

Safety-critical nonlinear optimal predictive control with adaptive error elimination algorithm for robotic system

Helin Wang*

Department of Electrical and Electronic Engineering, Shanghai Institute of Technology, Shanghai 201418, China

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Abstract Safety-critical control enables intelligent robots to have better secure operation and resistance to adverse environments, hence greatly enhancing their interaction and adaptability to the environment. In this paper, we propose a safety-critical control scheme for robotic systems using an adaptive error elimination algorithm and optimization-based nonlinear optimal predictive control (NOPC) framework. The novelty of the proposed work lies in that an adaptive error elimination controller is designed to deal with the problem of stabilization of walking gait, which ensures that robot joint trajectory can compensate for the limitation of the template model. In order to be independent of system parameters and disturbances, a sliding mode controller is further designed under an uncertain environment. This approach takes into account simultaneously with foot position and orientation based on NOPC optimization. It tracks the modified trajectories constrained with the centroidal momentum dynamics. Finally, simulations is utilized to verify the effectiveness of the mentioned methods. The results indicate that the tracking effect of joint trajectory is better safety-critical nonlinear optimal predictive control with adaptive error elimination algorithm.

Keywords Nonlinear optimal predictive control, Safety-critical control scheme, Robotic system, Adaptive error elimination algorithm

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1 Introduction

Security and safety are important for artificial intelligence due to the complexity and in-feasibility of related problems caused by uncertainty and external intrusion [1, 2]. With the continuous improvement of autonomous intelligence, ensuring the safety of control systems has become increasingly important. Nowadays, safety analysis and control of nonlinear systems have become one of the mainstream directions in the control field.

The application of safety-critical control in robotics is mainly reflected in ensuring the safe operation of robots in various complex environments [3, 4]. This includes real-time monitoring of the robot's status and environmental changes through multi-step testing, rolling optimization, and feedback correction to prevent potential risks and accidents. Safety critical control also involves precise planning and control of the robot's motion trajectory [5], ensuring that the robot does not deviate from the predetermined path or collide during task execution. In addition, security-critical control also focuses on data security and system security, preventing robots from being maliciously attacked or data leaked, thereby ensuring the

* Corresponding author (email: wh17228@126.com)

security of robots and their operating environment. These measures together form a solid barrier for the safe operation of robots.

Safety critical control is one of the fundamental issues in robot applications to meet the requirements of autonomy and intelligence of a closed-loop system. Thus, modern control systems sometimes need to satisfy the temporal logic constraints given by upper-level units. The current analysis of safety-critical control mainly includes model checking, reachability analysis barrier function, and so on. The research on safety-critical control can be traced back to the 1940s, in which a Japanese scholar Nagumo conducted research on the necessary and sufficient conditions for invariant sets. Many challenges in the field of robotics have been faced in the past decades. On the one hand, robots need to have high-precision control systems and sensors to solve accuracy problems, while also requiring learning ability to adapt to new fields of work [6, 7]. Besides, ensuring safety during high-speed and high-power operations is also an important challenge. On the other hand, Robots may involve a large amount of personal information, such as user behavior data, voice data, *etc.* The security and privacy protection of these data are important issues. Meanwhile, robot systems may also face the risk of hacker attacks, and it is necessary to ensure the security of the robotic system.

Some recent work formulates the above problems by using optimal predictive control. The emergence of optimal predictive control is closely related to the rapid development of space technology and the widespread application of computers in the early 1960s. During this period, the optimization theory of dynamic systems developed rapidly, forming the important discipline branch of optimal control. In [8], a multi-sampling model predictive control method is proposed to address the problem of large current control errors in conventional permanent magnet synchronous motor model predictive control at low load wave ratio. In [9], a new improved model predictive control algorithm based on discrete space vector modulation is proposed, which effectively improves the quality of grid side current output.

The optimal predictive control strategy involves selecting an appropriate nonlinear model to describe the system dynamics and representing its nonlinear characteristics through mathematical expressions. Subsequently, the continuous-time nonlinear model is discretized into a discrete-time model for numerical optimization [10–12]. It is necessary to minimize specified performance indicators, such as tracking error of system state, amplitude of control input, *etc.* Finally, various numerical optimization methods can be used to solve the optimization problem of discretization, and the stability conditions of the control system can be studied to ensure that the controller can generate a stable closed-loop system. Although optimal predictive control has good tracking performance and strong anti-interference ability, however, ensuring safety during the robot's motion remains a challenge. It may face challenges such as high computational complexity and real-time requirements in practical applications [13–15]. One important reason is that when the robot reaches its optimal performance or motion trajectory, the solution is often obtained at the boundary of the invariant state set [16]. When there is significant uncertainty in the kinematic model or observation of the current state of the robot, it often leads to the occurrence of dangerous situations and control errors.

Adaptive control has significant applications in error elimination. It can effectively reduce the steady-state and dynamic errors of the system by adjusting the controller parameters online and responding to system uncertainties in real time [17–19]. During the control process, adaptive control can identify and compensate for changes in system parameters and external disturbances, making the system output closer to the expected value. For example, in robot control, adaptive control can dynamically adjust control strategies based on the interaction between the robot and the environment, reducing position and attitude errors [20]; In the flight control system, adaptive control can cope with external disturbances such as airflow changes, maintain stable flight of the aircraft, and reduce flight errors. However, when there are unmodeled dynamics or random disturbances in the system, stability and safety analysis becomes difficult, which may affect the robustness of the system.

One solution is to adopt adaptive sliding mode control. It can address these uncertainties and maintain system stability and performance by adjusting the control strategy. A significant advantage of sliding mode control lies in fast response speed and insensitivity to changes in system parameters and external disturbances. This makes it advantageous in situations where fast response and strong anti-interference capabilities are required [21, 22]. Slotine proposed a method to establish the boundary layer continuity, which can generate negative feedback on the sliding mode function by continuous switching [23, 24].

Even though designing optimal control strategies has low energy consumption and strong robustness, there are still many unresolved issues due to its relatively late start in the safety analysis and control of

nonlinear systems [25–27]. Considering the presence of external interference in the robot control system, this paper intends to design a safety-critical control scheme to compensate for the interference forces, which explores a dynamic model and adaptive error elimination algorithm, and studies NOPC-based optimization. The main contributions of the article are reflected in the following aspects.

- (1) Taking the humanoid robot walking system as an example, the Lagrangian equation can be used to establish a dynamic model without constraint, which is utilized to input/output linearize the control system and track the desired trajectories of the robot each joint. It can also be used to solve the active force acting on the system in which the motion law is given.
- (2) An adaptive error elimination controller is proposed to deal with the stabilization of walking gait. It ensures that the robot joint trajectory can compensate for the limitation of the template model, which will improve the robot's anti-interference ability in the environment.
- (3) A sliding mode controller is further designed under an uncertain environment, which is independent of system parameters and disturbances. It is proven to have a strong suppression ability against system parameter changes and external disturbances, demonstrating good robustness.
- (4) It proposed a nonlinear reformulation of classical walking pattern generator, which is able to find simultaneously foot-step positions and orientations based on optimal predictive control. The nonlinear constraints are able to cope with obstacles in the environment, which not only ensures the robot's stable motion but also enhances safety.

1.1 Modelling

Take humanoid robots as an example. Robot dynamics modeling is a crucial step in robot design and control, involving modeling the dynamic characteristics of the robot body and its joints. This process requires consideration of information such as joint mass, inertia, and dynamic parameters, as well as the mutual influence between joints and the dynamic behavior of the robot in different motion states. The robot dynamics system has complex and severely nonlinear characteristics, as well as complex coupling between multiple inputs and multiple outputs. The main research work includes dynamic parameter identification, kinematic trajectory planning, and adaptive control.

The methods of dynamic modeling mainly include the Lagrange equation and Newton-Euler equation. The Lagrange equation establishes a dynamic model based on the energy of the system, simplifying the modeling process. The dynamic equation is established as follows,

$$D(q)\ddot{q} + C(q, \dot{q})\dot{q} + G(q) = \tau + J^T f \quad (1)$$

where $\dot{q}$ and $\ddot{q}$ are angular velocity and acceleration of each joint, respectively. $D(q)$ is the inertia matrix, $C(q, \dot{q})$ is centrifugal force and Coriolis force matrix, and $G(q)$ is gravity matrix. $J = \frac{\partial \phi}{\partial q}$ is the Jacobian matrix.

Let $x = [q, \dot{q}]^T$, the dynamic equation (1) is written into a form of state space,

$$\begin{aligned} \dot{x} = \begin{bmatrix} \dot{q} \\ \ddot{q} \end{bmatrix} &= \begin{bmatrix} \dot{q} \\ M^{-1}(q) [-C(q, \dot{q})\dot{q} - G(q) + Bu] \end{bmatrix} = \begin{bmatrix} \dot{q} \\ M^{-1}(q) [-C(q, \dot{q})\dot{q} - G(q)] \end{bmatrix} + \begin{bmatrix} \dot{q} \\ M^{-1}(q)B \end{bmatrix} u \\ &\triangleq f(x) + g(x) u. \end{aligned} \quad (2)$$

Therefore, an overall model of biped walking can be regarded as a hybrid system, which can be described by

$$\Sigma : \begin{cases} \dot{x} = f(x) + g(x)u & x \notin S \\ x^+ = \Delta(x^-) & x^- \in S \end{cases} \quad (3)$$

Remark 1: Through dynamic modeling, the joint torque during robot motion can be obtained, and then compensated to the driver control through a feed-forward, improving the response speed and control accuracy of the driver. The dynamic model can calculate joint torque in real-time, thereby monitoring whether the robot collides during motion. Once an abnormality is detected, the current planned trajectory can be immediately interrupted to ensure safety.

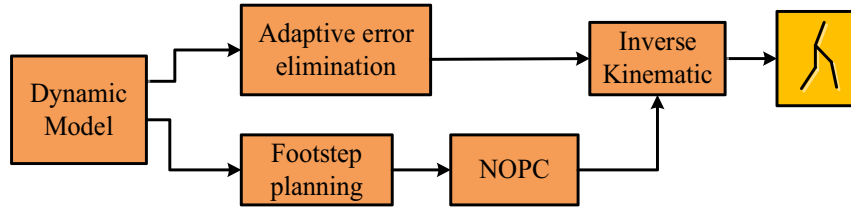


Figure 1. The control scheme

2 Safety-critical control scheme

The safety-critical control scheme is utilized to ensure system safety, especially in dealing with unknown systems or environments with uncertainty. It ensures that the system can maintain a safe state even when parameters are estimated or disturbed. By designing performance indicator functions, a balance is struck between reducing tracking errors and meeting safety requirements.

Taking robot walking as a specific application scenario. When Robots walk on irregular and unknown roads, it is impossible to make pre-modeling predictions or accurate modeling due to many irregular road conditions. In that case, if pure position control is used, it is impossible to plan a suitable position trajectory. Therefore, a safety-critical control scheme is introduced in Figure 1 to achieve real-time dynamic robot motion.

2.1 Adaptive controller for eliminating velocity errors

A globally stable adaptive controller is a type of controller that can automatically adjust its control parameters as the dynamic characteristics and environmental features of the controlled object change, ensuring global asymptotic stability for the system. It first constructs the design steps of a state feedback adaptive controller through back-stepping design techniques and then combines stability analysis methods (such as Barbalat's lemma) to ensure that the closed-loop system is globally asymptotically stable in state space and all other closed-loop signals are uniformly bounded. This controller is particularly suitable for nonlinear systems, such as robotic systems, power systems, and spacecraft control systems. It can significantly improve the control accuracy and robustness of the system.

Theorem 1. For the system (1), let λ_v be a symmetric positive definite matrix, μ_v be a positive definite matrix, if we design the following adaptive control law (4) and adaptive law (5),

$$\tau_v = \tilde{D}(q)\ddot{q}_r + \tilde{C}(q, \dot{q})\dot{q}_r + \tilde{G}(q) - \lambda_v \Delta q - \mu_v \Delta \dot{q} \quad (4)$$

where the vector τ_v is the generalized external force acting on the walking system, which is mainly caused by normal and tangential contact force. $\tilde{D}$, $\tilde{C}$ and $\tilde{G}$ are estimation matrix of D , C , G , $\tilde{C}$, $\Delta q = q - q_r$ indicates the tracking error of each joint.

$$\Delta \dot{\alpha}_v = -\mathfrak{S}^{-1} \Phi^T \Delta \dot{q} \quad (5)$$

where α_v is a matrix, which includes robot joint parameters and external force application parameters. $\Delta \alpha_v = \tilde{\alpha}_v - \alpha_v$ is the vector of estimated parameter error, where estimated value $\tilde{\alpha}_v$ is represent estimated value. Then the robot control system can achieve global stability, which ensures stable joint velocity with zero error.

Proof. In the first step, the candidate control Lyapunov function V_v for the system (1) is defined as,

$$V_v = \frac{1}{2} (\Delta \dot{q}^T D(q) \Delta \dot{q} + \Delta \alpha_v^T \mathfrak{S} \Delta \alpha + \Delta q^T \lambda_v \Delta q) . \quad (6)$$

Derive V_v function,

$$\begin{aligned}\dot{V}_v &= \Delta \dot{q}^T D(q) \Delta \ddot{q} + \frac{1}{2} \Delta \dot{q}^T \dot{D}(q) \Delta \dot{q} + \Delta \alpha_v^T \Im \Delta \dot{\alpha} + \Delta q^T \lambda_v \Delta q \\ &= \Delta \dot{q}^T (\tau_v - C(q, \dot{q}) \dot{q} - G(q) - D(q) \ddot{q}_r) + \Delta \dot{q}^T \left[\frac{1}{2} (D(q) - 2C(q, \dot{q})) + C \right] \Delta \dot{q} + \Delta \alpha_v^T \Im \Delta \dot{\alpha}_v + \Delta q^T \lambda_v \Delta q \\ &= \Delta \dot{q}^T [\tau_v - C(q, \dot{q}) \dot{q}_r - G(q) - D(q) \ddot{q}_r + \lambda_v \Delta q] + \Delta \alpha_v^T \Im \Delta \dot{\alpha}_v.\end{aligned}\tag{7}$$

Substitute the control law (4) into (7),

$$\begin{aligned}\dot{V}_v &= \Delta \dot{q}^T \left[(\tilde{D}(q) - D(q)) \ddot{q}_r + (\tilde{C}(q, \dot{q}) - C(q, \dot{q})) \dot{q}_r + (\tilde{G}(q) - G(q)) - \mu_v \Delta \dot{q} \right] + \Delta \alpha^T \Im \Delta \dot{\alpha} \\ &= \Delta \dot{q}^T [\Delta D(q) \ddot{q}_r + \Delta C(q, \dot{q}) \dot{q}_r + \Delta G(q) - \mu_v \Delta \dot{q}] + \Delta \alpha_v^T \Im \Delta \dot{\alpha}_v.\end{aligned}\tag{8}$$

Due to the linear nature of robots, in which exists the following equation relationship,

$$\Delta D(q) \ddot{q}_r + \Delta C(q, \dot{q}) \dot{q}_r + \Delta G(q) = \Phi \Delta \alpha_v\tag{9}$$

where $\Phi = \Phi(q, \dot{q}, q_r, \dot{q}_r)$.

Substitute the control law (4) into (8), we can get,

$$\dot{V}_v = -\Delta \dot{q}^T \mu_v \Delta \dot{q} + \Delta \alpha_v^T (\Im \Delta \dot{\alpha}_v + \Phi^T \Delta \dot{q}).$$

According to the adaptive law (5), we substitute the adaptive law (5) into (9),

$$\dot{V}_v = -\Delta \dot{q}^T \mu_v \Delta \dot{q} \leq 0.$$

Therefore, Theorem 1 is proved. It can be seen that we can obtain a steady-state error of zero for the velocity of each joint, but we cannot guarantee that the position error will also approach zero.

Remark 2: Reducing velocity errors can enable robots to perform predetermined tasks more accurately, improving product quality and work efficiency. Besides, it can also help robots maintain a stable operating state and reduce unexpected shutdowns or malfunctions caused by speed fluctuations. Accurate control of robot speed can reduce unnecessary energy consumption and improve energy efficiency.

2.2 Adaptive sliding mode controller for eliminating position errors

According to the implication of sliding mode control, we need to first design a sliding-mode surface. It needs to consider factors such as dynamic characteristics, and disturbances to ensure that the robot system can move according to the predetermined sliding surface.

$$\Delta \dot{q} + \Re \Delta q = 0$$

where $\Re$ is a constant matrix.

The virtual reference trajectory is defined as,

$$q_s = q_r - \Re \int \Delta q dt\tag{10}$$

where q_r represents expected motion trajectory of robot joints.

A sliding-mode surface can be described as follows,

$$\delta = \Delta \dot{q}_s = \dot{q}_s - \dot{q} = \Delta \dot{q} + \Re \Delta q\tag{11}$$

where $\dot{q}_s = \dot{q}_r - \Re \Delta q$, $\ddot{q}_s = \ddot{q}_r - \Re \Delta \dot{q}$.

Theorem 2. For the robotic system (1), let μ_p be a positive definite matrix. If we design the following adaptive sliding mode control law (12) and adaptive law (13),

$$\tau_p = \tilde{D}(q) \ddot{q}_s + \tilde{C}(q, \dot{q}) \dot{q}_s + \tilde{G}(q) - \mu_p \delta\tag{12}$$

$$\Delta \dot{\alpha}_p = -\Im^{-1} \Phi^T \Delta \dot{q}\tag{13}$$

where α_p is a matrix, which includes robot joint parameters and external force application parameters. $\Delta\alpha_p = \tilde{\alpha}_p - \alpha_p$ is the vector of estimated parameter error, where the estimated value $\tilde{\alpha}_p$ is represent estimated value. Then the position error will converge to the sliding surface, which ensures that the steady-state error of the joint position is 0.

Proof. The candidate control Lyapunov function V_p for the system (1) is defined as at first,

$$V_p = \frac{1}{2} (\delta^T D(q) \delta + \Delta\alpha_p^T \Im \Delta\alpha_p). \quad (14)$$

Take the derivation of V_p , we can get that,

$$\begin{aligned} \dot{V}_p &= \delta^T D \dot{\delta} + \frac{1}{2} \delta^T \dot{D} \delta + \Delta\alpha_p^T \Im \Delta\dot{\alpha}_p \\ &= \delta^T (D\ddot{q} - D\ddot{q}_s) + \frac{1}{2} \delta^T \dot{D} \delta + \Delta\alpha_p^T \Im \Delta\dot{\alpha}_p \\ &= \delta^T (\tau_p - C\dot{q} - G - D\ddot{q}_s) + \frac{1}{2} \delta^T \dot{D} \delta + \Delta\alpha_p^T \Im \Delta\dot{\alpha}_p \\ &= \delta^T (\tau_p - C(\delta + \dot{q}_s) - G - D\ddot{q}_s) + \frac{1}{2} \delta^T \dot{D} \delta + \Delta\alpha_p^T \Im \Delta\dot{\alpha}_p. \end{aligned} \quad (15)$$

Substitute (12) into (15),

$$\begin{aligned} \dot{V}_p &= \delta^T (\tilde{D}\ddot{q}_s + \tilde{C}\dot{q}_s + \tilde{G} - \mu_p\delta - C(\delta + \dot{q}_s) - G - D\ddot{q}_s) + \frac{1}{2} \delta^T \dot{D} \delta + \Delta\alpha_p^T \Im \Delta\dot{\alpha}_p \\ &= \delta^T (\Delta D\ddot{q}_s + \Delta C\dot{q}_s + \Delta G - \mu_p\delta - C\delta) + \frac{1}{2} \delta^T \dot{D} \delta + \Delta\alpha_p^T \Im \Delta\dot{\alpha}_p. \end{aligned} \quad (16)$$

In that of the dynamic characteristics of robots, there exists,

$$\Delta D(q)\ddot{q}_r + \Delta C(q, \dot{q})\dot{q}_r + \Delta G(q) = \Phi\Delta\alpha_p. \quad (17)$$

Hence,

$$\begin{aligned} \dot{V}_p &= \delta^T (\Phi\Delta\alpha_p - \mu_p\delta - C\delta) + \frac{1}{2} \delta^T \dot{D} \delta + \Delta\alpha_p^T \Im \Delta\dot{\alpha}_p \\ &= \delta^T (\Phi\Delta\alpha_p - \mu_p\delta) + \frac{1}{2} \delta^T (2C - \dot{D})\delta + \Delta\alpha_p^T \Im \Delta\dot{\alpha}_p \\ &= \delta^T (\Phi\Delta\alpha_p - \mu_p\delta) + \Delta\alpha_p^T \Im \Delta\dot{\alpha}_p \\ &= \Delta\alpha_p^T \Phi^T \delta - \delta^T \mu_p\delta + \Delta\alpha_p^T \Im \Delta\dot{\alpha}_p \\ &= \Delta\alpha_p^T (\Phi^T \delta + \Im \Delta\dot{\alpha}_p) - \delta^T \mu_p\delta = -\delta^T \mu_p\delta \leq 0. \end{aligned} \quad (18)$$

Therefore, the position error converges to the sliding surface, $\Delta\dot{q} + \Re\Delta q = 0$, hence, $\Delta q \rightarrow 0$ when $t \rightarrow \infty$. Theorem 2 is proved.

Remark 3: Error compensation technology allows for real-time compensation of robots during the production process, without the need for additional detection and calibration steps, which helps reduce production costs and shorten production cycles. Accurate robot motion control can avoid accidents during task execution, thereby ensuring the safety of the working environment.

3 Nonlinear optimal Predictive control and optimization

OPC-based solutions with whole-body models are more easily modified, thus they can provide more reliable solutions. In this section, in order to calculate automatic foot placement in real-time, extensions of the OPC scheme are presented, which makes it possible to correct footsteps. Meanwhile, this is also applied well to integrate obstacles with linear constraints.

Consider a frame ς_k^w attached to the robot support foot, with its current position and orientation on the ground given by ς_k^w , with $w \in \{a, b, \theta\}$. The future steps are denoted by

$$\begin{cases} \varsigma_{k+1}^w = [\varsigma_{k+1}^w & \varsigma_{k+2}^w & \cdots & \varsigma_{k+N}^w]^T \\ {}^{\text{ref}}\mathbf{v}_{k+1} = [{}^{\text{ref}}v_{k+1}^a & {}^{\text{ref}}v_{k+1}^b & {}^{\text{ref}}v_{k+1}^\theta]^T \end{cases} \quad (19)$$

where ς_{k+1}^w represents the foot support position at each time step, $\mathbf{v}_{k+1}^w$ indicates which step falls in the sampling interval.

The cost function used in the NOPC is given by,

$$\min \frac{\psi}{2} J_1(U_k) + \frac{\psi}{2} J_2(U_k) + \frac{\zeta}{2} J_3(U_k) \quad (20)$$

where ψ and ζ are the weights of the cost function, U_k are defined as follows,

$$\begin{cases} U_k^{x,y} = [\ddot{C}_k^x & \ddot{\varsigma}_k^a & \ddot{C}_k^y & \ddot{\varsigma}_k^b] \\ U_k^\theta = \varsigma_k^\theta \\ U_k = [U_k^{a,b} & U_k^\theta] \end{cases} \quad (21)$$

$J_1(U_k)$ represents the cost function which stands for the linear velocity tracking effect,

$$J_1(U_k) = \left\| \dot{C}_{k+1}^b - {}^{\text{ref}}v_{k+1}^a \right\|_2^2 + \left\| \dot{C}_{k+1}^b - {}^{\text{ref}}v_{k+1}^b \right\|_2^2 \quad (22)$$

$J_2(U_k)$ is the cost function which stands for the angular velocity tracking effect,

$$J_2(U_k) = \left\| \varsigma_{k+1}^\theta - \int {}^{\text{ref}}v_{k+1}^\theta dt \right\|_2^2 \quad (23)$$

$J_3(U_k)$ is the cost function that minimizes the distance between the COP and the projection of the robot ankle on the sole,

$$J_3(U_k) = \left\| \varsigma_{k+1}^a - C_{k+1}^a \right\|_2^2 + \left\| \varsigma_{k+1}^b - C_{k+1}^b \right\|_2^2 \quad (24)$$

4 Simulation results

To verify the control and optimization methods given in Sections 3 and 4, simulations are implemented. The simulation results of the adaptive error elimination algorithm and NOPC optimization are shown as follows. In order to better see the performance changes, the robot system with adaptive control for eliminating velocity and position errors is conducted respectively. The proposed safety-critical framework is verified in dynamics simulation. Table 1 describes the robot configuration parameters.

In Figure 2, the phase diagrams of joint angle and angular velocity show the form of a limit cycle, which indicates that the robot can realize periodic stable walking. Figure 3 shows the variation of output torque, and Figure 4 shows the changes in joint angle and angular velocity over time. It can be seen that the actual trajectory can track its reference trajectory. Figure 5 describes joint angle position with adaptive control for eliminating velocity and position errors, respectively. The blue curve represents the reference value, and the red curve represents the actual value. The tracking effect is better with sliding mode control. The tracking error will converge to 0 after a certain number of walking steps. Figures 6 and 7 indicate the convergence result of parameter normalization. The effect of obstacle avoidance on robot motion with NOPC is shown in Figure 8, which indicates that the robot can plan obstacle avoidance trajectories and freely move forward to avoid obstacles successfully. The above simulation results show that safety-critical control is robust to the varying environmental stiffness.

Table 1. The robot configuration parameters

Parameter	Value	Unit
Torso length L_T	0.204	m
Thigh length L_t	0.412	m
Calf length L_s	0.385	m
Torso mass m_T	5.9	kg
Thigh mass m_t	13.2	kg
Calf mass m_s	7.7	kg
Hip rotational inertia I_T	0.24	kgm ²
Thigh rotational inertia I_t	0.56	kgm ²
Calf rotational inertia I_s	0.28	kgm ²
Gravitational acceleration g	9.8	m/s ²

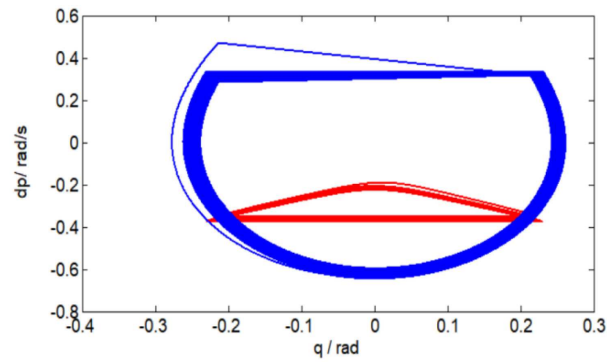


Figure 2. Phase diagram of joint angle and angular velocity

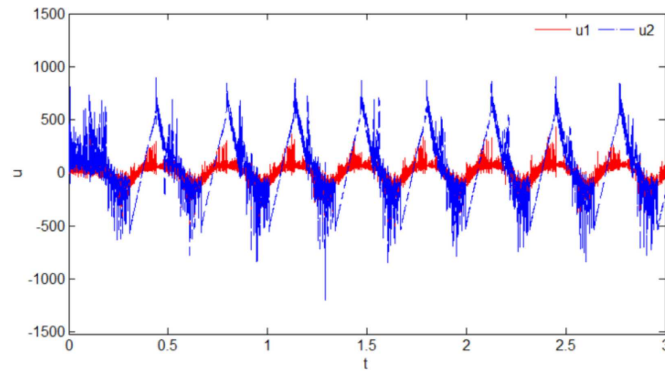


Figure 3. The variation of output torque over time

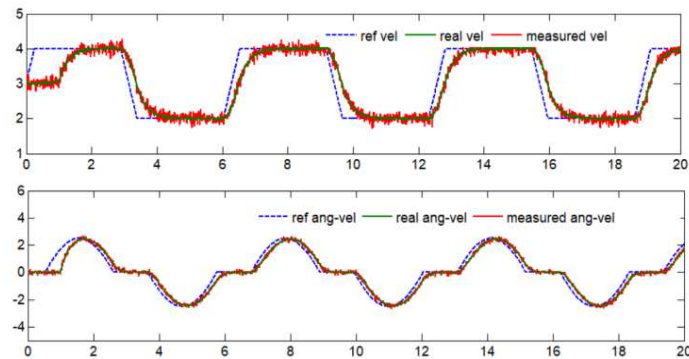
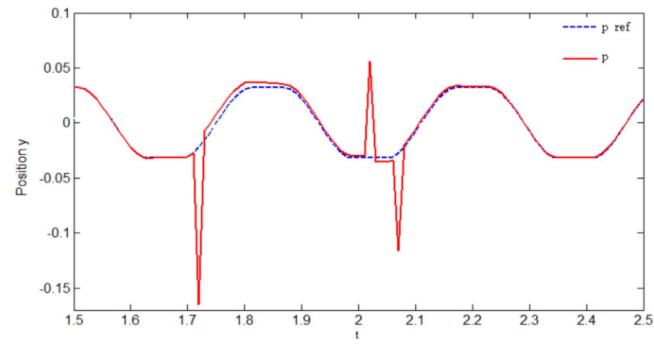
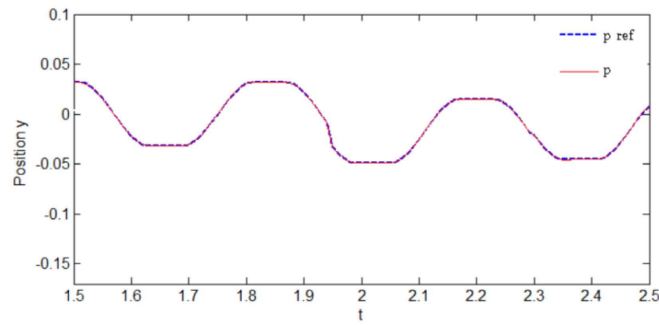


Figure 4. Changes in joint angle and angular velocity over time



(a)



(b)

Figure 5. Changes in joint angle position over time, (a) with adaptive control for eliminating velocity errors, (b) with adaptive sliding mode control for eliminating position errors

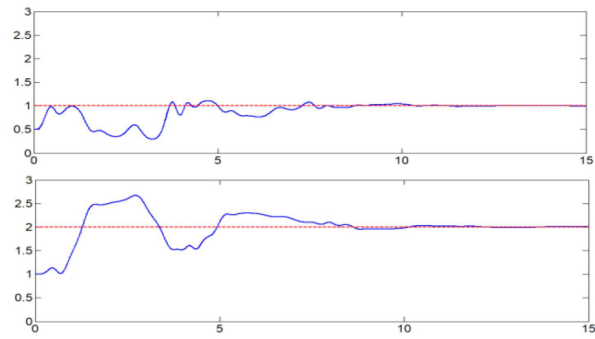


Figure 6. The convergence result of parameter normalization

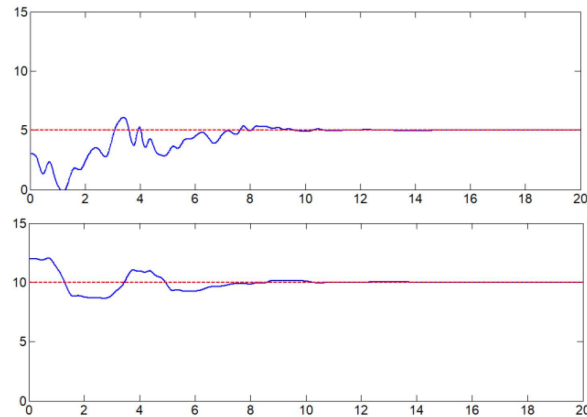


Figure 7. The convergence result of parameter normalization

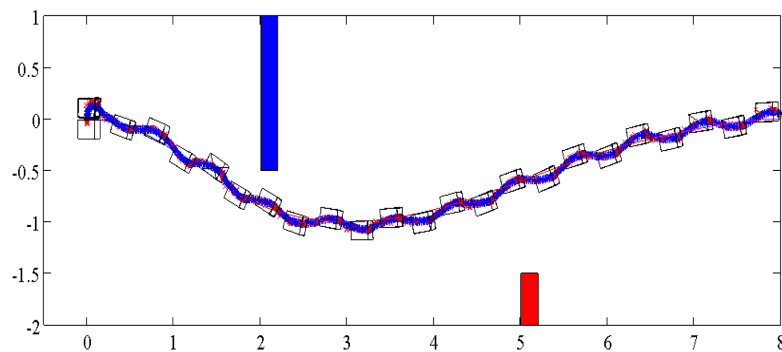


Figure 8. The effect of obstacle avoidance of robot motion with NOPC

5 Conclusion

As a driving force in the era of intelligence, intelligent robots represent a country's high-tech development level. Robots monitor their surroundings in real-time through efficient safety systems such as sensors, controllers, *etc.*, to avoid collisions with personnel and ensure their safety. The application of safety-critical control technology enables robot systems to maintain stable operation in complex environments, reducing the occurrence of failures and unexpected situations. With the continuous development of safety-critical control technologies, robots will become more intelligent and autonomous, promoting continuous innovation and application expansion of robot technology.

This paper aims not only to provide theoretical support for improving autonomous control and optimization in complex tasks and environmental uncertainties but also to provide strong technical support for promoting the industrialization and upgrading of intelligent robots. The focus is on the following aspects: (1) analyzing the mechanism of the robot dynamic model and studying safety-critical control strategies from the perspective of theoretical analysis; (2) designing an adaptive error elimination controller to eliminate speed and position errors, respectively; (3) constructing autonomous evolution mechanism based on nonlinear optimal predictive control to optimize the gait mode of robot. In future work, an extension of the human-inspired deep learning method will be taken into account, which will assist robots in autonomous decision-making and motion planning, enabling precise control and navigation in complex environments. Human-inspired methods are also used to enhance the decision-making and perception abilities of robots. By mimicking human behavior and the theory of environmental attraction domain, robots can better adapt to complex environments and achieve high-performance tasks. In addition, how to enhance the interaction ability between robots and humans, making robots more intelligent, safe, and user-friendly? It can not only improve the accuracy and adaptability of robots but also enhance the safety and naturalness of human-computer interaction. Through these technologies, robots can better complete tasks in complex environments while reducing conflicts and risks with humans.

Conflicts of interest

The author declares no conflict of interest.

Data Availability

No data are associated with this article.

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Helin Wang received her Ph.D. degree from Tongji University, Shanghai, China, in 2020. She has been working as a post-doctor at Tongji University from 2020 to 2024. She is now working as a teacher in the department of electrical and electronic engineering, the Shanghai Institute of Technology, Shanghai, China. Her current research interests are in the intelligent control of robotic systems.