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Gain Scheduling Model Predictive Path Tracking Controller for Autonomous Vehicle on Highway Scenario

Zulkarnain Ali Leman, Mohd Hatta Mohammed Ariff, Hairi Zamzuri, Mohd Azizi Abdul Rahman, and Fitri Yakub

Abstract The design of the controller tracking path is one of the important factors in the development of autonomous vehicles. One problem for autonomous vehicle operating on highway road must be able to do a satisfactory path tracking so any accidents do not occur. This paper will discuss designing tracking path controller using combination a model predictive controller (MPC), feed forward (FF) and particle swarm optimization (PSO) based on scenario road courses on the highway with several variations of the vehicle speed. The PSO algorithm used to determine optimal weighting gains on the cost function of the MPC and the FF used to reduce the lateral error of the vehicle to the desired trajectory. The approach solves a single adaptive FF-MPC problem for tracking road trajectories. The vehicle model was developed based on *3 DOF* non-linear vehicle model. This controller model was developed based on *X*, *Y* global position and yaw rate to get input in the form of front steering to the vehicle dynamic system. For path tracking strategy, comparisons with the Stanley controller are done to analyse MPC reliability as non-linear controller in low and middle speed scenario. Simulation results have found that the FF-gain scheduling MPC controller has the significant performance on tracking trajectory at mid and high of the vehicle speeds. In addition, with the using of feed forward and optimal gain weighting on MPC controller made the actuator lifetime is longer than Stanley controller due to reduce the actuator aggressiveness.

Keywords Gain scheduling MPC · Feed forward · Weighting gain · Autonomous vehicle · PSO

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1 Introduction

Path tracking and collision avoidance is currently a main issue of discussion for automotive vehicle safety. The path tracking particularly using active front steering (AFS) technology is consider as one of a feasible solution due to its potential to reduce traffic accidents as well as improving handling performance of the vehicle [1–6]. Most studies on path tracking design use dynamic or kinematic models to represent the behaviour of vehicle models [7–11]. The kinematic model ignores the dynamic effects. On the other hand, dynamic model considers the forces acting on the vehicle when moving.

The MPC controller have been applied in the automotive industry and applications for decades [2, 3]. The MPC able to plan tasks and carry out tasks is a major consideration in relation to planning and control systems. MPC uses a mathematical dynamic process model of the system to predict future values and optimize control process performance [10, 11]. This method also performs optimization to get the optimal value for input to the plant.

In Falcone [10] showed that model predictive control was implemented to predict an optimal steering input for obstacle avoidance task using both nonlinear and linear-time-varying (LTV) MPC. However, the implementation of this approach will require high computational resources especially in solving the optimisation problem in real time. Reference [12–14] implemented MPC in autonomous vehicles for orchard environment, while Tomatsu et al. [15] implemented MPC for path tracking on an excavator in digging operation with slow speed. More applications MPC controller for slow speed can be seen in previous studies [16–18]. Beal [19] applies predictive control models using custom C-Code tested on autonomous vehicles that can solved optimization. Also, in several studies that discussed solving MPC optimization problems using metaheuristic algorithms. This can be seen in two studies [20, 21] using the metaheuristic optimization method to implement the real-time optimization process. Merabti et al. [20] discusses three types of metaheuristic optimization algorithms to complete optimization of nonlinear MPC for control of tracking the mobile robot path. Falcone et al. [10] developed MPC combined with path planning based on bicycle vehicle model. Yakub and Mori [22] developed MPC based on Falcone et al. [10] concept combined with feed forward controller. However, all these studies assume the vertical force acting on the tire is constant and the actuator is still operating quite aggressively because larger prediction and control horizons are required in order to stabilize the vehicle along the path. In addition, the determination of the weighting gain value in standard MPC is done by trial-error based on the linearization process at a certain speed.

Therefore, the standard MPC controller developed with this method requires the optimal weighting gain tuning to minimize the cost function. In addition, the FF controller is used to reduce the aggressiveness of the actuator during manoeuvring. The main methodology used in this study is to use the gain scheduling MPC controller as a basic control law to increase its trajectory tracking performance to variations in speed parameters. Then the GS-MPC controller is combined with the FF controller.

The weighting gain of the lateral error, yaw error and wheel steering knowledge database are built by optimizing controller parameters for each combination of speed using particles swarm optimization (PSO). PSO control shows the potential in the application of the research field lane change manoeuvre and path tracking [2, 7]. So that it can be combined with the MPC controller to get the optimal tracking path in various trajectory scenarios. The PSO algorithms has used to determine the optimal weighting gain for MPC controllers, so vehicles can perform trajectory tracking with good performance at some speeds.

To develop a path tracking controller for an autonomous vehicle with input in the form of steering vehicles to 3 DOF non-linear vehicle model for various trajectory courses. The proposed controller was tested by simulating using MATLAB/Simulink to get vehicle response characteristics when doing manoeuvre on various trajectory. Weighting gain of the MPC values are calculated based on vehicle longitudinal speed parameters. The weighting gain parameter were optimized for the adaptive path tracking controller during the optimization process. Controller parameters will automatically be tuned based on vehicle speed and various trajectory courses. This was translated into three sets of MPC weighting gain which correspond to seven different vehicle speeds and three different sets of trajectory courses. This proposed controller called is Gain-Scheduling MPC (GS-MPC). Then the GS-MPC controller will be compared to the adaptive Stanley controller and standard MPC controller as used on reference [2, 23].

The paper is organized as follows: in Sect. 2 will present the non-linear model of the vehicle. The paper will discuss the standard MPC controller restrictions as a requirement for the vehicle to remain in a trajectory without collisions when operating in a rural space where the driver is deemed capable of maneuvering the vehicle. In Sects. 3 and 4, the methodology and the proposed GS-MPC controller were presented and in Sect. 5 we present the results of the validation of the proposed method. Finally, in Sect. 6 will provide some conclusions and describe future work.

2 Vehicle Dynamic Modelling

2.1 Non-linear Vehicle Model

The main source of forces acting on the vehicle are tire forces. The lateral longitudinal and vertical tire forces are the result of contact between the tire and the road [10, 11]. For path tracking, the control object is the non-linear dynamics of the vehicle. The vehicle on a horizontal road without considering the influence of the road gradient, establish two coordinate systems (Fig. 1), one coordinate system is fixed on the inertial space (X-Y), the other coordinate system is fixed on the vehicle body (x-y). Define the center of rotation of the car when steering is CG.

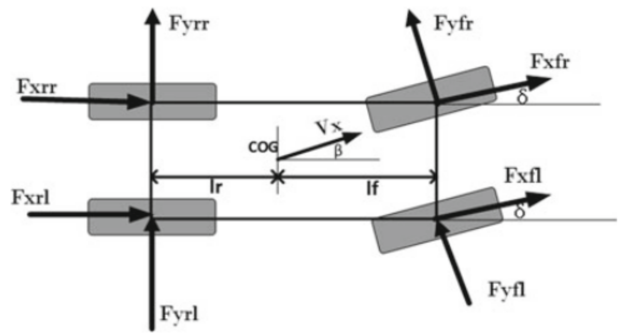

Fig. 1 The non-linear vehicle dynamic model

$$\begin{cases} m_b(\dot{v}_x - v_y\dot{\psi}) = (F_{xfl} + F_{xfr})\cos\delta - (F_{yfl} + F_{yfr})\sin\delta + F_{xrl} + F_{xrr} \\ m_b(\dot{v}_y + v_x\dot{\psi}) = (F_{yfl} + F_{yfr})\cos\delta + (F_{xfl} + F_{xfr})\sin\delta + F_{yrl} + F_{yrr} \\ I_z\ddot{\psi} = l_f((F_{yfl} + F_{yfr})\cos\delta + (F_{xfl} + F_{xfr})\sin\delta) - l_r(F_{yrl} + F_{yrr}) \\ \qquad + \dfrac{w}{2}((-F_{xfl} + F_{xfr})\cos\delta + (F_{yfl} - F_{yfr})\sin\delta - F_{xrl} + F_{xrr}) \\ \dot{X} = \dot{x}\sin\psi + \dot{y}\cos\psi \\ \dot{Y} = \dot{x}\cos\psi - \dot{y}\sin\psi \end{cases} \tag{1}$$

The vehicle dynamics used in Eq. 1 can be compactly written as:

$$\dot{\xi} = f(\xi(t), u(t)) \tag{2}$$

where $\xi(t) \in R^n$ is the state of the system; $u(t) \in R^m$ is the input; $n = 4$ is the number of states; $m = 1$ is the number of inputs. The four states are the lateral and longitudinal velocities in the vehicle body, the yaw angle, yaw rate and the lateral and longitudinal vehicle coordinates in the inertial frame, respectively. These factors are denoted as '$\zeta = [X, Y, \dot{\psi}, \psi]$'. The inputs are denoted as δ is the front steering angle.

Where m_b is the mass of the car, ψ is the yaw angle of the car (direction angle); v_x is the component of the vehicle speed in the x-axis direction; F_{yf}, F_{yr} are the lateral force of the front and the rear wheel; l_f and l_r are the distances of the front and rear axles from the center of gravity, I_z, the moment of inertia of the car.

2.2 Tire Model

This paper use non-linier tire properties based on the work of Nagai et al. [23]. In the dynamic nature of the wheel, the effect of load transfer is an important factor to be considered. Load transfer is a characteristic that is affected by longitudinal and lateral acceleration during running and disturbances. The static forces of the wheel are calculated by the following Eq. 3. It is assumed that the two coaxial wheels maintain the same angle of rotation. When the side angle is small, the following relationship exists between the tire lateral force and the side angle. In performing a maneuver where the tire makes a large slip angle, the tire forces will be in the nonlinear region. In this case, vehicles experience instability, so the use of linear tire models will get a performance that is not as expected. Therefore, nonlinear tire model should be used in controller design.

$$\begin{aligned} F_{z0f} &= \frac{mgl_r}{2L} \\ F_{z0r} &= \frac{mgl_f}{2L} \end{aligned} \tag{3}$$

$$\begin{aligned} \Delta F_{zfr} &= \frac{ma_x h}{2L} + \frac{ma_y hl_r}{wL} \\ \Delta F_{zfl} &= -\frac{ma_x h}{2L} + \frac{ma_y hl_r}{wL} \\ \Delta F_{zrr} &= -\frac{ma_x h}{2L} + \frac{ma_y hl_f}{wL} \\ \Delta F_{zrl} &= -\frac{ma_x h}{2L} - \frac{ma_y hl_f}{wL} \end{aligned} \tag{4}$$

where h denotes the height of center of gravity. The dynamic model of the vehicle 3 degrees of freedom can be seen in the Fig. 1 and Eq. 1. In general, vehicles operate by braking and traction during driving on the highway. Based on the concept of friction circle, the addition and reduction of longitudinal and lateral forces will cause a reduction in the tire's cornering force. The cornering force which is influenced by the nonlinear characteristics of the tire and the braking/traction action can be calculated using the equation.

$$\begin{aligned} F_{yi} &= K_{xi}\left[\frac{2}{\pi}(F_{z0i} + \Delta F_{zi})\right]\tan^{-1}\frac{\pi}{2\pi(F_{z0i} + \Delta F_{zi})}C_i\beta_i \\ K_{xi} &= \sqrt{1 - \left[\frac{F_{xi}}{\mu(F_{z0i} + \Delta F_{zi})}\right]^2} \end{aligned} \tag{5}$$

While the longitudinal forces, F_x, of the wheel are calculated based on the concept of friction force circles.

$$\begin{aligned} &\sqrt{F_y^2 + F_x^2} \le \mu F_z \\ &F_x \le \sqrt{(\mu F_z)^2 - F_y^2} \end{aligned} \tag{6}$$

where, C_{af} and C_{ar} are the cornering stiffnesses of the front and rear wheels respectively. Equations (3)-(6) fully considers the force characteristics of the car, the lateral motion law and the lateral deflection characteristics of the tire. Even if the vehicle is in complex road conditions such as high-speed cornering, the model can still better

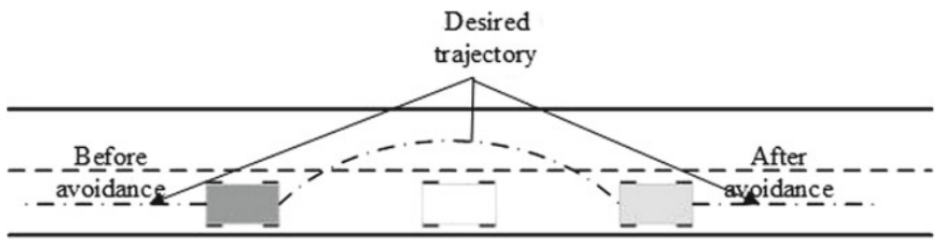

Fig. 2 double lane change scenario

reflect the lateral movement of the car, providing a basis for MPC-based steering control strategy design.

2.3 Trajectory Generation

During the steering of the car, the desired yaw rate ψ_{ref} should be determined by the road radius of curvature R_{ref} and the speed of the vehicle:

$$\dot{\psi}_{ref} = \frac{V_x}{R_{ref}} \tag{7}$$

The typical road shown in Fig. 2, the vehicle starts on a straight road at the initial moment, then enters the curve and then drives again. Out of the corner into the straight road.

Vehicle collisions are a major cause of road accidents. The design of vehicle control algorithms to avoid accidents is the goal of any collision avoidance system. There are two options that allow for collision avoidance maneuvers [22], namely longitudinal control (emergency braking only) and lateral control (active steering only). The reference trajectory yaw (ψ_{ref}), yaw rate (ψ_{ref}), lateral position (Y_{ref}), and longitudinal position X_{ref} fed to the controller.

3 Automatic Path Tracking Control Algorithm Based on Gain Scheduling MPC

Because MPC [23, 24] adopts the control ideas of multi-step prediction, feedback correction and rolling optimization, it has the advantages of good control effect and strong robustness, plus it can better balance control objectives and system constraints and maintain the system. The stability and performance optimization, so this paper designs the automatic path tracking control algorithm in the framework of MPC. Through analysis, the purpose of path tracking is to control the wheel steering to make the vehicle travel along the centreline of the lane. That is, during the driving process, the vehicle centre of mass and the centre displacement of the lane are zero, and the vehicle body orientation is consistent with the lane direction,

$$\begin{aligned} &\xi(k+1) = f(\xi(k), g(\Delta u(k))) \\ &g(\Delta u(k)) = u(k) - u(k-1) \\ &y(k) = C\xi(k) \end{aligned} \tag{8}$$

$$\begin{aligned} x(k+1) &= f(x(k), g(\Delta u(k))) \\ x(k+2) &= f(x(k+1), g(\Delta u(k+1))) \\ &= f(f(x(k), g(\Delta u(k))), g(\Delta u(k+1))) \\ &\vdots \\ x(k+Hp|k) &= f(\ldots f(x(k), g(\Delta u(k))), g(\Delta u(k+Hc-1))) \end{aligned} \tag{9}$$

where $u(k)$ and $\Delta u(k)$ are the control input and the increment of control input of step k, respectively; ξ(k) is the state variable of step k; $y(k)$ is the prediction output of step k. The specific expressions are as follows:

$$\begin{aligned} J(\xi(t), u(t), \Delta u(t)) = &\sum_{i=1}^{Hp} \|y(k+i|k) - r(k+i|k)\|_Q^2 + \\ &\sum_{i=1}^{Hc} (\|\Delta u(k+i-1)\|_R^2 + \|u(k+i-1)\|_S^2) \end{aligned} \tag{10}$$

Considering the limitation of the self-control ability of the car during the driving process, the front wheel steering angle has the following constraints:

$$\delta_{\text{min}} \le \delta \le \delta\text{max} \tag{11}$$

where δ_{min} and δ_{max} are the minimum and maximum steering angles of the front wheels, respectively. In order to smooth the dynamic response of the system during the steering process and improve the ride comfort of the vehicle, when optimizing the performance index, the expected reference trajectory in the form of exponential decay is introduced, so that the variable to be optimized approaches the optimal trajectory along the smooth value. Under the MPC framework, the purpose of automatic lane keeping control can be expressed as the following quadratic performance indicators, where Q, R and S are the weight coefficients in the cost function, Hp and Hc are the prediction time domain and control time domain of MPC respectively.

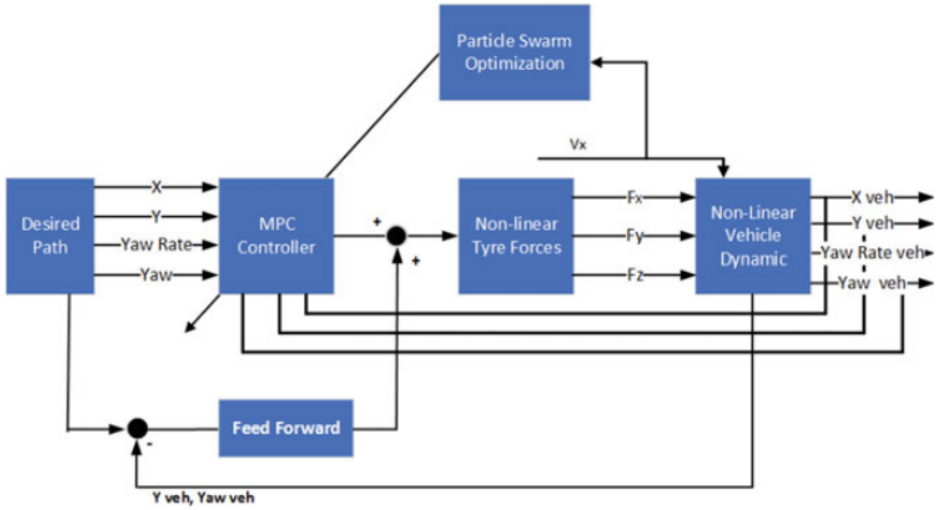

Fig. 3 Model predictive control for non-linear vehicle dynamic model

4 Control Architecture

In this study, a path tracking control system based on the FF-MPC is proposed. As is shown in Fig. 3, the control system consists of an online FF-MPC calculation module, a PSO module and a non-linear vehicle model. The reference trajectory [$\psi_{ref}, \psi_{ref}, Y_{ref}, X_{ref}$] is fed to the control algorithm.

The optimal inputs optimized by the MPC controller are sent to non-linear vehicle model. The state information of vehicle model is fed to the MPC controller again for the next receding horizon optimization. The algorithm for determining the optimal value of the gain cost function based on the PSO concept for speed variations is adopted based on Amer et al. [2]. While the FF controller design is based on the concepts discussed in Yakub and Mori [23].

5 Simulation Results

In order to verify the designed steering control algorithm, this paper carries out a simulation test under the MATLAB platform. The vehicle parameters are shown in Table 1.

$T_s = 0.1$ s, $H_p = 10$, $H_c = 2$, $\delta_{min} = -40°$, $\delta_{max} = 40°$. In the simulation test, the vehicle is simulated at a low speed of 10 m/s and a high speed of 25 m/s, respectively (Table 2).

Root mean square error (RMSE) lateral position and yaw error for MPC controller and Stanley controller summarized in Table 2. It has reported the maximum RMSE lateral and yaw deviation of each proposed controller with constants longitudinal

Table 1 Vehicle parameters

Parameters	Value	Units
Mass (m)	1573	kg
Front to COG	1.1	m
Rear to COG	1.58	m
Inertia mass moment	2873	kg m^2
Front cornering stiffness	80,000	N/rad
Rear cornering stiffness	40,600	N/rad
Lane width	6	m
Lane distance	250	m

Table 2 Root mean square yaw rate and lateral position for double lane change trajectory

	GS-MPC		MPC		Adaptive Stanley	
Vehicle speed (m/s)	Yaw	Lateral position	Yaw	Lateral position	Yaw	Lateral position
10	0.0073	0.0471	0.0351	0.2604	0.0086	0.0141
12.5	0.0082	0.0544	0.0275	0.2605	0.0179	0.1611
15	0.0103	0.0713	0.0263	0.2591	0.0137	0.1906
17.5	0.0169	0.0717	0.0552	0.2645	0.0135	0.2575
20	0.0171	0.0493	0.1731	0.3454	0.0149	0.3367
22.5	0.0216	0.0565	0.038	0.3804	0.0191	0.4459
25	0.0306	0.1078	0.0415	0.4201	0.0226	0.5254

vehicle speed for double lane change scenario. The GS-MPC controller shows good performance for trajectory tracking. The GS-MPC controller shows good performance compared to adaptive Stanley and standard MPC in trajectory tracking. This can be seen in the RMSE lateral error which is smaller than the RMSE lateral error using conventional MPC and adaptive Stanley. The RMSE lateral and yaw using the GS-MPC is smaller in all vehicle speed ranges that showed in Table 2.

Figure 4 shows a comparison of adaptive Stanley, standard MPC and GS-MPC controller for path tracking performance for vehicle speed of 20 m/s. The GS-MPC controller can do tracking path well when compared to Adaptive Stanley controller and MPC. This happens because GS-MPC with the optimal weighting gain value, so that the GS-MPC controller can minimize lateral errors when doing path tracking and avoidance obstacle maneuvers. However, the opposite applies with adaptive Stanley controllers, the control law of the controller is based on geometric calculations of vehicles and roads. So, the controller cannot anticipate the possibility that will happen in the future. Table 2 reported the maximum RMSE lateral and yaw deviation of each proposed controller with constants longitudinal vehicle speed for double lane change scenario. The GS-MPC controller shows good performance for double lane change, lane change and curvature trajectory tracking in vehicle speed of 10–25 m/s.

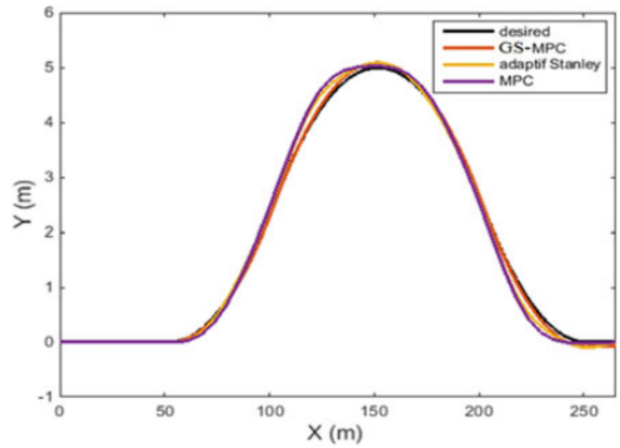

Fig. 4 Simulation results: comparison path tracking performance for double lane change trajectory at vehicle speed of 20 m/s

Figure 5 showed trajectory tracking performance of GS-MPC controller on the double lane change to test handling maneuver. Figure 5a shows the results of trajectory tracking the vehicle obtained using control law using GS-MPC. The autonomous vehicle can approach the desired yaw dan lateral position (Fig. 5a). The GS-MPC controller managed to guide the autonomous vehicle successfully along the trajectory as shown in Fig. 5 for the vehicle speed 20 m/s. This simulation has been conducted with road surface coefficient of 0.8. The simulation results using the GS-MPC controller better than adaptive Stanley controller and standard MPC to follow the trajectory properly in vehicle speed of 10–25 m/s. As can been seen lateral and yaw error on Fig. 5 and Table 1 which shows that the GS-MPC controller managed to produce lower lateral and yaw error than adaptive Stanley controller and standard MPC. Figure 5b shows the wheel steering as input control values of the MPC controller. Input control consists wheel steering with constraints ± 0.5 rad.

6 Conclusion

Through simulation experiments, it is proved that the control strategy can quickly eliminate the lateral displacement deviation and yaw angle deviation, ensure the vehicle travels along the road centerline, and effectively smooth the dynamic response of the system, whether at low speed or high speed, showing better adaptability and robustness.

This study proposed a path tracking controller based on Gain Scheduling MPC. The controller can track the given reference path by regulating the front steering angle. The GS-MPC system uses single track vehicle model and non-linear tire model to optimize the control inputs. The deviation of yaw angle and lateral displacement relative to the reference are added to the cost function to reflect the tracking performance. At the same time, the control inputs and control input increments constraints are applied to prevent actuator saturation as well. Simulation experiments verified

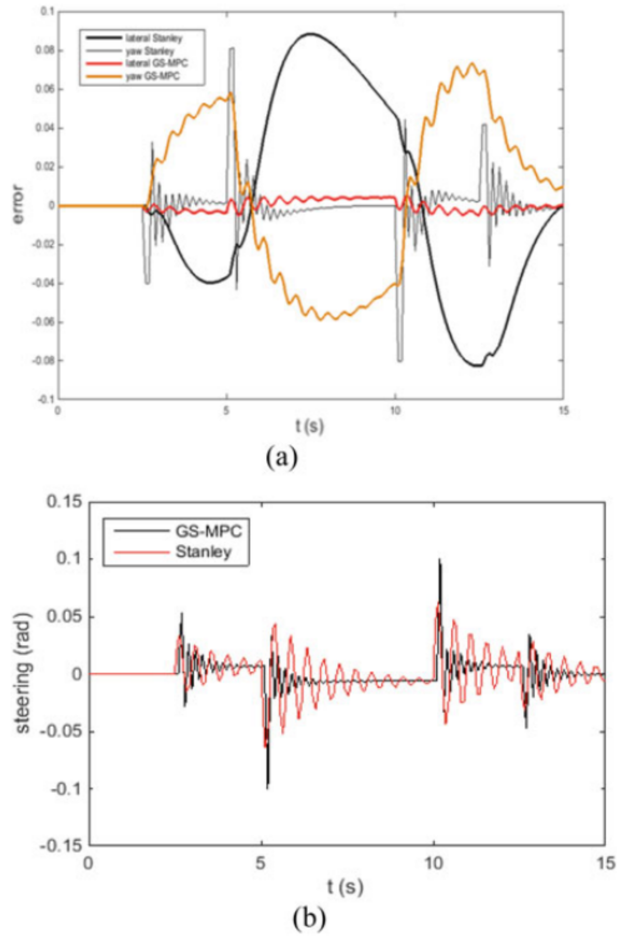

Fig. 5 Simulation results: **a** lateral and yaw error for 20 m/s vehicle speed, **b** wheel steering input at 20 m/s vehicle speed in double lane change manoeuvre

the effectiveness and accuracy of the path tracking in comparison with linear MPC controller under the speed of 80 km/h. The feasibility and stability of the GS-MPC are also confirmed in solving path tracking under speed of 80 km/h. In future work, we will focus on a linearized tire model that can represent the changing trend of the nonlinear tire force in the predictive horizon to reduce the computational burden.

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