

Sliding Mode Control for Trajectory Tracking on a Non-Holonomic Tractor-Trailer Autonomous Mobile Robot (AMR)

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ABSTRACT

Trajectory tracking of non-holonomic autonomous mobile robots (AMRs) becomes more demanding when a passive trailer is towed and wheel slip occurs. This study developed a two-surface sliding mode control (SMC) scheme that regulates the distance and heading errors of a pure-pursuit lookahead point and maps the desired accelerations to wheel torques through dynamic inversion, with boundary-layer saturation, heading-singularity safeguards, and jackknife protection. The controller was evaluated in ROS 2 Jazzy and Gazebo Harmonic and integrated with a breadth-first search (BFS) planner using mode-adaptive obstacle inflation. On an oval path with a rigid hitch, the tracking root-mean-square error (RMSE) was 0.042 m, whereas a replicated three-surface baseline diverged (RMSE 4.68 m) with 79.5% torque saturation; the proposed controller required approximately five times less control effort without saturation. A LuGre-based slip test showed that wheel-odometry feedback diverged substantially from ground truth, supporting map-based localization. Hardware validation remains necessary.

Keywords

Autonomous mobile robot; Sliding mode control; Tractor-trailer system; Trajectory tracking; LuGre friction model

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INTRODUCTION

Autonomous mobile robots (AMRs) are self-navigating systems that, unlike automated guided vehicles (AGVs) restricted to physical guideways, use onboard sensors, digital maps, and path-planning algorithms to determine their routes dynamically [1]. This flexibility makes AMRs relevant to Industry 4.0 applications such as warehouse logistics, flexible manufacturing, agriculture, healthcare, and hospitality [2], [3], where robot control is also expected to deliver stable, repeatable, and safe operation [4].

In internal logistics, an AMR may also tow a passive trolley, forming an underactuated tractor-trailer system in which the trailer is influenced only through the tractor and the hitch [5]. The tractor is usually a differential-drive platform, which is subject to non-holonomic constraints that act at the velocity level and restrict the instantaneous direction of motion [6]; this restriction becomes more consequential when a trailer enlarges the swept area of the vehicle. Trajectory tracking for such robots has been addressed with model predictive control [7], [8], neural-network and fuzzy-logic schemes [9], [10], and ROS-based controllers evaluated in simulation before deployment [11]. Most of these formulations, however, assume pure rolling, an assumption that fails at high speeds, large accelerations, or on slippery terrain [6], [12].

Once pure rolling is violated, wheel slip degrades both the model and the controller. For tractor-trailer robots, Alipour et al. [13] modeled lateral and longitudinal slip with the LuGre friction model and showed that slip-aware sliding mode control outperforms pure-rolling designs, while adaptive estimation and neural-network compensation have been used when slip parameters are unknown [9], [14]. Sliding mode control (SMC) suits this problem because, once the state reaches the sliding surface, the closed loop is invariant to bounded matched uncertainties [15], [16], and it has been applied to non-holonomic robots subject to slip and input saturation [17], [18]. Its main drawback, chattering caused by the discontinuous switching term, is commonly attenuated by boundary-layer saturation, hyperbolic-tangent, terminal, integral, or higher-order formulations [17], [19]. Slip-robustness studies further require a friction model such as LuGre, which represents wheel-ground contact through an internal bristle-deflection state [20] and reproduces stiction, the Stribeck effect, pre-sliding displacement, and frictional lag [21], [22], with better realism than static models such as the Magic Formula in mobile-robot applications [13], [22].

Despite this progress, the three-surface formulation of Alipour et al. [13] was assessed with an idealized numerical model, and its behavior under fixed-timestep physics integration, contact dynamics, discrete sensing, and a substantially larger robot has not been reported. Tractor-trailer controllers are also usually evaluated without a planner that accounts for the swept area of different towing configurations, and the reliability of proprioceptive feedback under slip is rarely examined in the same framework.

This study therefore designed and evaluated an SMC trajectory tracking controller for a non-holonomic tractor-trailer AMR in which wheel slip is treated as a bounded disturbance. Relative to [13], the contributions are (i) a simplification to two first-order sliding surfaces that regulate the distance and heading errors of a pure-pursuit lookahead point, combined with a feedback-linearizing dynamic-inversion stage; (ii) end-to-end validation in ROS 2 Jazzy and Gazebo Harmonic rather than an idealized numerical model; (iii) integration of the lookahead formulation directly into the sliding-surface error definition; and (iv) integration with a breadth-first search (BFS) planner whose obstacle inflation adapts to the towing mode (Solo, Fixed, or Pivot) on a map built by simultaneous localization and mapping (SLAM). The simplification is tested against a replicated three-surface baseline. All evidence is simulation-based and the gains were tuned manually; the findings therefore describe controller behavior under the simulated conditions rather than hardware performance.

METHOD

The study followed a model-based design and simulation-validation sequence: kinematic, dynamic, and friction modeling; derivation of the two-surface SMC law and torque mapping; integration with a mode-adaptive BFS planner; and evaluation in simulation scenarios. Figure 1 summarizes the resulting architecture, in which the planner output is converted into a lookahead point, the polar tracking errors are processed by the outer SMC loop, and the desired

accelerations are converted into wheel torques, while pose feedback is obtained from the transform chain map→odom→base_link and a safety supervisor limits motion near obstacles and at large hitch angles.

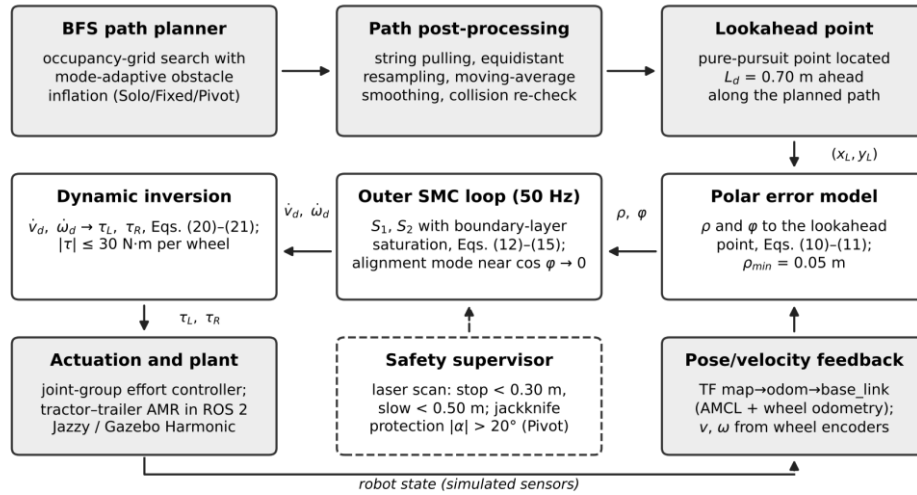


Figure 1. Architecture of the planning-and-control system for the tractor-trailer AMR (equation numbers refer to the Method section).

Kinematic and Dynamic Modeling

The tractor is a differential-drive AMR with two coaxial driven wheels and passive casters, a configuration also used for tractor units of tractor-trailer robots [5]. Its pose is $\mathbf{q} = [X, Y, \theta]^T$, where (X, Y) is the center-of-mass position and θ the heading. The linear and angular velocities v and ω relate to the right and left wheel velocities v_R and v_L by (1), where b is half of the wheel base.

$$v = \frac{v_R + v_L}{2}, \quad \omega = \frac{v_R - v_L}{2b} \quad (1)$$

Under pure rolling, the non-holonomic constraints $\mathbf{A}(\mathbf{q})\dot{\mathbf{q}} = 0$ prohibit lateral motion, and the admissible velocities lie in the null space $\mathbf{N}(\mathbf{q})$ of $\mathbf{A}(\mathbf{q})$, with $\mathbf{u} = [v, \omega]^T$:

$$\dot{\mathbf{q}} = \mathbf{N}(\mathbf{q}) \mathbf{u} \quad (2)$$

When slip occurs, these constraints are no longer strictly satisfied, and the lateral and longitudinal slip components are treated as bounded disturbances [12]. Because the controller commands wheel torques, a dynamic model was derived with the Newton-Euler method by drawing free-body diagrams of the body and wheels. For the main body,

$$m\ddot{X} = (F_1 + F_2)\cos\theta - (F_3 + F_4)\sin\theta \quad (3)$$

$$m\ddot{Y} = (F_1 + F_2)\sin\theta + (F_3 + F_4)\cos\theta \quad (4)$$

$$I_z\ddot{\theta} = (F_1 - F_2)b \quad (5)$$

where m is the body mass, I_z the yaw moment of inertia, and F_1 – F_4 the body-wheel interaction forces. Assembling the body and wheel equations gives the compact form [13].

$$\mathbf{M}\ddot{\mathbf{q}} = \mathbf{B}\boldsymbol{\tau} + \mathbf{f}(\dot{\mathbf{q}}) + \mathbf{C}(\mathbf{q}, \dot{\mathbf{q}}) + \mathbf{A}^T(\mathbf{q})\mathbf{R} \quad (6)$$

where $\mathbf{M}$ is the mass-inertia matrix, $\mathbf{B}$ the input matrix, $\boldsymbol{\tau} = [\tau_1, \tau_2]^T$ the wheel torques, $\mathbf{C}$ the Coriolis and centripetal vector, $\mathbf{f}$ the wheel-ground friction vector, and $\mathbf{R}$ the constraint forces (Lagrange multipliers).

LuGre Friction Model Implementation

The friction vector $\mathbf{f}(\dot{\mathbf{q}})$ determines the traction each wheel can transmit and was modeled with the dynamic LuGre model [20]:

$$\frac{dz}{dt} = v_w - \frac{\sigma_0 |v_w|}{g(v_w)} z \quad (7)$$

$$g(v_w) = F_c + (F_s - F_c) \exp \left[- \left(\frac{v_w}{v_s} \right)^2 \right] \quad (8)$$

$$F_{LuGre} = \sigma_0 z + \sigma_1 \frac{dz}{dt} + \sigma_2 v_w \quad (9)$$

where v_w is the slip velocity at the contact point (wheel surface speed minus the translational speed of the contact point), z the average bristle deflection, F_c and F_s the Coulomb and static friction forces, σ_0 – σ_2 the stiffness and damping coefficients, and v_s the Stribeck velocity [20], [21]. Most simulations used the built-in Coulomb contact friction of Gazebo, which produces negligible slip. For the dedicated slip experiment, a ROS 2 node computed (7)–(9) for each drive wheel at 50 Hz and applied the force to the wheel link through the Gazebo link-wrench interface; the native wheel friction was set to a negligible value so that LuGre governed the traction force while the contact solver supplied the normal force. The LuGre parameters were derived from the robot mass and wheel normal load because the values used in [13] were not available in the accessible portions of that work.

Two-Surface Sliding Mode Controller

The controller is a layered, torque-level SMC with feedback linearization adapted from [13], retaining first-order sliding surfaces, a reaching law of the form $u = u_{eq} + K \text{sat}(S/\Phi)$, and dynamic inversion, but simplified to two surfaces that regulate the tractor directly; double-loop sliding-mode structures with separate position and orientation loops have been effective for non-holonomic robots [23]. The robot tracks a lookahead point (x_L, y_L) located $L_d = 0.70$ m ahead along the path. With $\Delta x = x_L - x$ and $\Delta y = y_L - y$, the distance and heading errors are

$$\rho = \sqrt{\Delta x^2 + \Delta y^2}, \quad \varphi = \text{atan2}(\Delta y, \Delta x) - \theta \quad (10)$$

where φ is normalized to $[-\pi, \pi]$. Their kinematic rates are

$$\dot{\rho} = -v \cos \varphi, \quad \dot{\varphi} = \frac{v \sin \varphi}{\rho} - \omega \quad (11)$$

where $v = (R/2)(\omega_L + \omega_R)$ and $\omega = (R/B)(\omega_L - \omega_R)$ are reconstructed from the wheel encoders, with R the wheel radius, B the wheel base, and ω_L, ω_R the wheel angular velocities. One first-order surface was defined for each loop:

$$S_1 = \dot{\rho} + \lambda_1 \rho \quad (12)$$

$$S_2 = \dot{\varphi} + \lambda_2 \varphi \quad (13)$$

where $\lambda_1, \lambda_2 > 0$, so that ρ and φ converge with first-order dynamics once S_1 and S_2 reach zero. Imposing $\dot{S}_i = -K_i \text{sat}(S_i/\Phi_i)$, with $\text{sat}(x) = \max(-1, \min(1, x))$ replacing the sign function to attenuate chattering, and differentiating (12)–(13) along (11) gives the desired accelerations

$$\dot{v}_d = \frac{K_1 \text{sat}(S_1/\Phi_1) + v \dot{\varphi} \sin \varphi - \lambda_1 v \cos \varphi}{\cos \varphi} \quad (14)$$

$$\dot{\omega}_d = K_2 \text{sat}(S_2/\Phi_2) + \frac{\dot{v}_d \sin \varphi + v \dot{\varphi} \cos \varphi}{\rho} + \frac{v^2 \sin \varphi \cos \varphi}{\rho^2} + \lambda_2 \dot{\varphi} \quad (15)$$

where K_1, K_2 are switching gains and Φ_1, Φ_2 boundary-layer widths. Two safeguards keep the law well conditioned. When $\cos \varphi < \cos 81^\circ$, the division in (14) becomes ill conditioned, so the controller enters an alignment mode that decelerates toward a stop and corrects only the

heading through $\dot{\omega}_d = K_2 \text{sat}(S_2/\Phi_2) + \lambda_2 \dot{\phi}$; in the Pivot mode, a forward creep of 0.08 m/s is kept so that the trolley continues to follow the curve. In addition, ρ is lower-bounded at $\rho_{\min} = 0.05$ m to prevent the $\dot{\phi}$ term in (11) from diverging.

Reaching Condition and Stability

Assuming that the inner inversion and actuator stage tracks $\dot{v}_d$ and $\dot{\omega}_d$ with negligible lag relative to the 50 Hz outer loop, which is reasonable for the simulated effort-controlled actuator, each surface obeys

$$\dot{S}_1 = -K_1 \text{sat}(S_1/\Phi_1), \quad \dot{S}_2 = -K_2 \text{sat}(S_2/\Phi_2) \quad (16)$$

With $V_1 = S_1^2/2$, outside the boundary layer ($|S_1| \geq \Phi_1$),

$$\dot{V}_1 = -K_1 |S_1| \leq -\sqrt{2} K_1 \sqrt{V_1} < 0, \quad S_1 \neq 0 \quad (17)$$

which is the η -reachability condition; the boundary layer is reached in a finite time bounded by $|S_1(0)|/K_1$, and the same holds for S_2 . Inside the layer, (16) becomes $\dot{S}_1 = -(K_1/\Phi_1)S_1$, and under a bounded matched disturbance such as slip, S_1 remains uniformly ultimately bounded provided the switching gain dominates the disturbance [15]. Because $S_1 = \dot{\rho} + \lambda_1 \rho$ is a stable first-order filter, the steady-state errors satisfy

$$|\rho_{ss}| \lesssim \frac{\Phi_1}{\lambda_1}, \quad |\varphi_{ss}| \lesssim \frac{\Phi_2}{\lambda_2} \quad (18)$$

For the Solo parameters in Table 1 ($\Phi_1 = 0.30$, $\lambda_1 = 0.50$), (18) gives $|\rho_{ss}| \lesssim 0.60$ m. The analysis covers the regular regime of (14)–(15); the alignment mode exists because the S_1 law is ill conditioned as $\cos \varphi \rightarrow 0$, so only the S_2 law is enforced there until the heading is recovered.

Dynamic Inversion, Parameters, and Safety Constraints

The desired accelerations are mapped to wheel torques through the differential-drive model (19) and its inverse (20)–(21):

$$M_{eff} \dot{v} = \frac{\tau_L + \tau_R}{R}, \quad I_{eff} \dot{\omega} = \frac{(\tau_L - \tau_R) d}{R} \quad (19)$$

$$\tau_L = \frac{R}{2} \left(M_{eff} \dot{v}_d + \frac{I_{eff}}{d} \dot{\omega}_d \right) \quad (20)$$

$$\tau_R = \frac{R}{2} \left(M_{eff} \dot{v}_d - \frac{I_{eff}}{d} \dot{\omega}_d \right) \quad (21)$$

where $R = 0.079$ m, $B = 0.600$ m, $d = B/2 = 0.300$ m, $M_{eff} \approx 117.09$ kg (total mass plus wheel inertia contribution), and $I_{eff} \approx 15.73$ kg·m², all derived from the Simulation Description Format (SDF) model. Torque is saturated at $|\tau| \leq 30$ N·m per wheel, and the controller runs at 50 Hz. The gains were tuned manually for each towing mode, namely Solo (no trolley), Fixed (rigid hitch), and Pivot (revolute hitch), as listed in Table 1; the towing modes use lower velocity limits, and the Pivot mode has the most restrictive angular-velocity limit.

Table 1. Tuned sliding-mode control parameters for each towing mode

Parameter	Symbol	Solo	Fixed	Pivot
Distance-loop surface slope	λ_1	0.50	0.50	0.50
Distance-loop switching gain	K_1	1.0	2.0	2.0
Distance-loop boundary-layer width	Φ_1	0.30	0.35	0.35
Heading-loop surface slope	λ_2	1.2	1.0	1.5
Heading-loop switching gain	K_2	8.0	6.0	8.0
Heading-loop boundary-layer width	Φ_2	0.20	0.30	0.25
Maximum linear velocity (m/s)	$v_{\max}$	0.50	0.30	0.30
Maximum angular velocity (rad/s)	$\omega_{\max}$	1.50	0.50	0.35
Lookahead distance (m)	L_d	0.70	0.70	0.70
Goal tolerance (m)	–	0.15	0.15	0.15

Note: Solo = tractor without trolley; Fixed = rigid hitch; Pivot = revolute hitch.

During operation, laser-scan obstacle avoidance stops the robot below 0.30 m clearance and slows it below 0.50 m, and in the Pivot mode, jackknife protection brakes the robot and suspends turning when the hitch angle exceeds $|\alpha| > 20^\circ$.

Path Planner and Evaluation Scenarios

Reference paths were generated by a BFS over the SLAM occupancy grid, a classical grid-based planning strategy [24]. Collisions were checked with either an isotropic circular inflation or an oriented-rectangle footprint over discretized heading bins, and the inflation radius or footprint was enlarged from Solo to Fixed to Pivot to reflect the increasing swept area. The cell path was converted to world coordinates, simplified by string pulling, resampled at equidistant intervals, and smoothed with a moving-average window, with every smoothed point rechecked for collision.

All experiments were run in ROS 2 Jazzy and Gazebo Harmonic, which introduce fixed-timestep integration, discrete sensor updates, and contact dynamics, with the robot localized by Adaptive Monte Carlo Localization (AMCL) on a SLAM-generated map. The scenarios comprised a 2 m straight line and a 5 m diagonal motion; an oval path of radius 6 m centered at (5.5, 6.0) m in the Fixed and Solo modes; a replicated three-surface baseline [13] on the same oval; an ablation of the dynamic feedforward term; a LuGre slip test on 2 m straight segments with friction scales $\mu_{\text{scale}} = 1.00, 0.50, \text{ and } 0.25$ applied to F_c and F_s ; BFS planning on a depot map from (0, 0) to (–10, 6) m; and integrated planning and control on the SLAM map. Tracking was quantified by the RMSE and maximum of the lateral error for prescribed motions and by the mean and maximum following deviation for planned routes; control effort was expressed as the RMS wheel torque, and chattering as the mean $|d\tau/dt|$.

RESULTS AND DISCUSSION

Elementary Motions and Oval Path Following

For the 2 m straight-line motion, the lateral-error RMSE was 0.014 m and the maximum deviation 0.034 m; the linear velocity increased smoothly to approximately 0.40 m/s while the angular velocity stayed close to zero after the initial transient (Figure 2). For the 5 m diagonal motion, the RMSE was 0.057 m and the maximum deviation 0.196 m, occurring at the start (Figure 3). During the turn, high-frequency oscillation appeared in the angular velocity command, while the lateral error remained bounded and decreased after the turn.

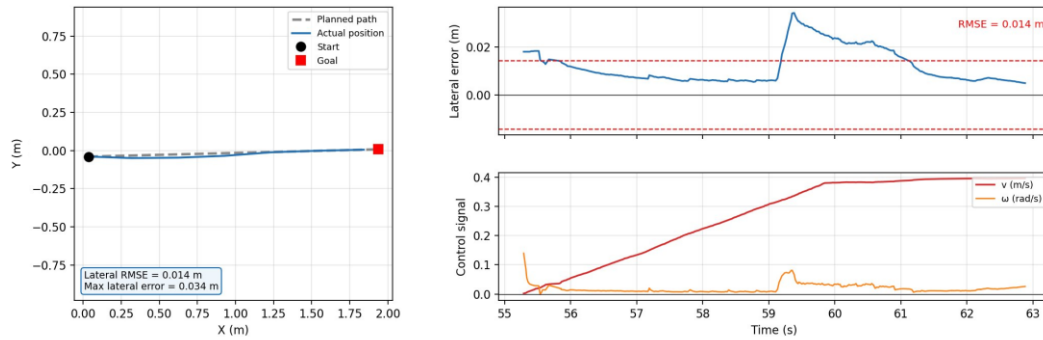


Figure 2. Straight-line (2 m) tracking: paths (left), lateral error (upper right), and velocity commands (lower right).

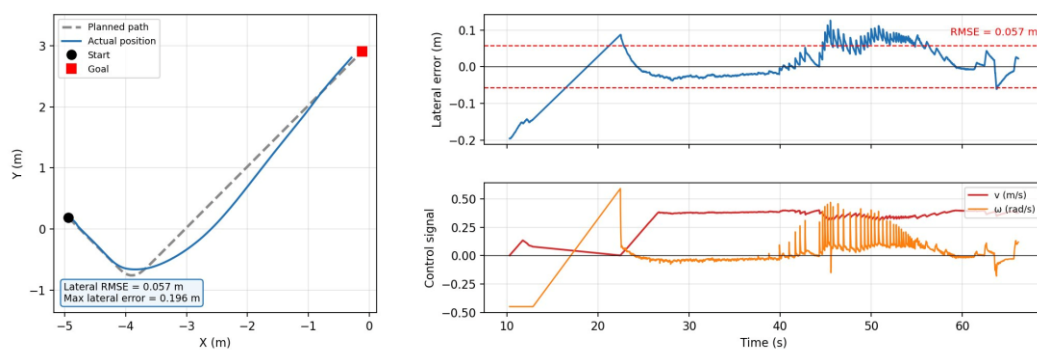


Figure 3. Diagonal (5 m) tracking: paths (left), lateral error (upper right), and velocity commands (lower right), showing bounded chattering during the turn.

On the oval path with the rigid (Fixed) hitch, the two-surface controller achieved an RMSE of 0.042 m and a maximum deviation of 0.093 m (Figure 4a), and the Solo mode yielded a comparable 0.040 m. Because the Fixed hitch has no rotational degree of freedom, the trailer is rigidly slaved to the tractor and has no independent tracking error, and the jackknife protection does not apply. A Pivot run on the same oval did not complete in the simulator and is treated as a limitation.

Baseline Comparison and Feedforward Ablation

The original three-surface formulation of [13], including its exact $H(\bar{q})$ and $\tilde{C}$ dynamic terms and tractor-trailer frame changes, was replicated on the same oval. It departed from the path shortly after the start and did not converge (Figure 4b). As Table 2 shows, it yielded an RMSE of 4.679 m, saturated the ± 30 N·m limit for 79.5% of the run, and produced a chattering index of 471.4 N·m/s, whereas the two-surface controller converged with an RMSE of 0.042 m (approximately 111 times lower), an RMS torque of 6.41 instead of 34.85 N·m (approximately 5.4 times lower), a chattering index approximately 35 times lower, and no saturation.

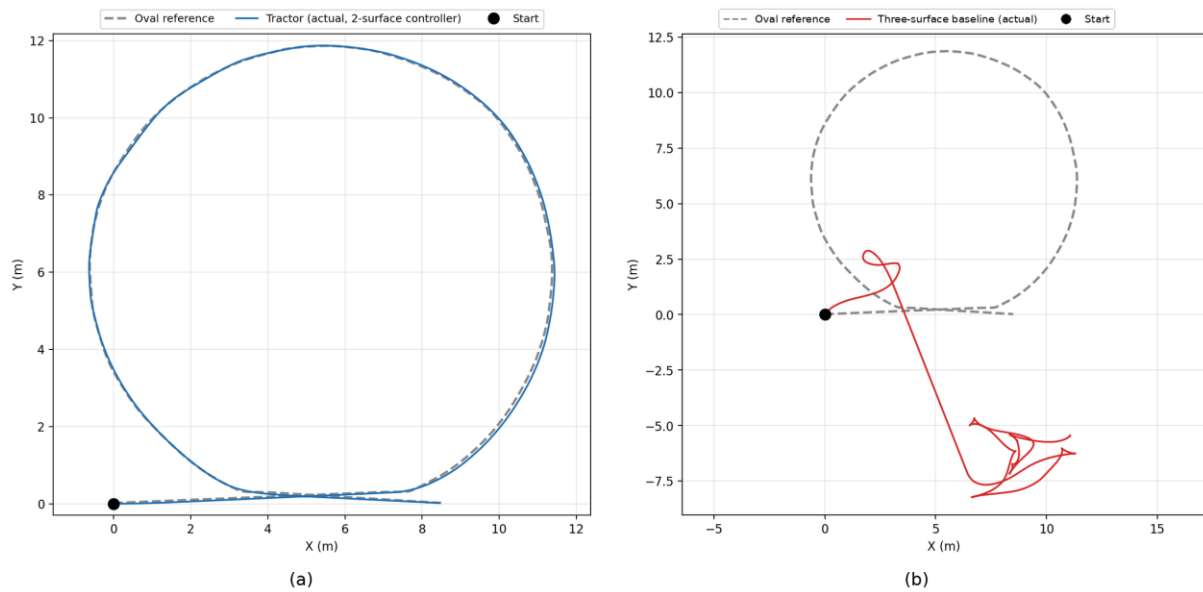


Figure 4. Oval path following ($r = 6$ m): (a) two-surface controller with the rigid (Fixed) hitch; (b) replicated three-surface baseline, which diverges from the reference.

Table 2. Replicated three-surface baseline versus the two-surface controller on the oval path

Metric	Three-surface baseline	Two-surface controller
Tracking RMSE (m)	4.679	0.042
Control effort, RMS τ (N·m)	34.85	6.41
Torque-saturation fraction (%)	79.5	0.0
Chattering index, mean $ \dot{\tau} $ (N·m/s)	471.4	13.5
Convergence to goal	Not converged	Converged

Note: Torque saturation refers to the ± 30 N·m per-wheel limit.

To identify which component carries this performance, the dynamic feedforward term of the inversion stage (M_{eff} , I_{eff}) was ablated on the oval reference. The RMSE was 0.126 m with the term and 0.135 m without it, a difference of less than 10 mm, and the two trajectories nearly coincide (Figure 5).

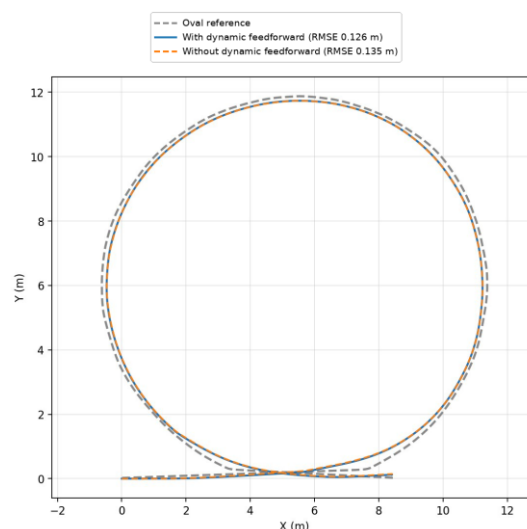


Figure 5. Ablation of the dynamic feedforward term on the oval reference (RMSE 0.126 m versus 0.135 m).

Robustness under Wheel Slip

The preceding results used Coulomb contact. With the LuGre model active, the 2 m straight-line scenario was repeated sequentially, without resetting accumulated drift, at three friction scales, and the divergence between the odometry-derived pose used for feedback and the Gazebo ground truth was recorded (Table 3).

Table 3. *Odometry-derived versus ground-truth pose under LuGre-modeled slip (Solo mode, sequential 2 m segments)*

μ_{scale}	Believed distance (m)	Divergence at end (m)	Observed outcome
1.00 (nominal)	1.88	3.54	Substantial drift despite nominal friction
0.50 (reduced)	1.85	5.20	No real displacement in ground truth
0.25 (further reduced)	0.00	–	Drift placed the robot on an occupied map cell; planner failed to start

Note: Drift accumulated across trials because the pose was not reset.

Under nominal friction, the believed pose diverged from ground truth by 3.54 m after one 2 m command. At $\mu_{\text{scale}} = 0.50$, the robot did not move in ground truth although odometry continued to register progress (divergence 5.20 m), and at 0.25 the accumulated drift placed the believed position on an occupied cell, so the planner failed to start.

Mode-Adaptive Planning and Integrated Operation

On the depot map, increasing the inflation radius from 0.55 m (Solo) to 0.68 m (Fixed) and 1.20 m (Pivot) reduced the free space from 66% to 58% and 35%, the explored cells from 83,240 to 75,003 and 49,984, and the planning time from 194 to 175 and 113 ms, while the path length increased only from 11.70 to 11.83 m (Table 4, Figure 6). Cell counts and lengths were identical across runs; planning times varied slightly with CPU load but stayed below approximately 210 ms and followed the same trend.

Table 4. *BFS planning metrics under mode-adaptive inflation (depot map, start (0, 0) m, goal (–10, 6) m)*

Mode	Inflation (m)	Time (ms)	Cells explored	Length, L (m)	L/L ₀	Free space (%)
Solo	0.55	194	83,240	11.70	1.01	66
Fixed	0.68	175	75,003	11.73	1.01	58
Pivot	1.20	113	49,984	11.83	1.02	35

Note: L/L₀ = path length normalized by the reference length L₀.

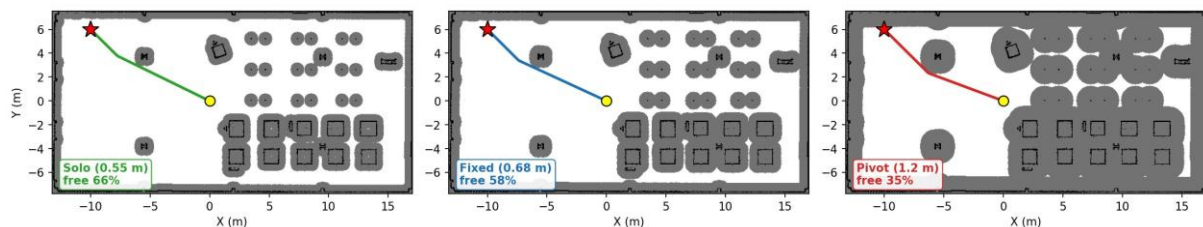


Figure 6. BFS routes for the Solo (0.55 m), Fixed (0.68 m), and Pivot (1.20 m) inflation radii, with inflated obstacles (gray), start (circle), goal (star), and free-space fraction.

In the integrated test on the SLAM-built map, the tractor followed the planned route and stopped 0.18 m from the goal, with a mean following deviation of 0.39 m and a maximum of

2.79 m (Figure 7). The maximum occurred during the initial turning maneuver required because the goal lay behind the initial heading; afterward, the trajectory converged to the planned route.

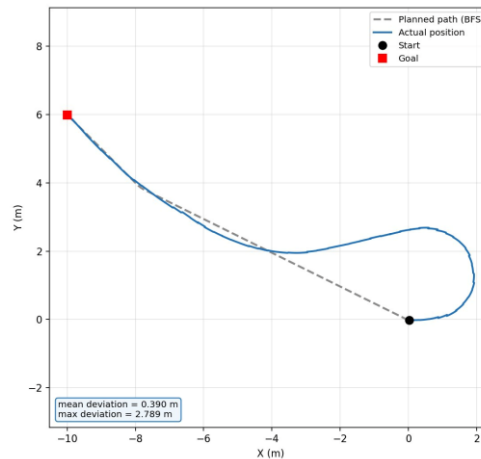


Figure 7. Integrated BFS planning and SMC tracking on the SLAM-built map: planned route and executed trajectory.

Discussion

The oval RMSE of 0.042 m (Figure 4a) lies well within the 0.60 m bound of (18), consistent with the boundary-layer argument but showing that the bound is conservative. The near-identical Solo and Fixed results indicate that, within the tested speed limits, a rigid trailer did not measurably degrade tractor tracking, which is plausible because a rigid hitch adds inertia without the articulation degree of freedom that makes tractor–trailer control underactuated [5].

The baseline comparison (Figure 4b, Table 2) provides the main evidence for the simplification. The three-surface law of [13] performed well with an exact idealized model, but in the present simulator it saturated the actuators for most of the run and diverged. A plausible explanation is that the exact $H(\bar{q})$ and $\tilde{C}$ terms and frame changes amplify the mismatch introduced by fixed-timestep integration, contact dynamics, and a robot roughly an order of magnitude larger than that in [13]. Once torque saturates, the commanded action cannot be delivered and the matched-disturbance invariance of SMC is lost [15]; input saturation is a known source of degraded tracking that requires explicit treatment [18]. The two-surface controller never saturated and used about one-fifth of the effort, so it remained in the regime where the reaching-law argument holds, which agrees with the tractability gained by separating position and orientation loops [23] and extends it to a towing platform.

The ablation (Figure 5) is a deliberately reported null result: at the moderate speeds and accelerations imposed by Table 1, inertial effects appear small relative to the corrective action of the kinematic-level surfaces, so tracking was governed mainly by these surfaces. The dynamic model is still required for the torque mapping in (19)–(21), and its feedforward contribution may matter more at higher accelerations, where model-based and adaptive compensation improve tracking [16], [19]. Because the ablation pair (0.126 and 0.135 m) was run under its own configuration, it should be compared within the pair rather than with the 0.042 m main result. The chattering in Figure 3 reflects the boundary-layer width relative to the fixed simulation timestep rather than an implementation defect; saturation bounded it, as expected from boundary-layer designs [15], [17], and smoother hyperbolic-tangent or higher-order reaching laws could reduce it further [15], [19].

The slip experiment (Table 3) shows that robustness of the control law is not sufficient if the feedback itself is inconsistent with the real motion. Because the surfaces act on the believed pose, the controller can drive the measured error toward zero while the robot is stationary, as observed at $\mu_{\text{scale}} = 0.50$. This agrees with analyses showing that skidding and slipping violate the kinematic assumptions underlying odometry and non-holonomic control [6], [12], and it explains why slip-aware methods estimate slip parameters or disturbances explicitly [9], [14]. The integrated experiment therefore used AMCL-based localization on a SLAM map, in line with the role of sensor fusion in AMR navigation [2].

Mode-adaptive inflation translated the larger swept area of towing configurations into planning conservatism at a cost of at most 1.1% additional path length relative to the Solo route (Table 4), because inflation removes cells from the search space while enforcing larger clearance. In the integrated test (Figure 7), the 2.79 m maximum deviation was concentrated in the initial heading reversal, which reflects the maneuvering required by a non-holonomic tractor-trailer rig that cannot move laterally [5], [6], and should not be read as a steady tracking error.

These interpretations are bounded by several limitations. All results are from simulation; previous ROS-based work evaluated tracking controllers both in simulation and on hardware [11], and the same progression is required here. The gains were tuned manually without systematic optimization or a broader robustness study. The Pivot oval run did not complete: as the hitch angle approached 17° – 20° , the simulated actuation stopped responding to commanded torque while the control loop executed normally, a behavior that diagnostic testing isolated to the simulated revolute joint, since the Solo and Fixed runs on the same oval completed reliably. Finally, the LuGre model was used only in the slip experiment, whereas all other results used negligible-slip Coulomb contact.

CONCLUSION

This study developed a two-surface sliding mode controller for trajectory tracking of a non-holonomic tractor-trailer AMR, in which two first-order surfaces regulate the distance and heading errors of a pure-pursuit lookahead point and a dynamic-inversion stage maps the desired accelerations to wheel torques, with boundary-layer saturation, heading-singularity safeguards, and jackknife protection. In physics-based simulation, the controller tracked straight-line, diagonal, and oval paths accurately, achieving an RMSE of 0.042 m on the oval with a rigid trailer, whereas the replicated three-surface formulation diverged under the same conditions; the proposed controller used about one-fifth of the control effort without actuator saturation. Tracking performance was carried mainly by the kinematic-level sliding surfaces, and wheel-odometry feedback diverged substantially from the true motion under slip, which justified map-based localization in the integrated test, where the mode-adaptive planner and controller guided the robot to the goal region. Future work should validate the controller on a physical platform, resolve the revolute-hitch simulation limitation, and add state estimators or disturbance observers that keep feedback consistent with the actual motion.

REFERENCES

- [1] R. Bernardo, J. M. C. Sousa, and P. J. S. Gonçalves, "Survey on robotic systems for internal logistics," *J. Manuf. Syst.*, vol. 65, pp. 339–350, Oct. 2022, doi: 10.1016/j.jmsy.2022.09.014.
- [2] M. B. Alatise and G. P. Hancke, "A review on challenges of autonomous mobile robot and sensor fusion methods," *IEEE Access*, vol. 8, pp. 39830–39846, 2020, doi: 10.1109/ACCESS.2020.2975643.

-
- [3] A. K. Grover and M. H. Ashraf, "Leveraging autonomous mobile robots for Industry 4.0 warehouses: A multiple case study analysis," *Int. J. Logist. Manag.*, vol. 35, no. 4, pp. 1168–1199, 2024, doi: 10.1108/IJLM-09-2022-0362.
 - [4] Risfendra, R. Nursalam, E. Purnama, and Defri, "Implementation of finite state automata for 6-axis robot in the screwing process," *MOTIVECTION: J. Mech. Electr. Ind. Eng.*, vol. 7, no. 2, pp. 189–200, 2025, doi: 10.46574/motivection.v7i2.445.
 - [5] A. Khanpoor, A. K. Khalaji, and S. A. A. Moosavian, "Modeling and control of an underactuated tractor-trailer wheeled mobile robot," *Robotica*, vol. 35, no. 12, pp. 2297–2318, Dec. 2017, doi: 10.1017/S0263574716000886.
 - [6] D. Wang and C. B. Low, "Modeling and analysis of skidding and slipping in wheeled mobile robots: Control design perspective," *IEEE Trans. Robot.*, vol. 24, no. 3, pp. 676–687, Jun. 2008, doi: 10.1109/TRO.2008.921563.
 - [7] J. Wei and B. Zhu, "Model predictive control for trajectory-tracking and formation of wheeled mobile robots," *Neural Comput. Appl.*, vol. 34, no. 19, pp. 16351–16365, Oct. 2022, doi: 10.1007/s00521-022-07195-4.
 - [8] E. Kayacan, H. Ramon, and W. Saeys, "Robust trajectory tracking error model-based predictive control for unmanned ground vehicles," *IEEE/ASME Trans. Mechatronics*, vol. 21, no. 2, pp. 806–814, Apr. 2016, doi: 10.1109/TMECH.2015.2492984.
 - [9] N.-B. Hoang and H.-J. Kang, "Neural network-based adaptive tracking control of mobile robots in the presence of wheel slip and external disturbance force," *Neurocomputing*, vol. 188, pp. 12–22, May 2016, doi: 10.1016/j.neucom.2015.02.101.
 - [10] T. A. Mai, T. S. Dang, D. T. Duong, V. C. Le, and S. Banerjee, "A combined backstepping and adaptive fuzzy PID approach for trajectory tracking of autonomous mobile robots," *J. Braz. Soc. Mech. Sci. Eng.*, vol. 43, no. 3, Art. no. 156, Mar. 2021, doi: 10.1007/s40430-020-02767-8.
 - [11] P. Angraeni, M. N. Rizal, H. Khoirunnisa, and T. Kristian, "Experimental of quadcopter trajectory tracking control based ROS," *MOTIVECTION: J. Mech. Electr. Ind. Eng.*, vol. 5, no. 2, pp. 295–302, 2023, doi: 10.46574/motivection.v5i2.232.
 - [12] X. Gao, L. Yan, and C. Gerada, "Modeling and analysis in trajectory tracking control for wheeled mobile robots with wheel skidding and slipping: Disturbance rejection perspective," *Actuators*, vol. 10, no. 9, Art. no. 222, Sep. 2021, doi: 10.3390/act10090222.
 - [13] K. Alipour, A. B. Robat, and B. Tarvirdizadeh, "Dynamics modeling and sliding mode control of tractor-trailer wheeled mobile robots subject to wheels slip," *Mech. Mach. Theory*, vol. 138, pp. 16–37, Aug. 2019, doi: 10.1016/j.mechmachtheory.2019.03.038.
 - [14] M. Cui, H. Liu, W. Liu, and Y. Qin, "An adaptive unscented Kalman filter-based controller for simultaneous obstacle avoidance and tracking of wheeled mobile robots with unknown slipping parameters," *J. Intell. Robot. Syst.*, vol. 92, no. 3–4, pp. 489–504, Dec. 2018, doi: 10.1007/s10846-017-0761-9.
 - [15] V. Utkin, A. Poznyak, Y. Orlov, and A. Polyakov, "Conventional and high order sliding mode control," *J. Franklin Inst.*, vol. 357, no. 15, pp. 10244–10261, Oct. 2020, doi: 10.1016/j.jfranklin.2020.06.018.
 - [16] K. Liu, H. Gao, H. Ji, and Z. Hao, "Adaptive sliding mode based disturbance attenuation tracking control for wheeled mobile robots," *Int. J. Control Autom. Syst.*, vol. 18, no. 5, pp. 1288–1298, May 2020, doi: 10.1007/s12555-019-0262-7.
 - [17] B. Jiang, J. Li, and S. Yang, "An improved sliding mode approach for trajectory following control of nonholonomic mobile AGV," *Sci. Rep.*, vol. 12, no. 1, Art. no. 17763, Oct. 2022, doi: 10.1038/s41598-022-22697-w.
 - [18] E. A. Martínez, H. Ríos, and M. Mera, "Robust tracking control design for unicycle mobile robots with input saturation," *Control Eng. Pract.*, vol. 107, Art. no. 104676, Feb. 2021, doi: 10.1016/j.conengprac.2020.104676.
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- [19] H. Van Doan and N. T.-T. Vu, "Adaptive sliding mode control for uncertain wheel mobile robot," *Int. J. Electr. Comput. Eng.*, vol. 13, no. 4, pp. 3939–3947, Aug. 2023, doi: 10.11591/ijece.v13i4.pp3939-3947.
 - [20] K. J. Åström and C. Canudas-de-Wit, "Revisiting the LuGre friction model," *IEEE Control Syst. Mag.*, vol. 28, no. 6, pp. 101–114, Dec. 2008, doi: 10.1109/MCS.2008.929425.
 - [21] A. Mashayekhi, S. Behbahani, A. Nahvi, M. Keshmiri, and M. Shakeri, "Analytical describing function of LuGre friction model," *Int. J. Intell. Robot. Appl.*, vol. 6, no. 3, pp. 437–448, Sep. 2022, doi: 10.1007/s41315-021-00220-0.
 - [22] O. N. Şahin and M. İ. C. Dede, "Investigation of longitudinal friction characteristics of an omnidirectional wheel via LuGre model," *Robotica*, vol. 39, no. 9, pp. 1654–1673, Sep. 2021, doi: 10.1017/S0263574720001423.
 - [23] X. Zhang, D. Qin, S. Wang, Y. Xie, H. Li, and S. Li, "Position/attitude cascade regulation of nonholonomic four-wheeled mobile robot via double-loop sliding-mode control mechanism," *Entropy*, vol. 25, no. 1, Art. no. 27, 2023, doi: 10.3390/e25010027.
 - [24] B. K. Patle, G. Babu L, A. Pandey, D. R. K. Parhi, and A. Jagadeesh, "A review: On path planning strategies for navigation of mobile robot," *Def. Technol.*, vol. 15, no. 4, pp. 582–606, Aug. 2019, doi: 10.1016/j.dt.2019.04.011.

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