RBF Neural Network Based Correction Iterative Learning Control for Direct-drive Pump-controlled Clutch Actuator

Jieyu Wang¹, Bingzhao Gao¹ and Hong Chen²,

¹ State Key of Automotive Simulation and Control, Jilin University, Changchun, Jilin, 130000, China
² Clean Energy Automotive Engineering Center, Tongji University, Shanghai, 201804, China

Abstract. This paper mainly focuses on the motion control of a novel direct-drive pump-controlled clutch-actuator system. The RBF neural network and iterative learning control method are combined to perform fast and accurate position tracking for dynamic nonlinear systems with high uncertainty. And the simulink and AMEsim co-simulation is carried out under different conditions. The simulation results confirm that the proposed RBF neural network based correction ILC controller has sufficient practicability and is suitable for the direct-drive pump-controlled actuator motion control conditions.

1. Introduction

Electro-hydraulic actuators are widely used due to the advantages of large capacity, fast response and space-saving arrangement [1]. And the actuator control strategy affects the performance of the clutch and the ride comfort of the vehicle [2]. Because of some uncertainties and nonlinearities, such as time-varying leakage, friction and load force, it is a difficult task to model nonlinear effects explicitly [3].

Iterative learning control (ILC) can generates excellent control effect through practice in the iteration domain, which is highly robust to system [4]. Many PID type ILC schemes are used on deterministic nonlinear systems to effectively control the system to track the given trajectory [5]. ILC essentially achieves ideal control effects by storing and memorizing dynamic errors over multiple iterations [6]. For real clutch actuator, the controller is required to be able to deal with model inaccuracy or model change between iterations. So a controller with the ability to approximate nonlinear systems over a cycle used in combination with the ILC is the best approach to improve tracking accuracy and learning ability [7]. Radial basis function neural network (RBF NN) has been successfully applied to complex time-varying uncertain nonlinear plants [8]. For example, adaptive neural control is formed for strict-feedback stochastic nonlinear system and for unknown dead zones of nonlinear systems [9].

This paper is related to the motion control of a novel direct-drive pump-controlled clutch actuator. The actuator system eliminates control valves, and dc motor and pump are directly connected to provide hydraulic pressure that drives the clutch to disengagement or engagement [10]. In order to generate the desired control effect, RBF NN based correction ILC controller is proposed for the plants. The rest of this paper is organized as follows: In section 2, the novel actuator structure is expressed and the physical model is described in detail. Section 3 proposes the RBF NN based correction ILC
controller. In section 4, some simulations under various controllers are reported and analysed. And, section 5 presents conclusions about this paper and provides suggestions for future work.

2. Actuator system modeling

The direct-drive pump-controlled clutch actuator system is shown in Figure 1. DC motor transmits the torque to the external gear pump to form the hydraulic pressure. The release bearing (hydraulic cylinder) is moved forward by the pressure and pushes the diaphragm spring, thus completing the disengagement of the clutch. As the motor rotates in the reverse direction, a vacuum is formed in the oil passage, and the diaphragm returns to its original position under the elastic force of the diaphragm spring.

![Figure 1. Schematic of direct-drive pump-controlled clutch actuator](image)

2.1. System modeling

2.1.1. DC motors. The brush DC motor driven by an H-bridge circuit can be described as

\[
L_a \dot{i}_a = V_{bat} u - I_a R_a - k_v \omega
\]

(1)

\[
T_m = k_v I_a - c_m \omega - J_m \dot{\omega}
\]

(2)

where \(L_a\) is the armature inductance, \(I_a\) is the armature current, \(V_{bat}\) is the battery voltage, \(u\) is the PWM duty ratio, \(R_a\) is the armature resistance, \(k_v\) is the back electromotive force coefficient, \(T_m\) is the torque, \(c_m\) is the motor rotation damping coefficient, \(k_t\) is the torque coefficient, and \(J_m\) is the inertia.

2.1.2. External gear pump. The motor and the external gear pump are directly connected. The rotation of the motor affects the flow of hydraulic oil between the hydraulic cylinder and the tank. The instantaneous pressure change of the pump and output torque can be obtained as follows:

\[
\dot{p}_p = \frac{\beta}{V_t} (V_{th} \omega \eta_{vol} - Q_{clt} - Q_{leak})
\]

(3)

\[
T_a = T_m = \frac{T_{th}}{\eta_m} = \frac{T_{th} \omega}{\eta_m \omega} = \frac{\text{Power}}{\eta_m \omega} = \frac{V_{th} p_p \omega}{\eta_m \omega}
\]

(4)

where \(V_{th}\) is the theoretical pump displacement, \(\omega\) is the pump speed (equal to motor speed), \(p_p\) is the export pressure, \(\beta\) is the fluid bulk modulus, \(\eta_{vol}\) is the volumetric efficiency, \(Q_{clt}\) is the flow loss in the pipeline, \(Q_{leak}\) is the leakage flow at the port, \(\text{Power}\) is the pump power (equal to motor power), \(T_a\) is the actual output torque, \(T_{th}\) is the theoretical torque, \(\eta_m\) is the mechanical efficiency.

2.1.3. Driven component. The hydraulic pressure received by the release bearing is transmitted directly to the diaphragm spring. The model can be described as follows:
\[ m_{clt} \ddot{x}_{clt} = p_{clt} A_{clt} - F_{clt}(x_{clt}) - F_{damp}(\dot{x}_{clt}) \]  
where \( A_{clt} \) is the piston area of hydraulic cylinder, \( p_{clt} \) is the pressure difference, \( m_{clt} \) is the piston mass, and \( F_{clt} \) is load force of the diaphragm spring, \( F_{damp} \) is the combination of damping force and friction.

2.2. Model reduction

Based on the structural mentioned above, the dynamic model is reasonably simplified as follows:

- The influence of motor inductance can be ignored, since the value \( (L_a/R_a \approx 1.3 \times 10^{-6}) \) corresponding to the time constant is relatively small;
- the hydraulic flow is laminar flow, considering the consideration of the tube diameter size and hydraulic oil (DOT4) performance;
- the flow loss in the pipeline is zero, \( Q_{clt} = 0, p_{clt} = p_p \) (since the pipeline hydraulic pressure is 1.66 Mpa, and the maximum pressure loss along the path is: 1.18 \times 10^6 Mpa);
- the forces can be simplified near the secondary level to establish a linear system:

\[
F_{clt}(x_{clt}) = k_{clt} x_{clt}, \quad k = 1.8 \times 10^5 N/m
\]

\[
F_{damp}(\dot{x}_{clt}) = \sigma \cdot \dot{x}_{clt}, \quad \sigma = 60N/(m/s)
\]

Thus, we have the system dynamics of the actuator system

\[
K_2 \ddot{x}_{clt} + K_1 \dot{x}_{clt} + K_0 x_{clt} - K_u u = 0
\]

where

\[
K_2 = \frac{J_m A_{clt}}{V_{th} \eta_{vol} + V_{th} \omega \left( \frac{\partial \eta_{vol}}{\partial \omega} \right)} + \frac{V_{th} m_{clt}}{A_{clt} \eta_m}
\]

\[
K_1 = \frac{(k_v + R c_m) A_{clt}}{R_a V_{th} \eta_{vol}} + \frac{V_{th} \sigma}{A_{clt} \eta_m}
\]

\[
K_0 = \frac{V_{th} k_{clt}}{A_{clt} \eta_m}
\]

\[
K_u = \frac{k_v V_{bat}}{R_a}
\]

The parameters involved in the dynamic system are given in Table 1.

| Parameter                                              | Value(unit)     |
|--------------------------------------------------------|-----------------|
| Battery voltage \( (V_{bat}) \)                        | 12V             |
| Armature inductance \( (L_a) \)                        | 0.0003H         |
| Torque coefficient \( (k_t) \)                         | 0.0405 N/m/A    |
| Back electromotive force coefficient \( (k_v) \)       | 0.0405 V/(rad/s)|
| Resistance of the armature circuit \( (R_a) \)         | 0.2Ω            |
| Rotating damping coefficient of the motor \( (c_m) \)  | 0.001 N ms/rad  |
| Inertia \( (J_m) \)                                    | 0.0001 kg m^2   |
| Piston area of hydraulic cylinder \( (A_{clt}) \)       | 578.25 mm^2     |
| Piston mass \( (m_{clt}) \)                            | 0.312 kg        |
| Theoretical volumetric displacement \( (V_{th}) \)     | 0.8 ml/r        |

The time-varying nonlinear dynamic effects are reasonably simplified. The remnant tracking error incurred in each iteration period of the standard linear system should, thus, be considered. And an
adequate modeling tool for nonlinear functions should be used to solve the challenging control problem.

3. Controller design
The main work of this part is the design of RBF NN based correction ILC controller for the novel actuator, the control algorithm can be seen in Figure 2. The RBF NN model makes full use of the information of the real plant, which is stored in memory, and provides correction for the next cycle.

3.1. ILC controller scheme
ILC is a memory-based control scheme that needs to store the tracking errors and control efforts of previous iterations so that the present control can be constructed to achieve satisfactory performance. The PD-type learning function used in nonlinear systems can be written as

\[ u_{j+1}(i) = u_j(i) + k_p e_j(i+1) + k_d \left[ e_j(i+1) - e_j(i) \right] \]

where \( j \) denotes the number of iterations, \( i \) denotes the number of times in the time domain, \( i \in [0, M] \), \( M = t/ts \) (\( t \) is the run duration, \( ts \) is the sampling time). \( k_p \) and \( k_d \) are the proportional and derivative gain.

For the above actuator system, the discrete state equations are as follows:

\[
\begin{align*}
\dot{x}_j(i+1) &= A_j x_j(i) + B_j u_j(i) \\
y_j(i) &= C_d x_j(i)
\end{align*}
\]

The input, output and tracking error vectors have the following relationships in iteration \( j \):

\[
\begin{align*}
Y(j) &= \begin{bmatrix} y_j(1) & y_j(2) & \cdots & y_j(M) \end{bmatrix} \\
U(j) &= \begin{bmatrix} u_j(0) & u_j(1) & \cdots & u_j(M-1) \end{bmatrix} \\
E(j) &= \begin{bmatrix} y_d(j-1) - y_j(1) & \cdots & y_d(j-M) - y_j(M) \end{bmatrix}
\end{align*}
\]

Hence, Then, the tracking error for the next iteration is

\[ E(j+1) = H_e \cdot E(j) \]

where

\[
H_e = I - (k_p + k_d) H + k_d HF
\]

\[
F = \begin{bmatrix} 0 & 0 & \cdots & 0 \\
1 & 0 & \cdots & 0 \\
0 & 1 & \cdots & 0 \\
\vdots & \vdots & \ddots & \vdots \\
0 & 0 & \cdots & 1 \end{bmatrix}_{M+1}
\]

In order to converge the system, we need to choose appropriate selection of the gains \( k_p \) and \( k_d \) so that all eigenvalues of \( H_e \) lie into the unit circle. That is
\[
\left| 1 - C_d B_d (k_p + k_d) \right| < 1
\]  

(15)

3.2. RBF NN based correction

As shown in Figure 3, the RBF NN can correct for uncertain nonlinear disturbances in a cycle. The input of RBF NN is the control input \( u \) for each cycle. The output and neurons of the hidden layer \( h=[h_1, h_2, ..., h_m]^T \) are activated by Gaussian radial base function as:

\[
y_{RBF}(k) = h_1 w_1 + \cdots + h_j w_j + \cdots + h_m w_m
\]  

(16)

\[
h_j = \exp \left( -\frac{\|u_k - c_j\|^2}{2b^2} \right)
\]  

(17)

where \( j=1,2,\ldots,m \), \( m \) is the number of hidden layer; \( c_j \) and \( b \) are the central vector and the base width vector of the \( j^{th} \) neuron, \( c_j=[c_{1j},c_{2j},\ldots,c_{mj}] \), \( w_j \) is the weight vector, \( w_j=[w_{1j},w_{2j},\ldots,w_{mj}]^T \), the weights adaptation rule derived from the steepest descent method can be expressed as:

\[
\Delta w_j(k) = -\eta \frac{\partial E(k)}{\partial w_j} = \eta e_j(k) h_j
\]  

(18)

\[
w_j(k) = w_j(k-1) + \eta \Delta w_j(k) + \alpha (w_j(k-1) - w_j(k-2))
\]

where \( \eta \) is learning rate, \( \eta \in [0,1] \); \( \alpha \) is momentum factor, \( \alpha \in [0,1] \).

The criterion on function used performance index of the RBF NN correction can, thus, be defined as:

\[
E(k) = \frac{1}{2} \left[ y_{plan}(k) - y_{RBF}(k) \right]^2
\]  

(19)

4. Simulation result and analysis

In this section, the effectiveness of the controller is verified by Simulink and AMEsim co-simulation.

In order to cover more operating conditions of the clutch actuator, step signal (6mm) tracking and multi-step step (4mm 3.5mm 6mm) signal tracking are simulated, and the results are shown in Figure 4 and Figure 5 (In the figure, \( k \) represents the number of iterations). It can be seen that the steady-state tracking error of the proposed controller is close to 0mm after 6 iterations, which is much smaller than the PID (\( k=1 \)) error of 0.1mm. Specifically, the proposed controller has reduced the overshoot.
In addition, set the time-varying sinusoidal signal as a tracking reference to test the proposed controller's transient performance, as actual driving state conditions may change at any time. The sinusoidal response is shown in Figure 6. Obviously, the control effect is still very impressive, that is, the tracking error is within 0.03 mm. And the norm of the error under the sinusoidal signal response is shown in Table 2. The tracking error decreases rapidly with the number of iterations. So, the scheme is extremely critical for the combination of ILC and RBF to be applied to the novel clutch actuator.

![Figure 6. Schematic of direct-drive pump-controlled clutch actuator](image)

| Table 2. the norm of the error under the sinusoidal response |
|-----------------------------------------------------------|
| k=1 | k=2 | k=3 | k=4 | k=5 | k=6 |
|---|---|---|---|---|---|
| Norm | 246.605 | 100.355 | 75.328 | 63.193 | 57.339 | 54.673 |

5. Conclusion
This paper mainly focuses on the motion control problem of a novel direct-drive pump-controlled clutch actuator. The control challenge is caused by the fluid compressibility, friction and leakage. The RBF NN based correction ILC method is used to implement accurate position tracking for nonlinear systems. And it is solved by learning the dynamic characteristics through ILC and neural network. The Simulink and AMESim co-simulation results demonstrate that the proposed controller is enough sustainable and applicable for the actuator motion control conditions. In future research, the actuator should be controlled to operate under more complex driving conditions, which requires a more stable algorithm. Moreover, clutch wear and changes in hydraulic oil temperature will be discussed in details.

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