Event-Triggered Optimal Control with Safety Guarantees for Obstacle-Avoidant Navigation of Nonholonomic Robots

Ritirupa Dey, Allan Paiz

***Abstract*—This paper presents a unified framework for obstacle-avoidant trajectory planning and resource-efficient control of nonholonomic wheeled mobile robots (WMRs). We first formulate path planning as a constrained nonlinear optimization problem that generates dynamically feasible, obstacle-avoiding trajectories with minimal deviation from a reference. We then design an adaptive event-triggered optimal controller to track the planned trajectory while reducing control updates. The control problem is posed as a zero-sum differential game to account for sampling-induced uncertainties, leading to a Hamilton–Jacobi–Isaacs (HJI) formulation. Safety is enforced via control barrier functions embedded directly in the cost. An adaptive neural network-based critic approximates the value function, yielding a tractable solution. The proposed approach guarantees uniformly ultimately bounded tracking and forward invariance of the safe set, while significantly reducing communication and computation. Simulations validate safe, efficient, and optimal performance, while avoiding obstacles.**

I. Introduction

Autonomous navigation of wheeled mobile robots (WMRs) in constrained environments requires the simultaneous satisfaction of multiple objectives, including trajectory tracking, obstacle avoidance, safety, and efficient use of computational and communication resources. In many applications such as autonomous driving, warehouse automation, and multi-robot systems, these requirements must be addressed under nonholonomic motion constraints and limited onboard resources, making the control problem particularly challenging.

Traditional approaches often treat path planning and control as separate modules. Path planners generate feasible trajectories that avoid obstacles, while low-level controllers track these trajectories. However, this separation can lead to suboptimal performance, particularly when the planned trajectories are not explicitly compatible with system dynamics or when control constraints are not accounted for during planning. Furthermore, continuous-time feedback control strategies typically require frequent updates, which can be inefficient in resource-constrained systems.

To address these challenges, event-triggered control has emerged as a promising paradigm that reduces unnecessary control updates by executing feedback actions only when certain conditions are violated. While event-triggered methods improve efficiency, ensuring stability and safety in the presence of aperiodic updates remains a significant challenge, especially for nonlinear systems with constraints. In parallel, control barrier functions (CBFs) have been widely used to enforce safety constraints such as obstacle avoidance and lane-keeping by guaranteeing forward invariance of safe sets. However, integrating CBFs with optimal control and event-triggered strategies in a unified framework is still an open problem.

In this paper, we propose a comprehensive framework that integrates optimal path planning, event-triggered control, and safety guarantees for nonholonomic WMRs. First, we formulate an obstacle-avoidant trajectory planning problem as a constrained nonlinear optimization problem that generates dynamically feasible reference trajectories. These trajectories serve as inputs to the control layer. Next, we design an adaptive event-triggered optimal controller that tracks the planned trajectories while minimizing control effort and reducing update frequency. The control problem is cast as a two-player zero-sum differential game to account for worst-case sampling-induced errors, leading to a Hamilton–Jacobi–Isaacs (HJI) formulation. To enforce safety, lane-keeping constraints are incorporated using control barrier functions embedded within the cost function, ensuring that the system remains within a safe set.

Since solving the HJI equation analytically is generally intractable, we employ an adaptive neural network-based critic to approximate the optimal value function. A hybrid weight update law is developed to ensure convergence of the approximation under a persistence of excitation condition. The proposed framework guarantees uniformly ultimately bounded tracking performance and forward invariance of the safe set, while significantly reducing control updates through event-triggered execution.

The main contributions of this paper are summarized as follows:

- An optimal obstacle-avoidant trajectory planning formulation that ensures compatibility with nonholonomic dynamics.
- A unified event-triggered optimal control framework that reduces control updates while maintaining performance.
- Integration of control barrier functions into the optimal control cost to enforce safety constraints.
- An adaptive neural network-based solution to approximate the HJI equation for nonlinear systems.
- Formal guarantees of stability and safety, including uniformly ultimately bounded tracking and forward invariance of the safe set.

II. Related Works

Prior work on mobile robots shows that collision avoidance and trajectory tracking are often coupled through constrained optimization or predictive control formulations. Classical work on nonholonomic mobile robots emphasizes that feasible motion generation must respect the robot's kinematic structure rather than rely on geometry alone [1].Optimization based control methods such as model predictive control (MPC) provide a framework for handling state and input constraints [2]. More recent work applies MPC together with safety constraints or barrier function ideas to differential drive robots, demonstrating that obstacle avoidance can be incorporated while preserving tracking performance [3]. Related trajectory tracking formulations for nonholonomic robots also study bounded velocity sets and obstacle aware motion generation under performance constraints [4].

III. Problem Description

System Dynamics: Consider a nonholonomic WMR, represented using the unicycle kinematic model

$$\dot{x}(t) = v(t)\cos\theta(t), \quad \dot{y}(t) = v(t)\sin\theta(t), \tag{1}$$

where (x, y) denotes the robot's position in an inertial frame, θ denotes the heading angle measured from the x-axis, and (v, ω) represents its linear and angular velocities. This model can be represented as an affine nonlinear system as

$$\dot{\zeta} = f(\zeta) + g(\zeta)u, \tag{2}$$

where $\zeta_i = [x, y, \theta]^T \in \mathcal{D} \subset \mathbb{R}^3$ denotes the system state of robot i, the vector $f(\zeta) = \mathbf{0} \in \mathbb{R}^3$ is its internal dynamics and $g(\zeta) = \begin{bmatrix} cos\theta & 0 \\ sin\theta & 0 \\ 0 & 1 \end{bmatrix} \in \mathbb{R}^{3\times 2}$ is the control coefficient and $u = [v, \omega_i]^T \in \mathcal{U}_c \subset \mathbb{R}^2$ is the control input.

Given a reference trajectory ζ_d and a known obstacle, the planner should develop an optimal path ζ'_d which minimally deviates from the reference trajectory while avoiding the obstacle. The trajectories obtained from the planner is subsequently considered as the new trajectory to be tracked. The control objective is therefore to design an adaptive controller which tracks the new desired trajectories $\zeta'_d(t)$ for each robot while optimizing control input and event updates, and simultaneously adhering to lane keeping constraints.

Assumption 1 (Reference Feasibility)**.** *The reference dynamics $\dot{\zeta}_d = h(\zeta_d)$ are assumed to be feasible for the unicycle kinematics, i.e., $h(\zeta_d) \in \mathrm{Range}\big(g(\zeta_d)\big), \quad \forall\zeta_d$ Equivalently, there exist scalar functions $v_d(\zeta_d)$ and $\omega_d(\zeta_d)$ such that* $h(\zeta_d) = \begin{bmatrix} v_d(\zeta_d)\cos\theta_d \\ v_d(\zeta_d)\sin\theta_d \\ \omega_d(\zeta_d) \end{bmatrix}$.

So, given a desired trajectory $\zeta_d(t)$, the planner should generate an obstacle-avoidant path such that the new paths $\zeta'_d(t)$ are feasible for the unicycle robots. Assuming this assumption is satisfied, define the tracking error $e = \zeta - \zeta'_d$, where ζ is system state as defined in (2). The error dynamics is then given by

$$\dot{e} = f(e + \zeta'_d) + g(e + \zeta'_d)u - h(\zeta'_d) \tag{3}$$

The steady-state input corresponding to ζ_d can be expressed as [5]

$$u_{steady} = g^{\dagger}(\zeta'_d)(h(\zeta'_d) - f(\zeta'_d)). \tag{4}$$

Since the dynamics in (2) is time-varying, we employ an augmented time-invariant system formulation for the subsequent analysis. Defining the augmented state $z = \begin{bmatrix} e \\ \zeta_d \end{bmatrix}$, the dynamics can be expressed as

$$\dot{z} = F(z) + G(z)u_{mm}, \tag{5}$$

where $F(z) = \begin{bmatrix} f(e + \zeta'_d) + g(e + \zeta'_d)u_{\text{steady}} - h(\zeta'_d) \\ h(\zeta'_d) \end{bmatrix}$, $G(z) = \begin{bmatrix} g(e + \zeta'_d) \\ 0 \end{bmatrix}$, and $u_{mm} = u - u_{\text{steady}}$ is the mismatch input. The augmented system (5) transform the tracking problem to a regulation problem, where the goal is to design u_{mm} to compute the control input $u = u_{mm} + u_{steady} \in \mathbb{R}^2$, such that the tracking error $e \to 0$ as $t \to \infty$.

In practical robotic systems, the control inputs $u = [v \;\; \omega]^\top$ are subject to actuator limitations and must remain within prescribed bounds. Accordingly, define the admissible control input set as

$$\mathcal{U}_c := \left\{ u = \begin{bmatrix} v \\ \omega \end{bmatrix} \in \mathbb{R}^2 \;\middle|\; v_{\min} \le v \le v_{\max}, \;\; \omega_{\min} \le \omega \le \omega_{\max} \right\}, \tag{6}$$

where $v_{\min}, v_{\max}$ and $\omega_{\min}, \omega_{\max}$ denote the actuator limits, with $|v_{min}| < v_{max}$, $|\omega_{min}| < \omega_{max}$.To ensure feasibility, the controller must generate velocities $u = [v \;\; \omega]^\top$ such that $u(t) \in \mathcal{U}_c$ for all $t \ge 0$.

So the problem at hand is threefold: (i) Develop an optimal path planning algorithm for obstacle avoidance (ii) Design an optimal resource-efficient controller which when deployed on the robotic system tracks the trajectories provided by the planner accurately (iii) Establish formal system stability and safety guarantees even in the presence of resource-constraints.

IV. Proposed Method

A. Obstacle Avoidance

We formulate obstacle-avoiding trajectory generation as a constrained optimization problem for path planning. The goal is to track a desired trajectory while ensuring dynamic feasibility and collision avoidance. Let $\zeta(t) = \big[x(t) \; y(t) \; \theta(t)\big]$ denote the system state and $\mathbf{u}(t) = \big[v(t) \; \omega(t)\big]$ denote the control inputs, where $(x(t), y(t))$ is the robot position, $\theta(t)$ is the heading angle, $v(t)$ is the linear velocity, and $\omega(t)$ is the angular velocity.

The optimization problem is framed as

$$min_{\zeta,v,\omega} J = min_{\zeta,v,\omega} \int_0^T \Big[w_p\big((x(t) - x_d(t))^2 + (y(t) - y_d(t))^2\big) + w_\theta(\theta(t) - \theta_d(t))^2 + w_v(v(t) - v_d(t))^2 + w_\omega(\omega(t) - \omega_d(t))^2 \Big] dt, \tag{7}$$

$$\text{s.t.} \quad \dot{x}(t) = v(t)\cos\theta(t), \;\; \dot{y}(t) = v(t)\sin\theta(t), \;\; \dot{\theta}(t) = \omega(t), \tag{8}$$

$$(x(t) - x_o)^2 + (y(t) - y_o)^2 \ge (R + r + \epsilon)^2, \quad \forall t \in [0, T], \tag{9}$$

$$x(0) = x_0, ; y(0) = y_0, \theta(0) = \theta_0. \tag{10}$$

The objective function (7) minimizes the deviation of the state and control trajectories from a desired reference trajectory $\zeta_d(t) = (x_d(t), y_d(t), \theta_d(t)), u_{ss} = (v_d(t), \omega_d(t))$, where the weights $w_p, w_\theta, w_v, w_\omega > 0$ balance tracking accuracy and control effort. The kinematic constraints (8) correspond to the nonholonomic unicycle model and enforce dynamic feasibility of the robot motion, ensuring that the trajectory is physically realizable. The obstacle avoidance constraint (9) ensures that the robot, with base radius r maintains a minimum safe distance from a circular obstacle centered at (x_o, y_o) with radius R. An additional margin ϵ is considered around the robot, guaranteeing collision-free motion for all $t \in [0, T]$. The initial condition fixes the starting configuration of the robot. We solve the proposed constrained path planning problem using Sequential Least Squares Programming (SLSQP), a gradient-based nonlinear optimization solver. The resulting optimal obstacle-avoidant solution is denoted by $\zeta'_d = (x'_d, y'_d, \theta'_d), u^*_{ss} = (v'_d, \omega'_d)$, corresponding to the optimal state and control inputs over the planning horizon.

Lemma 1. *The planner generates paths which avoids the obstacles as well as satisfies Assumption 1, i.e, $h(\zeta'_d) \in Range(g(\zeta_d))$.*

Proof. The planner outputs $\zeta'_d = (x'_d, y'_d, \theta'_d), u^*_{ss} = (v', \omega')$. So, there exists scalars v', ω' such that $h(\zeta') = \begin{bmatrix} v'_d cos(\theta'_d) \\ v'_d sin(\theta'_d) \\ \omega'_d \end{bmatrix}$. Therefore $h(\zeta'_d) \in Range(g(\zeta'_d))$ and the new trajectories are feasible paths for the nonholonomic WMR.

So new desired trajectories $\zeta'_d = (x'_d, y'_d, \theta'_d)$ have dynamics given by

$$h(\zeta') = \begin{bmatrix} v'_d cos(\theta'_d) \\ v'_d sin(\theta'_d) \\ \omega'_d \end{bmatrix} \tag{11}$$

B. Optimal Event-trigerred controller

Given the optimal obstacle-avoidant reference trajectory $\zeta'_d(t) = (x'_d(t), y'_d(t), \theta'_d(t))$, we formulate an aperiodic event-triggered control scheme that ensures accurate trajectory tracking while reducing control updates. In event-triggered control [6], feedback is available only at a discrete set of triggering instants $\{t_k\}_{k=0}^{\infty} \subset \mathbb{R}_{\geq 0}$, with $t_0 = 0$ and $t_k < t_{k+1}$. At each t_k, the system state and reference are sampled and held constant between events via zero-order hold (ZOH), so that $\zeta_{es}(t) = \zeta(t_k)$, $\zeta_{ds}(t) = \zeta'_d(t_k)$, and $u_{es}(t) = \mu(\zeta_{es}(t))$ for all $t \in [t_k, t_{k+1})$. The event-sampled augmented state is defined as $z_{es}(t) = z(t_k) = [e^\top(t_k), \zeta_{ds}^\top(t)]^\top$, and the sampling-induced errors are $e_s(t) = z_{es}(t) - z(t)$ and $e_u(t) = u_{es}(t) - u(t)$. Under this implementation, the system dynamics in (2) can be e expressed as

$$\dot{\zeta} = f(\zeta) + g(\zeta)u + g(\zeta)e_u, \tag{12}$$

and the augmented error dynamics in (5) becomes

$$\dot{z} = F(z) + G(z)u_{mm} + G(z)e_u, \tag{13}$$

where the term $G(z)e_u$ captures the effect of sampling-induced control mismatch.

To guarantee that the control input satisfies actuator constraints (6), we define the admissible mismatch input set

$$\begin{aligned} \mathcal{U}_{cmm} := \big\{ u_{mm} \in \mathbb{R}^2 \mid v_{\min} - v_{\text{steady}} \leq v_{mm} \leq v_{\max} - v_{\text{steady}}, \\ \omega_{\min} - \omega_{\text{steady}} \leq \omega_{mm} \leq \omega_{\max} - \omega_{\text{steady}} \big\}. \end{aligned} \tag{14}$$

Under Assumption 1 and with $u_{\text{steady}} \in \mathcal{U}_c$, any control of the form $u = u_{mm} + u_{\text{steady}}$ with $u_{mm} \in \mathcal{U}_{cmm}$ is guaranteed to satisfy $u \in \mathcal{U}_c$.

Before formulating the optimization, we embed safety directly into the control design via a CBF. To ensure the WMR remains within a lane of half-width r_{hw} around the reference trajectory, we define the lateral deviation $d_{\text{proj}} = |\eta^\top(\zeta - \zeta_d)|$, where η is the unit normal to the reference at the projection point. We define the safe-set for lane-keeping as

$$\mathcal{C}_{aug} = \{z \in \mathbb{R}^6 | h_{cbf}(z) = (r_{hw} - d_{proj}) \geq 0\}. \tag{15}$$

Safety is encoded in the cost function of the corresponding optimization problem, presented next, via the reciprocal barrier penalty

$$B(z) = k_p \, \frac{s(z)}{h_{\text{cbf}}(z)}, \qquad k_p > 0, \tag{16}$$

with the smooth scheduling function $s(z) = \frac{1}{2} + \frac{1}{2}\cos(\pi h_{\text{cbf}}(z)/r_{hw})$, which activates near the boundary and vanishes near the centerline. By construction, $B(z) \to \infty$ as $z \to \partial\mathcal{C}_{\text{aug}}$ and $B([0^\top, \zeta_d^\top]^\top) = 0$, imposing no penalty at zero tracking error.

Given the mismatch input constraints and augmented dynamics (13), the instantaneous safe cost is

$$\begin{aligned} r_{\text{safe}}(z, u_{mm}) = z^\top \bar{Q}\, z + R_u(u_{mm}) + B(z), \\ \bar{Q} = \begin{bmatrix} Q & 0 \\ 0 & 0 \end{bmatrix}, \; Q \succ 0, \end{aligned} \tag{17}$$

where Q penalizes tracking error (the reference state is excluded since it need not converge to the origin), and the non-quadratic input penalty

$$R_u(u_{mm}) = 2 \sum_{i=1}^{2} \int_0^{u_i} \bar{u}_i \, r_i \tanh^{-1}\!\Big(\frac{\xi}{\bar{u}_i}\Big)\, d\xi \tag{18}$$

grows unbounded as u_{mm} approaches actuator limits, enforcing input constraint feasibility smoothly. Here $R = \text{diag}(r_1, r_2)$ and $\bar{u} = [\bar{v}, \bar{\omega}]^\top$ with $\bar{v} = \min\{|v_{\max} - v_{\text{steady}}|, |v_{\min} - v_{\text{steady}}|\}$ and $\bar{\omega}$ defined analogously.

To simultaneously minimize tracking cost and promote aperiodic execution by maximizing admissible inter-event times, the problem is cast as a two-player zero-sum differential game [7]– the controller minimizes cost with respect to u_{mm}, while an adversarial player maximizes it by selecting the worst-case sampling-error bound $\hat{e}_u$. The resulting performance index is

$$\begin{aligned} J_{\text{safe}}(z, u_{mm}, \hat{e}_u) = \int_0^\infty \big(r_{\text{safe}}\big(z(\tau), u_{mm}(\tau)\big) - \\ \frac{\alpha}{2} \hat{e}_u^\top(\tau)\hat{e}_u(\tau)\big) d\tau, \end{aligned} \tag{19}$$

where $\alpha > \alpha^* > 0$ is the H_∞ attenuation level. The saddle-point value function is

$$V^*(z) = \min_{u_{mm}} \max_{\hat{e}_u} \int_0^\infty (z^\top \bar{Q} z + R_u(u_{mm}) + B(z) - \frac{\alpha}{2} \hat{e}_u^\top \hat{e}_u) d\tau, \quad (20)$$

and the associated Hamilton–Jacobi–Isaacs (HJI) equation requires $\min_{u_{mm}} \max_{\hat{e}_u} H(z, u_{mm}, \hat{e}_u, \nabla V^*) = 0$, where the Hamiltonian is given by

$$H := z^\top \bar{Q} z + R_u(u_{mm}) + B(z) - \tfrac{\alpha}{2} \hat{e}_u^\top \hat{e}_u + \nabla V^{*\top}(z)\big(F(z) + G(z) u_{mm} + G(z)\hat{e}_u\big). \quad (21)$$

First-order optimality condition yields the saddle-point policies

$$u_{mm}^*(z) = -\mathrm{diag}(\bar{u})\,\mathrm{Tanh}\big(\tfrac{1}{2}\,\mathrm{diag}(\bar{u})^{-1} R^{-1} G^\top(z) \nabla V^*(z)\big), \quad (22)$$

$$\hat{e}_u^*(z) = \tfrac{1}{2\alpha^2}\, G^\top(z) \nabla V^*(z), \quad (23)$$

where $\mathrm{Tanh}(\beta) := [\tanh(\beta_1), \tanh(\beta_2)]^\top$. Combining with the steady-state feedforward in (4), the event-sampled control law is given by

$$u_{es}^*(t) = -\bar{u}\,\mathrm{Tanh}\big(\tfrac{1}{2}\,\mathrm{diag}(\bar{u})^{-1} R^{-1} G^\top(z_{es}) \nabla V^*(z_{es})\big) + g^\dagger(\zeta_{ds})\big(h(\zeta_{ds}) - f(\zeta_{ds})\big), \quad (24)$$

and treating $\hat{e}_u^*$ as the worst-case sampling error, the event-triggering condition is

$$t_{k+1} = \inf\{t > t_k |\ e_u^\top e_u \geq \max(\gamma^2, \frac{1}{4\alpha^4} \nabla V^{*\top}(z)\, G(z) G^\top(z)\, \nabla V^*(z))\}, \quad (25)$$

where $\gamma > 0$ ensures a strictly positive lower bound on inter-event times, preventing Zeno behavior.

Since the solution to HJI equation is generally intractable for nonlinear systems, the value function is approximated with the structured decomposition

$$V^*(z) \approx \hat{V}(z_{es}) = \hat{W}^\top \Phi(z_{es}) + B_{\mathrm{bound}}(z_{es}), \quad (26)$$

where $B_{\mathrm{bound}}(z) = s(z)/(h_{\mathrm{cbf}}(z) + c)$ with $c > 0$ regularizes the barrier near the boundary and achieves numerical stability, $\Phi : \mathbb{R}^6 \to \mathbb{R}^{l_N}$ is the critic activation map with $\Phi(0) = 0$, and $\hat{W}$ are the estimated adaptive critic weights. Over each inter-event interval, the Bellman residual is computed as

$$\delta_k = \int_{t_{k-1}}^{t_k} \big(z^\top \bar{Q} z + R_u(u_{mm}) + B(z) - \tfrac{\alpha}{2} \hat{e}_u^\top \hat{e}_u\big)\, d\tau + \hat{W}^\top \Delta\Phi(\tau_{k-1}) + \Delta B_{\mathrm{bound}}(\tau_{k-1}), \quad (27)$$

where $\Delta\Phi(\tau_{k-1}) = \Phi(z(t_k)) - \Phi(z(t_{k-1}))$ and $\Delta B_{\mathrm{bound}}(\tau_{k-1})$ is defined analogously. The critic weights are updated by the hybrid law

$$\hat{W}(t_k^+) = \hat{W}(t_k^-) - \frac{\alpha_2\, \Delta\Phi(\tau_{k-1})\, \delta_k}{\big(1 + \|\Delta\Phi(\tau_{k-1})\|^2\big)^2}, t_k = \text{trigger events} \quad (28)$$

$$\dot{\hat{W}} = -\frac{\alpha_1\, \Delta\Phi(\tau_{k-1})\, \delta_k}{\big(1 + \|\Delta\Phi(\tau_{k-1})\|^2\big)^2}, \quad t \in (t_k, t_{k+1}), \quad (29)$$

with learning gains $\alpha_1, \alpha_2 > 0$.

Theorem 1. *Consider the nonholonomic WMR with kinematic model under the event-triggered control given by* (12)*. Let ζ_d' be the obstacle-avoidant path generated by the offline planner with dynamics given by* (11) *. Let the optimal value function be approximated using the adaptive neural-network critic using* (26)*, with weight-tuning laws given by* (28)*. Let the sampling instants be determined by the event-triggering condition given by* (25) *with $\nabla V^*(z) = \nabla \Phi^T(z) \hat{W} + \nabla B_{bound}(z)$. If the regressor vector satisfies a persistence of excitation condition and the learning gains are chosen such that $0 < \alpha_1 < 1$ and $0 < \alpha_1 < \frac{1}{2}$, then the closed-loop tracking error and the neural network weight estimation errors are both locally UUB.*

Theorem 2. *Consider the nonholonomic WMR with kinematic model under the event-triggered control given by* (12) *and let its initial state $\zeta_0 \in \mathcal{C}_{aug}$. Let ζ_d' be the obstacle-avoidant path generated by the offline planner with dynamics given by* (11) *. Let the optimal value function be approximated using the adaptive neural-network critic using* (26)*, with weight-tuning laws given by* (28)*. Let the sampling instants be determined by the event-triggering condition given by* (25) *with $\nabla V^*(z) = \nabla \Phi^T(z) \hat{W} + \nabla B_{bound}(z)$. If the regressor vector satisfies a persistence of excitation condition and the learning gains are chosen such that $0 < \alpha_1 < 1$ and $0 < \alpha_1 < \frac{1}{2}$, then $h_{cbf}(c)$ defined in* (15) *will satisfy* (**??**) *and the set $\mathcal{C}_{aug}$ will be forward invariant, thereby guaranteeing system safety.*

Remark 1. *Theorem 2 guarantees that if the robots start in their respective pre-defined lanes, they are guaranteed to remain within these lanes until they reach their goal positions.*

V. Experimental Setup and Results

We evaluate the proposed obstacle-avoidant planning framework on a planar WMR navigating a straight-line reference trajectory in the presence of a circular obstacle. The planner generates an optimized trajectory that satisfies kinematic feasibility while ensuring collision avoidance.

Fig. 1 shows the resulting trajectories and corresponding state and control profiles. The optimized trajectory deviates smoothly from the desired straight path to avoid the obstacle and subsequently converges back to the reference, demonstrating effective obstacle avoidance with minimal tracking deviation. The robot maintains a safe clearance from the obstacle, respecting the inflated safety boundary.

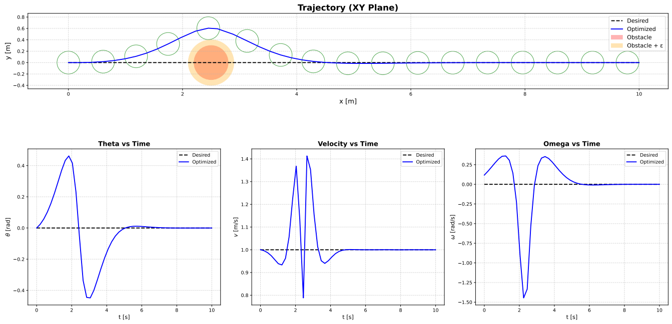

Fig. 1. Obstacle-avoidant trajectory and corresponding state/control profiles. The optimized trajectory deviates from the desired path to avoid the obstacle and smoothly returns to the reference.

The orientation profile exhibits a transient adjustment as the robot reorients to navigate around the obstacle, followed by convergence to the desired heading. Similarly, the control inputs remain well-behaved, with temporary deviations in linear and angular velocities to facilitate avoidance maneuvers. The velocity profile shows brief acceleration and deceleration phases, while the angular velocity exhibits a sharp but bounded response during the turning phase.

Overall, the results validate that the proposed optimization-based planner successfully generates dynamically feasible, obstacle-avoidant trajectories with smooth state and control profiles. The solution balances tracking performance and safety, ensuring minimal deviation from the desired trajectory while guaranteeing collision-free motion.

VI. Conclusion

This paper presented a unified framework for obstacle-avoidant trajectory planning and resource-efficient control of nonholonomic wheeled mobile robots. An optimization-based planner was developed to generate dynamically feasible trajectories that minimize deviation from a desired path while ensuring obstacle avoidance. Building on this, an adaptive event-triggered optimal control strategy was proposed to track the planned trajectories while reducing control updates and computational burden. The control design was formulated as a differential game to account for sampling-induced uncertainties, and safety was incorporated through control barrier functions embedded in the cost. An adaptive neural network-based critic was employed to approximate the solution to the Hamilton–Jacobi–Isaacs equation, enabling a tractable implementation for nonlinear systems. The proposed framework guarantees uniformly ultimately bounded tracking performance and forward invariance of the safe set, ensuring both stability and safety. Simulation results demonstrated that the planner generates smooth, feasible, and obstacle-avoidant trajectories, while the event-triggered controller achieves accurate tracking with reduced update frequency. Overall, the approach provides an integrated solution for safe, optimal, and resource-aware navigation of nonholonomic robots. Future work will focus on extending the framework to multi-robot scenarios, incorporating dynamic and uncertain environments, and validating the approach on real robotic platforms.

References

[1] R. Fierro and F. L. Lewis, "Control of a nonholonomic mobile robot using neural networks," *IEEE Transactions on Neural Networks*, vol. 9, no. 4, pp. 589–600, 1998.

[2] D. Q. Mayne, J. B. Rawlings, C. V. Rao, and P. O. M. Scokaert, "Constrained model predictive control: Stability and optimality," *Automatica*, vol. 36, no. 6, pp. 789–814, 2000.

[3] A. M. Ali, C. Shen, and H. A. Hashim, "A linear MPC with control barrier functions for differential drive robots," *IET Control Theory & Applications*, vol. 18, no. 18, pp. 2693–2704, 2024.

[4] P. S. Trakas, S. I. Anogiatis, and C. P. Bechlioulis, "Trajectory tracking with obstacle avoidance for nonholonomic mobile robots with diamond-shaped velocity constraints and output performance specifications," *Sensors*, vol. 24, no. 14, p. 4636, 2024.

[5] A. Sahoo and V. Narayanan, "Event-based near optimal sampling and tracking control of nonlinear systems," in *2018 IEEE Conference on Decision and Control (CDC)*, pp. 55–60, IEEE, 2018.

[6] P. Tabuada, "Event-triggered real-time scheduling of stabilizing control tasks," *IEEE Transactions on Automatic control*, vol. 52, no. 9, pp. 1680–1685, 2007.

[7] A. Sahoo and V. Narayanan, "Optimization of sampling intervals for tracking control of nonlinear systems: A game theoretic approach," *Neural Networks*, vol. 114, pp. 78–90, 2019.