Adaptive Neural Network Sliding Mode Control based on Particle Swarm Optimization for Rotary Steering Drilling Stabilized Platform

Yuantao Zhang, Taifu Li, Jun Yi

Abstract

This study focuses on the robust control of stabilized platform of rotary steering drilling system. Firstly, the uncertain and nonlinear mathematical model of stabilized platform is given by considering the outside interference, drilling technology and geometrical parameter perturbation of the borehole on stabilized platform under work condition. Then, an adaptive neural network sliding mode control strategy is introduced, which uses sliding mode control to guarantee system robustness, makes the uncertain upper bound adjust adaptively with RBF neural network to nonlinear approximate the upper bound of overall uncertainty, reduces chattering by quasi-sliding mode control method. Finally, particle swarm optimization algorithm is applied to search the optimal controller parameters, including adaptive parameter of neural network weight, boundary layer thickness and switching function coefficient. Simulation results demonstrate that the control strategy proposed can make stabilized platform get optimal control performance and robustness.

Keywords: Stabilized Platform, Rotary Steering Drilling System, Sliding Mode Control, Neural Network, Particle Swarm Optimization

1. Introduction

Drilling technology will directly affect the oil and gas recovery and efficiency. Rotary steering drilling technology can achieve accurate automatic control of well trajectory of horizontal well, extended reach well, branch well and other complex wells. It requires the stabilized platform of rotary steering drilling tool has rapid large angle attitude change, high control accuracy, good robustness and adaptability [1]. However, due to the influences of strong nonlinearity and time-variant parameters under bad working condition, stabilized platform is unable to obtain satisfactory static and dynamic performance, and robustness is also poor. With the development of nonlinear control and intelligent control technologies, many scholars begin to use these advanced control technologies to improve the control performance and robustness of stabilized platform [2, 3, 4, 5, 6, 7].

Sliding mode control (SMC) is the most commonly used nonlinear robust control strategy for uncertain system. Q.L. Cui, et al [6] designed a sliding mode controller using exponential reaching law and soft sign function law to reduce chattering, but the impact of uncertainties on the stabilized platform is not considered. A.Q. Huo, et al. [7] presented a fuzzy sliding mode controller to solve the uncertainty Striebeck friction problem of stabilized platform, which took adaptive fuzzy system to gradually approximate the equivalent control and switching term. SMC requires knowing the system uncertainty upper bound value, while the upper bound of the actual system generally cannot be measured. Therefore neural network can be used to reduce chattering by studying the uncertain upper bound adaptively. Z.L. Liu, et al [8] used some decentralized BP neural networks to approximate the uncertain upper bounds of a class of large scale nonlinear high-order interconnect subsystems, and SMC is applied to compensate for the approximation error. H.C. Zhao, et al [9] designed a neural network sliding mode controller for each channel thrust vectoring system of three-channel ballistic missile, and RBF neural network was applied to estimate the upper bound of the overall uncertainty. L. Qin and M. Yang [10] discussed the problem of accurate real-time tracking of the satellite using terminal sliding mode control combined with RBF neural network to study the upper bound of uncertainty adaptively.
Particle swarm optimization (PSO) that optimizes the parameters of sliding mode controller is superior to conventional experience to select the parameters, which can further enhance the performance of sliding mode control system. K.W. Yu and S.C. Hu [11] proposed a scheme to use PSO to optimize the switching gain of SMC for AC servo motor, and the control performance is superior to conventional SMC. A.E. Serbencu, et al. [12] designed a sliding mode controller based on exponential reaching law for nonlinear wheeled robot firstly, then used PSO to search the optimal two parameters of exponential reaching law. Z.M. Chen, et al. [13] used an improved PSO to optimize the three parameters of SMC including switching function and exponential reaching law coefficients, which solved the quality control and chattering problem, the simulation of inverted pendulum system verified the effectiveness.

This paper introduces neural network and PSO into SMC, presents an adaptive neural network sliding mode control based on PSO for rotary steering drilling stabilized platform. The simulation results show that the closed-loop system can obtain optimal control performance and robustness.

2. Mathematical model of stabilized platform

Rotary steering drilling stabilized platform is composed of upper turbo-dynamotor, lower turbo-dynamotor, electronic control unit, upper plate valve and lower plate valve (Figure 1). Upper turbo-dynamotor provides power for electronic control unit. Lower turbo-dynamotor is a variable torque generator. Electronic control unit is a detection and control component. Linear accelerometer is used to detect tool face angle and deviation angle of stabilized platform, and rate gyro is used to detect rotation trend and angular velocity of stabilized platform in electronic control unit. Look from top to bottom, upper turbo-dynamotor rotates clockwise, while lower turbo-dynamotor rotates counterclockwise, and rotary table drive tool shell and lower plate valve rotate clockwise. The torque of lower turbo-dynamotor must balance the torques of upper turbo-dynamotor, lower and upper plate valve and rotary friction. The torque of upper turbo-dynamotor is small and can be considered as constant, and the other torques are variable under work condition. In order to achieve steerable drilling, it only needs to control the torque of lower turbo-dynamotor to make the upper plate valve driven by stabilized platform stable to the preset tool face angle.

The stabilized platform of rotary steering drilling tool is a SISO system, and it can be seen as generator-style single-axis inertial stabilized platform. Figure 2 shows the structure of control model of stabilized platform.

In Figure 2, the transfer function of lower turbo-dynamotor is $K_n (1 + T_w s)^{-1}$, where $T_w = J/f$, $K_n = 1/f$, and $J$ is platform moment of inertia, $f$ is platform rotation friction coefficient.
\( \tau_M \) denotes output torque of lower turbo-dynamotor. \( \theta \) and \( \theta_p \) is tool face angle and preset tool face of stabilized platform respectively. \( \dot{\theta} \) is angular velocity of stabilized platform.

\( M_T \) denotes total disturbance torque, mainly including electromagnetic torque of upper turbo-dynamotor \( M_{\text{elec}} \), bearing friction torque \( M_{\text{bearing}} \), viscous friction torque of rotary drilling mud \( M_{\text{mud}} \) and friction torque of plate valve system on stabilized platform \( M_{\text{valve}} \) [5, 14].

\[
\begin{align*}
M_{\text{elec}} &= 0.033 \mu (n_b - n) \text{sgn}(n_b - n) \\
M_{\text{mud}} &= 0.0178 \mu (n_b - n) \text{sgn}(n_b - n) \\
M_{\text{bearing}} &= 23.29 \text{sgn}(n_b - n)(0.008 \sin \text{DEV} + 0.02 \cos \text{DEV})
\end{align*}
\]

(1) (2) (3)

where \( \mu \) is mud viscosity coefficient, \( n_b \) is drill pipe speed, \( n \) is stabilized platform speed and \( \text{DEV} \) is deviation angle.

Choose \( x = [x_1, x_2]^T = [\theta, \dot{\theta}]^T \) as state variables and \( y = \theta = x_1 \) as output variable. The uncertain nonlinear mathematical model of platform is

\[
\begin{align*}
\dot{x}_1 &= x_2 \\
\dot{x}_2 &= f(x) + bu + d(t) \\
y &= x_1
\end{align*}
\]

(4)

where \( f(x) = -\frac{1}{T_n} x_2 \), \( b = \frac{K_n}{T_n} \).

\[
\begin{align*}
d(t) &= \frac{K_n}{T_n} \left[M_s + 0.05 \mu (\eta_b - \frac{30}{\pi}) \text{sgn}(\eta_b - \frac{30}{\pi}) + 23.29 \text{sgn}(\eta_b - \frac{30}{\pi})(0.008 \sin \text{DEV} + 0.02 \cos \text{DEV}) \right]
\end{align*}
\]

3. Controller design of stabilized platform

3.1. Design of adaptive rbf neural network sliding mode controller

Let the uncertain upper bound of system be \( \text{\textbar}d(t)\text{\textbar} \), that is \( \text{\textbar}d(t)\text{\textbar} < \text{\textbar}\text{\textbar} \). Define tracking error as \( e = y - y_d = x_1 - y_d \), and design switching function as \( s = ce + \hat{e} \) (\( c \) is positive constant namely switching function coefficient), then \( \dot{s} = c \hat{e} + \dot{e} = c \dot{e} + f(x) + bu + d(t) - \ddot{y}_d \).

Define Lyapunov function as \( V = \frac{1}{2} s^2 \), thus the sliding mode control law can be designed as follows:

\[
\begin{align*}
u &= \frac{1}{b} \left[ -f(x) + \ddot{y}_d - c \dot{e} - \text{\textbar}d(t)\text{\textbar} \text{sgn}(s) \right]
\end{align*}
\]

(5)

Stability analysis:

\[
\begin{align*}
\dot{V} &= ss \dot{s} \\
&= s \left[ c \dot{e} + f(x) + bu + d(t) - \ddot{y}_d \right] \\
&= s \left[ d(t) - \text{\textbar}d(t)\text{\textbar} \text{sgn}(s) \right] \\
&\leq \text{\textbar}d(t)\text{\textbar} \text{\textbar}e\text{\textbar} \text{\textbar}d(t)\text{\textbar} \\
&\leq 0
\end{align*}
\]

The uncertain upper bound \( d(t) \) is often unable to predict in fact, therefore control law (2) cannot be realized. Considering the Universal Approximation Theorem of RBF neural network, RBF neural network has been applied to study the uncertain upper bound \( d(t) \) adaptively. Figure 3 shows the structure diagram of RBF neural network.
Figure 3. Structure Diagram of RBF Neural Network

The input of RBF neural network is \( x = [\theta, \dot{\theta}]^T \), and the output is \( \hat{d}(x, \omega) \) namely estimated value of uncertain upper bound.

\[
\hat{d}(x, \omega) = \hat{\omega}^T \phi(x)
\]  

(7)

where \( \hat{\omega}^T \) is weight of RBF neural network, \( \phi(x) \) is Gaussian Function.

\[
\phi_i(x) = \exp(-\frac{\|x - m_i\|^2}{\sigma_i^2}) \quad i = 1, 2, 3, 4, 5
\]

(8)

where \( m_i \) and \( \sigma_i \) is the center and width of \( i^{th} \) neuron respectively. Then the control law (5) can be modified as follows:

\[
u = \frac{1}{\eta} \left[ f(x) + \dot{\theta} - c\dot{\theta} - \hat{d}(t) \text{sgn}(x) \right]
\]

(9)

Hypothesis 1: The optimal weight \( \hat{\omega}^* \) of RBF neural network satisfies

\[
\hat{\omega}^* \phi(x) - \tilde{d}(t) = \varepsilon(t) \quad \text{and} \quad |\varepsilon(t)| < \varepsilon_1
\]

(10)

Hypothesis 2: The uncertain upper bound satisfies

\[
|\tilde{d}(t) - |d(t)|| > \varepsilon_o > \varepsilon_1
\]

(11)

Define Lyapunov function as

\[
V = \frac{1}{2} s^2 + \frac{1}{2} \eta^{-1} \hat{\omega}^T \hat{\omega}
\]

(12)

where \( \hat{\omega} = \omega^* - \hat{\omega} \).

Stability analysis:

Use adaptive algorithm to adjust weight, take \( \dot{\hat{\omega}} = \eta \| \phi(x) \| \) and \( \eta = \varepsilon_o - \varepsilon_1 > 0 \)

\[
\dot{V} = s \dot{s} - \eta^2 \hat{\omega}^T \hat{b} \dot{\hat{\omega}}
\]

\[
= s \left[ \dot{c} + f(x) + h \dot{\theta} + d(t) - \dot{\theta}_0 \right] - \eta^2 \hat{\omega}^T \hat{\omega}
\]

\[
= s \left[ d(t) - \hat{d}(t) \text{sgn}(x) \right] - \eta^2 \hat{\omega}^T \hat{\omega}
\]

\[
= s \left[ d(t) - |d(t)| \right] - \eta^2 \hat{\omega}^T \hat{\omega}
\]

\[
\leq -\|d(t) - |d(t)|\| \|\phi(x)\| - \eta^2 \hat{\omega}^T \hat{\omega}
\]

\[
= -\|d(t) - |d(t)|\| |\phi(x)| - \eta^2 \hat{\omega}^T \hat{\omega}
\]

\[
= -\|d(t) - |d(t)|\| \|\phi(x)\| - \eta^2 \hat{\omega}^T \hat{\omega}
\]

(13)

From Hypothesis 1, yields \( |\varepsilon(t)| < \varepsilon_1 \).

From Hypothesis 2, yields \( -\tilde{d}(t) + |d(t)| < -\varepsilon_o \).
From the above two inequalities, yields \[ |\varepsilon(x) - \hat{T}(t) + \hat{d}(t)| < \varepsilon_i - \varepsilon_a, \]
then \[ \dot{V} \leq -\eta |s| \leq 0 \] (14)

In order to further weaken the chattering, replace sign function \( \text{sgn}(s) \) as saturation function \( \text{sat}(s \mid a) \) by using quasi-sliding mode control method.

\[
\text{sat}(s \mid a) = \begin{cases} 
1 & s > a \\
\frac{s}{a} & |s| \leq a \\
-1 & s < -a 
\end{cases}
\] (15)

where \( a \) is positive constant namely boundary layer thickness.

Then the final control law is

\[
u = \frac{1}{b} \left[ -f(x) + \hat{y}_d - ce - \hat{d}(t) \text{sat}(s \mid a) \right]
\] (16)

### 3.2. Particle swarm optimization for controller parameters

Particle swarm optimization (PSO) algorithm is a new evolution of computing technology based on social group behavior. The basic idea of PSO algorithm is derived from study on the behavior of birds prey. In PSO, each iteration cycle of the particle updates itself by tracking personal optimal position and group optimal position until now. Therefore, this algorithm is an efficient parallel search algorithm, which can be used to solve a large number of nonlinear, non-differentiable, and multi-peak complex optimization problems. The basic PSO algorithm can be described as follows:

Assume \( m \) particles compose a group in \( D \)-dimensional target search space, where the \( i^{th} \) particle is expressed as a \( D \)-dimensional vector \( x_i = (x_{i1}, x_{i2}, \cdots x_{id}) \), that is the potential solution. The best previous position of any particle is recorded and represented as \( \text{pbest}_i \). The best particle among all particles is called as \( \text{gbest} \). The flight velocity denoted by \( v_i = (v_{i1}, v_{i2}, \cdots v_{id}) \) is also a \( D \)-dimensional vector. The position and velocity of particles are updated according to the following equations.

\[
v_{id}(t+1) = \omega v_{id}(t) + c_1 r_1 [\text{pbest}_{id}(t) - x_{id}(t)] + c_2 r_2 [\text{gbest}_d(t) - x_{id}(t)]
\] (17)

\[
x_{id}(t+1) = x_{id}(t) + v_{id}(t+1)
\] (18)

where \( i = 1, 2, \cdots, m, d = 1, 2, \cdots, D \), \( \omega \) is inertia weight which decides the impact of particle present speed to next generation. \( c_1 \) and \( c_2 \) are acceleration coefficients with positive values. The relative sizes of \( c_1 \) and \( c_2 \) reflect the relative importance of \( p_i \) and \( p_g \) in evolution. \( r_1 \) and \( r_2 \) are random numbers between 0 and 1. \( v_{id} \in [-v_{id}^{\min}, v_{id}^{\max}] \), \( x_{id} \in [-x_{id}^{\min}, x_{id}^{\max}] \), \( v_{id}^{\min}, v_{id}^{\max}, x_{id}^{\min}, x_{id}^{\max} \) represent actual bounds.

In control law (16), adaptive parameter of neural network weight \( \eta \), boundary layer thickness \( a \) and switching function coefficient \( c \) are usually selected according to experience, while the values of these three parameters have a great impact on the final control system dynamic and static performance [15, 16]. Here PSO algorithm is applied to achieve optimal control performance and robustness by offline global optimizing three controller parameters.

Suitable selection of inertia weight provides a balance between global and local explorations, thus requiring less iteration on average to find a sufficiently optimal solution. As originally developed, often decreases linearly from about 0.9 to 0.4 during a run. The inertia weight is set according to the following equation.

\[
\omega = \omega_{\text{start}} - (\omega_{\text{start}} - \omega_{\text{end}}) \ast k / G_{\text{max}}
\] (19)

where \( \omega_{\text{start}} \) is initial inertia weight, \( \omega_{\text{end}} \) is inertia weight iterated to maximum number, \( k \) is the number of iterations, \( G_{\text{max}} \) is the maximum number of iterations.

The searching procedures are shown as follow:
Step 1) Specify the lower and upper bounds of the three controller parameters, the number of particle (swarm size) and number of iteration as termination criterion (in here, 20 particles and 30 iterations are applied). Randomly initialize particle position and velocity.

Step 2) For each particle \( p = (\eta, a, c) \), calculate the evaluation value of each individual in the population using the minimum target function given by

\[
J = a_1 \sum e^T e + a_2 |\delta_{\text{max}}| \tag{20}
\]

where \( e \) is tracking error, \( \delta_{\text{max}} \) is maximum overshoot, \( a_1 \) and \( a_2 \) are positive constants.

Step 3) Compare each particle’s evaluation value with its \( p_{\text{best}} \). The best evaluation value among the \( p_{\text{best}} \) is denoted as \( g_{\text{best}} \).

Step 4) Modify the number velocity \( v \) of each particle \( p \) according to equation (17), the value of \( \omega \) is set by Equation (19).

Step 5) If \( v_{d}(t+1) > v_{d}^{\text{max}} \), then \( v_{d}(t+1) = v_{d}^{\text{max}} \).

If \( v_{d}(t+1) < v_{d}^{\text{min}} \), then \( v_{d}(t+1) = v_{d}^{\text{min}} \).

Step 6) Modify the position of each particle \( p \) according to Equation (18), and

If \( x_{d}(t+1) > x_{d}^{\text{max}} \), then \( x_{d}(t+1) = x_{d}^{\text{max}} \).

If \( x_{d}(t+1) < x_{d}^{\text{min}} \), then \( x_{d}(t+1) = x_{d}^{\text{min}} \).

Step 7) If the number of iterations reaches the maximum, then end the searching process. Otherwise, go to Step 2.

The particle that generates the latest \( g_{\text{best}} \) contains optimal controller parameters.

4. Simulation results

During the practical measurement of system parameters, moment of inertia \( J \) is 0.0253 kg \( \cdot \) m\(^2\), friction coefficient \( f \) is 0.01, drill pipe speed \( n_0 \) changes in the range of 60 \( \pm \) 6 (r/ min), slurry viscosity coefficient \( \mu \) changes in the range of 12 \( \pm \) 1.2 \times 10^{-3}. Let deviation angle \( \text{DEV} = 0^\circ \) and electromagnetic torque of upper turbo-dynamotor \( M_U = 0.15 \text{N} \cdot \text{m} \).

Before using PSO algorithm, take adaptive parameter of neural network weight \( \eta = 0.03 \), boundary layer thickness \( a = 0.5 \) and switching function coefficient \( c = 70 \) by experience. In PSO algorithm, the lower and upper bounds of the three controller parameters are shown in Table 1. Take particle number \( m = 20 \), maximum iteration number \( D = 30 \), acceleration coefficients \( c_1 = c_2 = 1.45445 \), inertia weight \( \omega = 0.9 - 0.5 \times k / 30 \) and the minimum target function \( J = 10 \sum e^T e + 10 |\delta_{\text{max}}| \). Set the output tool face angle be \( 30^\circ \), simulation results between PSO and NO PSO for adaptive RBF neural network sliding mode controller are shown as Figure 4 to Figure 9.
From the simulation results above we can see that the best individual fitness is 0.5648 and system begin to converge after 19 iterations (Figure 4). In such a case, the corresponding adaptive parameter of neural network weight $\eta = 0.0829$, boundary layer thickness $a = 0.32$ and switching function coefficient $c = 62.3839$. Obviously, the performance and robustness of RBF neural network adaptive sliding mode controller with PSO are significantly improved.

5. Conclusion

Considering the influencing nonlinear and uncertain factors of outside interference, drilling technology and geometrical parameter perturbation of the borehole on stabilized platform under work condition, this paper proposes an adaptive neural network sliding mode control strategy based on PSO, which uses SMC to ensure the system robustness, makes the uncertain upper bound adjust adaptively with RBF neural network to nonlinear approximate the upper bound of overall uncertainty, reduces chattering by quasi-sliding mode control method, and uses PSO to search the optimal controller parameters. This paper provides a new method to improve the control performance and robustness of stabilized platform, thus it has some engineering and academic significance.

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7. References