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Original Article

Experimental Study on Navigation Control of Autonomous Vehicles Using A Predictive Control Model

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***Abstract** - The article discusses experimental research on the navigation control of self-driving cars using predictive control. The effectiveness of the solution lies in its ability to steer the vehicle within its lane and avoid collisions. Model Predictive Control (MPC) proves highly effective at speeds of 1 meter per second, ensuring smooth position changes, quick setup, and minimal steering angle deviations. This control approach could enhance the development of autonomous vehicles. The study lays the groundwork for future research and progress in autonomous vehicle navigation control. Recognizing the limitations of the current MPC controller at higher speeds, future studies could focus on integrating additional intelligent and adaptive control algorithms to enhance overall performance in various dynamic scenarios. Experimental validation is crucial for bridging theoretical concepts with real-world applications, providing a solid foundation for implementing MPC control systems in autonomous vehicles.*

***Keywords** - Autonomous vehicles, MPC, Self-driving cars, Navigation control, Predictive control.*

1. Introduction

In recent years, self-driving cars have been researched and produced by many scientists and manufacturers [1]. Autonomous vehicles have made technological breakthroughs for all levels of driving, independent of the driver [2]. Autonomous cars are equipped with driving, control, and monitoring support systems to help control the vehicle and ensure it operates properly. For example, if a driver steers past the desired angle and wants to return the desired value, a system that responds to sensors about the steering angle is needed [3].

During travel, the vehicle aligns itself and actively turns left or right according to road markings, identifying objects on the road and crossing the road to brake and avoid obstacles automatically [4]. Therefore, autonomous vehicle technology is increasingly demanding, with higher requirements for improving control performance and optimizing processes integrated into the design of the control system. The optimization process is subject to increasing factors, such as environmental constraints, weather, safety and energy efficiency, size, and cost [5, 6]. This topic has received much attention. Specifically, many companies operating in the automotive sector are developing control systems that allow vehicle automation at different levels.

A model describing vehicle dynamics has been presented [7]. The authors [8] researched focusing on trajectory and velocity tracking while combining horizontal and vertical control methods mentioned in [9]. Lane-keeping studies are found in [10], collision avoidance [11], trajectory planning and tracking [12], cruise control [13], vehicle platooning, and vehicle clustering [14]. There are currently several collision avoidance solutions in vehicle control applications for autonomous vehicles, addressing challenges such as static or moving obstacle recognition [15], pedestrian detection [16], lane changing [17], lane merging [18], or route planning [19].

In this context, Model Predictive Control (MPC) is a powerful optimization strategy for model-based feedback control of a system. Essentially, the MPC controller runs a set of timely predictions on the system model for different drive strategies. MPC determines the following control action immediately based on optimization. Next, it reinitiates the optimization process to determine the following control input. Current and future control inputs are chosen to minimize the difference between the target set point and the predicted output [20]. The MPC features and capabilities effectively meet requirements and achieve optimization tasks. The primary MPC controller solves Linear Programming (LP) problems, improving the classic PI controller.

Additionally, MPC controllers have the natural ability to handle soft and hard constraints. That means the requirements imposed by operating conditions can be managed and formulated using constraints. However, the MPC controller implementation has challenges, such as high computational load and power consumption, while embedded system applications have resource limitations. This research project makes the following key contributions:

- Successfully designed an MPC controller for navigation control of self-propelled vehicles, focusing on position and steering angle requirements at speeds of 1m/s and 3m/s. The self-vehicle operates under normal conditions and encounters obstacles. However, the MPC controller fails to adjust the vehicle's navigation appropriately when its dynamics change at higher speeds. Thus, there is a need to enhance the autonomous vehicle navigation controller by integrating other intelligent, adaptive controllers in the future.
- Experimental validation confirms the research findings. These results establish a theoretical foundation for implementing MPC control in practical scenarios involving self-propelled vehicles.
- This research paves the way for further exploration and development in the field of autonomous vehicle navigation control. By acknowledging the limitations of the current MPC controller at higher speeds, future research can focus on integrating additional intelligent and adaptive control strategies to enhance the overall performance of self-propelled vehicles in various dynamic environments. The experimental validation serves as a crucial step towards bridging the gap between theoretical concepts and real-world applications, setting a solid foundation for the practical implementation of MPC control systems in autonomous vehicles.

The article is divided into four main parts. Part 1 presents the research motivation and urgency of research to improve the performance of autonomous vehicles. Part 2 builds a kinematic and lateral dynamic model of a self-propelled vehicle with a 2-wheel front axle pulling 02 rear wheels. The following section presents the predictive navigation design for autonomous vehicles based on the autonomous vehicle's lateral dynamics model. Part 4 demonstrates the effectiveness of MPC for autonomous cars in controlling position and steering angle by experiment. Finally, there are conclusions and future research directions to improve the limitations of MPC control.

2. Lateral Dynamics Model of Autonomous Vehicle

The lateral dynamics model of the autonomous vehicle is shown in Figure 1. Figure 1 depicts the dynamic model of a car's motion with an axle, illustrating the primary forces affecting the vehicle.

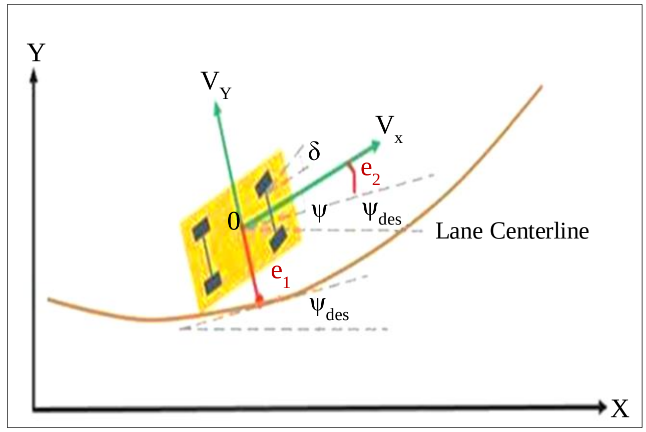

Fig. 1 The lateral dynamics model of the autonomous vehicle

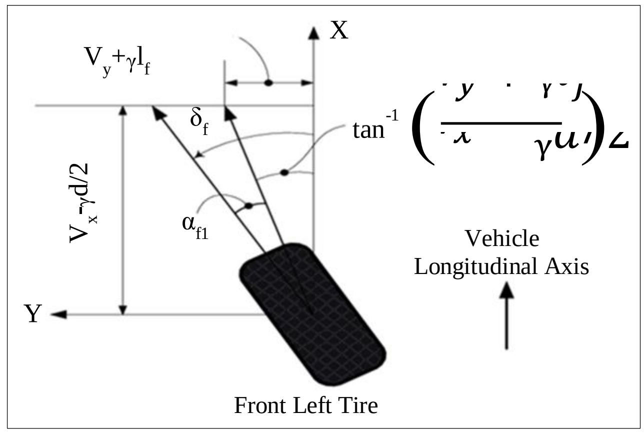

Fig. 2 Tire slip angle

We consider the oxygen coordinate system, representing the vertical and horizontal directions within the vehicle frame. In contrast, the OXY coordinate system denotes the vertical and horizontal directions in the absolute reference system. Here, ψ signifies the rotation angle of the vehicle body in the OXY reference system. By applying Newton's Law principle, the differential equations governing the car's motion in Figure 1 can be derived as follows:

$$\begin{cases} m(\ddot{y} + V_x\dot{\psi}_y) = F_{yf} + F_{yr} \\ I_r\ddot{\psi} = I_f F_{xf} - I_f F_{yr} \end{cases} \tag{1}$$

Where: m and I_r are the vehicle mass and moment of inertia, respectively, and I_r represent the mass and moment of inertia of the vehicle, respectively; F_{yf}, F_{yr} are the forces acting on the wheels in the x and y directions, respectively.

Empirical evidence suggests that the sideways force exerted by a tire is precisely proportional to the angle at which it slips (for modest slip angles). This relationship is known as the "cornering stiffness" of the tire, and it plays a crucial role in the handling and stability of a vehicle during cornering maneuvers.

Manufacturers carefully design tires to optimize this cornering stiffness, balancing factors such as grip, wear, and rolling resistance to achieve the desired performance characteristics. By understanding and manipulating this fundamental property, engineers can fine-tune a vehicle's handling dynamics to provide the best possible combination of grip and control. The tire slip angle is shown in Figure 2.

The slip angle of the tire is written as Equation (2):

$$a_f = \delta - \theta_{vf} \quad (2)$$

Where δ is the front tire steering angle.

The forces acting on the wheels in y directions, respectively or rear and fond tire, are calculated in Equation (3).

$$\begin{cases} F_{yf} = 2C_{af}(\delta - \theta_{vf}) \\ F_{yr} = 2C_{ar}(-\theta_{vf}) \end{cases} \quad (3)$$

Where C_{af}, C_{ar} are cornering stiffness.

And

$$\begin{cases} \tan\theta_{vf} = \frac{V_y + l_f\dot{\psi}}{V_x} \\ \tan\theta_{vr} = \frac{V_y - l_r\dot{\psi}}{V_x} \end{cases} \quad (4)$$

If θ_{vf} &θ_{vr} are small. The θ_{vf} &θ_{vr} are calculated by Equation (5)

$$\begin{cases} \theta_{vf} = \frac{\dot{y} + l_f\dot{\psi}}{V_x} \\ \theta_{vr} = \frac{\dot{y} - l_r\dot{\psi}}{V_x} \end{cases} \quad (5)$$

The forces exerted on the rear and front tires in the vertical direction are computed in Equation (6).

$$\begin{cases} F_{yf} = 2C_{af}(\delta - \frac{\dot{y} + l_f\dot{\psi}}{V_x}) \\ F_{yr} = 2C_{ar}(-\frac{\dot{y} - l_r\dot{\psi}}{V_x}) \end{cases} \quad (6)$$

The dynamic model of the autonomous vehicle is rewritten as follows: Equations (7) & (8):

$$\ddot{y} + V_x\dot{\psi} = \frac{2C_{af}\delta}{m} - \frac{2C_{af}(\dot{y} + l_f\dot{\psi})}{mV_x} - \frac{2C_{ar}(\frac{\dot{y} - l_r\dot{\psi}}{V_x})}{mV_x} \quad (7)$$

$$\ddot{y} = \frac{l_f}{I_r}(2C_{af}\delta - \left(\frac{2C_{af}(\dot{y} + l_f\dot{\psi})}{V_x}\right) + \frac{l_f}{I_r}\frac{2C_{ar}\delta(\dot{y} + l_r\dot{\psi})}{V_x} \quad (8)$$

Equations (7) and (8) are rewritten as Equations (9) & (10):

$$\ddot{y} = \frac{2C_{af}\delta}{m} - \frac{2(C_{af} + C_{ar})}{mV_x}\dot{y} - (V_x + \frac{2(C_{af}l_f - C_{ar}l_r)}{mV_x})\dot{\psi} \quad (9)$$

$$\ddot{y} = \frac{l_f 2C_{af}\delta}{I_r} - \frac{2(C_{af}\,l_f - C_{ar}l_r)}{I_z V_x}\dot{y} - \frac{2\left(C_{af}\,l_f^2 - C_{ar}l_r^2\right)}{I_z V_x}\dot{\psi} \quad (10)$$

The dynamic state space model of the autonomous vehicle is rewritten as follows in Equation (11).

$$\frac{d}{dt}\begin{Bmatrix} y \\ \dot{y} \\ \psi \\ \dot{\psi} \end{Bmatrix} = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & -\frac{2(C_{\alpha f} + C_{\alpha r})}{mV_x} & 0 & -V_x - \frac{2(C_{\alpha f} + C_{\alpha r})}{mV_x} \\ 0 & 0 & 0 & 1 \\ 0 & -\frac{2\left(C_{\alpha f}l_f + C_{\alpha r}l_r\right)}{I_z V_x} & 0 & -\frac{2\left(C_{\alpha f}l_f^2 + C_{\alpha r}l_r^2\right)}{I_z V_x} \end{bmatrix}\begin{Bmatrix} y \\ \dot{y} \\ \psi \\ \dot{\psi} \end{Bmatrix} + \begin{bmatrix} 0 \\ \frac{2C_{\alpha f}}{m} \\ 0 \\ \frac{2C_{\alpha f}l_f}{I_z} \end{bmatrix}\delta \quad (11)$$

3. Controller Designing A Model Predictive Navigation Controller for Autonomous Vehicles

Linear MPC and dynamic matrix control methods have gone viral these past two decades. Although most real processes are nonlinear, the majority of MPC techniques applied in industrial processes are linear models for one of the following reasons:

- Linear models are quick and easy to deploy compared to nonlinear models.
- Stability and sustainability are still challenges for nonlinear models.

Some nonlinear models and constraint conditions require solving non-convex nonlinear optimization problems, so the solution is very complicated. Therefore, linear MPC control and dynamic matrix control methods are widely used in industrial processes due to their simplicity, stability, and ease of deployment. While nonlinear models are more accurate representations of natural processes, the challenges associated with their implementation often make linear models the preferred choice for many applications. The model prediction controller utilizes object models and input and output noise to predict and approximate the state.

Figure 3 displays the model structure used in the MPC controller. The model prediction controller computes the most favorable control input by minimizing a cost function penalizing departure from the target state trajectory. Subsequently, the anticipated condition is used to dynamically modify the control input dynamically, enabling the controller to follow the intended trajectory precisely. The controller's ability to adapt to system dynamics and disturbances uncertainties is crucial for ensuring robust performance. The

MPC controller can effectively handle variations and disturbances by continuously updating its predictions based on feedback from the actual system behavior, maintaining stability and tracking accuracy. This adaptive capability allows the controller to respond to changing conditions in real-time, making it a versatile and reliable tool for various control applications.

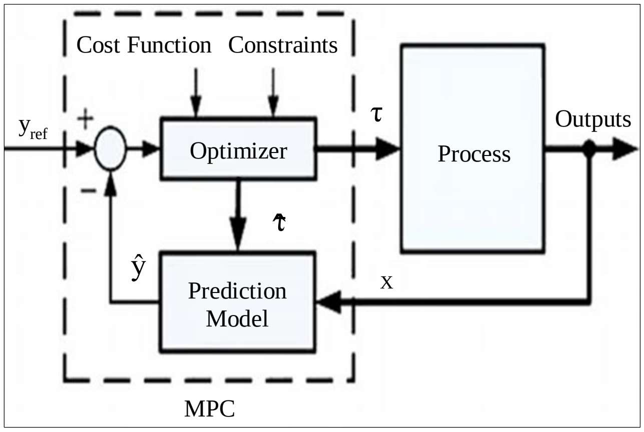

Fig. 3 The MPC controller architecture

3.1. Object Model

The car state model is written as the Equations (12) & (13):

$$x_p(k+1) = A_p x_p(k) + BS_i u_p(k) \tag{12}$$

$$y_p(k) = S_0^{-1} C x_p(k) + S_0^{-1} D S_i u_p(k) \tag{13}$$

Where:
x_p,y_p is the input and output variable of the object.
A_p, B, and C are state space matrices with constant zero delay
S_i is the input diagonal matrix
S_0 is the output diagonal matrix
x_p is the state vector that includes all delay states
u_p is a vector of input variables consisting of manipulated variables, measured noise, and unmeasured input noise
y_p is a vector of output variables.

State model Equations (7) and (8) do not include input and output noise. Thus, the car state model is rewritten as the Equations (14) & (15):

$$x_p(k+1) = A_p x_p(k) + B_{pu}(k) + B_{pv}(k) + B_{pd}(k) \tag{14}$$

$$y_p(k) = C_p x_p(ks) D_{pu}(k) + D_{pv}(k) + D_{pd}(k) \tag{15}$$

Where:
$C_p = S_0^{-1} C, B_{pu}, B_{pv}, B_{pd}$ is a parameter of BS_i. $D_{pu}, D_{pv}, D_{pd}$is a parameter of $S_0^{-1} D S_i$.
$(k), v(k), d(k)$ are the measured and unmeasured input noises.

The MPC controller is limited, so $D_{pu} = 0$, means that the MPC controller does most allow direct transmission from any controlled variable to any output of the control object. Matrix A, B, C and D are determined as follows:

$$A = \begin{bmatrix} A_p & B_{pd}C_{id} & 0 & 0 \\ 0 & A_{id} & 0 & 0 \\ 0 & 0 & A_{od} & 0 \\ 0 & 0 & 0 & A_n \end{bmatrix} \tag{16}$$

$$B = \begin{bmatrix} B_{pu} & B_{pv} & B_{pd}D_{id} & 0 & 0 \\ 0 & 0 & B_{id} & 0 & 0 \\ 0 & 0 & 0 & B_{0d} & 0 \\ 0 & 0 & 0 & 0 & B_n \end{bmatrix} \tag{17}$$

$$C = [C_p \quad D_{pd}C_{id} \quad C_{0d}] \begin{bmatrix} C_n \\ 0 \end{bmatrix}; \tag{18}$$

$$D = 0\ D_{pv} \quad D_{pd}D_{id} \quad D_{0d} \begin{bmatrix} D_n \\ 0 \end{bmatrix}; \tag{19}$$

3.2. Input Noise Model

The input noise model is determined by the Equations (20) and (21):

$$x_{id}(k+1) = A_{id} x_{id}(k+1) + B_{id} w_{id}(k+1) \tag{20}$$

$$d(k) = C_{id} x_{id}(k) + D_{id} w_{id}(k) \tag{21}$$

Where:
A_{id}, B_{id}, C_{id} are constant state matrices.
$x_{id}(k)$ is the vector of the measured input noise when $n_{xid} \geq 0$.
d(k) is the vector of input noise $n_d$cannot measure.
w_{id} is the input noise vector whose mean value is 0 when $n_{id} \geq 1$.

3.2.1. Output Noise Model

The Equations determine the output noise model (22) & (23):

$$x_{0d}(k+1) = A_{0d} x_{0d}(k+1) + B_{0d} w_{d0}(k+1) \tag{22}$$

$$y_{0d}(k) = C_{0d} x_{0d}(k) + D_{0d} w_{0d}(k) \tag{23}$$

Where,
$A_{0d}, B_{0d}, C_{0d}, D_{0d}$ are constant state matrices.
$x_{0d}(k)$ is the vector of the measured output noise when $n_{x0d} \geq 0$.
$y_{0d}(k)$ is the vector of the output noise n_yCannot measure.
w_{0d} is the vector of input noise whose mean value is 0, when $n_{0d} \geq 1$.

3.3. Measured Noise Pattern

The measured noise pattern is determined by the Equation (24):

$$x_n(k+1) = A_n x_n(k+1) + B_n w_n(k+1) \quad (24)$$

Where,
A_n, B_n, C_{0d} are constant state matrices.
$x_n(k)$ is the vector of the measured noise when $n_{xn} \geq 0$;
$w_n(k)$is the input noise vector whose mean value is 0, when $n_n \geq 1$.

4. Results of Experiment and Assessment

The experimental model showcased in Figure 4 demonstrates the effectiveness of utilizing the MPC for autonomous vehicle navigation. By employing this advanced control technique, the vehicle is able to make real-time decisions based on predictive models, enhancing its ability to navigate complex environments with precision and efficiency. This innovative approach represents a significant step forward in the development of autonomous driving systems, paving the way for safer and more reliable transportation solutions in the future.

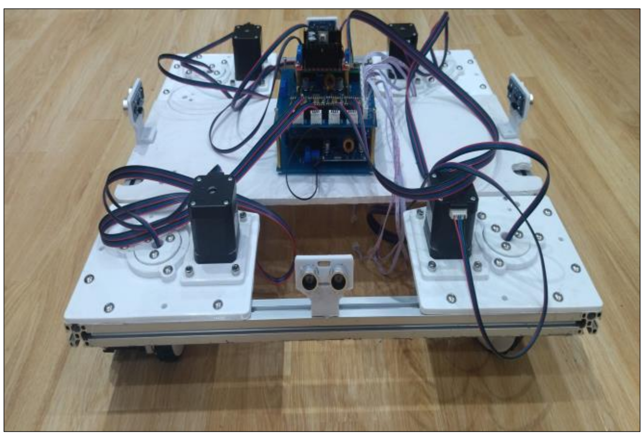

Fig. 4 The experimental model of an autonomous car

The autonomous car's experimental model with multi-directional wheels is deployed and controlled based on the algorithm flow chart in Figure 5. The algorithm ensures precise navigation and obstacle avoidance, making the autonomous car a safe and efficient mode of transportation.

The experimental model showcased in Figure 5 demonstrates the effectiveness of utilizing the MPC for autonomous vehicle navigation. By employing this advanced control technique, the vehicle is able to make real-time decisions based on predictive models, enhancing its ability to navigate complex environments with precision and efficiency.

This innovative approach represents a significant step forward in the development of autonomous driving systems, paving the way for safer and more reliable transportation solutions in the future.

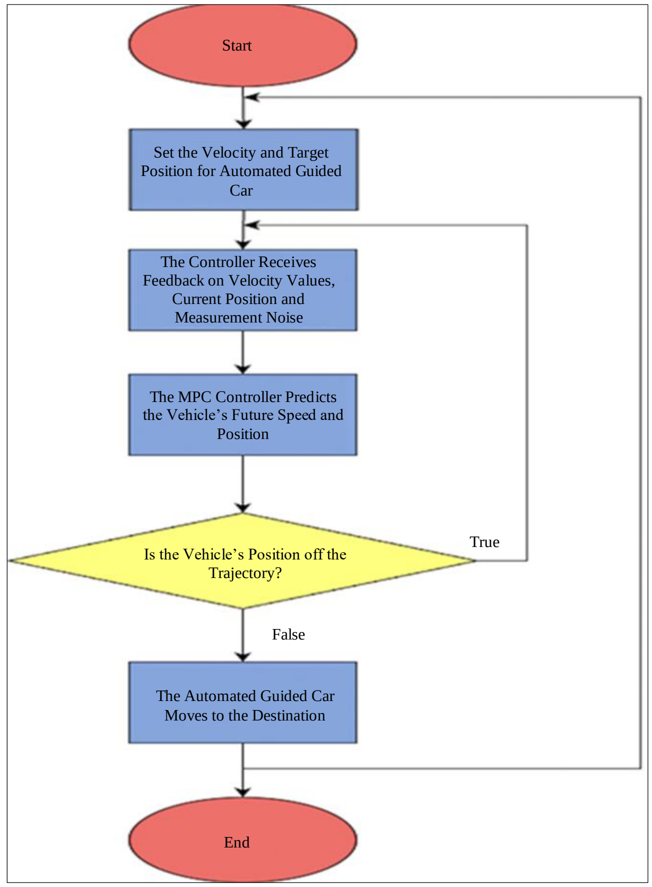

Fig. 5 Flow chart of navigation algorithm for autonomous vehicle model

Table 1. Experimental specifications

Engine Size	42*42*47mm (H*W*H)
Shaft Size	5mm
Corner Step	1.8^0
Accuracy	+/- 5%
Torque	0.45 Nm
Voltage	12-24 VDC
Electric	1.5 A

Experiment with the MPC controller with sampling time $T_s = 0.1$. Output weight (2,2,3). The control variable constraints are [min -5; max +5]. The obstacle in this paper is the assumption of an immobile object in the middle of the center lane of the same size car. The MPC controller matrices have the following values:

$$A_d = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix};\ B_d = \begin{bmatrix} 0.1 & 0 \\ 0 & 0 \\ 0 & 0 \end{bmatrix};$$

$$C_d = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix};\ D_d = \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ 0 & 0 \end{bmatrix}$$

Develop four experimental scenarios to demonstrate the effectiveness of the MPC navigation control algorithm for autonomous vehicles.

4.1. Scenario 1

The autonomous vehicle moves from position A (right lane) to position B (left lane) at a speed of 1m/s. The experimental results are shown in Figure 6.

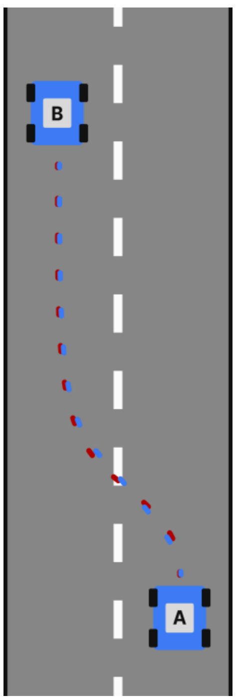

Fig. 6 The autonomous vehicle moves from position A (right lane) to position B (left lane) at a speed of 1m/s

4.2. Scenario 2

The autonomous vehicle moves from position A (right lane) to position B (left lane) at a speed of 3m/s. The experimental results are shown in Figure 7. Given the challenges encountered at higher speeds, it is evident that further optimization and fine-tuning of the MPC controller are necessary to enhance the autonomous vehicle's performance.

Addressing the inaccuracies in steering angle control and trajectory tracking will be crucial in ensuring safe and efficient navigation in real-world scenarios. By refining the controller's parameters and incorporating robust feedback mechanisms, we can mitigate the observed deviations and improve the overall stability and responsiveness of the self-propelled vehicle. These insights underscore the importance of continuous testing, validation, and refinement to advance the capabilities of autonomous systems in dynamic environments.

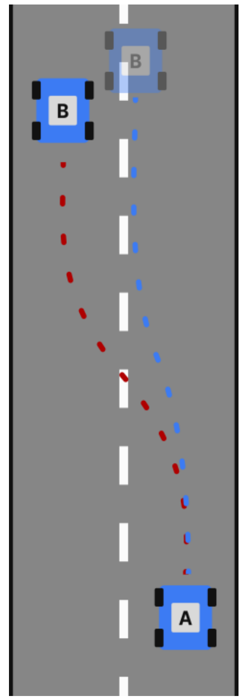

Fig. 7 The autonomous vehicle moves from position A (right lane) to position B (left lane) at a speed of 3m/s

5. Conclusion

Successfully designed the MPC prediction algorithm to control the motion of self-propelled vehicles. The self-propelled vehicle is transported according to the set trajectory, with the required response time and the most minor actual and set steering angle errors. In which the MPC controller only responds when the autonomous vehicle's dynamics do not change. The correctness of the proposed solution is verified by experiment. However, this controller needs to be designed in the intermittent domain, depending on the accuracy of the autonomous vehicle model. These are the first steps to realize experimental results. Therefore, motion control for autonomous vehicles requires continued research and the design of intelligent control methods (machine learning, deep learning, reinforcement learning, iterative learning) and implementation in actual autonomous cars. Improving and enhancing MPC control to respond to dynamic system changes brings good performance in autonomous vehicle navigation. Integrating adaptive learning algorithms, such as neural networks and reinforcement learning, into the MPC framework shows promise for effectively addressing dynamic system changes.

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