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https://doi.org/10.1109/SMC53654.2022.9945290

Optimal MPC Horizons Tunning of Nonlinear MPC for Autonomous Vehicles Using Particle Swarm Optimisation

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***Abstract*—The autonomous vehicle (AV) has been studied by many researchers recently because of its valuable points in transportation, aviation, military, smart city, and aerospace. The model predictive control (MPC) is employed to track the artificial intelligent regenerated motion signals with higher accuracy than other error- and model-based controllers as it can consider the constraints of the system in extracting the optimal solution. However, the accuracy and applicability of the MPC rely on the MPC horizons, including prediction and control horizons. The higher prediction horizons mean a higher computational load of the system, which reduces the real-time applicability of the system. On the other hand, a higher prediction horizon increases the system's stability in facing abrupt motion signals. In addition, higher control horizons mean more dexterity in the system facing an unknown situation. On the other hand, a longer control horizon increases the computational load of the system exponentially. This study employs particle swarm optimisation (PSO) to extract the optimal MPC horizons considering the accuracy and computational load. The cost function is defined to increase the accuracy of the longitudinal time-varying velocity tracking, decrease the lateral deviation, decrease the relative yaw angle and decrease the computational load of the system. It should be noted that the lateral deviation and relative yaw angle are extracted using the vehicle four wheels dynamic model in order to evaluate the AVs' passenger motion comfort. The proposed method is designed and developed under MATLAB/Simulink. The extracted optimal MPC horizon is compared with some other arrangements of the MPC horizons to prove the efficiency of the proposed method compared with the trial-and-error method.**

Keywords—autonomous vehicle, nonlinear model predictive control, particle swarm optimisation, computational load, motion tracking error, motion comfort

I. Introduction

Autonomous vehicles (AVs) are recently employed in lots of area such as aviation, space discovery, military mission and transportation because of safety and cost effectiveness [1-4]. The usage of AVs is bounded to the development of the smart cities with fully artificial intelligence operating mechanism. The safety and economic efficiency of the AVs are considered a lot by researchers as it is the main goal of the AVs. However, the regeneration of the high-fidelity motion cues via AVs is not seriously considered. Whereas the regeneration of the high-fidelity motion cues for the AVs' users have the direct effect of the public luck in the usage of these gadgets. In addition, motion simulator platforms can be employed for laboratory experiment of AVs before doing the road test in order to minimize the risk of damage [5-11]. Recently, different structures including serial, parallel and hybrid manipulators are employed to regenerate the motion signals for the user as same as the real car [12-19]. The usage of motion simulator to imitate the AVs motion signal in the limited workspace area of the laboratory is possible via usage of motion cueing methods including classical , adaptive, optimal [20, 21], and model predictive control (MPC) [22].

AVs consist of three different sections including road detection (online sequencing algorithm), motion signal regeneration (artificial intelligence) and motion tracking (controller unit) [23]. There are two different type of controller mechanism including error- and model-based units. The error-

based controllers are affordable and easy to implement [24-26]. On the other hand, they are not accurate enough facing abrupt motion signals [27]. The model-based controllers are expensive and complicated, however they are accurate and robust facing uncertainty and abrupt motion signals [28]. MPC is one of the highest efficient model-based controllers that has high power of handling the uncertainty and noises. MPC has been used in automation industry for regeneration of motion cues for the simulator platform [29]. Qazani et al. [30, 31] has been accomplished a research to deal with stability problem of MPC in motion cueing with definition of terminal conditions. MPC in AVs is employed by Falcone *et al*. [32] for controlling the lateral position using steering angle as an input. Handling the nonlinear plant model using linear MPC is only possible with operating around the equilibrium point [33-35]. Then, linear MPC can accomplish the job via linearising the nonlinear plant model [26, 36, 37]. However, it is not possible to reach 100% efficiency of the system without using nonlinear MPC. Then, Falcone *et al.* [38] proposed the nonlinear MPC for handling the lateral and yaw position of the AVs using two inputs including steering angle and brake. Du and Tan [39] proposed the nonlinear MPC using four wheels vehicle dynamic model to control the steering angle and velocity with additional consideration of user motion comfort. Philippe *et al*. [40] achieved the consideration of safety and motion comfort in AVs using linear MPC targeting the regeneration of smooth motion cues for the user without a higher chance of motion sickness or artifact [41-46]. Kayacan *et al*. [47] practically investigate the implementation of linear and nonlinear MPC in autonomous tractor–trailer system. They found that nonlinear MPC and linear MPC are able of extracting the optimal solution using 12 and 2 (ms), respectively. Also, the results of NMPC is more accurate and robust in comparison with linear MPC in the existence of fast microprocessors. Qazani et al. [48] customised the AVs' driver style using machine learning method targeting the light computational load.

The nonlinear MPC consists of lots of parameters including weighting and MPC horizon parameters that should be tuned properly. The proposed selection of the MPC horizon is critical as it relates directly to the computational load and efficiency of the system facing high-frequency motion signals. Qazani et al. [49] proposed the butterfly optimisation algorithm-based (BOA-based) tuning method for optimal selection of the MPC horizons in motion cueing algorithm. Later, Qazani et al. [50] used the grey wolf optimizer (GWO) for extracting the optimal weights of linear MPC in motion cueing domain with consideration of different washout speed. Also, Qazani et al. [51] used the whale optimization algorithm (WOA) for weight tuning of linear MPC in motion cueing domain. Different type of evolutionary-based algorithm such as genetic algorithm [52] for optimisation purposes are used by Qazani et al. [53] to extract the optimal layout of fixture in 3-2-1 technique.

In this paper, particle swarm optimisation (PSO) is employed to extract the MPC horizons of the nonlinear MPC-based controller of the AVs. The objective function is defined to achieve the task of lower longitudinal time-varying velocity tracking error, higher motion comfort of the AVs' users and the lower computational load. The first task of the objective function is achieved via calculating the longitudinal velocity tracking error. The second and third task is achieved via the calculation of the lateral deviation and relative yaw angle using the four wheel vehicle dynamic model. The fourth task is achieved via adding the CPU running time inside the objective function during the regeneration of the motion cues via the nonlinear MPC. The proposed model is designed in MATLAB/Simulink and the results are extracted using the different set of MPC horizons.

The four wheels vehicle dynamic model, nonlinear MPC and PSO are explained in the next Section as the proposed methodology of this study. In Section III, the proposed method is developed under MATLAB/Simulink and the results are extracted using the developed model. The remark of this study is presented in Section IV.

In this study, LTV MPC model based on the four wheels' nonlinear vehicle dynamic model is designed and proposed to control the longitudinal velocity,

II. Methodology

This Section consists of three subsections, including four wheels dynamic vehicle model, mathematical representation of nonlinear MPC and PSO.

A. Vehicle Dynamic Model

The four wheels dynamic model of the vehicle is used in this study as the dynamical model of the system inside the nonlinear MPC. In addition, the user's motion comfort is evaluated via adding the lateral deviation e_1 and relative yaw angle e_2 inside the dynamic model of the vehicle [39]. It should be noted that the chassis' roll and pitch motions are not considered inside the vehicle dynamic model for the sake of simplicity and real-time applicability.

Fig. 1 shows the vehicle dynamic model which is used in this study. The vehicle has 3-degrees-of-freedom (3-DoF), while the motion of the vehicle can be captured as:

$$\frac{d}{dt}\begin{bmatrix} v_y \\ \dot{\psi} \\ v_x \\ \dot{v}_x \\ e_1 \\ e_2 \end{bmatrix} = \begin{bmatrix} -\frac{2C_f+2C_r}{mv_x} & -v_x-\frac{2C_fl_f-2C_rl_r}{mv_x} & 0 & 0 & 0 & 0 \\ -\frac{2C_fl_f-2C_rl_r}{I_zv_x} & -\frac{2C_fl_f^2-2C_rl_r^2}{I_zv_x} & 0 & 0 & 0 & 0 \\ \dot{\psi} & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & -\frac{1}{\tau} & 0 & 0 \\ 1 & 0 & e_2 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \end{bmatrix} \underbrace{\begin{bmatrix} v_y \\ \dot{\psi} \\ v_x \\ \dot{v}_x \\ e_1 \\ e_2 \end{bmatrix}}_{\xi} + \begin{bmatrix} 0 & \frac{2C_f}{m} \\ 0 & \frac{2C_fl_f}{I_z} \\ 0 & 0 \\ \frac{1}{\tau} & 0 \\ 0 & 0 \\ 0 & 0 \end{bmatrix} \underbrace{\begin{bmatrix} a \\ \delta \end{bmatrix}}_{\mathbf{u}} + \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ -v_x \end{bmatrix} \rho \tag{1}$$

where m and I_z are the mass and moment of inertia of the vehicle along the *z*-axis, respectively. Also, v_y, $\dot{\psi}$, v_x, $\dot{v}_x$, a, δ and ρ are lateral velocity, yaw rate, longitudinal velocity, longitudinal acceleration, car acceleration, car steering angle and road curvature, respectively. Also, C_f, C_r, l_f, l_r and τ are cornering stiffness of the front tires, cornering stiffness of the

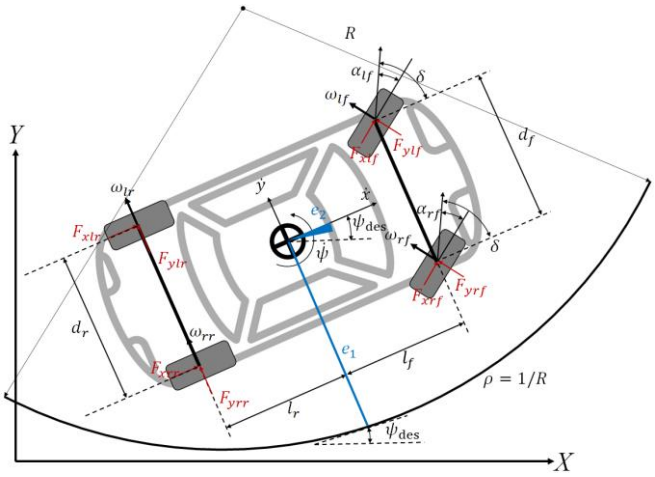


Fig. 1. The dynamic model of the vehicle.

rear tires, the distance between the centre of gravity and front axle, distance between the centre of gravity and rear axle, and longitudinal acceleration tracking time constant, respectively.

B. Nonlinear Model Predictive Controller

The vehicle dynamic model presented in the previous subsection is used as the nonlinear plant model for developing the nonlinear MPC in this subsection. The dynamic model of the AV is used to calculate the states of the AV along the prediction horizons with implementation of control actions along control horizon. The combination of prediction and control horizons called MPC horizons which has a significant influence in the performance of the system in point of computational load, accuracy and efficiency facing abrupt motion signals.

Referring to the dynamic model of the AV in Eq. (1), using the states $\boldsymbol{\xi}$, inputs $\mathbf{u}$ and outputs $\mathbf{z}$, the nonlinear plant model can be expressed as:

$$\dot{\boldsymbol{\xi}} = F(\boldsymbol{\xi}, \mathbf{u}) \tag{2. a}$$

$$\mathbf{z} = h(\boldsymbol{\xi}) \tag{2. b}$$

where F and h are the nonlinear state and output functions of the AV. Also, $\mathbf{z} = [v_x \quad e_1 \quad e_2 + x_{\text{od}}]^{\text{T}}$ is the output vector of the system.

The represented nonlinear dynamic model in Eq. (2) is continuous. It should be discretised in order to be used inside the nonlinear MPC as follows:

$$\boldsymbol{\xi}(k+1) = \big(\boldsymbol{\xi}(k), \Delta\mathbf{u}(k)\big) \tag{3. a}$$

$$\mathbf{z}(k) = h\big(\boldsymbol{\xi}(k)\big) \tag{3. b}$$

$$\mathbf{u}(k) = \mathbf{u}(k-1) + \Delta\mathbf{u}(k) \tag{3. c}$$

This research is focused on third objective goals simultaneously. Initially, the lower longitudinal time-varying velocity tracking error is considered and added inside the cost function. It is the first argument of the output vector shown as v_x inside Eq. (3b). In addition, the lateral deviation and relative yaw angle is considered inside the cost function as the second and third argument of the output vector to increase the motion comfort for AVs' users. The easy way for consideration of the computational time inside the model is to calculate a use of CPU running time inside the objective function of the evolutionary-based optimisation algorithm rather than the nonlinear MPC cost function. This part is going to be handled in the next subsection. Therefor, the cost function of the nonlinear MPC at each sampling time can be written as:

$$J(\xi(t), \Delta\mathbf{u}_t^*) = \sum_{k=0}^{N_p-1} \|\hat{z}(t+k|t) - z(t+k|t)\|^2_{\text{W}_{\text{out}}} + \sum_{k=0}^{N_c-1} \|\Delta u(t+k|t) + \|^2_{\text{W}_{\text{in}}} \tag{4}$$

where $\Delta\mathbf{u}_t^*$ is an optimised control vector that is extracted by the nonlinear optimiser. Also, $\hat{z}(t+k|t)$ is the calculated output of the system using Eq. (3b). $\text{W}_{\text{out}} \in \mathbb{R}^{3\times3}$ and $\text{W}_{\text{in}} \in \mathbb{R}^{2\times2}$ are the weighting matrices of the output and input vectors, respectively. N_p and N_c are the prediction and control horizons of the nonlinear MPC, respectively. The aim of this study is the extraction of the optimal prediction horizon N_p and control horizon N_c reaching lower computational load, lower longitudinal time-varying velocity error and higher motion comfort using the evolutionary-based optimisation method in the next subsection.

C. Particle Swarm Optimisation

PSO is a swarm-based technique developed in 1995 [54]. Many modifications have been proposed, e.g. [55]. The procedure of PSO is straightforward. It starts by defining the initial particles and computes the fitness function according to the position of each particle. The lowest objective function is determined as the best location. It then calculates the new velocities based on the best position of the particles and their neighbours as well as the current velocity. The procedure continues iteratively until the algorithm fulfils the stopping criteria. Similar to the GA, four parameters in PSO should be determined carefully, namely the current position vector, the current velocity vector, the best location vector, and the global best location. The particles are updated by the new values based on the velocity vector to produce the new locations.

Weights and horizons are the vital elements of the model predictive control-based motion cueing are. MPC horizons affect MPC computation time due to their direct impact on the QP problem size. On the other hand, the weights of the MPC influence the error of the sensed motion and displacement of the simulator. The fitness function, J_{MCA}, is defined as an integration of the motion cueing indexes, as in Eq. (7):

$$J\big(N_c, N_p\big) = W_{v_x} \int (v_x - v_{\text{ref}})^2 dt + W_{e_1} \int {e_1}^2 dt + W_{e_2} \int {e_2}^2 dt + W_{CPU} \int \text{CPU}_t{}^2 dt \tag{5}$$

where W_{v_x}, W_{e_1}, W_{e_2} and W_{CPU} are the influence factors of the longitudinal time-varying velocity, lateral deviation, relative yaw angle and CPU running time of system.

III. Results and Discussions

This section is composed of two main part regarding the optimisation part of the study as well as the extracting the result using extracted optimal nonlinear MPC as well as the manually tuned nonlinear MPCs.

Initially Simulink model of the investigated nonlinear MPC in Section II.B is developed using MATLAB/Simulink via NonlinearMPC block. The developed model is designed parametric as a function based on different set of prediction N_p and control N_c horizons. Then, the developed Simulink model is defined as the objective function for PSO, while the objective value (penalty value) is calculated based on the regenerated output of the system using simout block. This block has been applied in the time-varying reference longitudinal velocity, longitudinal velocity, lateral deviation,

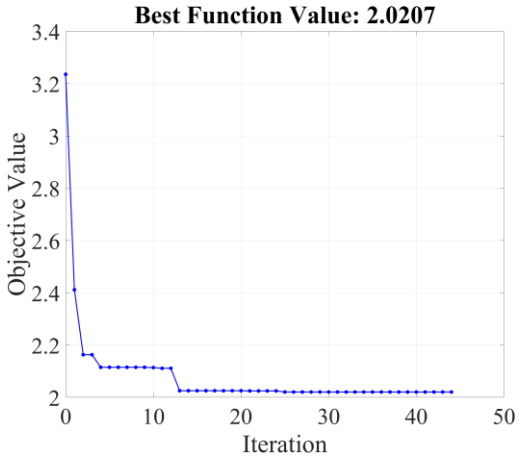


Fig. 2. The convergence plot of the PSO in calculation of the optimal MPC horizons of nonlinear MPC.

relative yaw angle, linear acceleration, steering angle and CPU running time to captured the values towards the workspace in order to calculate the objective value of the function in each trial. The hyperparameters of the PSO is defined as follows:

1. Swarm size = 5.
2. Maximum of iteration = 50.
3. Maximum running time = 5 hours
4. Error threshold = 10^{-14}
5. The range of control horizon = 1-10
6. The range of prediction horizon = 5-100

The convergence plot of the PSO using 50 times iteration limitation is shown in Fig. 2. It aims to reduce the computational load, motion tracking error and motion discomfort for the AVs' users based on Eq. (5). The proposed PSO captured the optimal MPC horizons after 44 iterations. The PSO is terminated because the maximum running time limitations is reached. The extracted optimal solution using PSO is $N_p = 10$ and $N_c = 2$. In addition to the extracted optimal MPC horizons using PSO, other arrangement of N_p and N_c are used to prove the efficiency of the proposed optimal nonlinear MPC compared to manually tuned method.

The testing motion path is extracted for 15 seconds to evaluate the proposed methods. Fig. 3a-b represents the road path and the road's curvature for 15 seconds, respectively. Based on Fig. 3a, there are two turns left and one turn right in the road between 20 and 70 seconds of the motion. After 70 seconds of the motion, the car is moving along the straight road without any lane-changing manoeuvre.

The reduction of the computational load of the system is the main and first objective of this study which is shown in Fig. 4a-b. The mean square error of the total CPU running time during the 15 (s) of motions are shown in Fig. 4a. Fig. 4a is used to show the total running time of the proposed nonlinear MPC using the optimal MPC horizons ($N_p = 10$ and $N_c = 2$) as well as some other arrangement of the MPC horizons. The proposed optimal nonlinear MPC is able to reach the lowest total CPU running time (0.00154973 seconds) in comparison with other arrangement of MPC horizons. It should be noted that the highest computational load relates to the highest prediction and control horizons nonlinear MPC with 100 and

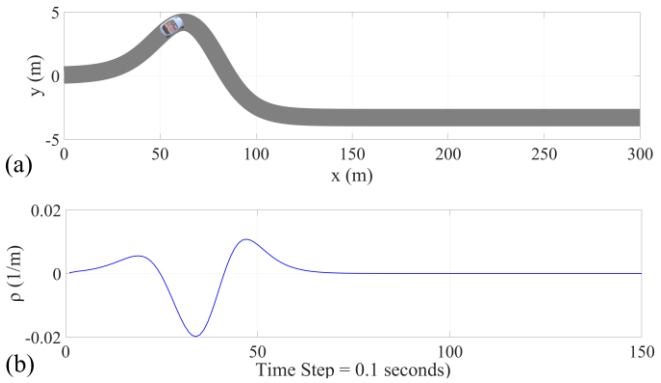


Fig. 3. The reference signal of the AV including (a): motion path along *x-y* plan; (b): curvature of the road in each time-step of the AV's motion.

10 time-steps, respectively. In addition, Fig. 4b shows the CPU run time during the 15 seconds of the motion scenario

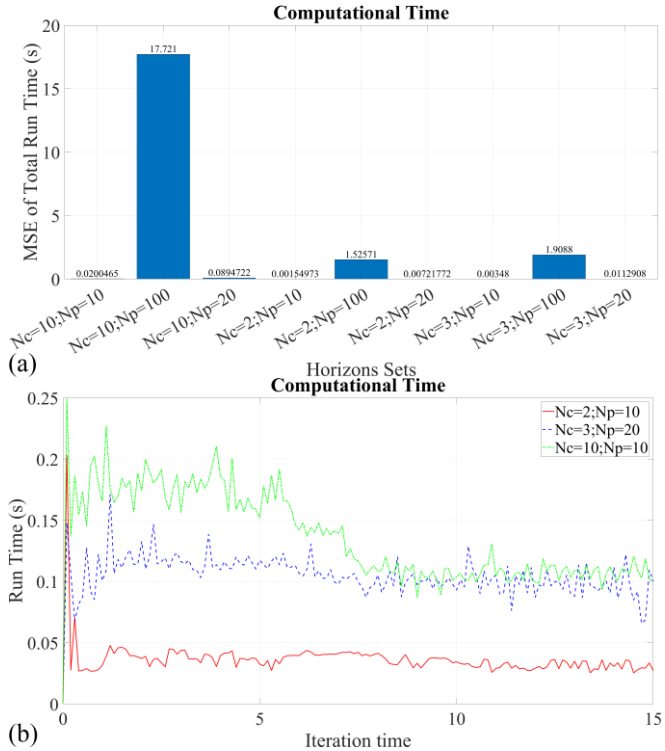


Fig. 4. The total CPU run time of the proposed nonlinear MPC using different sets of MPC horizons.

for three different arrangements of the MPC horizons as $N_p = 10;\ N_c = 2$, $N_p = 20;\ N_c = 3$ and $N_p = 10;\ N_c = 10$. Based on the represented results on Fig. 4a-b, the extracted optimal MPC horizon including $N_p = 10;\ N_c = 2$ has the lowest computational load with 0.05 (seconds) maximum running time in each time-step, while the time-step is 0.1 (seconds) in the application.

The second objective of the optimisation is the accurate longitudinal time-varying velocity tracking compared to trial-and-error tuning methods. In order to evaluate the velocity tracking accuracy of the proposed method, the time-varying reference and time-varying longitudinal velocity of the AVs are shown in Fig. 5a for different arrangement of the MPC horizons including $N_p = 10;\ N_c = 2$, $N_p = 20;\ N_c = 3$ and $N_p = 10;\ N_c = 10$. Also, the error between the reference and

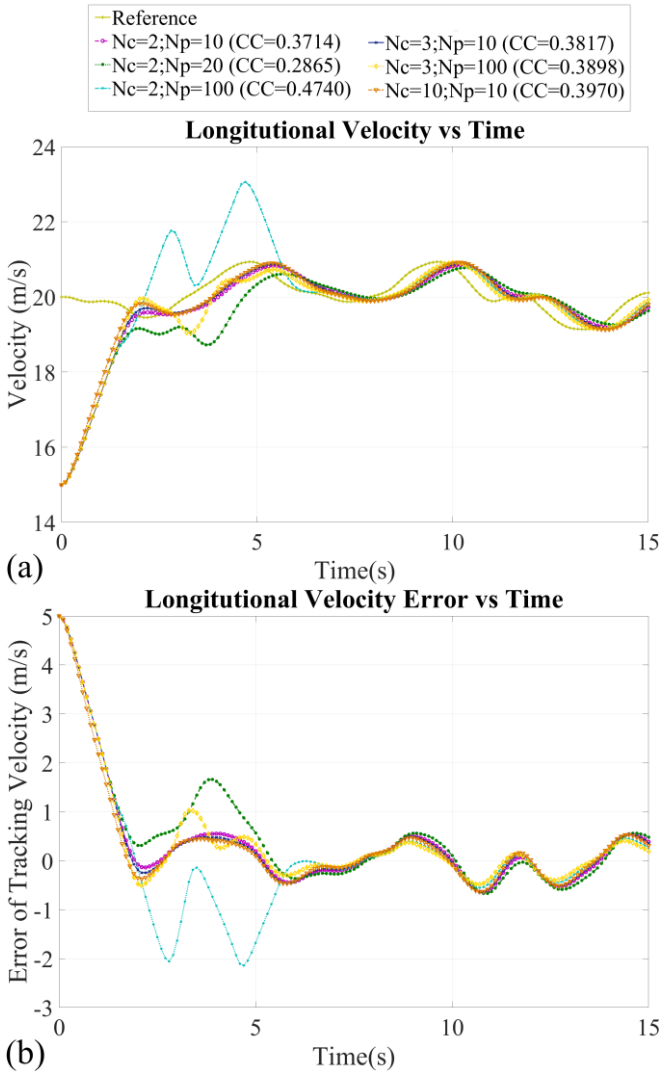


Fig. 5. (a): The reference and followed time-varying longitudinal velocity using different arrangement of MPC horizons; (b): The error between the reference and followed time-varying longitudinal velocity using different arrangement of MPC horizons.

followed time-varying longitudinal velocity using different arrangement of MPC horizons including $N_p = 10$; $N_c = 2$, $N_p = 20$; $N_c = 3$ and $N_p = 10$; $N_c = 10$ are shown in Fig. 5b. Based on the represented results in Fig. 5a, the highest correlation coefficient (CC) between the reference and followed time-varying longitudinal velocity is achieved by $N_p = 100$ and $N_c = 2$ with 0.4740. However, It is not possible to be implement for real-time application because of the long prediction horizon or expensive computational load. In addition, the CC between the reference and followed time-varying longitudinal velocity using optimal MPC horizons $N_p = 10$ and $N_c = 2$ is 0.3714, which is acceptable as a high accurate system. Based on Fig. 5b, MSE between the reference and followed time-varying longitudinal velocity using optimal MPC horizons $N_p = 10$ and $N_c = 2$ is 1.3521 (m/s) as and accurate nonlinear MPC for AV. The highest MSE between the reference and followed time-varying longitudinal velocity is achieved with $N_p = 100$ and $N_c = 2$ with 1.7354 (m/s).

The final evaluation of the proposed method is related to the motion comfort of the AV users, which is achieved by monitoring the lateral deviation as well as relative yaw angle

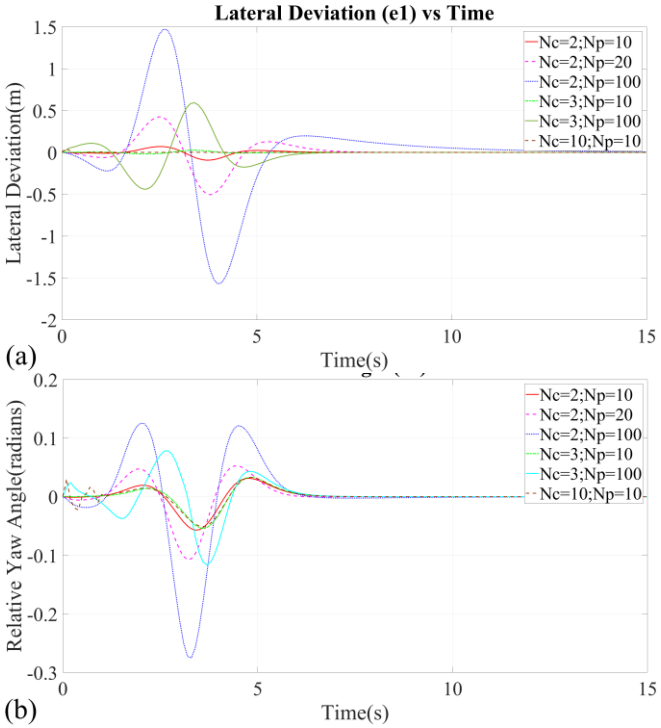


Fig. 6. The AV users motion comfort evaluation using (a): lateral derivative; (b): relative yaw angle.

of the AV during the implementation of motion signals. Fig. 6a-b shows the lateral deviation and relative yaw angle during 15 seconds of the motion signal implementation, respectively. Based on represented results in Fig. 6a, the MSE of the lateral deviation using optimal MPC horizons is 6.329×10^{-4} (m). The highest MSE of the lateral deviation is belong to $N_p = 100$ and $N_c = 2$ with 2.547×10^{-1} (m). In addition, the MSE of the relative yaw angle using optimal MPC horizons is 2.2837×10^{-4} (rad). Also, the highest MSE of the relative yaw angle is reached by $N_p = 100$ and $N_c = 2$ with 4.6×10^{-3} (rad).

The represented results in this Section prove the efficiency of the proposed optimal nonlinear MPC in motion tracking of AV in points of cheapest computational load, most accurate longitudinal velocity tracking and highest motion comfort for the AV users.

IV. Conclusion

There is a significant growth in the usage of AVs, owing to their great potential in reducing the cost of transportation as well as safety risks of travellers. Three major components of an AV are perception, path planning and motion tracking. This study aims to extract the optimal MPC horizons using PSO in order to reduce the computational load of the system as the first objective. The second main objective of this study is to increase the accuracy of the longitudinal time-varying velocity tracking. The third objective of this study is the highest motion comfort for the AV users in order to increase the general luck for usage of AVs. The PSO is employed to achieve this task by calculating the optimal MPC horizons including prediction and control horizons. The proposed method is developed in MATLAB/Simulink and compared with pairs of trial-and-error tuned nonlinear MPCs. The results prove the efficiency of the proposed method in three points including cheapest computational load most accurate longitudinal velocity tracking and highest motion comfort for the AV users. As a future study, the idea of machine learning [56-68] with

consideration of human physiological data [69, 70] can be used to decrease the computational load of the system, while increasing the efficiency of the controller unit.

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