**Fast Stabilizing Control for Uncertain Nonlinear Systems Under Event-Triggered Schemes**

**Gong Chikun *a* , Guo Kai *a*,** **Yuan Lipeng*b,\****

aSchool of mechanical engineering, University of Shanghai for Science and Technology, shanghai 200093.China

bSchool of Mechanical and Electrical Engineering, Harbin Institute of Technology, Harbin 150001, China

**Abstract:** This paper presents an adaptive neural network event-triggered control approach to address the challenges of input dead zones and full-state constraints in nonlinear systems. These issues can severely degrade system performance and stability in practical industrial applications. The proposed control strategy integrates a barrier Lyapunov function within the backstepping framework and utilizes a radial basis function neural network to approximate the unknown nonlinear dynamics of the system. To mitigate the effects of input dead zones and reduce communication load, an adaptive event-triggering mechanism is introduced to dynamically update control signals with reduced frequency. Leveraging fast finite-time stabilization theory, the approach ensures bounded system signals and accelerates the convergence of tracking errors to a predefined compact set. Simulation results demonstrate the effectiveness and robustness of the proposed strategy in enhancing system performance under uncertainty.

**Keywords:** Input dead zones; full-state constraints; nonlinear systems; barrier Lyapunov function; backstepping control; event-triggering mechanism; fast finite-time stabilizatio

# 0 Introduction

Input deadband is one of the common nonlinear problems in many practical industrial systems, and has become a hot research topic in the field of control [1-4]. Hou et al [1] introduced a finite-time control approach for deadband-containing nonlinear systems by combining the barrier Lyapunov function with adaptive backstepping control. However, the method assumes that the slope, turning point, or boundary conditions of the deadband are known, which is more difficult to satisfy in practical applications. He et al [2] used adaptive fuzzy inference systems to approximate the width of the deadband, and Xi et al [3] designed an adaptive control method based on neural networks, combining backstepping control and dynamic surface techniques, all of which avoid a priori assumptions on the boundedness of the deadband parameters. In addition, the problem of full state constraints is a major challenge [1,5-7]. In the literature [1], barrier Lyapunov functions are gradually incorporated into each design step to guarantee that all states remain confined within a specified compact set. Sun et al [5] dealt with full-state constraints using higher-order tangent-type barrier Lyapunov functions, and Feng et al [6] converted the constrained system into an unconstrained system through a nonlinear mapping. In addition, uncertainty and nonlinear problems usually exist in the system. In recent years, fuzzy logic systems (FLSs) [8-10] and radial basis function neural networks (RBFNNs) [11-13] have been widely used to approximate unknown nonlinear functions. For example, Lin et al [13] studied the adaptive neural network tracking problem for nonlinear systems with uncertainties, input time lag, and saturation by combining RBFNNs and backstepping control methods. However, real industrial systems usually have higher requirements on convergence speed.

In recent years, numerous scholars have proposed various finite-time control design schemes [14-21]. For example, Gao et al [17] proposed an adaptive neural control strategy based on a semi-global finite-time stability criterion, but the convergence speed of the method decreases significantly when the initial state of the system is far from the equilibrium point. To overcome this challenge, Yu et al [18] developed an enhanced finite-time command filtered backstepping control technique grounded in fast finite-time stability theory, which ensures rapid convergence and system stability by designing a control law that satisfies the Lyapunov stability condition. However, in many practical engineering applications, the nonlinear smoothing gain function is usually unknown. For this reason, Qiu et al. [19] further relaxed the boundary assumptions on the gain function and combined backstepping control with the theory of fast finite-time stabilization to address the issue of adaptive fast finite-time trajectory tracking control for a class of uncertain nonlinear strict-feedback systems.

Most of the existing studies rely on the time-triggered mechanism framework. However, the traditional sampling cycle consumes a lot of communication resources, thus increasing the communication load of the system. With the rapid progress of network and information technology, event-triggered mechanism (ETM) has received widespread attention. As a result, many scholars have proposed ETM methods to replace the traditional time-triggered mechanism [22-26]. For example, Peng et al [24] conducted a detailed review and prospective analysis of existing event-triggered mechanisms. For nonlinear systems with external disturbances and dynamic uncertainties, Abdelrahim et al [25] improved the nonlinear small gain theorem and designed a new event-triggered control method by combining input-to-state stability (ISS). However, it is still challenging to satisfy the ISS assumption in nonlinear systems. Zhang et al [26] achieved consistent outputs for all agents by jointly designing a controller and an event-triggered mechanism, effectively avoiding the dependence on the ISS assumption.

In summary, this paper presents a novel fast finite-time adaptive neural network event-triggered control approach for uncertain nonlinear systems with input dead zones and full state constraints, aiming to alleviate their effects on the system. In contrast to previous works, the proposed method offers the following innovative features:

1. For common input deadband and full-state constraint issues in real industrial systems, traditional compensation methods often consume significant communication resources. For this reason, this paper designs an adaptive event-triggered mechanism that employs the hyperbolic tangent function to design a control law to dynamically compensate for the input deadband and minimize the consumption of communication resources. Meanwhile, the introduction of the logarithmic-type symmetric barrier Lyapunov function ensures that all system states operate within a predefined full-state constraint interval, making the method highly applicable in practical engineering.
2. Drawing on fast finite-time stability theory and incorporating the unknown gain function and the system’s nonlinear dynamics, this study proposes a rapid finite-time adaptive control strategy using neural networks. The method approximates the unknown nonlinear function using a neural network and develops an adaptive law with a fractional exponential term to ensure that the system satisfies the conditions of the fast finite-time stability theorem. This approach enhances the convergence rate and tracking precision of the closed-loop system, while also directing the tracking error to converge swiftly within a configurable bounded region in a finite duration, with the convergence rate closely dependent on the design parameters.

# 1Problem Description and Related

**1.1 System Model**

Assume the following nonlinear system:

|  |  |
| --- | --- |
|  | (1) |

where denotes the state vector of the system, stands for the input deadband, is the output of the system, and and are unknown smooth nonlinear functions. To simplify the analysis, denote and as and , respectively. all states of the system are required to satisfy the constraints and .

The input deadband is modelled as follows:

|  |  |
| --- | --- |
|  | (2) |

where is the control input to the system. Parameters and subsections are defined as follows:

Here, and represent the unknown slopes of the input deadband curve on the negative and positive semi-axes, respectively, while and correspond to the unknown turning points.

**1.2 Preliminary Knowledge**

The objective of this paper is to develop an adaptive event-triggered control law. To maintain generality, the subsequent assumptions and lemmas are presented.

**Assumption 1** [27] For the function , it is assumed to be a bounded function and satisfies , where and are unknown constants.

**Assumption 2** [27-28] The desired signal and its order derivatives are continuous and bounded functions, The desired signal ​ and its order derivatives are continuous and bounded functions. and there exist positive numbers and satisfying and .

**Lemma 1** [19] For a nonlinear system , the system will be rapidly stable in finite time if there exists a positive definite smooth and continuous function , and constants and such that , then the system will be rapidly stable in finite time. The compact set of solutions of the system is:

|  |  |
| --- | --- |
| . | (3) |

where satisfies . Its stabilisation time T is:

|  |  |
| --- | --- |
|  | (4) |

**Lemma 2** [29] For any and any variable , there are:

|  |  |
| --- | --- |
|  | (5) |

**Lemma 3** [30] For any and any positive number , the following inequality holds:

|  |  |
| --- | --- |
|  | (6) |

**Lemma 4** [19] For any , there are:

|  |  |
| --- | --- |
|  | (7) |

**Lemma 5** [31] For any and , there are:

|  |  |
| --- | --- |
|  | (8) |

**Lemma 6** Radial-base neural networks (RBFNNs) are capable of arbitrarily approximating nonlinear functions:

|  |  |
| --- | --- |
|  | (9) |

The Gaussian function is chosen as the radial basis function with the expression:

|  |  |
| --- | --- |
|  | (10) |

# 2 Fast Finite-Time Event-Triggered Control Design

A rapid finite-time event-based control approach is designed to address the issue that input deadband and full-state constraints can affect the system's performance and cause instability.

**2.1 Controller Design**

Initially, define the discrepancy system as follows:

|  |  |
| --- | --- |
|  | (11) |

where is the deviation variable, is the desired signal, and is the auxiliary control law.

Step 1: Combine equations (1) and (11):

|  |  |
| --- | --- |
|  | (12) |

Select the following barrier Lyapunov function:

|  |  |
| --- | --- |
|  | (13) |

where: is the estimation deviation, represents the estimation of the unknown parameter, and . Derivation of gives:

|  |  |
| --- | --- |
|  | (14) |

where is the unknown combination term. The approximation of using RBFNNs is expressed as follows:

|  |  |
| --- | --- |
|  | (15) |

where is the estimation error and . According to Lemma 2:

|  |  |
| --- | --- |
|  | (16) |

where is a two-parameter number and .

Construct the virtual control law as follows:

|  |  |
| --- | --- |
|  | (17) |

where . Further derivation gives:

|  |  |
| --- | --- |
|  | (18) |

Design and the adaptive law as follows:

|  |  |
| --- | --- |
|  | (19) |
|  | (20) |

where: and are all positive and .

Substituting Eq. (15)-(20) into Eq. (14), we obtain:

|  |  |
| --- | --- |
|  | (21) |

Step i : obtained from Eqs. (1) and (11):

|  |  |
| --- | --- |
|  | (22) |

Define the following barrier Lyapunov function:

|  |  |
| --- | --- |
|  | (23) |

where: represents the estimation deviation, is the predicted value of the unknown parameter, and . Derivation of is obtained:

|  |  |
| --- | --- |
|  | (24) |

where is the unknown combination term. Same as step 1, use RBFNNs to approximate to get:

|  |  |
| --- | --- |
|  | (25) |

where

is the estimation error, .

Design the virtual control strategy as follows:

|  |  |
| --- | --- |
|  | (26) |

where . Further derivation gives:

|  |  |
| --- | --- |
|  | (27) |

and the adaptive rule are formulated as follows:

|  |  |
| --- | --- |
|  | (28) |
|  | (29) |

where and are positive.

Substituting Eq. (25)-(29) into (24), we obtain:

|  |  |
| --- | --- |
|  | (30) |

Step n: In this step, the real control input will be formulated. The event triggering mechanism is designed as follows:

|  |  |
| --- | --- |
|  | (31) |

where satisfies , and are positive; where is defined as the measurement error ; and denotes the moment of event triggering with ,and .

The specific design of the intermediate control law is as follows:

|  |  |
| --- | --- |
|  | (32) |

where . However, in practical applications, accurately determining the parameter is typically difficult. To solve this problem, the estimation parameter is introduced and is defined as the estimation error, where , and and are the estimates of and , respectively. Therefore, the intermediate control law is designed as follows:

|  |  |
| --- | --- |
|  | (33) |

From equation (31), we can derive , where and are time-varying parameters and . Further derivation leads to the following inequality:

|  |  |
| --- | --- |
|  | (34) |

By combining equation (11) and system equation (1), it can be derived:

|  |  |
| --- | --- |
|  | (35) |

Design the following barrier Lyapunov function:

|  |  |
| --- | --- |
|  | (36) |

where represents the estimation error, and is an estimate of the uncertainty parameter n, with . Additionally, is a positive semidefinite matrix, and represents its inverse matrix. Derivation of results in:

|  |  |
| --- | --- |
|  | (37) |

where : , which belongs to the undetermined combinatorial terms. Similarly to step 1, can be approximated by RBFNNs to obtain:

|  |  |
| --- | --- |
|  | (38) |

where: ;

is the estimation error, and.

The result can be derived from Eq. (31) and (34) along with Lemma 3:

|  |  |
| --- | --- |
|  | (39) |

Constructing virtual control laws:

|  |  |
| --- | --- |
|  | (40) |

where: . Further, it is obtained:

|  |  |
| --- | --- |
|  | (41) |

Design , the adaptive law and as follows:

|  |  |
| --- | --- |
|  | (42) |
|  | (43) |
|  | (44) |

where and are positive numbers.

Substituting equations (38)-(44) into (37), we obtain:

|  |  |
| --- | --- |
|  | (45) |

Obtained by Lemma 2:

|  |  |
| --- | --- |
|  | (46) |
|  | (47) |

According to Lemma 4, setting one can obtain the following inequality:

|  |  |
| --- | --- |
|  | (48) |

Ditto:

|  |  |
| --- | --- |
|  | (49) |

Substituting equations (46) and (49) into equation (45) gives:

|  |  |
| --- | --- |
|  | (50) |

where denotes the maximum eigenvalue of , ,according to Lemma 5 for further derivation:

|  |  |
| --- | --- |
|  | (51) |

where: .

Ultimately, it can be deduced:

|  |  |
| --- | --- |
|  | (52) |

where:

**Remark 1** According to literature [32], for any constant satisfying , it follows that holds. As a corollary, also holds when .

**2.2 Convergence Analysis**

**Theorem 1** Consider a nonlinear system with input dead zones and full state constraints under uncertainty. Assuming that Assumptions 1 and 2 are valid, and the virtual control laws (17), (26), (40) along with the adaptive laws (20), (29), (43), (44) are satisfied, the system will meet the following criteria:

1. All system signals remain bounded, and the tracking error ​ rapidly approaches a confined region within finite time.
2. All system states are preserved within the defined limits.
3. No Zeno phenomenon occurs.

**Proof:** By Eq. (52) and Lemma 1, the system's error signal vector can be demonstrated to rapidly converge in finite time to the following constrained set:

|  |  |
| --- | --- |
|  | (53) |

where takes the value of and the convergence time is:

|  |  |
| --- | --- |
|  | (54) |

From Eq. (53), the error signal is bounded, while is constant and is also in the bounded range. Therefore, both and are bounded quantities. Further combining Eq. (17), (19) and the boundedness of , it can be deduced that and are also bounded. Analogously, it can be derived that and are bounded quantities. Since and is also bounded, it can be concluded that all signals within the closed-loop system remain confined to a bounded state. Finally, based on Eq. (36), the following conclusion can be obtained:

|  |  |
| --- | --- |
|  | (55) |

It follows that the tracking error ​ can rapidly settle within a configurable narrow set in finite time, i.e.

|  |  |
| --- | --- |
|  | (56) |

From and it follows that ∣∣ satisfies . Since is bounded and is bounded, if is assumed, then also satisfies . Thus, the system state is always within the predetermined constraint interval.

According to equation (31):

|  |  |
| --- | --- |
|  | (57) |

According to the formula is both bounded and continuous, and there exists a positive constant such that . It follows that the trigger interval is full when . Thus, the occurrence of the Zeno phenomenon is avoided.

**3 Simulation**

To validate the performance of the control approach presented in this paper, numerical examples are analyzed, and simulation tests are performed on a second-order robotic arm system.

**3.1 Numerical Simulation**

Consider the following nonlinear uncertain system with input saturation and complete state constraints:

|  |  |
| --- | --- |
|  | (58) |

where ; the full state constraint interval is . The initial state of the system is and the desired signal .

The Gaussian radial basis functions listed below are chosen as the foundation functions for the RBFNNs:

|  |  |
| --- | --- |
|  | (59) |

The center points of the Gaussian functions are all set in the range [-1, 1].

The parameter settings cover control laws, adaptive laws, and event triggering mechanisms, as described in detail below:

Based on the simulation outcomes of Fig.1~Fig.5, it is evident that all variables within the closed-loop system remain confined, and the control strategy ensures the stability and constraint compliance of the closed-loop framework. As shown in Fig.1, the system output accurately follows the reference signal ​, and the design of the virtual control rate within the controller, along with the Lyapunov stability analysis, demonstrates its effectiveness. Fig.2 illustrates the trajectory of state , and when combined with Fig.1, it is evident that the output and system state remain within the predefined constraint bounds, with the obstacle Lyapunov function effectively limiting both the system's signal and state. From Fig.3, it can be seen that the tracking error swiftly converges to a confined region within 0.13s, and the fast finite-time stability theory plays a role in the error convergence. Fig.4 displays the control signal ϖ(t) prior to the event-based action and the control signal u(t) following the event-based action, respectively. The control input following the event-triggered action is updated only when it meets the triggering condition, which realizes the discrete control. Fig.5 illustrates the temporal intervals for event-based triggering. In a 10-second period, the total number of activations using the event-triggering mechanism is 321. In contrast to the time-triggering mechanism, the event-triggering mechanism effectively saves 67.9% of the communication resources and avoids the Zeno phenomenon.

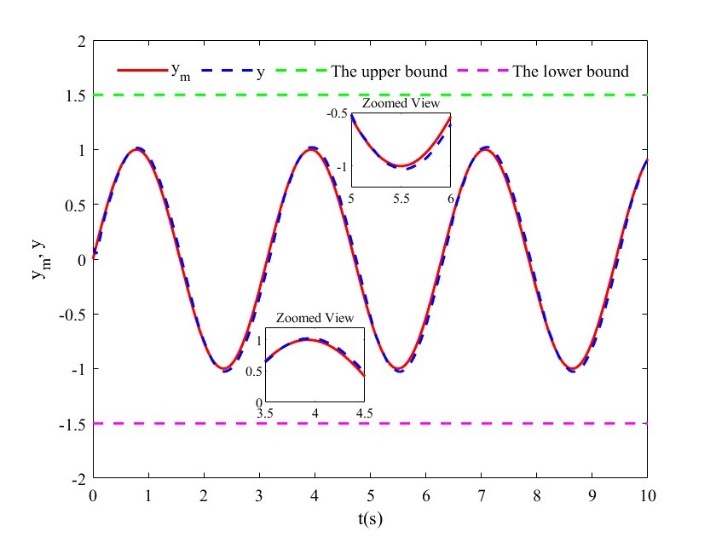


Fig. 1 Trajectory of the system output with respect to the desired signal (1)

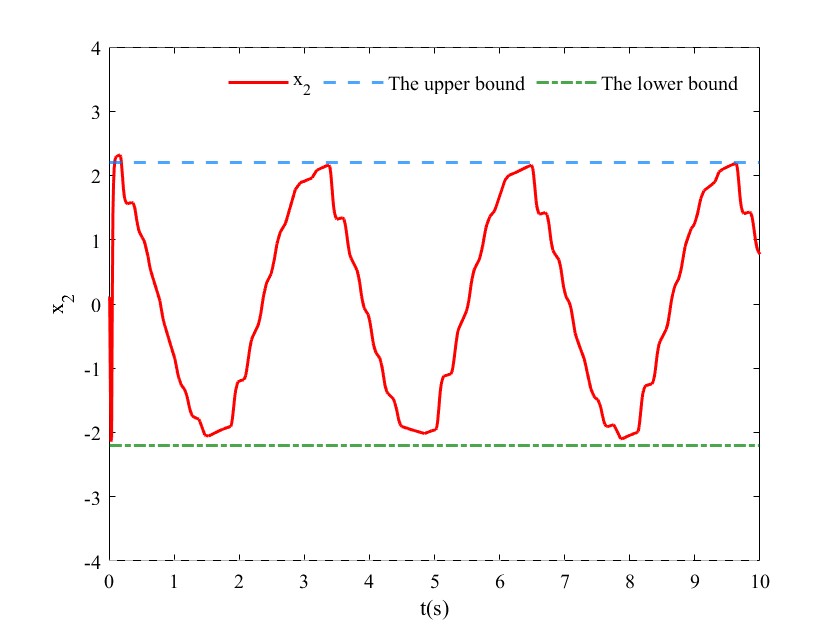


Fig. 2 Trait variable with constraint boundaries (1)

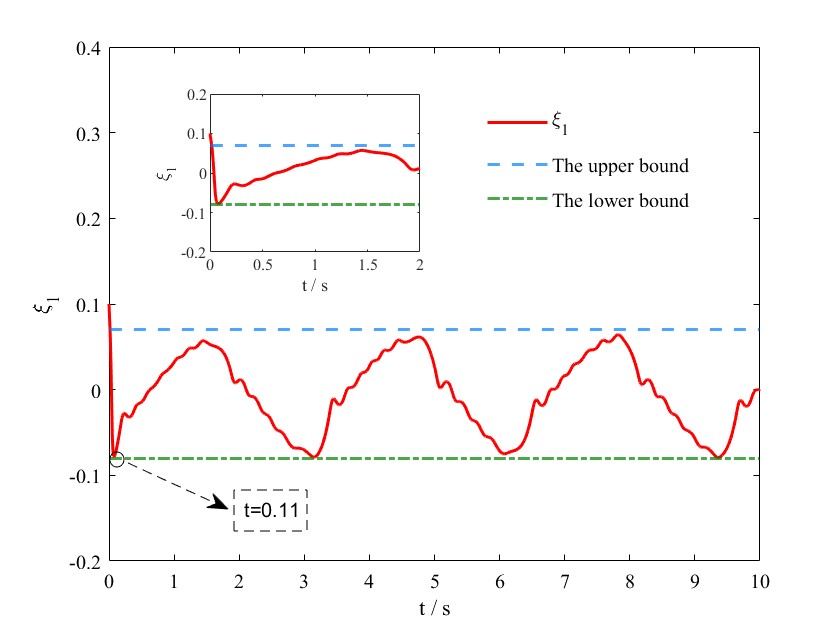


Fig. 3 Tracking error (1)

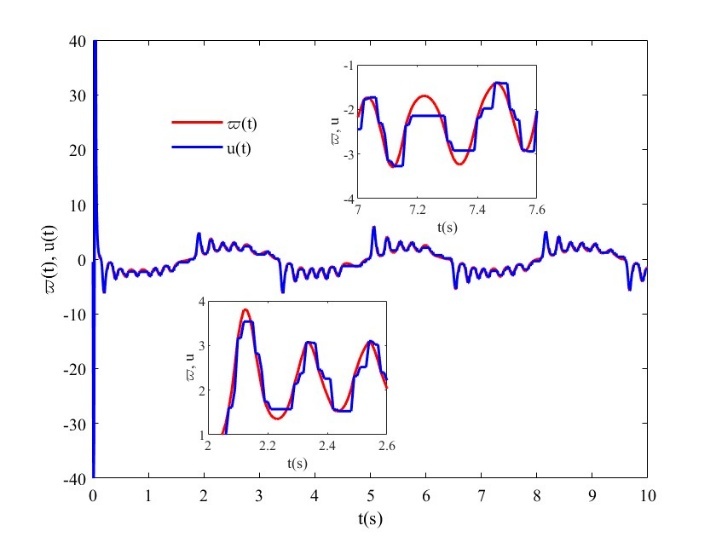


Fig. 4 Control inputs (1)

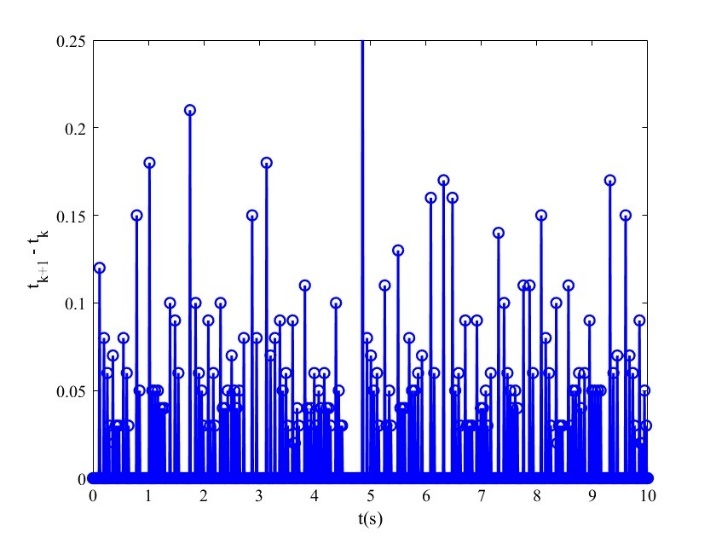


Fig. 5 Event Trigger Interval (1)

**3.2 Case Simulation**

To assess the effectiveness of the proposed control approach for real-world application, The following single-link robotic arm system is considered:

|  |  |
| --- | --- |
|  | (60) |

In this system, the variables and ̇ represent the displacement and the rate of change of position of the mechanical joints, respectively. The input deadband is defined by the function , where denotes the applied torque and represents the system's output response. The uncertainties in the system dynamics are described by the expression: . Additionally, the system parameters are set as follows: moment of inertia , damping factor , and . The system is subject to strict state constraints: the position does not exceed 1.5, and the velocity does not exceed 3, to guarantee the safety and performance of the operation.

The initial state of the system is and , with the reference signal given by . The basis functions are selected as in the numerical example, and the remaining relevant design parameters are consistent with those used in the numerical simulation.

Figures 6 to 10 display the computational outcomes of the single link robotic arm system described using equation (60). Based on the results from Fig. 6 to Fig. 10, it is evident that all signals within the closed-loop system remain bounded, and the control strategy achieves stability and constraint satisfaction of the closed-loop system. As illustrated in Fig.6, the system output successfully tracks the reference signal , and the design of the virtual control rate within the controller, along the Lyapunov stability analysis are effective. Fig. 7 shows the curve of state , and combined with Fig. 6, it can be observed that the output signal and the system state remain within the predefined constraint boundaries, and the obstacle Lyapunov function effectively constrains both the system's signal and state. From Fig.8, it can be seen that the tracking error quickly converges to within the bounded tight set within 0.13s, and the fast finite-time stability theory plays a role in the error convergence. Fig. 9 presents the control input ϖ(t) prior to the event-triggered action and the control signal u(t) following the event-triggered action, respectively. The control input after the event-triggered action updates the control only when the control input satisfies the triggering condition, which realizes the discrete control. Fig.10 illustrates the time intervals of event triggering. In 10 seconds, the total number of triggers determined by the event-triggering mechanism is 332. Compared with the time-triggering mechanism, the event-triggering mechanism effectively saves 65.8% of the communication resources, and the occurrence of the Zeno phenomenon is prevented.

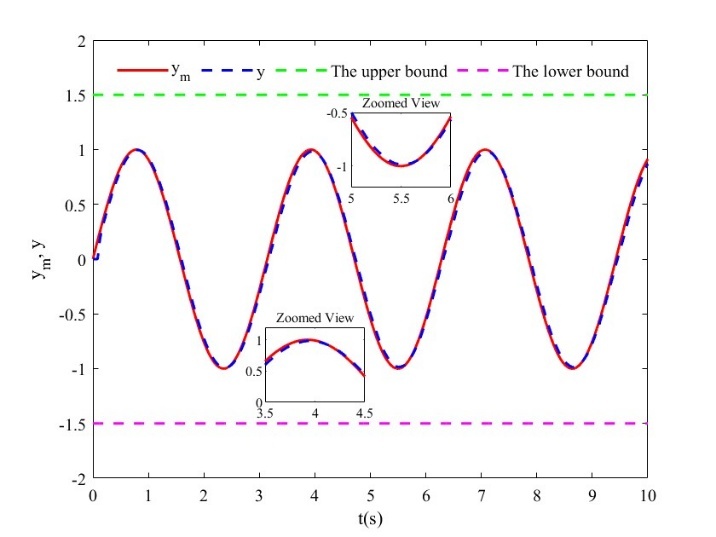


Fig. 6 Trajectory of the system output with respect to the desired signal (2)

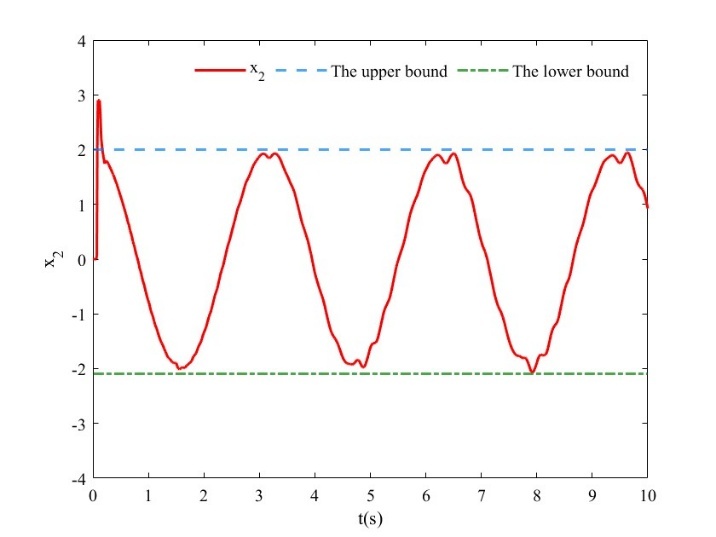


Fig. 7 Trait variable with constraint boundaries (2)

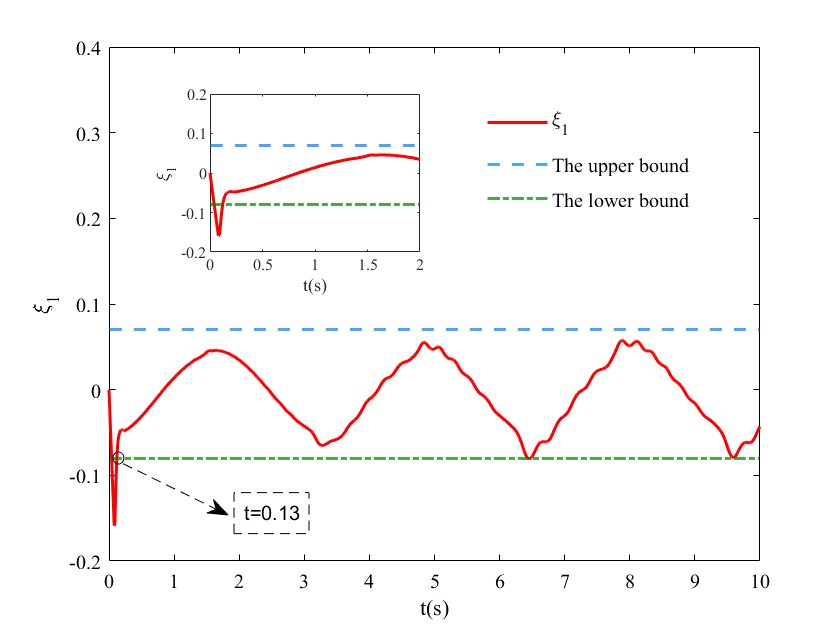


Fig. 8 Tracking error (2)

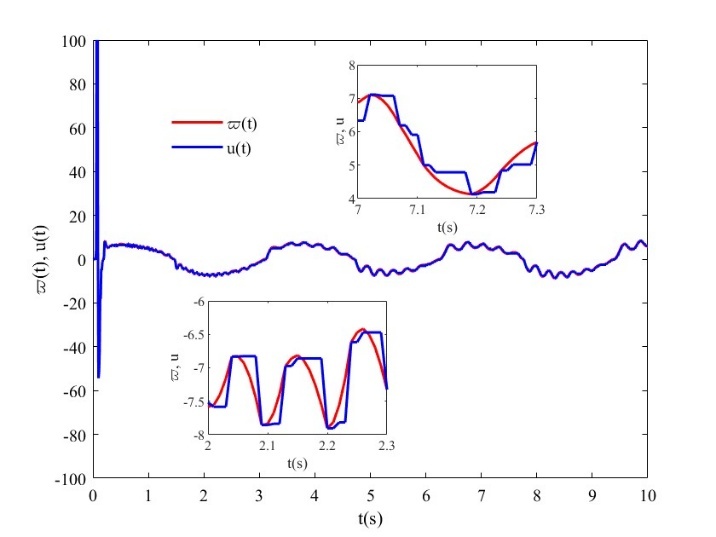


Fig. 9 Control inputs (2)

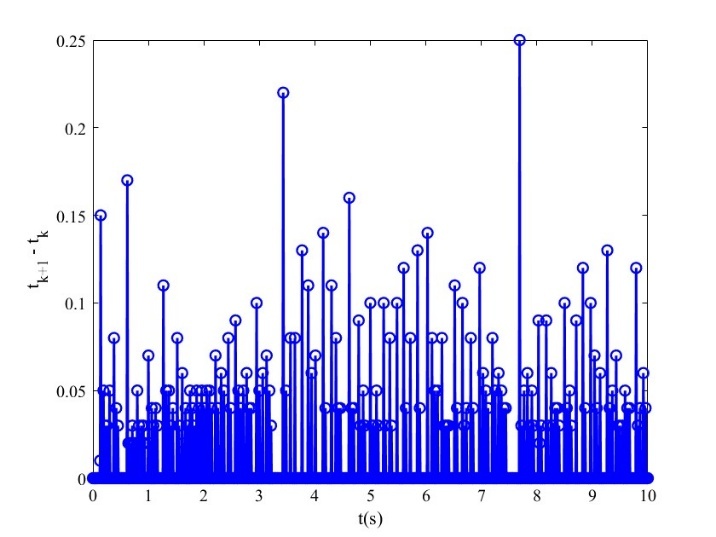


Fig. 10 Event Trigger Interval (2)

**4 Conclusion**

A new fast finite-time adaptive neural network event-triggered control strategy is introduced in this study for uncertain nonlinear systems with input dead zones and complete state restrictions. The scheme effectively reduces the dependence on communication resources and effectively avoids the Zeno phenomenon by real-time dynamic compensation of the input deadband. By employing the obstacle Lyapunov function together with fast finite-time stability theory, this approach not only guarantees the boundedness of the closed-loop system's signals, but also accelerates the rapid convergence of the tracking error to the predefined region, ensuring that the system state consistently remains within the established constraints. Through a series of simulation experiments, this study validates the efficiency and dependability of the suggested control approach.

**Disclosure statement**

The authors declared that they have no conflicts of interest to this work. We declare that we do not have any commercial or associative interest that represents a conflict of interest in connection with the work submitted.

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