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Robust Learning Control for Tank Gun Control Servo Systems Under Alignment Condition

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ABSTRACT This paper proposes an adaptive learning control scheme to solve high-precision velocity tracking problem for tank gun control servo systems. Lyapunov approach is used to design the learning controller, with alignment condition used to cope with initial problem of iterative learning control. Robust control technique and adaptive learning control technique are synthesized to handle nonlinear uncertainties and external disturbances. The unknown parameters are estimated according to the full saturation difference learning strategy. As the iteration number increases, the system state can accurately track the reference signal over the whole time interval, and all signal are guaranteed to be bounded.

INDEX TERMS Tank gun control servo systems, iterative learning control, adaptive control.

I. INTRODUCTION

As a kind of useful weapons in battle fields, tanks can both improve the efficiency of artillery firepower and strengthen the surviving ability. In actual fighting situations, military tanks usually need to track the moving targets in complex and harsh environments where there exists friction, various complex uncertainties and outside disturbances. For the reason that accuracy, stability and speed of response are essential to mission accomplishment, the gun control servo systems of tank should be well designed to have high tracking precision and good dynamic quality, but also strong robustness and survivability. Therefore, it is a meaningful job for us to investigate the control design for tank gun control servo systems.

The motion control of tank gun barrels has been an ongoing topic in the past three decades, and a lot of control schemes have been proposed for achieving better control performance. In [1], PID control strategy is applied to design control system to obtain the firing precise control for the tanks in motion. In [2], a variable structure control scheme is proposed to solve the position tracking for tank guns with large uncertainties. Refs. [3] and [4] studied the optimal control algorithm for tanks. In [5], sliding mode control based on optimization was reported to cope with the motion control of tank guns. In [6], Feng *et al.* investigated the adaptive fuzzy control method for tank systems. In [7], a tank gun elevation control system was developed by using direct adaptive control method. In [8], adaptive robust control method for tank systems was discussed. Xia *et al.* proposed an active disturbance rejection control scheme to solve the problem of position tracking for a tank gun control system with inertia uncertainty and external disturbance, using the extended state observer to estimate the inertia uncertainty and external disturbance [9]. Hu *et al.* investigated the disturbance-observer base control [10] and adaptive neural network control [11] for tank gun control system, respectively. The above-mentioned works have presented meaningful results of tank gun control servo systems. However, in these above-mentioned existing works, it is still very hard to achieve high tracking precision in the complicated application environment for the great difficulties in accurate system modeling and the defects of control technologies themselves. Therefore, the precision control of tank systems is still a topic to be further studied.

On the other hand, iterative learning control (ILC) is effective in dealing with those repetitive control tasks over a finite time interval [12]–[21]. This control technique takes advantage of system error to updated control input cycle by cycle. As iteration number increases, the system output or state can follow its reference signal over the full interval. Up to now, ILC has been widely applied in many high-precision control cases, such as robotic manipulators, power electronic circuits, hard disk drives, and chemical plants [22]–[27]. In the past two decades, adaptive ILC has aroused great scholarly interest in ILC area. French *et al.* designed a differential

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learning law to estimate the unknown constant for the nonlinear systems over a fixed time interval [28]. Xu *et al.* proposed a difference learning control law to compensate unknown time-varying but iteration-independent vector [12]. Yin *et al.* investigated the trajectory-tracking problem for nonlinear system with unknown time-iteration-varying parameters [29]. Khanesar *et al.* proposed a sliding mode control theory-based learning algorithm which benefits from elliptic type-2 fuzzy membership functions [30]. In addition, the ILC research for nonparametric systems [31] and nonlinear parametric systems [32] have received close attentions in recent years.

In most existing ILC schemes, the initial system error is required to be zero at each iteration [33]–[35]. However, perfect system resetting for each iteration is not implementable in actual industries. Otherwise, a slight initial error may lead to divergence of the tracking error. Therefore, relaxing or removing the zero-error resetting condition has practical significance. Adaptive ILC without zero-error resetting condition has been explored in some works, and the presented solutions include time-varying boundary layer technique [36], error-tracking method [37]–[39], initial rectifying action [40]–[42] and so on. Besides, letting the final state of the previous iteration become the initial state of the current iteration, named as alignment condition, is effective at mitigating zero-error initial resetting condition for adaptive ILC where the reference trajectory is spatially closed, meaning that the starting point of the reference trajectory is also the end point in each iteration [43].

Up to now, there have been many ILC results on the position/velocity control of motors [45], [46]. In [47], an ILC scheme was proposed to reduce periodic torque pulsations in permanent magnet synchronous motors. In [48], the motion control of permanent magnet synchronous motors was considered, and ILC technique was used to eliminate the influence of force ripple for a position servo system. In [49], Precup *et al.* proposed a 2-DOF proportional-integral-fuzzy control scheme for a class of servo systems, and the extended symmetrical optimum method accompanied by an iterative feedback tuning algorithm was adopted to control law design. However, the ILC results on the trajectory-tracking problem for gun control servo systems of tank is few. How to develop ILC algorithms for gun control servo systems of tank is still an open issue.

In this paper, referring to the ILC algorithms design for PMLSMs and PMSMs, we want to solve the trajectory-tracking problem for gun control servo systems of tank by using ILC approaches. A robust learning control scheme is designed to obtain high-precision tracking performance regardless of nonzero initial errors. Compared with existing results, the main contributions of this work lie in the following:

(1) Difference from those existed results, in this work, robust adaptive iterative learning control technique is introduced to develop the control algorithm for tank gun control servo systems, which is helpful to get better tracking performance for the corresponding systems.

(2) In the process of ILC design for tank gun servo systems, alignment condition is used to remove/relax the zero initial error condition, which should be observed in most traditional ILC algorithms.

(3) The controller is designed by using Lyapunov approach, synthesizing learning control and robust control methods, which owns better capacity of handling the complex uncertainties. The parametric uncertainties and the bound of perturbations are estimated according to difference learning strategy, respectively.

The remainder of this paper is organized as follows. The problem formulation is given in Section 2. The design of iterative learning controller is given in Section 3. Section 4 presents the convergence analysis of the closed loop system. To demonstrate the effectiveness of the proposed ILC scheme, an illustrated example is shown in Section 5, followed by Section 6 which concludes the work.

II. PROBLEM FORMULATION

A. STRUCTURE OF TANK GUN CONTROL SYSTEMS

In a all-electric tank gun control system, the adjustments of turret and gun in both horizontal direction and vertical direction are accomplished by motor drive. Compared with the traditional electro-hydraulic/full-hydraulic gun control system, the full-electric one has some advantages including simple structure, excellent performance and high efficiency. Hence, it has been adopted widely in recent years. The structure diagram of vertical servo system of all-electrical tank gun is given in Fig 1. We can see that the controlled device mainly includes AC motor, speed reducer and barrel.

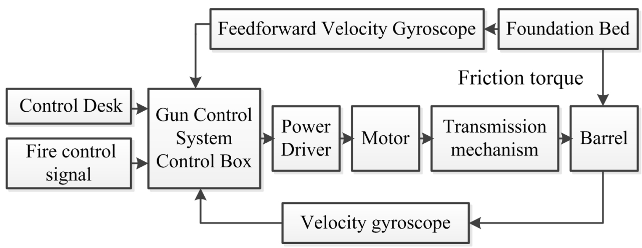

FIGURE 1. Structure diagram of vertical servo system of all-electrical tank gun.

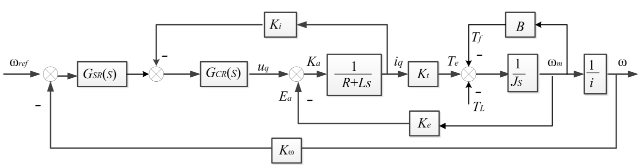

FIGURE 2. Block diagram of tank gun control systems.

B. MODEL OF TANK GUN CONTROL SYSTEMS

The block diagram of tank gun control systems is presented in Fig. 2, where ω_{ref} and ω represent the desired angular velocity and the real angular velocity of the cannon, repectively. $G_{SR}(s)$ is velocity regulator, and $G_{CR}(s)$ is current regulator. u_q is the output voltage of the current loop. R and L

represent the resistance and inductance of the motor armature circuit, respectively. K_a is the amplifier gain. E_a is the armature back electromotive force of motor. K_i is the current feedback coefficient of q axis. 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. K_ω is the angular velocity feedback coefficient of cannon. 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.

We can get the model of gun control servo systems of tank as

$$\dot{i}_q = -\frac{R}{L}i_q - \frac{K_e i}{L}\omega + \frac{K_a}{L}u_q, \tag{1}$$

$$\dot{\omega} = \frac{K_t}{Ji}i_q - \frac{1}{Ji}T_{Ls}, \tag{2}$$

where $T_{Ls} = T_L + T_f$. Combing (1) with (2), we obtain

$$\ddot{\omega} = -\frac{R}{L}\dot{\omega} - \frac{K_t K_e}{LJ}\omega + \frac{K_a K_t}{LJi}u_q - \left(\frac{R}{LJi}T_{Ls} + \frac{1}{Ji}\dot{T}_{Ls}\right) \tag{3}$$

Define $x_1 = \omega$, $x_2 = \dot{\omega}$. Then, from (3), the dynamics of tank gun control systems at the kth iteration can be written as

$$\begin{cases} \dot{x}_{1,k} = x_{2,k}, \\ \dot{x}_{2,k} = -\frac{R}{L}x_{2,k} - \frac{K_t K_e}{LJ}x_{1,k} + \frac{K_a K_t}{LJi}u_{q,k} \\ \quad +\Delta f(\boldsymbol{x}_k, t), \end{cases} \tag{4}$$

where $\boldsymbol{x}_k = (x_{1,k}, x_{2,k})$, $\Delta f(\boldsymbol{x}_k, t) = -(\frac{R}{LJi}T_{Ls} + \frac{1}{Ji}\dot{T}_{Ls})$, and $k = 0, 1, 2, \ldots,$ represents the number of iteration cycle.

For the given reference signal $\boldsymbol{x}_d(t) = (x_d, \dot{x}_d)^T$, which satisfies $\boldsymbol{x}_d(t) \in C^1[0, T]$ and $\boldsymbol{x}_d(T) = \boldsymbol{x}_d(0)$, the control objective is to design proper adaptive learning control law so as to make the system state $\boldsymbol{x}_k$ accurately track its reference signal $\boldsymbol{x}_d$ over $[0, T]$, under the condition $\boldsymbol{x}_k(0) = \boldsymbol{x}_{k-1}(T)$. For the sake of brevity, the arguments in this paper are sometimes omitted when no confusion is likely to arise.

Assumption 1:

$$\Delta f(\boldsymbol{x}_k, t) = f_1(\boldsymbol{x}_k) + f_2(\boldsymbol{x}_k, t).$$

where $f_1(\boldsymbol{x}_k)$ meets Liphitz continuous condition, i.e., $|f_1(\boldsymbol{x}_k) - f(\boldsymbol{x}_d)| \le l\|\boldsymbol{x}_k - \boldsymbol{x}_d\|$ with l an unknown positive constant; $f_2(\boldsymbol{x}_k, t)$ represents the noncontinuous but bounded perturbations. There exists an unknown smooth continuous function $f_{2m}(t)$, $f_2(\boldsymbol{x}_k, t) \le f_{2m}(t)$.

III. CONTROL SYSTEM DESIGN

Let us define $\boldsymbol{e}_k(t) = [e_{1,k}, \ldots, e_{n,k}]^T = \boldsymbol{x}_k(t) - \boldsymbol{x}_d(t)$ and

$$s_k = ce_{1,k} + e_{2,k},$$

$$s_{\phi k} = s_k - \phi\,\mathrm{sat}\left(\frac{s_k}{\phi}\right) \tag{5}$$

In this paper, sat.$(\cdot)$ represents saturation operator, defined as follows. For $\hat{a} \in R$,

$$\mathrm{sat}_{\bar{a}}(\hat{a}) = \begin{cases} \hat{a}, & |a| < \bar{a} \\ \bar{a}\,\mathrm{sign}(\hat{a}), & \text{else}, \end{cases}$$

in which, $\bar{a}$ is the proper upper limit. While $\bar{a} = 1$, we denote $\mathrm{sat}_{\bar{a}}(\hat{a})$ briefly by $\mathrm{sat}(\hat{a})$. For a vector $\hat{\boldsymbol{a}} = (\hat{a}_1, \hat{a}_2, \ldots, \hat{a}_m) \in \boldsymbol{R}^m$, $\mathrm{sat}_{\bar{a}}(\hat{\boldsymbol{a}}) \triangleq \left(\mathrm{sat}_{\bar{a}}(\hat{a}_1), \mathrm{sat}_{\bar{a}}(\hat{a}_2), \ldots, \mathrm{sat}_{\bar{a}}(\hat{a}_m)\right)^T$.

From (1), we can obtain

$$\begin{cases} \dot{e}_{i,k} = e_{i+1,k}, \\ \dot{e}_{2,k} = -\frac{R}{L}x_2 - \frac{K_t K_e}{LJ}x_1 + \frac{K_a K_t}{LJi}u_{q,k} + f_1(\boldsymbol{x}_k) \\ \quad +f_2(t) - \ddot{x}_d \end{cases}$$

and

$$\dot{s}_k = ce_{2,k} - \frac{R}{L}x_2 - \frac{K_t K_p}{LJ}x_1 + \frac{K_a K_t}{LJi}u_{q,k} + f_1(\boldsymbol{x}_k) + f_2(\boldsymbol{x}_k, t) - \ddot{x}_d. \tag{6}$$

Then, we choose a candidate control Lyapunov function at the kth iteration as

$$V_k = \frac{1}{2}s_{\phi k}^2 \tag{7}$$

Denoting $\eta = \frac{K_a K_t}{LJi}$ and taking the time derivative to V_k yield

$$\begin{aligned} \dot{V}_k &= s_{\phi k}[ce_{2,k} - \frac{R}{L}x_2 - \frac{K_t K_e}{LJ}x_1 + \frac{K_a K_t}{LJi}u_{q,k} \\ &\quad +f_1(\boldsymbol{x}_k) + f_2(\boldsymbol{x}_k, t) - \ddot{x}_d] \\ &= s_{\phi k}\eta\Big[\frac{1}{\eta}(ce_{2,k} - \frac{R}{L}x_2 - \frac{K_t K_e}{LJ}x_1 + f_1(\boldsymbol{x}_k) \\ &\quad +f_2(\boldsymbol{x}_k, t) - \ddot{x}_d) + u_{q,k}\Big]. \end{aligned} \tag{8}$$

While $|s_k| > \phi$, we have

$$\begin{aligned} \frac{1}{\eta}s_{\phi k}f_1(\boldsymbol{x}) &= \frac{1}{\eta}s_{\phi k}(f_1(\boldsymbol{x}) - f_1(\boldsymbol{x}_d)) + \frac{1}{\eta}s_{\phi k}f_1(\boldsymbol{x}_d) \\ &\le \frac{l}{\eta}s_{\phi k}\|\boldsymbol{e}_k\|\mathrm{sat}\left(\frac{s_k}{\phi}\right) + \frac{1}{\eta}s_{\phi k}f_1(\boldsymbol{x}_d) \end{aligned} \tag{9}$$

and

$$\frac{1}{\eta}s_{\phi k}f_2(\boldsymbol{x}_k, t) \le \frac{1}{\eta}|s_{\phi k}|f_{2m}(t) = \frac{1}{\eta}s_{\phi k}f_{2m}\mathrm{sat}\left(\frac{s_k}{\phi}\right). \tag{10}$$

Substituting (9) and (10) into (8) yields

$$\dot{V}_k = s_{\phi k}\eta(\boldsymbol{\theta}^T\boldsymbol{\varphi}_k + \boldsymbol{\vartheta}^T\boldsymbol{\psi}_k + u_{q,k})\} \tag{11}$$

with

$$\begin{aligned} \boldsymbol{\theta} &\triangleq \left(\frac{1}{\eta}, -\frac{R}{\eta L}, -\frac{K_t K_e}{\eta LJ}, \frac{f_1(\boldsymbol{x}_d)}{\eta}\right)^T, \\ \boldsymbol{\varphi}_k &\triangleq (ce_{2,k} - \ddot{x}_d, x_{2,k}, x_{1,k}, 1)^T, \\ \boldsymbol{\vartheta} &\triangleq \left(\frac{1}{\eta}, \frac{c}{\eta}f_{2m}\right)^T, \\ \boldsymbol{\psi}_k &\triangleq \left(\|\boldsymbol{e}_k\|\mathrm{sat}\left(\frac{s_k}{\phi}\right), \mathrm{sat}\left(\frac{s_k}{\phi}\right)\right)^T. \end{aligned}$$

On the basis of (11), we propose the following learning control law for system (1) as

$$u_{q,k} = -\gamma_1 s_{\phi k} - \boldsymbol{\theta}_k^T\boldsymbol{\varphi}_k - \boldsymbol{\vartheta}_k^T\boldsymbol{\psi}_k, \tag{12}$$

in which,

$$\boldsymbol{\theta}_k = \mathrm{sat}_{\bar{\theta}}(\boldsymbol{\theta}_{k-1}) + \gamma_2 s_{\phi k}\boldsymbol{\varphi}_k, \quad \boldsymbol{\theta}_{-1} = 0, \tag{13}$$

$$\boldsymbol{\vartheta}_k = \mathrm{sat}_{\bar{\vartheta}}(\boldsymbol{\vartheta}_{k-1}) + \gamma_2 s_{\phi k}\boldsymbol{\psi}_k, \quad \boldsymbol{\vartheta}_{-1} = 0. \tag{14}$$

IV. CONVERGENCE ANALYSIS

In this section, we will analyze the stability and error convergence of closed-loop system. Here we present the main result in the following.

Theorem 1: For the closed loop dynamic system (4) with Assumption 1, control law (12) and learning laws (13)-(14), all system variables are guaranteed to be bounded at each iteration. Moreover, as the iteration number k increases,

$$|s_k(t)| \le \phi, \quad \forall t \in [0, T] \tag{15}$$

and

$$|e_{1,k}(t)| \le \frac{\phi}{c}, \quad \forall t \in [0, T] \tag{16}$$

can be obtained.

Proof:

Part I Difference of $L_k(t)$:

Let us calculate the difference of the Lyapunov functional $L_k(t)$, which is defined as

$$L_k = V_k + \frac{\eta}{2\gamma_2}\int_0^t \tilde{\boldsymbol{\theta}}_k^T\tilde{\boldsymbol{\theta}}_k d\tau + \frac{\eta}{2\gamma_3}\int_0^t \tilde{\boldsymbol{\vartheta}}_k^T\tilde{\boldsymbol{\vartheta}}_k d\tau, \tag{17}$$

with $\tilde{\boldsymbol{\theta}}_k = \boldsymbol{\theta} - \boldsymbol{\theta}_k$, $\tilde{\boldsymbol{\vartheta}}_k = \boldsymbol{\vartheta} - \boldsymbol{\vartheta}_k$. For (11) and (12), we deduce that

$$V_k = V_k(0) - \gamma_1\eta\int_0^t s_{\phi k}^2 d\tau + \eta\int_0^t s_{\phi k}(\tilde{\boldsymbol{\theta}}_k^T\boldsymbol{\varphi}_k + \tilde{\boldsymbol{\vartheta}}_k^T\boldsymbol{\psi}_k)d\tau.$$

Therefore, while $k > 0$, the difference of $L_k(t)$ between two adjacent iterations is taken as

$$\begin{aligned} &L_k - L_{k-1} \\ &= V_k(0) - \gamma_1\eta\int_0^t s_{\phi k}^2 d\tau + \eta\int_0^t s_{\phi k}(\tilde{\boldsymbol{\theta}}_k^T\boldsymbol{\varphi}_k + \tilde{\boldsymbol{\vartheta}}_k^T\boldsymbol{\psi}_k)d\tau \\ &\quad - V_{k-1} + \frac{\eta}{2\gamma_2}\int_0^t (\tilde{\boldsymbol{\theta}}_k^T\tilde{\boldsymbol{\theta}}_k - \tilde{\boldsymbol{\theta}}_{k-1}^T\tilde{\boldsymbol{\theta}}_{k-1})d\tau \\ &\quad + \frac{\eta}{2\gamma_3}\int_0^t (\tilde{\boldsymbol{\vartheta}}_k^T\tilde{\boldsymbol{\vartheta}}_k - \tilde{\boldsymbol{\vartheta}}_{k-1}^T\tilde{\boldsymbol{\vartheta}}_{k-1})d\tau \end{aligned} \tag{18}$$

From (13) and (14), we have

$$\begin{aligned} &\frac{1}{2\gamma_2}(\tilde{\boldsymbol{\theta}}_k^T\tilde{\boldsymbol{\theta}}_k - \tilde{\boldsymbol{\theta}}_{k-1}^T\tilde{\boldsymbol{\theta}}_{k-1}) + s_{\phi,k}\tilde{\boldsymbol{\theta}}_k^T\boldsymbol{\varphi}_k \\ &\quad \le \frac{1}{2\gamma_2}[(\boldsymbol{\theta} - \boldsymbol{\theta}_k)^T(\boldsymbol{\theta} - \boldsymbol{\theta}_k) - (\boldsymbol{\theta} - \mathrm{sat}_{\bar{\theta}}(\boldsymbol{\theta}_{k-1}))^T \\ &\qquad (\boldsymbol{\theta} - \mathrm{sat}_{\bar{\theta}}(\boldsymbol{\eta}_{k-1}))] + s_{\phi,k}\tilde{\boldsymbol{\eta}}_k^T\boldsymbol{\varphi}_k \\ &\quad \le \frac{1}{2\gamma_2}(2\boldsymbol{\theta} - \boldsymbol{\theta}_k - \mathrm{sat}_{\bar{\theta}}(\boldsymbol{\theta}_{k-1}))^T(\mathrm{sat}_{\bar{\theta}}(\boldsymbol{\theta}_{k-1}) - \boldsymbol{\theta}_k) \\ &\qquad + s_{\phi,k}\tilde{\boldsymbol{\theta}}_k^T\boldsymbol{\varphi}_k \\ &\quad \le \frac{1}{\gamma_2}(\boldsymbol{\theta} - \boldsymbol{\theta}_k)^T(\mathrm{sat}_{\bar{\theta}}(\boldsymbol{\theta}_{k-1}) - \boldsymbol{\theta}_k) + s_{\phi,k}\tilde{\boldsymbol{\theta}}_k^T\boldsymbol{\varphi}_k \\ &\quad = 0 \end{aligned} \tag{19}$$

and

$$\begin{aligned} &\frac{1}{2\gamma_3}(\tilde{\boldsymbol{\vartheta}}_k^T\tilde{\boldsymbol{\vartheta}}_k - \tilde{\boldsymbol{\vartheta}}_{k-1}^T\tilde{\boldsymbol{\vartheta}}_{k-1}) + s_{\phi,k}\tilde{\boldsymbol{\vartheta}}_k^T\boldsymbol{\psi}_k \\ &\quad \le \frac{1}{2\gamma_3}[(\boldsymbol{\vartheta} - \boldsymbol{\vartheta}_k)^T(\boldsymbol{\vartheta} - \boldsymbol{\vartheta}_k) - (\boldsymbol{\vartheta} - \mathrm{sat}_{\bar{\vartheta}}(\boldsymbol{\vartheta}_{k-1}))^T \\ &\qquad (\boldsymbol{\vartheta} - \mathrm{sat}_{\bar{\vartheta}}(\boldsymbol{\eta}_{k-1}))] + s_{\phi,k}\tilde{\boldsymbol{\eta}}_k^T\boldsymbol{\psi}_k \\ &\quad \le \frac{1}{2\gamma_3}(2\boldsymbol{\vartheta} - \boldsymbol{\vartheta}_k - \mathrm{sat}_{\bar{\vartheta}}(\boldsymbol{\vartheta}_{k-1}))^T(\mathrm{sat}_{\bar{\vartheta}}(\boldsymbol{\vartheta}_{k-1}) - \boldsymbol{\vartheta}_k) \\ &\qquad + s_{\phi,k}\tilde{\boldsymbol{\vartheta}}_k^T\boldsymbol{\psi}_k \\ &\quad \le \frac{1}{\gamma_3}(\boldsymbol{\vartheta} - \boldsymbol{\vartheta}_k)^T(\mathrm{sat}_{\bar{\vartheta}}(\boldsymbol{\vartheta}_{k-1}) - \boldsymbol{\vartheta}_k) + s_{\phi,k}\tilde{\boldsymbol{\vartheta}}_k^T\boldsymbol{\psi}_k \\ &\quad = 0, \end{aligned} \tag{20}$$

respectively. Substituting (19) and (20) into (18), we have

$$L_k - L_{k-1} = V_k(0) - \gamma_1\eta\int_0^t s_{\phi k}^2 d\tau - V_{k-1} \tag{21}$$

Under the alignment condition, both $\boldsymbol{x}_{k-1}(T) = \boldsymbol{x}_k(0)$ and $\boldsymbol{x}_d(T) = \boldsymbol{x}_d(0)$ hold. Hence, $\boldsymbol{e}_{k+1}(0) = \boldsymbol{e}_k(T)$ holds for $k = 0, 1, 2, 3, \cdots$. On the basis of this conclusion, now (21) becomes

$$L_k(T) - L_{k-1}(T) \le -\gamma_1\eta\int_0^T s_{\phi k}^2 d\tau, \tag{22}$$

which further implies

$$L_k(T) \le L_0(T) - \gamma_1\eta\sum_{j=1}^k\int_0^T s_{\phi j}^2 d\tau. \tag{23}$$

Part II Finiteness of $L_0(t)$:

By direct calculation, the time derivatives of

$$L_0 = V_0 + \frac{\eta}{2\gamma_2}\int_0^t \tilde{\boldsymbol{\theta}}_0^T\tilde{\boldsymbol{\theta}}_0 d\tau + \frac{\eta}{2\gamma_3}\int_0^t \tilde{\boldsymbol{\vartheta}}_0^T\tilde{\boldsymbol{\vartheta}}_0 d\tau, \tag{24}$$

may be obtained as

$$\begin{aligned} \dot{L}_0 = -\gamma_1 g s_{\phi 0}^2 + \eta s_{\phi 0}(\tilde{\boldsymbol{\theta}}_0^T\boldsymbol{\varphi}_0 + \tilde{\boldsymbol{\vartheta}}_k^T\boldsymbol{\psi}_k) + \frac{\eta}{2\gamma_2}\tilde{\boldsymbol{\theta}}_0^T\tilde{\boldsymbol{\theta}}_0 \\ + \frac{\eta}{2\gamma_3}\tilde{\boldsymbol{\vartheta}}_0^T\tilde{\boldsymbol{\vartheta}}_0 \end{aligned} \tag{25}$$

From (13), we can see that $\hat{\boldsymbol{\theta}}_0 = \gamma_2\, s_{\phi 0}\boldsymbol{\varphi}_0$. Thus,

$$\tilde{\boldsymbol{\theta}}_0 = \boldsymbol{\theta} - \gamma_2 s_{\phi 0}\boldsymbol{\varphi}_0 \tag{26}$$

holds. Similarly, from (14), we obtain

$$\tilde{\boldsymbol{\vartheta}}_0 = \boldsymbol{\vartheta} - \gamma_3 s_{\phi 0}\boldsymbol{\psi}_0. \tag{27}$$

Substituting (26) and (27) and into (25) shows

$$\begin{aligned} \dot{L}_0 &= -\gamma_1\eta s_{\phi 0}^2 + \eta s_{\phi 0}\boldsymbol{\theta}^T\boldsymbol{\varphi}_0 - \gamma_2\eta s_{\phi 0}^2\boldsymbol{\varphi}_0^T\boldsymbol{\varphi}_0 \\ &\quad + \frac{1}{2\gamma_2}\eta\boldsymbol{\theta}^T\boldsymbol{\theta} + \frac{\gamma_2}{2}\eta s_{\phi 0}^2\boldsymbol{\varphi}_0^T\boldsymbol{\varphi}_0 - \eta\boldsymbol{\theta}s_{\phi 0}\boldsymbol{\varphi}_0 \\ &\quad + \eta s_{\phi 0}\boldsymbol{\vartheta}^T\boldsymbol{\psi}_0 - \gamma_3\eta s_{\phi 0}^2\boldsymbol{\psi}_0^T\boldsymbol{\psi}_0 + \frac{1}{2\gamma_3}\eta\boldsymbol{\vartheta}^T\boldsymbol{\vartheta} \\ &\quad + \frac{\gamma_3}{2}\eta s_{\phi 0}^2\boldsymbol{\psi}_0^T\boldsymbol{\psi}_0 - \eta\boldsymbol{\vartheta}s_{\phi 0}\boldsymbol{\psi}_0 \\ &\le -\gamma_1\eta s_{\phi 0}^2 + \frac{1}{2\gamma_2}\eta\boldsymbol{\theta}^T\boldsymbol{\theta} - \frac{\gamma_2}{2}\eta s_{\phi 0}^2\boldsymbol{\varphi}_0^T\boldsymbol{\varphi}_0 \\ &\quad + \frac{1}{2\gamma_3}\eta\boldsymbol{\vartheta}^T\boldsymbol{\vartheta} - \frac{\gamma_3}{2}\eta s_{\phi 0}^2\boldsymbol{\psi}_0^T\boldsymbol{\psi}_0 \\ &\le \frac{1}{2\gamma_2}\eta\boldsymbol{\theta}^T\boldsymbol{\theta} + \frac{1}{2\gamma_3}\eta\boldsymbol{\vartheta}^T\boldsymbol{\vartheta}. \end{aligned} \tag{28}$$

Since $0 \leq L_0(0) < +\infty$ and $|\frac{1}{2\gamma_2}\eta\boldsymbol{\theta}^T\boldsymbol{\theta} + \frac{1}{2\gamma_3}\eta\boldsymbol{\vartheta}^T\boldsymbol{\vartheta}| < +\infty$, from (28), we can see that $L_0(t)$ is bounded for all $t \in [0, T]$, which implies

$$L_0(T) < +\infty. \tag{29}$$

Part III Convergence of Tracking Errors:
Combining (23) with (29) gives

$$\lim_{k\to+\infty} \int_0^T s_{\phi k}^2 d\tau = 0 \tag{30}$$

From (21), we can obtain

$$L_k(t) \leq L_{k-1}(T) - \gamma_1\eta \int_0^T s_{\phi k}^2 d\tau \tag{31}$$

Therefore, by the definition of L_k, we can draw a conclusion that $s_{\phi k}$ is bounded, which furthermore leads to the boundedness of $\boldsymbol{e}_k$, $\dot{\boldsymbol{e}}_k$ and other signals. Then, by the definition of $s_{\phi k}$, we can see

$$|\dot{s}_{\phi k}| < +\infty, \tag{32}$$

which means $s_{\phi k}$ is equicontinuous. On the basis of (32) and (30), we have

$$\lim_{k\to\infty} s_{\phi k}(t) = 0, \quad t \in [0, T], \tag{33}$$

which implies that

$$\lim_{k\to\infty} |s_k(t)| \leq \phi, \quad \forall t \in [0, T]. \tag{34}$$

From (34), we thus get that

$$|e_{1,k}(t)| \leq \frac{\phi}{c}, \quad \forall t \in [0, T], \tag{35}$$

holds for the enough large k [44]. Therefore, we can see that the predetermined control precision can be obtained by choosing an appropriate small positive number ϕ.

By the property of saturation function, from (13) and (14), we can see that $\hat{\boldsymbol{\theta}}_k$ and $\hat{\boldsymbol{\vartheta}}$ are both bounded. Further, Since $s_{\phi k}$, $\boldsymbol{x}_k$, $\boldsymbol{e}_k$ $\hat{\boldsymbol{\theta}}_k$ and $\hat{\boldsymbol{\vartheta}}$ are all bounded, we can obtain the boundedness of u_k from (12). ■

To guarantee the boundedness of the estimation in learning laws, the partial saturation strategy is chosen in this work. One may also utilize the full saturation learning strategy to design the adaptive learning laws, which can also guarantee the parameter estimation bounded during the difference learning.

V. NUMERICAL SIMULATION

Consider the tank gun control system as follows [5]:

$$\begin{cases} \dot{x}_{1,k} = x_{2,k}, \\ \dot{x}_{2,k} = -\dfrac{R}{L}x_{2,k} - \dfrac{K_tK_e}{LJ}x_{1,k} + \dfrac{K_aK_t}{LJi}u_{q,k} \\ \qquad +\Delta f(\boldsymbol{x}_k, t), \end{cases} \tag{36}$$

where $R = 0.4\Omega$, $J = 5239\text{kg}\cdot\text{m}^2$, $i = 1039$, $L = 2.907 \times 10^{-3}\text{H}$, $K_t = 0.195N\cdot\text{m/A}$, $K_e = 0.197\ V/(\text{rad}\cdot s^{-1})$,

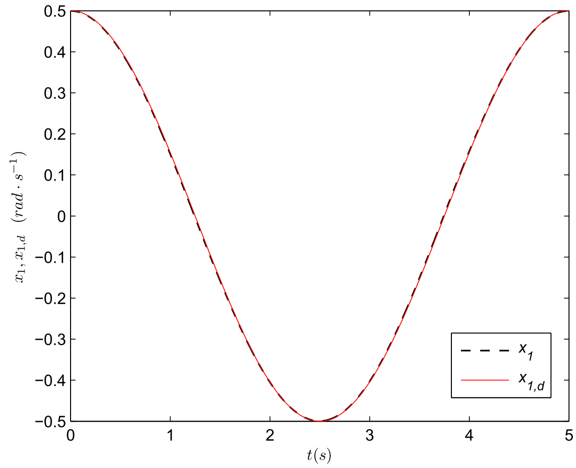

FIGURE 3. x_1 and its reference signal $x_{1,d}$ (ILC).

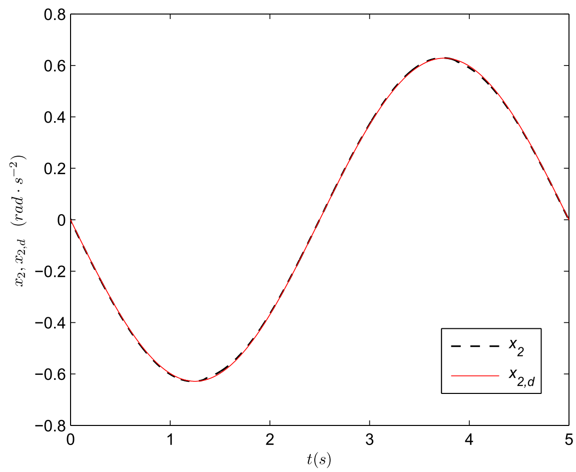

FIGURE 4. x_2 and its reference signal $x_{2,d}$ (ILC).

$B = 1.43 \times 10^{-4}$ N · m, $K_a = 2$, $\Delta f(\boldsymbol{x}_k, t) = 13.2 + 0.1\ x_{1,k} + 0.2\ x_{2,k} + 0.2\text{sign}(x_{2,k}) + 0.2\text{rand}(k)\sin(0.5t)$, $\boldsymbol{x}_k(0) = [0.7, 0]^T$, $x_d = 0.5\cos(0.5\pi t)$, $T = 5$. Here, rand(·) denotes a random number between 0 and 1. We can easily verify that $\Delta f(\boldsymbol{x}, t)$ satisfies Assumptions 1. The control objective is to make $x_{1,k}$ accurately track its reference x_d. The robust adaptive ILC law (12) and adaptive learning laws (13)-(14) are used to do this simulation, and the control parameters are chosen as $\gamma_1 = 5$, $\gamma_2 = 5$, $\gamma_3 = 0.05$, $\bar{\theta} = 50$, $\bar{\vartheta} = 20$. After 70 cycles, the simulation results are shown in Figs. 3–8. Figs. 3-4 show the state profiles over $[0, T]$ at the 70th iteration, with the corresponding state tracking error profiles presented in Figs. 5-6. According to Figs. 3–6, we conclude that $x_1(t)$ can precisely track $x_d(t)$ over [0, T] as the iteration number increases. The control input signal at the 70th iteration is shown in Fig. 7. Fig. 8 gives the convergence history of $s_{\phi k}$, where $J_k \triangleq \max_{t\in[0,T]} |s_{\phi k}(t)|$.

For comparison, PID control algorithm for the tank gun control system (36) is simulated, with $u_k(t) = k_p(x_d(t) - x_{1,k}(t)) + k_i[\sum_{j=0}^{k-1}\int_0^{jT}(x_d(\tau) - x_{1,k}(\tau))d\tau + \int_0^t(x_d(\tau) - x_{1,k}(\tau))(\tau)d\tau] + k_d\frac{d(x_d(t)-x_{1,k}(t))}{dt}$. The proportion

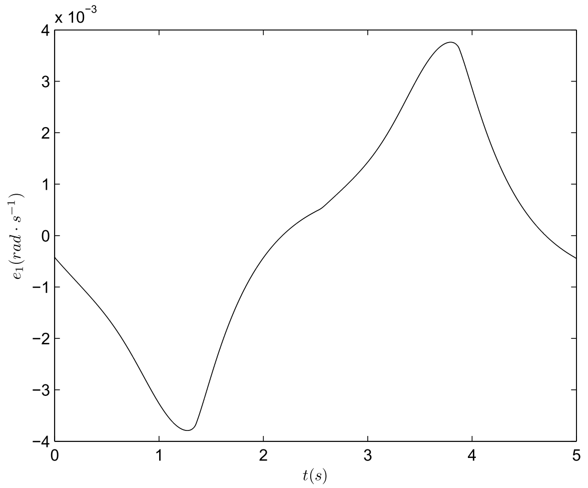

FIGURE 5. The error e_1 (ILC).

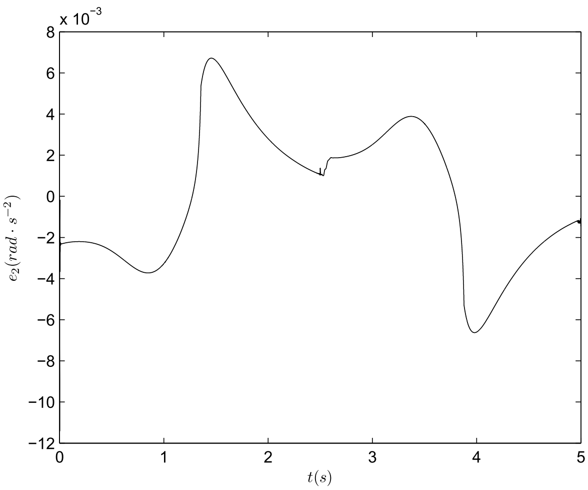

FIGURE 6. The error e_2 (ILC).

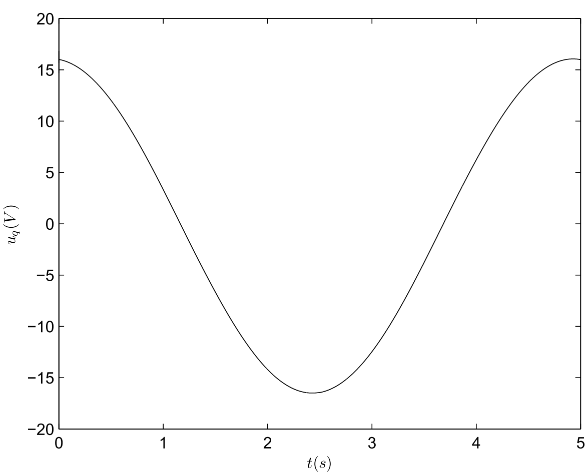

FIGURE 7. Control input (ILC).

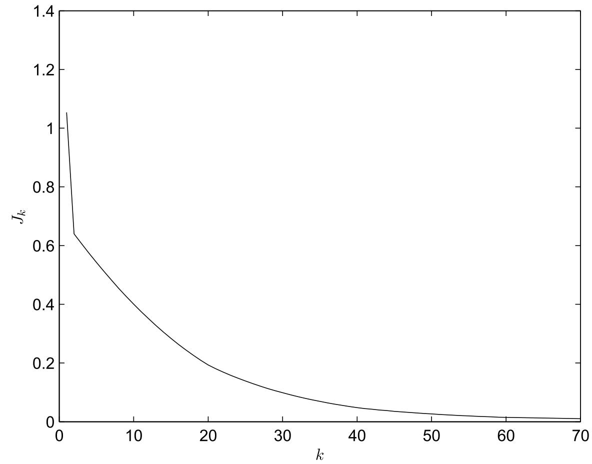

FIGURE 8. History of $s_{\phi k}$ convergence (ILC).

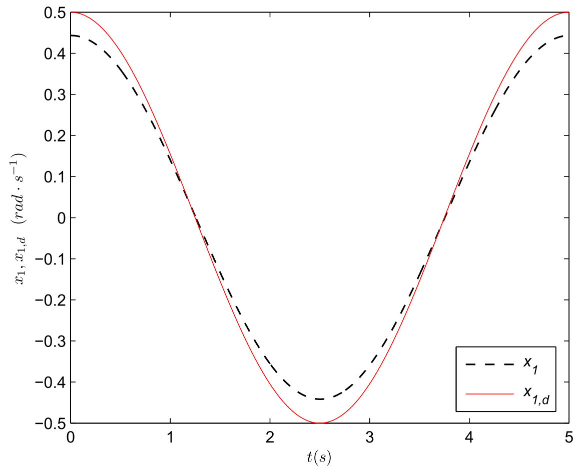

FIGURE 9. x_1 and its reference signal $x_{1,d}$ (PID).

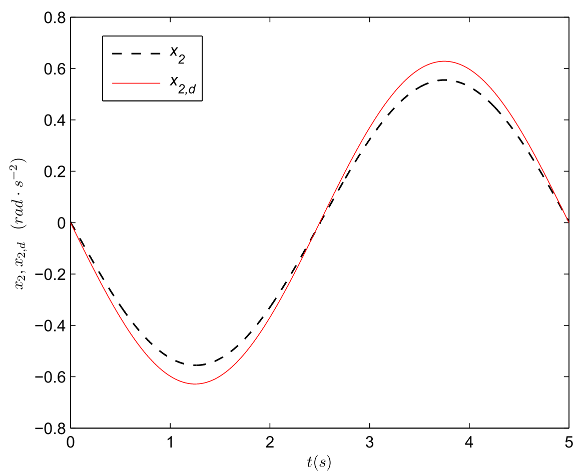

FIGURE 10. x_2 and its reference signal $x_{2,d}$ (PID).

parameter k_p, integral parameter k_i and differential coefficient k_d chosen to be 20, 10 and 5, respectively. The initial state, control objective and cycle number are the same as the ones in the simulation of ILC algorithm. Simulation results are presented in Figs. 9–12. Figs. 9–10 show the system state profiles of PID control, while the corresponding error results are presented in Figs. 11–12. Comparing Figs. 9-10

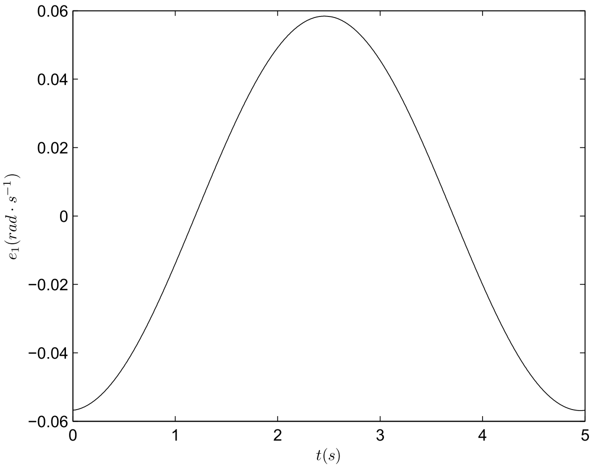

FIGURE 11. The error e_1 (PID).

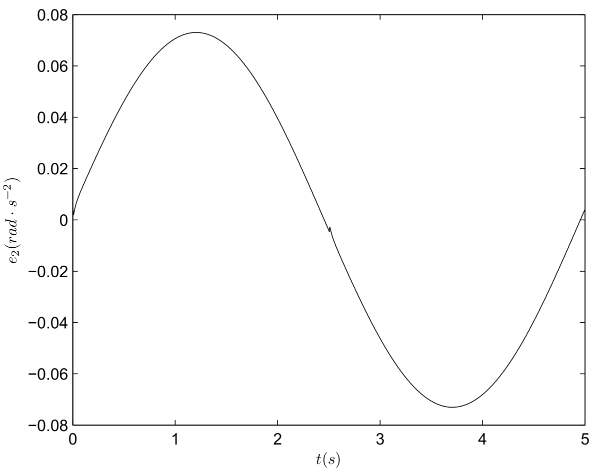

FIGURE 12. The error e_2 (PID).

with Figs. 3-4, and comparing Figs. 11-12 with Figs. 5-6, we can see our proposed ILC scheme has higher control precision than PID control algorithm. The above simulation results verify the effectiveness of theoretical analysis in this paper.

VI. CONCLUSION

This paper studies the velocity tracking problem for tank gun control servo systems. A robust adaptive learning control scheme is proposed to undertake the high-precision velocity tracking task for tank gun control servo systems. The alignment condition is used to remove zero initial error condition of iterative learning control, while robust control technique and learning control technique are combinedly applied to handle nonlinear uncertainties and external disturbances. As the iteration number increases, the system output can perfectly track its reference signal over the full time interval, and all signal are guaranteed to be bounded. Simulation results show the effectiveness of our proposed robust adaptive ILC scheme.

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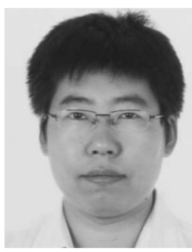

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