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

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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, collision avoidance

Abstrak

Penjejakan trajektori yang tepat dan pergerakan bebas pertangkaran telah menjadi topik aktif yang dibincangkan dalam bidang penyelidikan kendaraan berautonomi. Semasa pergerakan menjauhi halangan dalam
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 an 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 is adopted as the control input. The vehicle parameters I_x, I_y and F_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_x, longitudinal, lateral and yaw moment of inertia of the vehicle as shown in Equation 1 [24-32].

![Figure 1 The non-linear vehicle dynamic model](image)

\[
\begin{align*}
F_{z0f} &= \frac{mgl_f}{2L} \\
F_{z0r} &= \frac{mgl_f}{2L}
\end{align*}
\]
Here, $F_{d|f}$ and $F_{d|r}$ were static forces at front and rear tyres respectively. The dynamics load transfers ($\Delta F_{d|f}$, $\Delta F_{d|r}$, $\Delta F_{f|f}$, $\Delta F_{f|r}$) 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.

\[
F_{yi} = K_{yi} \left[ \frac{2}{\pi} (F_{zi} + \Delta F_{zi}) \right] \tan^{-1} \left[ \frac{\mu F_{zi}}{2\pi (F_{zi} + \Delta F_{zi})} \right] C_{yi} \beta_{yi} \right]
\]

\[
K_{yi} = \sqrt{1 - \left[ \frac{F_{yf}}{\mu F_{zi}} \right]^2}
\]

\[
\mu F_{zi} \geq F_{zi} \geq \left( \frac{F_{yi}}{\mu} \right)^2
\]

Where subscripts $l, C, \beta, i$, and $\mu$ denote 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, $\Psi$ is the yaw angle of the vehicle, while $\dot{x}$ and $\dot{y}$ are the longitudinal and lateral velocity of the vehicle respectively.

\[
\dot{X} = \dot{x} \sin \psi + \dot{y} \cos \psi
\]

\[
\dot{Y} = \dot{x} \cos \psi - \dot{y} \sin \psi
\]

### 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.

\[
m_b (\dot{v_x} + \dot{v_y} \dot{\psi}) = F_{yf} + F_{yr}
\]

\[
I_{zf} \dot{l} = l_f (F_{yf} - l_r F_{yr})
\]

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.

\[
F_{yf} = C_f \alpha_f
\]

\[
F_{yr} = C_r \alpha_r
\]

Where $C_l$ and $C_r$ are the front and rear tyre cornering stiffness respectively. Whereas $\alpha_f$ and $\alpha_r$ are front and rear wheel slip angles which can be calculated using Equation 9.

\[
\alpha_f = \delta - \frac{v_y + \psi l_f}{v_x}
\]

\[
\alpha_r = -\frac{v_y - \psi l_f}{v_y}
\]

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

\[
m_b (v_x + v_y \dot{\psi}) = C_f \left( \frac{v_y + \psi l_f}{v_x} \right) + C_r \left( -\frac{v_y - \psi l_f}{v_y} \right)
\]

\[
I_{zf} \dot{l} = l_f C_f \left( \frac{v_y + \psi l_f}{v_x} \right) - l_r C_r \left( -\frac{v_y - \psi l_f}{v_y} \right)
\]

### 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 $\psi_{ref}$ as a function of the longitudinal position $X$.

![Proposed Control Structure](image)

**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
The application of PSO in best id

\[ x(k+1)=Ax(k)+Bu(k) \]
\[ y(k)=Cx(k) \]

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.

\[ J(\zeta(t),u(t),\Delta u(t)) = \sum_{i=1}^{H_p} \left( \zeta_{i+1,1} - \zeta_{\text{ref},1,1} \right)^2 + \sum_{i=0}^{H_c} \left( \Delta u_{r,1,1}^2 + \left| u_{t,1,1} \right|^2 \right) \]

The reference signal, \( \zeta_{\text{ref}} = [f_{\text{ref}}, y_{\text{ref}}, \psi_{\text{ref}}] \) 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.

\[ x(t+1)_{id} = x(t)_{id} + \nu(t+1) \]
\[ \nu(t+1) = i\omega \times v(t) + c_{\text{rand}}(0.1) \times (p_{\text{best}} - x(t)_{id}) + s \times \text{rand}(0.1) \times (g_{\text{best}} - x(t)_{id}) \]
\[ F(Q_1, Q_2, S) = \sum_{i=1}^{n} \|e(t)|^2 \]

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.
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, $\phi$ 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].

$$\delta = k_1 \phi + \tan^{-1}\left(\frac{k_2 e(t)}{v(t)}\right)$$ (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 1. PSO parameters and MPC setting used in building knowledge database.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Social coefficient, $s$</td>
<td>1.42</td>
</tr>
<tr>
<td>Cognitive coefficient, c</td>
<td>1.42</td>
</tr>
<tr>
<td>Inertial weight, $iw$</td>
<td>0.9</td>
</tr>
<tr>
<td>No. of dimensions, $Nd$</td>
<td>3 ($Q_1$, $Q_2$ and $S$)</td>
</tr>
<tr>
<td>Upper bound limit</td>
<td>$10; 10; 10$</td>
</tr>
<tr>
<td>Lower bound limit</td>
<td>$-10; -10; -10$</td>
</tr>
<tr>
<td>No. of particles, $N_p$</td>
<td>25</td>
</tr>
<tr>
<td>No. of iterations, $N_i$</td>
<td>15</td>
</tr>
<tr>
<td>MPC prediction horizon</td>
<td>10 steps</td>
</tr>
<tr>
<td>MPC control horizon</td>
<td>3 steps</td>
</tr>
</tbody>
</table>

### Table 2. Optimized parameters using PSO algorithm.

<table>
<thead>
<tr>
<th>Vehicle Speed (m/s)</th>
<th>Adaptive MPC</th>
<th>Conventional MPC</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>$Q_1$</td>
<td>0.25</td>
</tr>
<tr>
<td></td>
<td>$Q_2$</td>
<td>0.11</td>
</tr>
<tr>
<td></td>
<td>$S$</td>
<td>1.00</td>
</tr>
<tr>
<td>12.5</td>
<td>$Q_1$</td>
<td>0.25</td>
</tr>
<tr>
<td></td>
<td>$Q_2$</td>
<td>0.11</td>
</tr>
<tr>
<td></td>
<td>$S$</td>
<td>1.05</td>
</tr>
<tr>
<td>15</td>
<td>$Q_1$</td>
<td>0.25</td>
</tr>
<tr>
<td></td>
<td>$Q_2$</td>
<td>0.10</td>
</tr>
<tr>
<td></td>
<td>$S$</td>
<td>1.03</td>
</tr>
<tr>
<td>17.5</td>
<td>$Q_1$</td>
<td>0.50</td>
</tr>
<tr>
<td></td>
<td>$Q_2$</td>
<td>0.12</td>
</tr>
<tr>
<td></td>
<td>$S$</td>
<td>0.11</td>
</tr>
<tr>
<td>20</td>
<td>$Q_1$</td>
<td>1.00</td>
</tr>
<tr>
<td></td>
<td>$Q_2$</td>
<td>0.23</td>
</tr>
<tr>
<td></td>
<td>$S$</td>
<td>0.12</td>
</tr>
<tr>
<td>22.5</td>
<td>$Q_1$</td>
<td>2.50</td>
</tr>
<tr>
<td></td>
<td>$Q_2$</td>
<td>0.50</td>
</tr>
<tr>
<td></td>
<td>$S$</td>
<td>0.10</td>
</tr>
<tr>
<td>25</td>
<td>$Q_1$</td>
<td>2.50</td>
</tr>
<tr>
<td></td>
<td>$Q_2$</td>
<td>0.50</td>
</tr>
<tr>
<td></td>
<td>$S$</td>
<td>0.11</td>
</tr>
</tbody>
</table>

### Table 3. Optimized parameters using PSO algorithm.

<table>
<thead>
<tr>
<th>Vehicle Speed (m/s)</th>
<th>Adaptive Stanley</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>$k_1$</td>
</tr>
<tr>
<td></td>
<td>$k_2$</td>
</tr>
<tr>
<td>12.5</td>
<td>$k_1$</td>
</tr>
<tr>
<td></td>
<td>$k_2$</td>
</tr>
<tr>
<td>15</td>
<td>$k_1$</td>
</tr>
<tr>
<td></td>
<td>$k_2$</td>
</tr>
<tr>
<td>17.5</td>
<td>$k_1$</td>
</tr>
<tr>
<td></td>
<td>$k_2$</td>
</tr>
<tr>
<td>20</td>
<td>$k_1$</td>
</tr>
<tr>
<td></td>
<td>$k_2$</td>
</tr>
<tr>
<td>22.5</td>
<td>$k_1$</td>
</tr>
<tr>
<td></td>
<td>$k_2$</td>
</tr>
<tr>
<td>25</td>
<td>$k_1$</td>
</tr>
<tr>
<td></td>
<td>$k_2$</td>
</tr>
</tbody>
</table>

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 $\psi_{ref}$, 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].

$$\psi_{ref} = \tan^{-1}\left(\frac{1}{\cosh(z_1)}\right) - \frac{1}{d_{x1}} - y_{ref} - \frac{1}{\cosh(z_2)} \frac{1}{d_{x2}}$$

$$y_{ref} = \arctan\left(\frac{1}{\cosh(z_1)}\right) \frac{1}{d_{x1}} + \frac{1}{\cosh(z_2)} \frac{1}{d_{x2}}$$

$$z_1 = \frac{-2.4}{25}(x-27.19) - 1.2; \quad y_{ref} = 4.05; \quad d_{x1} = 2.5; \quad d_{x2} = 21.95$$

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.

### Table 4. Vehicle parameters.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$m$</td>
<td>2032 kg</td>
</tr>
<tr>
<td>$I_x$</td>
<td>1.26 m</td>
</tr>
<tr>
<td>$I_y$</td>
<td>1.90 m</td>
</tr>
<tr>
<td>$I_z$</td>
<td>6286 kg/m²</td>
</tr>
<tr>
<td>$C_l$</td>
<td>40,200 N.rad</td>
</tr>
<tr>
<td>$C_r$</td>
<td>62,800 N.rad</td>
</tr>
</tbody>
</table>

![Figure 4. Double lane obstacle avoidance scenario.](image_url)
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.

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).
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 6(c) and 7(c) 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 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.

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