Neural network based adaptive rise control of tank gun systems

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Abstract. With the development of the all-electric fourth-generation tank, higher requirements have been put forward for the accuracy and response speed of tank gun control and the traditional tank gun system modeling methods and control strategies failed to meet the requirements. For this reason, a neural network based adaptive robust integral of the error sign (ARISE) control for tank gun system is proposed considering two-axis dynamic coupling and nonlinear friction characteristics. Firstly, a two-axis coupling nonlinear dynamic model of the tank gun system is established and a continuous static friction model is used to characterize the nonlinear friction characteristics of the system. Then, an adaptive law is designed based on the desired position instruction to realize the online update of unknown system parameters. In addition, the neural network is used to compensate other unmodeled dynamic errors and the influence of neural network approximation error is suppressed by the nonlinear integral robust control term. The stability analysis results show that the proposed neural network based adaptive robust integral of the sign of the error control strategy can obtain excellent asymptotic tracking performance, and the simulation results verify its effectiveness.

1. Introduction
The striking ability of the tank gun determines the combat effectiveness of the tank in the war, in particular, the control system of the tank gun determines the hit rate and destructive power of the projectile to a large extent [1]. Therefore, the tank gun control system is very important for the improvement of tank's combat capability and survivability. With the development of the tank, what also began to use is tank-gun mode using the unmanned turret. In the process of its movement, because of the azimuth and pitch effects of the coupling torque, it is necessary to take the coupling dynamics into consideration [2,3]. The traditional modeling method of anti-tank system adopts the single-input and single-output method, which fails to meet the control requirements because the coupling dynamics are neglected. No matter the gun is tracking the rotation process of the target or firing, the load transient changes greatly due to the strong recoil force, which will cause the azimuth and pitch axis to vibrate. In order to suppress the strong interference and satisfy the control requirements of the tank gun's fast response and stability, the controller design with robustness against unknown dynamics has become an important research content.

In [4], the nonlinearity of the tank gun control system was established and related mathematical models were established, but the model is not accurate enough. In [5], LADRC control method was
proposed to control tank gun system for non-linear problems such as friction, parameter change and unmodeled error, however, the influence of tank gun/turret two-axis coupling on the overall control was not considered. In [6], the horizontal and vertical modeling methods based on ac motor driving mode were respectively developed for electrical anti-tank system. The control method was combined with the traditional direct feedback linearization control strategy and wavelet neural network. However, the nonlinear friction effects were not modeled in detail in the model, and the influence of the coupling characteristics of the two axes on the whole control system was not considered. In [7], a neural network was introduced into the control system of two-axis coupled dynamics. In [8], the two-axis coupling mathematical model of the new ammunition automatic loader was established, and PD control was adopted to control the whole system.

In this paper, the LuGre model [9] is used to compensate the friction force while considering the model's nonlinearity. Furthermore, the neural network structure [10] is used to compensate the unmodeled errors and other disturbances. Since the two-axis coupling system itself needs strong robustness, it is proposed to adopt the RISE controller for this system.

2. Dynamic models and properties

The class of two-axis coupling nonlinear dynamic model of tank gun systems considered in this brief is assumed to be modeled by the following Euler–Lagrange formulation:

\[
M_a(q)\ddot{q} + M_b(q, \dot{q})\dot{q} + M_g(q) - T_f(q) = T + d
\]  

(1)

![Figure 1. Kinematics of tank gun system diagram.](image)

In (1) \( q = [q_1 \; q_2]^T \), \( q_1 \) represents the azimuth angle of the tank gun system, \( q_2 \) represents the pitch Angle of the tank gun system; \( M_a(q) \) represents the matrix of inertia symmetry, \( M_b(q) \) represents the Coriolis force centrifugal matrix; \( M_g(q) \) represents the weight torque vector; \( M_g = [T_{g1} \; T_{g2}]^T \), \( T_{g1} \) represents gravitational moment of azimuth; \( T_{g2} \) represents gravitational moment in the direction of pitch; \( T = [T_1 \; T_2]^T \), \( T_1 \) represents azimuth moment input, \( T_2 \) represents pitch input; \( d = [d_1 \; d_2]^T \) represents unmodeled error and disturbance, \( d_1 \) represents unmodeled error and disturbance of azimuth, \( d_2 \) represents unmodeled error and disturbance of pitch; \( T_f = [T_{f1} \; T_{f2}] \) represents friction moment, \( T_{f1} \) represents azimuth moment friction, \( T_{f2} \) represents pitch moment friction; then we could use the LuGre model to approximate friction moment:

\[
T_{fi} = l_1 \tanh(v_i\dot{q}_i) + l_2[\tanh(v_i\dot{q}_i) - \tanh(v_i\dot{q}_i)] + l_3\dot{q}_i \quad (i = 1, 2)
\]  

(2)

where \( l_i (i = 1, 2)(j = 1, 2, 3) \) represent different friction levels; and \( v_j (j = 1, 2, 3) \) denote shape coefficients to approximate friction effects of tank gun system.
Property 1: The inertia matrix \( M_a(q) \) is symmetric and positive definite and satisfies the following inequality:
\[
m_i \| y \|^2 \leq y^T M_a(q) y \leq \bar{m}_i(q) \| y \|^2
\]
where \( m_i \) is a known positive constant, \( \bar{m}_i(q) \) is a known positive function, and \( \| \cdot \| \) denotes the standard Euclidean norm.

Property 2: If \( q(t), \dot{q}(t) \in L_\infty \) and \( M_a(q), M_b(q) \) and \( M_g(q) \) are bounded.

Property 3: The total disturbance of the system \( d = [d_1 \; d_2]^T \) is smooth enough so that \( \dot{d} \) and \( \ddot{d} \) exist and is bounded:
\[
|\dot{d}_i| \leq \delta_{it}, |\ddot{d}_i| \leq \delta_{zt}, (i = 1, 2)
\]
where \( \delta_{it}, \delta_{zt} (i = 1, 2) \) are unknown positive constant with uncertain upper bounds.

Define state variables: \( x = [x_1 \; x_2]^T = [q, \dot{q}]^T \) and let \( u = T_j(i = 1, 2) \). So the dynamic equations (1) can be express by:
\[
\begin{align*}
\dot{x}_i &= x_2 \\
M_a(x_i) \dot{x}_2 &= u - M_b(x_1, x_2) x_2 - M_g(x_i) - \phi_i(x_2) \dot{\theta}_i - \phi_k(x_2) \dot{\theta}_2 - \phi_q(x_2) \dot{\theta}_q + d(x, t)
\end{align*}
\]
where \( d(x, t) \) is the total interference of the system, including external load interference, unmodeled friction, unmodeled dynamics, and the interference caused by the deviation between the actual parameters of the system and the modeling parameters.

3. Neural network based adaptive RISE controller design

3.1. Control objective

The control objective is to ensure that the tank gun tracks a desired time-varying angle, denoted by \( x_{id} \), in spite of the uncertainties in the dynamic model. To quantify this objective, an angle tracking error, denoted by \( z_1 \), is defined as:
\[
z_1 = x_1 - x_{id}
\]
\( x_2 \) is defined as the virtual control, \( x_{2eq} \) is the desired value of the virtual control, the error between \( x_2 \) and \( x_{2eq} \) is \( z_2 = x_2 - x_{2eq} \). Design a virtual control law as follows:
\[
x_{2eq} = \dot{x}_{id} - k_1 z_1
\]
where \( k_1 = diag[k_{11} \; k_{12}] \) denote positive constant diagonal gain matrix.

To obtain an additional controller design degree of freedom, an auxiliary error signal is defined as \( r \) :
\[
r = \dot{z}_2 + k_2 z_2
\]
where \( k_2 = \text{diag}[k_{21}, k_{22}] \), denote positive constant diagonal gain matrix. Because \( r \) contains acceleration signal of position, it is considered to be unmeasurable in practice, that is, \( r \) is only used for auxiliary design and does not appear specifically in the designed controller. Because the LuGre model friction parameters are difficult to measure in the tank gun system, the on-line parameter updating method is adopted to estimate the friction parameters. In the tank gun system, there are many reasons for the uncertainty of internal parameters, so its parameter matrix can be expressed as: \( M_a = M_{a0} + \Delta M_a \), \( M_b = M_{b0} + \Delta M_b \), \( M_g = M_{g0} + \Delta M_g \) and \( M_{a0}, M_{b0}, M_{g0} \) are nominal values of real matrices, \( \Delta M_{a0}, \Delta M_{b0}, \Delta M_{g0} \) are the measurement deviations of the system. Utilizing (1), (2), and (8) to obtain the following expression:

\[
M_d r = F_d + Y_d \theta + S + \Delta_d + \Delta - u
\]

where \( F_d \), \( Y_d \theta \) and \( S \) are defined as:

\[
F_d = M_{a0}(\dot{x}_{2d})\dot{x}_{2d} + M_{b0}(x_{id}, x_{2d})x_{2d} + M_{g0}(x_{id})
\]

\[
S = M_{a0}(x_i)(k_1\dot{x}_1 + k_2x_2) - \Delta M_{a0}(x_i)r + M_{a0}(x_i)x_{2d} - M_{a0}(x_{id})\dot{x}_{2d} + M_{b0}(x_{id}, x_{2d})x_{2d} + M_{g0}(x_i) - M_{g0}(x_{id}) + \Delta M_{a}(x_i)\dot{x}_2 - \Delta M_{a}(x_{id})x_{2d} + \Delta M_{b}(x_{id}, x_{2d})x_{2d} + \Delta M_{g}(x_i) - \Delta M_{g}(x_{id}) + \phi(x_2)\theta_1 + \phi(x_2)\theta_2 + \phi(x_2)\theta_3
\]

In addition, the total interference \( d \) is divided into \( \Delta \) and \( \Delta_d \). The uncertainty \( \Delta \) is disturbance that is only relevant to the system and bounded by the second derivative based on Property 3. The disturbance \( \Delta_d \) can be fitted by a three-layer neural network, whose expression is:

\[
\Delta_d = \Delta M_a(\dot{x}_{2d})\dot{x}_{2d} + \Delta M_b(x_{id}, x_{2d})x_{2d} + \Delta M_{g0}(x_{id}) + d(x_d)
\]

The expression of its neural network is as follows:

\[
\Delta_d = [\Delta_{d1}, \Delta_{d2}]^T = [W^T_1 h(x) + \varepsilon_1, W^T_2 h(x) + \varepsilon_2]^T
\]

\[
h_k = \exp\left(\frac{||x - c_k||^2}{2b_k^2}\right)
\]

where \( q_i = [1, q_{id}, \dot{q}_{id}, \ddot{q}_{id}]^T (i = 1, 2) \); \( x \) is the input of network, \( k \) is the \( k \)-th node of hidden layer, \( h = [h_k]^T \) is the output of network’s Guass radial function, \( W = [W^T_1, W^T_2]^T \) is the bounded constant ideal weight matrices for representing, \( \varepsilon = [\varepsilon_1, \varepsilon_2]^T \) is the approximation error of the network.
3.2. Controller design

Based on the above process, the controller can be designed as:

\[ u = u_a + u_s \]  
\[ u_a = F_d + Y_d \dot{\theta} + \dot{\Lambda}_d \]  
\[ u_{s1} = -(k_r + I_m)z_2 - (k_r + I_m)z_2(0) \]  
\[ u_{s2} = -\int_0^t (k_r + I_m)k_zz_2 + \beta \text{sgn}(z_2) d\tau \]

The specific expression of \( \dot{\theta} \) in equation (17) is:

\[ \dot{\theta} = \Gamma \dot{Y}_d^T r \]

where \( \Gamma \) is the a known, constant, diagonal, positive definite adaptation gain matrix. Since \( \dot{Y}_d \) is only a function of the known desired time varying trajectory, (20) can be integrated by parts as follows:

\[ \dot{\theta}(t) = \dot{\theta}(0) + \Gamma Y_d^T z_2(\tau) \bigg|_0^\tau - \int_0^\tau \{ Y_d^T z_2(\tau) - k_2 Y_d^T z_2(\tau) \} d\tau \]

The specific expression of \( \dot{\Lambda}_d \) in equation (17) is:

\[ \dot{\Lambda}_d = \dot{W}^T h(q_d) \]

In equation (18), the weight value of the neural network \( \dot{W} \) is updated in the following way:

\[ \dot{W} = \Gamma_h \dot{h} \dot{x}_d \dot{x}_d^T \]

where \( \Gamma_h \) is the a known, constant, diagonal, positive definite adaptation gain matrix. Utilizing the expressions in (9), (16), (17), (18) and (19) to obtain the following expression:

\[ M_{a0r} = Y_d \dot{\theta} + S + f_d - \dot{f}_d + \Delta - u_{s2} \]

Further, the derivative of equation (23) can be obtained as follows:

\[ M_{a0r} = -\dot{M}_{a0r} + \dot{Y}_d^T \theta + \dot{S} + W^T h'(x_d) \dot{x}_d + \dot{\epsilon} \]

\[ -\dot{W}^T h(x_d) - \dot{W}^T h(x_d) \dot{x}_d + \Delta - u_{s2} \]
Figure 3. The neural network based robust integral of the error sign strategy diagram.

According to equation (25), we could obtain the following expression:

$$M_a \dot{r} = -\frac{1}{2} \dot{M}_a r - \dot{Y}_d r + \dot{N} + N - z_2 - (k_r + I_m)r - \beta \text{sgn}(z_2)$$  \hspace{1cm} (26)

where:

$$\dot{N} = -\frac{1}{2} \dot{M}_a r - \Gamma_a \dot{h} \dot{x}_d z_2^T \dot{h} - Y_a \dot{Y}_d r + \dot{S} + z_2$$  \hspace{1cm} (27)

$$N = N_d + N_B$$  \hspace{1cm} (28)

$$N_d = \dot{\Delta} + \dot{\epsilon}$$  \hspace{1cm} (29)

$$N_B = \dot{W}^T h(x_d) \dot{x}_d$$  \hspace{1cm} (30)

The upper bound of equation (27) can be determined through the mean value theorem:

$$\|\dot{N}\| \leq \rho\|Z\|$$  \hspace{1cm} (31)

where $Z$ can be expressed as follow:

$$Z = \begin{bmatrix} z_1^T & z_2^T & r^T \end{bmatrix}^T$$  \hspace{1cm} (32)

$$\|N_d\| \leq \zeta_1$$  \hspace{1cm} (33)

$$\|N_B\| \leq \zeta_2$$  \hspace{1cm} (34)

where $\zeta_1, \zeta_2, \zeta_3, \zeta_4$ are positive constants.

3.3. Stability Analysis

Lemma 1: define an auxiliary function $L(t)$ as:
\[ L(t) = r^T [N_d - \beta \text{sgn}(z_2)] + \dot{z}_2^T N_B \]  
\[ P(t) = \beta |z_z(0)| - z_z(0) \dot{N}(0) - \int_0^t L(\tau) d\tau \]

where \( z_z(0) \) and \( \dot{d}(0) \) respectively represent the initial value of \( z_z(t) \) and \( \dot{d}(x,t) \).

It can be seen that there indeed exists a constant \( \beta_1 \) satisfying the following condition:

\[ \beta_1 \geq \zeta_1 + \frac{1}{k_{2s}} \zeta_2 + \frac{1}{k_{2s}} \zeta_4, (i = 1, 2) \]

**Proof of the lemma:**

Integrate both sides of equation (35) and apply equation (8) to get:

\[ \int_0^t L(\tau) d\tau = \int_0^t \left[ (\dot{z}_z + k_{2s} z_z)^T (N_d - \beta \text{sgn}(z_2)) + z_2^T N_B \right] d\tau = \int_0^t \dot{z}_2^T N_d d\tau - \int_0^t \dot{z}_2^T \beta \text{sgn}(z_2) d\tau + \int_0^t k_{2s} z_z^T N_d d\tau - \int_0^t k_{2s} z_2^T \beta \text{sgn}(z_2) d\tau + \int_0^t \dot{z}_2^T N_B d\tau \]

Integration by parts of equation (38) can be obtained:

\[ \int_0^t L(\tau) d\tau = \dot{N}_d z_2^T \beta + \int_0^t \dot{z}_2^T \beta \text{sgn}(z_2) d\tau + \int_0^t k_{2s} z_z^T N_d d\tau - \int_0^t k_{2s} \beta z_2 \text{sgn}(z_2) d\tau + \dot{N}_B z_2^T \beta \]

So it turns out to be as:

\[ \int_0^t L(\tau) d\tau \leq \beta |z_z(0)| - z_z(0) \dot{N}(0) \]

Let

\[ h(t) = [z^T(t) \sqrt{P(t)} \sqrt{Q(t)}]^T \]

where the another \( Q(t) \) is defined as:

\[ Q(t) = \frac{k_{2s}}{2} \text{tr} \left( \hat{W}^T \Gamma^{-1} \hat{W} \right) \]

Set the lyapunov function is defined as:

\[ V(h,t) = \frac{1}{2} \left( z_1^T z_1 + z_2^T z_2 + r^T M_0 r + \dot{\theta}^T \Gamma^{-1} \ddot{\theta} \right) + P(t) + Q(t) \]

where the equation (42) satisfies the following condition:

\[ U_1(y) \leq V(y, t) \leq U_2(y) \]

where \( U_1(y) = \frac{1}{2} \min \{1, m_i\} \|y\|_2^2 \), \( U_2(y) = \frac{1}{2} \min \{\frac{1}{2} \bar{m}(x), 1\} \|y\|_2^2 \).

Derivative of lyapunov function (41) as:

\[ \dot{V} = -k_{1s} z_1^T z_1 + z_1^T \dot{z}_2 - k_{2s} z_2^T z_2 + z_2^T \dot{r} - r^T \dot{r} + k_{1s} r^T r + r^T \dot{N} + [\dot{\theta}^T \Gamma^{-1} \dot{Y}_d r] \dot{\theta} + \left[ \hat{W}^T \Gamma^{-1} - z_2^T h (x_d) \dot{x}_d \right] \hat{W} \]

\[ \leq -k_{1s} \|z_1\|^2 + z_1^T z_2 - k_{1s} \|z_2\|^2 - (1 + k_{1s}) \|z_2\|^2 + r^T \dot{N} \]

Based on the fact that:

\[ z_1 z_2 \leq \frac{1}{2} (\|z_1\|^2 + \|z_2\|^2) \]

and using (26), the expression in (46) can be simplified as:
\[
\dot{V} \leq -(k_1 - \frac{1}{2})z^T z_1 - (k_2 - \frac{1}{2})z_2^T z_2 - (k_3 + 1)r^T r - r^T \tilde{N} \leq
-\lambda_3 \|Z\|^2 + \|r\|^2 \rho(\|Z\|)\|Z\| - \lambda_{\min}(K_r)\|r\|^2 \\
-\left(\frac{\rho(\|Z\|)}{4\lambda_{\min}(K_r)}\right)\|z\|^2 = -\rho^2\|Z\|^2 = -J
\]

where \( \lambda_3 = \min\{\lambda_{\min}(k_1 - \frac{1}{2}I_m), \lambda_{\min}(k_1 - \frac{1}{2}I_m), 1\} \), and in order to make \( \dot{V} \) seminegative, the Equation (47) must satisfy that \( r \geq 0 \) and satisfies the following condition:

\[
\lambda_{\min}(k_r) > \frac{1}{4\lambda_3} \rho^2\|Z\|.
\]

According to equation (47), it can be obtained that \( \forall t > 0, V(t) \leq V(0), V \in L_\infty \), then it can be concluded that \( z_1, z_2 \) and \( r \) are bounded.

Integral against equation (47) can obtain:

\[
\int_0^t J(\tau)d\tau \leq -\int_0^t \dot{V}(\tau)d\tau = V(0) - V(t) \leq V(0).
\]

According to equation (47), we can obtain that \( z_1, z_2 \) and \( r \in L_2 \) norm, and according to the equation (7), (8), (9) and proof lead to:

\( \dot{z}_1, \dot{z}_2, \dot{r} \in L_\infty \), so \( J \) is uniformly continuous, according to Barbalat's lemma: \( j \to 0 \), as \( t \to \infty \). So \( z_1 \) and \( z_2 \) are all tend to zero as \( t \to \infty \).

4. Simulation results

To illustrate the above designs, simulation results are obtained for tank gun control system discussed in section 2 having the following actual parameters:

\[
M_a = \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix}, \quad M_b = \begin{bmatrix} 0 & B_{12} \\ B_{21} & B_{22} \end{bmatrix}, \quad M_g = \begin{bmatrix} 0 \\ G_z \end{bmatrix}.
\]

where: \( A_{11} = 2547 + 5400 \cos^2(q_2) - 2 \cos(q_2) \cdot \sin(q_2) + 224 \sin^2(q_2) \), \( A_{12} = 13.7 \sin(q_2) + 2.8 \cos(q_2), A_{22} = 5443, B_{12} = [10352 \cos(q_2) \sin(q_2) + 1.6(\cos^2(q_2) - \sin^2(q_2)])q_1 - (13.7 \cos(q_2) - 2.8 \sin(q_2))q_2 ; B_{11} = -0.5 \cdot B_{21}, B_{22} = [1.4 \sin(q_2) - 6.85 \cos(q_2)]q_1 ; G_z = 7462 \cos(q_2) \). In addition \( v_1 = 15, v_2 = 1.5, v_3 = 300, l_1 = l_2 = 100, l_12 = 140, l_{13} = l_{23} = 200 \). The actual value of \( \theta_g(i = 1, 2), (j = 1, 2, 3) \) is \( \theta_g(i = 1, 2), (j = 1, 2, 3) \). The initial estimate of \( \theta_g \) are chosen as \( \theta(0)_{\theta_g} = 100(i = 1, 2), (j = 1, 2, 3) \) which differs from its actual value of \( \theta_g \) to test the effect of parametric uncertainties.

The following three controllers are compared in order to test the tracking performance of proposed controller in this paper.

NN-ARISE: This is the proposed Neural Network based Adaptive RISE Controller in this paper. The controller parameters are: \( k_{11} = k_{12} = 15, k_{21} = k_{22} = 50, k_{1j} = k_{2j} = 80, \beta_1 = \beta_2 = 1000 \). The adaptation gain \( \Gamma \) for estimation parameters \( \theta : \Gamma = diag \{18, 5, 15, 60, 15, 30\} \). Parameters of
NN are chosen as  \( c_i = [2 \ 1 \ 0 \ -1 \ -2 \ 2 \ 1 \ 0 \ -2 \ -1] \) and  \( b_k = 5 \) according to the range of NN’s input  \( q_d, \dot{q}_d \) and  \( \ddot{q}_d \).

FLC: The Feedback Linearization Controller, which is characterized by clear physical concept and simple controller design. The linear feedback term parameters of this controller are the same as the controller settings proposed.

PID: The proportional-integral-derivative controller, which is widely used in industrial and can be treated as reference controller for comparison. Through online try-and-error method, the controller parameters are chosen as:  \( k_{p1} = 318000 \),  \( k_{i1} = 0 \),  \( k_{d1} = 120000 \);  \( k_{p2} = 220000 \),  \( k_{i2} = 0 \),  \( k_{d2} = 850000 \); which represent the P-gain, I-gain, D-gain, respectively.

Case 1:

The control objective is for \( y(t) \) to track a trajectory  \( x_{id} = \pi / 2 \sin(\pi / 6 \cdot t)[1 - e^{-t^2}] \) (rad) and  \( x_{2d} = \pi / 4 \cdot \sin(\pi / 6 \cdot t)[1 - e^{-t^2}] \) (rad) to make the tracking error as small as possible in the tank gun system, which ensure the accuracy of tank gun tracking moving target.

**Figure 4.** Azimuth Command and Output in case 1.

**Figure 5.** Pitch Command and Output in case 1.

**Figure 6.** Azimuth Tracking Error in case 1.
Figure 7. Pitch Tracking Error in case 1.

Figure 8. \( \theta_{11}, \theta_{12}, \theta_{13} \) Estimations in case 1.

Figure 9. \( \theta_{21}, \theta_{22}, \theta_{23} \) Estimations in case 1.

Figure 10. \( \Delta_{d1}, \Delta_{d2} \) Estimations in case 1.

Simulation results of case 1 are presented in figure 4-10. The comparison of the command and output of are shown in figure 4 and 5, they can be seen that output trajectory converge to the desired trajectory based on the proposed NN-AREISE controller. The tracking errors of the three controllers are shown in figure 6 and 7, they can be seen that tracking error eventually converge to very small values for NN-ARISE controller. In addition, by comparing the performance of FLC and PID controller can not only reduce the tracking error, but also solve the zero drift problem. The parameter adaptation and the disturbance estimation of controller is shown in figure 8-10 and they show that estimate values are eventually close to their actual values, which verify the effectiveness of the proposed adaptive algorithms to parameter uncertainties.
Case 2:
The control objective is for \( y(t) \) to track a desired trajectory \( x_{1d} = \pi / 2 \cdot \arctan(500t) \ (rad) \) and \( x_{2d} = \pi / 4 \cdot \arctan(500t) \ (rad) \) to make the tracking error as small as possible in the tank gun system, which ensure the accuracy of tank gun tracking fixed target.

Figure 11. Azimuth Command and Output in case 2.

Figure 12. Pitch Command and Output in case 2.

Figure 13. Azimuth Tracking Error in case 2.

Figure 14. Pitch Tracking Error in case 2.
Simulation results of case 2 are presented in figure 11-14. The comparison of the NN-ARISE controller’s command and output of are shown in figure 11 and 12, they can be seen that output can also converge to the desired trajectory in a short time under case 2. The tracking errors of the three controllers are shown in figure 13 and 14, they can be seen that the proposed controller has faster convergence speed, which is vital for application in hitting fixed targets.

5. Conclusion
In this paper, the problem of tracking control for tank gun systems. Different from traditional model methods, in which turret and gun are coupled dynamically, the proposed modeling method combines the modeling method of the mechanical arm joint and adopts the LuGre model for friction compensation. The proposed neural network based adaptive RISE controller imposed on the error signals, Lyapunov function and adaptive law, thus cannot only enhances the dynamic performance but also reduces the gain of controller. Extensive comparative simulation results are obtained to illustrate the effectiveness of the proposed scheme.

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