

RESEARCH ARTICLE

Improved Barrier Function With Adjustable Parameter-Based Tracking Control for Robot Under Position Constraints

TAN ZHANG¹, DUANSONG WANG¹, JINZHONG ZHANG¹, AND PIANPIAN YAN

School of Electrical and Optoelectronic Engineering, West Anhui University, Lu'an 237012, China

Corresponding author: Duansong Wang (dswangsd@126.com)

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ABSTRACT An improved time-variant asymmetric integral barrier function with adjustable parameters is constructed for the first time in this study. The presented barrier function, which is constructed by designing an integral upper limit function, can be used in the constraint issues of nonlinear systems. With the aid of the adjustable parameters in the barrier function, the control performance of the system can be improved by only changing the adjustment parameters when fixing the control parameters of the controller. Then, the tracking controller is developed by using the presented barrier function with adjustable parameters to solve the position constraint of the robot with n -degrees. Additionally, a disturbance observer is designed to enhance the robustness of the system. We prove that under the presented controller, the robotic system's error signals can trend to zero asymptotically and the position constraint boundary is not broken at all time with the help of the proposed Theorem 1 and Lyapunov analysis. In the end, the effectiveness of the presented improved barrier function with adjustable parameters in handling state constraints is clarified by completing multiple simulation cases.

INDEX TERMS Barrier Lyapunov function, constraint control, disturbance observer, robot, tracking control.

I. INTRODUCTION

With the ongoing development of science and technology, the robots have become an indispensable part of industrial production. The emergence of robots not only improves production efficiency but also reduces production costs. Therefore, the role and significance of robots in industrial production are increasingly valued in today's world [1], [2], [3], [4]. As one of the core technologies of robots, automatic control can provide automated and intelligent loading and transportation tools for human beings, and extend to fields such as road condition testing, national defense and military security [5], [6], [7].

The control system is the brain of the robot and the main factor determining its function and performance. The main task of robot control technology is to control the

position, posture, motion trajectory, and action time of robots in the workspace. Recently, the intelligent control technique has been widely applied to robot motion control and achieved many meaningful results. Model predictive control, for instance, as an effective control way to solve the performance requirements is extensively used in robotic fields [8], [9], [10]. Sliding mode control is used to handle external disturbances and model uncertainties in robot systems due to its simple design and strong robustness [11], [12], [13], [14]. The backstepping control method applied to both linear system and nonlinear systems is used to recursively design controllers for robots [15], [16], [17]. In [18], [19], [20], and [21], several state or output feedback adaptive controls are developed for uncertain robotic systems. In [22], [23], [24], and [25], some outstanding motion control methods with performance requirements are designed for robotic systems. Nevertheless, the above results rarely consider system state or error constraint issues.

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As is well known, the state of the system in the actual workspace cannot be arbitrary and will inevitably be limited by the actuator and physical conditions. Therefore, when designing controllers in specific situations, it is necessary to consider the problem of system state constraints. As far as the author knows, the barrier Lyapunov function (BLF) is the most popular method for constraint control of the systems [26], [27]. In [28], a time-invariant symmetric logarithmic BLF is used to restrict the full states of permanent magnet synchronous motors within a bounded compact set. In [29], a high-order tangent BLF-based approach is used in completing full state constraint control of the high-order uncertain nonlinear system. To stabilize the uncertain nonlinear block-triangular constraint systems, an integral BLF combining with neural networks and the backstepping method is constructed to ensure the constraint condition of the states is always met [30].

To address the issues of robotic state or error limitations, many types of BLFs are used in robotic systems. The adaptive control of the time-invariant logarithmic BLF integrating with neural networks for robotic manipulators is proposed to handle the output constraints and system uncertainties [31], [32]. In [33], the time-invariant logarithmic BLF is also applied to handling full state constraint issue of the robot. In [34] and [35], the time-invariant tangent BLF combining with fuzzy logic system and neural networks is used to address output error and full state constraints of the robot, respectively. However, the time-invariant constraint situations are just a particular case of the time-variant one. Therefore, the time-variant tangent BLF is introduced into handling the full state constraints of the robotic manipulators under time-variant delays and actuator saturation [36]. In [37], the improved logarithmic BLF is used to handel time-varying state constraints of the robotic systems. Unfortunately, sometimes the workspace of the robotic arm is not symmetrical, so its constraint conditions are also asymmetric. Thereby, the time-invariant symmetrical logarithmic BLF is changed to a time-variant asymmetric type after the efforts of researchers. The final improved structure of the logarithmic BLF is utilized to deal with the asymmetric constraint issues of many systems. For instance, the modified logarithmic BLF-based tracking control is designed to cope with the asymmetric output constraints of the robot systems [38], [39]. In this article, the difficulty are how to design an integral type asymmetric barrier function based on the existing barrier function structure. The study on the logarithmic BLFs mentioned above found that the control parameters of the controller designed based on them are relatively single, and when the boundary conditions are fixed, it is difficult to adjust the control performance solely through the control parameters.

Considering the reasons aforementioned, an improved time-variant asymmetric integral barrier function with adjustable parameters is framed for the first time in this paper. The barrier function first proposed can improve the control performance of the robot tracking system only by adjusting

the parameters of the barrier function. The main contributions are listed below:

1) Inspired by the structure of existing integral and logarithmic barrier functions, a novel integral BLF with adjustable parameters is proposed for the first time to deal with the state or error constraint issues of the constrained systems.

2) Unlike existing integral barrier functions, such as [40], [41], and [42], there exist adjustable parameters in the proposed barrier function, thereby, the control performance of controlled systems can be adjusted by adjustable parameters when the control parameters are fixed.

3) With the proposed control strategy, the robotic error signals are proved to be asymptotically stable, the robotic position remains within an open set always. In the end, simulation experiments are conducted to verify the effectiveness of the proposed method by assigning different values to adjustable parameters.

II. PRELIMINARIES AND PROBLEM FORMULATION

A. DYNAMIC MODEL OF A ROBOT AND PRELIMINARIES

Draw lessons from results of the papers [33], [39], the dynamic model of an n-link robot is depicted as

$$M_0(q)\ddot{q} + C_0(q, \dot{q})\dot{q} + G_0(q) = \tau(t) + d \quad (1)$$

where $d = -\Delta C(q, \dot{q})\dot{q} - \Delta M(q)\ddot{q} - \Delta G(q) - J^T(q)f(t)$ denotes the system uncertain terms and external disturbances. $J^T(q)f(t)$ is the product of the external unknown force and Jacobian matrix. $M_0(q) \in R^{n \times n}$ is positive definite symmetric matrix. $G_0(q) \in R^n$ and $C_0(q, \dot{q}) \in R^{n \times n}$ represent the gravity vector and the Coriolis-centripetal torque. q denotes the position vector of the robot. $\tau(t)$ is control input of the robotic system.

To facilitate the control design, the dynamic model (1) is transformed into the following form:

$$\begin{cases} \dot{x}_1 = x_2 \\ \dot{x}_2 = M_0^{-1}(x_1)(\tau(t) + d - C_0(x_1, x_2)x_2 - G_0(x_1)) \end{cases} \quad (2)$$

where

$$\begin{cases} x_1 = q \\ x_2 = \dot{q}. \end{cases} \quad (3)$$

The **control objective** of this paper tries to develop an adaptive tracking control for the robot using the improved integral BLF with adjustable parameters to ensure that the position vector $x_1 = q = [q_1, q_2, \dots, q_n]^T$ tracks the reference trajectory $x_d = q_d = [x_{d1}, x_{d2}, \dots, x_{dn}]^T$ with corresponding control performance under the different adjustable parameters, and the position constraint boundaries are not broken all the time when the control parameters are fixed and only the adjustment parameters are changed.

The position constraint condition is set as $k_{cl}(t) < x_1 < k_{ch}(t), \forall t \geq 0$, where $k_{ch}(t) = [k_{ch1}(t), k_{ch2}(t), \dots, k_{chn}(t)]^T$, $k_{cl}(t) = [k_{cl1}(t), k_{cl2}(t), \dots, k_{cln}(t)]^T$, and $k_{chi} > 0, k_{cli} > 0, i = 1, 2, \dots, n$. The position

error boundaries is set as $-k_{ql}(t) < e_1 < k_{qh}(t)$ with $e_1 = [e_{11}, e_{12}, \dots, e_{1n}]^T = x_1 - x_d$, $k_{ql}(t) = [k_{ql1}(t), k_{ql2}(t), \dots, k_{qln}(t)]^T$ and $k_{qh}(t) = [k_{qh1}(t), k_{qh2}(t), \dots, k_{qhn}(t)]^T$. And the constraint conditions k_{ch} and k_{cl} satisfy the following Assumption 1.

Assumption 1: The position boundaries satisfy $|k_{cli}| \geq K_{cli}$ and $|k_{chi}| \leq K_{chi}$, $\forall t \geq 0, i = 1, 2, \dots, n$ with K_{cli} and K_{chi} being the positive constant. The reference trajectory meets $X_{l1} \leq x_d \leq X_{h1}$ with $X_{l1} > k_{cl}(t)$ and $X_{h1} < k_{ch}(t)$. To ensure that the position boundary is satisfied always, we set the constraint condition of the position error to be $-k_{qli}(t) < e_{1i} < k_{qhi}(t)$ with $k_{qli}(t) = x_{di} - k_{cli}(t)$ and $k_{qhi}(t) = k_{chi}(t) - x_{di}$.

Assumption 2: The lumped unknown term d of the robotic system is bounded, differentiable, and slowly varying signal, that is, there exists positive constant d_m such that $|d| \leq d_m$ and $\dot{d} \approx 0$.

Next, the constrained error is normalized as follows:

$$\begin{cases} \xi_{qli} = \frac{e_{1i}}{k_{qli}(t)}, & \xi_{qhi} = \frac{e_{1i}}{k_{qhi}(t)} \\ \xi_{qi} = h_1(e_{1i}) \xi_{qhi} + (1 - h_1(e_{1i})) \xi_{qli}, & i = 1, 2, \dots, n \end{cases} \quad (4)$$

where

$$h_1(e_{1i}) = \begin{cases} 1, & e_{1i} > 0 \\ 0, & e_{1i} \leq 0. \end{cases} \quad (5)$$

Lemma 1: According to the definition of the normalization error in (4), the two inequalities $|\xi_{qi}| < 1$ and $-k_{qli}(t) < e_{1i}(t) < k_{qhi}(t)$ are equivalent.

Proof of Lemma 1: Please refer to [43].

B. AN IMPROVED BLF WITH ADJUSTABLE PARAMETER

According to the definition of ξ_{qi} , an improved integral BLF with adjustable parameters is constructed for the first time in the open set $|\xi_{qi}| < 1$ as follows:

$$V = \int_0^{\xi_{qi}} \frac{2\beta_{pi}\theta}{1-\theta^2} d\theta \quad (6)$$

where β_{pi} is a positive adjustment parameter. From the definition of V , we can see that the function V is positive, continuous, differentiable, and radially unbounded as $|\xi_{qi}| \rightarrow 1$ in the open set $|\xi_{qi}| < 1$.

Remark 1: The adjustment parameter β_{pi} in the integral barrier function is used to adjust the size of control inputs and the control performance. The purpose of designing this parameter is to effectively ensure the satisfaction of boundary conditions, that is, when the constrained error approaches the boundary slightly, an appropriate input is given to the system. Additionally, the control performance can be improved by changing the adjustment parameters when the control parameter and the boundary function are fixed.

Theorem 1: In the open set $|\xi_{qi}| < 1$, the barrier function (6) has the following inequality conditions:

$$\frac{\beta_{pi}\xi_{qi}^2}{2} \leq \int_0^{\xi_{qi}} \frac{2\beta_{pi}\theta}{1-\theta^2} d\theta \leq \frac{\beta_{pi}\xi_{qi}^2}{1-\xi_{qi}^2}. \quad (7)$$

Proof of Theorem 1: 1) The inequality $\frac{\beta_{pi}\xi_{qi}^2}{2} \leq \int_0^{\xi_{qi}} \frac{2\beta_{pi}\theta}{1-\theta^2} d\theta$ will be proved to be true. First, an auxiliary function is designed as:

$$f(\xi_{qi}) = \int_0^{\xi_{qi}} \frac{2\beta_{pi}\theta}{1-\theta^2} d\theta - \frac{\beta_{pi}\xi_{qi}^2}{2}. \quad (8)$$

Taking the derivation of $f(\xi_{qi})$ with respect to normalization error ξ_{qi} yields:

$$\begin{aligned} \frac{df(\xi_{qi})}{d\xi_{qi}} &= \frac{2\beta_{pi}\xi_{qi}}{1-\xi_{qi}^2} - \beta_{pi}\xi_{qi} \\ &= \frac{\beta_{pi}\xi_{qi}(1+\xi_{qi}^2)}{1-\xi_{qi}^2}. \end{aligned} \quad (9)$$

According to the derivation of $f(\xi_{qi})$, we have $\frac{df(\xi_{qi})}{d\xi_{qi}} < 0$ as

$\xi_{qi} < 0$ and $\frac{df(\xi_{qi})}{d\xi_{qi}} > 0$ as $\xi_{qi} > 0$ over the open set $|\xi_{qi}| < 1$.

Furthermore, we know that $f(\xi_{qi}) = 0$ is true all the time as $\xi_{qi} = 0$. Hence, $\int_0^{\xi_{qi}} \frac{2\beta_{pi}\theta}{1-\theta^2} d\theta \geq \frac{\beta_{pi}\xi_{qi}^2}{2}$ is always true over the open set $|\xi_{qi}| < 1$.

2) The inequality $\int_0^{\xi_{qi}} \frac{2\beta_{pi}\theta}{1-\theta^2} d\theta \leq \frac{\beta_{pi}\xi_{qi}^2}{1-\xi_{qi}^2}$ will be indicated to hold. We design first an auxiliary function:

$$g(\xi_{qi}) = \frac{\beta_{pi}\xi_{qi}^2}{1-\xi_{qi}^2} - \int_0^{\xi_{qi}} \frac{2\beta_{pi}\theta}{1-\theta^2} d\theta. \quad (10)$$

Differentiating $g(\xi_{qi})$ yields:

$$\begin{aligned} \frac{dg(\xi_{qi})}{d\xi_{qi}} &= \frac{2\beta_{pi}\xi_{qi}}{(1-\xi_{qi}^2)^2} - \frac{2\beta_{pi}\xi_{qi}}{1-\xi_{qi}^2} \\ &= \frac{2\beta_{pi}\xi_{qi}^3}{(1-\xi_{qi}^2)^2}. \end{aligned} \quad (11)$$

In the open set $|\xi_{qi}| < 1$, considering the derivation of $g(\xi_{qi})$, we can obtain that $\frac{dg(\xi_{qi})}{d\xi_{qi}} < 0$ as $\xi_{qi} < 0$ and

$\frac{dg(\xi_{qi})}{d\xi_{qi}} > 0$ as $\xi_{qi} > 0$. In addition, according to the definition of the auxiliary function (10), we have $g(\xi_{qi}) = 0$ as $\xi_{qi} = 0$.

In summary, $\frac{\beta_{pi}\xi_{qi}^2}{1-\xi_{qi}^2} \geq \int_0^{\xi_{qi}} \frac{2\beta_{pi}\theta}{1-\theta^2} d\theta$ is true all the time over the open set $|\xi_{qi}| < 1$. \square

III. CONTROL DESIGN

To constrain the position of the robot with n-degrees, the improved integral BLF with adjustment parameter proposed for the first time is used in this section. The BLF is constructed as:

$$V_1 = \sum_{i=1}^n \int_0^{\xi_{qi}} \frac{2\beta_{pi}\theta}{1-\theta^2} d\theta. \quad (12)$$

Differentiating V_1 with respect to time over the open set $|\xi_{qi}| < 1$ yields:

$$\begin{aligned} \dot{V}_1 &= \sum_{i=1}^n \frac{2\beta_{pi}\xi_{qi}}{1-\xi_{qi}^2} \dot{\xi}_{qi} \\ &= \sum_{i=1}^n \frac{2\beta_{pi}\xi_{qi}}{(1-\xi_{qi}^2)} (h_1(e_{1i}) \dot{\xi}_{qhi} + (1-h_1(e_{1i})) \dot{\xi}_{qli}) \\ &= \sum_{i=1}^n \frac{2\beta_{pi}h_1(e_{1i})\xi_{qhi}}{(1-\xi_{qhi}^2)} \dot{\xi}_{qhi} \\ &\quad + \sum_{i=1}^n \frac{2\beta_{pi}(1-h_1(e_{1i}))\xi_{qli}}{(1-\xi_{qli}^2)} \dot{\xi}_{qli} \\ &= \sum_{i=1}^n \frac{2\beta_{pi}h_1(e_{1i})\xi_{qhi}}{k_{qhi}(t)(1-\xi_{qhi}^2)} \left(\dot{e}_{1i} - e_{1i} \frac{\dot{k}_{qhi}(t)}{k_{qhi}(t)} \right) \\ &\quad + \sum_{i=1}^n \frac{2\beta_{pi}(1-h_1(e_{1i}))\xi_{qli}}{k_{qli}(t)(1-\xi_{qli}^2)} \left(\dot{e}_{1i} - e_{1i} \frac{\dot{k}_{qli}(t)}{k_{qli}(t)} \right). \end{aligned} \tag{13}$$

Define velocity error as $e_2 = [e_{21}, e_{22}, \dots, e_{2n}]^T = x_2 - \alpha$ with α denoting the desired velocity, and differentiating e_1 yields:

$$\begin{aligned} \dot{e}_1 &= \dot{x}_1 - \dot{x}_d \\ &= e_2 + \alpha - \dot{x}_d \\ \dot{e}_{1i} &= e_{2i} + \alpha_i - \dot{x}_{di}. \end{aligned} \tag{14}$$

Taking (14) into (13) becomes:

$$\begin{aligned} \dot{V}_1 &= \sum_{i=1}^n \psi_{qhi} \left(e_{2i} + \alpha_i - \dot{x}_{di} - e_{1i} \frac{\dot{k}_{qhi}(t)}{k_{qhi}(t)} \right) \\ &\quad + \sum_{i=1}^n \psi_{qli} \left(e_{2i} + \alpha_i - \dot{x}_{di} - e_{1i} \frac{\dot{k}_{qli}(t)}{k_{qli}(t)} \right) \end{aligned} \tag{15}$$

where $\psi_{qhi} = \frac{2\beta_{pi}h_1(e_{1i})\xi_{qhi}}{k_{qhi}(t)(1-\xi_{qhi}^2)}$ and $\psi_{qli} = \frac{2\beta_{pi}(1-h_1(e_{1i}))\xi_{qli}}{k_{qli}(t)(1-\xi_{qli}^2)}$.

The desired velocity α is designed as:

$$\begin{aligned} \alpha &= \dot{x}_d - (K + K_h(t)) e_1 \\ \alpha_i &= \dot{x}_{di} - (k_{1i} + k_{h1i}(t)) e_{1i} \end{aligned} \tag{16}$$

where

$$K = \text{diag}(k_{11}, k_{12}, \dots, k_{1n}) \tag{17}$$

$$K_h(t) = \text{diag}(k_{h11}(t), k_{h12}(t), \dots, k_{h1n}(t)) \tag{18}$$

and $k_{h1i}(t) = \sqrt{\left(\frac{\dot{k}_{qli}(t)}{k_{qli}(t)}\right)^2 + \left(\frac{\dot{k}_{qhi}(t)}{k_{qhi}(t)}\right)^2} + o_i$ with o_i and k_{1i} being the positive constants.

Substituting (16) into (15) yields:

$$\dot{V}_1 = \sum_{i=1}^n \psi_{qhi} \left(e_{2i} - (k_{1i} + k_{h1i}(t)) e_{1i} - e_{1i} \frac{\dot{k}_{qhi}(t)}{k_{qhi}(t)} \right)$$

$$\begin{aligned} &+ \sum_{i=1}^n \psi_{qli} \left(e_{2i} - (k_{1i} + k_{h1i}(t)) e_{1i} - e_{1i} \frac{\dot{k}_{qli}(t)}{k_{qli}(t)} \right) \\ &= \sum_{i=1}^n \left(\frac{2\beta_{pi}h_1(e_{1i})}{k_{qhi}^2(t) - e_{1i}^2} + \frac{2\beta_{pi}(1-h_1(e_{1i}))}{k_{qli}^2(t) - e_{1i}^2} \right) e_{1i}e_{2i} \\ &\quad - \sum_{i=1}^n \frac{2\beta_{pi}\xi_{qi}^2}{(1-\xi_{qi}^2)} \left((k_{1i} + k_{h1i}(t)) + h_1(e_{1i}) \frac{\dot{k}_{qhi}(t)}{k_{qhi}(t)} \right) \\ &\quad - \sum_{i=1}^n \frac{2\beta_{pi}\xi_{qi}^2}{(1-\xi_{qi}^2)} \left((1-h_1(e_{1i})) \frac{\dot{k}_{qli}(t)}{k_{qli}(t)} \right). \end{aligned} \tag{19}$$

Because the inequality $k_{h1i}(t) + h_1(e_{1i}) \frac{\dot{k}_{qhi}(t)}{k_{qhi}(t)} + (1-h_1(e_{1i})) \frac{\dot{k}_{qli}(t)}{k_{qli}(t)} \geq 0$ is true all the time, then (19) can be rewritten as:

$$\begin{aligned} \dot{V}_1 &\leq - \sum_{i=1}^n \frac{2k_{1i}\beta_{pi}\xi_{qi}^2}{(1-\xi_{qi}^2)} \\ &\quad + \sum_{i=1}^n \left(\frac{2\beta_{pi}h_1(e_{1i})}{k_{qhi}^2(t) - e_{1i}^2} + \frac{2\beta_{pi}(1-h_1(e_{1i}))}{k_{qli}^2(t) - e_{1i}^2} \right) e_{1i}e_{2i}. \end{aligned} \tag{20}$$

Next, the control input τ will be designed. First, taking the derivation of e_2 yields:

$$\begin{aligned} \dot{e}_2 &= \dot{x}_2 - \dot{\alpha} \\ &= M_0^{-1}(x_1)(\tau(t) + d - C_0(x_1, x_2)x_2 - G_0(x_1)) - \dot{\alpha}. \end{aligned} \tag{21}$$

We can see that the system uncertain term exists in \dot{e}_2 , thus, the disturbance observer is designed to estimate it:

$$\begin{cases} \dot{\hat{d}} = \kappa_1(x_2 - \hat{x}_2) \\ \dot{\hat{x}}_2 = M_0^{-1}(\hat{d} + \tau - m_d + \kappa_2(x_2 - \hat{x}_2)) \end{cases} \tag{22}$$

where $m_d = C_0(x_1, x_2)x_2 + G_0(x_1)$, κ_1 and κ_2 are the positive constants. \hat{d} and \hat{x}_2 are estimation values of the d and x_2 , respectively. And the estimation errors are defined as $\tilde{d} = d - \hat{d}$ and $\tilde{x}_2 = x_2 - \hat{x}_2$.

Next, the stability of the observer will be proved. Constructing the Lyapunov function $V_d = \frac{1}{2\kappa_1} \tilde{d}^T \tilde{d} + \frac{1}{2} \tilde{x}_2^T M_0 \tilde{x}_2$ and differentiating it yields:

$$\begin{aligned} \dot{V}_d &= \frac{1}{\kappa_1} \tilde{d}^T \dot{\tilde{d}} + \tilde{x}_2^T M_0 \dot{\tilde{x}}_2 \\ &= \frac{1}{\kappa_1} \tilde{d}^T (\dot{d} - \dot{\hat{d}}) + \tilde{x}_2^T M_0 (\dot{x}_2 - \dot{\hat{x}}_2) \\ &= \frac{1}{\kappa_1} \tilde{d}^T \dot{d} - \frac{1}{\kappa_1} \tilde{d}^T \dot{\hat{d}} + \tilde{x}_2^T (\dot{x}_2 - \kappa_2 \tilde{x}_2) \\ &= \frac{1}{\kappa_1} \tilde{d}^T \dot{d} - \kappa_2 \tilde{x}_2^T \tilde{x}_2. \end{aligned} \tag{23}$$

According to (23) and Assumption 2, as long as we choose the parameter κ_1 that is large enough, we can obtain $\dot{V}_d = -\kappa_2 \tilde{x}_2^T \tilde{x}_2 \leq 0$. Therefore, the estimation errors \tilde{d} and \tilde{x}_2 can trend to zero asymptotically.

Then, according to Lyapunov stability theory, the controller is designed as:

$$\tau(t) = m_d + M_0\dot{\alpha} - \hat{d} - K_2e_2 - D \quad (24)$$

where

$$D = \begin{bmatrix} \left(\frac{2\beta_{p1}h_1(e_{11})}{k_{qh1}^2(t) - e_{11}^2} + \frac{2\beta_{p1}(1-h_1(e_{11}))}{k_{ql1}^2(t) - e_{11}^2} \right) e_{11} \\ \left(\frac{2\beta_{p2}h_1(e_{12})}{k_{qh2}^2(t) - e_{12}^2} + \frac{2\beta_{p2}(1-h_1(e_{12}))}{k_{ql2}^2(t) - e_{12}^2} \right) e_{12} \\ \dots \\ \left(\frac{2\beta_{pn}h_1(e_{1n})}{k_{qhn}^2(t) - e_{1n}^2} + \frac{2\beta_{pn}(1-h_1(e_{1n}))}{k_{qln}^2(t) - e_{1n}^2} \right) e_{1n} \end{bmatrix} \quad (25)$$

and $K_2 = \text{diag}(k_{21}, k_{22}, \dots, k_{2n})$ is the positive definite matrix.

Next, we will give Theorem 2 to analyze the stability of the robotic system.

Theorem 2: For the robotic dynamics depicted by (1), under Assumptions 1-2, with control laws (16) and (24) together with observer (22), for initial position errors satisfy $-k_{qli}(t) < e_{1i}(0) < k_{qhi}(t)$, $i = 1, 2, \dots, n$. The robotic system's all error signals are asymptotically stable, the position constraint is never violated, i.e., $k_{cl}(t) < x_1 < k_{ch}(t)$, $\forall t \geq 0$, and the position errors e_{1i} will locate always within the open set $-k_{qli}(t) < e_{1i}(t) < k_{qhi}(t)$, $i = 1, 2, \dots, n$.

Proof of Theorem 2: Construct the Lyapunov candidate function V_2 as follows:

$$V_2 = \sum_{i=1}^n \int_0^{\xi_{qi}} \frac{2\beta_{pi}\theta}{1-\theta^2} d\theta + \frac{1}{2} e_2^T M_0 e_2. \quad (26)$$

Differentiating V_2 yields:

$$\begin{aligned} \dot{V}_2 &= \dot{V}_1 + e_2^T M_0 \dot{e}_2 \\ &= - \sum_{i=1}^n \frac{2k_{1i}\beta_{pi}\xi_{qi}^2}{(1-\xi_{qi}^2)} + e_2^T (\tau(t) + d - m_d - M_0\dot{\alpha}) \\ &\quad + \sum_{i=1}^n \left(\frac{2\beta_{pi}h_1(e_{1i})}{k_{qhi}^2(t) - e_{1i}^2} + \frac{2\beta_{pi}(1-h_1(e_{1i}))}{k_{qli}^2(t) - e_{1i}^2} \right) e_{1i}e_{2i}. \end{aligned} \quad (27)$$

Substituting (24) and (25) into (27) yields:

$$\begin{aligned} \dot{V}_2 &= \dot{V}_1 + e_2^T M_0 \dot{e}_2 \\ &= - \sum_{i=1}^n \frac{2k_{1i}\beta_{pi}\xi_{qi}^2}{(1-\xi_{qi}^2)} + e_2^T (-K_2e_2 - D + \tilde{d}) \\ &\quad + \sum_{i=1}^n \left(\frac{2\beta_{pi}h_1(e_{1i})}{k_{qhi}^2(t) - e_{1i}^2} + \frac{2\beta_{pi}(1-h_1(e_{1i}))}{k_{qli}^2(t) - e_{1i}^2} \right) e_{1i}e_{2i} \\ &= - \sum_{i=1}^n \frac{2k_{1i}\beta_{pi}\xi_{qi}^2}{(1-\xi_{qi}^2)} - e_2^T K_2 e_2 + e_2^T \tilde{d}. \end{aligned} \quad (28)$$

According to Theorem 1 and when the observer (22) is successful in tracking d and x_2 , (28) can be rewritten as:

$$\begin{aligned} \dot{V}_2 &\leq - \sum_{i=1}^n 2k_{1i} \int_0^{\xi_{qi}} \frac{2\beta_{pi}\theta}{1-\theta^2} d\theta - e_2^T K_2 e_2 \\ &\leq -\lambda V_2 \leq 0 \end{aligned} \quad (29)$$

where $\lambda = \min(2k_{1i}, \frac{2\lambda_{\min}(K_2)}{\lambda_{\max}(M_0)})$.

Solving the differential equation (29) yields:

$$0 \leq V_2 \leq V_2(0) e^{-\lambda t}. \quad (30)$$

Considering (26), we have:

$$\int_0^{\xi_{qi}} \frac{2\beta_{pi}\theta}{1-\theta^2} d\theta \leq V_2(0) e^{-\lambda t} \leq V_2(0). \quad (31)$$

According to (31), we have $\xi_{qi}^2 \leq \left(1 - e^{-\frac{V_2(0)}{\beta_{pi}}}\right)$ and

$|\xi_{qi}| \leq \sqrt{\left(1 - e^{-\frac{V_2(0)}{\beta_{pi}}}\right)} < 1$. In terms of Lemma 1, we have $-k_{qli}(t) < e_{1i}(t) < k_{qhi}(t)$. However, we will use the mathematical derivation to prove this condition. Subsequently, considering the definition of ξ_{qi} and $e_{1i} > 0$, we have

$$\frac{e_{1i}}{k_{qhi}(t)} \leq \sqrt{\left(1 - e^{-\frac{V_2(0)}{\beta_{pi}}}\right)} \text{ and } e_{1i} \leq k_{qhi}(t) \sqrt{\left(1 - e^{-\frac{V_2(0)}{\beta_{pi}}}\right)}.$$

And then, when $e_{1i} \leq 0$, we have $-\frac{e_{1i}}{k_{qli}(t)} \leq \sqrt{\left(1 - e^{-\frac{V_2(0)}{\beta_{pi}}}\right)}$

and $e_{1i} \geq -k_{qli}(t) \sqrt{\left(1 - e^{-\frac{V_2(0)}{\beta_{pi}}}\right)}$. Therefore, we can infer that $-k_{qli}(t) < e_{1i}(t) < k_{qhi}(t)$. In light of Assumption 1, we can further deduce that $k_{cl}(t) < x_1 < k_{ch}(t)$.

Additionally, in view of (30), (31), and Theorem 1, we have:

$$\begin{aligned} |\xi_{qi}| &\leq \sqrt{\frac{2V_2(0) e^{-\lambda t}}{\beta_{pi}}} \\ |e_2| &\leq \sqrt{\frac{2V_2(0) e^{-\lambda t}}{\lambda_{\min}(M_0)}}. \end{aligned} \quad (32)$$

According to the definition of the normalization error ξ_{qi} , we have $e_{1i} \leq k_{qhi}(t) \sqrt{\frac{2V_2(0)e^{-\lambda t}}{\beta_{pi}}}$ as $e_{1i} > 0$ and $e_{1i} \geq -k_{qli}(t) \sqrt{\frac{2V_2(0)e^{-\lambda t}}{\beta_{pi}}}$ as $e_{1i} \leq 0$. Hence, the constrained position errors can trend to zero exponentially and asymptotically. Considering (23) and (32), the robotic system's all error signals are asymptotically stable when choosing the parameter κ_1 that is large enough. \square

Remark 2: According to the proof process of Theorem 2, the inequality $-k_{qli}(t) \sqrt{\frac{2V_2(0)e^{-\lambda t}}{\beta_{pi}}} \leq e_{1i} \leq k_{qhi}(t) \sqrt{\frac{2V_2(0)e^{-\lambda t}}{\beta_{pi}}}$ holds always. We can achieve that not only the tracking error e_{1i} can eventually converge exponentially and asymptotically to zero but also the proposed integral BLF has adjustable parameters that can adjust the convergence accuracy and speed at the initial convergence stage. Thus, the proposed BLF is more advantageous.

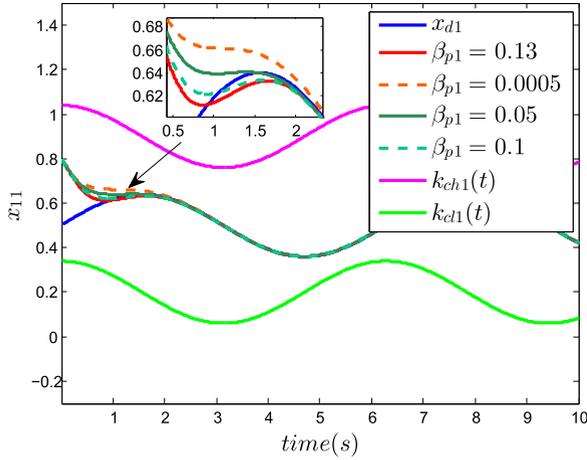


FIGURE 1. Tracking effect of x_{11} .

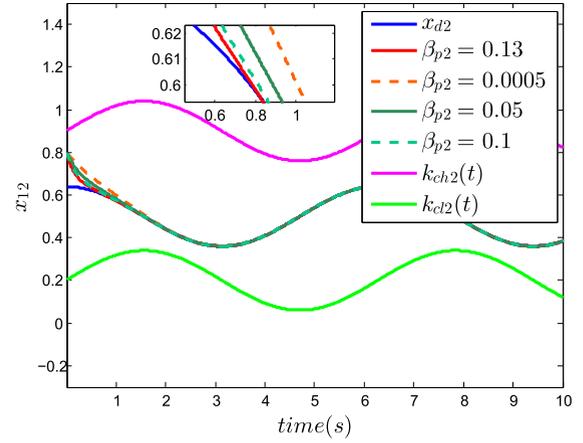


FIGURE 3. Tracking effect of x_{12} .

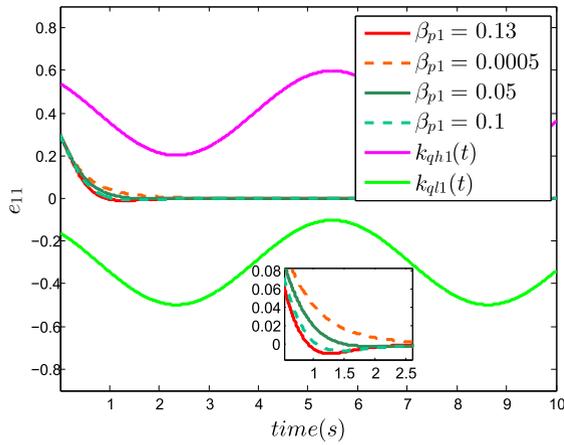


FIGURE 2. Tracking error e_{11} .

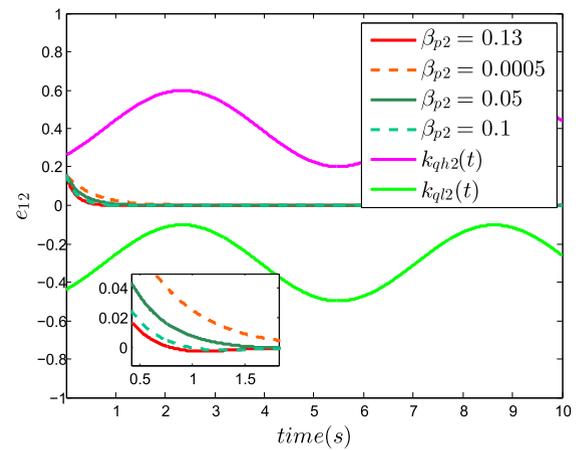


FIGURE 4. Tracking error e_{12} .

IV. SIMULATIONS

To indicate the effectiveness of the improved BLF with adjustable parameters in dealing with constraint issues of the constrained systems, the simulations based on a robot with two degrees are performed in this section. The position vector and the robotic system's matrixes are shown as:

$$q = \begin{bmatrix} q_1 \\ q_2 \end{bmatrix} = \begin{bmatrix} \theta_1 \\ \theta_2 \end{bmatrix} \quad (33)$$

$$M_0(q) = \begin{bmatrix} M_{11} & M_{12} \\ M_{21} & M_{22} \end{bmatrix} \quad (34)$$

$$C_0(q, \dot{q}) = \begin{bmatrix} C_{11} & qC_{12} \\ C_{21} & C_{22} \end{bmatrix} \quad (35)$$

$$G_0(q) = \begin{bmatrix} G_{11} & G_{12} \end{bmatrix} \quad (36)$$

$$J(q) = \begin{bmatrix} -(l_1 \sin q_1 + l_2 \sin(q_1 + q_2)) & -l_2 \sin(q_1 + q_2) \\ l_1 \cos q_1 + l_2 \cos(q_1 + q_2) & l_2 \cos(q_1 + q_2) \end{bmatrix} \quad (37)$$

where

$$M_{11} = m_1 r_1^2 + m_2 (l_1^2 + r_2^2 + 2l_1 r_2 \cos q_2) + I_1 + I_2$$

$$M_{12} = m_2 (r_2^2 + l_1 r_2 \cos q_2) + I_2$$

$$M_{21} = m_2 (r_2^2 + l_1 r_2 \cos q_2) + I_2$$

$$M_{22} = m_2 r_2^2 + I_2$$

$$C_{11} = -m_2 l_1 r_2 \dot{q}_2 \sin q_2$$

$$C_{12} = -m_2 l_1 r_2 (\dot{q}_2 + \dot{q}_1) \sin q_2$$

$$C_{21} = m_2 l_1 r_2 \dot{q}_1 \sin q_2$$

$$C_{22} = 0$$

$$G_{11} = (m_1 r_2 + m_2 l_1) g \cos q_1 + m_2 r_2 g \cos(q_1 + q_2)$$

$$G_{12} = m_2 r_2 g \cos(q_1 + q_2) \quad (38)$$

and please refer to [33] and [39] for the main parameters of the robotic system.

The system's initial values, desired circle path, and system uncertain terms are selected as:

$$\begin{cases} q_1(0) = 0.8, q_2(0) = 0.8 \\ \dot{q}_1(0) = 0, \dot{q}_2(0) = 0 \end{cases} \quad (39)$$

$$x_d = [0.14 \sin(t) + 0.5, 0.14 \cos(t) + 0.5]^T \quad (40)$$

$$d = M_0[0.3 \sin(t), 0.3 \cos(t)]^T + C_0[0.3 \cos(0.5t), 0.3 \sin(0.5t)]^T \quad (41)$$

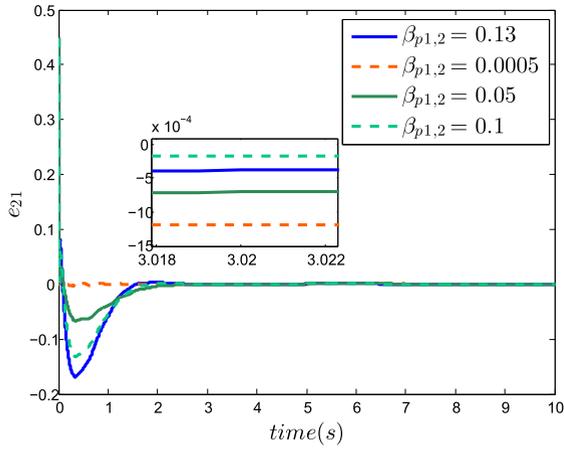


FIGURE 5. Tracking error e_{21} .

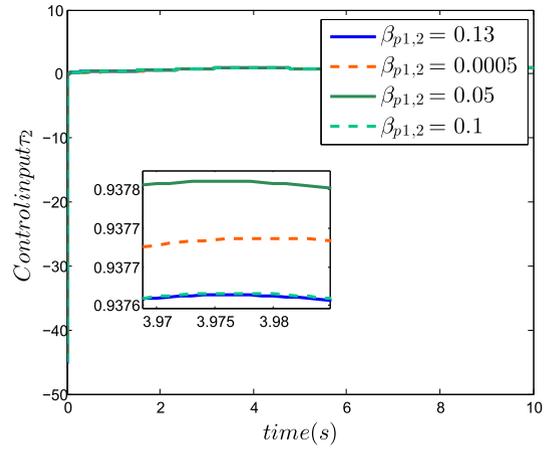


FIGURE 8. Control input τ_2 .

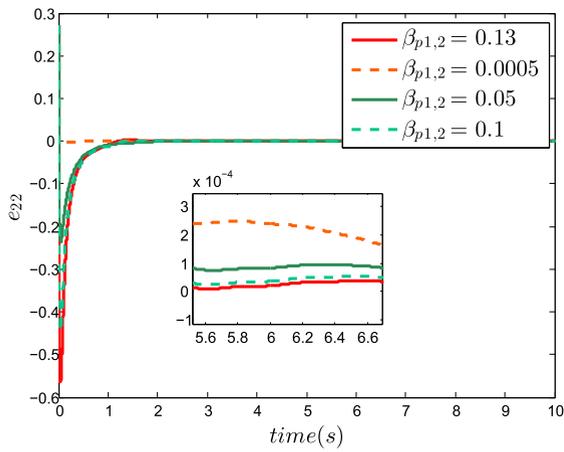


FIGURE 6. Tracking error e_{22} .

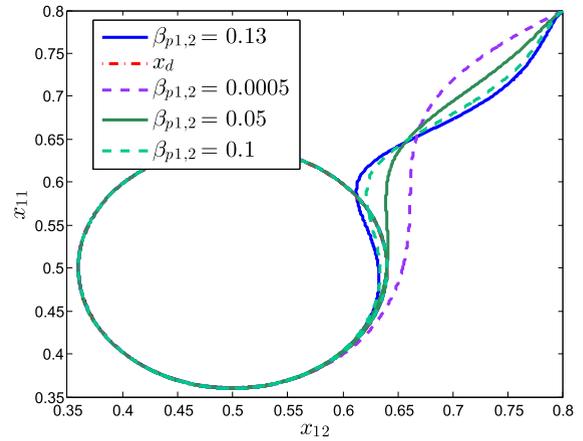


FIGURE 9. Phase portrait of x_{11} and x_{12} .

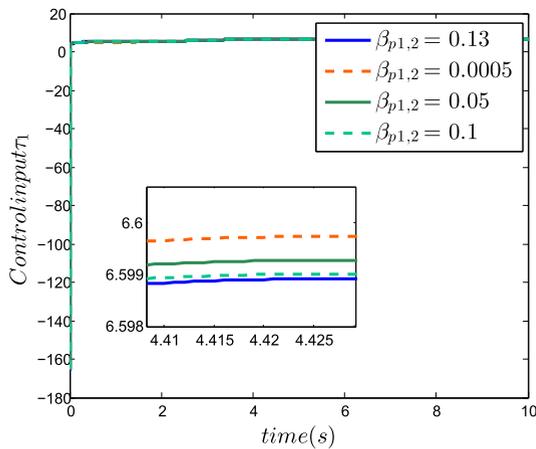


FIGURE 7. Control input τ_1 .

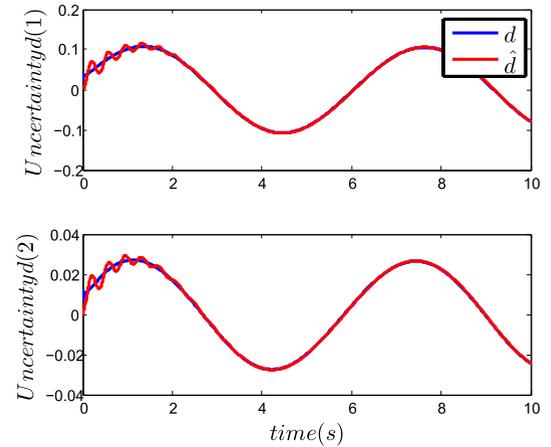


FIGURE 10. Uncertain term d .

The constraint boundaries of the position is chosen as:

$$\begin{aligned}
 k_{cl} &= [k_{cl1}, k_{cl2}]^T \\
 &= [0.2 + 0.14\cos(t), 0.2 + 0.14\sin(t)]^T \\
 k_{ch} &= [k_{ch1}, k_{ch2}]^T \\
 &= [0.9 + 0.14\cos(t), 0.9 + 0.14\sin(t)]^T \quad (42)
 \end{aligned}$$

The constraint condition of the position error is selected based on Assumption 1 as follows:

$$\begin{aligned}
 k_{ql} &= [k_{ql1}, k_{ql2}]^T \\
 &= \begin{bmatrix} 0.3 + 0.14\sin(t) - 0.14\cos(t) \\ 0.3 + 0.14\cos(t) - 0.14\sin(t) \end{bmatrix} \\
 k_{qh} &= [k_{qh1}, k_{qh2}]^T \\
 &= \begin{bmatrix} 0.4 + 0.14\cos(t) - 0.14\sin(t) \\ 0.4 + 0.14\sin(t) - 0.14\cos(t) \end{bmatrix} \quad (43)
 \end{aligned}$$

The parameters of the controller are chosen as $k_{11} = k_{12} = 1$, $o_1 = o_2 = 0.1$ and $K_2 = \text{diag}(1, 1)$. The parameters of the observer are selected as $\kappa_1 = 100$ and $\kappa_2 = 0.8$. The adjustment parameters of the improved integral BLF presented for the first time in this paper are chosen respectively as $\beta_{p1} = \beta_{p2} = 0.0005, 0.05, 0.1, \text{ and } 0.13$ to verify that these parameters can adjust the convergence accuracy and speed at the initial convergence stage.

The simulation results of the improved integral BLF with adjustment parameters presented for the first time handling the position constraint are given in Figures 1, 2, 3, 4, 5, 6, 7, 8, 9, and 10. The tracking performance of the robotic joint 1 and 2 is depicted in Figures 1 and 3. The position tracking errors are shown in 2 and 4. The velocity errors are described in Figures 5 and 6. Figures 7 and 8 depict the control inputs of the robotic system. Figure 9 describes the overall effect of a dual joint robotic arm tracking a circular trajectory. Figure 10 shows the curves of the disturbance observer estimating the system uncertainties.

The purpose of simulation experiments is twofold: one is to verify the ability of the proposed improved BLF with adjustable parameters to constrain the system state, and the other one is to investigate the impact of adjustable parameter changes on system control performance. Therefore, the simulations are performed when the controller's parameters k_{11} , k_{12} , K_2 , and the observer's parameters κ_1 , and κ_2 are fixed and the adjustment parameters β_{p1} , and β_{p2} are altered. From analyzing Figures 1, 2, 3, and 4 we can see that the improved BLF with adjustment parameters proposed for the first time in this paper is successful in constraining the position and its error of the robot although under different adjustment parameters. Meanwhile, the trajectory tracking effects are satisfactory. This proves that the control system has stability and accuracy. By further analyzing simulation results in Figures 1, 2, 3, and 4, we have that with the increase of the adjustment parameter's values β_{p1} and β_{p2} , joint positions can reach the desired trajectory faster. This proves that the control system has rapidity. However, from 9, we conclude that the adjustment parameter's values cannot be arbitrarily increased, otherwise excessive overshoot will affect control performance. This also confirms the conclusion in Remark 2. Additionally, as the adjustment parameters β_{p1} and β_{p2} increase, the overshoot of velocity tracking error also increases. But from the partially enlarged image, it can be seen that the steady-state value of the velocity error decreases as the adjustment parameters increase. Accordingly, the control inputs in steady-state is minimal in Figures 7 and 8 when the adjustment parameters are assigned a maximum value, that is $\beta_{p1} = \beta_{p2} = 0.13$. Considering the curves of the observer estimating system uncertain term d in Figure 10, we know that the estimated curves have some fluctuations at the initial stage, but it quickly stabilized.

V. CONCLUSION

In this paper, an improved integral BLF with adjustment parameters is proposed for the first time. The integral BLF

developed by constructing an integral upper limit function is used to constrain the state of the systems. The adjustment parameters are utilized to adjust the control performance of the robotic system when the parameters of the controller and observer are not changed. Through the proof of Theorem 2, we have concluded that the robot position vector and position tracking error can be limited to the open intervals, the tracking error can asymptotically trend to zero, and the convergence accuracy and speed at the initial convergence stage can be adjusted by changing the size of adjustment parameter values. To enhance the system's robustness, a disturbance observer is designed, and a satisfactory effect of the estimation is obtained. In the end, the simulation experiments conducted by changing adjustment parameter values also demonstrate that the method proposed for the first time in this paper can effectively constrain the system state, and improve system performance through parameter adjustment. In future work, the improved BLF with adjustment parameters proposed first in this study will be used in full-state constraint issues of the nonlinear systems.

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TAN ZHANG received the M.E. degree from the College of Automation, Harbin Engineering University, Harbin, China, in 2017, and the Ph.D. degree in control science and engineering from Harbin Engineering University, in 2021. He is currently a Lecturer with the School of Electrical and Optoelectronic Engineering, West Anhui University. His research interests include computation intelligence, robot motion control, and ship motion control.



DUANSONG WANG received the Ph.D. degree in control science and engineering from Harbin Engineering University, China, in 2020. He was a joint Ph.D. Student with the Department of Electrical and Computer Engineering, National University of Singapore, from 2019 to 2020. Prior to 2022, he was a Senior Engineer with the Jiangsu Institute of Automation. He is currently a Senior Engineer with the School of Electrical and Photoelectronic Engineering, West Anhui University, China. His research interests include robotic control, networked system cooperation, and adaptive systems.



JINZHONG ZHANG was born in Fuyang, China, in 1989. He received the M.S. degree in computer science from Guangxi University for Nationalities, in 2018, and the Ph.D. degree in control science and engineering from Harbin Engineering University, in 2022. He is currently a Lecturer with the School of Electrical and Optoelectronic Engineering, West Anhui University. His research interests include computation intelligence, image processing, and evolutionary computation.



PIANPIAN YAN received the M.E. degree in control engineering from Shenyang Ligong University, Shenyang, China, in 2017. She is currently an Assistant with West Anhui University. Her research interests include computation intelligence, big data technology and application, and robotic control.

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