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Predefined-Time Event-Triggered Tracking Control for Nonlinear Servo Systems: A Fuzzy Weight-Based Reinforcement Learning Scheme

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Abstract: In this article, a novel reinforcement-learning-based predefined-time control method for nonlinear servo systems with prescribed performance is proposed under an event-triggered strategy. First, the nonlinear dynamics and control behaviors of the systems can be trained effectively through fuzzy logic systems under the identifier–critic–actor framework. Moreover, by employing the prescribed performance control and a switching event-triggered rule, system tracking performance can be ensured while decreasing the data transmission frequency. With the assistance of the predefined-time stability criteria, the boundedness of system variables and the convergence of tracking errors within a predetermined time can be guaranteed. Comparisons with some existing control schemes are addressed regarding tracking performance and action costs. The availability and superiority.

INTRODUCTION

Nonlinear servo systems (NSSs) are ubiquitous in many real-world industrial applications, such as throttle systems [1], motor drive systems [2], and wind turbine systems [3]. Unfortunately, the performance of NSSs is susceptible to various constraints. In this regard, the topic of achieving high-performance control for NSSs is very meaningful and challenging. The difficulties are mainly concentrated in the following four aspects.

1) Nonlinear Processing
The existence of transmission equipment and mechanical deceleration within NSSs inevitably introduces nonlinearity. Therein, friction dynamics with non-smooth and highly nonlinear characteristics can significantly degrade system performance. Therefore, it is necessary to deal with the friction to ensure system performance.

2) Implementation of Optimal Control
The core of achieving optimal control is solving the Hamiltion–Jacobi–Bellman (HJB the suggested scheme are verified in the simulations equation. However, it is virtually impossible due to the severe partial differential and nonlinear properties inherent in the HJB equation. Consequently, effective strategies need to be found to overcome the difficulty and realize optimal control for NSSs.

3) Acceleration of System Stabilization
Convergence time is a vital indicator of system stability. Furthermore, some specific time-response requirements need to be satisfied in actual industrial control. So, it is essential to design valid control methods to hasten system convergence and improve control performance.

4) Performance Guarantees and Resource Savings
Considering the limited communication resources and the goal of high-precision tracking in actual systems, a control scheme featuring excellent tracking performance and low communication costs needs to be developed.

An effective online learning method, namely, reinforcement learning (RL), has been proven to obtain optimal control strategies relying on continuous training, rather than solving the HJB equation directly. For this reason, the application of RL in nonlinear systems has made tremendous progress [4], [5], [6]. Just to name a few, an actor–critic structure was constructed in [7] to achieve RL-based optimized control for nonlinear systems in the presence of unmeasurable states. In [5], the optimized tracking task of multiagent systems was accomplished via an identifier–actor–critic (IAC) structure, in which the adaptive identifier was utilized to approximate the unknown nonlinearity. Recently, RL was employed in the research of optimized control for practical drive systems, resulting in [8] and [9]. In these existing reports, the friction dynamics are treated as a component of the system nonlinearity and estimated by fuzzy logic systems (FLSs) or neural networks [10], [11], [12], [13], [14], [15], [16]. However, actual friction models often have non smooth properties, which may render the approximation ineffective [17]. In view of this, an optimized control scheme for NSSs with nonlinear. Smooth friction dynamics needs further investigation.

Contributions

Inspired by the aforementioned accounts, this article explores event-triggered optimized predefined-time control (OPTC) for NSSs with prescribed performance. The predefined-time optimization theoretical model is successfully constructed with the aid of the projection modification method, the IAC structure, and the predefined-time stability criterion. Furthermore, by introducing friction compensation technology to rebuild unsmooth friction, PPC to constrain the tracking error, and STETS to save communication resources, the event-triggered OPTC is applied to NSSs for the first time. The primary contributions can be listed as follows

In contrast with the existing works for NSSs in [8] and [9], the friction dynamics compensation technology is further incorporated under the IAC structure in this work. By approaching non smooth friction with, the proposed scheme can be applied to NSSs containing discontinuous nonlinearity while minimizing the cost function, which is more universal and applicable.

Different from the finite/fixed-time control results [22], [23], [24], as a first attempt, the OPTC is considered for NSSs in the framework of the predefined-time theory. The key feature of the control method is that the boundary of the system settling time can be preset by a single parameter, thus getting rid of the restrictions from initial values and controller parameters. Compared with the majority of event-triggered control approaches. In contrast with the existing works for NSSs in [8] and [9], the friction dynamics compensation technology is further incorporated under the IAC structure in this work. By approaching non smooth friction with, the proposed scheme can be applied to NSSs containing discontinuous nonlinearity while minimizing the cost function, which is more universal and applicable. first attempt, the OPTC is considered for NSSs in the framework of the predefined-time theory. The key feature of the control method is that the boundary of the system settling time can be preset by a single parameter, thus getting rid of the restrictions from initial values and controller parameters. Compared with the majority of event-triggered control approaches for NSSs [33], [34], an STETS is introduced in this article to avoid the occurrence of excessively large event errors caused by the overly large amplitude of the control input.
Moreover, by integrating with the PPC.

Organization and Notation

The rest of this article is organized as follows. Section II shows the problem statement for NSSs. The main results of the OPTC and stability analysis for NSSs are presented in Section III. The simulation results are stated in Section IV, and finally, Section V concludes this article.
Notations: R and Rn stand for the real number set and the *n*-dimensional real vector, respectively. ‖·‖ denotes the Euclidean norm.

SECTION II.
Problem Statement and Preliminaries

A. Nonlinear Servomechanisms Model

In this article, a class of NSSs equipped with a servo motor, a transmission, a mechanical system, and position sensors are considered [17], which can be modeled as

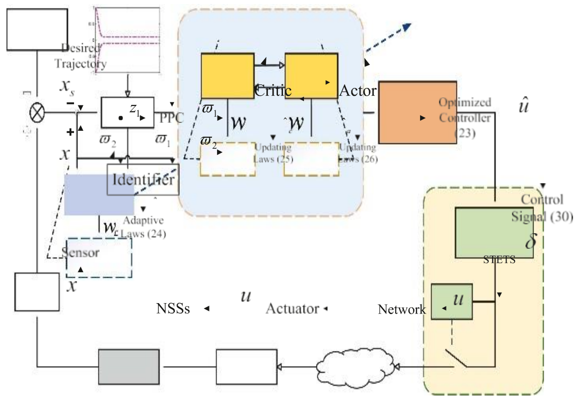


Fig. 1. Structure of OPTC for NSSs with STETS.

The meaning of the variables are presented in Nomenclature. In terms of [17], the transient dynamics term LadIa/dt can be ignored in the process of controller design.

To effectively compensate for the friction dynamics of the servo system.

Tf=p1(tanh(μ1x2)−tanh(μ2x2))+p2tanh(μ3x2)+p3x2(3)

Here $p1, p2, p3, \mu1, \mu2$, and $\mu3$ are given positive constants.
and $F(x)=(-f(x)-Tl-Tf)/J$ with $x=[x1,x2]T$ represents the lumped uncertainties composed of the unknown nonlinearity, load torque, and normalized friction. $TD=Td/J$ stands for the unknown time-varying disturbance.

Remark 1:
The widespread friction dynamics are generally discontinuous, which may be detrimental to obtaining smooth control behaviors. Therefore, a typical continuous differentiable friction model is utilized to perform the friction dynamics Tf. In this case, the feature of (3) is continuous and differentiable, which provides more flexibility for realizing subsequent control objectives.

Assumption 1:
The unknown time-varying disturbance TD is bounded and satisfies $|TD|<D$, with $D>0$ being a constant.

B. Performance Function
To achieve the PPC for the angular position of NSSs, the tracking error can be defined as
$z1=x1-x_s(5)$
where x_s is a given trajectory. Then, z1 can be formulated as
$-\hbar(t)<z1<\hbar(t)(6)$
where $\hbar(t)$ is a performance function, and its form is
$\hbar(t)=\{(\hbar0-\hbar\infty)\cos a(\pi t2Tq)+\hbar\infty,\hbar\infty 0\leq t<Tqt\geq Tq(7)$
In which $0<\hbar\infty<|z1(0)|<\hbar0$, $\hbar0=\hbar(0)$, and $\hbar\infty=\lim t\to+\infty\hbar(t)$. Tq is the predefined maximum convergence time for $\hbar(t)$ converging from $\hbar0$ to $\hbar\infty$, and a is a positive parameter that can regulate the convergence rate.

RESULTS & DISCUSSION

RL-Based Predefined-Time Optimized Controller Design
In what follows, an OPTC scheme is developed under the frameworks of the back stepping technique and the RL approach. Therein, the unknown nonlinearity, performance function, and control behavior are, respectively, approximated by the identifier, critic, and actor. Otherwise, performance guarantees for NSSs can be implemented by employing the function.

By observing ideal optimization controllers, it is evident that the main obstacle to obtaining the optimal solution comes from the unknown dynamics existing in $dG*jd\varpi j$. In view of this, the critic–actor structure is considered in this article to implement the synchronous online training of the performance index and control behaviors, thereby seeking the numerical solution of the HJB equation and obtaining the approximated optimal controllers.

Remark 4:
Note that the general learning laws designed in terms of the gradient descent method cannot directly meet the requirements of optimization control design. The designed weight updating laws for optimization are presented as follows.

Algorithm 1: The Predefined-Time Event-Triggered Optimization Control Algorithm.
Step I: Initialization: Define the angular position tracking error policy
Step II: Define the performance function and obtain the transformed error:
$z1=\hbar(t)\zeta(\varpi1)\to\varpi1=\tan(\pi 2z1\hbar)$.
Step III: For the admissible control policies containing ϖj, define the optimal performance index as:
$G*j(\varpi j)=\int\infty te-rj(s-t)Aj(\varpi j(s),\psi*j(\varpi j))ds$.
Step IV: Obtain the ideal optimization controllers and by solving the HJB equation.
Step V: Utilize critic FLS to online training $\psi*j$.
Step VI: Design the weight learning laws then obtain the approximated optimal controllers .
Step VII: Design the STETS as
stop Algorithm

SIMULATION RESULTS

In this subsection, the reference signal is given as $xs=0.8\sin(0.5\pi t)+0.2$. Figs. 2 and 3 reflect the tracking performance of the presented scheme. It can be concluded that the system can achieve the tracking of the target within a predefined time, and the error steers into a small range of predetermined accuracy. Fig. 4 describes the control input u. The norms of weight estimations are depicted in Fig. 5. Fig. 6 illustrates the corresponding triggered event intervals by using the STETS. The time step of the simulation is set at 0.01, and the controller necessitates 570 samples. Compared with the 2000 samples required under time-triggered control, this proposed event-triggered scheme reduces the updating frequency by about 70%, which greatly saves communication resources. Overall, the aforementioned results indicate that the proposed scheme can not only efficiently realize the tracking task while saving resources, but also ensure all signals in NSSs are PPTB

Fig. 2.Responses of x1 and xs.

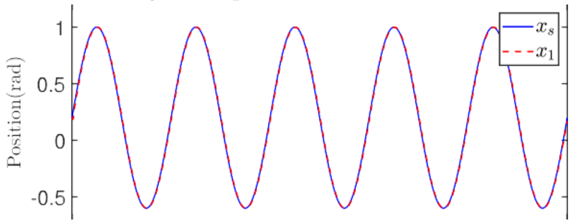


Fig. 3. Tracking error z1.

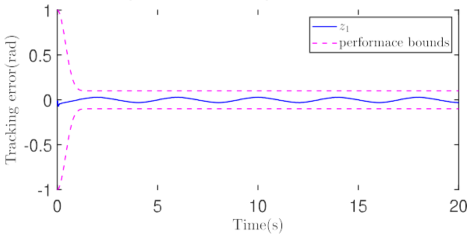


Fig. 4. Control input u.

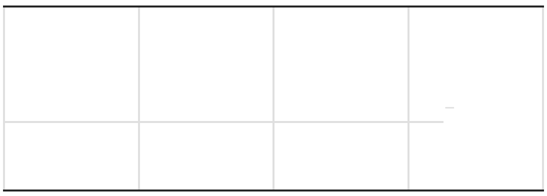
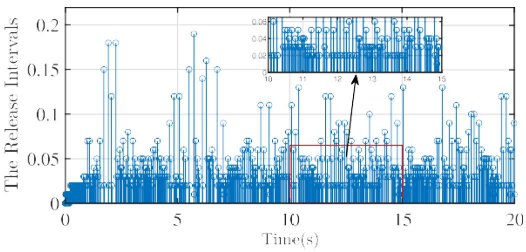


Fig. 5.Triggering intervals.



CONCLUSION:

This article has focused on event-triggered optimized PTC for nonlinear servo systems with prescribed performance. To this end, the RL method has been employed under the IAC Structure to obtain optimization results. Under the skeleton of PPC, FLS, STETS and the predefined time theory, an event-triggered OPTC scheme for NSSs has been proposed.

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