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Abstract—Cogging effect is a serious disadvantage of the permanent magnetic synchronous motor (PMSM), and cogging force is a position-dependent periodic disturbance. In our previous work [1], a dual high-order periodic adaptive learning compensation (DHO-PALC) method for state-dependent periodic disturbance was presented, where the long term stability issue was not addressed. The simulation in [1] were performed on authentic complex PMSM position servo system, but the system model which is used in the theory analysis is an approximated model, where many extra parasitic dynamics which have very low amplitude in frequency response and give negligible contribution to the typical system behavior have been neglected, and the neglected dynamics may exist in the real system. So, when the DHO-PALC is performed on the simulation system, the large components of the initial tracking errors at low frequencies decay fast, while the high frequency components start very small but eventually grow dominant [17]. Therefore, when we perform the system with DHO-PALC for a long time, we may observe that the tracking errors decrease quickly in the beginning, and can achieve a basically stable stage for a period of time, then the errors start to grow, the system may become even unstable eventually. This phenomenon also appears in many other practical motion control systems using ILC or RC strategies.

In this paper, in order to achieve long term stability, we propose a new dual high-order dynamic periodic adaptive learning compensation (DHO-D-PALC) method for cogging effect in PMSM position servo system. In this method, stored information of more than one previous periods are included for both the composite tracking error and the estimate of cogging force. Particularly, since we use a dynamic learning control law to update the current estimate of cogging, the long term stability can be guaranteed.

Extensive simulation results are included to demonstration, 1) high-order in composite tracking error offers faster convergence, 2) high-order in cogging estimate better accommodates the case of varying reference signal, 3) dual high-order scheme has the potential of much better performance over the conventional first-order scheme, 4) the introduction of dynamic learning updating scheme helps achieving the long term stability of the adaptive learning controller.

Index Terms—State-dependent disturbance, adaptive control, dual-high-order periodic adaptive learning control, dynamic learning compensation, PMSM motor.

I. INTRODUCTION

Due to the features of super power density, high torque to current ratio, fast response and better accuracy, and high frequency and low noise, permanent magnet synchronous motors (PMSM) are becoming attractive in many fields [2] [3] [4]. However, as a serious disadvantage of PMSM, the cogging effect degrades the servo control performance of application, much degradation takes place in a low-speed range. There are many lectures to introduce the cogging effect compensation techniques [5] [6] [7] [8]. As the cogging force is considered as a position-dependent disturbance that is periodic [9], so an effective approach catering to this problem is the learning control method [10] [11] [12] [13] [14] [15].

In our previous work [16], a simple high-order periodic adaptive learning compensation method was proposed for cogging effect in PMSM position servo system. In this method, we used only the stored tracking errors of more than one previous periods to update the current adaptive learning law.

In [1], a dual high-order periodic adaptive learning compensation (DHO-PALC) method for state-dependent periodic disturbance was presented, where, stored information of more than one previous periods are included for both of the composite tracking error and the estimate of cogging force. Experimental results are presented to illustrate the effectiveness of the proposed DHO-PALC scheme over the first order periodic adaptive learning compensation (FO-PALC). However, in [1], the long term stability

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respectively; \( R \) is the stator resistance; \( L_d \) and \( L_q \) are the stator self-inductances in the \( d \) and \( q \) axes, respectively, it has been assumed that as the surface mounted PMSM is non-salient, \( L_d \) and \( L_q \) are the same denoted by \( L \).

An authentic simulation model of PMSM position servo system is used in our simulation study in this paper and the details can be found in [15].

**B. Analysis of Cogging Effect**

Cogging force is produced by the magnetic attraction between the rotor mounted permanent magnets and the stator [15]. It is the circumferential component of attractive force that attempts to maintain the alignment between the stator teeth and the permanent magnets. The cogging force spectrum depends only on the geometry and number of the stator slots. Cogging force harmonics appear at frequencies that are multiple of the \( N_{slot-pp} f_s \), where \( N_{slot-pp} \) is the number of slots per pole pair and \( f_s \) is the electrical frequency of the rotor. Analytical modeling of the cogging force is changing since its production mechanism involves complex field distribution around stator slots [19].

By using the concept of field oriented control of the PMSM, the \( d \)-axis current is controlled to zero to maximize the output torque. Under this assumption, \( T_m \) is the motor electromagnetic torque, in the general case, is given by the following

\[
T_m = K_t i_{ds} = \frac{3}{2} P \psi_{ds} i_q, \quad (4)
\]

where \( K_t \) is the actual torque coefficient and \( P \) is the number of poles in the motor. However, in practice the motor torque can be expressed as

\[
T_m = \frac{3}{2} P \psi_{ds} i_q + F_{cogging}, \quad (5)
\]

where \( F_{cogging} \) is the periodic torques due to cogging. In this paper, we also consider the cogging force as the general multi-harmonic form as considered in [15]

\[
F_{cogging} = \sum_{i=1}^{\infty} A_i \sin(\omega_i t + \phi_i), \quad (6)
\]

where \( A_i \) is the amplitude, \( \omega_i \) is the state-dependent cogging force frequency, and \( \phi_i \) is the phase angle. In order to compensate the cogging force of general signal shape, it is suggested to make use of the periodicity of the position-dependent cogging disturbance.

**III. Dual-High-Order Dynamic Periodic Adaptive Learning Compensation for Cogging Effect**

In this section, a high order state-dependent periodic adaptive learning compensator for cogging is designed. The cogging force of \( (6) \) can be written as: \(-a(\theta)\), where \( a(\theta) \) is the function of \( \theta \). In this paper, to present our ideas clearly, without loss of generality. The motion control system is modeled as follows

\[
\dot{\theta}(t) = v(t), \quad (7)
\]

\[
\dot{v}(t) = u - \frac{a(\theta)}{J} - T_{11} - B_1 v, \quad (8)
\]

\[
u = \frac{1}{J} T_m, T_{11} = \frac{1}{J} T_1, B_1 = \frac{B}{J}
\]

where \( \theta \) is the periodic rotor angle position; \( v \) is the velocity; \( u \) is the control input and \( a(\theta) \) is the unknown position-dependent cogging disturbance which is repeating in every pole-pitch, at the same time \( a(\theta) \) should be bounded as

\[
|a(\theta)| \leq b_0. \quad (9)
\]

First, before proceeding our main results, the following definitions are necessary which are adapted from [10] for self-containing purpose.

**Definition 3.1**: The total passed trajectory is given as:

\[
s(t) = \int_0^t \frac{\text{d}\theta}{\text{d}t} \text{d}t = \int_0^t v(\tau) \text{d}\tau,
\]

where \( \theta \) is the angle position, and \( v \) is the velocity. Physically, \( s(t) \) is the total passed trajectory, hence it has the following property:

\[
s(t_1) \geq s(t_2), \quad \text{if} \quad t_1 \geq t_2.
\]

With notation \( s(t) \), the position corresponding to \( s(t) \) is denoted as \( \theta(s(t)) \) and the cogging force corresponding to \( s(t) \) is denoted as \( a(s(t)) \). In our definition, since \( s(t) \) is the summation of absolute position increasing along the time axis, just like \( t \), \( s(t) \) is a monotonous growing signal, so we have

\[
a(\theta(s)) = a(s(t)) = a(t).
\]

**Definition 3.2**: Since cogging force is periodic with respect to position, so, based on Definition 3.1, the following relationship is derived:

\[
\theta(s(t)) = \theta(s(t) - s_p), \quad a(s(t)) = a(s(t) - s_p).
\]

where \( s_p \) is the periodicity of the trajectory.

**Definition 3.3**: In Definition 3.2, \( s_p \) was defined as the period of the periodic trajectory. So, \( s(t) - s_p \) is one past trajectory point from \( s(t) \) on the \( s \)-axis. Fig. 1 shows the trajectory and time diagram. Let us denote the time corresponding to \( s(t) - s_p \) as \( t_{k-1} \). Then, \( t - t_{k-1} := P_k \) is the time-ellipse to complete one periodic trajectory from the time \( t_{k-1} \) to time \( t \). This time-ellipse is called "cycle". \( k \) is the integral part of the quotient \( s/s_p \), and we denote \( P_k = t - \sum_{j=1}^{k} P_j \). When considering \( n \) passed cycles from the current time \( t \), let us denote the time at the "\( (k-1) \)-th past trajectory cycle" as \( t_{k-n} \) and denote \( P_k \) the time-ellipse to complete the first past cycle. So, \( t_{k-n} = t - \sum_{j=0}^{k-1} P_j \). We can use the so-called "search process" to find \( P_k \) at time instant \( t \) by interpolating the stored data array in the memory as in [10]. Note \( P_k \) is depended on \( t \), so in fact it should be \( P_k(t) \).
The adaptation law is designed as follows:

\[ \hat{a}(t) + \dot{a}(t) = A(t) + \frac{K}{J} S(t) \quad \text{if} \quad s \geq s_p, \]
\[ \hat{a}(t) = -\mu v \quad \text{if} \quad s < s_p, \]

with

\[ A(t) := \sum_{i=1}^{N} h_i \hat{a}_i(t), \quad S(t) := \sum_{i=1}^{N} \beta_i m_i(t), \]

where

\[ \hat{a}_i(t) = \hat{a}(t - j \cdot P_{k+1-j}), \quad \sum_{i=1}^{N} h_i = 1, \]
\[ m_i(t) = m(t - j \cdot P_{k+1-j}), \quad (i = 1, 2, ..., N) \]

\( P_k \) is the trajectory cycle defined in Definition 3.2, \( P_1 \) is the first trajectory cycle, \( K \) is a positive design parameter (it is called the periodic adaptation gain); \( \mu \) is also a positive parameter; \( h_i \) are the coefficients of high order estimation values; and \( \beta_i \) are the coefficients of high order feedback errors, which are chosen to be the bounded and their upper bound denoted by \( b_3 \) is defined as below

\[ b_3 = \max_{1 \leq k \leq N} |\beta_k|; \]

In our analysis part, the following tuning mechanism is required for \( z \):

\[ \dot{z} = \mu [\dot{v}_d(t) + \alpha m(t) + \gamma v_e(t)] - \frac{c_v(t)}{J}. \]

**Remark 3.1:** In (14), our adaptation law tends to be the format below without dynamics as \( v \to 0 \).

\[ \hat{a}(t) = A(t) + \frac{K}{J} S(t) \quad \text{if} \quad s \geq s_p, \]
\[ \hat{a}(t) = -\mu v \quad \text{if} \quad s < s_p. \]

Assume the control system (7) with the control law (12) and the dual-high-order dynamic PALC (14) is asymptotically stable, then the same control system with the control law (12) and DHO-PALC without dynamic (18) should also be asymptotically stable.

Now, based on the above discussions, the following stability analysis of the proposed DHO-D-PALC scheme is performed. Our \( N \)-th order periodic adaptive learning compensation approach is summarized as follows:

- When \( s(t) < s_p \), the system is controlled to be bounded input bounded output.
- When \( s(t) \geq s_p \), the system is stabilized to follow the desired speed at the desired position. By trajectory periodic adaptation, the unknown the cogging is estimated.

Consider two cases: 1) when \( 0 \leq t < P_p \) (\( 0 \leq s < s_p \)) and 2) when \( t \geq P_p \) (\( s \geq s_p \)). The key idea is that, for case 1), it is required to show the finite time boundedness of equilibrium points; for case 2), it is necessary to show the asymptotic stability of equilibrium points.

First, let us consider the case 1) when \( t < P_p \) (\( s < s_p \)).

**Proof:** The proof of this theorem can be completed by base on the proof of Theorem 3.1 of [1]. Due to a page limitation we omit the proof.

Remark 3.2: Using same property of state-periodic disturbance, it can be said that if \( e_a(t) \to 0 \) as \( t \to \infty \), then \( e_a(s) \to 0 \) as \( s \to \infty \). Thus, in what follows, the stability analysis of \( \tilde{a}(\theta) \) is performed on the time axis.

**Theorem 3.1:** [1] If \( \alpha + \beta > \frac{\sqrt{J(h_0 + a_{B1})^2}}{4\rho} - B1 \), the equilibrium points of \( e_a, e_v, \) and \( e_a \) are bounded, when \( t < P_p \) (\( s < s_p \)).
TABLE I
PMSM SPECIFICATIONS

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
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</thead>
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<tr>
<td>Rated power</td>
<td>1.64 Kw</td>
</tr>
<tr>
<td>Rated speed</td>
<td>2000 rpm</td>
</tr>
<tr>
<td>Rated torque</td>
<td>8 Nm</td>
</tr>
<tr>
<td>Stator resistance</td>
<td>4.125 Ω</td>
</tr>
<tr>
<td>Stator inductance</td>
<td>11.6 mH</td>
</tr>
<tr>
<td>Magnet flux</td>
<td>0.387 T</td>
</tr>
<tr>
<td>Number of poles</td>
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<tr>
<td>Moment of Inertia</td>
<td>0.00289 kgm²</td>
</tr>
<tr>
<td>Friction coefficient</td>
<td>0.0003 Nm/s</td>
</tr>
</tbody>
</table>

A. Case-1: High-order PALC performance comparison

From Remark 3.1, as $\nu \rightarrow 0$ in (14), the control system (7) using DHO-PALC without dynamic learning law should also be asymptotically stable in theory as in [1]. So firstly, we use the high-order PALC without dynamic learning law to compare the performance with first-order PALC in the PMSM position servo system.

For this case simulation test, the control gains in (12) were selected as: $\alpha = 50$, $\gamma = 20$, $\mu = 5$ and $K = 0.2$, and the following reference trajectory and velocity signals are used:

\[
\begin{align*}
\hat{s}_d(t) &= 5t \text{ (rad)}, \\
\hat{v}_d(t) &= 5 \text{ (rad/s)}. \\
\end{align*}
\]

1) First order PALC (FO-PALC): First, we use the first order PALC, the adaptation law (14) is presented as:

\[
\hat{a}(t) = \begin{cases} 
\hat{a}_1(t) + \frac{K}{2} m_1(t) & \text{if } s \geq s_p \\
\hat{a}_2(t) + \frac{K}{2} m_1(t) & \text{if } s < s_p 
\end{cases}
\]

Figures 4(a) and 4(b) show the position/speed tracking errors with compensation of using the FO-PALC. We can observe that, as time increases, the position/speed tracking errors become smaller and smaller. The FO-PALC works efficiently comparing with the tracking errors without compensation in Figures 3(a) and 3(b).

2) Second order of the composite tracking error S PALC (S-SO-PALC): Second, we only use the second order of the composite tracking error $S$ to test the HO-PALC. At the same time, in order to compare with the FO-PALC fairly, we design $\beta_1 = \beta_2 = 0.5$, so the adaptation law (14) is presented as:

\[
\hat{a}(t) = \begin{cases} 
A(t) + \frac{K}{2} S(t) & \text{if } s \geq s_p \\
\hat{a}_2(t) + \frac{K}{2} S(t) & \text{if } s < s_p 
\end{cases}
\]

with

\[A(t) = \hat{a}_1(t), \]
\[S(t) = 0.5 m_1(t) + 0.5 m_1(t).\]

Figures 5(a) and 5(b) show the positive/speed tracking errors with the S-SO-PALC. Comparing with Figures 4(a) and 4(b), the position/speed tracking errors convergence speed using the S-SO-PALC is faster than that using the FO-PALC. In order to illustrate the comparison more clearly, Figures 11(a) and 11(b) are presented, the red lines represent the root mean squares (RMS) of position/speed tracking errors using the FO-PALC, and the blue lines are for the RMS of position/speed tracking errors using the S-SO-PALC. It is obvious that using the S-SO-PALC method makes the system obtain a faster convergence speed than using the FO-PALC method.

3) Second order of the estimate of $A$ for cogging PALC (A-SO-PALC): Third, we only use the second order of the estimate of $A$ for cogging to test the HO-PALC. The weighting coefficients are designed as, $h_1 = 1.5$, $h_2 = -0.5$, so the adaptation law (14) is presented as:

\[
\hat{a}(t) = \begin{cases} 
A(t) + \frac{K}{2} S(t) & \text{if } s \geq s_p \\
\hat{a}_2(t) + \frac{K}{2} S(t) & \text{if } s < s_p 
\end{cases}
\]

with

\[A(t) = 1.5 \hat{a}_1(t) - 0.5 \hat{a}_2(t), \]
\[S(t) = m_1(t).\]

Figures 6(a) and 6(b) show the positive/speed tracking errors using the A-SO-PALC. Comparing with Figures 4(a) and 4(b), the position/speed tracking errors convergence speed using the A-SO-PALC is also faster than that using the FO-PALC. From the RMS illustrated Figures 12(a) and 12(b), it is also obvious that using the A-SO-PALC method makes the system obtain a faster convergence speed than using the FO-PALC method.

We also use the A-SO-PALC to test the high-order PALC performance with varying reference over the first-order PALC. For this test, the following varying reference trajectory and velocity

A. Case-2: Varying reference over the first-order PALC

Performance with first-order PALC in the PMSM position servo

For this case simulation test, we choose the reference trajectory and velocity signals are used:

\[
\alpha = 50, \gamma = 20, \mu = 5, K = 0.2.
\]

The FO-PALC works efficiently comparing with the tracking errors without compensation in Figures 3(a) and 3(b).

The FO-PALC works efficiently comparing with the tracking errors without compensation in Figures 3(a) and 3(b).
(b) Velocity

Fig. 8. Varying reference tracking errors without compensation.

(b) Velocity

Fig. 9. Varying reference tracking errors with compensation using FO-PALC.

\[
s_d(t) = \int_0^t v_d(\tau) d\tau,
\]

\[
v_d(t) = \begin{cases} 
2 \text{ (rad/s)} & \text{if } j s_p \leq s < (j + 1) s_p \\
4 \text{ (rad/s)} & \text{if } (j + 1) s_p \leq s < (j + 2) s_p
\end{cases}
\]

where \( j = 0, 2, 4, \ldots \).

when we use the first order PALC, the adaptation law (14) is presented as:

\[
\hat{\alpha}(t) = \begin{cases} 
\hat{\alpha}_1(t) + \frac{K}{s} m_1(t) & \text{if } s \geq s_p \\
\frac{z - \mu v}{s} & \text{if } s < s_p
\end{cases} \quad (24)
\]

Figures 9(a) and 9(b) show the position/speed tracking errors with compensation using FO-PALC. We can observe that, the FO-PALC works comparing with the tracking errors without compensation in Figures 8(a) and 8(b), but the compensation residual is not satisfactory.

Then, we use the A-SO-PALC, choosing \( h_1 = 0 \) and \( h_2 = 1 \), so the adaptation law (14) is presented as:

\[
\hat{\alpha}(t) = \begin{cases} 
\hat{\alpha}_2(t) + \frac{K}{s} m_1(t) & \text{if } s \geq s_p \\
\frac{z - \mu v}{s} & \text{if } s < s_p
\end{cases} \quad (25)
\]

Figures 10(a) and 10(b) show the positive/speed tracking errors with using A-SO-PALC. Comparing with figures 9(a) and 9(b), we can clearly see that the performance of using A-SO-PALC is much better than that of using FO-PALC with alternatively varying reference.

4) Dual second order PALC (DSO-PALC): Finally, the dual second order information of the composite tracking error \( S \) and the estimate of \( A \) for cogging are used to test the HO-PALC performance. We design the weighting coefficients \( \hat{\beta}_1 = \hat{\beta}_2 = 0.5 \), \( h_1 = 1.5 \) and \( h_2 = -0.5 \), then the adaptation law (14) is presented as:

\[
\hat{\alpha}(t) = \begin{cases} 
A(t) + \frac{K}{s} S(t) & \text{if } s \geq s_p \\
\frac{z - \mu v}{s} & \text{if } s < s_p
\end{cases} \quad (26)
\]

with

\[
A(t) = 1.5\hat{\alpha}_1(t) - 0.5\hat{\alpha}_2(t),
\]

\[
S(t) = 0.5m_1(t) + 0.5m_2(t).
\]

Figures 7(a) and 7(b) show the positive/speed tracking errors using the SA-SO-PALC. Comparing with Figures 4, 5 and 6, the position/speed tracking errors convergence speed using the DSO-PALC is the fastest. Figures 13(a) and 13(b) can give a clearer comparison between the four different types of PALC, the black lines represent RMS of position/speed tracking errors of FO-PALC, and the blue lines are for the RMS of position/speed tracking errors of S-SO-PALC. It is obvious that using the DSO-PALC method makes the system obtain the fastest tracking errors convergence speed.

Fig. 10. Varying reference tracking errors with compensation using A-SO-PALC.

Fig. 11. Tracking errors RMS comparison between the FO-PALC and S-SO-PALC; the red lines represent the RMS of position/speed tracking errors of FO-PALC, and the blue lines are for the RMS of position/speed tracking errors of S-SO-PALC.

Fig. 12. Tracking errors RMS comparison between the FO-PALC and A-SO-PALC; the red lines represent the RMS of position/speed tracking errors of FO-PALC, and the blue lines are for the RMS of position/speed tracking errors of A-SO-PALC.

Fig. 13. Tracking errors RMS comparison between the four types of PALC; the red, green, blue and black lines represent the RMS of position/speed tracking errors of FO-PALC, S-SO-PALC, A-SO-PALC and DSO-PALC respectively.

B. Case-2: Long term stability comparison

For this case simulation test, the control gains in (12) were selected as: \( \alpha = 50 \), \( \gamma = 10 \) and \( \mu = 2 \), the following reference trajectory and velocity signals are also used:

\[
s_d(t) = 5t \text{ (rad)},
\]

\[
v_d(t) = 5 \text{ (rad/s)}.
\]
1) **DHO-PALC**: First, the dual high-order PALC without dynamic learning law was tested for the long term stability. We design the weighting coefficients $\beta_1 = \beta_2 = 0.5$, $h_1 = 1.2$, $h_2 = -0.2$ and $K = 0.2$. Setting $\nu = 0$, the adaptation law (14) is presented as:

$$\dot{\hat{a}}(t) = \begin{cases} A(t) + \frac{K}{J} S(t) & \text{if } s \geq s_p \\ z - \nu \hat{v} & \text{if } s < s_p \end{cases}$$

with

$$A(t) = 1.2\hat{a}_1(t) - 0.2\hat{a}_2(t),$$

$$S(t) = 0.5m_1(t) + 0.5m_2(t).$$

From Figures 14(a) and 14(b), when the experiment last for 400s, at the beginning of 70s, the position/speed tracking error decrease fast and achieve a basically stable stage for about 100s, but after 200s point, we can observe that the position/speed tracking errors grow and become bigger and bigger, finally, the system even tends to be unstable. Furthermore, in the course of experiment, we also observed that, when the periodic adaptation gain $K$ was changed bigger, the tracking error grew faster correspondingly.

2) **DHO-D-PALC**: Now, we use the dual high-order PALC with the dynamics learning updating law, namely, the DHO-PALC, to test the long term stability of the system. We design the weighting coefficients $\nu = 0.004$, $\beta_1 = \beta_2 = 0.5$, $h_1 = 1.2$, $h_2 = -0.2$ and $K = 0.8$, then the adaptation law (14) is presented as:

$$\dot{\hat{a}}(t) + 0.004\dot{\hat{a}}(t) = A(t) + \frac{K}{J} S(t)$$

$$\dot{\hat{a}}(t) = z - \nu \hat{v},$$

with

$$A(t) = 1.2\hat{a}_1(t) - 0.2\hat{a}_2(t),$$

$$S(t) = 0.5m_1(t) + 0.5m_2(t).$$

Figures 15(a) and 15(b) show that the proposed DHO-D-PALC for state-dependent period disturbance guarantees the long term stability of the system, we can observe that, when the experiment last for a long time, the tracking errors sustain without increasing after 200s point, the system can persist in stable for long term.

![Position](image1.png) ![Velocity](image2.png)

Fig. 14. Tracking errors with compensation using DHO-PALC.

![Position](image3.png) ![Velocity](image4.png)

Fig. 15. Tracking errors with compensation using DHO-D-PALC.

**V. CONCLUDING REMARKS**

In this paper, a new high-order cogging effect compensation method with dynamic learning updating law is proposed for a PMSM position and velocity control system to ensure the long term stability. Both stability analysis and simulation illustrations are presented. From the extensive simulation results, the following have been illustrated: 1) high-order in composite tracking error offers faster convergence, 2) high-order in cogging estimate better accommodates the case of varying reference signal, 3) dual high-order scheme has the potential of much better performance over the conventional first-order scheme, 4) the introduction of dynamic learning updating scheme helps achieving the long term stability of the adaptive learning controller.

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