

FIXED-TIME TRAJECTORY TRACKING CONTROL FOR WHEELED MOBILE ROBOTS WITH PRESCRIBED PERFORMANCE

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ABSTRACT. *This work proposes a fixed-time convergent event-triggered control scheme for wheeled mobile robots with prescribed performance trajectory tracking. First, a system model of the wheeled mobile robot is established, and then the tracking error is ensured to converge to the specified region via barrier Lyapunov functions. Secondly, fuzzy logic systems (FLSs) are employed to approximate the unknown nonlinear dynamics inherent in the wheeled mobile robot (WMR) system. Subsequently, a fixed-time trajectory tracking controller is designed with a dynamic event-triggered mechanism to ensure system stability and achieve high-precision control of the wheeled mobile robot. Unlike conventional static triggering approaches, this work develops a dynamic event-triggered mechanism (DETM) by introducing an innovative auxiliary function, significantly reducing controller-actuator communication demands. Finally, through the designed Lyapunov function, it is proven that the proposed scheme guarantees fixed-time stability of the system, and the simulation results verify the effectiveness of the trajectory tracking control scheme.*

Keywords: Fixed-time control, Dynamic event-triggered mechanism, Trajectory tracking, Wheeled mobile robots, Prescribed performance, Fuzzy logic systems

1. Introduction. In recent years, with the development of wheeled mobile robots, their motion control has attracted widespread attention [1-3]. Owing to their exceptional mobility and uncomplicated control schemes, wheeled mobile robots have proven particularly effective for inspection tasks, security operations, and autonomous navigation applications [4-6]. Several advanced control methodologies have been developed for wheeled mobile robot systems, including sliding mode control [7] and robust control techniques [8]. For wheeled robot systems with unknown nonlinear dynamics, these control methods cannot solve this problem. To address this objective, multiple adaptive intelligent control strategies have been developed by leveraging the function approximation capabilities of neural networks (NNs) and fuzzy logic systems [9-11]. In [12], a novel adaptive fuzzy control strategy with prescribed performance guarantees was developed to address trajectory tracking problems for wheeled mobile robots subject to model uncertainties. In addition, in [13], a fuzzy adaptive method is proposed for decoupling visual servo control of wheeled mobile robots. Chen et al. [14] proposed an adaptive neural network control method for underactuated surface vessels. In [15], an adaptive neural control method was proposed for underactuated surface vessels with predetermined performance guarantees.

Although the aforementioned methods have achieved remarkable performance, fixed-time prescribed-performance tracking control still requires careful consideration. Fixed-time control, a robust method for managing system uncertainties and external disturbances, has been extensively studied in wheeled mobile robot trajectory tracking [16,17]. Therefore, many scholars have conducted research on fixed-time control. Wang and Lai [18] investigated the problem of fixed-time control for uncertain nonlinear systems and proposed a novel adaptive control strategy for the trajectory tracking control problem. To address the control problem of the leader-follower formation tracking issue of wheeled mobile robots with prescribed performance, Chang et al. [19] proposed a novel fixed-time prescribed performance strategy. To address the control problem of wheeled mobile robots external disturbances, Chang et al. [20] developed a fixed-time active disturbance rejection control strategy.

Moreover, the control strategies proposed in the aforementioned studies operate under time-triggered sampling mechanisms, resulting in excessive data transmissions and inefficient utilization of communication resources. To address this issue, event-triggered control strategies have been proposed, which effectively alleviate communication load by executing control updates only upon occurrence of specified events [21]. A fixed-time static event-triggered control strategy was proposed in [22] to simultaneously improve control performance and conserve communication resources, with its practical implementations subsequently demonstrated in [23-27]. To achieve further reductions in triggering frequency and enhance resource efficiency, a dynamic event-triggered control strategy with adaptive threshold adjustment was investigated in [28,29]. Subsequently, the adaptive finite-time tracking control problem was examined within a dynamic event-triggered framework in [30].

Despite the aforementioned advancements, several challenges remain unaddressed in the realm of fixed-time trajectory tracking for WMRs. Firstly, many existing fixed-time control schemes operate under time-triggered mechanisms, which inherently lead to inefficient communication resource utilization due to continuous data transmission. Although static event-triggered mechanisms have been introduced to mitigate this issue [22-27], they often result in conservative triggering thresholds and higher triggering frequencies. Secondly, while prescribed performance control has been explored in adaptive fuzzy and neural control [12,13], its integration within a fixed-time framework under a dynamic event-triggered mechanism has received limited attention. The DETM offers a more flexible and resource-efficient paradigm by incorporating an adaptive internal dynamic variable, yet its synergy with fixed-time prescribed performance control for WMRs remains largely unexplored. Therefore, this paper aims to bridge these gaps by proposing a novel control scheme that simultaneously ensures fixed-time convergence, prescribed transient and steady-state performance, and significantly reduced communication burden via a novel DETM.

To address these challenges in trajectory tracking, the main technical contributions of this study are outlined below.

- 1) A dynamic event-triggered mechanism (DETM) is adopted, which, in contrast to conventional static approaches, features an adaptive threshold capable of dynamically adjusting to system states, thereby significantly reducing the communication frequency between the controller and actuator.

- 2) A fixed-time prescribed performance control scheme is synthesized for WMRs with unknown dynamics. By integrating barrier Lyapunov functions with fuzzy logic systems, the tracking errors are guaranteed to converge to a predefined residual set within a fixed time, while respecting prescribed transient performance bounds.

3) The proposed control framework systematically combines fixed-time control, prescribed performance, and DETM, addressing the limitations of prior works that often treat these aspects in isolation. The stability of the closed-loop system is rigorously proven to be practical fixed-time stable via Lyapunov analysis.

The remainder of this article is organized as follows. Section 2 analyzes the model of wheeled mobile robots, providing the corresponding state-space equations; it then presents several essential lemmas for the subsequent theoretical development and introduces the dynamic event-triggered mechanism. The design of fixed-time control laws and adaptive parameters is proposed, and corresponding Lyapunov functions are designed to prove the convergence in Section 3. Simulation results and analysis are presented in Section 4. Finally, this article is summarized in Section 5.

2. Problem Formulation and Preliminaries.

2.1. System description. Consider a type of underactuated wheeled mobile robots in Figure 1, whose state-space model is expressed by

$$\begin{cases} \dot{q} = J(\psi)\bar{\nu}, \\ \bar{M}\dot{\bar{\nu}} = -N(\dot{\psi})\bar{\nu} - \bar{E}\bar{\nu} + u, \end{cases} \quad (1)$$

where $q = (\zeta, \mu, \psi)^T$ includes the robot's coordinates (ζ, μ) ; ψ is yaw angle; $\nu = (v, \omega)^T$, v is the linear velocity, and ω is the angular velocity; $u = (u_1, u_2)^T$ is the control torque provided by motors, $J(\psi)$, $\bar{M}$, $\bar{E}$ and $N(\dot{\psi})$ are the kinematics masses/inertia matrices, and the Coriolis and damping matrices are defined as

$$J(\psi) = \frac{\gamma_1}{2} \begin{pmatrix} \cos \psi & \cos \psi \\ \sin \psi & \sin \psi \\ b^{-1} & -b^{-1} \end{pmatrix}, \quad \bar{M} = \begin{bmatrix} m_c & m_d \\ m_d & m_c \end{bmatrix},$$

$$N(\dot{\psi}) = \begin{bmatrix} 0 & \epsilon \dot{\psi} \\ -\epsilon \dot{\psi} & 0 \end{bmatrix}, \quad \bar{E} = \begin{bmatrix} d_1 & 0 \\ 0 & d_2 \end{bmatrix}.$$

In the aforementioned matrices, γ_1 denotes the wheel radius, b represents half of the robot's width, while d_1 and d_2 correspond to the damping coefficients. The remaining parameters are

$$\begin{aligned} m_c &= 0.25b^{-2}\gamma_1^2(mb^2 + H) + H_{w_1}, \quad m = m_b + 2m_w, \\ m_d &= 0.25b^{-2}\gamma_1^2(mb^2 - H), \quad \epsilon = 0.5ob^{-1}\gamma_1^2m_b, \\ H &= m_b o^2 + 2m_w \gamma_1^2 + H_b + 2H_{w_2}. \end{aligned}$$

The symbol m_b refers to the main chassis weight, while m_w denotes the mass of each wheel. The parameter o describes the displacement between the robot's geometric center and the wheel axle. Additionally, d measures the length from the rear wheel to the mass centroid, and b represents the rotational inertia along the vertical axis. The parameter w_1 denotes the rotational inertia of the wheel axle, while w_2 corresponds to the inertia relative to the wheel's diameter. P_r indicates the robot's mass centroid, and P_m represents the geometric midpoint between the driven wheels. $\bar{M}$ stands for a positive-definite inertia matrix, where the condition $m_c > m_d$ holds. This study treats the variables ϵ , d_1 , and d_2 as fixed but unspecified quantities.

Figure 1 illustrates a wheeled mobile robotic system with underactuation characteristics.

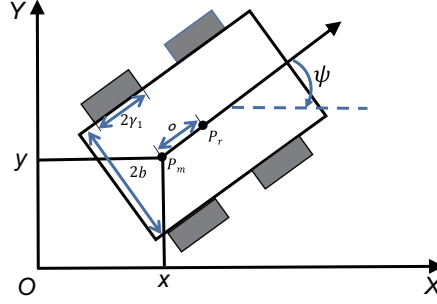


FIGURE 1. Architecture of a wheeled mobile robot

Let $x_1 = \zeta$, $x_2 = \mu$, $x_3 = \psi$, $x_4 = v$, $x_5 = \omega$, Equation (1) can be rewritten as

$$\begin{cases} \dot{x}_1 = v \cos \psi, \\ \dot{x}_2 = v \sin \psi, \\ \dot{x}_3 = \omega, \\ \dot{x}_4 = h_1(x) + m_1 u_1, \\ \dot{x}_5 = h_2(x) + m_2 u_2, \\ y_1 = \zeta, \\ y_2 = \mu, \\ y_3 = \psi. \end{cases} \quad (2)$$

In Equation (2), $x = [x_1 \ x_2 \ x_3 \ x_4 \ x_5]^T$, $m_1 = \frac{1}{m_c^2 - m_d^2}$, $m_2 = \frac{1}{m_c^2 - m_d^2}$, $h_1(x) = \frac{m_d(d_2\omega - \epsilon v\psi) - m_c(d_1v + \epsilon\omega\psi)}{m_c^2 - m_d^2}$, and $h_2(x) = \frac{m_d(d_1v + \epsilon\omega\psi) - m_c(d_2\omega - \epsilon v\psi)}{m_c^2 - m_d^2}$.

2.2. Necessary lemmas and dynamic event-triggered mechanism.

Lemma 2.1. [31] Assume that $f(\chi)$ is a continuous function on a compact set Ω . Then, for an arbitrary constant $\varepsilon > 0$, there exists an FLS $\hat{f}(\chi|\theta^*) = \theta^{*T}\varphi(\chi)$ such that

$$f(\chi) = \theta^{*T}\varphi(\chi) + \varepsilon, \quad (3)$$

where ε is the minimum approximation error.

Lemma 2.2. [33, 34] A nonlinear system is given as $\dot{\chi} = g(\chi, t)$, $g(0) = 0$, $\chi \in \mathbb{R}^n$, if a continuous differentiable function $V(\chi, t)$ satisfies the inequation $\dot{V}(\chi) \leq -\mu_1 V^{l_1}(\chi) - \mu_2 V^{l_2}(\chi) + K$, where scalars $\mu_1 > 0$, $\mu_2 > 0$, $l_1 \in (0, 1)$, $l_2 > 1$, $K > 0$, then the system is practical fixed-time stable, and the system states will converge to the residual set $\Omega_\chi = \{\chi | V(\chi) \leq \min\{([K/(1-\beta)\mu_1])^{1/l_1}, ([K/(1-\beta)\mu_2])^{1/l_2}\}\}$, $\beta \in (0, 1)$, when $T \geq T_{\max}$, where $T_{\max}$ is the settling time and can be given as

$$T \leq T_{\max} := \frac{1}{\mu_1\beta(1-l_1)} + \frac{1}{\mu_2\beta(l_2-1)}. \quad (4)$$

Lemma 2.3. [35] As $k_b > 0$ is a constant, the inequality holds for $|z_1| < k_b$

$$\log \frac{k_b^2}{k_b^2 - z_1^2} < \frac{z_1^2}{k_b^2 - z_1^2}. \quad (5)$$

2.3. Dynamic event-triggered mechanism. To mitigate the controller update frequency, a dynamic event-triggered mechanism is proposed.

$$u_i(t) = \tau_i(t_r) \quad (i = 1, 2) \quad \forall t \in [t_r, t_{r+1}), \quad (6)$$

$$t_{r+1} = \inf\{t > t_r | \gamma|u(t)| - |\chi_e(t)| + m_1(t) \leq 0\}, \quad (7)$$

$$\dot{m}_1 = -\pi_1 m_1 + \pi_2 [2 + \tanh(\gamma|u(t)| - |\chi_e(t)|)]. \quad (8)$$

The controller's activation moments are represented by t_r ($r \in N$), where the first trigger occurs at $t_0 = 0$. Initial conditions satisfy $m_1(0) = \underline{m}_1 > 0$, $0 < \gamma < 1$. Parameters π_1, π_2 are positive constants satisfying $\pi_2/\pi_1 > m_1(0)$, and we define $\bar{m}_1 = 3\pi_2/\pi_1$. $\chi_e(t) = u_e(t) - u(t)$ represents the sampling error, where $u_e(t)$ denotes the continuous control input without triggering, $u(t)$ represents the sampled input. When condition (7) is satisfied, the current time instant is recorded as t_{r+1} , and the revised control input $u(t_{r+1})$ is immediately sent to the actuator. Throughout the period between consecutive triggers $t \in [t_r, t_{r+1})$, the actuator receives an unchanging control input $u(t) = u(t_r)$. For the dynamic event-triggered mechanism, the inequality $\gamma|u(t)| - |\chi_e(t)| + m_1(t) \geq 0$ holds for all $\forall t > 0$. Substituting this inequality into Equation (8) yields

$$\dot{m}_1 \geq -\pi_1 m_1 + \pi_2[2 + \tanh(-m_1)] \geq -\pi_1 m_1 + \pi_2. \quad (9)$$

Recalling the comparison lemma, it obtains that $m_1(t) \geq e^{-\pi_1 t} \underline{m}_1 + (\pi_2/\pi_1)(1 - e^{-\pi_1 t}) \geq \underline{m}_1$ for $\forall t > 0$. In addition, it follows from Equation (8) that $\dot{m}_1 \leq -\pi_1 m_1 + 3\pi_2$, then we deduce that $m_1(t) \leq e^{-\pi_1 t} \underline{m}_1 + (3\pi_2/\pi_1)(1 - e^{-\pi_1 t}) \leq \bar{m}_1$, implying that $m_1(t)$ is a positive and bounded function.

Remark 2.1. A notable feature of the proposed dynamic event-triggered mechanism formulation (7) lies in its dynamic trigger threshold $m_1(t)$, which is adaptively regulated through update law (8) rather than remaining fixed. This design offers flexibility, as evidenced by the fact that setting parameters $\pi_1 = \pi_2 = 0$ in Equation (8) effectively reduces the dynamic event-triggered mechanism to its static counterpart.

$$t_{r+1} = \inf\{t > t_r | \gamma|u(t)| - |\chi_e(t)| + \underline{m}_1 \leq 0\}. \quad (10)$$

This approach shares similarities with the relative threshold strategy discussed in [36, 37], commonly referred to as the static event-triggered mechanism (SETM). In contrast to conventional SETM, the proposed DETM offers enhanced adaptability in control signal transmission.

3. Control Design and Convergence Analysis. Define the following coordinate changes as

$$\zeta_e = \zeta - \zeta_d, \quad (11)$$

$$\mu_e = \mu - \mu_d, \quad (12)$$

$$z_e = \sqrt{\zeta_e^2 + \mu_e^2}, \quad (13)$$

$$\psi_e = \psi - \psi_d, \quad (14)$$

$$z_3 = v - \partial_{11}, \quad (15)$$

$$z_4 = \omega - \partial_{12}, \quad (16)$$

where ∂_{11} and ∂_{12} are virtual control signals.

From Equations (11)-(14), we can obtain

$$\dot{z}_e = v \cos \psi_e + \omega \sin \psi_e - \dot{\zeta}_d \cos \psi_d - \dot{\mu}_d \sin \psi_d, \quad (17)$$

$$\dot{\psi}_e = \dot{\psi} - \dot{\psi}_d. \quad (18)$$

Construct the Lyapunov function candidate V_1 as

$$V_1 = \frac{1}{2} \log \frac{k_{b1}^2(t)}{k_{b1}^2(t) - z_e^2} + \frac{1}{2} \log \frac{k_{b2}^2(t)}{k_{b2}^2(t) - \psi_e^2}. \quad (19)$$

From Equations (15)-(18), the time derivative of V_1 is as follows:

$$\dot{V}_1 = \frac{z_e}{k_{b1}^2(t) - z_e^2} \dot{z}_e - \frac{z_e^2 \dot{k}_{b1}(t)}{k_{b1}(t)(k_{b1}^2(t) - z_e^2)} + \frac{\psi_e}{k_{b1}^2(t) - \psi_e^2} \dot{\psi}_e - \frac{\psi_e^2 \dot{k}_{b2}(t)}{k_{b2}(t)(k_{b2}^2(t) - \psi_e^2)}$$

$$\begin{aligned}
&= \frac{z_e}{k_{b1}^2(t) - z_e^2} \left(\dot{z}_e - \frac{z_e \dot{k}_{b1}(t)}{k_{b1}(t)} \right) + \frac{\psi_e}{k_{b2}^2(t) - \psi_e^2} \left(\dot{\psi}_e - \frac{\psi_e \dot{k}_{b2}(t)}{k_{b2}(t)} \right) \\
&= \frac{z_e}{k_{b1}^2(t) - z_e^2} \left((z_3 + \partial_{11}) \cos \psi_e + w \sin \psi_e - \dot{z}_d \cos \psi_d - \dot{\mu}_d \sin \psi_d - \frac{z_e \dot{k}_{b1}(t)}{k_{b1}(t)} \right) \\
&\quad + \frac{\psi_e}{k_{b2}^2(t) - \psi_e^2} \left(z_4 + \partial_{12} - \dot{\psi}_d - \frac{\psi_e \dot{k}_{b2}(t)}{k_{b2}(t)} \right). \tag{20}
\end{aligned}$$

To avoid singularity issue, define

$$\rho_1(z_e) = \begin{cases} z_e^{l_1} (k_{b1}^2(t) - z_e^2)^{(1-l_1)/2}, & \text{if } |z_e| \geq \ell_1 \\ o_1 z_e + \nu_1 z_e^3, & \text{otherwise} \end{cases} \tag{21}$$

$$\rho_2(\psi_e) = \begin{cases} \psi_e^{l_1} (k_{b2}^2(t) - \psi_e^2)^{(1-l_1)/2}, & \text{if } |\psi_e| \geq \ell_1 \\ o_2 \psi_e + \nu_2 \psi_e^3, & \text{otherwise} \end{cases} \tag{22}$$

where ℓ_1 and $l_1 \in (0, 1)$ are constants. Besides, $\nu_i = (1-l_1)(1/2\ell_1^{-1}) \ell_1^{l_1} [(k_{bi}^2(t) - \ell_1^2)^{-(1+l_1)/2} + \ell_1^{-2} (k_{bi}^2(t) - \ell_1^2)^{(1-l_1)/2}]$, $o_i = \ell_1^{l_1-1} (k_{bi}^2(t) - \ell_1^2)^{(1-l_1)/2} - \nu_i \ell_1^2$, ($i = 1, 2$), $\ell_1 < \bar{q}$. To be specific, $\rho_1(z_e)$ and $\rho_2(\psi_e)$ can guarantee that ideal optimal virtual control and its derivative are continuous by devising o_i and ν_i properly.

To guarantee the transient performance, including convergence rate and overshoot, the tracking error z_e and ψ_e is kept within a predefined region, referred to as the prescribed performance bound. Thus, a smooth decaying function $k_{bi}(t)$ ($i = 1, 2$) satisfying $\lim_{t \rightarrow \infty} k_{bi}(t) = k_d > 0$ is selected as the performance function, such that $k_{bi}(t) = (k_a - k_d)e^{-\beta t} + k_d$ with constants $k_a > 0$, $k_d > 0$, $\beta > 0$. Besides, $\bar{q} = k_d + k_a$ is the boundary of overshoot and the decreasing rate of $k_{bi}(t)$ presents a lower bound on the convergence rate for z_e and ψ_e .

Design the following virtual control signals ∂_{11} and ∂_{12} as

$$\begin{aligned}
\partial_{11} = (\cos \psi_e)^{-1} &\left(-k_{11}\rho_1(z_e) - \sigma_{11} \frac{z_e^{2l_2-1}}{(k_{b1}^2(t) - z_e^2)^{l_2-1}} - \omega \sin \psi_e + \dot{z}_d \cos \psi_d + \dot{\mu}_d \sin \psi_d \right. \\
&\quad \left. + \frac{z_e \dot{k}_{b1}(t)}{k_{b1}(t)} - k_{11}z_e \right), \tag{23}
\end{aligned}$$

$$\partial_{12} = -k_{12}\rho_1(\psi_e) - k_{12}\psi_e + \dot{\psi}_d + \psi_e \frac{\dot{k}_{b2}(t)}{k_{b2}(t)} - \sigma_{12} \frac{\psi_e^{2l_2-1}}{(k_{b2}^2(t) - \psi_e^2)^{l_2-1}} \tag{24}$$

$$\dot{z}_3 = \dot{v} - \dot{\partial}_{11} = h_1(x) + m_1 u_1 - \dot{\partial}_{11}, \tag{25}$$

$$\dot{z}_4 = \dot{\omega} - \dot{\partial}_{12} = h_2(x) + m_2 u_2 - \dot{\partial}_{12}. \tag{26}$$

Substituting Equations (23) and (24) into (20) yields

$$\begin{aligned}
\dot{V}_1 = &\frac{z_e z_3 \cos \psi_e}{k_{b1}^2(t) - z_e^2} - k_{11} \frac{z_e \rho_1(z_e)}{k_{b1}^2(t) - z_e^2} - k_{11} \frac{z_e^{2l_2}}{k_{b1}^2(t) - z_e^2} - \sigma_{11} \frac{z_e^{2l_2}}{(k_{b1}^2(t) - z_e^2)^{l_2}} + \frac{\psi_e z_4}{k_{b2}^2(t) - \psi_e^2} \\
&- k_{12} \frac{\psi_e \rho_1(\psi_e)}{k_{b2}^2(t) - \psi_e^2} - k_{12} \frac{\psi_e^2}{k_{b2}^2(t) - \psi_e^2} - \sigma_{12} \frac{\psi_e^{2l_2}}{(k_{b2}^2(t) - \psi_e^2)^{l_2}} \tag{27}
\end{aligned}$$

For the continuous but unidentified functions $h_j(x)$ ($j = 1, 2$), fuzzy logic systems $\hat{f}_j(x|\hat{\theta}) = \hat{\theta}_j^T \varphi_j(x)$ are employed to estimate $f_j(x) = h_j(x) - \dot{\alpha}_{1j}$, as established in Lemma 2.1, where the approximation satisfies the following condition

$$f_j(x) = \theta_j^{*T} \varphi_j(x) + \varepsilon_j(x), \quad j = 1, 2, \quad (28)$$

where θ_j^* denote the optimal parameter vectors and $\varepsilon_j(x)$ represent the minimal approximation errors, $\varepsilon_j(x)$ satisfy $|\varepsilon_j(x)| \leq \varepsilon_j^*$, ε_j^* are positive constants, and $\varphi_j(x)$ are the fuzzy basis functions.

Select a Lyapunov function as

$$V_2 = \frac{1}{2}z_3^2 + \frac{1}{2}z_4^2 + \frac{1}{2\lambda_1}\tilde{\theta}_1^T\tilde{\theta}_1 + \frac{1}{2\lambda_2}\tilde{\theta}_2^T\tilde{\theta}_2, \quad (29)$$

where $\hat{\theta}_i$ is the estimate of θ_i^* ; $\tilde{\theta}_i = \theta_i^* - \hat{\theta}_i$ ($i = 1, 2$) is the parameter estimation error, and $\lambda_k > 0$ ($k = 1, 2$) are designed parameters.

From Equations (25), (26), and (28), the time derivative of V_2 is as follows:

$$\begin{aligned} \dot{V}_2 &= z_3 \left[h_1(x) + m_1 u_1 - \dot{\alpha}_{11} \right] + z_4 \left[h_2(x) + m_2 u_2 - \dot{\alpha}_{12} \right] - \frac{1}{\lambda_1} \tilde{\theta}_1^T \dot{\hat{\theta}}_1 - \frac{1}{\lambda_2} \tilde{\theta}_2^T \dot{\hat{\theta}}_2 \\ &= z_3 \left[m_1 u_1 + \theta_1^{*T} \varphi_1(x) + \varepsilon_1 \right] + z_4 \left[m_2 u_2 + \theta_2^{*T} \varphi_2(x) + \varepsilon_2 \right] - \frac{1}{\lambda_1} \tilde{\theta}_1^T \dot{\hat{\theta}}_1 - \frac{1}{\lambda_2} \tilde{\theta}_2^T \dot{\hat{\theta}}_2. \end{aligned} \quad (30)$$

Based on the dynamic event-triggered mechanism (7), it is obvious that the control input is updated to $\tau_i(t_{r+1})$ at the triggering time t_{r+1} , which indicates that the inequality $|\tau_i(t) - u(t)| \leq \gamma|u(t)| + m_1(t)$ holds during the interval $[t_r, t_{r+1})$. Consequently, there exist time-varying functions satisfying $|\nu_1(t)| \leq 1$ and $|\nu_2(t)| \leq 1$ such that $\tau_i(t) = (1 + \nu_1(t)\gamma)u(t) + \nu_2(t)m_1(t)$ for $\forall t \in [t_r, t_{r+1})$. And $0 < \gamma < 1$ are design scalars, $\bar{m}/(1 - \gamma) = \bar{m}_1$. An equivalent representation is given by

$$u_i(t) = \frac{\tau_i(t)}{1 + \nu_1(t)\gamma} - \frac{\nu_2(t)m_1(t)}{1 + \nu_1(t)\gamma} \quad (i = 1, 2) \quad (31)$$

by invoking $|\nu_1(t)| \leq 1$, $|\nu_2(t)| \leq 1$ and $\bar{m}/(1 - \gamma) = \bar{m}_1 \geq m_1(t)$, and we obtain

$$\begin{aligned} -\frac{\nu_2(t)m_1(t)}{1 + \nu_1(t)\gamma} &\leq \bar{m}, \\ \frac{1}{1 + \nu_1(t)\gamma} &\leq \frac{1}{1 + \gamma}. \end{aligned} \quad (32)$$

From Equation (31), we can obtain

$$u_i \leq \frac{\tau_i}{1 + \gamma} + \bar{m} \quad (i = 1, 2). \quad (33)$$

Design the following control signals as

$$\tau_1 = (1 + \gamma) \left[m_1^{-1} \left(-k_1 z_3^{\frac{l_1-1}{2}} - \hat{\theta}_1^T \varphi_1(x) - \frac{z_e}{k_{b1}^2(t) - z_e^2} \cos \psi_e - \sigma_1 z_3^{l_2-1} \right) \right], \quad (34)$$

$$\tau_2 = (1 + \gamma) \left[m_2^{-1} \left(-k_2 z_4^{\frac{l_1-1}{2}} - \hat{\theta}_2^T \varphi_2(x) - \frac{\psi_e}{k_{b2}^2(t) - \psi_e^2} - \sigma_2 z_4^{l_2-1} \right) \right]. \quad (35)$$

From Equations (34), and (35), the time derivative of V_2 is as follows:

$$\begin{aligned} \dot{V}_2 &= -k_1 z_3^{\frac{l_1+1}{2}} - z_3 \hat{\theta}_1^T \varphi_1(x) - \frac{z_e z_3}{k_{b1}^2(t) - z_e^2} \cos \psi_e - \sigma_1 z_3^{l_2} + z_3 \hat{\theta}_1^T \varphi_1(x) + z_3 \tilde{\theta}_1^T \varphi_1(x) \\ &\quad + z_3 \varepsilon_1 - k_2 z_4^{\frac{l_1+1}{2}} - z_4 \hat{\theta}_2^T \varphi_2(x) - \frac{\psi_e z_4}{k_{b2}^2(t) - \psi_e^2} - \sigma_2 z_4^{l_2} + z_4 \hat{\theta}_2^T \varphi_2(x) + z_4 \tilde{\theta}_2^T \varphi_2(x) \end{aligned}$$

$$+ z_4 \varepsilon_2 - \frac{1}{\lambda_1} \tilde{\theta}_1^T \dot{\hat{\theta}}_1 - \frac{1}{\lambda_2} \tilde{\theta}_2^T \dot{\hat{\theta}}_2. \quad (36)$$

The adaptive laws for the parameter estimates $\dot{\hat{\theta}}_1$ and $\dot{\hat{\theta}}_2$ are designed as

$$\dot{\hat{\theta}}_1 = \lambda_1 z_3 \varphi_1(x) - \sigma_3 \hat{\theta}_1, \quad (37)$$

$$\dot{\hat{\theta}}_2 = \lambda_2 z_4 \varphi_2(x) - \sigma_4 \hat{\theta}_2. \quad (38)$$

Substituting Equations (37) and (38) into Equation (36) yields

$$\begin{aligned} \dot{V}_2 \leq & -k_1 z_3^{\frac{l_1+1}{2}} - \frac{z_e \cdot z_3}{k_{b1}^2(t) - z_e^2} \cos \psi_e - \sigma_1 z_3^{l_2} + \frac{\sigma_3}{\lambda_1} \tilde{\theta}_1^T \hat{\theta}_1 + z_3 \varepsilon_1 \\ & - k_2 z_4^{\frac{l_1+1}{2}} - \frac{\psi_e \cdot z_4}{k_{b2}^2(t) - \psi_e^2} - \sigma_2 z_4^{l_2} + \frac{\sigma_4}{\lambda_2} \tilde{\theta}_2^T \hat{\theta}_2 + z_4 \varepsilon_2, \end{aligned} \quad (39)$$

where

$$\frac{\sigma_3}{\lambda_1} \tilde{\theta}_1^T \hat{\theta}_1 = -\frac{\sigma_3}{\lambda_1} \tilde{\theta}_1^T \tilde{\theta}_1 + \frac{\sigma_3}{\lambda_1} \tilde{\theta}_1^T \theta_1^* \leq -\frac{\sigma_3}{2\lambda_1} \tilde{\theta}_1^T \tilde{\theta}_1 + \frac{\sigma_3}{2\lambda_1} \theta_1^{*T} \theta_1^*, \quad (40)$$

$$\frac{\sigma_4}{\lambda_2} \tilde{\theta}_2^T \hat{\theta}_2 = -\frac{\sigma_4}{\lambda_2} \tilde{\theta}_2^T \tilde{\theta}_2 + \frac{\sigma_4}{\lambda_2} \tilde{\theta}_2^T \theta_2^* \leq -\frac{\sigma_4}{2\lambda_2} \tilde{\theta}_2^T \tilde{\theta}_2 + \frac{\sigma_4}{2\lambda_2} \theta_2^{*T} \theta_2^*. \quad (41)$$

Using Young's inequality yields

$$z_3 \varepsilon_1 \leq \frac{1}{2} z_3^2 + \frac{1}{2} \varepsilon_1^2, \quad (42)$$

$$z_4 \varepsilon_2 \leq \frac{1}{2} z_4^2 + \frac{1}{2} \varepsilon_2^2. \quad (43)$$

According to Equations (40)-(43), we have

$$\begin{aligned} \dot{V}_2 \leq & -k_1 z_3^{\frac{l_1+1}{2}} - \frac{z_e \cdot z_3}{k_{b1}^2(t) - z_e^2} \cos \psi_e - \sigma_1 z_3^{l_2} - \frac{\sigma_3}{2\lambda_1} \tilde{\theta}_1^T \tilde{\theta}_1 + \frac{\sigma_3}{2\lambda_1} \theta_1^{*T} \theta_1^* + \frac{1}{2} z_3^2 + \frac{1}{2} \varepsilon_1^2 \\ & - k_2 z_4^{\frac{l_1+1}{2}} - \frac{\psi_e \cdot z_4}{k_{b2}^2(t) - \psi_e^2} - \sigma_2 z_4^{l_2} - \frac{\sigma_4}{2\lambda_2} \tilde{\theta}_2^T \tilde{\theta}_2 + \frac{\sigma_4}{2\lambda_2} \theta_2^{*T} \theta_2^* + \frac{1}{2} z_4^2 + \frac{1}{2} \varepsilon_2^2, \end{aligned} \quad (44)$$

$$\begin{aligned} \dot{V} = \dot{V}_1 + \dot{V}_2 \\ = & -k_{11} \frac{z_e \rho_1(z_e)}{k_{b1}^2(t) - z_e^2} - k_{11} \frac{z_e^2}{k_{b1}^2(t) - z_e^2} - \sigma_{11} \frac{z_e^{2l_2}}{(k_{b1}^2(t) - z_e^2)^{l_2}} - k_{12} \frac{\psi_e \rho_1(\psi_e)}{k_{b2}^2(t) - \psi_e^2} \\ & - k_{12} \frac{\psi_e^2}{k_{b2}^2(t) - \psi_e^2} - \sigma_{12} \frac{\psi_e^{2l_2}}{(k_{b2}^2(t) - \psi_e^2)^{l_2}} - k_1 z_3^{\frac{l_1+1}{2}} - \sigma_1 z_3^{l_2} - \frac{\sigma_3}{2\lambda_1} \tilde{\theta}_1^T \tilde{\theta}_1 + \frac{\sigma_3}{2\lambda_1} \theta_1^{*T} \theta_1^* \\ & + \frac{1}{2} z_3^2 + \frac{1}{2} \varepsilon_1^2 - k_2 z_4^{\frac{l_1+1}{2}} - \sigma_2 z_4^{l_2} - \frac{\sigma_4}{2\lambda_2} \tilde{\theta}_2^T \tilde{\theta}_2 + \frac{\sigma_4}{2\lambda_2} \theta_2^{*T} \theta_2^* + \frac{1}{2} z_4^2 + \frac{1}{2} \varepsilon_2^2. \end{aligned} \quad (45)$$

In accordance with the definition of $\rho_1(z_e)$, the following two situations about the term $\Gamma_1 = -k_{11} [z_e \rho_1(z_e) / (k_{b1}^2(t) - z_e^2)]$ should be considered.

Case 1: If $|z_e| \geq \ell_1$, it follows that

$$\Gamma_1 = -k_{11} \frac{z_e^{l_1+1}}{(k_{b1}^2(t) - z_e^2)^{(l_1+1)/2}} = -k_{11} \left(\frac{z_e^2}{k_{b1}^2(t) - z_e^2} \right)^{(l_1+1)/2}. \quad (46)$$

Case 2: If $|z_e| < \ell_1$ and according to the inequality $|c|^\mu |d|^\rho \leq \mu/(\mu + \rho) \bar{\gamma} |c|^{\mu+\rho} + \rho/(\mu + \rho) \bar{\gamma}^{-\mu/\rho} |d|^{\mu+\rho}$ (μ, ρ , and $\bar{\gamma}$ are positive constants), we have

$$\begin{aligned}\Gamma_1 &= -k_{11} \frac{o_1 z_e^2 + \nu_1 z_e^4}{(k_{b1}^2(t) - z_e^2)} \\ &\leq -k_{11} \left(\frac{z_e^2}{(k_{b1}^2(t) - z_e^2)} \right)^{(l_1+1)/2} + k_{11} \left(1 - \frac{l_1+1}{2} \right) \bar{\gamma}_1 \\ &\quad + k_{11} \frac{z_e^2}{(k_{b1}^2(t) - z_e^2)} - k_{11} \frac{(o_1 + \nu_1) z_e^2}{(k_{b1}^2(t) - z_e^2)^{(l_1+1)/2}},\end{aligned}\quad (47)$$

where $\bar{\gamma}_1$ is a positive constant.

Considering that $o_1 + \nu_1 > 0$ and following the two cases of analysis above yields

$$\Gamma_1 \leq -k_{11} \left(\frac{z_e^2}{(k_{b1}^2(t) - z_e^2)} \right)^{(l_1+1)/2} + k_{11} \left(1 - \frac{l_1+1}{2} \right) \bar{\gamma}_1 + k_{11} \frac{z_e^2}{(k_{b1}^2(t) - z_e^2)}. \quad (48)$$

Similarly, considering $\Gamma_2 = -k_{12} [\psi_e \rho_2(\psi_e) / (k_{b2}^2(t) - \psi_e^2)]$, it can be deduced that

$$\Gamma_2 \leq -k_{12} \left(\frac{\psi_e^2}{(k_{b2}^2(t) - \psi_e^2)} \right)^{(l_1+1)/2} + k_{12} \left(1 - \frac{l_1+1}{2} \right) \bar{\gamma}_2 + k_{12} \frac{\psi_e^2}{(k_{b2}^2(t) - \psi_e^2)}, \quad (49)$$

where $\bar{\gamma}_2$ is a positive constant.

Similar to Equations (48) and (49), the following inequalities hold:

$$-\frac{\sigma_3}{2\lambda_1} \tilde{\theta}_1^T \tilde{\theta}_1 \leq -\frac{\sigma_3}{2} \left(\frac{1}{2\lambda_1} \tilde{\theta}_1^T \tilde{\theta}_1 \right)^{l_2} - \frac{\sigma_3}{2} \left(\frac{1}{2\lambda_1} \tilde{\theta}_1^T \tilde{\theta}_1 \right)^{\frac{1+l_1}{2}} + \frac{\sigma_3}{2} \bar{\eta}_1, \quad (50)$$

$$-\frac{\sigma_4}{2\lambda_2} \tilde{\theta}_2^T \tilde{\theta}_2 \leq -\frac{\sigma_4}{2} \left(\frac{1}{2\lambda_2} \tilde{\theta}_2^T \tilde{\theta}_2 \right)^{l_2} - \frac{\sigma_4}{2} \left(\frac{1}{2\lambda_2} \tilde{\theta}_2^T \tilde{\theta}_2 \right)^{\frac{1+l_1}{2}} + \frac{\sigma_4}{2} \bar{\eta}_1, \quad (51)$$

where $\bar{\eta}_1 = (1 - \bar{l}_1) \bar{l}_1^{\bar{l}_1/(1-\bar{l}_1)} + (\bar{\vartheta}_1^2/2\lambda_1)^{l_2}$, $\bar{l}_1 = ([1 + l_1]/2)$, $\eta_1 = (1 - \bar{l}_1) \bar{l}_1^{\bar{l}_1/(1-\bar{l}_1)} + (\vartheta_1^2/2)^{l_2}$. Then, invoking Young's inequality yields

$$\frac{1}{2} z_i^2 \leq \frac{l_1 - 3}{1 + l_1} \left(\frac{1}{2} \right)^{\frac{1+l_1}{l_1-3}} + \frac{4}{1 + l_1} z_i^{\frac{1+l_1}{2}} \quad (i = 3, 4). \quad (52)$$

From Lemma 2.3 and Equations (48)-(52), we have

$$\begin{aligned}\dot{V} &\leq -2^{\frac{l_1+1}{2}} k_{11} \left(\frac{1}{2} \log \frac{z_e^2}{k_{b1}^2(t) - z_e^2} \right)^{\frac{l_1+1}{2}} + k_{11} \left(1 - \frac{l_1+1}{2} \right) \bar{\gamma}_1 - k_{11} 2^{l_2} \left(\frac{1}{2} \log \frac{z_e^2}{(k_{b1}^2(t) - z_e^2)} \right)^{l_2} \\ &\quad - 2^{\frac{l_1+1}{2}} k_{12} \left(\frac{1}{2} \log \frac{\psi_e^2}{k_{b2}^2(t) - \psi_e^2} \right)^{\frac{l_1+1}{2}} + k_{12} \left(1 - \frac{l_1+1}{2} \right) \bar{\gamma}_2 - k_{12} 2^{l_2} \left(\frac{1}{2} \log \frac{\psi_e^2}{(k_{b2}^2(t) - \psi_e^2)} \right)^{l_2} \\ &\quad - k_1 z_3^{\frac{l_1+1}{2}} - \sigma_1 z_3^{l_2} - \frac{\sigma_3}{2} \left(\frac{1}{2\lambda_1} \tilde{\theta}_1^T \tilde{\theta}_1 \right)^{l_2} - \frac{\sigma_3}{2} \left(\frac{1}{2\lambda_1} \tilde{\theta}_1^T \tilde{\theta}_1 \right)^{\frac{1+l_1}{2}} + \frac{\sigma_3}{2} \bar{\eta}_1 + \frac{\sigma_3}{2\lambda_1} \theta_1^{*T} \theta_1^* \\ &\quad + \frac{l_1 - 3}{1 + l_1} \left(\frac{1}{2} \right)^{\frac{1+l_1}{l_1-3}} + \frac{4}{1 + l_1} z_3^{\frac{1+l_1}{2}} + \frac{1}{2} \varepsilon_1^2 - k_2 z_4^{\frac{l_1+1}{2}} - \sigma_2 z_4^{l_2} - \frac{\sigma_4}{2} \left(\frac{1}{2\lambda_2} \tilde{\theta}_2^T \tilde{\theta}_2 \right)^{l_2} \\ &\quad - \frac{\sigma_4}{2} \left(\frac{1}{2\lambda_2} \tilde{\theta}_2^T \tilde{\theta}_2 \right)^{\frac{1+l_1}{2}} + \frac{\sigma_4}{2} \bar{\eta}_1 + \frac{\sigma_4}{2\lambda_2} \theta_2^{*T} \theta_2^* + \frac{l_1 - 3}{1 + l_1} \left(\frac{1}{2} \right)^{\frac{1+l_1}{l_1-3}} + \frac{4}{1 + l_1} z_4^{\frac{1+l_1}{2}} + \frac{1}{2} \varepsilon_2^2 \\ &\leq -c_1 V^{\bar{l}_1} - c_2 V^{l_2} + \varrho,\end{aligned}\quad (53)$$

where $c_1 = \min\left\{2^{\frac{l_1+1}{2}}k_{11}, 2^{\frac{l_1+1}{2}}k_{12}, k_1 - \frac{4}{1+l_1}, \frac{\sigma_3}{2}, k_2 - \frac{4}{1+l_1}, \frac{\sigma_4}{2}\right\}$, $c_2 = \min\left\{-k_{11}2^{l_2}, -k_{12}2^{l_2}, \sigma_1, \frac{\sigma_3}{2}, \sigma_2, \frac{\sigma_4}{2}\right\}$, $\varrho = k_{11}\left(1 - \frac{l_1+1}{2}\right)\bar{\gamma}_1 + k_{12}\left(1 - \frac{l_1+1}{2}\right)\bar{\gamma}_2 + \frac{\sigma_3}{2}\bar{\eta}_1 + \frac{\sigma_3}{2\lambda_1}\theta_1^{*T}\theta_1^* + \frac{l_1-3}{1+l_1}(2)^{\frac{4}{3-l_1}} + \frac{4}{1+l_1}z_3^{\frac{1+l_1}{2}} + \frac{4}{1+l_1}z_4^{\frac{1+l_1}{2}} + \frac{\sigma_4}{2}\bar{\eta}_1 + \frac{\sigma_4}{2\lambda_2}\theta_2^{*T}\theta_2^* + \frac{1}{2}\varepsilon_1^2 + \frac{1}{2}\varepsilon_2^2$.

The system achieves practical fixed-time stability and the convergence time T satisfies $T \leq T_{\max} := \frac{1}{c_1\beta(1-l_1)} + \frac{1}{c_2\beta(l_2-1)}$, where $0 < \beta < 1$.

4. Simulations. In this section, numerical simulations are carried out in Matlab for the designed system. The physical parameters of the wheeled mobile robot system are adopted from [32], with their values summarized in Table 1.

TABLE 1. Parameters

	Value	Unit
b	0.75	m
γ_1	0.15	m
m_b	30	kg
m_w	1	kg
d_1	5	kg.m ² /s
d_2	5	kg.m ² /s
H_b	15.625	kg.m ²
H_{w1}	0.005	kg.m ²
H_{w2}	0.0025	kg.m ²

The reference trajectory is defined by the following signals: $\zeta_d = 2\sin(0.5t)$, $\mu_d = 2\cos(0.5t)$, $\psi_d = -0.5t$. To guarantee the satisfactory performances, one chooses $k_{b1}(t) = k_{b2}(t) = 0.9e^{-0.8(t)} + 0.1$. The parameters in virtual control signals (23), (24), the actual controllers (34) and (35), adaptive laws of parameters (37), (38) are chosen as $l_1 = 27/111$, $l_2 = 207/111$, $k_{11} = k_{12} = 0.38$, $\sigma_{11} = 1.6$, $\sigma_{12} = 1.6$, $k_1 = 0.34$, $k_2 = 0.34$, $\sigma_1 = 10$, $\sigma_2 = 10$, $\lambda_1 = 0.01$, $\lambda_2 = 0.01$, $\sigma_3 = 1.4$, $\sigma_4 = 1.4$. Furthermore, we choose the DETM parameters in Equation (7) as $\gamma = 0.3$, $\underline{m}_1 = 0.5$, $\pi_1 = 0.6$, and $\pi_2 = 0.36$.

The control parameters are meticulously selected to achieve a balance between convergence speed, control effort, and tracking accuracy. The exponents l_1 and l_2 for the fixed-time controller are chosen as $l_1 = 27/111$ and $l_2 = 207/111$ to satisfy the stability condition $0 < l_1 < 1 < l_2$ outlined in Lemma 2.2. The gains k_{11} , k_{12} , k_1 , k_2 and σ_{11} , σ_{12} , σ_1 , σ_2 are tuned via trial-and-error to ensure rapid error convergence without inducing excessive control input chattering. The adaptation gains λ_1 and λ_2 are set to small values 0.01 to guarantee smooth parameter estimation, while the σ -modification terms σ_3 and σ_4 are selected to be 1.4 to robustly prevent parameter drift. For the DETM, the threshold parameter $\gamma = 0.3$ and the initial value $\underline{m}_1 = 0.5$ are chosen to maintain a low triggering frequency while avoiding significant performance degradation. The dynamic law parameters $\pi_1 = 0.6$ and $\pi_2 = 0.36$ are designed to satisfy the condition $\pi_2/\pi_1 > m_1(0)$.

The simulation results are shown in Figures 2-8. Figures 2 and 3 demonstrate precise trajectory tracking, with system outputs (ζ, μ, ψ) converging smoothly and rapidly to their references without overshoot or chattering – confirming high-precision tracking and excellent transient performance achieved through the integrated prescribed performance and fixed-time control framework. Figure 4 verifies that tracking errors z_e and ψ_e remain strictly within the predefined performance boundaries $k_{b1}(t)$ and $k_{b2}(t)$, converging to a

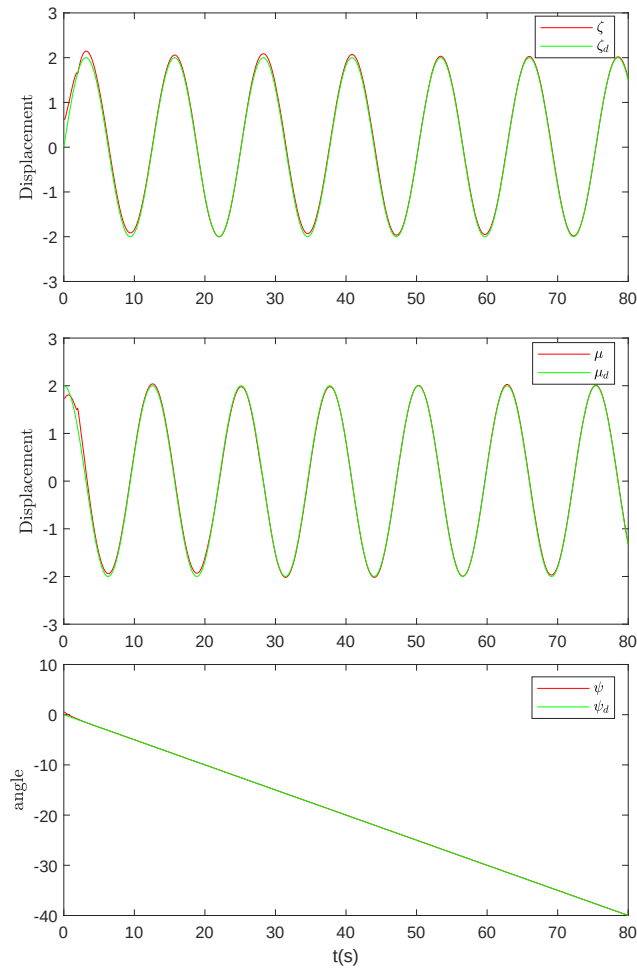


FIGURE 2. Experimental tracking error results

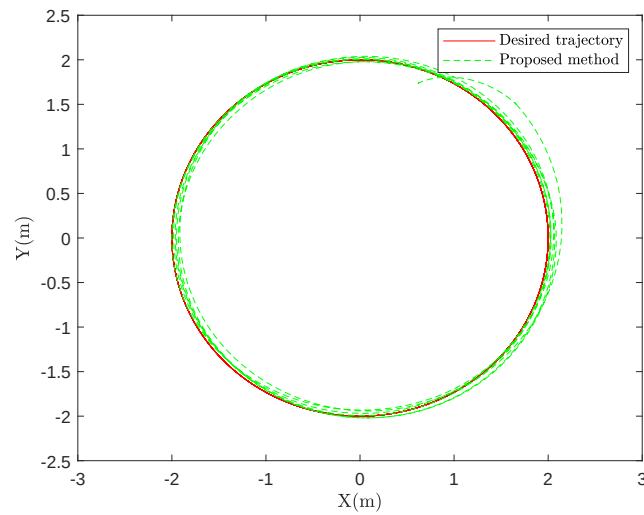


FIGURE 3. Experimental tracking results

negligible neighborhood of zero within approximately 5 seconds, consistent with the theoretical fixed-time guarantee. Figure 5 shows the adaptive parameters $\hat{\theta}_1$ and $\hat{\theta}_2$ converging rapidly to constants, indicating successful approximation of unknown dynamics and stable

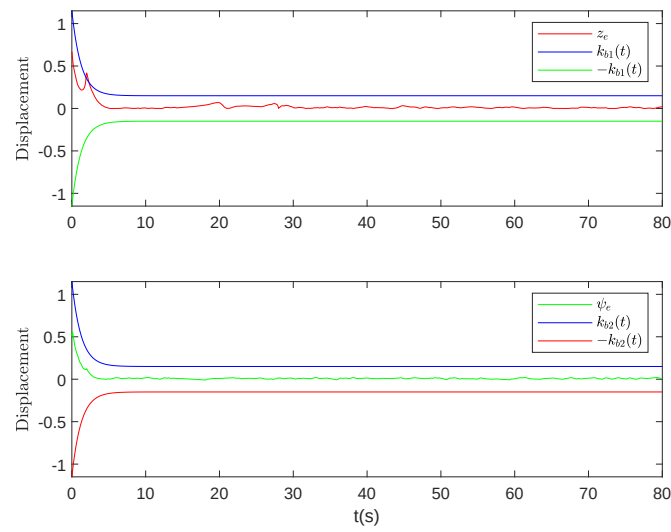


FIGURE 4. Experimental tracking error and prescribed performance functions

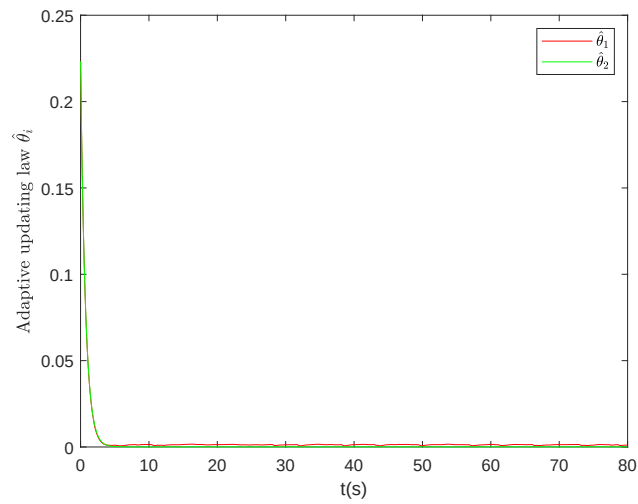


FIGURE 5. Adaptive parameter

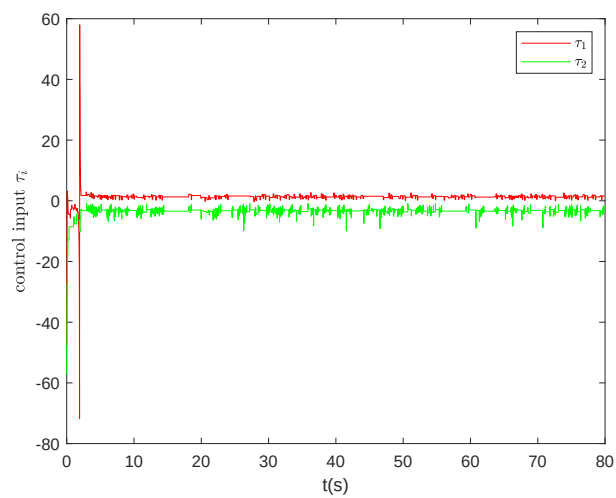
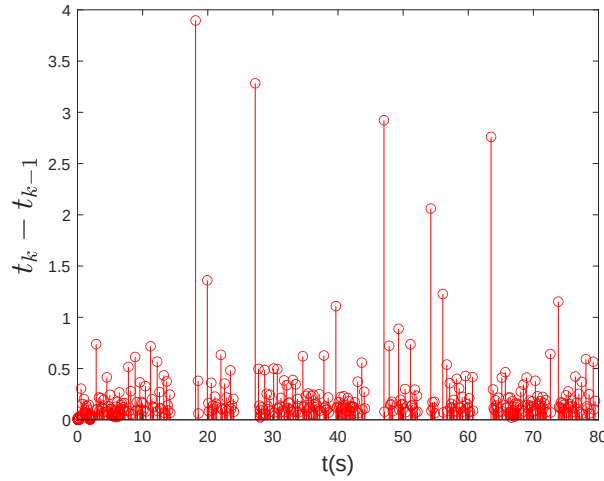
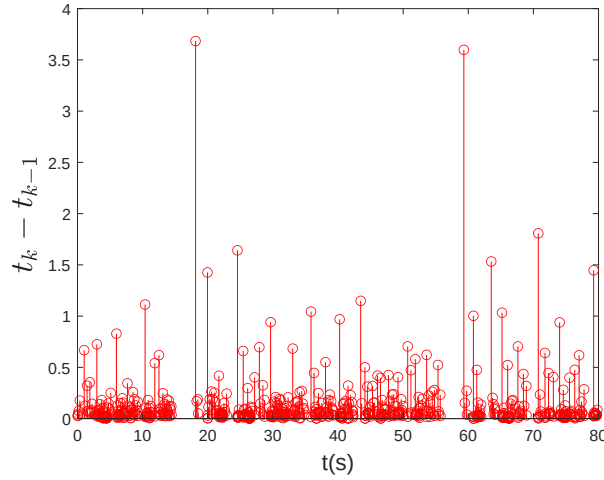


FIGURE 6. Experimental control input

FIGURE 7. Event-triggered interexecution interval of controller τ_1 FIGURE 8. Event-triggered interexecution interval of controller τ_2

learning. The control inputs τ_1 and τ_2 in Figure 6 are smooth and bounded, settling near zero after the transient phase, confirming controller feasibility without excessive control effort. Figures 7 and 8 quantify communication efficiency: the event-triggered intervals for τ_1 and τ_2 confirm that updates occur only at discrete instants, substantially reducing trigger instances compared to time-triggered paradigms while avoiding Zeno behavior. This demonstrates that the novel DETM effectively minimizes communication burden without compromising closed-loop performance.

5. Conclusions. This paper investigates the trajectory tracking control problem for wheeled mobile robots with prescribed performance specifications. A novel fixed-time trajectory tracking control scheme is proposed. First, the system model of the wheeled mobile robots is established. Subsequently, fuzzy logic systems are employed to approximate unknown nonlinear dynamics, while a barrier Lyapunov function is introduced to enforce constraints on position and orientation errors. Furthermore, energy consumption considerations are incorporated through a dynamic event-triggered mechanism, for which a corresponding controller is designed. Additionally, the fixed-time stability of the closed-loop system is rigorously proven using Lyapunov analysis, achieving guaranteed

trajectory tracking control for wheeled mobile robots. Finally, numerical simulations validate the effectiveness of the proposed control scheme. Despite the satisfactory results achieved in this work, several aspects warrant further investigation. Future research will focus on extending the proposed control scheme to more complex and realistic scenarios, such as multi-robot cooperative systems with communication delays and packet losses, along with the integration of more advanced disturbance observers to bolster robustness against time-varying external disturbances.

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