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The Tracking Problem in Tank Gun Control Systems With Periodic Reference Signals

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ABSTRACT In this paper, the position tracking control for tank gun control systems with periodic reference signal is studied. On the basis of corresponding system modeling, a novel repetitive controller is developed by using Lyapunov synthesis. During the controller design, signal replacement mechanism is used to deal with the nonparametric uncertainties under Lipschitz-like continuous condition, and repetitive learning laws are developed to estimate the unknown periodic parameters. Meanwhile, robust learning approach is used to compensate the sum of random disturbances, whose upper bound is estimated according repetitive learning mechanism. Hyperbolic tangent function, rather than sign function, is applied to design a robust feedback term to release the occurrence of chattering phenomenon. Numerical simulations demonstrate the effectiveness of the proposed repetitive control scheme.

INDEX TERMS Tank gun control systems, repetitive control, Lyapunov approach, Lipschitz-like continuous condition.

I. INTRODUCTION

Researchers have long been exploiting and searching the controller design methods for nonlinear systems and great progress has been gained in recent years [1]–[9]. Repetitive control (RC) is well-known for the prominent ability of rejecting periodic uncertainties [10]. RC and iterative learning control(ILC) [11]–[18] are two branches of learning control, and the repeatability principle of uncertainties is their common theoretical basis. While a RC systems works, the control input is gradually updated according to the system error in the previous cycle, cycle by cycle, until the good control performance is obtained. Since the advent of RC in the late 1970s, it has been widely used in the accurate control design for robot manipulators [19], permanent-magnet synchronous motor [20], hard disk drives [21], etc.

Most early works on RC focuses on frequency domain analysis and design for linear time-invariant systems [22]. In early 1990s, some researchers started to study Lyapunov-based RC desgin for uncertain systems [23], [24]. Since the beginning of this century, Lyapunov-based RC has been a hot issue in learning control area. Dixon *et al.* investigated Lyapunov-based RC for uncertain robotic systems with an periodic exogenous disturbance [19]. Xu *et al.* developed robust repetitive learning control laws for nonparametric systems [25]. Chen *et al.* considered the repetitive control algorithms for nonlinearly parameterized systems with periodically time-varying delays [26]. Chen *et al.* studied the output-feedback repetitive controller design for a class of nonlinear systems with unmatched periodic disturbances, which is rejected by using adaptive repetitive rejection method [27]. Huang *et al.* proposed an observer-based repetitive learning control scheme for a class of nonparametric systems [28]. Zhu *et al.* presented an adaptive backstepping repetitive learning algorithm for nonlinear discrete-time systems [29]. Yan *et al.* addressed the dual-period repetitive control design for nonparametric uncertain systems [30]. Ma *et al.* investigated the dual-period repetitive control for nonparametric uncertain systems with deadzone input [31].

Tanks have been widely used in modern battlefields for the sake of improving soldiers' surviving ability and enhancing efficiency of artillery firepower. During fighting, tank gun control systems need fire shells under tough circumstances. In the past several decades, some works have been done to heighten the control precision and robust stability for tank gun control systems, such as PID control schemes [32], variable

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structure control schemes [33], optimal control schemes [34], adaptive control schemes [35], [36] and active disturbance rejection control schemes [37]. For getting better control performance, some researchers have explored the iterative learning control algorithms for tank gun control systems [38]–[40]. In [38], Zhu *et al.* considered the velocity tracking problem of tank gun control systems, with an iterative learning control scheme proposed for tank gun control systems under alignment condition. In [39], Zhang *et al.* investigated the adaptive iterative learning velocity control algorithm for tank gun control systems with input deadzone. In [40], Yang *et al.* proposed an iterative learning velocity control algorithm for tank gun control systems with arbitrary initial states. So far, to the best of authors' knowledge, few results have discussed the position tracking problem for tank gun control systems with periodic reference signals.

Motivated by the above discussions, this work focuses on the position tracking control algorithm for tank gun control systems with periodic reference signals. A repetitive learning controller is designed by using Lyapunov approach. Compared to the existing results, the main contributions of this work mainly lie in the several aspects as follows.

(1) A Lyapunov functional is constructed to design the adaptive repetitive controller for tank gun control systems, and the corresponding convergence analysis of closed loop system is given.

(2)The nonparametric uncertainties are well resolved by using signal replacement mechanism, with Lipschitz-like continuous condition being used.

(3) The unknown parameters are estimated by using repetitive learning approach. The bounded perturbation is compensated by robust control mechanism, and the hyperbolic tangent function is adopted to the construction of compensation term.

The remainder of this paper is organized as follows. The system model and the control objective are introduced in Section 2. The design process of repetitive controller is introduced in Section 3, with the corresponding convergence analysis being given in Section 4. In Section 5, an illustrative example is provided to demonstrate the effectiveness of the proposed repetitive control scheme. Section 6 concludes this paper.

II. PROBLEM FORMULATION

Electro-hydraulic transmission mode and full electric transmission mode are two different transmission modes applied in tank gun control systems. The former is applied in traditional gun control systems, and the latter is the current mainstream transmission mode of tank gun control systems. A full electric-transmission-mode tank gun conrtol system is composed of a vertical subsystem and a horizontal subsystem. The above-mentioned vertical subsystem is actually a AC servo driving system, which is made up of an AC motor, a deceleration device, a barrel and etc. The structure diagram of this subsystem is shown in Fig. 1. The block diagram of the AC servo driving system, a careful reduction of a complex

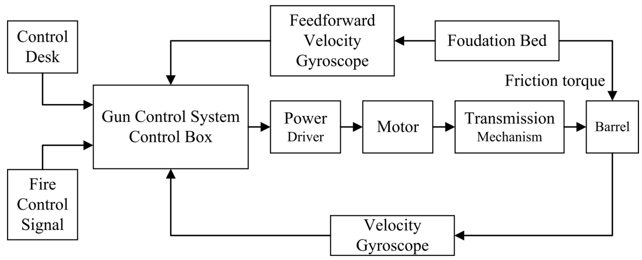

FIGURE 1. Structure diagram of full-electrical tank gun vertical servo system.

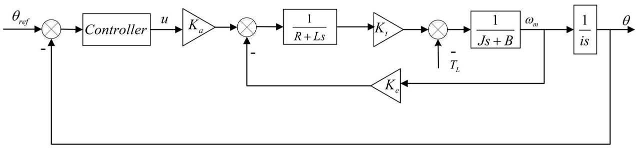

FIGURE 2. Transfer function block diagram of AC servo driving system.

nonlinear simulation model, is shown in Fig. 2, where θ_{ref} and θ represent the reference position angle and the real position angle, repectively. ω_m is the angular velocity. u is the output voltage of the position loop. R and L represent the resistance and the inductance of motor armature circuit, respectively. K_a is the amplifier gain. K_t is the motor torque factor. K_e denotes the electric torque coefficient. T_e, T_L and T_f are the motor torque, load torque disturbance and friction torque disturbance, respectively. J is the total moment of inertia to the rotor. B is the viscous friction coefficient. i is the moderating ratio. s denotes the Laplace operator.

Remark 1: The traditional electro-hydraulic gun control system has some inherent shortcomings, such as possible leakage of hydraulic oil and difficulties of equipment maintenance. In addition, if the tank is hit in a battle, it is easy to cause the explosion of hydraulic oil, resulting in secondary injury. Full electric gun control system overcomes the above shortcomings. The full electric tank gun vertical subsystem studied in this paper is an AC driving system, and the controlled device mainly includes AC motor, reducer and barrel. The vertical subsystem can be simplified as a second-order system. The controller converts the position error to a voltage value corresponding to the ideal speed of the motor, and then transmits it to the amplifier.

From Fig. 2, we can obtain

$$(K_a u(s) - K_e \omega_m(s)) \cdot \frac{1}{R + Ls} \cdot K_t = T_e(s), \tag{1}$$

$$(T_e(s) - T_L(s))(\frac{1}{Js + B}) = \omega_m(s) \tag{2}$$

and

$$\omega_m(s) = is\theta(s), \tag{3}$$

respectively. The electrical time constant of executive motor is very small, therefore, $\frac{L}{R} \ll 1$, which leads to [42]

$$\frac{1}{R + Ls} = \frac{1}{R(1 + Ls/R)} \approx \frac{1}{R}. \tag{4}$$

Combining (1) with (4) leads to

$$(K_a u(s) - K_e\omega_m(s)) \cdot \frac{K_t}{R} = T_e(s). \quad (5)$$

From (2), we obtain

$$T_e(s) = (Js + B)\omega_m(s) + T_L(s). \quad (6)$$

Then, combining (5) with (6), we have

$$\frac{K_t(K_a u(s) - K_e\omega_m(s))}{R} = T_L(s) + (Js + B)\omega_m(s) \quad (7)$$

Substituting (3) into (7), and through simple algebraic calculations, we obtain

$$iRJs^2\theta(s) + (K_tK_e + RB)is\theta(s) - K_tK_a u(s) + RT_L(s) = 0, \quad (8)$$

whose time domain expression is

$$\ddot{\theta}(t) = -(\frac{B}{J} + \frac{K_eK_t}{JR})\dot{\theta}(t) + \frac{K_aK_t}{iJR}u(t) - \frac{T_L(t)}{iJ}. \quad (9)$$

Define $x_1(t) = \theta(t), x_2(t) = \dot{\theta}(t)$. From (4), we get the dynamics of tank gun control systems as

$$\begin{cases} \dot{x}_1(t) = x_2(t), \\ \dot{x}_2(t) = -(\frac{B}{J} + \frac{K_eK_t}{JR})x_2(t) + \frac{K_aK_t}{iJR}u(t) - \frac{T_L(t)}{iJ}. \end{cases} \quad (10)$$

The control objective of this work is to design a repetitive control law $u(t)$ to let the position state $x_1(t)$ accurately track $x_{1,d}(t)$ as the number of repetitive cycle increases. For brevity, in the rest of this paper, we often omit arguments while no confusion occurs. Let $x_{2,d} = \dot{x}_{1,d}$, $\boldsymbol{x} = [x_1, x_2]^T$ and $\boldsymbol{x}_d = [x_{1,d}, x_{2,d}]^T$. Without loss of generality, the following assumption is made.

Assumption 1:

$$\frac{T_L}{iJ} = h_1(x_1, x_2) + h_2(x_1, x_2, t) \quad (11)$$

where, $h_2(x_1, x_2, t)$ is a bounded variable, representing the sum of discontinuous uncertainties and external disturbance, and $h_1(x_1, x_2)$ is Lipschitz-like continuous, i.e.,

$$|h_1(x_1, x_2) - h_1(x_{1,d}, x_{2,d})| \leq \alpha(\boldsymbol{x}, \boldsymbol{x}_d)\|\boldsymbol{x} - \boldsymbol{x}_d\|, \quad (12)$$

with $\alpha(\boldsymbol{x}, \boldsymbol{x}_d)$ being continuous with respect to $\boldsymbol{x}$ and $\boldsymbol{x}_d$.

III. CONTROL SYSTEM DESIGN

Define $e_1 = x_1 - x_{1,d}, e_2 = x_2 - x_{2,d}, \boldsymbol{e}(t) = [e_1, e_2]^T$. From (10), we obtain

$$\begin{cases} \dot{e}_1 = e_2, \\ \dot{e}_2 = -(\frac{B}{J} + \frac{K_eK_t}{JR})x_2 + \frac{K_aK_t}{iJR}u - \frac{T_L}{iJ} - \dot{x}_{2,d}, \end{cases} \quad (13)$$

which means

$$\dot{\boldsymbol{e}} = A\boldsymbol{e} + \boldsymbol{b}[e_1 + 2e_2 - (\frac{B}{J} + \frac{K_eK_t}{JR})x_2 + \frac{K_aK_t}{iJR}u - \frac{T_L}{iJ} - \dot{x}_{2,d}]. \quad (14)$$

where, $\boldsymbol{b} = [0, 1]^T$,

$$A = \begin{bmatrix} 0 & 1 \\ -1 & -2 \end{bmatrix}. \quad (15)$$

For such a matrix A, there exist symmetric positive definite matrices P and Q, which satisfy $PA + A^TP = -Q$. Let us choose a candidate control Lyapunov function $V_1 = \frac{1}{2\eta}\boldsymbol{e}^TP\boldsymbol{e}$ with $\eta = \frac{K_aK_t}{iJR}$. The time derivative of V_1 is

$$\begin{aligned} \dot{V}_1 &= -\frac{1}{2\eta}\boldsymbol{e}^TQ\boldsymbol{e} + \boldsymbol{e}^TP\boldsymbol{b}[\frac{1}{\eta}(e_1 + 2e_2 - \dot{x}_{2,d}) \\ &\quad -\frac{1}{\eta}(\frac{B}{J} + \frac{K_eK_t}{JR})x_2 + u - \frac{T_L}{iJ\eta}] \\ &= \frac{1}{2\eta}\boldsymbol{e}^TQ\boldsymbol{e} + \boldsymbol{e}^TP\boldsymbol{b}[\frac{1}{\eta}(e_1 + 2e_2 - \dot{x}_{2,d}) - \frac{1}{\eta}(\frac{B}{J} \\ &\quad + \frac{K_eK_t}{JR})x_2 + u + h_1(\boldsymbol{x}_d)] + \frac{1}{\eta}\boldsymbol{e}^TP\boldsymbol{b}[h_1(\boldsymbol{x}_d) \\ &\quad - h_1(\boldsymbol{x})] - \frac{1}{\eta}\boldsymbol{e}^TP\boldsymbol{b}h_2(\boldsymbol{x}, t). \end{aligned} \quad (16)$$

Based on Assumption 1, we have

$$\begin{aligned} \frac{1}{\eta}\boldsymbol{e}^TP\boldsymbol{b}[h_1(\boldsymbol{x}_d) - h_1(\boldsymbol{x})] &\leq \frac{1}{\eta}|\boldsymbol{e}^TP\boldsymbol{b}|\alpha(\boldsymbol{x}, \boldsymbol{x}_d)\|\boldsymbol{e}\| \\ &\leq \frac{1}{2\eta}\|\boldsymbol{e}\|^2 + \frac{2}{\eta}\alpha^2(\boldsymbol{x}, \boldsymbol{x}_d)(\boldsymbol{e}^TP\boldsymbol{b})^2. \end{aligned} \quad (17)$$

Substituting (17) into (16) leads to

$$\begin{aligned} \dot{V}_1 &\leq \frac{1}{2\eta}(1 - \lambda_Q)\boldsymbol{e}^T\boldsymbol{e} + \boldsymbol{e}^TP\boldsymbol{b}[\frac{1}{\eta}(e_1 + 2e_2 - \dot{x}_{2,d}) \\ &\quad -\frac{1}{\eta}(\frac{B}{J} + \frac{K_eK_t}{JR})x_2 + h_1(\boldsymbol{x}_d) + \frac{2}{\eta}\alpha^2(\boldsymbol{x}, \boldsymbol{x}_d)\boldsymbol{e}^TP\boldsymbol{b} \\ &\quad +u] - \frac{1}{\eta}\boldsymbol{e}^TP\boldsymbol{b}h_2(\boldsymbol{x}, t) \\ &\leq \frac{1}{2\eta}(\lambda_Q - 1)\boldsymbol{e}^T\boldsymbol{e} + \boldsymbol{e}^TP\boldsymbol{b}[\boldsymbol{\varpi}^T\boldsymbol{\varphi} + u] + \rho|\boldsymbol{e}^TP\boldsymbol{b}| \end{aligned} \quad (18)$$

where, $\boldsymbol{\varpi} := [\frac{1}{\eta}, -\frac{1}{\eta}(\frac{B}{J} + \frac{K_eK_t}{JR}), h_1(\boldsymbol{x}_d), \frac{2}{\eta}]^T$, $\boldsymbol{\varphi} := [(e_1 + 2e_2 - \dot{x}_{2,d}), x_2, 1, \alpha^2(\boldsymbol{x}, \boldsymbol{x}_d)\boldsymbol{e}^TP\boldsymbol{b}]^T$, ρ denotes the upper bound of $|\frac{1}{\eta}h_2(\boldsymbol{x}, t)|$, and λ_Q is the minimum eigenvalue of Q. Through choosing a proper matrix P, we can get a matrix Q, which satisfies $\lambda_Q > 1$.

On the basis of (18), we design the control law as

$$u = -\mu_0\boldsymbol{e}^TP\boldsymbol{b} - \hat{\boldsymbol{\varpi}}^T\boldsymbol{\varphi} - \hat{\rho}\tanh(\hat{\rho}(j+1)^2\boldsymbol{e}^TP\boldsymbol{b}) \quad (19)$$

and the repetitive learning laws as

$$\begin{cases} \hat{\boldsymbol{\varpi}}(t) = \text{sat}_{\underline{\varpi}, \bar{\varpi}}(\hat{\boldsymbol{\varpi}}(t-T)) + \gamma(t)\mu_1\boldsymbol{\varphi}\boldsymbol{e}^TP\boldsymbol{b}, & t > 0, \\ \hat{\boldsymbol{\varpi}}(t) = 0, & t \in [-T, 0], \end{cases} \quad (20)$$

$$\begin{cases} \hat{\rho}(t) = \text{sat}_{0, \bar{\rho}}(\hat{\rho}(t-T)) + \gamma(t)\mu_2|\boldsymbol{e}^T(t)P\boldsymbol{b}|, & t > 0, \\ \hat{\rho}(t) = 0, & t \in [-T, 0]. \end{cases} \quad (21)$$

In (19)−(21), $j(=0,1,2,3,\cdots)$ is the number of repetition cycle, $\mu_0-\mu_2$ are positive constants, and

$$\gamma(t)=\begin{cases}0, & t\le 0\\ 1, & t>T\\ 1-\sigma(t), & 0<t\le T.\end{cases} \tag{22}$$

with $\sigma(t)=\frac{10(T-t)^3}{T^3}-\frac{15(T-t)^4}{T^4}+\frac{6(T-t)^5}{T^5}$. In repetitive learning laws (20)-(21), the saturation functions $\mathrm{sat}_{\underline{\cdot},\bar{\cdot}}(\cdot)$ is defined as follows: for scalar $\hat{a}$,

$$\mathrm{sat}_{\underline{a},\bar{a}}(\hat{a})\triangleq\begin{cases}\bar{a} & \hat{a}>\bar{a}\\ a & \underline{a}\le\hat{a}\le\bar{a}\\ \underline{a} & \hat{a}<\underline{a};\end{cases}$$

for a vector $\hat{\boldsymbol{a}}=[\hat{a}_1,\hat{a}_2,\cdots,\hat{a}_m]\in\boldsymbol{R}^p$, $\mathrm{sat}_{\underline{a},\bar{a}}(\hat{\boldsymbol{a}})\triangleq\left[\mathrm{sat}_{\underline{a},\bar{a}}(\hat{a}_1),\ \mathrm{sat}_{\underline{a},\bar{a}}(\hat{a}_2),\cdots,\mathrm{sat}_{\underline{a},\bar{a}}(\hat{a}_p)\right]^T$.

Remark 2: Actually, the controller design given in (19)− (21) is a combination of repetitive control and robust control. Due to $\boldsymbol{\varpi}$ is not a time-invariant constant vector, traditional adaptive control is not a suitable technology in such an occasion. In order to release the chattering phenomenon, hyperbolic tangent function is adopted in the design of control law, instead of sign function.

IV. CONVERGENCE ANALYSIS

Theorem 1: Consider the tank servo dynamic system consisting of plant (10), satisfying Assumption 1, the repetitive control law (19), and the parameter learning laws (20)-(21). The system is stable in the sense that all signals in the closed loop are bounded. Furthermore, the system error approaches 0 asymptotically, i.e.

$$\lim_{t\to\infty}\|\boldsymbol{e}(t)\|=0. \tag{23}$$

Proof: Substituting (19) into (18), we have

$$\dot{V}_1\le-\frac{1}{2\eta}\lambda_\beta\boldsymbol{e}^T\boldsymbol{e}+\boldsymbol{e}^T\boldsymbol{P}\boldsymbol{b}\tilde{\boldsymbol{\varpi}}^T\boldsymbol{\varphi}+\rho|\boldsymbol{e}^T\boldsymbol{P}\boldsymbol{b}| -\boldsymbol{e}^T\boldsymbol{P}\boldsymbol{b}\hat{\rho}\tanh(\hat{\rho}(j+1)^2\boldsymbol{e}^T\boldsymbol{P}\boldsymbol{b}) \tag{24}$$

where, $\lambda_\beta=\lambda_Q-1>0$. Let us define a Lyapunov functional

$$V_2=V_1+\frac{1}{2\mu_1}\int_{t-T}^{t}\tilde{\boldsymbol{\varpi}}^T\tilde{\boldsymbol{\varpi}}d\tau+\frac{1}{2\mu_2}\int_{t-T}^{t}\tilde{\rho}^2d\tau, \tag{25}$$

whose derivative with respect to time is

$$\begin{aligned}\dot{V}_2\le&-\frac{1}{2\eta}\lambda_\beta\boldsymbol{e}^T\boldsymbol{e}+\boldsymbol{e}^T\boldsymbol{P}\boldsymbol{b}\tilde{\boldsymbol{\varpi}}^T\boldsymbol{\varphi}+\tilde{\rho}|\boldsymbol{e}^T\boldsymbol{P}\boldsymbol{b}|\\&-\boldsymbol{e}^T\boldsymbol{P}\boldsymbol{b}\hat{\rho}\tanh(\hat{\rho}(j+1)^2\boldsymbol{e}^T\boldsymbol{P}\boldsymbol{b})\\&+\frac{1}{2\mu_1}[\tilde{\boldsymbol{\varpi}}^T(t)\tilde{\boldsymbol{\varpi}}(t)-\tilde{\boldsymbol{\varpi}}^T(t-T)\tilde{\boldsymbol{\varpi}}(t-T)]\\&+\frac{1}{2\mu_2}[\tilde{\rho}^2(t)-\tilde{\rho}^2(t-T)]d\tau\end{aligned} \tag{26}$$

For $\omega\in R$, $\epsilon\in R^+$, the inequality $0\le|\omega|-\omega\tanh(\frac{\omega}{\epsilon})\le 0.2785\epsilon$ holds [41]. By using this property, we get

$$\begin{aligned}&\rho|\boldsymbol{e}^T\boldsymbol{P}\boldsymbol{b}|-\boldsymbol{e}^T\boldsymbol{P}\boldsymbol{b}\hat{\rho}\tanh(\hat{\rho}(j+1)^2\boldsymbol{e}^T\boldsymbol{P}\boldsymbol{b})\\&=\rho|\boldsymbol{e}^T\boldsymbol{P}\boldsymbol{b}|-\hat{\rho}|\boldsymbol{e}^T\boldsymbol{P}\boldsymbol{b}|+\hat{\rho}|\boldsymbol{e}^T\boldsymbol{P}\boldsymbol{b}|\\&\quad-\boldsymbol{e}^T\boldsymbol{P}\boldsymbol{b}\hat{\rho}\tanh(\hat{\rho}(j+1)^2\boldsymbol{e}^T\boldsymbol{P}\boldsymbol{b})\\&\le\tilde{\rho}|\boldsymbol{e}^T\boldsymbol{P}\boldsymbol{b}|+\frac{0.2785}{(j+1)^2}.\end{aligned} \tag{27}$$

Now, combining (27) with (26) yields

$$\begin{aligned}\dot{V}_2\le&-\frac{1}{2\eta}\lambda_\beta\boldsymbol{e}^T\boldsymbol{e}+\tilde{\rho}|\boldsymbol{e}^T\boldsymbol{P}\boldsymbol{b}|+\boldsymbol{e}^T\boldsymbol{P}\boldsymbol{b}\tilde{\boldsymbol{\varpi}}^T\boldsymbol{\varphi}\\&+\frac{1}{2\mu_1}[\tilde{\boldsymbol{\varpi}}^T(t)\tilde{\boldsymbol{\varpi}}(t)-\tilde{\boldsymbol{\varpi}}^T(t-T)\tilde{\boldsymbol{\varpi}}(t-T)]\\&+\frac{1}{2\mu_2}[\tilde{\rho}^2(t)-\tilde{\rho}^2(t-T)]+\frac{0.2785}{(j+1)^2}\end{aligned} \tag{28}$$

Note that $\boldsymbol{\varpi}(t)=\boldsymbol{\varpi}(t-T)$ holds. While $t\ge T$, $\gamma(t)=1$, by using (20), we obtain

$$\begin{aligned}&\frac{1}{2\mu_1}[\tilde{\boldsymbol{\varpi}}^T(t)\tilde{\boldsymbol{\varpi}}(t)-\tilde{\boldsymbol{\varpi}}^T(t-T)\tilde{\boldsymbol{\varpi}}(t-T)]+\boldsymbol{e}^T\boldsymbol{P}\boldsymbol{b}\tilde{\boldsymbol{\varpi}}^T(t)\boldsymbol{\varphi}\\&\le\frac{1}{2\mu_1}[(\boldsymbol{\varpi}(t)-\hat{\boldsymbol{\varpi}}(t))^T(\boldsymbol{\varpi}(t)-\hat{\boldsymbol{\varpi}}(t))-(\boldsymbol{\varpi}(t-T)-\\&\quad\mathrm{sat}_{\underline{\varpi},\bar{\varpi}}(\hat{\boldsymbol{\varpi}}(t-T)))^T(\boldsymbol{\varpi}(t-T)-\mathrm{sat}_{\underline{\varpi},\bar{\varpi}}(\hat{\boldsymbol{\varpi}}(t-T)))]\\&\quad+\boldsymbol{e}^T\boldsymbol{P}\boldsymbol{b}\tilde{\boldsymbol{\varpi}}^T(t)\boldsymbol{\varphi}\\&\le\frac{1}{2\mu_1}(2\boldsymbol{\varpi}(t)-\hat{\boldsymbol{\varpi}}(t)-\mathrm{sat}_{\underline{\varpi},\bar{\varpi}}(\hat{\boldsymbol{\varpi}}(t-T)))^T(\mathrm{sat}_{\underline{\varpi},\bar{\varpi}}(\hat{\boldsymbol{\varpi}}(t\\&\quad-T))-\hat{\boldsymbol{\varpi}}(t))+\boldsymbol{e}^T\boldsymbol{P}\boldsymbol{b}\tilde{\boldsymbol{\varpi}}^T(t)\boldsymbol{\varphi}\\&\le\frac{1}{\mu_1}(\boldsymbol{\varpi}(t)-\hat{\boldsymbol{\varpi}}(t))^T(\mathrm{sat}_{\underline{\varpi},\bar{\varpi}}(\hat{\boldsymbol{\varpi}}(t-T))-\hat{\boldsymbol{\varpi}}(t))\\&\quad+\boldsymbol{e}^T\boldsymbol{P}\boldsymbol{b}\tilde{\boldsymbol{\varpi}}^T(t)\boldsymbol{\varphi}\\&=0.\end{aligned} \tag{29}$$

In the above deduction, the property $(a-\hat{a})^2\ge(a-\mathrm{sat}_{\underline{a},\bar{a}}(\hat{a}))^2$ has been used. For more detail on this property, see Reference [19]. In a similar way, by using (21), we have

$$\begin{aligned}&\frac{1}{2\mu_2}[\tilde{\rho}^2(t)-\tilde{\rho}^2(t-T)]+|\boldsymbol{e}^T\boldsymbol{P}\boldsymbol{b}|\tilde{\rho}(t)\\&\le\frac{1}{2\mu_2}[(\rho(t)-\hat{\rho}(t))^2-(\rho(t-T)-\mathrm{sat}_{0,\bar{\rho}}(\hat{\rho}(t-T)))^2]\\&\quad+|\boldsymbol{e}^T\boldsymbol{P}\boldsymbol{b}|\tilde{\rho}(t)\\&\le\frac{1}{2\mu_2}(2\rho(t)-\hat{\rho}(t)-\mathrm{sat}_{0,\bar{\rho}}(\hat{\rho}(t-T)))(\mathrm{sat}_{0,\bar{\rho}}(\hat{\rho}(t-T))\\&\quad-\hat{\rho}(t))+|\boldsymbol{e}^T\boldsymbol{P}\boldsymbol{b}|\tilde{\rho}(t)\\&\le\frac{1}{\mu_2}(\rho(t)-\hat{\rho}(t))(\mathrm{sat}_{0,\bar{\rho}}(\hat{\rho}(t-T))-\hat{\rho}(t))+|\boldsymbol{e}^T\boldsymbol{P}\boldsymbol{b}|\tilde{\rho}(t)\\&=0\end{aligned} \tag{30}$$

holds while $t\ge T$.

Combining (28)-(30), we conclude that while $t>T$,

$$\dot{V}_2\le-\frac{1}{2\eta}\lambda_\beta\boldsymbol{e}^T\boldsymbol{e}+\frac{0.2785}{(j+1)^2}. \tag{31}$$

Therefore, while $t > T$,

$$V_2(t) \le V_2(T) - \frac{\lambda_\beta}{2\eta}\int_T^t \boldsymbol{e}^T(\tau)\boldsymbol{e}(\tau)d\tau + \int_T^t \frac{0.2785}{(j+1)^2}d\tau. \quad (32)$$

By direct calculation, we conclude

$$\begin{aligned}
&\int_T^\infty \frac{0.2785}{(j+1)^2}d\tau \\
&\le 0.2785\Big(\int_T^{2T}\frac{1}{2^2}d\tau + \int_{2T}^{3T}\frac{1}{3^2}d\tau + \int_{3T}^{4T}\frac{1}{4^2}d\tau \\
&\quad + \cdots + \lim_{k\to\infty}\int_{kT}^{(k+1)T}\frac{1}{(k+1)^2}d\tau\Big) \\
&= 0.2785T\lim_{k\to\infty}\left(\frac{1}{2^2}+\frac{1}{3^2}+\frac{1}{4^2}+\cdots+\frac{1}{(k+1)^2}\right) \\
&= 0.2785(\frac{\pi^2}{6}-1)T = 0.18T. \quad (33)
\end{aligned}$$

From (32) and (33), we have

$$V_2(\infty) \le V_2(T) - \frac{\lambda_\beta}{2\eta}\int_T^\infty \boldsymbol{e}^T(\tau)\boldsymbol{e}(\tau)d\tau + 0.18T. \quad (34)$$

Meanwhile, it is not difficult to prove

$$0 \le V_2(t) < +\infty, \quad t \in [0, T] \quad (35)$$

and

$$0 \le \int_0^T \boldsymbol{e}^T(\tau)\boldsymbol{e}(\tau)d\tau < +\infty \quad (36)$$

holds. Since $V_2(\infty) \ge 0$ and $0 \le V_2(T) + 0.18T < +\infty$, it follows from (34) and (35) that

$$0 \le \int_T^\infty \boldsymbol{e}^T(\tau)\boldsymbol{e}(\tau)d\tau < +\infty. \quad (37)$$

Furthermore, from (36) and (37), we have

$$0 \le \int_0^\infty \boldsymbol{e}^T(\tau)\boldsymbol{e}(\tau)d\tau < +\infty. \quad (38)$$

The boundedness of $V_2(t), t \in [0, +\infty]$ may be obtained from (32) and (35). Based on this and the definition of $V_2(t)$, it is immediate that $\boldsymbol{e}(t)$ is bounded for $t \in [0, +\infty]$. Then, according to the definition of $\boldsymbol{e}(t)$, we conclude $\boldsymbol{x}(t)$ is bounded for $t \in [0, +\infty]$. With the help of the above conclusions and the definition of saturation functions, we can see that $\hat{\boldsymbol{\varpi}}(t)$, $\hat{\rho}(t)$, $h_1(x_1, x_2)$ and $u(t)$ are all bounded. Furthermore, from (14), we deduce

$$0 < \|\dot{\boldsymbol{e}}\| < +\infty. \quad (39)$$

According to Barbalet lemma, (38) and (39) leading to

$$\lim_{t\to+\infty} \boldsymbol{e} = 0, \quad (40)$$

which implies that the position state error

$$\lim_{t\to+\infty} e_1 = 0. \quad (41)$$

■

In the above design scheme, the partial saturation strategies are adopted to guarantee the the boundedness of the learning variables, which helps to strengthen the security and reliability of closed loop tank gun control systems. If the learning laws are designed according to unsaturation learning strategies, how to prove the boundedness of learning variables is still a difficult problem.

V. NUMERICAL SIMULATION

Let us consider a tank gun control system as follows [40]:

$$\begin{cases} \dot{x}_1 = x_2, \\ \dot{x}_2 = -(\frac{B}{J} + \frac{K_e K_t}{JR})x_2 + \frac{K_a K_t}{iJR}u - \frac{T_L}{iJ}. \end{cases} \quad (42)$$

where, $R = 0.4\Omega$, $J = 0.0067\text{kg}\cdot\text{m}^2, i = 1039$, $L = 2.907 \times 10^{-3}$H, $K_t = 0.195N \cdot$ m/A, $K_e = 0.197\ V/($ rad $\cdot\ s^{-1})$, $B = 1.43 \times 10^{-4}$ N $\cdot$ m, $K_a = 2$, $h_1(x_1, x_2) = 5.3 + 0.5\,x_1 + 0.7\,x_2 + x_1x_2$; $h_2(x_1, x_2, t) = 0.2\text{sign}(x_2) + 0.2\sin(0.5t)\text{rand}(t)$, with rand$(\cdot)$ being a random number between 0 and 1. $x_1(0) = 0.7, x_2(0) = 0$. The reference signal is $\boldsymbol{x}_d = [x_{1,d}, x_{2,d}]^T = [\cos(\frac{\pi}{2}t), \frac{\pi}{2}\cos(\frac{\pi}{2})]^T$.

The repetitive control law (19) and learning laws (20)-(21) (as follows called RC Algorithm) are adopted for this simulation with $T = 4, \mu_0 = 10, \mu_1 = 5, \mu_2 = 0.05$, $\alpha = 2 + (x_1^2 + x_2^2 + x_{1,d}^2 + x_{2,d}^2)^{0.5}$, $\underline{\varpi} = -50$, $\bar{\varpi} = 50$, $\bar{\rho} = 20$. Figs. 3 and 4 show the position trajectory and velocity trajectory of tank gun control systems, respectively. The profiles of corresponding error are given in Figs. 5 and 6, respectively. Figs. 3-6 show that the closed-loop tank gun control system has better control performance. Fig. 7 illustrates the system control input during 30 seconds. Fig. 8 shows the average value of control input with respect to time, where $J_u \triangleq \frac{\int_0^t u_q(\tau)d\tau}{t}$. From Fig. 8, we can see that the average value of controller output is finite in the control stage. The above simulation results have verified the effectiveness of the proposed repetitive control algorithm.

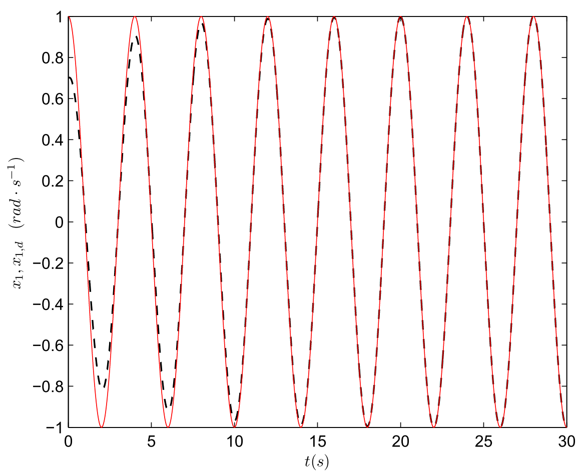

FIGURE 3. Position trajectory (RC Algorithm, x_1:dotted line, $x_{1,d}$: solid line).

For comparison, the following adaptive neural network control algorithm (as follows called Compared Algorithm)

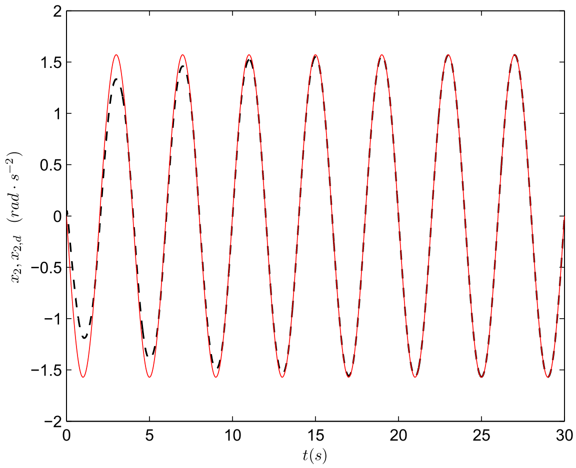

FIGURE 4. Velocity trajectory (RC Algorithm, x_2:dotted line, $x_{2,d}$: solid line).

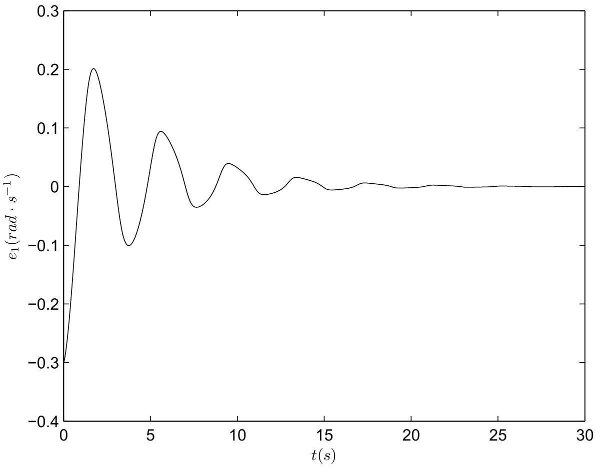

FIGURE 5. Position error e_1 (RC Algorithm) .

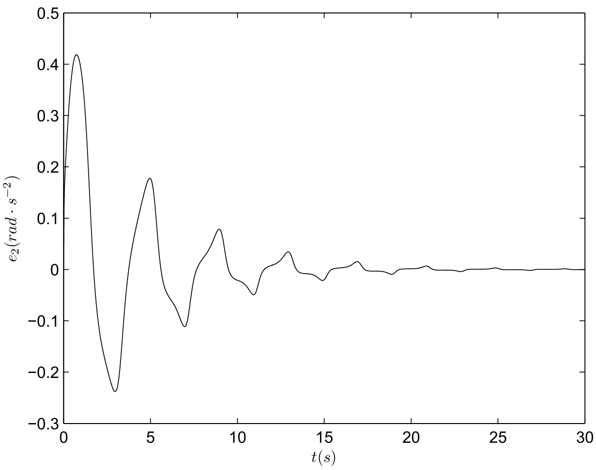

FIGURE 6. Velocity error e_2 (RC Algorithm).

is adopted for simulation [42].

$$u = \frac{1}{\hat{\boldsymbol{w}}_g^T \boldsymbol{\phi}_g(\boldsymbol{x})}(\hat{\boldsymbol{w}}_f^T \boldsymbol{\phi}_f(\boldsymbol{x}) - l_1 e_1 - l_2 e_2 - l_3 \mathrm{sgn}(s)), \quad (43)$$

$$\dot{\hat{\boldsymbol{w}}}_f = \mu_3 s \boldsymbol{\phi}_f(\boldsymbol{x}), \quad (44)$$

$$\dot{\hat{\boldsymbol{w}}}_g = \mu_4 s \boldsymbol{\phi}_g(\boldsymbol{x}), \quad (45)$$

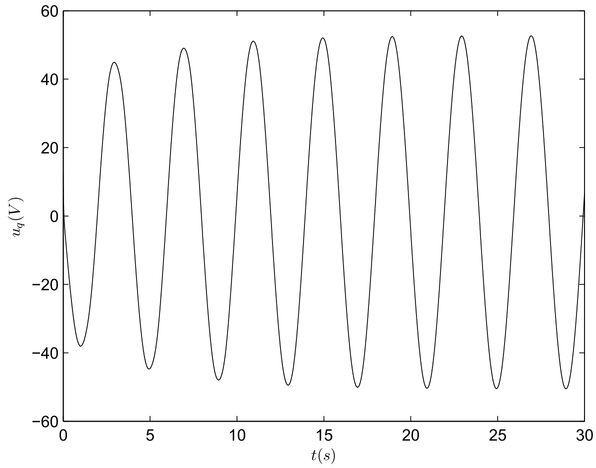

FIGURE 7. Control input (RC Algorithm).

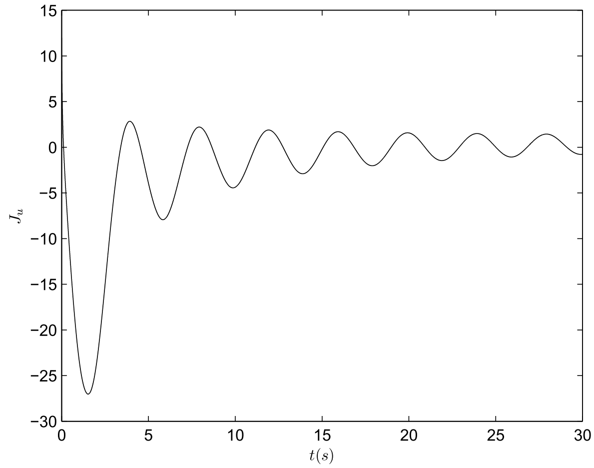

FIGURE 8. Average value of control input with respect to time (RC Algorithm).

where, $s = l_1 \int_0^t e_1 d\tau + l_2 e_1 + e_2$,

$$\boldsymbol{\phi}_f(\boldsymbol{x}) = [\phi_{f,1}, \phi_{f,2}, \cdots, \phi_{f,m}]^T \quad (46)$$

$$\boldsymbol{\phi}_g(\boldsymbol{x}) = [\phi_{g,1}, \phi_{g,2}, \cdots, \phi_{g,p}]^T \quad (47)$$

$$\phi_{f,j} = \mathrm{e}^{-\frac{\|\boldsymbol{x}-\boldsymbol{c}_{f,j}\|^2}{2b_{f,j}^2}}, \quad j = 1, 2, \cdots, m. \quad (48)$$

$$\phi_{g,j} = \mathrm{e}^{-\frac{\|\boldsymbol{x}-\boldsymbol{c}_{g,j}\|^2}{2b_{g,j}^2}}, \quad j = 1, 2, \cdots, p. \quad (49)$$

Here, $\boldsymbol{c}_{\nu,j} = [c_{\nu,j1}, c_{\nu,j2}]^T$ and $b_{\nu,j}$ are the center vector and the width of the hidden layer, respectively, $\nu \in \{f, g\}$. In this simulation, the gains and parameters in (43)-(49) are chosen as $l_1 = 1$, $l_2 = 2$, $l_3 = 2$, $\mu_1 = 3$, $\mu_2 = 3$, $m = 5$ and $p = 5$, with $\boldsymbol{c}_{f,j}$ and $\boldsymbol{c}_{g,j}$ being evenly spaced on $[-3, 3] \times [-3, 3]$, respectively. The simulation results are shown in Figs. 9-13. From Figs. 9-13, we can see that the compared algorithm is also effective to solve the trajectory tracking problem for tank gun control systems. Comparing Figs. 5-6 with Figs. 11-12, the proposed repetitive control algorithm may obtain a little better control performance than the compared

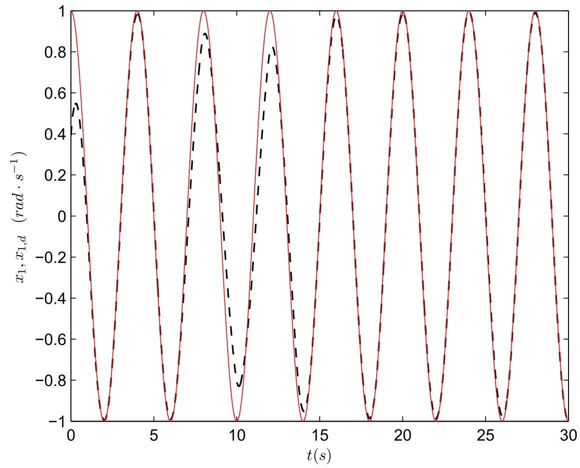

FIGURE 9. Position trajectory (Compared Algorithm, x_1:dotted line, $x_{1,d}$: solid line).

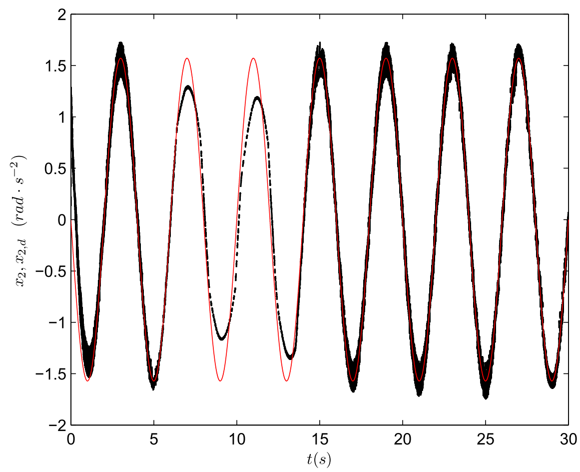

FIGURE 10. Velocity trajectory (Compared Algorithm, x_2:dotted line, $x_{2,d}$: solid line).

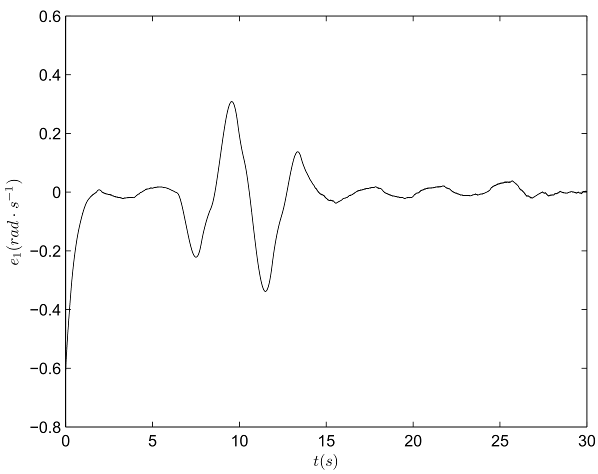

FIGURE 11. Position error e_1 (Compared Algorithm).

control algorithm (43)-(45). In addition, from Fig. 13, we can see chattering phenomenon has happened, which may be avoid by replacing $\tanh(\cdot)$ with $\mathrm{sgn}(\cdot)$.

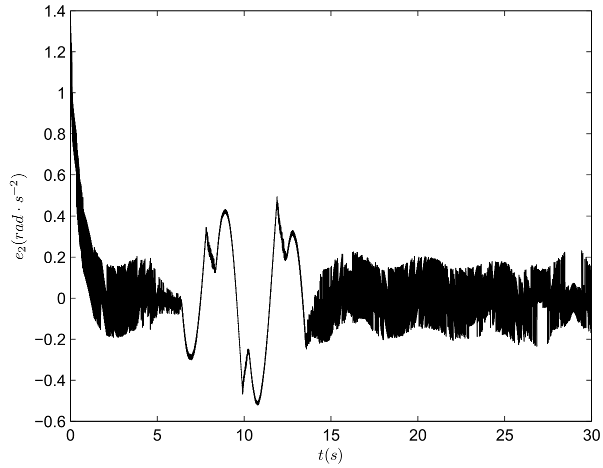

FIGURE 12. Velocity error e_2 (Compared Algorithm).

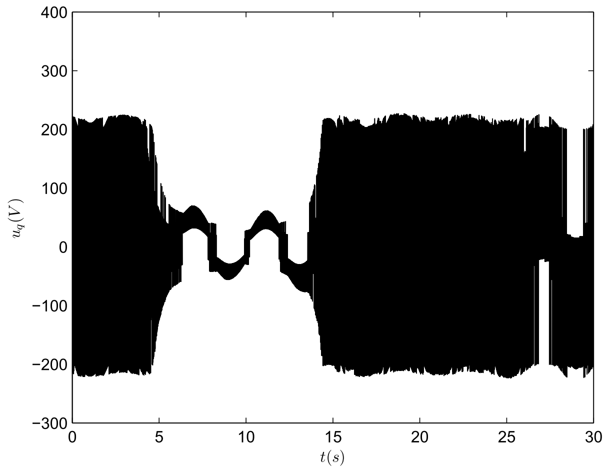

FIGURE 13. Control input (Compared Algorithm).

VI. CONCLUSION

The position tracking problem for tank gun control systems has been discussed in this paper. Signal replacement mechanism is used to deal with the nonparametric uncertainties under Lipschitz-like continuous condition. Robust learning approach is used to compensate the sum of random disturbances and discontinuous uncertainties, whose upper bound is estimated according to repetitive learning mechanism. To release the occurrence of chattering phenomenon, robust feedback term is designed by means of hyperbolic tangent function, rather than sign function. The theoretical analysis and simulations show that the closed loop tank gun control system has better performance. Future research will focus on developing neural network-based repetitive control laws for tank gun control systems.

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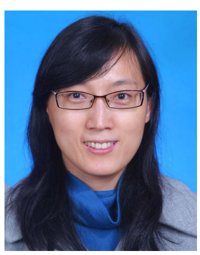

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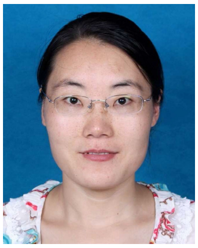

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