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By zulkarnain

WORD COUNT 5186

TIME SUBMITTED 03-MAR-2023 08:47PM

PAPER ID 97236170

Jurnal Teknologi

Full Paper

ADAPTIVE MODEL PREDICTIVE CONTROLLER FOR TRAJECTORY TRACKING AND OBSTACLE AVOIDANCE ON AUTONOMOUS VEHICLE

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Article history
Received
23 April 2019
Received in revised form
15 April 2022
Accepted
25 April 2022
Published Online
20 June 2022

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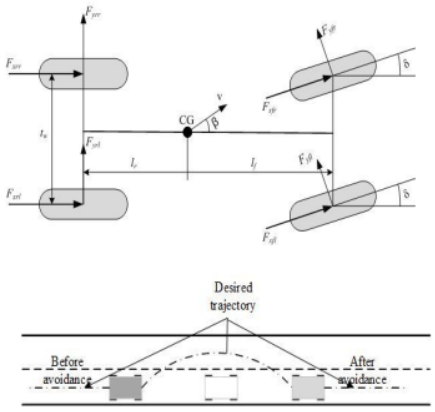
Graphical abstract



Abstract

Accurate vehicle trajectory tracking and collision free motion have become an active topic being discussed in autonomous vehicle research field. During an emergency obstacle avoidance manoeuvre condition, tyre force saturation greatly affects the trajectory tracking performance of the vehicle. Existing controllers such as conventional model predictive controller (MPC) and geometric controller (Stanley) need proper gain tuning to cope with this condition. This is due to the control gains were determined via linearization process at a certain targeted speed. Therefore, the control performance is limited considering the presence of speed variations with extreme manoeuvre trajectory. This paper proposes an adaptive MPC controller to solve aforementioned issues. First, optimized weighting gains for the steering control were obtained using PSO algorithm. The optimised weighting gains were then scheduled into the proposed adaptive MPC via a look-up table strategy. In this work, adaptive MPC was designed by using the linearization of the 7 degree-of-freedom (DOF) non-linear vehicle model. Here, the linearized model for controller design was updated based on the instantaneous longitudinal speed of the vehicle system plant. To evaluate adaptive MPC performance, comparisons with the adaptive Stanley controller and conventional MPC are conducted to analyse its effectiveness in low, middle and high-speed scenario. Simulation results showed that adaptive MPC improved the tracking error performance with respect to the speed variation in extreme collision avoidance manoeuvre. In high-speed manoeuvre (i.e. 25 m/s), lateral error improvement of 27.3% and 42.3% compared to conventional MPC controller and adaptive Stanley controller were obtained respectively.

Keywords: Autonomous vehicle, adaptive MPC controller, trajectory tracking, collisions avoidance

Abstrak

Penjejakan trajektori yang tepat dan pergerakan bebas perlanggaran telah menjadi topik aktif yang dibincangkan dalam bidang penyelidikan kenderaan berautonomi. Semasa pergerakan menjauhi halangan dalam

keadaan kecemasan, ketepuan daya tayar sangat mempengaruhi prestasi penjejakan trajektori kenderaan. Pengawal sedia ada seperti pengawal ramalan model konvensional (MPC) dan pengawal geometri (Stanley) memerlukan gandaan penalaan yang sesuai untuk mengatasi keadaan ini. Ini disebabkan oleh gandaan kawalan ditentukan melalui proses pelurusan pada kelajuan yang tertentu. Oleh itu, prestasi kawalan adalah terhad disebabkan terdapatnya variasi kelajuan serta trajektori pergerakan yang ekstrim. Dalam kertas kajian, pengawal suai MPC akan dicadangkan untuk menyelesaikan isu-isu tersebut. Pertama, gandaan pengawalan yang dioptimumkan untuk kawalan stereng diperoleh menggunakan algoritma PSO. Gandaan kawalan yang dioptimumkan kemudian dijadualkan ke dalam suai MPC yang dicadangkan melalui strategi jadual lihat-rujukan. Dalam kajian ini, pengawal suai MPC yang direka bentuk dengan menggunakan pelurusan model kenderaan tak-lelurus yang mempunyai 7 darjah kebebasan (DOF). Di sini, model terlelurus untuk rekabentuk pengawal, dikemaskini berdasarkan kelajuan membujur ketika bagi kenderaan. Untuk menilai prestasi pengawal suai MPC, perbandingan dengan pengawal suai Stanley dan MPC konvensional telah dijalankan untuk menganalisis keberkesanannya dalam senario kelajuan kenderaan yang rendah, sederhana dan tinggi. Hasil simulasi menunjukkan bahawa pengawal suai MPC dapat meningkatkan prestasi ralat penjejakan dengan variasi kelajuan semasa pergerakan menghindari pelanggaran yang ekstrim. Dalam pergerakan berkelajuan tinggi (iaitu 25 m/s), peningkatan ralat sisi masing-masing sebanyak 27.3% dan 42.3% telah diperolehi berbanding pengawal MPC konvensional dan pengawal suai Stanley.

Kata kunci: Kenderaan autonomi, pengawal MPC Suai, penjejakan trajektori, pengelakkan pertembungan

1.0 INTRODUCTION

In the face of increasingly prominent traffic accidents, road congestion, environmental pollution and other issues, autonomous vehicle (AV) effectively integrates advanced information communication, control, sensor, computer and system integration technology used in road transportation systems [1-6]. In autonomous vehicle, advanced vehicle control and safety systems are used to develop various assisted driving techniques that assist drivers in controlling vehicles, thereby making driving safer and more efficient, such as adaptive cruise control system and trajectory tracking [3-8]. The adaptive cruise control is mainly focused on solving the longitudinal control of the vehicle, while trajectory tracking focuses on the lateral control of the vehicle to ensure that the vehicle travels along the trajectory.

Common trajectory tracking controllers includes geometrical, PID, feedforward-feedback, preview tracking optimal and linear quadratic controller [4]. In reference [4, 9], a linear quadratic regulator (LQR) path tracking controller is obtained based on a linearized 2DOF vehicle model, which focuses on dynamic modelling and path tracking control of autonomous vehicle.

Previously, large numbers steering control strategies in context of trajectory tracking had been proposed by researchers. Nevertheless, most of the reported works mainly focussed on the speed of either a fixed value or within the linear region of vehicle dynamic (i.e. low speed manoeuvre) [4, 10]. Gaining *et al*. [2] considering the time-varying parameters of vehicle lateral dynamics and designed BP neural network-based PID lane keeping control algorithm. Amer *et al*. in [1] consider the uncertainty of vehicle model and proposed the adaptive steering control algorithm. However, the selection of control parameters was fixed with respect to the targeted manoeuvre speed and the controller performance was assessed at low speed scenario. Soualmi *et al*. [10] studied the velocity disturbance in the vehicle driving process and studied the fuzzy based on Takagi-Sugeno (T-S) lane keeping control rate. Although the algorithm has lower requirements on model accuracy, but the control accuracy was limited likely due to the trade-off issue.

In lateral motion, vehicle lateral dynamics have characteristics such as non-linearity, time-varying and uncertainty and there are many disturbance factors in the vehicle during driving. Vehicle speed variations especially at high speed manoeuvre can be considered as one of the factors that significantly changed the vehicle dynamic behaviour [11]. In addition, when an emergency condition occurs, for the obstacle avoidance manoeuvre conditions, tyre saturation is easily happened. Tyre saturation occurs when the lateral tyre forces no longer increases with

increasing steering angle. This greatly affects the accuracy of tracking [12-13].

The lateral displacement of the vehicle must be adjusted during the control process. It is necessary to control the yaw angle, also to smooth the system's driving response as much as possible to ensure the ride comfort of the vehicle [14]. Model Predictive Control (MPC) has good robustness against model mismatch, time-varying and uncertainty, and can effectively deal with multivariable and system constraints [15-21].

In Falcone *et al*. [22], model predictive control was implemented to predict optimal steering input for obstacle avoidance task using dSPACE rapid prototyping module using both nonlinear MPC 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. Ref [13-14] 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. Beal [23] applied predictive control models using custom C-Code tested on autonomous vehicles that can solved optimization.

Moreover, there were several studies that discussed solving MPC optimization problems using meta-heuristic algorithms [19-20]. Merabti *et al*. [19] discussed three types of metaheuristic optimization algorithms to complete optimization of nonlinear MPC for control of tracking the mobile robot path. Falcone *et al*. [22] developed MPC combined with path planning based on bicycle vehicle model. Yakub and Mori [21] developed MPC based on Borelli concept combined with feed forward controller. However, these studies used trial and error methods in determining the MPC controller gain value. In addition, the linearization of the dynamic model of the vehicle used by the MPC controller is carried out at a selected speed.

In order to address the shortcoming in terms of control parameter selection and speed variation issues, this paper proposes an adaptive MPC controller consist of gain scheduling weighting parameters which optimally tuned using meta-heuristic approach. Here, a PSO algorithm was adopted to determine the optimal weighting value for MPC controllers. The weighting gain values are calculated based on vehicle longitudinal speed. The effectiveness of the proposed controller was verified by numerical simulation. The adaptive MPC controller performance was compared to the conventional MPC [21-23] and adaptive Stanley controller [1] in a broader speed range.

The paper is organized as follows: Section 2 presents the methodology adopted consist of sequential description on the non-linear vehicle model, controller design. Subsequently, non-linear vehicle model and controller design, trajectory generation, simulation setup and performance evaluation of the proposed controller will be discussed in Section 3. Finally, in Section 4 will describe the conclusion and description of potential future work.

2.0 METHODOLOGY

2.1 Non-Linear Vehicle Model

The mathematical modelling of vehicle dynamic motion is obtained based on Newton's 2nd law that describes the forces and moments acting on the vehicle body and tyres. In this work, a 7DOF non-linear vehicle model was adopted as the system plant as depicted in Figure 1. Here, front wheel steer angle δ was adopted as the control input. The vehicle parameters l_f, l_r and t_w are distance from front and rear axle to centre of gravity (CG) and width track the vehicle respectively, v is longitudinal speed of the vehicle on centre of gravity. Other vehicle parameters are vehicle mass m, moment inertia I_z. Longitudinal, lateral and yaw moment dynamic motion of the vehicle as shown in Equation 1 [24-32].

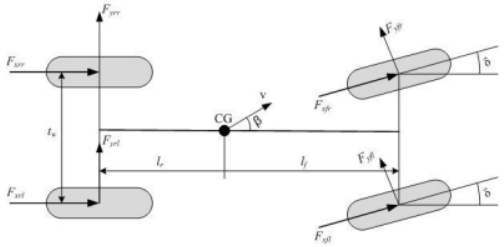


Figure 1 The non-linear vehicle dynamic model

$$\left.\begin{aligned} m_b(\dot{v}_x - v_y\dot{\psi}) &= (F_{xfl}+F_{xfr})\cos\delta-(F_{yfl}+F_{yfr})\sin\delta+F_{xrl}+F_{xrr}\\ m_b(\dot{v}_y + v_x\dot{\psi}) &= (F_{yfl}+F_{yfr})\cos\delta+(F_{xfl}+F_{xfr})\sin\delta+F_{yrl}+F_{yrr}\\ I_z\ddot{\psi} &= l_f((F_{yfl}+F_{yfr})\cos\delta+(F_{xfl}+F_{xfr})\sin\delta)-l_r(F_{yrl}+F_{yrr})\\ &\quad+\frac{w}{2}((-F_{xfl}+F_{xfr})\cos\delta+(F_{yfl}-F_{yfr})\sin\delta-F_{xrl}+F_{xrr}) \end{aligned}\right\} \quad (1)$$

2.2 Tyre Forces

The generated tyre forces longitudinal and lateral directions depend on the load transfer of vertical direction force at the wheels. The load transfer in vertical direction at each wheel was presented by two terms of forces that are static and dynamic. The static and dynamic forces of the wheel were calculated using Equation 2 and Equation 3 respectively.

$$\left.\begin{aligned} F_{z0f} &= \frac{mgl_r}{2L}\\ F_{z0r} &= \frac{mgl_f}{2L} \end{aligned}\right\} \quad (2)$$

$$\left.\begin{aligned}\Delta F_{zfr}&=\frac{ma_x h}{2L}+\frac{ma_y hl_r}{wL}\\ \Delta F_{zfl}&=-\frac{ma_x h}{2L}+\frac{ma_y hl_r}{wL}\\ \Delta F_{zrr}&=-\frac{ma_x h}{2L}+\frac{ma_y hl_f}{wL}\\ \Delta F_{zrl}&=-\frac{ma_x h}{2L}-\frac{ma_y hl_f}{wL}\end{aligned}\right\} \quad (3)$$

Here, F_{z0f} and F_{z0r} were static forces at front and rear tyres respectively. The dynamics load transfers (ΔF_{zfr}, ΔF_{zfl}, ΔF_{zrr}, ΔF_{zrl}) due to longitudinal acceleration and lateral acceleration are as described in Equation 3.

On the other hand, the generation longitudinal and lateral forces are limited by the friction circle concept. This is to make sure the validity of available cornering force generated at the tyre model. The generation of longitudinal and lateral force are as described in Equation 4 and Equation 5 respectively.

$$\left.\begin{aligned}F_{yi}&=K_{xi}\left[\frac{2}{\pi}(F_{z0i}+\Delta F_{zi})\right]\tan^{-1}\frac{\pi}{2\pi(F_{z0i}+\Delta F_{zi})}C_i\beta_i\\ K_{xi}&=\sqrt{1-\left[\frac{F_{xi}}{\mu(F_{z0i}+\Delta F_{zi})}\right]^2}\end{aligned}\right\} \quad (4)$$

$$\left.\begin{aligned}\sqrt{F_y^2+F_x^2}&\le\mu F_z\\ F_x&\le\sqrt{(\mu F_z)^2-F_y^2}\end{aligned}\right\} \quad (5)$$

Where subscript *I*, C_i, β_i, and μ *denoted as* the index of indicating front and rear tyres, cornering stiffness, tyres side slip angle and friction coefficient of road respectively.

2.3 Vehicle Kinematic Model

Equation 6 described the position of the vehicle based on instantaneous velocity and yaw angle with respect to global coordinates *(X - Y)*. Here, Ψ is the yaw angle of the vehicle, while $\dot{x}$ and $\dot{y}$ are the longitudinal and lateral velocity of the vehicle respectively.

$$\left.\begin{aligned}\dot{X}&=\dot{x}\sin\psi+\dot{y}\cos\psi\\ \dot{Y}&=\dot{x}\cos\psi-\dot{y}\sin\psi\end{aligned}\right\} \quad (6)$$

2.4 Linearized Vehicle Model for Controller Design

In this work, linearized vehicle dynamic model was adopted in order to design the proposed MPC controller. Dynamic model as in Equation 1 was linearized by assuming a constant vehicle speed and a small steering angle. The linearized vehicle model can be written as in Equation 7.

$$\left.\begin{aligned}m_b(\dot{v}_x+\dot{v}_y\dot{\psi})&=F_{yf}+F_{yr}\\ I_z\dot{r}&=l_fF_{yf}-l_rF_{yr}\end{aligned}\right\} \quad (7)$$

Here, considering the vehicle has a small steering angle, and the tyre slip angle, the lateral tyre force can be calculated as in Equation 11.

$$\left.\begin{aligned}F_{yf}&=C_f\alpha_f\\ F_{yr}&=C_r\alpha_r\end{aligned}\right\} \quad (8)$$

Where C_f and C_r are the front and rear tyre cornering stiffness respectively. Whereas α_f and α_r are front and rear wheel slip angles which can be calculated using Equation 9.

$$\left.\begin{aligned}\alpha_f&=\delta-\frac{v_y+\psi l_f}{v_x}\\ \alpha_r&=-\frac{v_y-\psi l_f}{v_y}\end{aligned}\right\} \quad (9)$$

Substituting Equation 8 and Equation 9 into Equation 7, the linearize model of the vehicle can be presented as in Equation 10.

$$\left.\begin{aligned}m_b(\dot{v}_x+\dot{v}_y\dot{\psi})&=C_f\left(\delta-\frac{v_y+\psi l_f}{v_x}\right)+C_r\left(-\frac{v_y-\psi l_f}{v_y}\right)\\ I_z\dot{r}&=l_fC_f\left(\delta-\frac{v_y+\psi l_f}{v_x}\right)-l_rC_r\left(-\frac{v_y-\psi l_f}{v_y}\right)\end{aligned}\right\} \quad (10)$$

2.5 Proposed Control Structure

The proposed control structure is as depicted in Figure 2. The aim was to follow the desired trajectory as close as possible while avoiding obstacles. The desired path was in the form of a lateral position Y_{ref} and the yaw angle ψ_{ref} as a function of the longitudinal position *X*.

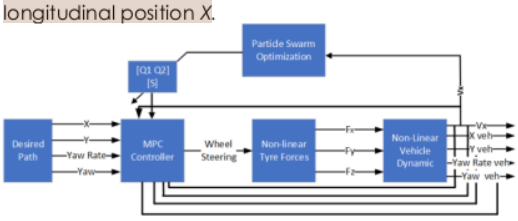


Figure 2 Proposed Control Structure

2.5.1 Adaptive Model Predictive Controller (Adaptive MPC)

The formulation of adaptive MPC in the state space has several advantages. It facilitates the representation of multivariable systems and analysis of closed loop properties. In this case, the system to be controlled can be described by a discrete time

invariant linear equation state space model as in Equation 11.

$$\left.\begin{aligned} x(k+1)&=Ax(k)+Bu(k)\\ y(k)&=Cx(k)\end{aligned}\right\} \quad (11)$$

Where x is the system state vector, u is the input vector, y is the output vector, A is the state matrix, B is the input matrix, C is the output matrix.

The proposed adaptive MPC controller computes the front wheel steering angle such that is followed as close as possible at a given longitudinal speed. Controller gains were computed using Quadratic programs (QP) solved using quadratic objective functions. Here, the cost function optimization combines a set of performance indexes with various desired control objectives as written in Equation 12.

$$\left.\begin{aligned} J(\zeta(t),\mathrm{u}(t),\Delta u(t))=&\sum_{i=1}^{Hp}\left\|\zeta_{t+1,1}-\zeta_{ref\,t+1,1}\right\|_Q^2\\ &+\sum_{i=0}^{Hc-1}\left(\left\|\Delta u_{t+1,1}\right\|_R^2+\left\|u_{t+1,1}\right\|_S^2\right)\end{aligned}\right\} \quad (12)$$

The reference signal, $\zeta = (X_{ref}, Y_{ref}, \psi_{ref})$ represents the desired input. The Q, R and S are weighting matrices of appropriate dimensions that a weighting coefficient that penalizes changes in the error to reference and control input. The output response of the model will follow the signal set-point when applying Q with a value greater than S. Conversely, if Q is smaller than S the difference from tracking reference to response plant output will rise. The Q, R, and S weights can change from one step to the next in the prediction horizon. Such a time-varying weight is an array containing the prediction horizon rows, and other number of outputs variable or control input columns. Using time-varying weights provides additional tuning possibilities. However, it will lead to tuning complexities. Here, PSO algorithm was adopted to optimally tune the weighting gains based on vehicle speed and the selection scheduled. Nevertheless, prediction horizon and control horizon were selected by trial and error basis.

2.5.2 Adaptive Mechanism using Weighting Gain Scheduling Technique

As reported in [3, 17], for accurate tracking performance, the tuning parameters in MPC need to be optimized in accordance to the instantaneous changes of the vehicle states. This results to computational burden of the control system. In this work, adaptive strategy with weighting gain scheduling was proposed aiming to adjust the tuning parameters of the MPC controller automatically to cope with the speed variation. Hence, it will reduce the effect of computational burden towards the control system. Here, PSO algorithm as in Equation 13 was used to solve the potential optimum solution for various manoeuvre speeds.

In order to generate the optimal weighting gain, the fitness function of the PSO as in Equation 14, for the path tracking utilized the root mean square (RMS) error value of the avoidance trajectory.

$$\left.\begin{aligned} \mathrm{x}(t+1)_{id}&=x(\mathrm{t})_{id}+v(t+1)\\ v(t+1)&=iw\times v(t)+c\times rand(0.1)\times(\mathrm{p}_{best}^{t}-x_{id}^{t})\\ &\quad +s\times rand(0.1)\times(\mathrm{g}_{best}^{t}-x_{id}^{t})\end{aligned}\right\} \quad (13)$$

$$F(\mathrm{Q}_1,\mathrm{Q}_2,\mathrm{S})=\sqrt{\frac{\sum[e(t)]^2}{n}} \quad (14)$$

The purpose of the proposed adaptive strategy was to build knowledge databases that provide optimal selection for the MPC controller to decide suitable values of controller weights gain parameters. The knowledge database should have a complete set of weight gain parameters, namely Q_1, Q_2, and S, for each selected manoeuvre speeds. Minimum of 10 m/s (≈36 km/h) and maximum of 25 m/s (≈90 km/h) were selected in this work. The application of PSO in this study is similar to previous researches by authors [1, 7]. The flowchart of PSO algorithm is as shown in Figure 3. Meanwhile, Table 1 and Table 2 shows the parameters used for the PSO algorithm and solution of optimized weighting gain respectively. Finally, the optimal weighting gain will be selected via a look up table and fed into MPC control law to produce appropriate wheel steering.

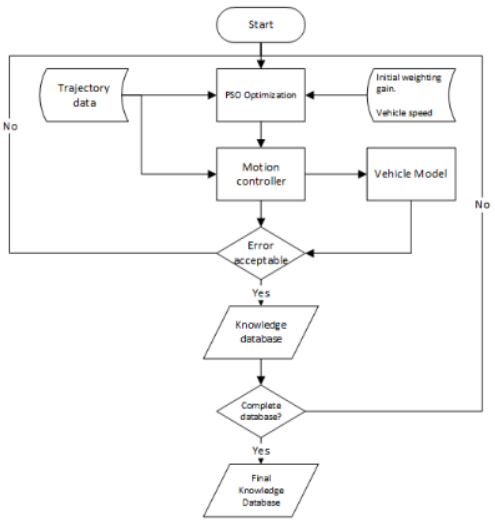


Figure 3 PSO algorithm flow

Table 1 PSO parameters and MPC setting used in building knowledge database

Parameter	Value
Social coefficient, *s*	1.42
Cognitive coefficient, *c*	1.42
Inertial weight, *iw*	0.9
No. of dimensions, *Nd*	3 (Q_1, Q_2 and *S*)
Upper bound limit	[10; 10; 10]
Lower bound limit	[−10; −10; −10]
No. of particles, *Np*	25
No. of iterations, *Ni*	15
MPC prediction horizon	10 steps
MPC control horizon	3 steps

Table 2 Optimized parameters using PSO algorithm

Vehicle Speed (m/s)	Adaptive MPC		
	Q_1	Q_2	S
10	0.25	0.1	1.00
12.5	0.25	0.11	1.05
15	0.25	0.10	1.03
17.5	0.50	0.12	0.11
20	1.00	0.23	0.12
22.5	2.50	0.5	0.10
25	2.50	0.5	0.11

2.6 Adaptive Stanley Controller

In this work, an Adaptive Stanley controller was adopted as the benchmark to for performance comparison purpose. Generally, a basic Stanley controller was presented by Hoffman *et al*. [27] considering two properties the heading error, ϕ and the lateral error, *e* as shown in Equation 15. The heading error and the lateral error measured from the centre of steering wheel axle to the nearest point on trajectory [36].

$$\delta = \mathrm{k}_1 \phi + \tan^{-1}\left(\frac{k_2 e(t)}{v(t)}\right) \tag{15}$$

In order to have a fair comparison with the proposed adaptive MPC controller, the gain of basic Stanley control was optimally tuned. Here, PSO algorithm was used to determine the optimal gain (k_1 and k_2) in Equation 15. The procedure for determining the gain value is carried out according to the explanation in section 2.5.2 and the optimized value of adaptive Stanley gains are as presented in Table 3.

Table 3 Optimized parameters using PSO algorithm

Vehicle Speed (m/s)	Adaptive Stanley	
	k_1	k_2
10	0.05	0.01
12.5	1.61	0.12
15	1.54	0.05
17.5	1.94	0.07
20	0.59	0.08
22.5	0.07	0.14
25	1.18	0.04

2.7 Conventional MPC Controller

In this work, a conventional MPC was also being developed for performance comparison purposes. Here, the nonlinear vehicle model as in Equation (1) was linearized at the speed of 10 m/s. Constant weighting gains that are; Q_1=0.25, Q_2=0.1 were used in this case. The selected prediction and control horizon value were kept at the same value as described in Section 2.5.2.

3.0 RESULTS AND DISCUSSION

3.1 Trajectory Generation and Simulation Setup

In order to evaluate the performance of the proposed controller, double-lane change maneuvers performed at several entry speeds had been simulated. The adopted generated trajectory emulated the scenario of lane change trajectory with a single static obstacle avoidance maneuver as shown in Figure 4. The desired trajectory was described in terms of yaw angle ψ_{ref}, lateral position Y_{ref}, parameters z_1 and z_2 as function of longitudinal position *X* [19, 20]. The generated reference trajectory was calculated based on Equation 16 which adopted from the work presented in [19].

$$\left.\begin{aligned}
\psi_{ref} &= \tan^{-1}\left(d_{y1}\left(\frac{1}{\cosh z_1}\right)^2\left(\frac{1.2}{d_{x1}}\right) - d_{y2}\left(\frac{1}{\cosh z_2}\right)^2\left(\frac{1.2}{d_{x2}}\right)\right)\\
Y_{ref} &= \arctan\left(d_{y1}\left(\frac{1}{\cosh(z_1)}\right)\left(\frac{1.2}{d_{x1}}\right) - d_{y2}\left(\frac{1}{\cosh(z_2)}\right)^2\left(\frac{1.2}{d_{x2}}\right)\right)^2\\
z_1 &= \frac{2.4}{25}(x-27.19) - 1.2;\quad d_{y1}=4.05;\quad d_{y2}=5.7\\
z_2 &= \frac{2.4}{21.95}(x-56.46) - 1.2;\quad d_{x1}=25;\quad d_{x2}=21.95
\end{aligned}\right\} \tag{16}$$

The control system was simulated for a various initial speed values ranging from 10 m/s to 25 m/s on a dry surface road condition. Here, tracking error was used to evaluate the tracking performance of the vehicle system. All adopted vehicle parameters are as tabulated in Table 4.

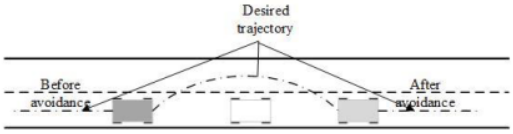


Figure 4 Double lane obstacle avoidance scenario

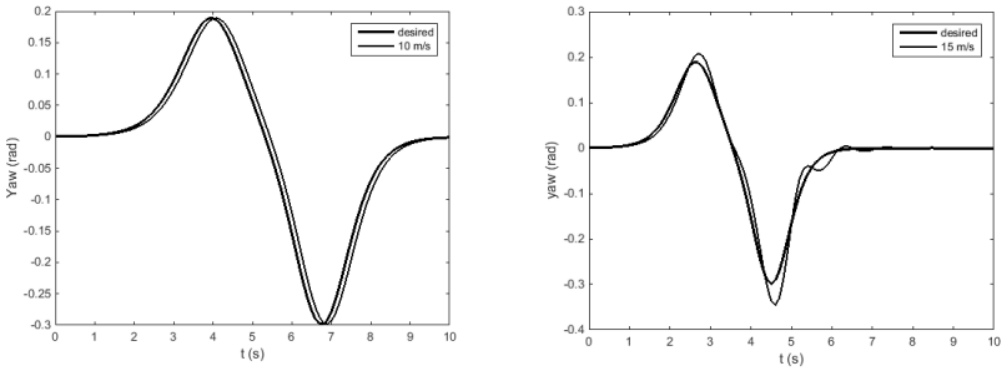
Table 4 Vehicle parameters

Parameter	Value
m	2032 kg
l_f	1.26 m
l_r	1.90 m
I_z	6286 kg/m²
C_f	40,200 N/rad
C_r	62,800 N/rad

3.2 Performance Evaluations

A series of simulations have been conducted to evaluate the performance and effectiveness of the proposed controller. Here, lateral position and yaw angle error were observed between the vehicle and the desired trajectory. Hence, performance comparison with the adaptive Stanley and conventional MPC controller was analysed. Figure 5(a) and 5(b) shows the results of the vehicle yaw tracking using adaptive MPC for velocities of 10 m/s and 15 m/s respectively. The results show that the vehicle able to perform the tracking task as desired although with the presence of negotiable oscillation at higher speed value.

Table 5 summarized the overall results of vehicle tracking performance. Three types of controllers were compared namely; the Proposed adaptive MPC, conventional MPC controller and adaptive Stanley controller. Based on Table 5, proposed adaptive MPC controller had showed performance superiority by its ability to produce lower lateral position and compared to the benchmark as well as conventional MPC controller. On the other hand, in terms of yaw angle error, adaptive Stanley had better performance compared to the proposed controller. This is due to dominant gain of Adaptive Stanley controller control law as in Equation 15 was made up mainly to penalize the yaw angle error.



(a) (b)

Figure 5 Simulation results: (a) yaw response at vehicle speed of 10 m/s and (b) yaw response at 15 m/s

Table 5 Root mean square error (RMSE) of the yaw and lateral position

	Adaptive MPC controller		Conventional MPC controller		Adaptive Stanley Controller	
Vehicle speed	Yaw	Lateral Position	Yaw	Lateral Position	Yaw	Lateral Position
10 m/s	0.0157	0.0098	0.0351	0.2604	0.0086	0.0141
12.5 m/s	0.0172	0.1544	0.0275	0.2605	0.0179	0.1611
15 m/s	0.0164	0.1522	0.0263	0.2591	0.0137	0.1906
17.8 m/s	0.0339	0.1517	0.0552	0.2645	0.0135	0.2575
20 m/s	0.0781	0.1665	0.1731	0.3454	0.0149	0.3367
22.5 m/s	0.1486	0.2265	0.0380	0.3804	0.0191	0.4459
25 m/s	0.1652	0.3033	0.0415	0.4201	0.0226	0.5254

Meanwhile, Figure 6 and Figure 7 depicted the graphical illustrations of vehicle tracking performance of the proposed adaptive MPC controller for the speed of 15 m/s and 20 m/s respectively. In terms of targeted global position, the adaptive MPC controller successfully managed to track the desired trajectory especially at the sharp cornering region for vehicle speed of 15 m/s. This is as shown in Figure 6(a). However, expected, the trajectory at higher speed (i.e. 20 m/s), an over-steer response was observed at the sharp cornering region and fluctuated trajectory response was noticed as the vehicle tries to get back to the straight line path as shown in Figure 7(a). This was the results of an aggressive steering response to cope with the extreme nature of the manoeuvre and wheel steer constraint as shown in Figure 7(c).

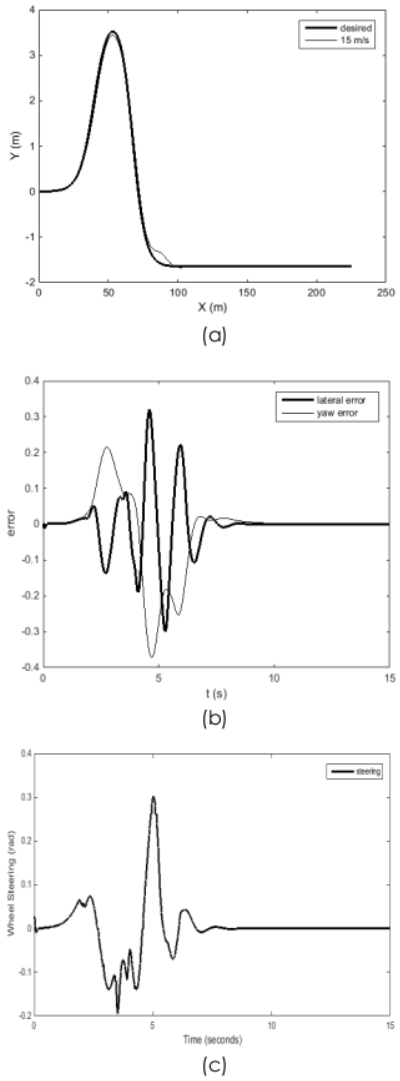


Figure 6 Simulation results: (a) Path tracking at vehicle speed of 15 m/s (b) lateral and yaw error for 15 m/s vehicle speed (c) wheel steering input at 15 m/s vehicle speed in double lane change manoeuvre

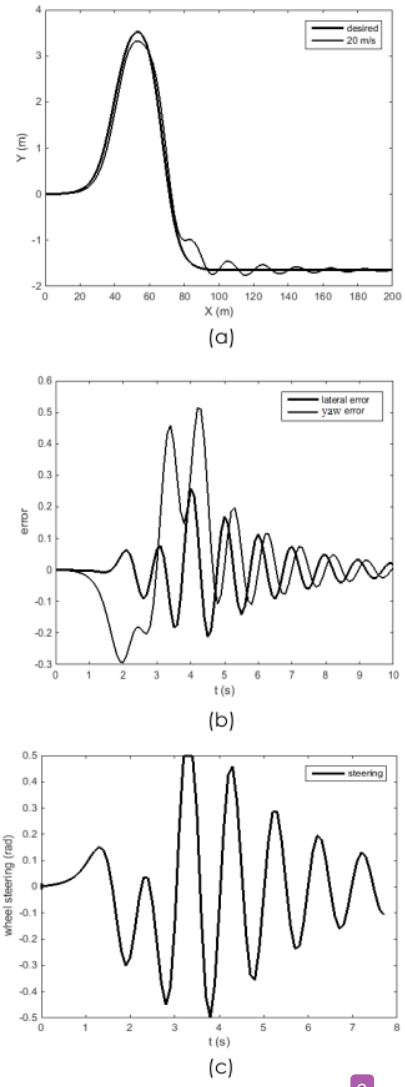


Figure 7 Simulation results: (a) Path tracking at speed of 20 m/s (b) lateral and yaw error for 20 m/s vehicle speed (c) wheel steering input at 20 m/s vehicle speed in double lane change manoeuvre

Concurrently, Figure 6(b) and 7(b) show the yaw and lateral tracking error with respect to time at velocity 15 m/s and 20 m/s. At both velocities, lateral tracking error had reached a maximum value of 0.3 m and 0.5 m respectively. As speed increases, higher yaw moment needed to prevent the vehicle from being further away from the desired obstacle avoidance trajectory. In critical manoeuvres (e.g. high speed), improper steering control input will cause the vehicle to most likely become unstable. The simulation results using the adaptive MPC controller better than adaptive Stanley controller and standard MPC to follow the trajectory properly in vehicle speed of 10 m/s - 25 m/s. As can been seen lateral and yaw error on Figure 5 and Table 5 which shows that the adaptive MPC controller managed to produce lower lateral and yaw error than adaptive Stanley controller and standard MPC. Figure 6c and 7c shows the wheel steering as input control values of the adaptive MPC controller. Input control consists wheel steering with constraints ± 0.5 rad.

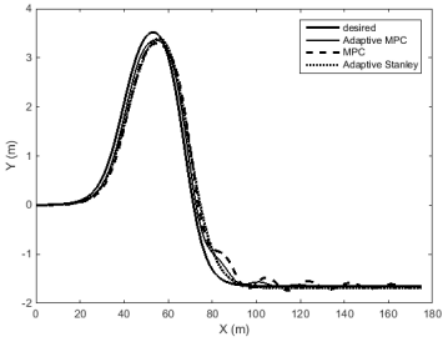


Figure 8 Comparison path tracking performance at vehicle speed of 17.5 m/s

Figure 8 shows a selected comparison of path tracking performance for vehicle speed of 17.5 m/s using adaptive Stanley, standard MPC and adaptive MPC controller. Adaptive MPC controller yielded a better result in terms of tracking accuracy than the adaptive Stanley and conventional MPC controller. This is due to the optimal weighting gain selection, of the adaptive MPC controller which further improved the lateral error with the capability to compromise the trade-off higher yaw angle generation. The adaptive MPC with optimal weighting gains can perform high entry speeds and thus further improve vehicle manoeuvring comparing with other controllers. 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 steering saturation as well.

4.0 CONCLUSION

This paper proposed a path tracking controller for autonomous vehicle at various speeds to analysis performance at avoidance obstacle manoeuvre. The proposed adaptive MPC controller using weighting gain scheduling had proved to perform satisfactory in avoidance obstacle scenario with various vehicle speeds. Here, the performance of the adaptive MPC controller was verified through simulation in MATLAB.

The proposed control method does not take into account the stability response characteristic of the vehicle. Moreover, controller performance evaluation was only being analysed in simulation environment. Therefore, for future works, consideration of vehicle stability will be investigated to further improve the method and hardware-in-loop implementation will be conducted to validate the proposed controller.

Acknowledgement

The work presented in this study is funded by Ministry of Education Malaysia, Fundamental research Grant Scheme, Universiti Teknologi Malaysia, FRGS/1/2019/TK08/UTM/02/10. Vot No. 01109.

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