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Control Methods Study of Rail-Mounted W-Beam Guardrail Inspection Robot

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Abstract: To address the limitations of traditional manual highway guardrail inspections, this paper proposes an obstacle-crossing and collaborative tracking control method for a rail-mounted robot. Static and dynamic analyses verify the robot's structural reliability and driving feasibility. Based on the leader-follower model, a triangular collaborative tracking model is developed, and a linear time-varying model predictive control (LTV-MPC) is designed to achieve smooth and precise collaborative control. For obstacle crossing, an acceleration reference model and a gradient-based adaptive law are proposed, leading to a model reference adaptive control (MRAC) that effectively suppresses vibrations and ensures synchronous control. Simulation results show that the MPC achieves a 0.415% overshoot and a 0.344 m steady-state accuracy, while also reducing the intensity of speed fluctuations by 35%. The MRAC ensures smooth obstacle-crossing speeds and adaptive strategy switching, validating the reliability and practicality of the rail-mounted robot under complex working conditions.

Key words: rail-mounted inspection robot; mechanical analysis; model predictive control (MPC); model reference adaptive control (MRAC)

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0 Introduction

Highway guardrails are vital for traffic safety, serving to delineate driving areas, reduce accident damage, and protect drivers' lives. However, over time, corrosion and mechanical damage may cause deterioration or failure. Traditional manual inspection methods face challenges such as poor adaptability, low efficiency, and limited accuracy. To address these issues, this paper proposes a rail-mounted inspection robot. Rail-mounted robots are gaining attention in inspection robotics due to

their stability and adaptability in confined^[1], hazardous, or difficult-to-reach areas. These robots offer autonomous navigation, multi-dimensional inspections, and AI-driven image recognition, significantly enhancing inspection efficiency and accuracy. Key research focuses on improving the stability and reliability of these robots in complex environments, equipping them with autonomous positioning, specialized cameras, and environmental sensors.

In the research on rail-mounted guardrail inspection robots, both domestic and international scholars have primarily focused on three aspects: guardrail inspection tech-

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nology, rail-mounted robot design, and control methods.

Guardrail inspection methods can be categorized into manual and automated approaches, with automated technologies becoming increasingly widespread due to their high efficiency. Rail-mounted robots, as autonomous inspection devices, offer distinct advantages in complex environments. For instance, Sheela *et al.*^[2] employed sensor technology to create a rail-mounted robot for monitoring industrial environments, such as natural gas industries. This system mainly focuses on detection and perception. Rui *et al.*^[3] developed the HanGrawler, a track-mounted, high-speed ceiling-moving robot capable of efficient load transportation via a mechanical suspension system. However, it focuses on high-speed scenarios. Li *et al.*^[4] developed an intelligent inspection system for substation rail-mounted robots, utilizing rail-mounted driving technology and automatic data collection to conduct inspections in the confined spaces of substation equipment rooms. However, the complexity of real-world environments, such as guardrail inspection scenarios, which often involve irregular terrains and diverse obstacles, was not fully addressed. Ouyang *et al.*^[5] optimized a diamond-shaped suspended basket robot for bridge cantilever casting operations, enhancing efficiency. Nevertheless, this optimization focused mainly on specific construction operations.

The performance of the robot in complex environments is largely determined by its control methods. Wang^[6] employed multi-sensor fusion techniques for obstacle avoidance and path planning, while Ji *et al.*^[7] combined adaptive neural networks and robust steering controllers to maintain yaw stability and minimize lateral path tracking errors. Zhang *et al.*^[8] applied fuzzy modeling to handle nonlinear path tracking with parameter variations and proposed a fuzzy observer-based vehicle dynamics output feedback steering control method. AlAttar *et al.*^[9] proposed a kinematic-model-free predictive controller (KMF-PC) for robot motion, enabling end-effector reaching and obstacle avoidance without prior knowledge of the robot's kinematics. It may not be applicable to the relatively well-defined motion models in the scenarios of guardrail collaborative inspection. Zhang *et al.*^[10] utilized an integrated potential field method for adaptive motion control, enhancing user comfort and safety. However, these approaches failed to focus on practical control strategies for collaborative inspection and obstacle-crossing operations in guardrail inspection.

Reviewing the aforementioned literature, although current advancements in inspection technologies and rail-mounted robotic systems have demonstrated notable progress with reference-worthy technical methodologies and applications, including exemplary cases in specific domains^[11-13], a comprehensive review reveals that several critical shortcomings persist in current research: (1) the precision and stability of automated inspection in complex guardrail environments are insufficient; (2) the obstacle-crossing and adaptability design of rail-mounted robots for guardrail inspection is not yet fully developed; (3) there is a lack of practical research on control strategies for collaborative inspection and obstacle-crossing operations.

To address these issues, this paper proposes a combined control strategy integrating model predictive control (LTV-MPC) and model reference adaptive control (MRAC). First, the feasibility and reliability of the structure are demonstrated through static structural analysis and dynamic driving analysis of the rail-mounted robot. Next, a control model is constructed based on the application scenario of collaborative tracking control, and a cost function for model predictive control is designed using a quadratic programming method. Finally, an acceleration model is developed based on the actual obstacle-crossing speed requirements, and an adaptive law for the model reference adaptive control is designed using the gradient method, resulting in the combined control strategy. These control methods provide essential guidance for practical inspection operations.

1 Guardrail Structural Features and Inspection Robot System

1.1 Guardrail Structural Features

Highway traffic safety guardrail facilities^[14] are primarily divided into three types: W-Beam guardrails, concrete guardrails, and cable guardrails. The inspection system in this study mainly focuses on W-Beam guardrails for inspection and analysis. A W-Beam guardrail typically consists of a waveform beam plate, posts, end units, fasteners, connecting components, surface coatings, and impact blocks^[15], as shown in Fig. 1.

Over time, issues such as corrosion, tilting, and mechanical damage can accumulate, affecting the structural strength and protective capacity of the guardrail plate, significantly increasing traffic safety risks. Therefore, precise inspection of key parameters of the guardrail

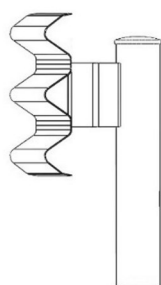


Fig. 1 Schematic diagram of W-Beam guardrail section

plate, such as plate thickness, coating thickness, and center height, becomes particularly important.

1.2 Composition of Rail-Mounted Inspection Robot System

The system primarily consists of an upper computer, motion control system (including wheel hub motors, Field-Oriented Control (FOC) drivers, and motion control units), and a parameter inspection system (including ultrasonic post identification unit, Inertial Inspection Unit (ISU) tilt inspection unit, distance inspection unit, coating thickness inspection unit, and laser thickness inspection unit). The functional block diagram is shown in Fig. 2.

The upper computer and the remote controller can send commands to the motion control unit. Based on the rail-mounted mobile platform studied in this paper, the

motion control system integrates real-time data from the Ultra Wide Band (UWB) collaborative module, ultrasonic post identification module, and IMU tilt inspection module to control the start/stop and speed regulation of the wheel hub motors. The upper computer is responsible for sending operational commands and receiving data on center height, coating thickness, guardrail plate thickness, tilt, and post identification from the parameter inspection system. It processes and digitally archives the acquired structural parameters of the guardrail and displays the inspection results on the interface in textual or graphical form.

The parameter inspection system is the core of the inspection robot system. Among its components, the laser thickness inspection module is a "V"-shaped dual-channel precision laser displacement sensor, capable of non-contact high-precision thickness inspection. The coating thickness module is equipped with a coating thickness gauge and a lead screw slide stepper motor for inspection. The center height inspection unit combines tilt inspection data with laser distance inspection data to obtain the center height after pose correction. The ultrasonic post identification module and IMU tilt inspection module can identify the arrival of posts and pose status in real time, providing status information to the motion control system.

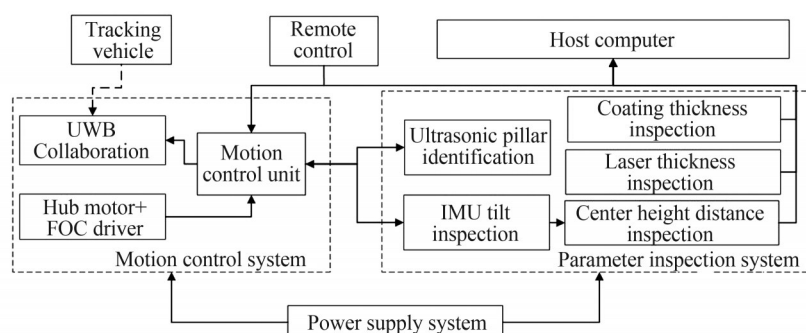


Fig. 2 Functional block diagram of the rail-mounted inspection robot system

2 Dynamics of Rail-Mounted Inspection Robot

The inspection robot is designed based on a rail-mounted operating platform, as shown in Fig. 3. The robot body consists of a structural frame, outer shell, wheel hub motor mount, pulleys, rollers, and other components. To minimize the size, the robot features a flip-top structure for the internal space, with a battery stor-

age compartment designed in the middle layer. The mechanical analysis of the rail-mounted robot body structure forms the foundation for ensuring the robot's stable and reliable operation on the guardrail.

2.1 Static Analysis

The objective of static analysis is to verify the structural feasibility of the robot when suspended on guardrails. When the robot is stationary and suspended on the guardrail, it is primarily supported by the guardrail plate

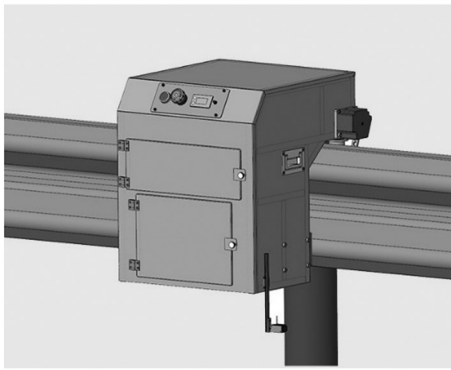


Fig. 3 Rail-mounted inspection robot body

and various contact points on the mobile platform. The forces mainly include the weight of the robot's battery, structural frame, outer shell, rollers, and other components.

As shown in Fig. 4, the rail-mounted inspection robot's structure relies on the contact forces between the guardrail plate and the wheel hub motors, pulleys, and rollers to maintain stability. The action lines of all the forces in the lateral plane form a planar concurrent force system, reflecting the stability of the rail-mounted structure between the mobile platform and the guardrail.

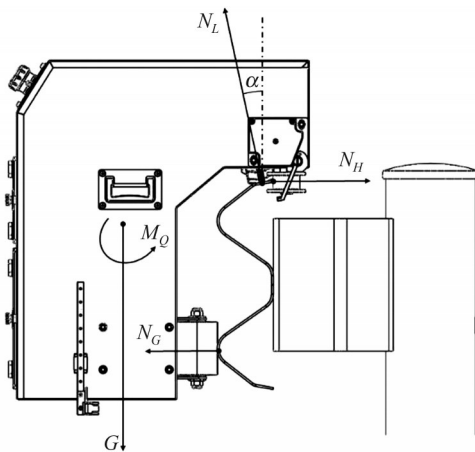


Fig. 4 Lateral view of the rail-mounted inspection robot

When stationary and stably supported, the mobile platform is in a state of equilibrium, and the resultant force and resultant moment of all forces in the system at any point are zero.

The vertical component N_{Ly} of the support force N_L from the guardrail plate on the wheel hub motor is balanced by the gravitational force G in the horizontal direction, the horizontal component N_{Lx} of N_L is balanced by the forces N_H and N_G from the support of the pulley

and roller, with N_H directed to the right and N_G directed to the left. The force balance equation is:

$$\begin{cases} N_H = N_{Lx} + N_G = N_L \times \sin \alpha + N_G, \\ G = N_{Ly} = N_L \times \cos \alpha, \end{cases} \quad (1)$$

where α is the angle between the support force N_L from the guardrail plate and the vertical direction.

Using the principle of force translation, the point of action of N_L is shifted to the center of mass, resulting in an overturning moment M_Q acting on the center of mass. According to the positions of the battery and main components, the center of mass is located below the point of action of N_H . By the principle of moments, the moments of N_H and N_L at the center of mass counteract the overturning moment M_Q .

The moment balance equation is:

$$N_G \times l_G + N_H \times l_H = M_Q = N_L \times l, \quad (2)$$

where l , l_G , and l_H represent the perpendicular distances from the action lines of N_L , N_G , and N_H to the center of mass, respectively.

By solving the force and moment balance equations, we obtain N_H and N_G as follows:

$$\begin{cases} N_G = \frac{G \times (l - l_H \times \sin \alpha)}{(l_G + l_H) \times \cos \alpha}, \\ N_H = \frac{G \times (l + l_G \times \sin \alpha)}{(l_G + l_H) \times \cos \alpha}. \end{cases} \quad (3)$$

The above analysis shows that the mechanical stability of the rail-mounted inspection robot on the guardrail depends on the force distribution at the contact points. The center of mass should be positioned as close as possible to the contact points, which can effectively improve the robot's operational stability in complex environments. The structural frame and outer shell of the rail-mounted inspection robot weigh approximately 110 N, with the battery weighing about 50 N. Therefore, the total gravitational force of the robot is less than 200 N, denoted as $G = 200$ N. Due to the excellent bending resistance of the rollers, pulleys, axle rods, guardrail fastening bolts, and guardrail plate, the robot's gravitational force has a limited impact on the internal structural stability. The guardrail plate provides sufficient support force to ensure the stable suspension of the mobile platform.

2.2 Dynamics Analysis

The objective of dynamic analysis is to investigate the motion characteristics of rail-mounted robots during navigation on straight or curved tracks.

2.2.1 Dynamics of robot straight-line motion

When the rail-mounted inspection robot operates while suspended on the guardrail, it is driven in the frontal plane by the hub motor, which rotates the wheel hubs. The motion of the robot is resisted by the dynamic friction forces generated between the pulleys, rollers, hub motors, and the surface of the guardrail. The force analysis of the robot's straight-line motion is shown in Fig. 5.

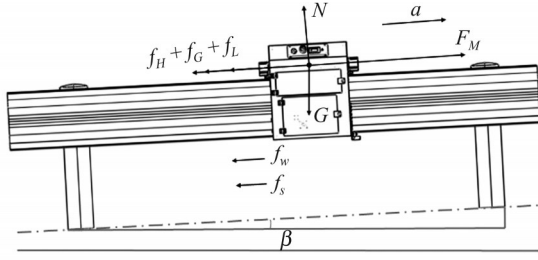


Fig. 5 Force analysis of robot straight-line motion

In analyzing the forces acting on a robot during its movement along a guardrail track, the case of the robot's motion on a slope is considered as an example. The robot's structure in the frontal plane can be approximated as symmetrical about the centerline, with the center of gravity located on the symmetry plane. The robot's weight G is supported by the vertical components of the total support forces N exerted by the guardrail plate. The slope of the ramp is denoted as β . Along the direction of motion of the rail-mounted platform, the hub motor driving force F_M counteracts the combined effects of rolling friction, sliding friction, aerodynamic drag f_w , and slope resistance f_s , while also generating the instantaneous acceleration a . The force balance equation is expressed as follows:

$$\begin{cases} N = G \times \cos \beta, \\ F_M - f_H - f_G - f_L - f_w - f_s = ma. \end{cases} \quad (4)$$

At the initial stage of motion, the friction between the pulleys, rollers, hub motors, and the guardrail plate can be regarded as a combination of rolling and sliding friction. Sliding friction generally ranges from 0.03 to 0.25, and because the contact areas are small and wheel-structured, the hub motor's driving force, combined with the robot's self-weight, can overcome the resistance at the contact points. The robot platform achieves pure rolling motion after this stage.

When the robot reaches steady motion, the friction at the contact points transitions to pure rolling friction. At this stage, the hub motor driving force is balanced by

static friction. The rolling friction coefficient is denoted as μ . Based on the calculations of N_G and N_H from the static analysis, the total friction force $f_H + f_G$ acting on the robot during straight-line motion can be determined. Additionally, the friction force between the hub motor and the guardrail plate can be calculated as follows:

$$\begin{cases} f_H + f_G = \frac{G \times 2l}{(l_H + l_G) \times \cos \alpha} \times \mu, \\ f_L = \frac{G}{\cos \alpha} \times \mu. \end{cases} \quad (5)$$

Given that the robot's operating speed is less than 5 km/h, the velocity is relatively low, and the overall size of the robot is small. Therefore, the aerodynamic drag f_w and slope resistance f_s can be calculated using classical formulas for aerodynamic drag and slope resistance:

$$\begin{cases} f_w = \frac{1}{2} \rho \Sigma S_i v_i^2 C_i, \\ f_s = G \times \sin \beta, \end{cases} \quad (6)$$

where ρ represents air density, S_i , v_i , and C_i denote the wind-facing area, relative velocity between the robot and air, and the air drag coefficient, respectively.

Based on the linear motion dynamics equation derived in this section, relevant values from the actual system are substituted for calculation.

The driving force of the motor is expressed by the relationship between motor output torque and force, as shown in equation (7):

$$F_M = \frac{T_M \times 2}{r}. \quad (7)$$

The selected hub motor is a FOC-driven brushless DC motor with a tire diameter of 105 mm, a rated torque of 3 N·m, and an instantaneous maximum torque of 7 N·m. The maximum and rated driving forces of the hub motor are calculated as follows:

$$\begin{cases} F_{M\max} = \frac{T_{M\max} \times 2}{r} = \frac{2 \times 7 \text{ N} \cdot \text{m}}{0.0525 \text{ m}} \approx 266.67 \text{ N}, \\ F_{Mr} = \frac{T_{Mr} \times 2}{r} = \frac{2 \times 3 \text{ N} \cdot \text{m}}{0.0525 \text{ m}} \approx 114.29 \text{ N}. \end{cases} \quad (8)$$

In the calculations of aerodynamic drag^[16] and slope resistance, the air resistance coefficient C_i is taken as the extreme value of 0.6, and the total wind-facing area is approximately 0.15 m². Given a wind speed of 70 km/h for a level 8 wind, the relative air velocity is approximately 20 m/s. At 20 °C, the air density is 1.205 kg/m³. On highways, the slope β is generally below 5%. Considering the slope resistance caused by uphill motion, the parameters are substituted into the calculations as shown below:

$$\begin{cases} f_{w\max} = 23.52 \text{ N}, \\ f_{s\max} = G_{\max} \times \sin 5^\circ \approx 17.43 \text{ N} < 20 \text{ N}. \end{cases} \quad (9)$$

Since the rolling friction coefficient^[17] is relatively small, typically no more than 0.1 in standard engineering environments, the total friction force can be calculated as follows:

$$f_{H\max} + f_{G\max} + f_{L\max} < 60 \text{ N} \quad (10)$$

By comparing the hub motor's rated driving force F_{Mr} with the maximum values of aerodynamic drag, slope resistance, and total friction force, the following relationship is obtained:

$$F_{Mr} > f_H + f_G + f_L + f_w + f_s \quad (11)$$

Therefore, under normal driving conditions, the driving force provided by the hub motor is sufficient to overcome all resistances in the direction of motion, ensuring that the robot maintains steady motion.

2.2.2 Robot dynamics in curve navigation and obstacle-crossing

When the rail-mounted robot moves along highway guardrails on curved roads, centripetal acceleration is generated. A comparison of the robot's dynamics during straight-line motion and curve navigation is shown in Fig. 6.

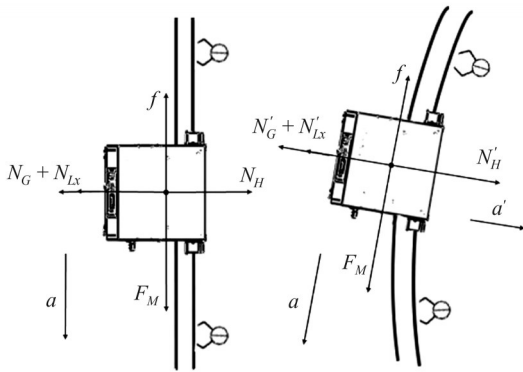


Fig. 6 Comparison of robot's straight-line and turning conditions

When the rail-mounted robot moves along highway guardrails on curved roads, centripetal acceleration is generated. This generation of centripetal acceleration leads to a net force in the direction of the guardrail's support on the robot's pulleys, rollers, and hub motors, as expressed in equation (12).

$$\begin{cases} \Delta F = m \frac{v^2}{r_0}, \\ N'_G + N'_{Lx} = N'_H + \Delta F. \end{cases} \quad (12)$$

According to the Highway Engineering Technical Standards^[18], the general and minimum values of the

minimum radius of a circular curve depend on the design speed. For a highway with a design speed of 80 km/h, the general minimum radius of a circular curve is 400 m. This value is determined based on ensuring safe and smooth driving through the curve.

Taking $r_0 = 400 \text{ m}$, the robot's low speed ensures that changes in the support forces and corresponding normal pressures at the contact surfaces are minimal. Although the friction force in the instantaneous motion direction varies, the change is minor and does not significantly affect the system's motion.

The rail-mounted robot, during its suspension operation on the guardrail, needs to overcome the guardrail connection and record the pillar number. Due to the bolt-based splicing at the connection, a complete tight fit cannot be achieved, resulting in a certain height difference, as shown in Fig. 7(a). The force analysis of the obstacle-crossing is also shown in Fig. 7(b) and (c).

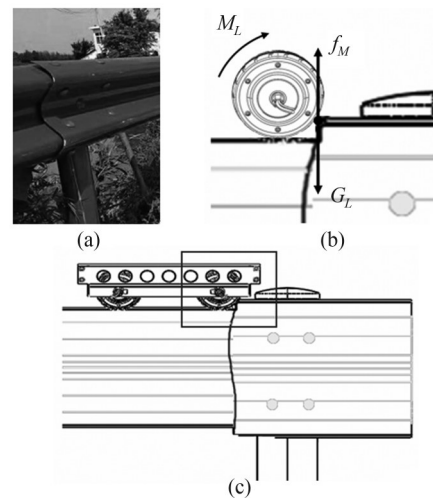


Fig. 7 Obstacle-crossing force conditions (a) and analysis (b) and (c)

The figure illustrates the scenario where the hub motor drives the robot to overcome the obstacle starting from the next section of the guardrail, which is tightly fitted after the connection. This reflects the hub motor's obstacle-crossing capability without relying on inertial forces. The forward friction force f_M generated by the rolling hub motor must overcome the gravity G_L acting on the hub on that side until the supporting force N_L of the guardrail on the hub motor is zero, as expressed in equation (13):

$$f_M = G_L - N_L. \quad (13)$$

The analysis indicates that when the hub motor does not rely on inertia, the forward friction force gener-

ated by the motor's maximum driving force is not significantly greater than the resistance caused by gravity and rolling friction. This is insufficient to generate translational motion. Solely relying on the forward friction force generated by rolling to drive the robot is unreliable. If f_M is insufficient to overcome gravity and rolling friction, the hub motor will slip in place, preventing the robot from successfully traversing the guardrail joint. In severe cases, this could result in circuit burnout due to overcurrent. Thus, inertia-based speed control is essential for obstacle crossing.

3 Control Methods for Inspection Robot Based on Mode Switching

Analysis and modeling of the inspection robot indicate that the rail-mounted structure ensures stable support and motion reliability, enabling collaborative tracking and obstacle-crossing control. For collaborative tracking, we apply the Linear Time-Varying Model Pre-

dictive Control (LTV-MPC) method—a well-established approach in the field of dynamic system control, particularly for handling time-varying process characteristics—to address the dynamic requirements of the collaborative tracking task. LTV-MPC effectively accommodates time-varying system dynamics while maintaining the predictive and real-time performance of traditional Linear Model Predictive Control (LMPC), thereby making it suitable for segmented rail-mounted guardrail inspections.

For obstacle-crossing control, the Model Reference Adaptive Control (MRAC) method is used. MRAC ensures that the system's actual output follows the reference model's output through an adaptive law, accommodating jolts when crossing guardrail joints. The figure below illustrates the motion control process of the rail-mounted inspection robot, where collaborative tracking and obstacle-crossing control switch based on pillar recognition and obstacle-crossing completion, as detailed in Fig. 8.

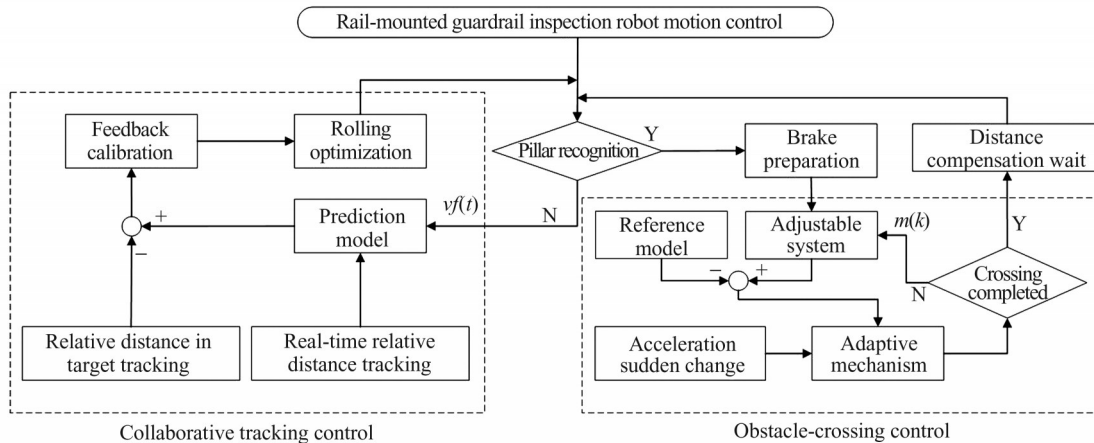


Fig. 8 Flowchart of the motion control method for rail-mounted guardrail inspection robot

3.1 LTV-MPC Collaborative Tracking

The collaborative tracking control method studied in this paper is based on a leader-follower approach. The leader is a guardrail inspection tracking vehicle operating in the highway emergency lane, characterized by constant-speed movement and periodic stops at inspection points. The follower is the rail-mounted robot, which must meet the synchronous inspection requirements on both sides of the lane. The rail-mounted robot needs to integrate system dynamics and relative position to track the tracking vehicle and maintain real-time collaborative operation.

3.1.1 Follower collaborative motion modeling

To ensure stable tracking of the leader by the follower, the collaborative motion process must be appropriately modeled based on the specific working scenario. As shown in Fig. 9, the rail-mounted robot and the tracking vehicle form a triangular tracking model on the side of the central greenbelt and emergency lane. In this model, the fixed lateral distance AB between the rail-mounted robot A and the tracking vehicle B forms one leg of the right triangle. The sum of the driving distance difference and curve compensation B_0B' forms the other leg. Together, they define the relative tracking distance

$A'B'$. The curve compensation is determined by the ra-

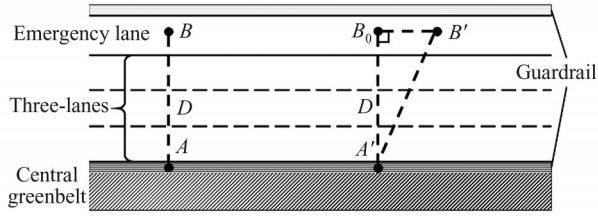


Fig. 9 Schematic diagram of the triangular tracking model

dius of the circular curve on the highway.

Considering the strong trajectory constraints of the rail-mounted robot, the follower's motion can be described using a simplified linear time-varying first-order system. Assume the velocity of the rail-mounted robot is a function of time and control input, i.e., the velocity $v_f(t)$ is the system's control input, the relative distance is denoted as $y(t)$, and the reference distance is denoted as $x(t)$. Since the motion of the rail-mounted robot is influenced by external factors (e.g., the leader's position and velocity), its kinematic model can be described by the following linear time-varying system equation, as shown in equation (14):

$$\begin{cases} \dot{x}(t) = -\alpha(t)x(t) + \beta(t)v_f(t) + d(t), \\ y(t) = \sqrt{x^2(t) + D^2}, \end{cases} \quad (14)$$

where $\alpha(t)$ and $\beta(t)$ are time-varying parameters related to the motion of the tracking vehicle. $d(t)$ is a disturbance term, primarily caused by curve errors and the periodic stops of the tracking vehicle, which introduces errors to the rail-mounted robot. D is the fixed lateral distance determined by lane conditions.

In LTV-MPC, the controller design is typically based on a discrete-time model. Assuming the system sampling period is Δt , the discretized state equation can be obtained using the Euler method, as shown in equation (15):

$$\begin{cases} x[k+1] = (1 - \alpha[k]\Delta t)x[k] + \beta[k]\Delta t \cdot v_f[k] + d[k]\Delta t, \\ y[k+1] = \sqrt{x^2[k+1] + D^2}. \end{cases} \quad (15)$$

3.1.2 LTV-MPC tracking controller design

To meet the speed and stability requirements of the guardrail inspection task, this paper designs an LTV-MPC controller and its cost function to minimize the relative distance error between the rail-mounted robot and the tracking vehicle over a finite time horizon.

The relative distance error between the rail-mounted robot and the tracking vehicle can be expressed

as $e(k) = x(k) - x_p(k)$, where $x_p(k)$ is the target relative distance determined by the synchronized inspection scenario of the tracking vehicle and the rail-mounted robot.

The cost function of the LTV-MPC tracking controller integrates the collaborative kinematic modeling, disturbance terms, and the motion characteristics of the tracking vehicle. Let the prediction horizon and control horizon be $N-1$ steps. At time step k , the cost function is designed as shown in equation (16):

$$\begin{cases} J = J_e + J_u, \\ J_e = \sum_{i=0}^{N-1} [e^2(k+i|k)Q + \Delta d^2(k+i|k)R], \\ J_u = \sum_{i=0}^{N-1} [v_f^2(k+i|k)T], \end{cases} \quad (16)$$

where Q, R, T are weighting coefficients used to weigh the relative distance error, velocity change, and control input, respectively. $\Delta d(k+i|k)$ represents the change in the disturbance term. $e(k+i|k)$ is the predicted relative distance error at $k+i$ based on the prediction at time k . $v_f(k+i|k)$ is the predicted control input increment at $k+i$. The cost function consists of two main components: The error term J_e and the control input term J_u , which aims to minimize the relative distance and velocity errors between the rail-mounted robot and the tracking vehicle and to minimize the changes in control inputs.

The input constraint is $v_{\min} \leq v_f(k) \leq v_{\max}$. In LTV-MPC collaborative tracking, the controller design involves solving the optimization problem defined by the cost function at each time step, as shown in equation (17):

$$\begin{cases} \min_{u_0, \dots, u_{N-1}} J = J_e + J_u, \\ \text{s.t. } v_{\min} \leq |v_f| \leq v_{\max}. \end{cases} \quad (17)$$

Starting from $t=0$, the LTV-MPC controller solves the optimization problem at each time step to obtain a series of future control inputs. Then, only the control input for the current time step k is implemented, and the process iteratively updates the control strategy.

3.2 Adaptive Control for Guardrail Obstacle-Crossing

The rail-mounted robot switches from tracking the guiding vehicle to obstacle-crossing mode upon detecting a guardrail post signal, which serves as the controller-switching trigger. The operation duration of the LTV-MPC controller on each guardrail segment is shorter than the interval between controller switches for

the rail-mounted inspection robot.

When the rail-mounted inspection robot detects the post signal, it switches to obstacle-crossing mode. At this point, a model reference adaptive control (MRAC) method is adopted to perform adaptive control in response to environmental disturbances caused by abrupt changes in acceleration. The MRAC controller comprises a reference model and an adjustable system, whose outputs are updated at discrete time steps. The output update equations for the reference model and adjustable system in discrete time are given in equation (18):

$$\begin{cases} y_r(k+1) = A_{\text{model}} \cdot y_r(k) + B_{\text{model}} \cdot r(k), \\ y_a(k+1) = A_x \cdot y_a(k) + A_r \cdot m(k), \end{cases} \quad (18)$$

where $y_r(k+1)$ and $y_r(k)$ denote the outputs of the reference model at time step $k+1$ and k , respectively. A_{model} and B_{model} are parameters of the reference model. $r(k)$ is the external input at the discrete time step. A_x and A_r are parameters of the adjustable system, and $m(k)$ represents the control velocity.

The controller aims to reduce the error $e(k)$ through adaptive adjustment, and the control objective is to minimize the error to zero. To achieve this, an adaptive law based on the gradient method^[19] is designed, introducing a loss function J_m . Since the system output $y_a(k)$ is driven by $m(k)$, the control velocity change rate $\dot{m}$ is derived using the gradient descent method. The adaptive law update equation for discrete time is given in equation (19), (20):

$$\begin{cases} J_m = \frac{1}{2} e_m^2, \\ \dot{m} = -\gamma e \frac{\partial e}{\partial m}, \end{cases} \quad (19)$$

$$\begin{cases} e(k) = y_r(k) - y_a(k), \\ m(k+1) = m(k) + \Gamma_m \cdot e(k) \cdot \frac{\partial e}{\partial m}. \end{cases} \quad (20)$$

During adaptive obstacle-crossing, the adjustable system dynamically adjusts the real-time velocity based on the reference model's first-order inertia acceleration process, ensuring the required velocity for obstacle-crossing. In the early acceleration phase, the system maintains higher acceleration and lower adaptive rate than the reference model to counteract speed loss from impacts. When a sudden acceleration change signals the obstacle-crossing state, the system maintains constant velocity briefly to reduce vibrations, then adjusts the adaptive rate to follow the acceleration model. After completing the acceleration, the robot compensates the

velocity to align with the ideal travel distance in collaborative tracking control.

4 Simulation Analysis of Control Methods and Physical Model Setup

Based on the reliable structure of the rail-mounted inspection robot, it is necessary to validate the effectiveness of the corresponding control strategies for the control models. The validation includes collaborative tracking control methods and adaptive obstacle-crossing control methods. For the collaborative tracking control method, this study simulates a highway scenario where dual-side guardrail inspection operations are conducted. In this scenario, the leader—an autonomous inspection vehicle—operates on the emergency lane side of the highway guardrail, while the follower—a rail-mounted robot—operates on the median barrier side. For the adaptive obstacle-crossing control method, simulation verification is performed using a first-order model based on the reference obstacle-crossing speed.

4.1 Collaborative Tracking Simulation

According to the relevant specifications in the Highway Engineering Technical Standards, the standard lane width for a design speed of 80 km/h is 3.75 m. In this study, a straight six-lane highway (three lanes per direction) is selected as the simulation example. The central median barrier and emergency lane are separated by three lanes. Considering the portions occupied by the shoulder and the emergency lane, the minimum relative distance for dual-side guardrail inspection operations is set to 15 m. Therefore, the initial tracking distance between the rail-mounted robot and the inspection vehicle is set to 15 m, meaning the rail-mounted robot and the inspection vehicle are placed at a relative distance of 15 m on the same visual horizontal plane on opposite guardrails.

Given that the tracking model follows a triangular configuration, the target tracking distance is set to 30 m to ensure an appropriate distance, allow for curve errors, and maintain a safe line of sight. With the initial distance being 15 m, and according to the triangular collaborative tracking model, the initial control distance is 0 m, and the target control distance is set to 25 m, resulting in a target adjustment distance of 20 m.

The prediction horizon N_p is set to 300 steps, and the control horizon N_c is also set to 300 steps, with a

time step of 200 ms. This configuration ensures a prediction and control 60 s, and the equivalence of the prediction and control horizons ensures real-time responsiveness in model prediction. The reference speed for the robot is set to 0.7 m/s, with a speed range limit of ± 1 m/s. The weighting coefficients for the error term and control input are set to 1 and 1 000, respectively, while the weighting coefficient for the disturbance is set to 10.

The experimental results are shown in the following figures. Figure 10(a) presents the closed-loop response curve of the control distance (i.e., the driving distance difference between guardrails on both sides). It can be observed that the tracking error for the control distance is minimal, with an overshoot of 0.415% and a steady-state error of 0.344 m. Figure 10(b) illustrates the closed-loop curve of the control input (i.e., the speed of the inspection robot), showing that the robot's speed increases smoothly to a stable value, with a standard deviation of 0.053 3 for the control input. Figure 10(c) shows the reference motion speed of the leader—the inspection vehicle—characterized by periodic motion and pauses. Considering the minimum relative distance for dual-side guardrail operations, the closed-loop response curve for the relative distance is shown in Fig. 10(d), where the rate of change of the curve initially rises and then falls.

Before using the LTV-MPC method for the collaborative tracking control of the inspection robot, this study compensates for the nonlinear components of the original system by introducing nonlinear compensation in the prediction value calculation. This approach also addresses the limitation where small disturbance values have a negligible effect on the cost function computation.

Figure 11 demonstrates the effect of nonlinear compensation on the control distance and control input of the inspection robot. With compensation, the final value of the control distance converges to an accurate value, and the cumulative control input is reduced, thereby lowering energy consumption to some extent.

Traditional proportional-integral-derivative (PID) control primarily focuses on immediate error correction and does not directly consider the future system states or handle system constraints. This paper uses the same reference motion speed for the inspection vehicle to simulate PID control, as shown in Fig. 12. In contrast, PID control exhibits poor disturbance resistance in control input variations, with a standard deviation of 0.083 for the control input and noticeable oscillations in the later

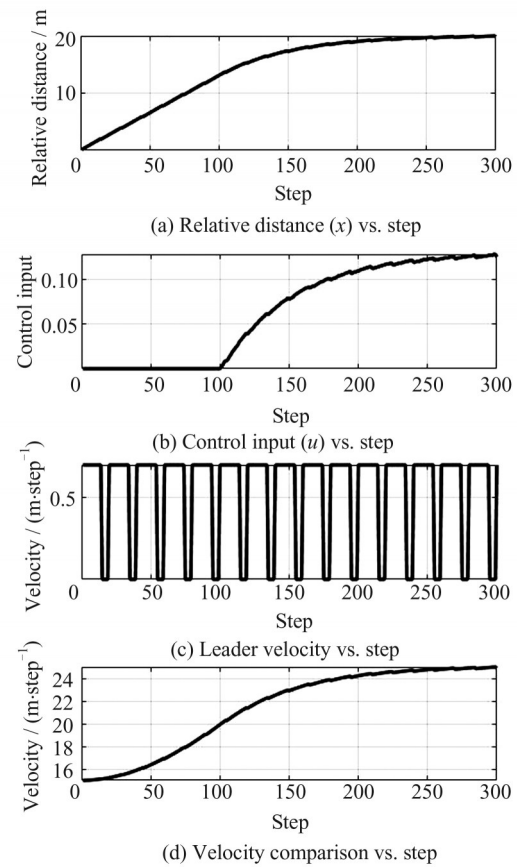


Fig. 10 Collaborative tracking response curve

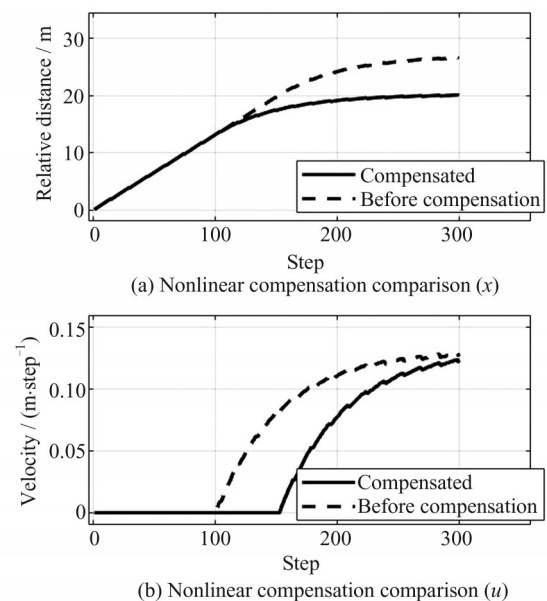


Fig. 11 Nonlinear compensation effect

stages. LTV-MPC control, however, produces a smoother control input curve, significantly reducing frequent speed fluctuations, and is effective in handling model uncertainties and external disturbances. In the collaborative tracking control of the rail-mounted inspec-

tion robot, the system has a relatively defined model and

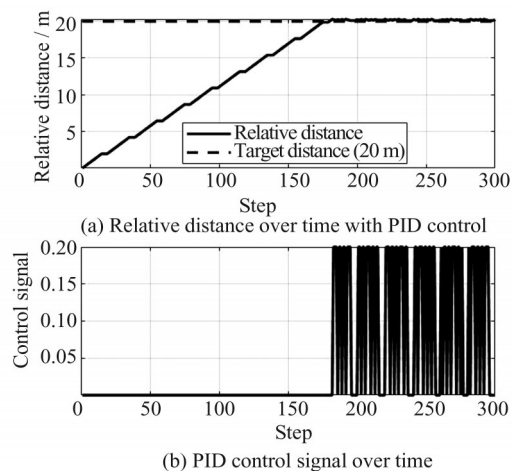


Fig. 12 PID control response curve

needs to address certain uncertainties and disturbances, where LTV-MPC control demonstrates clear advantages.

4.2 Adaptive Obstacle-Crossing Simulation

Based on the analysis of the obstacle-crossing problem, the rail-mounted inspection robot requires a suitable acceleration curve for obstacle-crossing. Since the guardrail surface may be relatively smooth, a smooth start for the robot is necessary to avoid sudden acceleration. Additionally, before the front wheels approach the guardrail joint, the robot should reach an adequate obstacle-crossing speed, which is simulated with a value of 300 mm/s. After crossing the obstacle, the robot should maintain a steady pace to avoid impacts. The control cycle is set to 1 000 steps. Once the obstacle-crossing speed is reached and acceleration mutation is detected, the robot maintains a constant speed for 50 steps to mitigate shock and gradually accelerates to a unified end speed of 500 mm/s, preventing failure of the rear wheels to cross the obstacle. After the control is finished, the robot brakes for inspection and prepares to switch to collaborative tracking control. The conversion relationship between the set speed and actual speed is determined by practical operational requirements. In this paper, the obstacle-crossing is considered successful if the end speed reaches 60% of the set speed. If this speed is not reached, the robot will brake and revert to obstacle-crossing.

Figure 13 shows the speed curve for obstacle-crossing control, reflecting the output of the adjustable system compared to the ideal model output, which displays the acceleration curves of the robot at different speeds before the obstacle-crossing. After reaching the

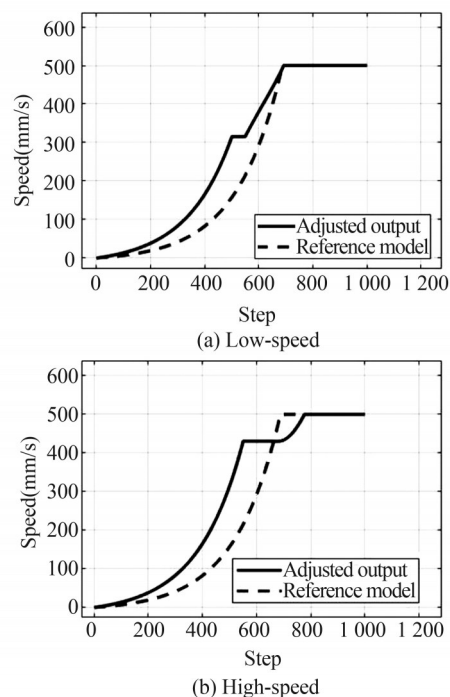


Fig. 13 Obstacle-crossing control speed curve in different scenarios

allowable obstacle-crossing speed, adaptive control is used to modify the adaptive rate to manage the control at different speeds before the obstacle-crossing, compensating for total displacement. By following the reference model through adaptive control, the robot returns to the end speed after the obstacle-crossing, ensuring that during the obstacle-crossing control process, distance errors only occur within a limited time step after detecting acceleration mutation, thereby reducing interference for collaborative tracking control.

4.3 Physical Model Setup

The inspection and control of the inspection robot system are inseparable, with system control needing to integrate with specific inspection operation plans. Based on the relevant structural analysis, this paper proposes the application of model predictive control and adaptive control methods for the motion control of the rail-mounted guardrail inspection robot. The development of the rail-mounted guardrail inspection system guides the collaborative tracking and obstacle-crossing of the rail-mounted inspection robot.

Using the rail-mounted guardrail parameter inspection robot prototype as the experimental platform, field remote control tests and collaborative communication hardware-in-the-loop experiments were conducted at the Chang'an University guardrail testing site, validating the

feasibility of the mechanical analysis and related control methods for the rail-mounted inspection robot. Figure 14 shows the physical setup of the rail-mounted guardrail parameter inspection robot system and the accompanying leader-follower vehicle.

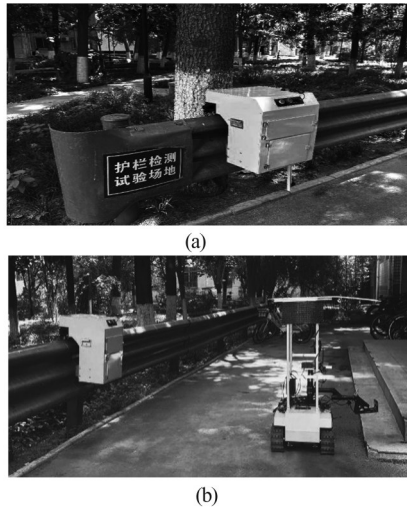


Fig. 14 Physical setup of inspection robot (a) and the accompanying vehicle (b)

5 Conclusion

This study proposes an MPC-based and MRAC-based motion control method for a rail-mounted guardrail inspection robot. Through simulation, we validated the effectiveness of the collaborative tracking and adaptive obstacle-crossing control strategies. Experimental results demonstrate that the proposed LTV-MPC strategy achieves effective control input smoothing, exhibiting superior velocity regulation performance with only 0.415% overshoot and a steady-state error of 0.344 m. Comparative analysis indicates a 35% reduction in velocity oscillations compared with conventional methods, a result attributed to the optimized sum of squared control inputs, accompanied by enhanced system robustness and 20.4% improvement in energy efficiency. The developed motion platform establishes a reliable foundation for detection modules, while rigorous verification of detection accuracy through sensor calibration and system integration is planned for subsequent research phases. The adaptive obstacle-crossing control adjusts speed in real-time to cope with acceleration variations, ensuring a smooth post-obstacle transition and preventing rear-wheel slipping or failure. The system prototype and experimental validation confirm the potential applicability

of the proposed control method in practical scenarios.

The contribution of this study lies in the proposed dual control strategy combining MPC and MRAC, which addresses environmental dynamics and disturbances, improving system accuracy and robustness. This approach is particularly suitable for complex environments, such as highways. Future work could further optimize the algorithm to enhance real-time performance and handling of more complex situations, while integrating intelligent and autonomous decision-making and collaborative operation technologies to improve the intelligence and adaptability.

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挂轨式波形梁护栏检测机器人的控制方法研究

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摘要: 为解决传统人工巡检方式在高速公路护栏检测中的局限性, 本文设计了一种挂轨式检测机器人越障与协同跟踪控制方法。通过静力学与动力学分析验证了机器人结构可行性及行驶可靠性。基于领航者-跟随者模型建立三角协同跟踪模型, 并设计线性时变模型预测控制器 (LTV-MPC), 实现平稳精准的协同控制; 针对实际越障需求, 提出加速参考模型并以梯度法推导得到自适应律, 构建模型参考自适应控制器 (MRAC), 有效抑制振动并保障协同控制。仿真结果表明, MPC控制器可实现0.415%的超调量与0.344m的稳态精度, 同时速度波动强度降低35%; MRAC保证了平稳的越障速度和自适应策略切换, 验证了所设计挂轨式检测机器人在复杂工况下的可靠性与实用性。

关键词: 挂轨式检测机器人; 力学分析; 模型预测控制; 模型参考自适应控制

