of predictive control theory and ILC can improve the control performance of ILC system. In [19], based on a two-dimensional (2D) cost function defined over a single-cycle or multi-cycle prediction horizon, two ILC schemes, referred respectively as single-cycle and multi-cycle generalized 2D predictive ILC schemes, are proposed, which have better control performance along the time index and the cycle index. However, in [19], a special form of ILC law is specified before deducing the ILC law containing prediction, so as to adapt to the derivation process of predictive control theory. In order to meet the specific formal needs, consideration for the control performance is less, and the optimal control performance that can be obtained is artificially limited at the initial point of control strategy design by setting the learning control law in this way.

GPC is designed according to the motor model. Whether its actual control effect meets expectations is directly related to the accuracy of the motor model used to design the controller. The ultrasonic motor presents time-varying characteristics, and the parameter values of the motor model are constantly changing during operation. If the motor model parameters are identified on-line, the changed model parameters are obtained in real time. The controller parameters are designed on-line according to the current motor model parameter values, which can improve the matching degree between the control parameters and the current motor operating state. It is possible to make the actual control performance of the motor more in line with expectation. In addition, the model structure of different models of ultrasonic motors is similar, but the model parameters are different. There are also differences in the model parameters of the same type of ultrasonic motor. There are also differences in the model parameters of the same type of ultrasonic motor. The controller including on-line identification can reduce the dependence of the control strategy on the model and make it adapt to different ultrasonic motors automatically.

Based on 2D system theory and aiming at the needs of ultrasonic motor motion control, a new 2D optimization objective function for predictive control is proposed in this paper. Based on the traditional GPC objective function, a product term of the control quantity and the error of the previous control process is added to the objective function. It attempts to integrate the generalized predictive control methods such as multi-step predictive and rolling optimization into the ILC law. Different from the existing methods, the predictive ILC law is derived by using GPC design method without specifying ILC law form in advance. The controller parameters are designed on-line through the on-line identification of the motor model and used for ultrasonic motor speed control. The proposed control method is validated both in simulation and experiment. It can obtain better control effect than GPC, and has more obvious characteristics of ILC. The control performance of the controller with on-line identification is good. It is robust to non-repetitive disturbance of load mutation. In the case of a new motor with different characteristics from the original motor, the control response can still maintain the desired performance.

II. PREDICTIVE ITERATIVE LEARNING CONTROL SCHEME

The controlled auto-regressive integrated moving average (CARIMA) process model is used by GPC for controller design [16], [17]. The CARIMA model has the characteristics of describing non-stationary disturbances, making the steady-state error of the system output zero, and eliminating the deviation caused by step disturbances. Consider the repeated processes described by the following CARIMA model.

\[
A(z^{-1})y_k(i) = B(z^{-1})u_k(i-1) + C(z^{-1})\xi_k(i)/\left(1-z^{-1}\right)
\]

\[\quad i = 0, 1, \ldots, T; k = 1, 2, \ldots \tag{1}\]

That is

\[
\tilde{A}(z^{-1})y_k(i) = B(z^{-1})\Delta_t u_k(i-1) + C(z^{-1})\xi_k(i) \quad \tag{2}\]

where, \(u_k(i), y_k(i)\) and \(\xi_k(i)\) are, respectively, the input, output and white noise of the process at time \(i\) in the \(k\)th cycle, \(T\) is the time duration of each cycle, \(z^{-1}\) indicates the time-wise unit backward-shift operator, \(\Delta_t = 1 - z^{-1}\) represents the time-wise backward difference operator, i.e. \(\Delta_t f_k(i) = f_k(i) - f_k(i-1), A(z^{-1})\) and \(B(z^{-1})\) are the operator polynomial.
A(z^{-1}) = 1 + a_1 z^{-1} + a_2 z^{-2} + \cdots + a_n z^{-n_a}
B(z^{-1}) = b_0 + b_1 z^{-1} + b_2 z^{-2} + \cdots + b_m z^{-m_b}
C(z^{-1}) = 1 + c_1 z^{-1} + c_2 z^{-2} + \cdots + c_n z^{-n_c}
\bar{A}(z^{-1}) = (1 - z^{-1})A(z^{-1}) = 1 + a_1 z^{-1} + \cdots + a_{n_a} + 1 z^{-(n_a+1)}$

To design the control law $u_k(i)$ with GPC method, the objective function form should be specified according to the control objective firstly. Consider the following objective function form

$$
J(i, k, n_1, n_2) = \sum_{j=1}^{n_1} \left[ \eta(j)y_r(i + j) - y_k(i + j)i^2 \right] 
+ \sum_{l=0}^{n_2-1} \left[ \beta(l)\Delta_r(u_k(i + l))^2 
+ \phi(l)u_k(i + l)e_k(i + 1 + l) \right]$$

(3)

where integers $n_1, n_2(n_2 \leq n_1)$ are referred as the predictive length and control length respectively, when $n_2$ is less than $n_1$, there is $u_k(i + n_2 - 1) = u_k(i + n_2) = \cdots = u_k(i + n_1)$, that is, within the interval $[n_2, n_1]$, the control quantity remains the same. $y_k(i + j)i$ represents the estimated output at time $i + j$ in the $k$th cycle based on the measurements at time $i$ of the $k$th cycle and previous input and output data, $y_r(i)$, $i = 0, 1, \ldots, T$, is the desired value, $e_k(i)$ is the error value at time $i$ in the $k$th cycle, $\eta(j) \geq 0$, $\beta(l) \geq 0$ and $\phi(l)$ are the weighting factors indicating the importance of each terms, and reflecting control performance requirements.

The design of objective function directly affects the form and control effect of control law. In order to integrate GPC and ILC organically to improve the robustness of ILC strategy and achieve the goal that the control performance of the resulting composite control strategy can be better than GPC, such as faster response speed, the objective function is designed as (3). The objective function of traditional GPC only contains the first two terms on the right side of (3). The error term $y_r(i) - y_k(i)$ is included in the objective function, so as to make the system’s output follow the given value, which reflects the basic requirements of control performance. The inclusion of $\Delta_r(u_k(i))$ in the objective function, not only makes the control performance along the time index adjustable, but also, if necessary, suppresses the amount of change of $u_k(i)$ along time index to prevent the divergent control problem along the time index for system with unstable inverse dynamic. The third term $u_k(i)e_k(i + 1)$ is added to the objective function, so that the current control quantity is related to the magnitude of the previous error and the ILC and predictive control are organically combined. In addition, the third term of (3) adopts this product form, which is also to obtain faster response speed than GPC. In ILC, the control quantity of the current control process is directly related to the error value of the previous control process. The larger the previous error value is, the larger the adjustment quantity of the current control quantity will be, in order to reduce the error as much as possible and speed up the convergence of iterative learning. Therefore, considering this essential characteristic of ILC, the coefficient before the third term of the objective function shown in (3) can be taken as negative value to obtain a faster convergence rate. However, it should also be noted that although the third item of (3) can make the control performance better than GPC, its form is different from the traditional quadratic function. Many forms of quadratic objective function have been tried to design the controller, and the control performance of the obtained control law is not better than that of GPC. Therefore, the objective function shown in (3) is designed to achieve this goal. In order to make (3) a positive value and thus ensure the existence of the minimum value that meets the control expectation, it is necessary to correctly select the weighting coefficient value in the objective function. In the ultrasonic motor control system described in this paper, $u_k(i)$ is directly related to $e_{k-1}(i + 1)$, and both are of the same order of magnitude, which means that their values are close to each other. The analysis of the experimental data shows that as long as the value of the coefficient $\beta(i)$ in (3) is greater than the absolute value of $\phi(i)$, the sum of the second and third terms in (3) can be positive, so as to ensure the existence of the minimum.

In (3), $n_1$ and $n_2$ are predictive length and control length respectively, $n_1$ represents that the estimated output can reach the expected output within the time length of $n_1$ steps after the current time $i$. $n_2$ represents the number of steps that control quantity need to be changed to make the output follow the reference output (i.e. the given value) in the prediction process of next $n_1$ step output. Obviously, considering the existence of the inertia of system and the order of the model, it should be satisfied that $n_2 \leq n_1$. If $n_1$ is too small, considering the existence of the inertia of system, model mismatch and interference factors, it is unrealistic to make the output quantity reach the expected output in the future $n_1$ step by selecting the optimal control quantity at the current time. If $n_1$ is too large, it will affect the rapidity of system response. Generally, the time length corresponding to $n_1$ should include most of the dynamic processes of the system, and $n_1$ should not be less than the order of the $B(z^{-1})$ item in the object model. The tradeoff between the stability, robustness and flexibility of system control should be taken into account in determining the value of $n_2$.

The optimal prediction model is derived by the same method as GPC, so that the output predicted value of the future moment can be given to calculate the objective function. Introduce the following Diophantine equations

$$
C(z^{-1}) = \bar{A}(z^{-1})E_j(z^{-1}) + z^{-j}G_j(z^{-1})
F_j(z^{-1}) = B(z^{-1})E_j(z^{-1}) = L_j(z^{-1})C(z^{-1}) + z^{-j}H_j(z^{-1})
$$

where

$$
E_j(z^{-1}) = 1 + e_{j,1} z^{-1} + \cdots + e_{j,j-1} z^{-(j-1)}, \quad j = 1, 2, \ldots, n_1
G_j(z^{-1}) = g_{j,0} + g_{j,1} z^{-1} + \cdots + g_{j,j-1} z^{-n_a}
$$
where

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\[ \beta L_i = \frac{(|2| - 1)}{(n + t - 1)} \]

\[ H_i(z^{-1}) = h_{0i} + h_{1i} z^{-1} + \ldots + h_{niu} z^{-\text{nh}}. \]

\[ n_h = \max\{n_b - 1, n_c - 1\} \]

The prediction model can be formulated as

\[ y_k(i+1|\eta_k) = L \Delta_t(u_k(i+1|\eta_k)) + H \Delta_t(u_k(i_0|\eta_k)) + G Y_k(i_0|\eta_k) + E K_k(i+1|\eta_k) \]

(6)

where \( f_k(i_0) = [f_k(1), f_k(1) \ldots f_k(i_2)]^T, f \in \{y, u, \xi\}. \)

The best prediction of the outputs over the prediction horizon can be determined by

\[ y_k(i+1|\eta_k) = L \Delta_t(u_k(i+1|\eta_k)) + H \Delta_t(u_k(i_0|\eta_k)) + G Y_k(i_0|\eta_k) \]

(7)

According to the objective function and predictive model, the optimal control law is derived. The objective function (3) can be expressed in the following matrix form.

\[ J(i, k, n_1, n_2) = \sum_{i=0}^{n_1} \left[ (L^T Q L + S) \Delta^T L (u_k(i+1|\eta_k)) + P \Delta^T Q F_k(i) - 0.5 P \Delta^T Q F_k(i) \right] \]

(12)

That is

\[ u_k(i+1|\eta_k) = u_k(i+1|\eta_k) - (L^T Q L + S)^{-1} \left[ L^T Q F_k(i) \right] - 0.5 P \Delta^T Q F_k(i) \]

(13)

The above equation is the calculation formula of control quantity for the future \( n_2 \) moments. Let \( K_1 \) and \( K_2 \) be the first rows of matrices \((L^T Q L + S + T)^{-1} L^T Q \) and \( (L^T Q L + S)^{-1} P \), respectively. Then, the calculation formula of the control quantity at the current moment, that is, the predictive ILC law, can be written as

\[ u_k(i) = u_k(i - 1) - K_1 F_k(i) - 0.5 K_2 e_k(i) \]

(14)

From an ILC system viewpoint, control law (14) can be decomposed as

\[ \Delta_t u_k(i) = u_{ILC, k}(i) + u_{GPC, k}(i) \]

(15)

where \( u_{ILC, k}(i) \) and \( u_{GPC, k}(i) \) are respectively determined by

\[ u_{ILC, k}(i) = -0.5 K_2 e_k(i) \]

(16)

\[ u_{GPC, k}(i) = -K_1 F_k(i) \]

(17)

Equations (15) to (17) indicate that the proposed controller can be considered as a parallel connection of ILC controller and GPC controller. Obviously, if \( P \) is set to zero, that is to say, delete the third item of (3), the value of \( K_2 \) is zero and the resulted control law will be the same as traditional GPC law. It is clear that \( u_{ILC, k}(i) \) refines the control input by using the errors of the last cycle to improve the control performance from cycle to cycle. In this parallel controller, the item \( u_{GPC, k}(i) \) ensures the control performance over the time of each cycle. In order to ensure good 2D control performance, the proposed method designs and optimizes control in 2D system framework, so that the control variable changes reasonably along the cycle index and the time index.

Under the condition that \( P \) is set to zero, the objective function (3) becomes the following form.

\[ J(i, k, n_1, n_2) = \sum_{j=1}^{n_1} \left[ \eta(j) \delta(i) - y_k^1(i + j) \right]^2 + \sum_{l=0}^{n_2-1} \left[ \beta(l) \Delta^T u_k(i + l) \right]^2 \]

(18)

where the weighting factors are specified the same as objective function (3). This is the objective function used by traditional GPC. The response of the system over horizon \([i + 1, i + n_1]\) is the same as (6). Therefore, the optimal control that
minimizes objective function (18) is given by
\[
\Delta_t(u_k(t_{i+n-1})) = (L^TQL + S)^{-1}L^TQ\left(y_r(t_{i+n}) - y(t_{i+n})\right) - H\Delta_t(u_k(t_{i+n-1})) - Gy_k(t_{i+n-1}) - E\xi_t(t_{i+n})
\]  

(19)

Theoretically, this is the optimal control within the GPC framework. It is noted from control law (19), however, that GPC depends on the unknown disturbances over the future time. Therefore, it is generally infeasible in actual applications.

For an ILC system that is robust stable and convergent along the cycle, the control performance achieved after a number of learning cycles can be analyzed. Under the condition of \( k \to \infty \), the following equation can be derived.
\[
\Delta_t(u_{\infty}(t_{i+n-1})) = (L^TQL + S)^{-1}\left[-L^TQ\left(H\Delta_t(u_{\infty}(t_{i+n-1})) + Gy_{\infty}(t_{i+n-1}) + E\xi_{\infty}(t_{i+n}) - y_r(t_{i+n})\right) - 0.5P\xi_{\infty}(t_{i+n})\right]
\]

If \( P = 0 \), equation (20) then becomes
\[
\Delta_t(u_{\infty}(t_{i+n-1})) = -(L^TQL + S)^{-1}L^TQ\left[H\Delta_t(u_{\infty}(t_{i+n-1})) + Gy_{\infty}(t_{i+n-1}) + E\xi_{\infty}(t_{i+n}) - y_r(t_{i+n})\right]
\]  

(21)

Equations (20) and (21) further indicate the difference between the proposed control method and GPC.

The values of coefficient matrix \( Q, S \) and \( P \) have an important influence on the control performance of the system. With the above analysis and the considerations of the impacts of the penalties in the objective function, some guidelines for the parameter tuning can be proposed. When the value of \( Q \) is large, the speed error decreases rapidly due to the increase of the weight of the speed error term in the objective function, which makes the dynamic response speed faster and the iterative learning convergence speed faster. However, the rapid reduction of error will also lead to a decrease in the smoothness of the response curve and affect the stability of the dynamic process, which may cause overshoot and oscillation. Larger values of \( S \), giving more penalty for the movement of \( u_k(i) \) along the time index, can suppress the change of the control quantity along the time index and result in a better time-wise robust stability. Therefore, it makes the response curve smoother, but the response speed is slower. Whereas, smaller values of \( S \), giving more freedom for the change of \( u_k(i) \) along the time index, will be beneficial for fast tracking of time-wise output. Small value of \( P \) will lead to a faster convergence rate along cycle.

### III. DESIGN OF PREDICTIVE ITERATIVE LEARNING SPEED CONTROLLER FOR ULTRASONIC MOTOR

In this section, the proposed predictive ILC control strategy is applied to the speed control of ultrasonic motor, and its effectiveness is verified by simulation and experiment. The linear dynamic part of Hammerstein model of ultrasonic motor system is as follows [20]
\[
y(z^{-1}) = \frac{y(z^{-1})}{x(z^{-1})} = \frac{0.8218 - 0.6928z^{-1}}{1 - 0.9416z^{-1} + 0.0623z^{-2} + 0.0471z^{-3} - 0.0255z^{-4}} * z^{-1}
\]  

(22)

Transform (22) into CARIMA model as shown in (1).
\[
\hat{A}(z^{-1}) = 1 - 1.9416z^{-1} + 1.0039z^{-2} - 0.0152z^{-3} - 0.0726z^{-4} + 0.0255z^{-5}
\]

\[
B(z^{-1}) = 0.8218 - 0.6928z^{-1}
\]  

(23)

According to (23), it can be obtained that \( n_a = 4 \) and \( n_b = 1 \). Set \( n_1 \) to 4 and \( n_2 \) to 1. The following matrix is obtained.
\[
G = \begin{bmatrix}
1.9416 & -1.0039 & 0.0152 & 0.0726 & -0.0255 \\
2.7659 & -1.9340 & 0.1021 & 0.1155 & -0.0495 \\
3.4363 & -2.6746 & 0.1575 & 0.1513 & -0.0705 \\
3.9974 & -3.2922 & 0.2035 & 0.1789 & -0.0876
\end{bmatrix}
\]

\[
L = \begin{bmatrix}
0.8218 \\
0.9028 \\
0.9279 \\
0.9077
\end{bmatrix}, \quad H = \begin{bmatrix}
-0.6928 \\
-1.3451 \\
-1.9162 \\
-2.3807
\end{bmatrix}
\]

In the following, it attempts to select different values of \( Q, S \) and \( P \) for simulation analysis of ultrasonic motor iterative learning speed control to determine appropriate values of \( Q, S \) and \( P \).

**FIGURE 1. Curve of speed step response (Q = diag(1, 1, 1, 1), S = 3, P = -2).**

The diagonal elements of weight matrix \( Q \) are set to the same value to simplify the parameter selection process. Analysis of simulation results shows that when \( P \) takes negative value, there is overshoot in the speed step response curve, and the response curve of adjacent iteration is one at the top and another at the bottom. As the iterative learning progresses, overshoot decreases gradually. It converges to a certain step response curve gradually and then basically remains unchanged, as shown in Fig. 1 and Fig. 2. The comparison shows that there is overshoot in both the second step response curves, but the overshoot in Fig. 2 is small, and the difference
between the iteration results except the first one is small. It is shown that overshoot can be reduced by decreasing the absolute value of $P$, and the iterative convergence speed can be accelerated, so that the iterations are required to reach the approaching step response curve is less. The adjustment time of the step response curve obtained by GPC using the same control parameter values is 0.0524s.

![Graph showing speed step response](image)

**FIGURE 2.** Curve of speed step response ($Q = \text{diag}[1,1,1], S = 3, P = -0.5$).

![Graph showing speed step response](image)

**FIGURE 3.** Comparison of the speed step response curves corresponding to three cases (the step response curves of $P = -0.5$ and $P = -2$ are the sixth result).

![Graph showing speed step response](image)

**FIGURE 4.** Curve of speed step response ($Q = \text{diag}[1,1,1], S = 3, P = -0.5$).

Fig. 3 shows the comparison of the results of GPC and the 6th iteration of $P = -2$ and $P = -0.5$. As can be seen from Fig. 3, the response speed under the condition that $P = -2$ is faster than that of GPC, and the response speed under the condition that $P = -0.5$ is not significantly different from that of GPC, and the adjustment time is the same. It indicates that the smaller the absolute value of $P$ is, the smaller the overshoot is, but the step response curve obtained by learning convergence is close to GPC. However, the larger the absolute value of $P$ is, the more the adjustment time of the step response obtained by learning is smaller than the adjustment time of GPC.

**IV. ON-LINE IDENTIFICATION OF MODEL PARAMETERS**

A layer of friction material is attached between the stator and the rotor of the ultrasonic motor. The stator drives the rotor to rotate by friction. Mainly due to the heating effect caused by friction, the temperature of the body rises during the operation of the motor. Therefore, the ultrasonic motor motion control system usually adopts the short-time working mode, so that the amount of data that can be collected in real time for one run and used for on-line identification is far less than that of ordinary identification applications. The least square method is a commonly used method for parameter identification, which has the characteristics of simple algorithm and fast convergence. In the least squares identification algorithm, initial parameters such as the initial value of the model parameters and the initial value of the error covariance matrix $P_1$ have an important influence on the convergence speed of the identification process and the accuracy of the model parameters obtained by identification. Generally, the initial value of the model parameters can be taken as 0, and the initial value of $P_1$ can be taken as $aI (a = 10^6 \sim 10^{10})$. However, because the amount of data that can be used for on-line identification is small in one operation of the ultrasonic motor, in this case, setting appropriate initial value of the identification algorithm parameters is a necessary prerequisite to obtain better on-line identification results. Therefore, the measured data is used for off-line identification firstly. The appropriate initial value for on-line identification is determined according to the offline identification results. In addition, due to the small amount of data obtained in one operation, in order to make the identification process better track the change process of the parameters of the ultrasonic motor system model, and avoid the old data weakening the update effect of the new data on parameter estimate, the recursive least squares algorithm with forgetting factor is considered to make the identification algorithm better use innovation to obtain parameter estimation close to the current actual value.

![Algorithm expression](image)

The recursive least squares algorithm with forgetting factor can be expressed as

$$\dot{\theta}(k) = \dot{\theta}(k - 1) + K(k) \left[ y(k) - \phi^T(k) \dot{\theta}(k - 1) \right]$$  \hspace{1cm} (24)

$$K(k) = \frac{P_1(k - 1) \phi(k)}{\lambda + \phi^T(k) P_1(k - 1) \phi(k)}$$  \hspace{1cm} (25)

$$P_1(k) = \frac{1}{\lambda} \left[ I - K(k) \phi^T(k) \right] P_1(k - 1)$$  \hspace{1cm} (26)

where, data matrix $\phi^T(k) = [-y(k - 1), -y(k - 2), \cdots, -y(k - n_d), u(k - d), u(k - d - 1), \cdots, u(k - d - n_b)]$, model parameters to be identified is $\theta = [a_1, a_2, \cdots, a_{n_d}, b_1, b_2, \cdots, n_{n_b}]^T$, model order $n_d = 4$ and $n_b = 1$, the forgetting factor $\lambda$ ranges from 0.95 to 0.99. Generally speaking, when the parameter changes quickly, $\lambda$ takes a smaller value, and conversely, when the parameter changes slowly, $\lambda$ takes a larger value.

For a certain identification algorithm, different design of the specific process of on-line identification will significantly affect the identification effect. Inappropriate specific application process may even cause the identification result to deviate from the actual condition of the identified motor. For the recursive least squares algorithm with forgetting factor, the design mainly includes two aspects. One is the selection
of recursive initial value and forgetting factor value, and the other is the determination of the starting point of on-line identification. The following first solves the first problem by off-line identification based on experimental data. Then, in the experimental evaluation process, how to use the iterative learning to improve the identification method is considered, and the identification starting point is determined.

**A. SELECTION OF INITIAL VALUE OF IDENTIFICATION ALGORITHM**

Firstly, the input and output data of the motor system for off-line identification are measured. During the experiment, in the case of five different temperatures, the speed step response data with the given speed of 30r/min and 90r/min are measured respectively to cover different operating states of the motor. For the ten groups of data, the dynamic data of one group is used for off-line identification, and the other is used to verify the identified model parameter values. The smaller the speed mean square error value, the closer the identified model parameters are to the current motor state. The parameter change in the recursive identification process is relatively small, which is closer to the actual condition of the motor. By comparing the speed mean square error of each group of data and the change process of model parameter values in the recursive process, $\lambda$ is determined to be 0.98, and the initial value of the recursive identification is $\theta$ and $P_1$, shown at the bottom of this page, where, $P_1$ is a symmetric matrix, and '*' represents symmetric data. In the case of using the above initial value of the $P_1$ matrix, the change of the model parameter values during the recursive process is relatively small, and the change process is relatively smooth. It indicates that the selected initial value of the identification algorithm is appropriate. The initial model parameter values obtained by identification are different from the original model parameter values. This group of initial model parameter values are identified from the latest experimental data, and the sum of the mean square errors of each group is smaller, which is more consistent with the current state of the motor. The validity of recursive identification is further ensured.

**B. DETERMINATION OF IDENTIFICATION STARTING POINT AND INITIAL VALUE OF MODEL PARAMETERS FOR ITERATION IDENTIFICATION**

The selected initial value of the identification algorithm is used for on-line identification, and the controller parameters are modified on-line according to the model parameter values obtained from the identification. Because the order of the model to be identified is four, if the identification starts from the first data point, the data in the data sequence used for identification is incomplete, which will lead to inaccurate identification of the first few data points. Therefore, on-line identification is started from the fifth sampling time. In addition, considering that the identification results of the initial data points are inaccurate and the obtained model parameter values change rapidly, it is attempted to start the on-line identification from the fifth sampling time and delay the time to start modifying the controller parameters. Attempts are made to modify the controller parameters from the fifth, sixth and seventh moments, respectively. The experimental results show that the result is better in the case of starting identification from the fifth moment and modifying the controller parameters from the seventh moment.

The initial value of $\theta$ is based on the experimental data of the motor and obtained by off-line identification in advance, and there must be a gap with the current state of the experimental motor. In the iterative learning control process, the six control processes are performed successively one by one. It is reasonable to think that the model parameter values identified in the last iterative control process are closer to the current motor state and can be used as the initial value of the current on-line identification. Using the $\theta$ value obtained from the previous identification as the initial value of the current identification, or more generally, using the past identification experience to improve the current identification process, can have different specific implementation forms. It is considered that the initial value of $\theta$ in each identification process is determined by ‘end-to-end’ in the six iterative learning control processes, that is, the final value of $\theta$ obtained by on-line identification during the last control process is used as the $\theta$ initial value of the current iteration identification.

In the on-line identification process of a step response, the dynamic response data reflects the characteristics of the identified system and can be used for on-line identification. However, when the response reaches steady state, the steady state data theoretically only contains the steady state gain information of the system, and due to the small amount of change in the steady state data, it is relatively more affected by interference factors such as noise. If the on-line identification is continued after the response reaches steady state, the dynamic information of the system identified by the

$$\theta = \begin{bmatrix} -0.6832522, 0.05965030, 0.004215877, 0.05665063, 0.3668307, 0.01439048 \end{bmatrix}^T$$

$$P_1 = \begin{bmatrix} 0.09781787 & -0.1004484 & 0.001254734 & 0.01528300 & 0.007085728 & 0.005516075 \\ 0.2046560 & -0.1023298 & -0.001158093 & 0.007336040 & -0.006694728 \\ 0.2017053 & -0.09913723 & -0.004626924 & 0.005976956 \\ 0.08399862 & -0.003317324 & 0.002314992 \\ 0.02352587 & -0.01771881 \\ 0.02414174 \end{bmatrix}$$
dynamic identification will be drowned in the continuously increasing steady state data. Combined with the accumulation of noise effects, the identification result will gradually deviate from the actual characteristics of the system. Therefore, only the dynamic data in the control process is identified, and the obtained $\theta_f$ final value is used as the parameter initial value for the next iteration identification.

The characteristics of the ultrasonic motor are different at different speeds, and the corresponding parameters of the model are different. The previous research process of off-line identification also shows it. In the process of step response, the speed of the motor changes continuously from low to high, and the speed and the model parameters are different at different time. The speed of the end point of the previous dynamic identification process and the corresponding model parameters are different from the current state of the start point of the identification process. Therefore, the model parameter value of the previous identification at the time that the speed is close to the speed value of the current iteration identification starting point is selected as the initial value of the current identification, so that the initial value of the identification is closer to the current motor state. It is possible to improve the identification effect. In the continuous iterative learning control process, each step response is different from the previous one, and the time point of the last iteration, which is close to speed of the starting point of current iterative identification can be determined by the on-line search at a certain point in the last iteration that is close to the speed of the starting point of current iterative identification.

For specific implementation, due to the existence of sampling time, the speed value at a certain moment during the last iteration step response may not be exactly the same as the speed value at the starting point of current iteration identification. It is more common that the speed value at two moments is above and below the speed value at the starting point of current iteration identification. Therefore, for the search results of the previous iteration speed value, there are two possible situations: one is to take the moment when the speed is slightly larger than the current speed value, and the other is to take the moment when the speed is slightly smaller than the current speed value. The experimental results show that the smoothness of the response curve obtained by the first method is relatively good. Taking into account that the speed is continuously increasing during the dynamic process of the step response, the motor running state that the speed is slightly larger than the current speed value is the operating state that will be reached in this iteration. The first method has a certain predictive effect.

Therefore, according to the speed value at the starting point of the current iteration identification, the moment that the speed is greater than or equal to that value in the last control process is searched, and the identified $\theta_f$ value corresponding to that time is taken as the initial value of the identification algorithm of this iteration.

V. EXPERIMENTAL STUDY ON PREDICTIVE ITERATIVE LEARNING SPEED CONTROL OF ULTRASONIC MOTOR

In the previous sections, based on the proposed new objective function, a new predictive iterative learning control method is derived by using GPC method. Subsequently, a method for effective on-line identification using a small amount of data is given, so that the parameters of controller can be adaptively adjusted according to the identified parameters of the model. In this section, DSP programming is used to implement these control strategies and identification algorithms. In order to verify the correctness and effectiveness of the aforementioned theoretical results, experiments are conducted. The ultrasonic motor for the experiment is the USR60 two-phase traveling wave ultrasonic motor of Shinsei Company of Japan.

![Figure 4](image-url). Curve of speed step response (measured data, $Q = \text{diag}(1, 1, 1), S = 3, P = -2$).

![Figure 5](image-url). Curve of speed step response (measured data, $Q = \text{diag}(1, 1, 1), S = 3, P = -0.5$).

A. NO-LOAD EXPERIMENTS

The same control parameter values as the above simulation are used for experiment, and the obtained speed step response is shown in Fig. 4 and Fig. 5. The corresponding performance index data of ILC is shown in Table 1. It can be seen that, with the progress of iteration, the overshoot of the speed step response gradually decreases to 0. The adjustment time remains unchanged after the fifth cycle under the condition that $P$ takes -2, but when $P$ takes -0.5, the adjustment time
TABLE 1. The performance index of iterative learning control under different values of $P$ (experimental results).

| Cycle | $P=-2$ (Fig. 4) | $P=-0.5$ (Fig. 5) |
|-------|-----------------|-------------------|
|       | Adjustment time (s) | Overshoot (%) | Adjustment time (s) | Overshoot (%) |
| 1     | 0.2227           | 0               | 0.2227             | 0             |
| 2     | 0.1310           | 21.53           | 0.0393             | 5.83          |
| 3     | 0.1310           | 0               | 0.0262             | 0             |
| 4     | 0.0393           | 5.53            | 0.0262             | 0             |
| 5     | 0.0262           | 2.43            | 0.0262             | 0             |
| 6     | 0.0262           | 0               | 0.0262             | 0             |
| 7     | 0.0262           | 1.4             | 0.0262             | 0             |
| 8     | 0.0262           | 0.07            | 0.0262             | 0.30          |
| 9     | 0.0262           | 0               | 0.0262             | 0             |
| 10    | 0.0262           | 0               | 0.0262             | 0             |

FIGURE 6. Comparison of the speed step response curves corresponding to three cases (the step response curves of $P = -0.5$ and $P = -2$ are the 10th result).

...does not change after the third cycle. The main characteristics and changing trends of the experimental results are consistent with the simulation results. The adjustment time of the GPC response curve shown in Fig. 6 is 0.0393s, the overshoot amount is 0, and the steady state fluctuation average value is 0.1838r/min. Fig. 6 shows the comparison between GPC control response and the 10th speed step response curves obtained under the conditions that $P = -2$ and $P = -0.5$. According to the adjustment time data given in Fig.6 and Table 1, the response speed under the conditions that $P = -2$ and $P = -0.5$ is faster than that of GPC, and the adjustment time of 0.0262s is less than 0.0393s of the response curve of GPC, which is consistent with the simulation results. It shows that, the generalized predictive ILC law (14) derived from objective function (3) can obtain better control effect than GPC, and has more obvious characteristics of ILC.

Because the step response in Fig. 4 and Fig. 5 is fast, it is not convenient to explain the control effect after adding on-line identification, so the control parameter values are adjusted, and the experimental result of not adding on-line identification as shown in Fig. 7 is obtained.

Fig. 8 shows the experimental results after adding on-line identification. The reduction rates of the adjustment time for the 2nd to 6th iterations in Fig. 7 are 20.00%, 26.67%, 33.33%, 33.33%, 33.33%, respectively. The reduction rates of the adjustment time for the 2nd to 6th iterations in Fig. 8 are 28.57%, 35.71%, 35.71%, 35.71%, 35.71%, respectively. The comparison shows that, compared with the case of Fig. 7 without identification, after the same number of iterations, the stepwise reduction rate of step response adjustment time with on-line identification is larger. It shows that the convergence speed of iterative learning is improved after adding on-line identification.

B. INTERMITTENT LOADING EXPERIMENTS

Fig. 9 shows the speed step response curve of intermittent loading. It has no steady-state error. The adjustment time of the first to sixth step responses are 0.1703s, 0.1572s, 0.1048s, 0.1310s, 0.1048s, and 0.1048s, respectively. In Fig. 9, the adjustment time of the fourth step response increases due to loading. The experimental results show that better on-line identification and control results can still be obtained under loading conditions.

C. EXPERIMENT AFTER MOTOR REPLACEMENT

The experimental motor is replaced with a new ultrasonic motor of the same model for experimental research to evaluate the effect of the on-line identification method. For comparison, the step response curve of the new motor without on-line identification is shown in Fig. 10. The adjustment
times of the six step responses and the corresponding adjustment time reduction rates is shown in Table 2. The response speed is slower than the original motor shown in Fig. 7, which indicates that the characteristics of the new motor are different from the original motor. The experimental result of the new motor with on-line identification is shown in Fig. 11. As can be seen from Fig. 11, in the iterative learning process, the speed step response curve gradually approaches the curve of the given value without overshoot, and the control performance is good. The adjustment time of each step response shown in Fig. 11 is given in Table 2. It can be seen that the adjustment time reduction rate of the six responses is larger than that in the case of Fig. 10 without identification, which indicates that after the identification is added, the influence of the difference between the original model parameters and the new motor on the control performance is weakened, and the control parameters can be adjusted on-line automatically to adapt to the new motor to obtain better control performance.

The intermittent loading experiment of the new motor is carried out, and the speed step response is obtained as shown in Fig. 12. Similar to the results of the original motor, there is no steady-state error. Table 2 also shows the comparison of the adjustment time of each step response in Fig. 12. Similar to the experimental results of the original motor, the adjustment time of the fourth step response in Fig. 12 also increases due to sudden loading.

Comparing the result after adding the on-line identification shown in Fig. 11 with the result without adding the identification shown in Fig. 10, it can be seen that the response speed is obviously increased by adding the identification. Comparing the data in Table 2 with the original motor no-load experimental results shown in Fig. 8 and intermittent loading experimental results shown in Fig. 9, it can be seen that the on-line identification and adaptive adjustment of control parameters make the control performance under different motor conditions close, and the difference is not obvious. The motor speed controller with on-line identification adjusts the
controller parameters according to the identification results, which significantly improves the control performance degradation of the new motor due to the model parameters different from the original motor. The controller can automatically adapt to the new characteristics of the new motor different from the original motor, so that the control response can still maintain the desired performance.

VI. CONCLUSION
In this paper, predictive ILC strategy is constructed by integrating ILC and generalized predictive control by introducing the speed error information of the previous control process into the optimization objective function, which can simultaneously guarantee the learning convergence along the iterative index and the control stability along the time index. By constructing the optimal prediction model and optimizing the control objective function, a definite and effective formula of control quantity can be proposed. At the same time, the on-line identification of the motor model parameters is considered, and the controller parameters are designed on-line according to the current motor model parameter values, so that the control parameters match the motor operating state to a higher degree. The experiment of ultrasonic motor speed control shows that the proposed control strategy can obtain better control effect than GPC, and has more obvious characteristics of ILC. The control performance of the controller with on-line identification is good. It can maintain the expected performance under the condition of intermittent loading and replacing the motor. The on-line identification method is effective and presents strong robustness.

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