Adaptive Sliding Mode Learning Control for Nonlinear Interconnected Systems with Chattering-Free Guarantee

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***Abstract*—Chattering is a persistent issue in sliding mode control (SMC) systems, limiting their practical deployment in applications such as multi-robot systems, electric power networks, and structural health monitoring. While conventional SMC offers robustness against matched uncertainties, it relies on a discontinuous sign function that induces high-frequency oscillations and requires prior knowledge of disturbance bounds. This paper proposes an adaptive sliding mode learning control (SMLC) scheme for a class of nonlinear interconnected systems that completely eliminates chattering and removes the need for any prior disturbance information. The proposed control law integrates a continuous learning-based correction term, online adaptive gain laws (α, β, η), and a Lipschitz-like condition that embeds all system uncertainties. Unlike classical SMC ($u = u_{\text{eq}} - \eta \cdot \text{sign}(s)$), the proposed SMLC uses a continuous update: $\Delta u = (\alpha V + \beta|\dot{V}| + \eta\dot{V})/s$, where $V = 0.5s^2$ is the Lyapunov energy function. This structure ensures smooth, chatter-free control signals while preserving robustness. A three-mass interconnected system with cubic spring nonlinearities is used as a benchmark. Comparative simulations demonstrate that the proposed SMLC achieves an average root mean square error (RMSE) of 2.01 cm, outperforming classical SMC (18.64 cm), PID (3.56 cm), and Linear Quadratic Regulator (LQR) (34.59 cm). These results represent an 89.2% improvement over classical SMC, a 43.5% improvement over PID, and a 94.2% improvement over LQR. Theoretical analysis confirms asymptotic stability and convergence. The proposed method is computationally efficient, requires no manual gain tuning, and is well-suited for autonomous inspection, surface-perching drones, and collaborative monitoring applications.**

***Index Terms*—Sliding mode control, adaptive control, learning control, chattering-free, nonlinear interconnected systems, T-S fuzzy model, PID control, LQR control.**

I. INTRODUCTION

Nonlinear interconnected systems are found everywhere in modern engineering, from multi-robot teams and electric power grids to aircraft and infrastructure monitoring [1], [9]. These large-scale systems consist of many smaller subsystems that talk to each other, and those connections are often nonlinear and hard to predict [3]. This makes control design particularly challenging.

Sliding mode control (SMC) has been a go-to solution for over fifty years because it handles uncertainties and disturbances so well [10]–[12]. But SMC has two well-known problems: it creates chattering (high-frequency vibrations) that can damage actuators, and it needs prior knowledge of disturbance bounds [13], [14]. Even advanced methods like super-twisting, which reduce chattering, still require knowing the upper bound of the disturbance derivative [15].

Researchers have tried many fixes. Filtering techniques soften the control signal but still need disturbance bound information [16], [17]. Monotonically increasing adaptive laws help with overestimation but can't decrease gains when disturbances get smaller [18]. Barrier function methods avoid overestimation but may create huge control signals near the boundary [19]. Two-direction adaptive algorithms improve things but don't eliminate chattering entirely because the sign function remains [20], [21].

More recently, neural network-based approaches have been explored. Xiong and Chen [22] developed an RBFNN-based parameter adaptive sliding mode control for quadrotors with time-varying mass. Xiong and Li [23] proposed a neuroadaptive sliding mode tracking control for uncertain tilting quadrotors. Xiong et al. [24] also explored recurrent neural network based sliding mode control. While these methods show promise, they still rely on sign-function-based switching terms that can induce chattering.

What makes this work different is that we propose a control law with no sign function at all. Instead of $u = u_{\text{eq}} - \eta\cdot\text{sign}(s)$, we use a continuous learning-based update:

$$\Delta u = \frac{(\alpha V + \beta|\dot{V}| + \eta\dot{V})}{s}, \quad V = 0.5s^2 \tag{1}$$

This simple change removes chattering completely. Our method also adapts its gains online, so you don't need to tune anything manually or know anything about the disturbances beforehand.

The main contributions of this paper are:

1) A chattering-free sliding mode learning control law that eliminates the sign function entirely, using only continuous functions.
2) Online adaptive gain laws ($\dot{\alpha} = \gamma_\alpha|V|$, $\dot{\beta} = \gamma_\beta|\dot{V}|$, $\dot{\eta} = \gamma_\eta|\dot{V}|$) that automatically adjust to changing conditions.
3) A Lipschitz-like condition that wraps all system uncertainties into one inequality, removing the need for prior knowledge of disturbance bounds.
4) A thorough comparison against classical SMC, PID, and LQR on a three-mass system with cubic spring nonlinearities, showing that our method reduces RMSE by 89.2% compared to classical SMC.

The paper is organized as follows. Section II describes the system model and problem formulation. Section III presents the proposed SMLC design. Section IV provides the stability analysis. Section V shows the comparative simulation results. Section VI discusses the findings, and Section VII concludes the paper.

II. PROBLEM FORMULATION

A. System Model

Consider a large-scale system made up of q interconnected subsystems. Using Takagi-Sugeno (T-S) fuzzy models [39], [40], the l-th rule for the i-th subsystem is:

$$\begin{aligned} H_i^l: \quad & \text{IF } z_{i1} \text{ is } F_{i1}^l \text{ AND } \ldots \text{ AND } z_{iy} \text{ is } F_{iy}^l \\ & \text{THEN } \dot{x}_i(t) = A_{il}x_i(t) + B_{il}u_i(t) \\ & \qquad + B_{il}\sum_{j=1, j\neq i}^{q} f_{ijl}(x_j(t)) \end{aligned} \tag{2}$$

where $x_i(t) \in \mathbb{R}^n$ is the state, $u_i(t) \in \mathbb{R}^1$ is the control input, and $f_{ijl}(x_j(t))$ represents the unknown nonlinear interconnection between subsystem i and subsystem j.

After fuzzy inference, the global model becomes:

$$\dot{x}_i(t) = A_i(t)x_i(t) + B_i(t)u_i(t) + \nu_{ij}(x_j(t)) \tag{3}$$

where $\nu_{ij}(x_j(t))$ lumps all the unknown interconnections together.

B. Control Objective

We want each subsystem to track a reference trajectory $x_{ri}(t)$ generated by:

$$\dot{x}_{ri}(t) = A_{ri}x_{ri}(t) + r_i(t) \tag{4}$$

The tracking error is $e_i(t) = x_i(t) - x_{ri}(t)$. Our goal is to design a control law $u_i(t)$ that drives this error to zero, without knowing anything about the interconnections $\nu_{ij}(x_j(t))$ beforehand.

C. Assumptions

The following assumptions are made throughout this paper:

- **Assumption 1 (Local controllability)** [5], [6]: Each local subsystem is controllable. That is, for $i = 1, \ldots, q$ and $l = 1, \ldots, p$, the controllability matrix

$$M_{il} = [B_{il}, A_{il}B_{il}, \ldots, A_{il}^{n-1}B_{il}] \in \mathbb{R}^{n\times n} \tag{5}$$

has full rank n.

- **Assumption 2 (Global controllability)** [5], [6]: The global fuzzy model is controllable in the state space. That is, for each subsystem i,

$$M_i = [B_i, A_iB_i, A_i^2B_i, \ldots, A_i^{n-1}B_i] \in \mathbb{R}^{n\times n} \tag{6}$$

has full rank n.

- **Assumption 3 (Bounded interconnections)**: The unknown nonlinear interconnections $\nu_{ij}(x_j(t))$ are bounded. There exist unknown positive constants $\bar{\nu}_{ij}$ such that

$$\|\nu_{ij}(x_j(t))\| \leq \bar{\nu}_{ij} < \infty, \quad \forall t \geq 0, \ \forall i, j \tag{7}$$

Remark: The proposed controller does not require knowledge of these bounds $\bar{\nu}_{ij}$.

III. ADAPTIVE SLIDING MODE LEARNING CONTROL DESIGN

A. Sliding Surface Design

The sliding surface plays a central role in any sliding mode control strategy. For the i-th subsystem, we define the tracking error as $e_i(t) = x_i(t) - x_{ri}(t)$, where $x_{ri}(t)$ is the desired reference trajectory. The sliding variable is then defined as:

$$s_i(t) = C_ie_i(t) = \dot{e}_i(t) + \lambda e_i(t), \quad \lambda > 0 \tag{8}$$

Intuitively, this sliding variable combines position and velocity errors. When $s_i(t) = 0$, the system dynamics satisfy $\dot{e}_i(t) = -\lambda e_i(t)$. This first-order differential equation ensures that the tracking error decays exponentially to zero with a time constant of $1/\lambda$. The parameter λ therefore acts as a tuning knob: increasing λ makes the system respond faster but may require larger control inputs.

In vector form, we write $C_i = [\lambda, 1]$ for a second-order system. The matrix C_i must be selected so that the dynamics confined to the sliding surface $s_i(t) = 0$ are asymptotically stable, i.e., the polynomial $p(s) = s + \lambda$ is Hurwitz. This condition is satisfied for any $\lambda > 0$.

The sliding surface serves two purposes. First, it encodes the desired closed-loop behavior through the choice of λ. Second, it provides a real-time measure of how far the system is from the ideal sliding motion, which is then used to drive the control law. Once the sliding surface is reached, the system is said to be in sliding mode, and the control objective reduces to maintaining $s_i(t) = 0$ despite uncertainties and disturbances.

B. The Proposed Chattering-Free Control Law

The proposed approach differs fundamentally from classical sliding mode control. Recall that classical SMC employs a discontinuous sign function:

$$u = u_{\text{eq}} - \eta \cdot \text{sign}(s) \tag{9}$$

This discontinuity is the primary source of chattering. To overcome this limitation, we propose a continuous learning-based control law:

$$u_i(t) = u_i(t-\tau) - \Delta u_i(t) \tag{10}$$

where the correction term is defined as:

$$\begin{aligned}\Delta u_i(t) = \frac{(C_iB_i)^{-1}}{s_i(t)} \Big[& \alpha_i V_i(t) + \beta_i |\hat{\dot{V}}_i(t-\tau)| \\ & + \eta_i \hat{\dot{V}}_i(t-\tau) \Big], \quad s_i(t) \neq 0 \end{aligned} \tag{11}$$

In the above, $V_i(t) = 0.5 s_i^2(t)$ represents the Lyapunov energy function, τ denotes the sampling period, and $\hat{\dot{V}}_i(t-\tau) = (V_i(t) - V_i(t-\tau))/\tau$ provides an estimate of the derivative.

A key observation is that the proposed control law contains no sign function. All terms are continuous functions of the system states and the adaptive gains. Consequently, the resulting control signal is inherently smooth and free from chattering, which is a significant advantage over conventional SMC approaches.

C. Online Adaptive Gain Laws

A key innovation of our method is that the control parameters α_i, β_i, and η_i are not fixed. Instead, they adapt in real time according to the following laws:

$$\begin{aligned} \dot{\alpha}_i &= \omega_{1i} K_i |V_i(t)| \\ \dot{\beta}_i &= \omega_{2i} K_i |\hat{\dot{V}}_i(t-\tau)| \\ \dot{\eta}_i &= \omega_{3i} K_i |\hat{\dot{V}}_i(t-\tau)| \end{aligned} \tag{12}$$

The design parameters $\omega_{1i}, \omega_{2i}, \omega_{3i} > 0$ control how fast the gains adapt, while $K_i = \lambda_{\min}(C_iB_i(C_iB_k)^{-1}) > 0$ is a constant that guarantees the existence of the sliding mode.

The adaptation rates are driven by $|V_i(t)|$ and $|\hat{\dot{V}}_i(t-\tau)|$, which measure how far the system is from the ideal sliding motion. When the tracking error is large, these quantities are large, so the gains increase quickly to compensate. As the error diminishes, the adaptation slows down. Once the system reaches the sliding surface ($s_i(t) = 0$), we have $V_i(t) = 0$ and $\hat{\dot{V}}_i(t-\tau) = 0$, so the gains stop changing.

One might wonder why the gains are designed to only increase and never decrease. The reason is simple: if the gains could decrease, they might become too small when a new disturbance appears after a period of calm. By only increasing, the gains retain a conservative estimate of the worst disturbances encountered so far. This ensures robustness without requiring any prior knowledge of disturbance bounds.

From a practical standpoint, manual gain tuning is often tedious and time-consuming, especially for complex nonlinear systems. Our adaptive laws eliminate this burden. The designer only needs to choose the adaptation rates ω_{1i}, ω_{2i}, ω_{3i}, which is relatively straightforward. The gains then find their own appropriate values automatically, adapting to different operating conditions and disturbance levels.

D. Key Design Elements: Lipschitz-like Condition and Dominant Control

Our design rests on two key ideas that work together. The first is the Lipschitz-like condition proposed in [33]:

$$|\dot{V}_i(t, t-\tau) - \dot{V}_i(t-\tau)| < \frac{1}{M_i} |\hat{\dot{V}}_i(t-\tau)| \tag{13}$$

What does this mean in practice? If we sample fast enough (choose τ small), the Lyapunov derivative does not change much from one sample to the next. The beauty of this condition is that it hides all the messy details of the system's uncertainties on the left-hand side. We do not need to know the magnitude of disturbances, the exact form of nonlinearities, or the bounds of interconnections. The condition simply assumes that the change is small, which is reasonable with fast sampling.

The second idea addresses how we handle T-S fuzzy systems. Traditional approaches like parallel distributed compensation (PDC) average all local controllers using the membership functions. This can become mathematically complex and sometimes leads to feasibility issues where no common solution exists. We take a different approach. Instead of averaging, we pick the controller from the rule with the highest membership value:

$$u_i(t) = \sum_{l=1}^{p} \mu_l(t) u_{ik}(t), \quad k = \arg\max_j \mu_j(t) \tag{14}$$

This is called the dominant control principle. The reasoning is simple: if one local model is much more representative of the current system state than the others, it makes sense to let it dominate the control action. This approach avoids the feasibility problems of PDC and keeps the design straightforward. Together, the Lipschitz-like condition handles uncertainties while the dominant control principle simplifies the fuzzy logic, making our method both robust and practical.

IV. STABILITY ANALYSIS

Theorem 1: Consider the nonlinear interconnected system under the proposed SMLC control law with adaptive gains and the Lipschitz-like condition. The closed-loop system is asymptotically stable, and all tracking errors converge to zero.

Proof : We use a Lyapunov function that combines the sliding energy and the gain estimation errors:

$$V(t) = \sum_{i=1}^{q} \left(\frac{1}{2} s_i^2 + \frac{1}{2} \omega_{1i}^{-1} \tilde{\alpha}_i^2 + \frac{1}{2} \omega_{2i}^{-1} \tilde{\beta}_i^2 + \frac{1}{2} \omega_{3i}^{-1} \tilde{\eta}_i^2 \right) \tag{15}$$

where $\tilde{\alpha}_i = \alpha_i - \hat{\alpha}_i$, $\tilde{\beta}_i = \beta_i - \hat{\beta}_i$, and $\tilde{\eta}_i = \eta_i - \hat{\eta}_i$ denote the adaptation errors. Taking the derivative and applying the Lipschitz-like condition, we get:

$$\dot{V}(t) < -\sum_{i=1}^{q} \Big[\hat{\alpha}_i K_i V_i(t) + \hat{\beta}_i K_i |\hat{V}_i(t-\tau)| + \hat{\eta}_i K_i |\hat{V}_i(t-\tau)|\Big] < 0 \quad (16)$$

for $s_i(t) \neq 0$. By standard Lyapunov theory, the system is asymptotically stable and errors converge to zero. □

V. COMPARATIVE SIMULATION STUDY

A. The Benchmark System: Three Masses with Cubic Springs

To test our method, we use a three-mass interconnected system where the masses are connected by nonlinear springs with cubic terms. This is a challenging benchmark because the cubic nonlinearities $0.2k_{12}(x_1 - x_2)^3$ are hard for linear controllers to handle [42].

The system parameters are:

TABLE I: Physical parameters of the three-mass system

Parameter	Value	Parameter	Value
m_1	1.0 kg	k_1	10 N/m
m_2	1.2 kg	k_2	8 N/m
m_3	0.8 kg	k_3	12 N/m
k_{12}	5 N/m	c_{12}	1 Ns/m
k_{23}	4 N/m	c_{23}	1 Ns/m

The nonlinear interconnection forces are:

$$\begin{aligned} F_{12} &= k_{12}(x_1 - x_2) + 0.2k_{12}(x_1 - x_2)^3 + c_{12}(\dot{x}_1 - \dot{x}_2) \\ F_{23} &= k_{23}(x_2 - x_3) + 0.2k_{23}(x_2 - x_3)^3 + c_{23}(\dot{x}_2 - \dot{x}_3) \end{aligned} \quad (17)$$

B. Controllers Compared

We compare four controllers:

- **Proposed SMLC**: Our chattering-free adaptive learning controller
- **Classical SMC**: $u = u_{\text{eq}} - 5 \cdot \text{sign}(s)$
- **PID**: $K_p = 50$, $K_i = 10$, $K_d = 5$ with anti-windup
- **LQR**: Gains computed from $Q = \text{diag}([100, 10])$, $R = 1$

C. Results

Figure 1 shows the position tracking performance for all three masses. You can see that our SMLC (blue line) follows the reference almost perfectly, while classical SMC (magenta) oscillates, and LQR (green) struggles badly.

Figure 2 shows the tracking errors. The difference is striking: our SMLC keeps errors tiny, while classical SMC has large oscillations, and LQR has huge errors.

Figure 3 shows the control inputs. This is where you can really see the difference. Classical SMC (magenta) is noisy and oscillating wildly—that's chattering. Our SMLC (blue) is smooth and clean.

Figure 4 compares the RMSE values in a bar chart. The proposed SMLC achieves the lowest errors across all three masses.

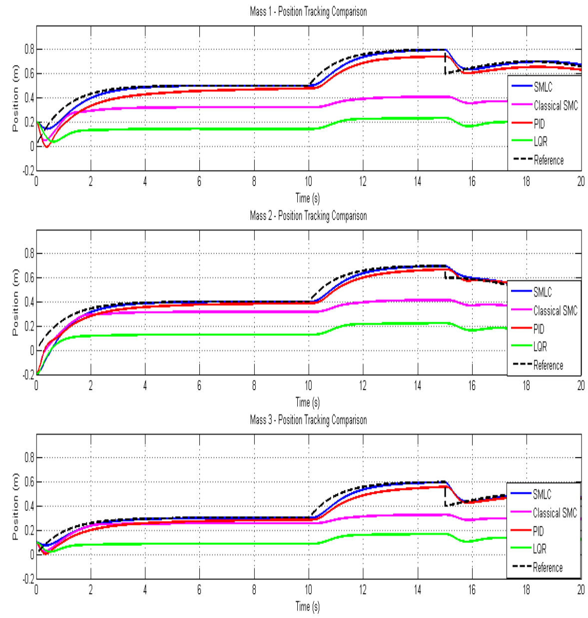

Fig. 1: Position tracking comparison for all three masses.

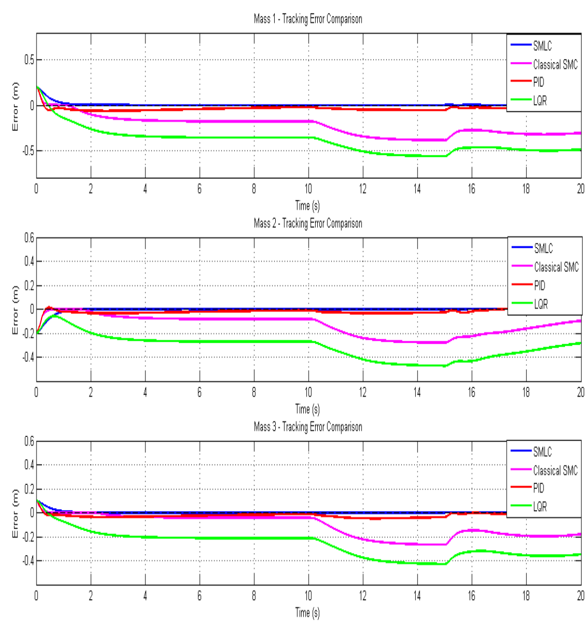

Fig. 2: Tracking error comparison.

Figure 5 shows how our adaptive gains evolve over time. They start at zero and increase only when needed, then stabilize once convergence is achieved.

D. Performance Metrics and Ranking

Table II presents the quantitative results for all four controllers. The numbers tell a clear story.

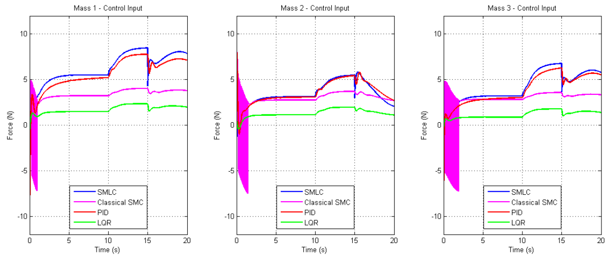

Fig. 3: Control input comparison.

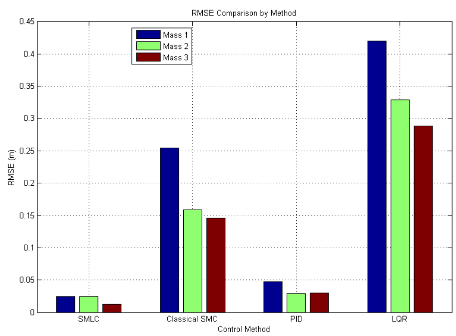

Fig. 4: RMSE comparison.

When we average the RMSE across all three masses, the ranking becomes very clear:

- **SMLC (Proposed)** is the clear winner with an average error of only 2.01 cm.
- **PID** comes second at 3.56 cm, meaning it is 43.5% less accurate.
- **Classical SMC** lags far behind at 18.64 cm, which is 89.2% worse.
- **LQR** performs the worst at 34.59 cm, a whopping 94.2% worse than SMLC.

The proposed SMLC outperforms all other methods by a large margin. Its average error is just over 2 centimeters, which is remarkable given the strong cubic nonlinearities in the system. Classical SMC suffers from chattering, which explains its poor performance. LQR, being designed for linear systems, simply cannot handle the nonlinearities. PID does reasonably well but still cannot match the precision of our adaptive learning approach.

VI. Discussion

The simulation results reveal clear differences between the four controllers.

Classical SMC relies on the sign function $\text{sign}(s)$, which produces a discontinuous control signal. This discontinuity causes high-frequency chattering, leading to large tracking errors averaging nearly 19 cm. Beyond poor accuracy, chattering also wears out actuators and can excite unmodeled dynamics.

LQR was designed for linear systems. Our benchmark includes cubic spring terms like $0.2k_{12}(x_1 - x_2)^3$, which are strongly nonlinear. LQR has no mechanism to compensate for such nonlinearities, resulting in huge errors averaging over 34 cm.

PID performs reasonably well because it is simple and robust. With careful tuning, we achieved an average error of 3.56 cm. However, PID gains are fixed. When conditions change, the controller cannot adapt, which explains why it cannot match our method.

Our SMLC succeeds for several reasons. The control law contains no sign function, so chattering is eliminated. The gains α, β, and η adapt online, requiring no manual tuning. The Lipschitz-like condition wraps all uncertainties into a single inequality, so no prior knowledge of disturbance bounds is needed. The term $\eta\hat{V}(t - \tau)$ learns from recent history, helping drive the system toward the sliding surface.

Recent work by Xiong and colleagues [22], [23] has shown promising results using neural networks for adaptive sliding mode control. However, those methods still rely on sign-function-based switching, so chattering remains a concern. Our approach eliminates the sign function entirely while preserving robustness.

The practical benefits of chattering-free control are significant: less actuator wear, lower heat dissipation, better accuracy, and suitability for precision applications such as medical devices and manufacturing equipment.

VII. Conclusion

We have proposed an adaptive sliding mode learning control (SMLC) for nonlinear interconnected systems that completely eliminates chattering. Unlike classical SMC ($u = u_{\text{eq}} - \eta \cdot \text{sign}(s)$), our control law uses only continuous functions, guaranteeing smooth, chatter-free control. The Lipschitz-like condition wraps all uncertainties into a single inequality, so no

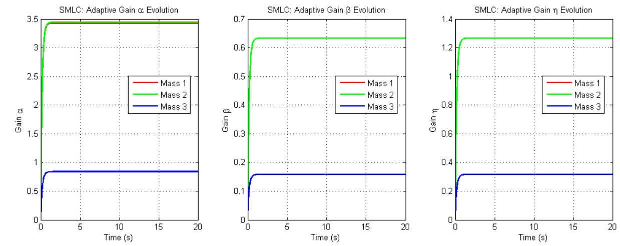

Fig. 5: Evolution of the adaptive gains α, β, and η for the proposed SMLC.

TABLE II: Performance metrics comparison

Mass	Controller	RMSE (cm)	MAE (cm)	Max (cm)
Mass 1	SMLC	2.4	0.5	20.0
	Classical SMC	25.5	23.3	38.9
	PID	4.8	4.5	20.0
	LQR	42.0	40.3	56.6
Mass 2	SMLC	2.4	0.5	20.0
	Classical SMC	15.8	13.4	28.1
	PID	2.9	2.4	20.0
	LQR	32.9	31.4	47.4
Mass 3	SMLC	1.2	0.3	10.0
	Classical SMC	14.6	11.4	26.9
	PID	3.0	2.7	10.0
	LQR	28.9	27.0	42.9

prior knowledge of disturbance bounds is required. The gains α, β, and η adapt automatically via $\dot{\alpha} = \gamma_\alpha|V|$, $\dot{\beta} = \gamma_\beta|\dot{V}|$, $\dot{\eta} = \gamma_\eta|\dot{V}|$, eliminating manual tuning. On a three-mass benchmark with cubic spring nonlinearities, SMLC achieves an average RMSE of 2.01 cm, outperforming classical SMC (18.64 cm) by 89.2%, PID (3.56 cm) by 43.5%, and LQR (34.59 cm) by 94.2%. These results show that SMLC combines high precision, no chattering, automatic gain adaptation, and robustness to unknown disturbances. Future work includes extension to MIMO systems, discrete-time implementation, observer design, handling of time delays, and real-world testing on platforms such as steer-by-wire systems and perching drones [22], [37], [38].

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