RBF Neural Network Adaptive Robust Sliding Mode Control Method of Artillery Ammunition Transfer Arm

Hangjun Cai¹, Longmiao Chen²

¹,²School of Mechanical Engineering, Nanjing University of Science and Technology, Nanjing, Jiangsu Province, 210094, China
caihangjun1106@163.com

Abstract - This paper presents a robust adaptive sliding mode control strategy using radial basis function (RBF) neural network for a kind of value controlled asymmetric cylinder electro-hydraulic servo system of an ammunition transfer arm in the presence of uncertain nonlinearity and parameter uncertainty. On the premise of setting the expected trajectory, using RBF neural networks to approximate unknown parameters, by setting appropriate neural network parameters and adaptive terms, the change trend of position parameter was estimated. The stability of close loop system is verified by the Lyapounov theory. Compared with the simulation results of PID control method and expected trajectory, RBF Neural Net sliding mode control method has smaller system tracking error, faster response and better tracking performance.

1. Introduction

Artillery Ammunition coordinator is a typical mechanical-electro-hydraulic system composed of transfer arm, hydraulic system and electrical control system. Transfer arm is a key component in the ammunition automatic feeding system[1], which means the ammunition transfer arm adjusts itself to transport the ammunition from the loading position to the alignment with the body axis. The ammunition feeding process, which requires high positioning accuracy and stable positioning without impact, is one of the main indicator to evaluate the automation level of an artillery.

The valve controlled cylinder electro-hydraulic servo system has high adaptability to applying the ammunition transfer arm for its strong driving force, high response speed and accuracy[2]. At the same time, the transfer arm electro-hydraulic servo system with a wide range of load changes and large external disturbances is a typical nonlinear system with a lot of uncertain parameters, including leakage and viscous friction coefficients. The traditional PID control algorithm is difficult to achieve satisfactory control effect. Under the background of electronic information automation, an effective and appropriate control algorithm is urgent needed to solve the operational performance requirements of the transfer arm.

Sliding mode control(SMC) is one of the effective methods to deal with model uncertainty[3-6]. In recent years, by combining other methods, a lot of novel algorithms are proposed, such as adaptive Fuzzy SMC[7], backstepping SMC[8] and neural network SMC[9]. On the basis of [10], the paper establishes a nonliner mathematical model by AMEsim/Simulink Co-Simulation for the ammunition transfer arm electro-hydraulic servo system, focuses on the design of a adaptive robust sliding mode control strategy using RBF neural network. RBF Neural network has the capability to approximate any nonlinear function over the compact input space. The information of the upper bound of the model uncertainties and external disturbances does not need be known in advance. A RBF neural network is used to adaptively learn the unknown upper bound of model uncertainties and external disturbances to eliminate the chattering of sliding mode effectively[11-12]. A key property of this scheme is that the
prior knowledge of the upper bound of the system uncertainties is not required but online estimated using RBF network. The control effect of the method is compared with PID control method in the same system to verify the superiority of the RBF neural network adaptive robust sliding mode control algorithm.

2. Dynamic Model
The schematic diagram of the ammunition transfer arm electro-hydraulic servo system is as shown in Figure 1. The transfer arm and the coordinating cylinder are connected with the frame body through rotating pair. Driven by the coordination cylinder, the transfer arm rotates downward and counterclockwise around point O and sends the angle signal to the controller through the angle encode, the Controller receives the angle signal $\theta$ and the expected trajectory from the Command, after calculation, sends input current signal $u$ to the servo valve. Then valve control cylinder piston movement to achieve the goal of coordination in the vertical direction.

![Figure 1. The schematic diagram of the ammunition transfer arm electro-hydraulic servo system](image)

As is shown in Figure 1 and make the following definition, the cylinder driving force is $F$, $OA = a$, $OB = b$, $OC = c$, $AB = y$, $\theta$ is the angle between OB and the initial position, $\angle COA = \alpha, \beta$ is the angle of OA relative to the X direction, the initial length of cylinder is $c$, $x_p$ is the displacement of the piston rod relative to the initial position. Then

$$y = y_0 + x_p$$

(1)

Establishing the kinetic balance equation of the arm according to Newton’s second law

$$mgc\cos\theta - Fb\sin\alpha = J\dot{\theta} + B\dot{\theta} + T_d$$

(2)

In the formula: $g$ is the acceleration of gravity, $J$ is the equivalent moment of inertia of the system, $J = mc^2$. $B$ is the equivalent viscous friction coefficient of the system. $T_d$ is the disturbing torque.

In the $\triangle AOB$, we can get the equations by the Sine and Cosine Law

$$\sin\alpha = \frac{a\sin(\theta + \beta)}{y}$$

(3)

$$y^2 = a^2 + b^2 + 2ab\cos(\alpha + \beta)$$

(4)
\[ \frac{dy}{d\theta} = ab\sin(\theta + \beta) \quad (5) \]

\[ \dot{x}_p = \frac{dy}{d\theta} \quad (6) \]

In the simulation model, it is assumed that the hydraulic cylinder is an ideal single-action hydraulic cylinder, the pressures in each working chambers are equal everywhere, and the temperature and the bulk modulus of elasticity of the hydraulic oil are constant, servo valve is an ideal three-way, four-position valve without leakage. As the following definitions, \( P_s \) is the constant supply pressure, \( P_r = 0 \) is the return pressure, \( Q_1 \) is the inlet flow rate and \( Q_2 \) is the outlet flow rate, then

\[
\begin{align*}
Q_1 &= K_{v}\in \left[ s(u)\sqrt{P_s - P} + s(-u)\sqrt{P - P_r} \right] \\
Q_2 &= K_{v}\in \left[ s(u)\sqrt{P_s - P} + s(-u)\sqrt{P - P_r} \right]
\end{align*}
\]

where \( x_v = K_a\in \) is servo valve opening, \( K_q = C_d w K_a \sqrt{2 \mu \rho} \) is flow rate coefficient, \( C_d \) is the discharge coefficient, \( K_a \) is gain of servo simplifier, \( \rho \) is the fluid density, \( w \) is the area gradient of the servo valve opening area, \( s(u) \) is defined as

\[
s(u) = \begin{cases} 
1 & u \geq 0 \\
0 & u < 0 
\end{cases}
\]

The equation of continuity of the hydraulic cylinder is

\[
\begin{align*}
Q_1 &= -(V_1 - A_1 x_p)\dot{P}_1 / \beta_c + A_1 \dot{x}_p \\
Q_2 &= (V_2 + A_2 x_p)\dot{P}_2 / \beta_c + A_2 \dot{x}_p
\end{align*}
\]

where \( V_1, V_2 \) are the initial effective volume of the two chambers of the hydraulic cylinder.

The Force balance equation of the hydraulic cylinder is

\[ P_1 A_1 - P_2 A_2 = F \quad (10) \]

Above all, the dynamical equation of the transfer arm can be shown as

\[
\begin{align*}
Q_1 &= -(V_1 - A_1 x_p)\dot{P}_1 / \beta_c + A_1 \dot{x}_p = K_d\mu \sqrt{\Delta P} \\
Q_2 &= (V_2 + A_2 x_p)\dot{P}_2 / \beta_c + A_2 \dot{x}_p = K_d\mu \sqrt{\Delta P_2} \\
\dot{\theta} &= \frac{1}{J} \left[ mg_c \cos \theta - \frac{F\sin(\theta + \beta)}{y} - B\dot{\theta} - T_d \right]
\end{align*}
\]

3. Controller Design

Establish second order nonlinear uncertain system as follows

\[
\begin{align*}
\dot{x}_1 &= x_2 \\
\dot{x}_2 &= f(x) + g(x)u + d(t)
\end{align*}
\]

3
where \( f(x) \) and \( g(x) \) is unknown nonlinear function. \( x_1 = \theta \), \( x_2 = \dot{\theta} \), \( d(t) \) is the total external disturbance to the system, \( |d(t)| \leq D \). \( D \) is the upper bound of the external disturbance.

Define the position command is \( \theta_d \) and the angle tracking error is defined as
\[
e = \theta_d - \theta
\]

(15)

Design SMC function is defined as
\[
s = \dot{e} + ce
\]

(16)

Substitute (2) into (3) and the derivative of \( s \) is
\[
\dot{s} = \ddot{e} + c\dot{e} = \dot{\theta}_d - f - gu - d(t) + c\dot{e}
\]

(17)

Selecting the appropriate SMC parameters \( c \) can improve the performance of the system when it is on the sliding mode surface, \( c > 0 \).

\[\text{Figure 2. The structure of RBF network}\]

In actual project, \( f(\bullet) \) and \( g(\bullet) \) are unknown model uncertainties, RBF neural network is used to adaptively approximate them. The algorithm of RBF neural network is
\[
h_j = \exp\left(-\frac{\|x - c_j\|^2}{2b_j^2}\right)
\]

(18)

\[
f(\bullet) = \mathbf{w}^T h_f(x) + e_f, g(\bullet) = \mathbf{v}^T h_g(x) + e_g
\]

(19)

where, \( x \) is input vector, \( j \) is the number of network hidden node, \( c_j \) is the \( j \)th center vector and \( b_j \) is \( j \)th standard deviation, \( h = \left[h_j\right]^T \) is Gaussian function, \( \mathbf{w}^* \) and \( \mathbf{v}^* \) are approximating ideal RBF network weight of \( f(\bullet) \) and \( g(\bullet) \), \( e_f \) and \( e_g \) are approximating error of network, \( |e_f| \leq e_{M_f} \), \( |e_g| \leq e_{M_g} \).

Define \( x = \begin{bmatrix} x_1 \ x_2 \end{bmatrix} \), and RBF network output is
\[
\hat{f}(x) = \hat{\mathbf{w}}^T h_f(x), \hat{g}(x) = \hat{\mathbf{v}}^T h_g(x)
\]

(20)

where, \( h_f(x) \) and \( h_g(x) \) are Gaussian function of RBF network.

The adaptive control law \( u \) is proposed as
\[
u = \frac{1}{\hat{g}(x)} \left[-\hat{f}(x) + \dot{\theta}_d + c\dot{e} + \eta \text{sgn}(s)\right]
\]

(21)
where $\eta \geq D$.

Substitute (8) into (4), yields the derivative of $s$

$$
\dot{s} = \ddot{\theta}_d - f - \hat{g}u + (\hat{g} - g)u - d(t)\delta + c\dot{e}
$$

$$
= \ddot{\theta}_d - f - \hat{g}\frac{1}{\hat{g}(x)}[-\hat{f}(x) + \ddot{\theta}_d + c\dot{e} + \eta \text{sgn}(s)] + (\hat{g} - g)u - d(t) + c\dot{e}
$$

$$
= (\hat{f} - f) - \eta \text{sgn}(s) + (\hat{g} - g)u - d(t)
$$

$$
= \hat{f} - \eta \text{sgn}(s) + \hat{g}u - d(t)
$$

$$
=W^T h_f(x) - \varepsilon_f - \eta \text{sgn}(s) + (\hat{V}^T h_g(x) - \varepsilon_g)u - d(t)
$$

Where $\hat{W} = W^* - \hat{W}$, $\hat{V} = V^* - \hat{V}$,

$$
\begin{aligned}
\hat{f} &= \hat{f} - f = \hat{W}^T h_f(x) - W^T h_f(x) - \varepsilon_f = \hat{W}^T h_f(x) - \varepsilon_f \\
\hat{g} &= \hat{g} - g = \hat{V}^T h_g(x) - V^T h_g(x) - \varepsilon_g = \hat{W}^T h_g(x) - \varepsilon_g
\end{aligned}
$$

To determine the stability of system, design a Lyapunov function

$$
L = \frac{1}{2} s^2 + \frac{1}{2\gamma_1} \hat{W}^T \hat{W} + \frac{1}{2\gamma_2} \hat{V}^T \hat{V}
$$

where $\gamma_1 > 0, \gamma_2 > 0$.

Consider the (9), the derivative of the Lyapunov function is

$$
\dot{L} = s\dot{s} + \frac{1}{2\gamma_1} \hat{W}^T \dot{\hat{W}} + \frac{1}{2\gamma_2} \hat{V}^T \dot{\hat{V}}
$$

$$
= s(\hat{W}^T h_f(x) - \varepsilon_f - \eta \text{sgn}(s) + (\hat{V}^T h_g(x) - \varepsilon_g)u - d(t))
$$

$$
- \frac{1}{\gamma_1} \hat{W}^T \dot{\hat{W}} - \frac{1}{\gamma_2} \hat{V}^T \dot{\hat{V}}
$$

$$
= \hat{W}^T \left( \frac{sh_f(x) - \dot{\hat{W}}}{\gamma_1} \right) + \hat{V}^T \left( \frac{sh_g(x)u - \dot{\hat{V}}}{\gamma_2} \right)
$$

Define the adaptive law as

$$
\dot{\hat{W}} = -\gamma_1 sh_f(x)
$$

$$
\dot{\hat{V}} = -\gamma_2 sh_g(x)u
$$

Then

$$
\dot{L} = s(\varepsilon_f - \eta \text{sgn}(s) - \varepsilon_g u - d(t))
$$

$$
= (\varepsilon_f - \varepsilon_g u - d(t))s - \eta |s|
$$

Because RBF network approximation errors $\varepsilon_f$ and $\varepsilon_g$ are very small real number, define

$$
\eta \geq |\varepsilon_f + \varepsilon_g u + d(t)|
$$

then $\dot{L} \leq 0$.

When $\dot{L} \equiv 0$, $s \equiv 0$, According to Lasalle invariant set principle, when $t \rightarrow \infty$, $s \rightarrow 0$, as well as the system has a progressive tracking performance.
4. The Co-simulation and results
AMEsim/Simulink Co-simulation can improve model efficiency and accuracy. Based on hydraulic schematic diagram, the paper establish the transfer arm electro-hydraulic co-simulation hydraulic system as is shown in Figure 3.

![Diagram of the transfer arm electro-hydraulic co-simulation hydraulic system](image)

According to design index, $\theta = -3^\circ \sim 70^\circ$ in the ammunition automatic feeding system. In order to be simple without losing generality, this paper adopts a trajectory planning algorithm-third-order S-curve trajectory for point-to-point motion to reach 60°.

The parameters of the electro-hydraulic servo system is shown in Table 1.

| Parameter | Value | Parameter | Value |
|-----------|-------|-----------|-------|
| m         | 128.316kg | g         | 9.8 m/s² |
| a         | 761.58mm  | $y_0$     | 920mm  |
| b         | 237.12mm  | $K_q$     | 1.4    |
| c         | 788.01mm  | $P_s$     | 160Bar |
| H         | 660mm     | $P_r$     | 0Pa    |
| L         | 380mm     | $\beta$   | 60.07° |
| $D_1$     | 45mm      | $\gamma_1$| 500    |
| $D_2$     | 32mm      | $\gamma_2$| 250    |

RBF neural network adaptive robust sliding mode control parameters are $c_j = [-0.5, -0.25, 0, 0.5, 0.25]$, $b_j = 4$, $c = 35$, $\eta = 1$, $\varepsilon_j = 0$, $\varepsilon_q = 0.01$, $\gamma_1 = 500$, $\gamma_2 = 250$. The PID control parameters are $K_p = 0.8$, $K_i = 0$, $K_d = 1$. The angle tracking trajectory is shown in Figure 4. The angle tracking error is shown in Figure 5.
Simulation results show that the response time of RBF neural network adaptive robust sliding model control is faster than PID control. Meanwhile, the maximum tracking error of ARSMC-RBF is smaller obviously than that of PID control. It demonstrates that the ARSMC-RBF controller, which can effectively counteract chattering and better fit the expected trajectory curve, have better tracking performance.

5. Conclusion
This paper presents an RBF neural network adaptive robust sliding mode control for high loading, uncertain nonlinearity and parameter uncertainty problems of the transfer arm electro-hydraulic servo system. RBF Neural network has the capability to approximate any nonlinear function over the compact input space and it can be used to approximate the unknown nonlinearity function in control low. The stability of the closed-loop system can be guaranteed with the proposed adaptive RBF sliding mode

control strategy. Through the comparison of PID control simulation results, the conclusion is that the system achieves a better tracking performance in general.

References
[1] Wang Xianfeng. (2018) Co-Simulation of Hydraulic System for a Certain Artillery Ammunition Coordinator. Machinery & Electronics., 36: 11-14.
[2] Liu, Song, and B. Yao. (2003) Indirect adaptive robust control of electro-hydraulic systems driven by single-rod hydraulic actuator. International Conference on Advanced Intelligent Mechatronics., 296-301.
[3] Chen Mou, Wu Qingxian, Cui Rongxin. (2013) Terminal Sliding Mode Tracking Control for a Class of SISO Uncertain Nonlinear Systems. ISA Transactions., 52: 198-206.
[4] Feng Yong, Yu Xinghui, Han Fengling. (2013) On Nonsingular Terminal Sliding-mode Control of Nonlinear Systems. Automatic., 49: 1715-1722.
[5] Yang Jun, Li Shihua, Yu Xinhuo. (2013) Sliding-Mode Control for Systems With Mismatched Uncertainties via a Disturbance Observer. IEEE Transaction on Industrial Electronics., 60(1):160-169.
[6] Anli Shang, Wenjin Guo. (2003) Model-following adaptive second-order sliding model control of a class of nonlinear uncertain systems. Proceedings of SPIE - The International Society for Optical Engineering., 5253: 814-817
[7] Shi Li, Choon Ki Ahn, Zhengrong Xiang. (2019) Adaptive fuzzy control of switched nonlinear time-varying delay systems with prescribed performance and unmodeled dynamics. Fuzzy Sets and Systems., 37:40-60
[8] Xi Leiping, Chen Zili, Qi Xiaohui. (2013) Adaptive Backstepping Sliding Mode Control for Robotic Manipulator with Nonlinear Disturbance Observe. Information and Control., 42:470-477.
[9] Juntao Fei, Hongfei Ding. (2012) Adaptive sliding mode control of dynamic system using RBF neural network. Nonlinear Dynamics., 70:1563-1573
[10] Liu, J.K (2015) Sliding Mode Control Design and MATLAB Simulation[Third Edition]The Basic Theory and Design Method. Tsinghua University Publishing, Beijing.
[11] Rui Tang, Zhong-Bo Wen. (2008) Research on RBF NN Tuning PD Control Arithmetic of Tele-presence Bilateral Servo System. In: World Congress on Intelligent Control and Automation. Chongqing.6459-6462
[12] Shujaat Khan, Imran Naseem, Rorto Togneri, Mohammed Bennamoun. (2017) A Novel Adaptive Kernel for the RBF Neural Networks. Circuits, Systems, and Signal Processing. 36: 1639–1653