

A NON-RECURSIVE CONTROL FRAMEWORK FOR AUTONOMOUS VEHICLES WITHOUT DEPENDENCE ON MODEL PARAMETERS AND VELOCITY SENSORS

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Abstract - This paper presents a trajectory tracking control method for autonomous vehicles (AVs) that does not depend on model parameters or velocity sensors, based on a non-recursive control framework. First, the position tracking error of the AVs is defined at a look-ahead reference point. Then, a state observer is designed to estimate the corresponding velocity tracking error, thereby eliminating the dependency of the control system on velocity sensors. Finally, an adaptive controller based on the non-recursive control framework is developed to ensure robust trajectory tracking performance of the AVs under external disturbances. The advantage of the proposed method is that it does not require prior knowledge of the model parameters of the AVs, while being capable of handling uncertainties through a single adaptive parameter. The stability of the method is proven based on Lyapunov theory and is validated through simulation examples in Matlab/Simulink.

Key words - Autonomous vehicles; Velocity-sensorless; Model-parameter-independent; Adaptive control

1. Introduction

The development of automotive technology in recent years has significantly promoted the popularity of autonomous vehicles (AVs) [1]. AVs provide many benefits to users, such as reducing fuel consumption and minimizing traffic accidents. Many modern automotive technologies have been integrated into AVs, including automatic emergency braking systems, hazard warning systems, and sensor systems. However, alongside these technical advances, many challenges have also arisen as automated driving systems increasingly replace humans [2]. Notable issues include ensuring passenger safety and maintaining stable operational performance in diverse environments and terrain conditions.

One of the important problems in AV control is lane changing, in which the vehicle needs to accurately track a curved reference trajectory. Therefore, the main states of interest in control design include the lateral position and the yaw angle of the vehicle. With only a single control input, namely the steering angle, the dynamics of AVs form a single-input-multiple-output (SIMO) system. Therefore, to address actuator limitations during control, many lane-changing control methods have been proposed. In [3], Khan et al. applied the backstepping control technique to transform the SIMO system into two component SISO systems before designing a robust sliding mode controller for AVs. The method of transforming the tracking error at a look-ahead reference point was proposed by Hwang et al. in [4], in which the lateral position error

and the yaw angle error are combined into a single quantity by considering the motion of the AVs at a look-ahead reference point. As a result, the SIMO system is converted into a SISO system without increasing the computational cost of the control system.

When designing control for the lane-changing problem of AVs, the main challenges to be addressed are external disturbances and uncertainties in model parameters. During motion, unpredictable factors such as aerodynamic drag, road friction, etc., are considered adverse disturbances, which degrade trajectory tracking performance if not properly handled. In [5], a Luenberger-type observer was designed with the capability to withstand time-varying lateral disturbances. Observer-based robust control methods were also presented in [4], or based on neural networks to approximate disturbances in [6]. However, a common drawback of these methods is that the inclusion of components such as observers or neural networks increases the computational burden of the system.

Based on the above analysis, this paper proposes a control method for AVs that does not depend on model parameters or velocity sensors in the presence of external disturbances. First, the position tracking error of the AVs is defined at a look-ahead reference point. Next, a state observer (SOB) is designed to estimate the corresponding velocity tracking error, thereby eliminating the dependency of the control system on velocity sensors. Finally, an adaptive controller based on the non-recursive control framework [7] is developed to ensure robust trajectory tracking performance of the AVs under external disturbances. Owing to its clear and compact control structure, the proposed method requires lower computational resources compared to existing complex nonlinear control methods. The main contributions of the paper can be summarized as follows:

- *Model parameter-independent design*: Based on non-recursive control theory, the controller is developed without requiring exact knowledge of the model parameters of the AVs. This approach allows applicability to AVs with various parameter configurations, thereby enhancing practicality and adaptability in real-world implementation.

- *Computational efficiency and low implementation cost*: The proposed method employs a SOB to estimate the velocity tracking error, thereby eliminating the need for

corresponding velocity sensors in practice [8]. In addition, the simple and explicit control structure reduces computational resource requirements compared to other complex nonlinear controllers [6], [9].

2. Lateral Dynamic of AVs

When designing control for the lane-changing problem of AVs, the lateral dynamics are of primary interest; therefore, it can be assumed that the longitudinal velocity of the autonomous vehicle v_x is constant over time. In this case, the vehicle dynamics can be described by the bicycle model, as illustrated in Figure 1.

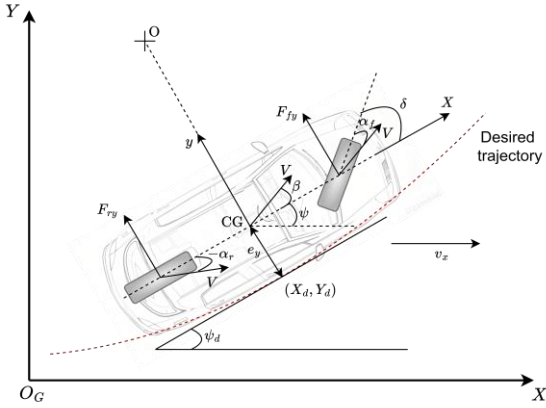


Figure 1. Lateral dynamic model

According to [4], the lateral dynamics of AVs are expressed by the following expression:

$$\begin{aligned}\ddot{y} &= \frac{F_{fy} + F_{ry}}{m} - v_x \dot{\psi} + d_1 \\ \ddot{\psi} &= \frac{1}{J} (l_f F_{fy} - l_r F_{ry}) + d_2\end{aligned}\quad (1)$$

where m is the mass of the AVs, J is the moment of inertia about the Oz axis, l_f and l_r are the distances from the vehicle's center of gravity to the front and rear axles, respectively. y is the lateral position, ψ is the yaw angle, F_{fy} and F_{ry} are the interaction forces between the tires and the road surface, and d_1 and d_2 are dynamic components arising from model parameter uncertainties and external disturbances. In this paper, we adopt the Dugoff tire model, in which F_{fy} and F_{ry} are described as follows:

$$F_{fy} = 2C_f \alpha_f, \quad F_{ry} = 2C_r \alpha_r \quad (2)$$

where C_f and C_r are the cornering stiffness of the front and rear tires, respectively, and α_f and α_r are the slip angles of the front and rear tires, described as follows:

$$\alpha_f = \delta - \frac{\dot{y} + l_f \dot{\psi}}{v_x}, \quad \alpha_r = -\frac{\dot{y} - l_r \dot{\psi}}{v_x} \quad (3)$$

where δ is the steering angle of the front wheels of the AVs. By combining expressions (1), (2), and (3), the lateral dynamics of the AVs are obtained as follows:

$$\begin{aligned}\ddot{y} &= -\frac{2(C_f + C_r)}{mv_x} \dot{y} - \left(\frac{2(C_f l_f - C_r l_r)}{mv_x} + v_x \right) \dot{\psi} + \frac{2C_f}{m} \delta + d_1 \\ \ddot{\psi} &= -\frac{2(C_f l_f^2 + C_r l_r^2)}{Jv_x} \dot{\psi} - \frac{2(C_f l_f - C_r l_r)}{Jv_x} \dot{y} + \frac{2C_f l_f}{J} \delta + d_2\end{aligned}\quad (4)$$

In the trajectory tracking problem, Khan et al. defined the lateral position tracking error as $e_y = y + v_x \int \psi dt - y_d$, while the yaw angle tracking error was defined as $e_\psi = \psi - \psi_d$ in [3]. In this study, we adopt a reference point located at a distance l ahead of the AVs, whereby e_y and e_ψ are combined into $e_1 = e_y + l e_\psi$. The derivative of e_1 is given as follows:

$$\begin{aligned}\dot{e}_1 &= e_2 \\ \dot{e}_2 &= f + g \delta + d\end{aligned}\quad (5)$$

where $g = \frac{2C_f}{m} + \frac{2lC_f l_f}{J}$, $d = d_1 + l d_2 - \ddot{y}_d - l \ddot{\psi}_d$, and

$$\begin{aligned}f &= -\left[\frac{2(C_f + C_r)}{mv_x} + \frac{2l(C_f l_f - C_r l_r)}{Jv_x} \right] \dot{y} \\ &\quad - \left[\frac{2(C_f l_f - C_r l_r)}{mv_x} + \frac{2l(C_f l_f^2 + C_r l_r^2)}{Jv_x} \right] \dot{\psi}\end{aligned}$$

Control objective: The control objective of this work is to drive the tracking error e_1 to converge to the origin without requiring precise knowledge of f and g , while ensuring that the proposed control system is capable of handling d .

The following assumptions are used in this paper:

Assumption 1. There exists a finite positive constant D such that $D > |d|$.

Assumption 2. There exists a finite positive constant $\bar{f}$ such that $f < \bar{f}(1 + |e_1| + |e_2|)$.

3. Velocity-sensorless model-free control

3.1. State observer

In this section, the SOB is designed to estimate e_2 in expression (5) as follows:

$$\begin{aligned}\dot{\hat{e}}_1 &= \hat{e}_2 + \mu_1 \varepsilon (e_1 - \hat{e}_1) \\ \dot{\hat{e}}_2 &= \mu_2 \varepsilon^2 (e_1 - \hat{e}_1)\end{aligned}\quad (6)$$

where $\hat{e}_1$ and $\hat{e}_2$ are the estimates of e_1 and e_2 , ε is a sufficiently large positive constant, and μ_1 and μ_2 are positive constants.

The convergence of the SOB in (6) is stated in the following theorem:

Theorem 1. If system (5) employs SOB (6), $\hat{e}_1$ and $\hat{e}_2$ will converge to e_1 and e_2 , with the corresponding

estimation errors converging to a neighborhood of zero.

Proof. The estimation error of the SOB (6) is defined as $\tilde{e}_1 = e_1 - \hat{e}_1$ and $\tilde{e}_2 = e_2 - \hat{e}_2$. Denote $\boldsymbol{\eta} = [\eta_1, \eta_2]^\top$, where $\eta_1 = \varepsilon^2 \tilde{e}_1$ and $\eta_2 = \varepsilon \tilde{e}_2$. Combining with (5) and (6), we obtain

$$\frac{1}{\varepsilon} \dot{\boldsymbol{\eta}} = \mathbf{A}\boldsymbol{\eta} + \frac{1}{\varepsilon} \mathbf{B}\dot{F} \quad (7)$$

$$\text{where } \mathbf{A} = \begin{bmatrix} -\mu_1 & 1 \\ -\mu_2 & 0 \end{bmatrix}, \quad \mathbf{B} = [0, 1]^\top, \quad F = f + d.$$

Expression (7) indicates that if the matrix $\mathbf{A}$ is Hurwitz, i.e. $\mu_1, \mu_2 > 0$, then the system is stable and convergent. In that case, for any given symmetric positive-definite matrix $\mathbf{Q} = \mathbf{Q}^\top \in \mathbb{R}^{2 \times 2}$ there exists a unique symmetric positive-definite matrix $\mathbf{P} = \mathbf{P}^\top \in \mathbb{R}^{2 \times 2}$ solving the Lyapunov equation $\mathbf{A}^\top \mathbf{P} + \mathbf{P}\mathbf{A} + \mathbf{Q} = 0$. Consider the following Lyapunov function $V_1 = \frac{1}{\varepsilon} \boldsymbol{\eta}^\top \mathbf{P} \boldsymbol{\eta}$, yields

$$\dot{V}_1 = \frac{1}{\varepsilon} \dot{\boldsymbol{\eta}}^\top \mathbf{P} \boldsymbol{\eta} + \frac{1}{\varepsilon} \boldsymbol{\eta}^\top \mathbf{P} \dot{\boldsymbol{\eta}} \quad (8)$$

Through a series of transformations, the following result is obtained:

$$\dot{V}_1 \leq -\boldsymbol{\eta}^\top \mathbf{Q} \boldsymbol{\eta} + \frac{2}{\varepsilon} \|\boldsymbol{\eta}\| \|\mathbf{P}\mathbf{B}\| |\dot{F}| \quad (9)$$

Expression (9) indicates that $\boldsymbol{\eta}$ will converge to $\|\boldsymbol{\eta}\| \leq \frac{2\|\mathbf{P}\mathbf{B}\|\|\dot{F}\|}{\varepsilon \lambda_{\min}(\mathbf{Q})}$. Accordingly, the convergence region of the estimation errors $\tilde{e}_1$ and $\tilde{e}_2$ is determined as follows

$$|\tilde{e}_1| \leq \frac{2\|\mathbf{P}\mathbf{B}\|\|\dot{F}\|}{\varepsilon^3 \lambda_{\min}(\mathbf{Q})}, \quad |\tilde{e}_2| \leq \frac{2\|\mathbf{P}\mathbf{B}\|\|\dot{F}\|}{\varepsilon^2 \lambda_{\min}(\mathbf{Q})} \quad (10)$$

The above result completes the proof of Theorem 1.

Remark 1. The proof of Theorem 1 has shown that as ε increases, the estimation error decreases. However, if ε is chosen too large, it may lead to high inertia of the SOB. In addition, accurately estimating e_2 allows the control system to operate without the need for lateral velocity $\dot{y}$ and yaw rate $\dot{\psi}$, thereby eliminating the requirement for related sensors in real-world implementation.

3.2. Model-free control based on non-recursive control scheme

The error transformation functions are defined as $z_1 = \frac{e_1}{L}$, and $z_2 = \frac{\hat{e}_2}{L^2}$, where L is a time-varying parameter with the update law designed as follows:

$$\dot{L} = \begin{cases} k_0 \mathbf{z}^\top \mathbf{z}, & \text{if } |e_1| > \rho \\ 0, & \text{if } |e_1| \leq \rho \end{cases} \quad (11)$$

where $L(0) = 1$, k_0 is a gain constant, ρ is a sufficiently small positive constant, and $\mathbf{z} = [z_1, z_2]^\top$. The control signal δ is designed as follows:

$$\delta = -k_1 L^2 e_1 - k_2 L \hat{e}_2 \quad (12)$$

where k_1 and k_2 are positive constants. The stability of the model-free controller (12) is stated as follows.

Theorem 2. If system (5) employs the model-free controller (12), then the lateral position tracking error e_y and the yaw angle tracking error e_ψ will converge to a neighborhood of zero.

Proof. Combining with (5) and (12), the following expression is obtained:

$$\dot{\mathbf{z}} = L\mathbf{g}\mathbf{C}\mathbf{z} - \frac{\dot{L}}{L}\mathbf{D}\mathbf{z} + \frac{1}{L^2}\mathbf{f} + \frac{1}{L^2}\mathbf{d} + \frac{1}{L}\mathbf{E}\tilde{e}_2 \quad (13)$$

$$\text{where } \mathbf{C} = \begin{bmatrix} 0 & \frac{1}{g} \\ -k_1 & -k_2 \end{bmatrix}, \quad \mathbf{D} = \begin{bmatrix} 1 & 0 \\ 0 & 2 \end{bmatrix}, \quad \mathbf{f} = \begin{bmatrix} 0 \\ f \end{bmatrix}, \quad \mathbf{d} = \begin{bmatrix} 0 \\ d \end{bmatrix},$$

$\mathbf{E} = \begin{bmatrix} 1, & -\frac{1}{L} \end{bmatrix}^\top$. It can be seen that if $k_1, k_2 > 0$, then the matrix $\mathbf{C}$ is Hurwitz; therefore, the stability of system (13) is guaranteed. In that case, there exists a unique symmetric positive-definite matrix $\mathbf{H} = \mathbf{H}^\top \in \mathbb{R}^{2 \times 2}$ satisfying $\mathbf{C}^\top \mathbf{H} + \mathbf{H}\mathbf{C} + \mathbf{I}_2 = 0$, where $\mathbf{I}_2$ denotes the 2×2 identity matrix. Considering the Lyapunov function $V_2 = \mathbf{z}^\top \mathbf{H} \mathbf{z}$, yields

$$\begin{aligned} \dot{V}_2 &= \dot{\mathbf{z}}^\top \mathbf{H} \mathbf{z} + \mathbf{z}^\top \mathbf{H} \dot{\mathbf{z}} \\ &= -L\mathbf{g}\mathbf{z}^\top \mathbf{z} - \frac{\dot{L}}{L}\mathbf{z}^\top (\mathbf{D}^\top \mathbf{H} + \mathbf{H}\mathbf{D})\mathbf{z} \\ &\quad + \frac{2}{L^2}\mathbf{z}^\top \mathbf{H}(\mathbf{f} + \mathbf{d}) + \frac{2}{L}\tilde{e}_2 \mathbf{z}^\top \mathbf{H} \mathbf{E} \\ &\leq -L\mathbf{g}\mathbf{z}^\top \mathbf{z} + \frac{2}{L^2}\mathbf{z}^\top \mathbf{H}(\mathbf{f} + \mathbf{d}) + \frac{2}{L}\tilde{e}_2 \mathbf{z}^\top \mathbf{H} \mathbf{E} \end{aligned} \quad (14)$$

From Assumption 1, Assumption 2 and Theorem 1, the three terms on the right-hand side of (14) are bounded as follows. Since $\dot{L} \geq 0$ and $L \geq L(0) = 1$ from (11), and $\mathbf{D}^\top \mathbf{H} + \mathbf{H}\mathbf{D} > 0$ for the adopted gains, the term involving $\dot{L}$ is non-positive and is discarded. Using (10) and $\|\mathbf{E}\| = \sqrt{1 + 1/L^2} \leq \sqrt{2}$, $|e_1| \leq L\|\mathbf{z}\|$, $|\hat{e}_2| \leq L^2\|\mathbf{z}\|$ with $|z_1| + |z_2| \leq \sqrt{2}\|\mathbf{z}\|$ for the remaining term, we have:

$$\begin{aligned} \frac{2}{L^2}\mathbf{z}^\top \mathbf{H}(\mathbf{f} + \mathbf{d}) &\leq \frac{2}{L^2}\|\mathbf{H}\|(\|\mathbf{z}\|\bar{D} + \sqrt{2}\bar{f}\|\mathbf{z}\|) \\ \frac{2}{L}\tilde{e}_2 \mathbf{z}^\top \mathbf{H} \mathbf{E} &\leq \frac{4\sqrt{2}}{L} \frac{\|\mathbf{H}\|\|\mathbf{P}\mathbf{B}\|\|\dot{F}\|}{\varepsilon^2 \lambda_{\min}(\mathbf{Q})} \|\mathbf{z}\| \end{aligned}$$

for brevity, denote $\bar{D} = D + \bar{f}$. Through a series of mathematical transformations, the following expression is obtained:

$$\begin{aligned} \dot{V}_2 &\leq -\mathbf{z}^\top \mathbf{z} \left(\frac{Lg - \frac{2}{L^2} \|\mathbf{H}\| \bar{D} - \frac{2\sqrt{2}}{L^2} \|\mathbf{H}\| \bar{f}}{L \|\mathbf{z}\| \varepsilon^2 \lambda_{\min}(\mathbf{Q})} \right) \\ &\leq -\mathbf{z}^\top \mathbf{z} \left(\frac{Lg - \frac{2}{\rho} \|\mathbf{H}\| \bar{D} - \frac{2\sqrt{2}}{L^2} \|\mathbf{H}\| \bar{f}}{\rho \varepsilon^2 \lambda_{\min}(\mathbf{Q})} \right), \end{aligned} \quad (15)$$

if $|e_1| > \rho$

Then, the solution for $\mathbf{z}$ and L is shown to exist uniquely within the time interval $[0, T_1]$. This can be achieved by contradiction. Suppose that $\limsup_{t \rightarrow T_1} \|\mathbf{z}(t)\| = +\infty$, ie. $\limsup_{t \rightarrow T_1} \|\mathbf{z}(t)\| = +\infty$. From the parameter update law in (11), L is monotonically non-decreasing. Thus, there exists a finite time constant $T_b \in (0, T_1)$ such that the following inequality is satisfied:

$$L(T_b) > \frac{1}{g} \left(1 + \frac{2}{\rho} \|\mathbf{H}\| \bar{D} + \frac{2\sqrt{2}}{L^2} \|\mathbf{H}\| \bar{f} + \frac{4\sqrt{2} \|\mathbf{H}\| \|\mathbf{P}\mathbf{B}\| \|\dot{\bar{f}}\|}{\rho \varepsilon^2 \lambda_{\min}(\mathbf{Q})} \right) \quad (15)$$

From (16), the bracket in (15) is greater than one for $L \geq L(T_b)$, hence $\dot{V}_2 \leq -\mathbf{z}^\top \mathbf{z} = -\dot{L}/k_0$. Then, with $t \in (T_b, T_1)$, (15) can be rewritten as $\int_{T_b}^{T_1} \dot{V}_2 dt \leq -\int_{T_b}^{T_1} \frac{1}{k_0} \dot{L} dt$.

We have $V(T_b) \geq V(T_b) - V(T_1) \geq \frac{1}{k_0} (L(T_1) - L(T_b)) = +\infty$,

which leads to a contradiction. Thus L is bounded on $t \in [0, T_1]$. From (15) and (16), when $L \rightarrow L \geq L(T_b)$, $\dot{V}_2 < 0$. Therefore, it is concluded that the lateral position and yaw angle tracking errors of the AVs converge to a neighborhood of zero. The proof of Theorem 2 is thus completed.

Remark 2. The proposed control method features a simple algorithmic structure, making it easy to implement in practice and eliminating the need for model information of the AVs. In the presence of large external disturbances, the adaptive parameter L automatically adjusts to an appropriate value to maintain vehicle stability, thereby enhancing the system's practicality compared to control methods that rely on fixed control parameters.

4. Simulation results

In this section, the simulation results are established based on the nominal model of AVs in [3]: $m = 1500$ kg, $J = 1350$ kgm², $l_f = 1.5$ m, $l_r = 2$ m, $C_f = 55$ kN/rad, $C_r = 120$ kN/rad. In practice, the model parameters are set 10% higher than those of the nominal model, and external disturbances are described using trigonometric functions as follows:

$$\begin{aligned} d_1 &= 0.5 \begin{pmatrix} 0.6 \sin(\pi t) + 0.3 \cos(2.4\pi t) \\ +0.2 \sin(3.6\pi t) \end{pmatrix} \\ d_2 &= 0.8 \begin{pmatrix} 0.8 \sin(1.4\pi t) + 0.1 \cos(1.8\pi t) \\ +0.5 \sin(4.5\pi t) \end{pmatrix} \end{aligned} \quad (16)$$

The control parameters of the proposed method are selected as: $k_0 = 10^4$, $k_1 = 30$, $k_2 = 100$, $\rho = 0.001$. In addition, to evaluate the control performance of the proposed method in comparison with existing AVs control methods, robust sliding mode control (RSMC) [3] and backstepping control using barrier Lyapunov function (BSP-BLF) [4] are reimplemented as benchmarks.

The AVs are required to follow the double lane-change trajectory as described in [3]. The time-varying behavior of the adaptive parameter L and the state estimation error of the SOB are illustrated in Figures 2 and 3. The results show that L varies smoothly without overshooting, while the SOB achieves high estimation performance.

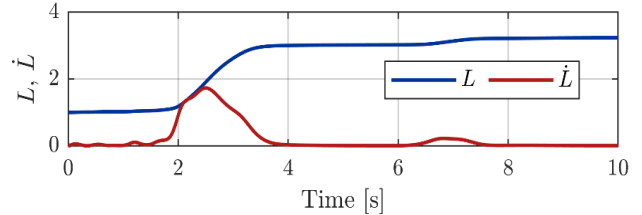


Figure 2. The adaptive parameter of the proposed method

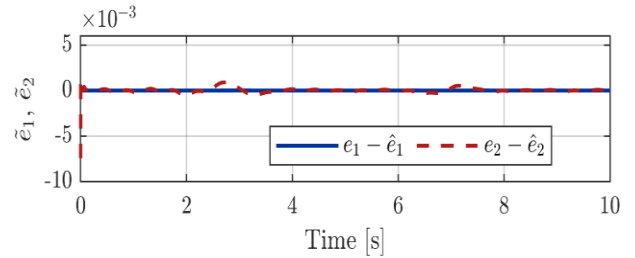


Figure 3. The estimation error of the SOB

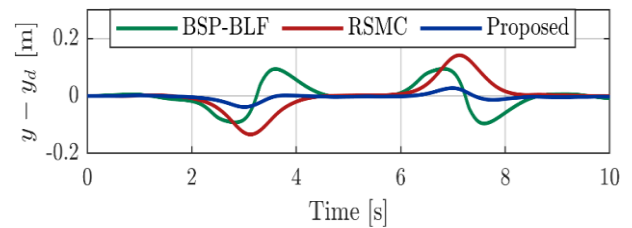


Figure 4. Lateral position tracking error

Compared to RSMC and BSP-BLF, the lateral position and yaw angle tracking errors are presented in Figures 4

and 5, while the steering angle is shown in Figure 6. The results indicate that the proposed method achieves the smallest tracking errors and the smoothest steering angle among the three controllers, whereas BSP-BLF exhibits overshoot and abrupt changes in steering. These results demonstrate that the proposed control method maintains high trajectory tracking performance despite its simple control structure, confirming its practical feasibility

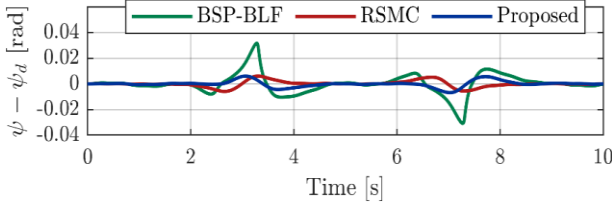


Figure 5. Yaw angle tracking error

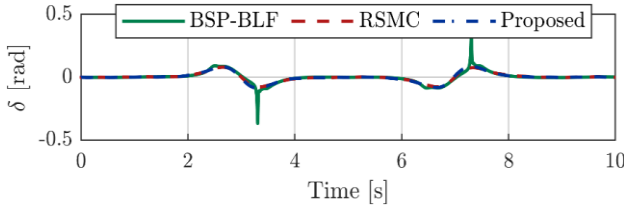


Figure 6. Steering angle

5. Conclusion

In this paper, we proposed a model-free and velocity-sensorless control method for AVs under the influence of external disturbances and model parameter uncertainties. Based on a SOB, the reliance on velocity sensors is eliminated, thereby reducing the cost of real-world implementation. Subsequently, leveraging non-recursive control theory, a model-free controller was developed for AVs, which does not require model information and is capable of effectively handling external disturbances. Simulation results using Matlab/Simulink demonstrated the superior performance of the proposed method compared to other controllers. In the future, we will extend

this approach to other AV structures, such as suspension systems, braking systems, etc.

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