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Model Free Adaptive Iterative Learning Control for Tool Feed System in Noncircular Turning

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ABSTRACT The linear motor tool feed system is an important part in noncircular turning. In this paper, the compact form dynamic linearization based model-free adaptive iterative control scheme (CFDL-MFAILC) and the full form dynamic linearization based model-free adaptive iterative control method scheme (FFDL-MFAILC) are designed for a complex nonlinear tool feed system. Theoretical analysis shows that the proposed scheme guarantees the output tracking error monotonic convergence along the iteration axis, and the FFDL-MFAILC is a complement and improvement to the CFDL-MFAILC. The designed control schemes are compared with PID and iterative learning feedforward and model-free adaptive predictive control feedback combination scheme (ILC-MFAPC) by simulations and experiments. Simulation results show that the proposed scheme can greatly decrease linear motor position error as iteration time increase, and has better position control advantages then other algorithms, the FFDL-MFAILC has faster convergence speed and smaller steady-state error than the CFDL-MFAILC. Experiment results prove that the proposed scheme is effective in linear motor tool feed system position control.

INDEX TERMS Dynamic linearization, iterative learning control, model free adaptive control, noncircular turning, tool feed system.

I. INTRODUCTION

Non-circular section parts are widely used in automobile, biology, medicine, aviation, aerospace and other mechanical equipment. The tool feed system is one of the key components in non-circular turning [1], [2]. Linear motor has the advantages of fast response and high acceleration, and is widely used in the tool feed system [3], [4]. However, in the turning process, nonlinear cutting force subjected by the system, tool vibration and the impact of other disturbances on the system brings difficulties to control linear motor feeding mechanism [5]–[8]. Therefore, it has been an important research topic to find a more optimal control algorithm and implement effective control [9]–[13].

The disturbance observer method can compensate the disturbance within a certain bandwidth, but the system accurate mathematical model needs to be determined [11]. The adaptive robust control, disturbance and model uncertainty observation and feedforward compensation technology [12], and sliding mode variable structure control technology [13], make the system insensitive to external disturbances and parameter perturbations, but it is difficult to achieve complete compensation for the linear servo system nonlinearity. The above model-based control methods are not suitable for dealing with the control problem of high precision linear tool feed system in non-circular turning which has strong un-modeled dynamics [14]. In addition, in the process of operation, no matter how many times the motor is repeatedly run, the position error is repeated, the above methods don't have the ability of self-learning to improve position error. Traditional PID algorithm can't satisfy the precision requirements [15]. Therefore, the compact form dynamic linearization based model-free adaptive iterative control scheme (CFDL-MFAILC) [14] and the full form dynamic linearization based model-free adaptive iterative control method scheme (FFDL-MFAILC) are designed in this paper. This schemes can modify the current control input by using input and output data of past operation and the data of

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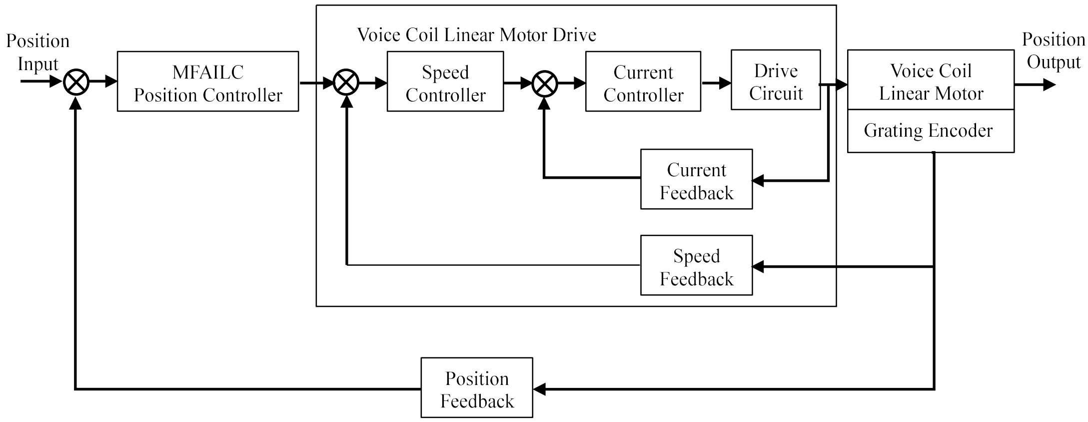

FIGURE 1. Structure of tool feed voice coil linear motor control system.

past tracking error, and can improve the position accuracy of linear motor.

The traditional iterative learning control (ILC) of repeatable processes is able to refine the control signals at current iteration by utilizing the information of control signals and tracking errors of previous iterative operations. Consequently, the tracking error accuracy is improved as the number of repetitions increases, various methods based on Iterative Learning Control (ILC) have been developed [16]–[19] and applied in the field of repetitive motion [20]–[22]. In this paper, by exploring the similarities between MFAC and ILC, the compact form dynamic linearization based model-free adaptive iterative control scheme (CFDL-MFAILC) [14] and the full form dynamic linearization based model-free adaptive iterative control method scheme (FFDL-MFAILC) are designed and analyzed for the linear feed system in non-circular turning based on an optimal cost function. The proposed control approach still retains the data-driven model-free feature, and mean-while possesses the ability of guaranteeing monotonic convergence of the output tracking error along the iteration axis for nonlinear system.

The basic idea of the approach is shown as follows: First, the compact form dynamic linearization (CFDL) and the full form dynamic linearization (FFDL) data model with a simple incremental form are given by introducing the concept of pseudo partial derivative (PPD) and pseudo gradient (PG) along the iteration axis. And then, CFDL data model based MFAILC scheme (CFDL-MFAILC) and FFDL data model based MFAILC scheme (FFDL-MFAILC) are designed.

Theoretical analysis, numerical simulation and physical experiment show that the tracking error of the MFAILC system converges monotonically to zero along the iteration axis although the initial errors are randomly varying with iterations.

II. MODELING AND ANALYSIS OF TOOL FEED SYSTEM

The tool feed system for non-circular turning is realized by the reciprocating motion of voice coil linear motor. Because the working principle of the non-circular turning tool feed linear servo system is known, the transfer function structure of the controlled plant can be deduced in the form of mechanism modeling. Considering the complexity of magnetic field distribution and the influence of non-linear factors such as friction, there are uncertainties and unknown factors in the linear servo system, the mathematical model of the voice coil linear motor is deduced according to its working mechanism, the mathematical model structure of the system is estimated, input and output data of the system are determined through experiments, and parameters of the model structure are finally identified. Modeling is only used for simulation research.

A. STRUCTURE OF TOOL FEED SYSTEM

The voice coil linear motor used in this experiment is the synchronous linear motor of Germany Company. The type is DTL85/708-StX-1-S. The main parameters of the voice coil linear motor are, cont. force 980N, maximum force 1520N, force constant 56.2N/A, continuous current 8.66A, maximum current 23.0A, maximum acceleration 431m/s^2, and maximum speed 3.44m/s.

The driver of voice coil linear motor is ARS2310 produced by Cooper Company. It uses three-phase alternating current(AC) power supply with short instruction cycle time. The current loop controller is a proportional (P) controller with a bandwidth of about 2 kHz. The speed loop controller is a proportional-integral (PI) controller with a bandwidth of about 500 Hz. It is a new type of AC servo controller with programmable and external parameter control functions. It can realize the current control, speed control and position control of voice coil linear motor. The structure of voice coil linear motor control system is shown in Fig. 1.

The tool feed control system adopts three-loop control. The current loop and speed loop are realized by the voice coil motor driver. The feedback element of the current loop is the current transformer inside the driver. The input of the current loop is the output of the speed loop after PI regulator. The current loop is P regulator according to the given value and feedback signal, then the driving current is output to the voice coil linear motor to control its motion. The output signal of grating encoder serves as feedback signal of speed loop and position loop. The output of speed loop is the output of voice coil linear motor driver, it is the analog voltage signal, which drives voice coil linear motor to move at ideal speed. The position loop achieves ideal position output by model-free adaptive iterative control and ensures machining accuracy.

B. MODELING OF TOOL FEED SYSTEM

As shown in Fig.1, the tool feed voice coil linear motor control system for non-circular turning is a single input and single output system (SISO). The controlled plant can be regarded as a voice coil linear motor and its driver. Its transfer function has specific structure and parameters.

1) ESTABLISHMENT OF MATHEMATICAL MODEL

According to the working principle of voice coil motor, the voltage balance equation of voice coil motor can be deduced as follows [6], [22]:

$$u = L\frac{di}{dt} + Ri + Blv \tag{1}$$

where u is the terminal voltage of the motor coil, L is the inductance of the coil, i is the current of the coil, R is the resistance of the coil, B is the strength of the air gap magnetic field of the motor, l is the effective length of the coil, v is motor speed. The dynamic equilibrium equation of the motor is as follows:

$$\begin{cases} F = ma \\ F = NBil \end{cases} \tag{2}$$

where F is the motor driving force, m is the mass of the motor, a is the acceleration of the motor. N is the number of turns of the motor coil. By Laplace transformation of (1) and (2), the relationship between the motor position and its speed and acceleration $\dot{y} = v$, $\ddot{y} = a$, then get

$$\begin{cases} U(s) = LsI(s) + RI(s) + BlsY(s) \\ NBlI(s) = ms^2Y(s) \end{cases} \tag{3}$$

In the servo control system of voice coil motor, the input signal of the motor is coil current i and the output signal is position y, According to (3), the transfer function of voice coil motor is obtained as follows.

$$G(s) = \frac{Y(s)}{I(s)} = \frac{NBl}{m} \cdot \frac{1}{s^2} \tag{4}$$

According to (4), the voice coil linear motor is a second-order system.

As mentioned above, the servo control system of voice coil linear motor is a three-loop control system. The position loop controller is studied in this paper, so the controlled object of the system includes the driver of voice coil linear motor besides voice coil linear motor and the speed loop and current loop in the three-loop control system are implemented on the driver. As shown in Fig. 1, in deriving the mathematical model of the controlled object, besides the transfer function of voice coil linear motor, current controller and speed controller should also be considered. The voice coil linear motor driver used in this paper is ARS2310 produced by Cooper Company. Its current loop controller is proportional (P) controller and speed loop controller is proportional-integral (PI) controller. The transfer function of PI controller is:

$$G_c(s) = K_P + \frac{K_I}{s} \tag{5}$$

where K_P is the proportional coefficient of the controller, K_I is the integral coefficient. Therefore, according to the three-loop control structure shown in Fig.1 and (5), the mathematical model of motor and driver can be obtained as follows:

$$G(s) = \frac{K(T_z s + 1)}{(T_{p1}s + 1)(T_{p2}s + 1)(T_{p3}s + 1)} \tag{6}$$

Thus the transfer function of the system is a third-order system with zero point. The system identification method will be used to determine the parameters of Equation (6).

2) IDENTIFICATION OF MODEL PARAMETERS

Firstly, the determined signal is input to the control plant, and then the output signal of the system is recorded. Finally, the unknown parameters in (6) are estimated by analyzing and processing the input signal and output signal.

M-sequence is a pseudo-random sequence, which is also called the maximum length first feedback shift register sequence. M-sequence can not only meet the relevant requirements of system identification of input signals, but also can be easily implemented in practice. In the experiment of system identification, the M sequence is used as the control voltage input of the voice coil motor driver, and the position feedback of the experimental platform is used to measure and record the output signal of the voice coil linear motor.

The input voltage signal of the controlled plant in the identification experiment is shown in Fig.2 and the output position signal is shown in Fig.3. The received experimental data is stored as a text file.

3) SYSTEM PARAMETERS IDENTIFICATION

After the input and output signals of the controlled plant are imported into the identification toolbox of MATLAB,

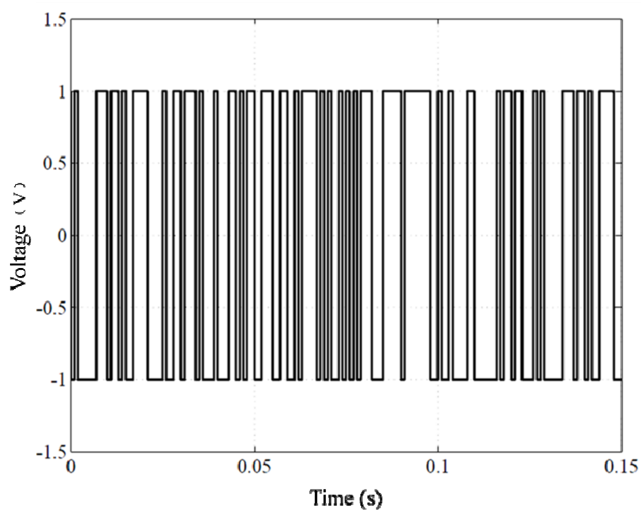

FIGURE 2. Input voltage signal of controlled object.

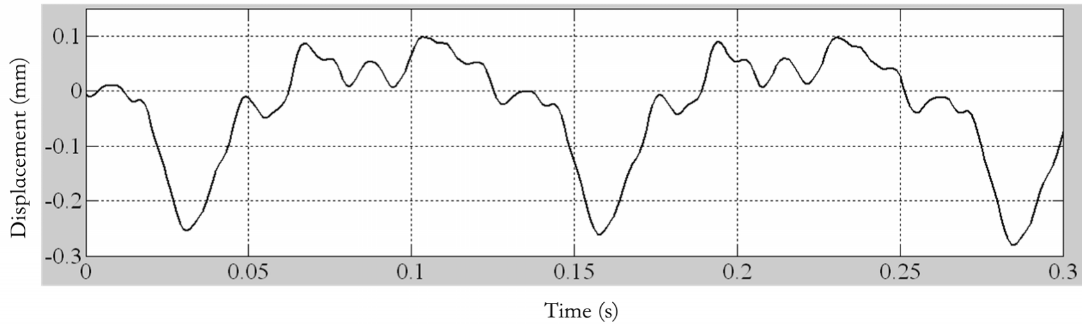

FIGURE 3. Output displacement of controlled object in identification experiment.

the data are analyzed and pretreated, then the mathematical model of the system is obtained, as shown in (7). Finally, the mathematical model of the estimation is verified.

$$G(s) = \frac{7437.7769(s - 928.2)}{(s + 474)(s + 474)(s + 6.404)} \quad (7)$$

4) SYSTEM MODEL VERIFICATION

After the system model identification is completed, the M sequence of Figure.3 used in the identification experiment is input into the identified system mathematical model (7), and the output signal of the model is obtained. By comparing the output signal with the actual measured output signal, the identification model can be verified. The verification results are shown in Fig. 4.

From Fig. 4, it can be seen that the output signal of the system identification model is basically consistent with the actual measured signal, which verifies the validity of the identified system model.

Through the modeling process, we can see that building input-output model of a practical plant is not an easy thing. Even if the model of the controlled plant is established, unmodeled dynamics is also inevitable. Thus the closed-loop control system design based on the system model with uncertainties under additional mathematical assumptions may cause unpredictable problems in practical applications, or even becomes unsafe. In view of this, an iterative learning control method based on model-free adaptive control is proposed in this paper.

The basic idea of model-free adaptive control (MFAC) design is implemented. Only the measurement I/O data of the closed-loop controlled system, rather than the information about system model, are required for the controller design, and this makes MFAC suitable for industrial systems[14].

III. MODEL-FREE ADAPTIVE ITERATIVE LEARNING CONTROL (MFAILC)

A. CFDL-MFAILC SCHEME

1) CFDL DATA MODEL IN THE ITERATION DOMAIN

Consider a discrete-time SISO nonlinear system that operates repeatedly in a finite time interval as follows [14], [18]:

$$y(k+1, i) = f(y(k, i), \ldots, y(k - n_y, i), u(k, i), \ldots, u(k - n_u, i)) \quad (8)$$

where $u(k, i)$ and $y(k, i)$ are the control input and the system output at time instant k of the $i-$th iteration, $k \in \{0, 1, \cdots T\}$, $i = 1, 2, \cdots$. n_y and n_u are two unknown positive integers, and $f(\cdots)$ is an unknown nonlinear function.

Two assumptions are made on system (8) before the CFDL data model is elaborated.

Assumption 1: The partial derivative of $f(\cdots)$ with respect to the $(n_y + 2) -$ th variable is continuous.

Assumption 2: Suppose that $\forall k \in \{0, 1, \cdots T\}$ and $\forall i = 1, 2, \cdots$, when $|\Delta u(k, i)| \neq 0$, system (1) satisfies generalized *Lipschitz* condition along the iteration axis, that is,

$$|\Delta y(k+1, i)| \leq b\,|\Delta u(k, i)| \quad (9)$$

where

$$\Delta y(k+1, i) = y(k+1, i) - y(k+1, i-1)$$
$$\Delta u(k, i) = u(k, i) - u(k, i-1)$$

$b > 0$ is a finite positive constant.

Theorem 1: Consider system (8) satisfying two Assumptions. If $|\Delta u(k, i)| \neq 0$, then there exists an iteration-dependent time-varying parameter $\phi_c(k, i)$, called ***pseudo partial derivative*** (PPD), such that system (1) can be transformed into the following CFDL data model, k is sampling time and i is the number of iterations. System (8) can be transformed into the following CFDL data model:

$$\Delta y(k+1, i) = \phi_c(k, i)\Delta u(k, i) \quad (10)$$

with bounded $|\phi_c(k, i)|$ for any time k and iteration i.

PPD is a time-varying parameter, even if system (8) is a linear time-invariant (LTI) system. We can see that PPD is related with the input and output signals till current time instant k and the $i -$ th iteration. For notation simplicity, we denote it as $\phi_c(k, i)$ without listing all the time indices before current time k *and* the $i -$ th iteration. $\phi_c(k, i)$ can be considered as a differential signal in some sense and it is bounded for any k *and* i. If the sampling period and $\Delta u(k)$ are not too large, $\phi_c(k, i)$ may be regarded as a slowly time-varying parameter. All the possible complicated behavior characteristics, such as nonlinearities, time-varying parameters or time-varying structure, *etc.*, of the original dynamic nonlinear system are compressed and fused into a single time-varying scalar parameter $\phi_c(k, i)$. Therefore, the dynamics of PPD $\phi_c(k, i)$ may be too complicated to be

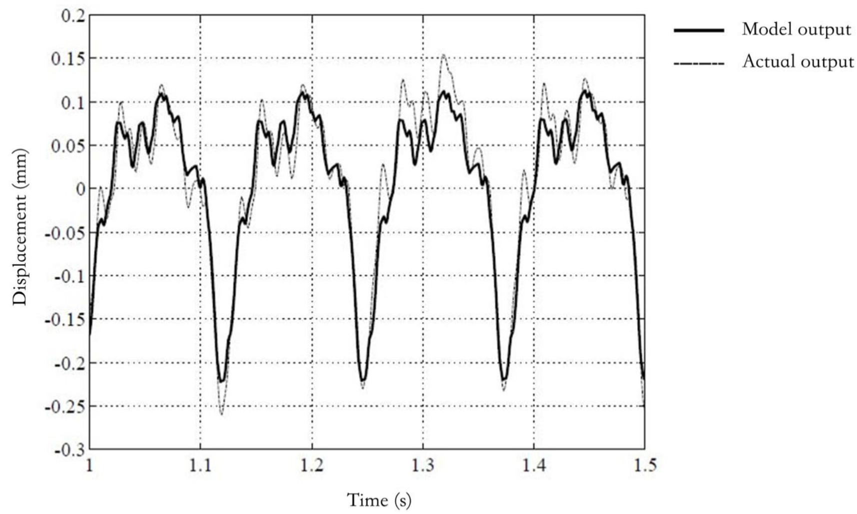

FIGURE 4. Validation results of identification model.

described mathematically. However, its numerical behavior may be simple and easily estimated. In other words, even though the time-varying parameter, structure and delay are explicit in the first principle model, which are hard to handle in the framework of the model-based control system design, the numerical change of the PPD behavior may not be sensitive to these time-varying factors.

PPD is merely a concept in mathematical sense. Existence of PPD is theoretically guaranteed by rigorous analysis from the proof of theorem [14], [18], [20], but generally PPD cannot be analytically formulated. It is determined jointly by the mean value of the partial derivative at some point within an interval and a nonlinear remaining term. Since the mean value in Cauchy's mean value theorem cannot be explicitly figured out in an analytical form even for a known simple nonlinear function, thus PPD cannot be computed analytically.

2) CFDL-MFAILC LEARNING CONTROL ALGORITHM

Given a desired trajectory $y_d(k)$, control object is that finding appropriate control inputs $u(k, i)$ which can make tracking error $e(k+1, i) = y_d(k+1) - y(k+1, i)$ converges to zero as the iteration number i approaches infinity.

Consider the cost function of the control input as follows, where $\lambda > 0$ is a weighting factor [14].

$$J(u(k,i)) = |e(k+1,i)|^2 + \lambda|u(k,i) - u(k,i-1)|^2 \tag{11}$$

(11) can be rewritten as:

$$J(u(k,i)) = |e(k+1,i-1) - \phi_c(k,i)(u(k,i) - u(k,i-1))|^2 + \lambda|u(k,i) - u(k,i-1)|^2.$$

Using the optimal condition: $\frac{\partial J}{2\partial u(k,i)} = 0$. We have CFDL-MFAILC algorithm:

$$u(k,i) = u(k,i-1) + \frac{\rho\phi_c(k,i)}{\lambda + |\phi_c(k,i)|^2} e(k+1,i-1) \tag{12}$$

where $\rho \in (0, 1]$ is the step factor to make CFDL-MFAILC algorithm more general.

3) CFDL-MFAILC PPD ITERATIVE UPDATING ALGORITHM

Since PPD is not available, CFDL-MFAILC algorithm (12) cannot be applied directly. A cost function of PPD estimation is that:

$$J(\phi_c(k,i)) = |\Delta y(k+1,i-1) - \phi_c(k,i)(\Delta u(k,i-1))|^2 + \mu|\phi_c(k,i) - \hat{\phi}_c(k,i-1)|^2$$

Using the optimal condition: $\frac{\partial J}{2\partial \hat{\phi}_c(k,i)} = 0$, PPD iterative updating algorithm is derived as follows:

$$\hat{\phi}_c(k,i) = \hat{\phi}_c(k,i-1) + \frac{\eta \Delta u(k,i-1)}{\mu + |\Delta u(k,i-1)|^2} \times (\Delta y(k+1,i-1) - \hat{\phi}_c(k,i-1)\Delta u(k,i-1)) \tag{13}$$

where $\eta \in (0, 1]$ is the step factor which can make PPD iterative updating algorithm (9) more general. $\hat{\phi}_c(k, i)$ is the estimation value of $\phi_c(k, i)$.

PPD estimation $\hat{\phi}_c(k, i)$ can be calculated by iteratively updating algorithm (13) which is quite different from the traditional ILC, where its learning gain is fixed and cannot be tuned iteratively.

4) CFDL-MFAILC CONVERGENCE ANALYSIS

Define the PPD estimation error as:

$$\tilde{\phi}_c(k,i) = \hat{\phi}_c(k,i) - \phi_c(k,i) \tag{14}$$

Subtracting $\phi_c(k, i)$ from both sides in (10):

$$\tilde{\phi}_c(k,i) = \tilde{\phi}_c(k,i-1) - (\phi_c(k,i) - \phi_c(k,i-1) + \frac{\eta \Delta u(k,i-1)}{\mu + |\Delta u(k,i-1)|^2} \times (\Delta y(k+1,i-1) - \hat{\phi}_c(k,i-1)\Delta u(k,i-1)).$$

Let:

$$\Delta\phi_c(k,i) = \phi_c(k,i) - \phi_c(k,i-1)$$

PPD estimation error can be written as:

$$\begin{aligned}
&\tilde{\phi}_c(k,i) \\
&= \tilde{\phi}_c(k,i-1) - \Delta\phi_c(k,i) \\
&\quad + \frac{\eta\Delta u(k,i-1)}{\mu + |\Delta u(k,i-1)|^2} \times (\phi_c(k,i-1)\Delta u(k+1,i-1) \\
&\quad - \hat{\phi}_c(k,i-1)\Delta u(k,i-1)) \\
&= \tilde{\phi}_c(k,i-1) - \frac{\eta|\Delta u(k,i-1)|^2}{\mu + |\Delta u(k,i-1)|^2}\tilde{\phi}_c(k,i-1) - \Delta\phi_c(k,i) \\
&= (1 - \frac{\eta|\Delta u(k,i-1)|^2}{\mu + |\Delta u(k,i-1)|^2})\tilde{\phi}_c(k,i-1) - \Delta\phi_c(k,i)
\end{aligned}$$

For $0 < \eta \leq 1$ and $\mu > 0$, the function $(\eta|\Delta u(k,i-1)|^2)/(\mu + |\Delta u(k,i-1)|^2)$ is increasing with respect to $|\Delta u(k,i-1)|^2$. Its minimum value is $\eta\varepsilon^2/(\mu+\varepsilon^2)$. Thus, there exists d_1 such that [5]

$$0 < \left|(1 - \frac{\eta|\Delta u(k,i-1)|^2}{\mu + |\Delta u(k,i-1)|^2})\right| \leq 1 - \frac{\eta\varepsilon^2}{\mu+\varepsilon^2} = d_1 < 1$$

From reference [5], $|\phi_c(k,i)|$ is bounded by a constant $\bar{b}$ which leads to $|\phi_c(k,i) - \phi_c(k,i-1)| \leq 2\bar{b}$.

$$\begin{aligned}
\tilde{\phi}_c(k,i) &= \left|1 - \frac{\eta|\Delta u(k,i-1)|^2}{\mu + |\Delta u(k,i-1)|^2}\right| \left|\tilde{\phi}_c(k,i-1)\right| + \Delta\phi_c(k,i) \\
&\leq d_1 \left|\tilde{\phi}_c(k,i-1)\right| + 2\bar{b} \\
&\vdots \\
&\leq d_1^{i-1}\left|\tilde{\phi}_c(k,1)\right| + \frac{2\bar{b}}{1-d_1}
\end{aligned}$$

Thus, $\tilde{\phi}_c(k,i)$ is bounded.

Using the CFDL data model, the tracking error can be rewritten as follows:

$$\begin{aligned}
e(k+1,i) &= y_d(k+1) - y(k+1,i) \\
&= y_d(k+1) - y(k+1,i-1) - \phi_c(k,i)\Delta u(k,i) \\
&= e(k+1,i-1) - \phi_c(k,i)\Delta u(k,i) \\
&= \left(1 - \phi_c(k,i)\frac{\rho\hat{\phi}_c(k,i)}{\lambda + |\hat{\phi}_c(k,i)|^2}\right) e(k+1,i-1)
\end{aligned}$$

Let $\lambda_{\min} = (b^2/4)$ and $\lambda > \lambda_{\min}$, there exists a positive constant M_1 such that:

$$\begin{aligned}
0 < M_1 &\leq \frac{\phi_c(k,i)\hat{\phi}_c(k,i)}{\lambda + |\hat{\phi}_c(k,i)|^2} \leq \frac{\bar{b}\hat{\phi}_c(k,i)}{\lambda + |\hat{\phi}_c(k,i)|^2} \leq \frac{\bar{b}\hat{\phi}_c(k,i)}{2\sqrt{\lambda}\hat{\phi}_c(k,i)} \\
&< \frac{\bar{b}}{2\sqrt{\lambda_{\min}}} = 1
\end{aligned}$$

Because of $\rho \in (0,1]$ and $\lambda > \lambda_{\min}$, there exists a positive constant $d_2 < 1$ such that:

$$\begin{aligned}
\left|1 - \frac{\rho\phi_c(k,i)\hat{\phi}_c(k,i)}{\lambda + |\hat{\phi}_c(k,i)|^2}\right| &= 1 - \frac{\rho\phi_c(k,i)\hat{\phi}_c(k,i)}{\lambda + |\hat{\phi}_c(k,i)|^2} \leq 1 - \rho M_1 \\
&= d_2 < 1
\end{aligned}$$

Tracking error can be written as:

$$\begin{aligned}
e(k+1,i) &= \left|\frac{\rho\phi_c(k,i)\hat{\phi}_c(k,i)}{\lambda + |\hat{\phi}_c(k,i)|^2}\right| |e(k+1,i-1)| \\
&\leq d_2\,|e(k+1,i-1)| \leq \cdots \leq d_2^{i-1}\,|e(k+1,1)|
\end{aligned} \tag{15}$$

Equation (13) implies that tracking error converges to zero as the number of iterations approaches infinity.

CFDL-MFAILC scheme for nonlinear system (8) is constructed by integrating learning control algorithm (12), parameter iterative updating algorithm (13).

B. FFDL-MFAILC SCHEME

Considering the complex dynamics of linear feed system in non-circular turning, we propose a model free adaptive iterative learning control based on full form dynamic linearization (FFDL-MFAILC), which fully considers all the influences on the system output increment at next time instant imposed by both the control input increments and the system output increments within input-related/output-related fixed length moving time windows at current time instant, respectively. Using the FFDL method, the possible complicated behavior of original system may be better captured and dispersed, by introducing more parameters than a scalar PPD in CFDL data model during the dynamic linearization transformation.

1) FFDL DATA MODEL IN THE ITERATIVE DOMAIN

Consider a discrete-time SISO nonlinear system (8) that operates repeatedly in a finite time interval.

Denote $\mathbf{H}_{L_y,L_u}(k,i)$ as the vector of the ith iteration, which consisting of all control input signals within an input-related moving time window $[k-L_u+1, k]$ and all system output signals within an output-related moving time window $[k-L_y+1, k]$, The integer L_u is the control input linearization length constant, and the integer L_y is the control output linearization length constant.

$$\mathbf{H}_{L_y,L_u}(k,i) = [y(k,i),\cdots,y(k-L_y+1,i),u(k,i),\cdots,u(k-L_u+1,i)]^T \tag{16}$$

For system (8), similar to Assumption 1 and Assumption 2, two assumptions are made in this subsection as follows.

Assumption 3: The partial derivatives of $f(\cdots)$ with respect to all variables are continuous.

Assumption 4: System (8) satisfies generalized *Lipschitz* condition along the iteration axis, that is,

$$|\Delta y(k+1,i)| \leq b\left\|\Delta\mathbf{H}_{L_y,L_u}(k,i)\right\| \tag{17}$$

where $\Delta y(k+1,i) = y(k+1,i) - y(k+1,i-1)$

$$\Delta\mathbf{H}_{L_y,L_u}(k,i) = \mathbf{H}_{L_y,L_u}(k,i) - \mathbf{H}_{L_y,L_u}(k,i-1), \quad b > 0.$$

Theorem 2: For system (1) satisfying Assumptions 3 and Assumptions 4, given L_y and L_u, when $\left\|\Delta\mathbf{H}_{L_y,L_u}(k,i)\right\| \neq 0$, there must be an iteration-dependent time-varying parameter vector $\mathbf{\Phi}_{L_y,L_u}(k,i)$ called pseudo gradient (PG), such that system (1) can be transformed into the following FFDL data model,

$$\Delta y(k+1,i) = \mathbf{\Phi}^T_{L_y,L_u}(k,i)\Delta \mathbf{H}_{L_y,L_u}(k,i) \tag{18}$$

with bounded $\mathbf{\Phi}_{L_y,L_u}(k,i)$ for any time k.

$$\begin{aligned}\mathbf{\Phi}_{L_y,L_u}(k,i) = [&\Phi_1(k,i),\cdots,\Phi_{L_y}(k,i),\cdots,\Phi_{L_y+L_u}(k,i)]^T\\ &\times \Delta\mathbf{H}_{L_y,L_u}(k,i) = [\Delta y(k,i),\cdots,\\ &\Delta y(k-L_y+1,i),\Delta u(k,i),\cdots\\ &\Delta u(k-L_u+1,i)]^T\end{aligned}$$

Proof:

$$\begin{aligned}&\Delta y(k+1,i)\\ &= y(k+1,i)-y(k+1,i-1)\\ &= f(y(k,i),y(k-1,i),\cdots,y(k-n_y,i),u(k,i),\\ &\quad u(k-1,i),\cdots,u(k-n_u,i))\\ &\quad -f(y(k,i-1),y(k-1,i-1),\cdots,y(k-n_y,i-1),\\ &\quad u(k,i-1),u(k-1,i-1),\cdots,u(k-n_u,i-1))\\ &= f(y(k,i),y(k-1,i),\cdots,y(k-L_y+1,i),y(k-L_y,i),\\ &\quad \cdots,y(k-n_y,i),u(k,i),u(k-1,i),\cdots,u(k-L_u+1,i),\\ &\quad u(k-L_u,i),\cdots,u(k-n_y,i))\\ &\quad -f(y(k,i-1),y(k-1,i-1),\cdots,y(k-L_y+1,i-1),\\ &\quad y(k-L_y,i),\cdots,y(k-n_y,i),u(k,i-1),u(k-1,i-1),\\ &\quad \cdots,u(k-L_u+1,i-1),u(k-L_u,i),\cdots,u(k-n_y,i))\\ &\quad +f(y(k,i-1),y(k-1,i-1),\cdots,y(k-L_y+1,i-1),\\ &\quad y(k-L_y,i),\cdots,y(k-n_y,i),u(k,i-1),u(k-1,i-1),\\ &\quad \cdots,u(k-L_u+1,i-1),u(k-L_u,i),\cdots,u(k-n_y,i))\\ &\quad -f(y(k,i-1),y(k-1,i-1),\cdots,y(k-L_y+1,i-1),\\ &\quad y(k-L_y,i-1),\cdots,y(k-n_y,i-1),u(k,i-1),\\ &\quad u(k-1,i-1),\cdots,u(k-L_u+1,i-1),u(k-L_u,i-1),\\ &\quad \cdots,u(k-n_y,i-1))\end{aligned} \tag{19}$$

Denote

$$\begin{aligned}&\psi(k,i)\\ &= f(y(k,i-1),y(k-1,i-1),\cdots,\\ &\quad y(k-L_y+1,i-1),y(k-L_y,i),\cdots,y(k-n_y,i),\\ &\quad u(k,i-1),u(k-1,i-1),\cdots,u(k-L_u+1,i-1),\\ &\quad u(k-L_u,i),\cdots,u(k-n_y,i))\\ &\quad -f(y(k,i-1),y(k-1,i-1),\cdots,y(k-L_y+1,i-1),\\ &\quad y(k-L_y,i-1),\cdots,y(k-n_y,i-1),u(k,i-1),\\ &\quad u(k-1,i-1),\cdots,u(k-L_u+1,i-1),u(k-L_u,i-1),\\ &\quad \cdots,u(k-n_y,i-1))\end{aligned}$$

By virtue of Assumption 4 and Cauchy's mean value theorem, (19) can be rewritten as

$$\begin{aligned}&\Delta y(k+1,i)\\ &= \frac{\partial f^*}{\partial y(k,i)}(y(k,i)-y(k,i-1))+\cdots+\\ &\quad \frac{\partial f^*}{\partial y(k-L_y+1,i)}(y(k-L_y+1,i)-y(k-L_y+1,i-1))\\ &\quad +\frac{\partial f^*}{\partial u(k,i)}(u(k,i)-u(k,i-1))+\cdots+\frac{\partial f^*}{\partial u(k-L_u+1,i)}\\ &\quad (u(k-L_u+1,i)-u(k-L_u+1,i-1))+\psi(k,i)\\ &= \frac{\partial f^*}{\partial y(k,i)}\Delta y(k,i)+\cdots+\frac{\partial f^*}{\partial y(k-L_y+1,i)}\Delta y(k-L_y+1,i)\\ &\quad +\frac{\partial f^*}{\partial u(k,i)}\Delta u(k,i)+\cdots+\frac{\partial f^*}{\partial u(k-L_u+1,i)}\\ &\quad \times\Delta u(k-L_u+1,i)+\psi(k,i)\end{aligned} \tag{20}$$

where $\frac{\partial f^*}{\partial y(k-m,i)}$, $0\le m\le L_y-1$ and $\frac{\partial f^*}{\partial u(k-j,i)}$ $0\le j\le L_u-1$ denote the partial derivatives of $f(\cdots)$ with respect to the $(m+1)$th variable and the (n_y+2+j)th variable at certain point between

$$\begin{aligned}&[y(k,i),y(k-1,i),\cdots,y(k-L_y+1,i),y(k-L_y,i),\\ &\cdots,y(k-n_y,i),u(k,i),u(k-1,i),\cdots,u(k-L_u+1,i),\\ &u(k-L_u,i),\cdots,u(k-n_y,i)]^T\end{aligned}$$

and

$$\begin{aligned}&[y(k,i-1),y(k-1,i-1),\cdots,y(k-L_y+1,i-1),\\ &y(k-L_y,i),\cdots,y(k-n_y,i),u(k,i-1),u(k-1,i-1),\\ &\cdots,u(k-L_u+1,i-1),u(k-L_u,i),\cdots,u(k-n_y,i)]^T\end{aligned}$$

For every fixed time and k each iteration i, consider following equation with a variable $\boldsymbol{\eta}(k,i)$,

$$\begin{aligned}\psi(k,i) &= \boldsymbol{\eta}^T(k,i)[\Delta y(k,i),\cdots\Delta y(k-L_y+1,i),\\ &\qquad \Delta u(k,i),\cdots,\Delta u(k-L_u+1,i)]^T\\ &= \boldsymbol{\eta}^T(k,i)\Delta\mathbf{H}_{L_y,L_u}(k,i)\end{aligned} \tag{21}$$

Since $\left\|\Delta\mathbf{H}_{L_y,L_u}(k,i)\right\| \neq 0$, each iteration i, there must exist a unique solution $\boldsymbol{\eta}^*(k)$ to equation (21).

Let

$$\begin{aligned}\mathbf{\Phi}_{L_y,L_u}(k,i) &= \boldsymbol{\eta}^*(k,i)+[\frac{\partial f^*}{\partial y(k,i)},\cdots,\frac{\partial f^*}{\partial y(k-L_y+1,i)},\\ &\qquad \cdots,\frac{\partial f^*}{\partial u(k,i)},\cdots,\frac{\partial f^*}{\partial u(k-L_u+1,i)}]^T\end{aligned}$$

Equation (20) can be rewritten as FFDL data model (18)

$$\Delta y(k+1,i) = \mathbf{\Phi}^T_{L_y,L_u}(k,i)\Delta\mathbf{H}_{L_y,L_u}(k,i) \tag{22}$$

$\mathbf{\Phi}_{L_y,L_u}(k,i)$ can also be rewritten as

$$\begin{aligned}\mathbf{\Phi}_{L_y,L_u}(k,i) = [&\Phi_1(k,i),\cdots,\Phi_{L_y}(k,i),\Phi_{L_y+1}(k,i),\\ &\cdots,\Phi_{L_y+L_u}(k,i),]^T\end{aligned}$$

$\Delta\mathbf{H}_{L_y,L_u}(k,i)$ can be rewritten as

$$\begin{aligned}\Delta\mathbf{H}_{L_y,L_u}(k,i) = [&\Delta y(k,i),\cdots,\Delta y(k-L_y+1,i),\\ &\Delta u(k,i),\cdots\Delta u(k-L_u+1,i)]^T\end{aligned} \tag{23}$$

Finally, using the FFDL data model (18) and Assumption 4, we have

$$|\Delta y(k+1,i)| = \left|\mathbf{\Phi}^T_{L_y,L_u}(k,i)\Delta\mathbf{H}_{L_y,L_u}(k,i)\right| \leq b\left\|\Delta\mathbf{H}_{L_y,L_u}(k,i)\right\|$$

holds for any k and $\left\|\Delta\mathbf{H}_{L_y,L_u}(k,i)\right\| \neq 0$. From above inequality we can see that, if any elements of $\mathbf{\Phi}_{L_y,L_u}(k,i)$ is unbounded, it would violate the inequality, so the boundedness of $\mathbf{\Phi}_{L_y,L_u}(k,i)$ for any k is guaranteed.

Remark 1: From the proof of the Theorem 2, we can see that $\mathbf{\Phi}_{L_y,L_u}(k,i)$is related with input and output signals till time instant k of $(i-1)-$ th and $i-$ th iterations. Thus, $\mathbf{\Phi}_{L_y,L_u}(k,i)$ is an iteration related time-varying parameter. On the other hand, $\mathbf{\Phi}_{L_y,L_u}(k,i)$ can be considered as a differential signal in some sense and it is bounded for any k and i. If the sampling period and $\Delta\mathbf{H}_{L_y,L_u}(k,i)$ are not too large, $\mathbf{\Phi}_{L_y,L_u}(k,i)$ may be regarded as a slowly iteration-varying parameter, consequently, we can implement adaptive iterative learning control of original system by designing a parameter estimator along the iteration axis.

2) FFDL-MFAILC LEARNING CONTROL ALGORITHM

Theoretically, the essence of compact format(CFDL) is the dynamic relationship between the output variation at the next time of the control system and the input variation at the current time. The essence of the full format(FFDL) is the dynamic relationship between the output variation of the control system at the next moment and some input variations and some output variations in the sliding time window. Therefore, full format can capture system dynamics better.

Given a desired trajectory $y_d(k), k \in \{0,1,\cdots T\}$, the control objective is to find a sequence of appropriate control inputs $u(k,i)$ such that the tracking error $e(k+1,i) = y_d(k+1) - y(k+1,i)$ converges to zero as the iteration number i approaches to infinity.

Consider the cost function of control input as follows

$$J(u(k,i)) = |e(k+1,i)|^2 + \lambda\,|u(k,i) - u(k,i-1)|^2 \quad (24)$$

Therefore, substitute FFDL data model (18) into the criterion function (24), derive $u(k,i)$ and make it equal to zero to obtain the model-free adaptive iterative learning control based on full form dynamic linearization (FFDL-MFAILC) scheme as follows

$$\begin{aligned} u(k,i) = u(k,i-1) &+ \frac{\Phi_{L_y+1}(k,i)}{\lambda + \left|\Phi_{L_y+1}(k,i)\right|^2} \\ &\times [\rho_{L_y+1}e(k+1,i-1) \\ &- \sum_{j=1}^{L_y}\rho_j\Phi_j(k,i)\Delta y(k-j+1,i) \\ &- \sum_{j=L_y+2}^{L_y+L_u}\rho_j\Phi_j(k,i)\Delta u(k+L_y-j+1,i)] \end{aligned} \quad (25)$$

where the step factor $\rho_j \in (0,1], j = 1,2,\cdots,L_y+L_u$ is added to make the control algorithm (25) more flexible.

3) FFDL-MFAILC PSEUDO GRADIENT(PG) ITERATIVE UPDATING ALORITHM

The estimation criterion function of PG vector is:

$$\begin{aligned} &J(\mathbf{\Phi}_{L_y,L_u}(k,i)) \\ &= \left|\Delta y(k+1,i-1) - \mathbf{\Phi}^T_{L_y,L_u}(k,i)\Delta\mathbf{H}_{L_y,L_u}(k,i-1)\right|^2 \\ &\quad + \mu\left\|\mathbf{\Phi}_{L_y,L_u}(k,i) - \hat{\mathbf{\Phi}}_{L_y,L_u}(k,i-1)\right\|^2 \end{aligned} \quad (26)$$

For Equation (26), the algorithm of estimating the PG vector is obtained by calculating the extreme value of $\mathbf{\Phi}_{L_y,L_u}(k,i)$ and using the matrix lemma.

$$\begin{aligned} \hat{\mathbf{\Phi}}_{L_y,L_u}(k,i) = \mathbf{\Phi}_{L_y,L_u}(k,i-1) &+ \frac{\eta\Delta\mathbf{H}_{L_y,L_u}(k,i-1)}{\mu + \left\|\Delta\mathbf{H}_{L_y,L_u}(k,i-1)\right\|^2}[\Delta y(k+1,i-1) \\ &- \hat{\mathbf{\Phi}}^T_{L_y,L_u}(k,i-1)\Delta\mathbf{H}_{L_y,L_u}(k,i-1)] \end{aligned} \quad (27)$$

where the step factor $\eta \in (0,2]$ is added to make the control algorithm (27) makes more flexible. $\hat{\mathbf{\Phi}}_{L_y,L_u}(k,i)$ is the estimated value of $\mathbf{\Phi}_{L_y,L_u}(k,i)$.

FFDL-MFAILC scheme for nonlinear system (8) is constructed by integrating learning control algorithm (25), parameter iterative updating algorithm (27).

Remark 2: The FFDL-MFAILC scheme is designed and analyzed only using I/O data of the plant. So it is a data-driven model-free control approach. It is worthy pointing out that the pseudo gradient (PG) estimation $\mathbf{\Phi}_{L_y,L_u}(k,i)$ affects the learning gains in learning control algorithm (21) virtually and can be iteratively calculated by iterative updating algorithm (23) together, which is quite different from traditional ILC, where its learning gain is fixed and cannot be tuned automatically and iteratively.

IV. SIMULATIONS

In noncircular turning tool system, the feed mechanism is voice linear motor. The control input is voltage signal and control output is voice linear motor position. For noncircular turning tool feed process, tool displacement can be expressed as follows:

$$y = f(Z) - G(Z)\cos 2\omega t \quad (28)$$

In the Z-axis feed speed $f(Z) = \Delta D(Z)/2 + G(Z)/4$, that is, while the voice coil linear motor vibrates sinusoidally along the radial direction of the machine tool, the central point of the sinusoidal vibration and the amplitude of the vibration also change with the change of Z-axis coordinates. In the actual non-circular piston, the elliptical long-axis variation $\Delta D(Z)$ and ellipticity $G(Z)$ are continuous functions, and the Z-axis feed speed f of the tool is usually slow in the process of machining. Therefore, the variation of $f(Z)$ and $G(Z)$ in (31) is very small and can be regarded as constants in a small processing time. So, when studying the position control of the tool feed linear motor, the motion of the tool can be approximately regarded as sinusoidal motion, so the sinusoidal signal can be used as the input signal of the system. The purpose of the research is to enable the voice coil linear motor to track the sinusoidal signal accurately.

In simulation, the desired output position curve of the voice coil linear motor is selected as a sinusoidal signal, its amplitude is 1 mm, and frequency is 0.5 Hz. At this time, the reciprocating vibration stroke of the turning tool is 1 mm, and the ellipticity of the processed piston is 2 mm. The tool's stroke is equal to the maximum cutting depth at the time of machining, and the sampling period is 1ms.

The linear motor transfer function model is obtained by identification, such as equation (7):

After Z-transformation

$$G(z) = \frac{0.001811z^2 - 0.00363z - 0.002546}{z^3 - 2.239z + 1.625z - 0.385}$$

Setting sampling time as 1 ms, the difference equation can be rewritten as

$$\begin{aligned} y(k) = 2.2386y(k-1) - 1.6246y(k-2) + 0.385y(k-3) \\ + 0.0018u(k-1) - 0.0036u(k-2) \\ - 0.0025u(k-3) \end{aligned} \quad (29)$$

Equation (29) can be rewritten as

$$\begin{aligned} y(k+3) = 2.2386y(k+2) - 1.6246y(k+1) + 0.385y(k) \\ + 0.0018u(k+2) - 0.0036u(k+1) - 0.0025u(k) \end{aligned}$$

A. CFDL-MFAILC ALGORITHM SIMULATION

According to the learning control algorithm (8) of the compact form model-free adaptive iterative learning scheme (CFDL-MFAILC) and the pseudo-partial derivative iterative updating algorithm (13), the parameters of the algorithm are selected as $\lambda = 1, \eta = 0.9$ $\mu = 1, \rho = 1$. Fig. 5 shows the curve that the absolute value of maximum position error increases with the number of iterations. From Fig.5, it can be seen that the maximum position error of voice coil linear motor decreases gradually with the increase of iterations.

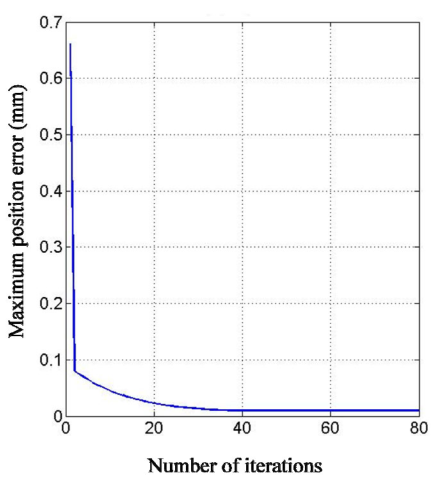

FIGURE 5. Maximum position error curve.

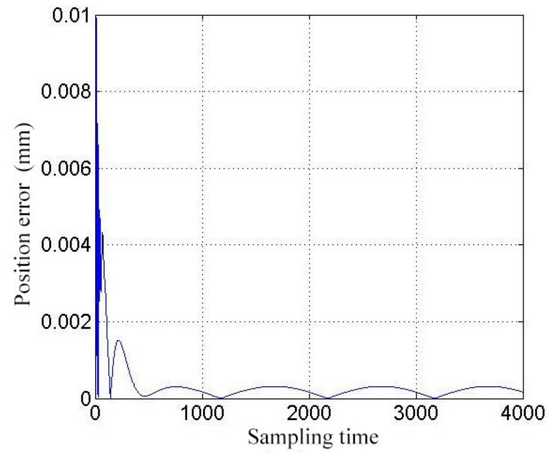

FIGURE 6. Position error curve after 80 iterations.

When the iteration is 35 times, the maximum position error is $10\mu m$. Setting the initial input signal for the first iteration as u(k, 1) = 0.

By changing the number of iterations, the steady-state error of voice coil linear motor position decreases gradually with the increase of iterations. When the iteration is 20 times, the steady-state error is about $18\mu m$. When the iteration is 30 times, the steady-state error is about $11\mu m$, 40 iterations are performed, the steady-state error is about $5.5\mu m$, the iteration is 50 times, the steady-state error is about $2.5\mu m$, and the iteration is 60 times, the steady-state error is about $1.5\mu m$, the iteration is 70 times, the steady-state error is about $0.5\mu m$, the iteration is 80 times, the steady-state error is about $0.3\mu m$, after 80 iterations, the error does not change. Fig.6 is position error curve after iteration 80 times.

Fig.7 is position error local enlargement curve after 80 iterations.

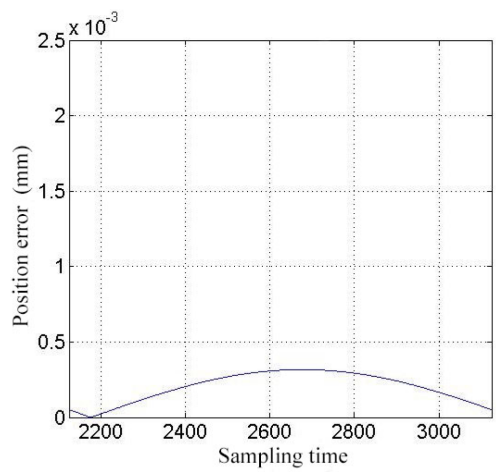

FIGURE 7. Local magnification of position error after 80 iterations.

Fig.8 is the tracking curve after 80 iterations of CFDL-MFAILC, where $X_d(t)$ represents the desired position

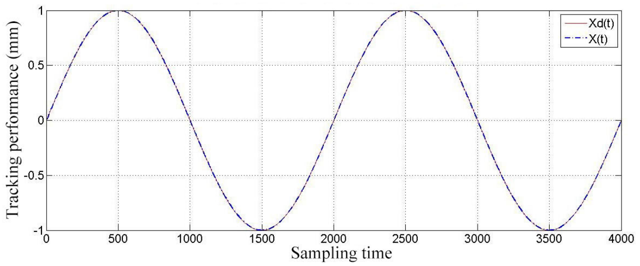

FIGURE 8. Tracking performance after 80 iterations.

curve of voice coil linear motor, $X(t)$ represents the actual position curve of voice coil linear motor.

B. FFDL-MFAILC ALGORITHM SIMULATION

According to the learning control algorithm (25) of the full form model-free adaptive iterative learning scheme (FFDL-MFAILC) and the pseudo gradient (PG) Iterative Updating Algorithm (27), the parameters of the FFDL-MFAILC are selected as:

$$\mu = 1.1, \quad L_y = 2, L_u = 2, \quad \lambda = 1.2, , \quad \eta = 1,$$
$$\rho_1 = \rho_2 = \rho_3 = \rho_4 = 0.98.$$

As iteration times increase, the steady-state error of linear motor position decreases gradually. The iteration is 20 times, the steady-state error is about $13\mu m$. When the iteration is 30 times, the steady-state error is about $2.5\mu m$, 40 iterations are performed, the steady-state error is about $0.5\mu m$, 50 iterations, the steady-state error is about $0.2\mu m$, and the steady-state error of 60 iterations is about $0.15\mu m$, after 60 iterations, the error does not change. Fig.9 shows the position error curve after 60 iterations using the full format model-free adaptive iterative learning method (FFDL-MFAILC).

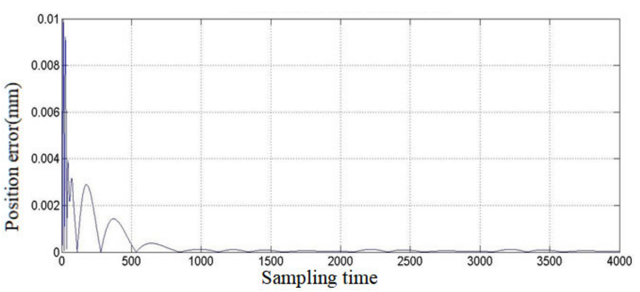

FIGURE 9. Position error curve after 60 iterations.

C. PID ALGORITHM SIMULATION

The PID control algorithm is a traditional control algorithm. In order to compare with the iterative learning model-free adaptive control method, the PID algorithm is used for simulation. When $K_p = -11.3$, $K_i = -0.028$, $K_d = 0$, the best PID control effect is achieved. the PID position error curve is shown in Fig.10. The maximum position error is $30\mu m$, and the steady-state error is $23\mu m$. It can be seen that the tracking

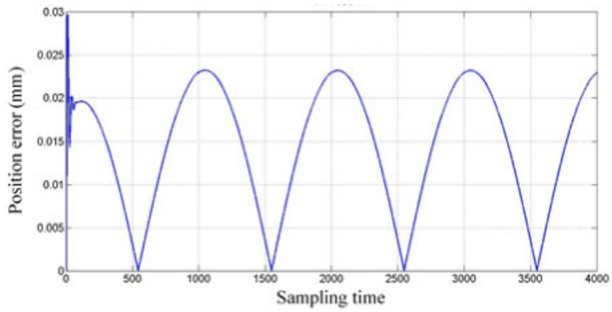

FIGURE 10. Position error of PID algorithm.

accuracy of PID control is not high, the position error is large, it is difficult to adjust parameters and it does not have the ability of self-learning to improve the error.

D. FEEDFORWARD AND FEEDBACK COMBINATION ALGORITHM SIMULATION

In order to compare with the iterative learning model-free adaptive control method, the same conditions, the feed-forward and feedback combined control method in reference [20], [22] is adopted. The feedforward control adopts the PID type iterative learning control law(ILC), which is responsible for improving the quality of the control system and achieving complete tracking. The feedback part adopts the compact form model-free adaptive predictive control(MFAPC), which is responsible for the stabilization of the system. Select the prediction step $N = 10$ and adjust the parameters to the best $\Gamma_p = 0.2$, $\Gamma_i = 0$, $\Gamma_d = 1$, $\lambda = 2$, $\eta = 0.9$, $\mu = 1$. The simulation results are shown in Fig. 11 and Fig. 12. When iterating 10 times, the error is about $8\mu m$, when iterating 15 times, the error is about $1.5\mu m$, and when iterating 20 times, the error is about $0.3\mu m$. The error is about $0.3\mu m$ after 30 iterations. The iteration is more than 30 times, the error does not change. It can be seen that although the convergence speed of ILC-MFAPC is faster, but the steady-state error is larger than the proposed method in this paper.

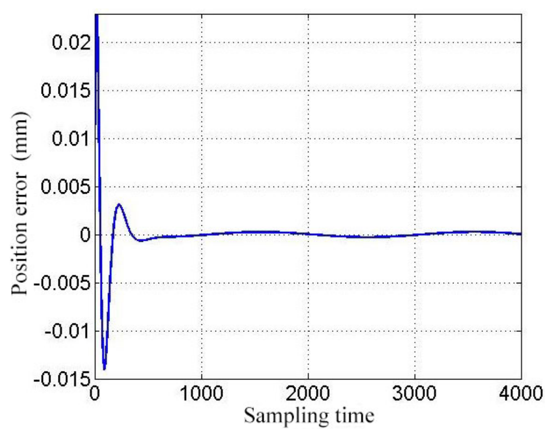

FIGURE 11. Position error after 30 iterations.

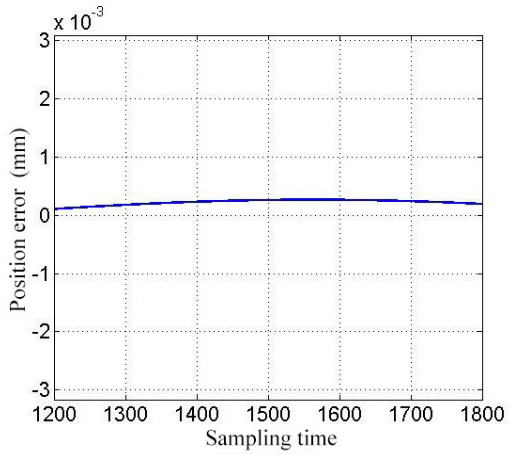

FIGURE 12. Local magnification of position error after 30 iterations.

E. COMPARISON OF SIMULATION RESULTS

The steady-state errors comparison of three different algorithms is given in Table 1.

TABLE 1. Various algrithems comparison.

Iteration Times	CFDL-MFAILC	FFDL-MFAILC	ILC-MFAPC
20	18μm	13μm	0.3μm
30	11μm	2.5μm	no change
40	5.5μm	0.5μm	no change
50	2.5μm	0.2μm	no change
60	1.5μm	0.15μm	no change
70	0.5μm	no change	no change
80	0.3μm	no change	no change
more times	no change	no change	no change

As can be seen from the table, the control effect of FFDL-MFAILC is better than CFDL-MFAILC, with fast convergence speed and small steady-state error. Theoretically, the essence of the CFDL-MFAILC is the dynamic relationship between the output variation at the next time of the control system and the input variation at the current time. The essence of the FFDL-MFAILC is the dynamic relationship between the output variation at the next time of the control system and some input variations and some output variations in the sliding time window [14]. Therefore, FFDL-MFAILC can capture system dynamics better.

The same conditions, the compact form model-free iterative learning control algorithm (CFDL-MFAILC), the full form model-free iterative learning control algorithm (FFDL-MFAILC), the PID algorithm, and the combination method of Iterative Learning Feedforward and model-free adaptive predictive control feedback(ILC-MFAPC) are simulated and compared. It is concluded that the model-free iterative learning control scheme is superior to PID and other algorithms in the steady-state position error and tracking accuracy of voice coil linear motor. The simulation results of compact form model-free iterative learning control (CFDL-MFAILC), full form model-free iterative learning control (FFDL-MFAILC) and iterative learning feedforward and model-free adaptive predictive control feedback combination method (ILC-MFAPC) with different iteration times are compared. It is concluded that the steady-state position error of voice coil linear motor decreases gradually with the iteration times increase. The effect of full form model-free iterative learning control (FFDL-MFAILC) is better than that of compact form model-free iterative learning control (CFDL-MFAILC). Iterative learning feedforward and model-free adaptive predictive control feedback combination method (ILC-MFAPC) converge faster, but compared with the proposed method in this paper, the steady-state error is larger.

V. EXPERIMENTS

A. HARDWARE COMPOSITION AND WORKING PRINCIPLE

The experiment is carried out in the laboratory, the tool feed process for noncircular turning is realized by the reciprocating motion of voice coil linear motor, so voice coil linear motor control system is used, and it is a real-time control platform based on dSPACE (Digital Signal Processing and Control Engineering).

The algorithm module is built by Simulink in industrial computer, it is automatically converted into C program code and written into DS1104 control card by dSPACE. The DS1104 control card receives the compiled algorithm, and receives the instructions to adjust the parameters of the control algorithm. The output of the DS1104 control card controls the operation of the voice coil linear motor through the driver. DS1104 control card receives the position signal of voice coil linear motor collected by grating encoder through PPC port card. The minimum indexing of grating encoder is 0.1μm.

The hardware includes ARS2310 driver, DTL85/708-3stx-1-S voice coil linear motor, grating encoder, PPC port card, DS1104 control card, industrial computer and monitor. The structure of real-time control platform for noncircular turning tool feed system based on dSPACE is shown in the fig.13.

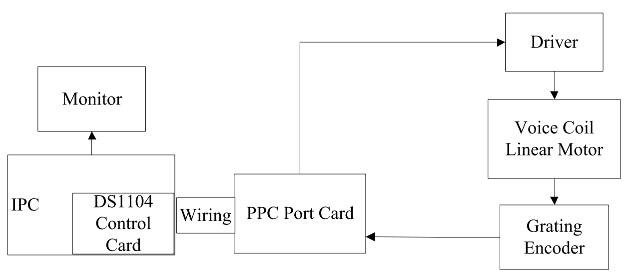

FIGURE 13. Hardware structure of real-time control experimental platform.

Local material object diagram of experimental platform is shown in fig.13.

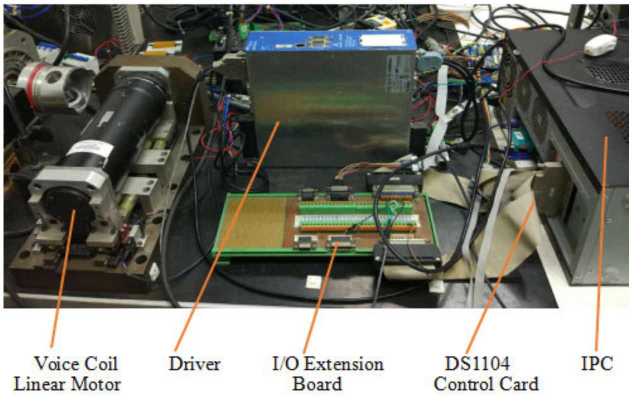

FIGURE 14. Local material object diagram of experimental platform.

B. EXPERIMENTS FOR CFDL-MFAILC ALGORITHM

Based on dSPACE, the external structure of "CFDL-MFAILC algorithm module" is built. The "For Iterator Subsystem module" is an iteration subsystem. In the interior of the iteration subsystem, CFDL-MFAILC can be built. Inside the iteration sub-module, "For Iterator module" is the iterator module of "For cycle", which can set the maximum iteration times. DS1104ENC_POS_C1 is a real position signal acquisition module of linear motor which is acquired by grating ruler. "DS1104DAC_C1" is an analog output module, which outputs the result of arithmetic operation to the driver through "DAC unit", and then controls the linear motor to run. "Saturation module" is used to limit the voltage signal input to the driver, to prevent excessive voltage amplitude and damage equipment.

The desired position curve of the voice coil linear motor is a sinusoidal curve with 1 mm amplitude, and the sampling period is 1 ms, same as in previous simulations. Choosing different frequencies, reflecting the different speed of voice coil linear motor, the maximum iteration times is 80, the iteration time is increases, errors remain unchanged. λ, η, μ, ρ represent CFDL-MFAILC parameters and the initial values of pseudo-partial derivatives(PPD).

The sinusoidal curve frequency is 0.1Hz, the position error is about $\pm 4\mu m$, the sinusoidal curve frequency is 0.2Hz, the position error is about $\pm 7\mu m$, the sinusoidal curve frequency is 0.3Hz, the position error is about $\pm 9\mu m$, the sinusoidal curve frequency is 0.4Hz, the position error is about $\pm 12\mu m$, the sinusoidal curve frequency is 0.5Hz, the position error is about $\pm 16\mu m$. The position tracking and position error at frequency 0.5Hz are shown in Fig.15 and Fig.16, λ is 1.5.

In Fig.15 and Fig.16, the horizontal axis represents time (s) and the vertical axis is tracking position (mm).

In the parameter adjustment process of CFDL-MFAILC, with the motor speed increase, the error will increase. The adjustment parameter is only λ, its selection should not be too large, which will cause violent vibration of linear motor, even cause equipment damage. The μ, η, ρ value has little effect on the error and is fixed, All three parameters are 1. The initial value of pseudo partial derivative(PPD) should not

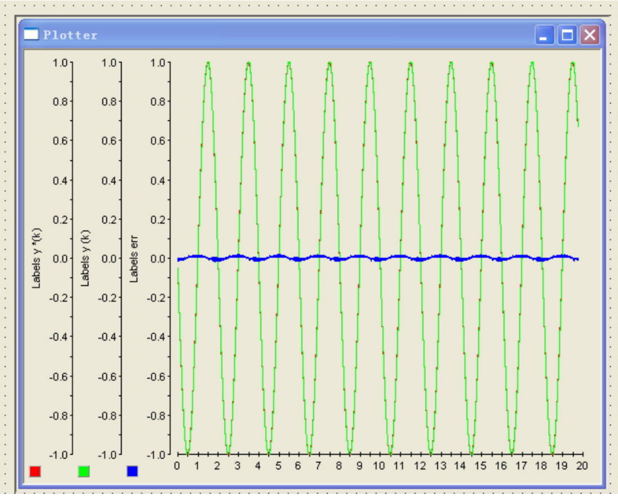

FIGURE 15. CFDL-MFAILC position tracking with frequency 0.5 Hz.

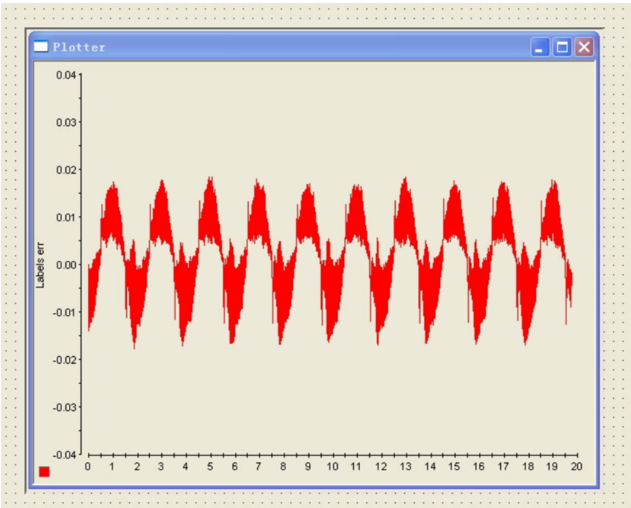

FIGURE 16. CFDL-MFAILC position error with frequency 0.5 Hz.

be too large, and it is more appropriate to choose about 1. If the initial value of PPD is too large, it will also cause violent oscillation of linear motor and even damage the motor.

C. EXPERIMENTS FOR PID ALGORITHM

The PID control algorithm is a traditional control algorithm. In order to compare with the iterative learning model-free adaptive control method (MFAILC), the PID algorithm is used for experiment. The desired position curve of the voice coil linear motor is a sinusoidal curve with 1 mm amplitude, and the sampling period is 1 ms, same as in previous simulations.

The sinusoidal curve frequency is 0.1Hz, the position error is about $\pm 10\mu m$, the sinusoidal curve frequency is 0.2Hz, the position error is about $\pm 15\mu m$, the sinusoidal curve frequency is 0.3Hz, the position error is about $\pm 19\mu m$, the sinusoidal curve frequency is 0.4Hz, the position error is about $\pm 23\mu m$, the sinusoidal curve frequency is 0.5Hz, the position error is about $\pm 28\mu m$. The position tracking and position error at frequency 0.5Hz are shown in Fig.17 and Fig.18, PID algorithm's parameters are adjusted to the best. $K_p = 0.29$, $K_i = 0.006$, $K_d = 0$.

In Fig.17 and Fig.18, the horizontal axis represents time (s) and the vertical axis is tracking position (mm).

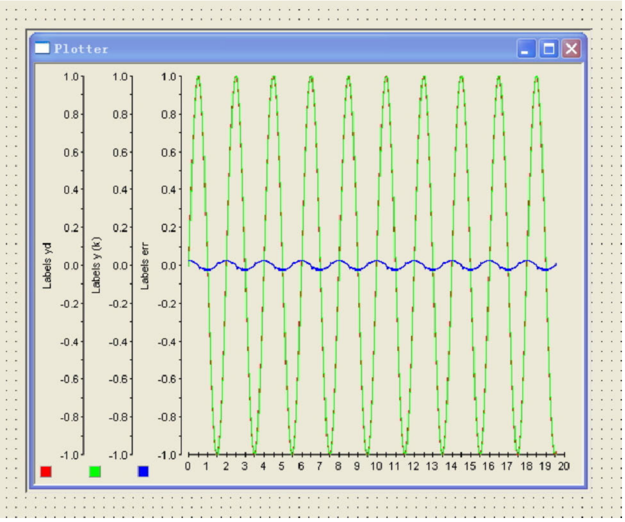

FIGURE 17. PID position tracking with frequency 0.5Hz.

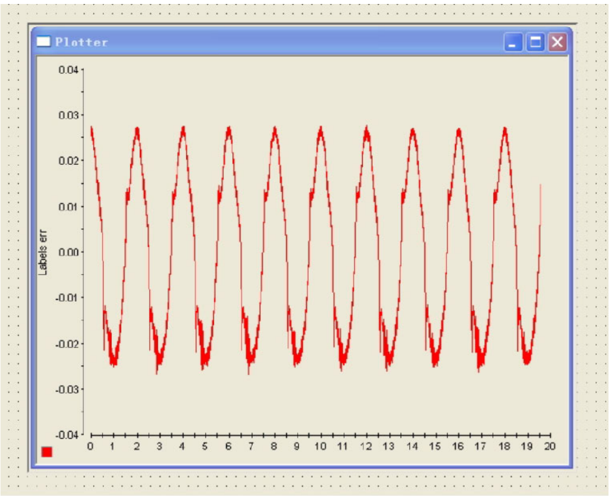

FIGURE 18. PID position error with frequency 0.5Hz.

Comparisons between the experimental results of CFDL-MFAILC and PID are shown in Table 2.

The same conditions, accelerating the frequency, the position error will also increase slightly.

Choosing different frequencies, reflecting the different speed of voice coil linear motor, the maximum iteration time is 80 in the CFDL-MFAILC, the iteration time is increases, errors remain unchanged at difference frequency. In the feed system of noncircular turning, the error of the CFDL-MFAILC scheme is less than that of PID algorithm when linear motor operates at different frequencies,

TABLE 2. Comparison between MFAILC and PID.

Iteration Times	Frequency	CFDL-MFAILC	PID
80	0.1	$\pm 4\mu m$	$\pm 10\mu m$
80	0.2	$\pm 7\mu m$	$\pm 15\mu m$
80	0.3	$\pm 9\mu m$	$\pm 19\mu m$
80	0.3	$\pm 12\mu m$	$\pm 23\mu m$
80	0.3	$\pm 16\mu m$	$\pm 28\mu m$

Moreover, with the frequency increase, the PID position error increases rapidly, and that of the CFDL-MFAILC increases relatively slowly. The only adjustment parameter λ ensures the convenience of parameter adjustment. The experimental results verify the feasibility and superiority of the CFDL-MFAILC scheme.

VI. CONCLUSION

In this paper, the MFAILC scheme is proposed to solve the problem that the non-circular turning feed system does not have the ability of self-learning and high control accuracy. The conclusions are summarized as follows:

1) The MFAILC controller is designed for precise control of non-circular turning feed system. The FFDL-MFAILC scheme is proposed, the theories are discussed, it is complement and improvement to CFDL-MFAILC.
2) The simulation results of the four methods are compared, it is verified that the MFAILC method proposed in the paper can achieve high-precision control of non-circular turning feed system.
3) The CFDL-MFAILC scheme and PID algorithms are experimented in dSPACE system. The non-circular turning feed system is debugged with different frequencies (different speeds), the experimental results verify the feasibility and superiority of the CFDL-MFAILC scheme.
4) The simulation and experiment results validate the theoretical analysis of the second part in the paper. The MFAILC scheme is suitable for the unknown nonlinear control problem with repetitive operation, and can ensure the monotonic convergence of the system output error along the iteration axis. Therefore, the MFAILC scheme is suitable for non-circular turning tool feed system control. It has the ability of self-learning to improve the position steady-state error, and has a good control effect.

In addition, if the feed system of DSP is built directly, the designed scheme in this paper is used to control the voice coil linear motor, which will greatly eliminate the difference between the physical experiment and the simulation results.

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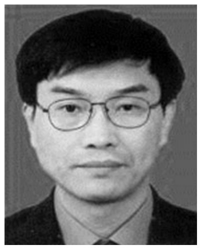

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