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ORIGINAL PAPER

Predictive Control Applied to the Steering System of an Autonomous Vehicle

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Abstract

Purpose This paper proposes the computational modeling of a lateral and longitudinal action Model Predictive Control (MPC) controller to immediately control and correct the steering system of an autonomous/intelligent vehicle considered robust during its displacement.

Methods and Results The control is defined by the input variable δ (steering system) and projected by the MPC controller considering input and output restrictions, the mathematical model of the vehicle steering system and experimental parameters are set to validate vehicular steering control regarding its precision and safety. The configuration of the vehicle system block diagram and simulations were performed with the aid of Matlab/Simulink software.

Conclusions The results of the computational simulations are represented by the output variables (lateral position Y and yaw angle ψ) that positively validates the MPC to take over the steering and braking of a preferably autonomous vehicle in in situations of sudden longitudinal and lateral movements and in front of obstacles. The linear and discrete answers presented classify the MPC controller as robust.

Keywords Model Predictive Control · Autonomous Vehicle · Intelligent Vehicle · Non-linear Systems · Vehicular Systems

Introduction

In the vehicular systems noise and disturbances are unavoidable adverse conditions during vehicle displacement whether on the highway, local road or parking lot. In [1, 2] the controller project must be robust to meet the longitudinal and lateral control with higher precision, safety, control, fuel consumption reduction and driving comfort are expected parameters in the vehicle dynamics response, it is a subject with great occupation in scientific and operational researches of the main automotive industries. The stability and performance of the vehicle system depends on the longitudinal and lateral controller, the power train and the brake pedal assembly are responsible for the longitudinal motion control. In normal cases the driver's steering control is responsible for lateral motion control classified as more complex [3]. For sudden dynamic lateral movements, the lateral slip angle is large and the yaw rate is high. The lateral movement must be manipulated by the active safety system (one of them is the electronic stability and control system-ESC) otherwise the vehicle will permanently lose stability, in this way this paper studies solutions for the application of lateral dynamics and some longitudinal references based on the behavior of the Model Predictive Control (MPC) controller according to [4, 5]. Model Predictive Control can perform a leading role in both guidance and control of aerospace systems, for its ability to deal with constraints and uncertainties, provides the notion of optimization for minimizing the control actions and maximizing the trip duration [6]. In [7] is presented a new method to solve the problems related to obstacles during controller-solved hybrid planning (MPC), the tests were performed on a Renault Twizy automated vehicle and showed good performance in complex scenarios involving static and moving obstacles at a maximum velocity of 60 km/h. In [8] the controller (MPC) was implemented to directly

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solve the longitudinal and lateral coupling control problem, the convex optimization method was used to solve the MPC reference value problem, the real-time simulation and actual vehicle results showed that the algorithm can solve both lateral and longitudinal disturbance problems. In [9] is presented a review on MPC and its broad applications for autonomous and multiple vehicles (AGVs), MPC is a control method that uses predicted future information to optimize control actions while explicitly considering constraints and AGVs are able to make predictions and adapt their decisions in uncertain environments, the work highlights existing issues and future research directions that will further the development of high performance MPC schemes in AGVs. In [10] is developed a coalition distribution model predictive control (C-DMPC) methodology, the control strategy was tested for a vehicle platooning application consisting of a virtual leader and four follower vehicles with unidirectional leader–follower communication topology, the stability of the algorithm is ensured by formulating the terminal constraint region with positively invariant robust sets, the simulation results showed the efficiency of the proposed DMPC coalition algorithm in which coalitions between different agents are formed when needed.

In this paper a steering scenario is developed where geometric points are inserted through which the vehicle follows the trajectory with a constant (standard) longitudinal velocity, the vehicle's front steering angle is considered as the input variable and the output variables are described as the vehicle's lateral position and yaw angle. The linearization of the vehicle plant allows the MPC controller to have advanced data of its output in order to correct or approximate the output signal with respect to the input signal, in this way the MPC controller must be robust to withstand disturbances or dynamic lateral movements called discrete (nonlinear systems).

Context of the Problem

The parametric uncertainties of a vehicle in particular the total mass (kg) is a determining factor regarding tire stiffness in curves that can be uncertain or show wear during displacement. The nonlinear behavior of tires depends on vertical load, friction, longitudinal and lateral forces.

Regardless of the obstacles, whether the road surface is dry or wet, the steering system controller must be valid for the safety of one or more vehicle occupants.

In [11, 12] is presented the multivariable system also known as Multi Input-Multi Output (MIMO) being the system that must have more than one input and more than one output, the multivariable control system determines a system with strict interaction from variable to variable, the interaction is a result of the project and cannot be avoided, as a solution the system must correct/compensate for the interaction, a perturbation in any input variable changes one of the responses of the output variables, a square system is considered when the number of input variables is equal to the number of output variables, the most common characteristics of multivariable/MIMO control systems are highlighted by a system with perturbation and/or feedback. For the control system with feedback, a 2×2 matrix system can be considered (system with 2 input variables and 2 output variables) as shown in Fig. 1.

The variables of the multivariable system with feedback presented above are described as:

- Y: is a vector ($l \times 1$) for both cases (inputs and outputs);
- U: is a vector ($m \times 1$) for both cases (inputs);
- G_P: is a transfer function matrix ($l \times m$)—referring to plant/process;
- G_C: is considered a control matrix ($l \times m$)—referring to the plant controller;
- E: is a vector ($l \times 1$) for both cases (inputs).

PID controllers do not always meet the controls required for more complex systems/processes as described in [13]. Therefore, this paper proposes the MPC controller classified as robust to meet the complex vehicular system.

MPC Controller Mathematical Model

In this section, the mathematical model of the MPC controller is based on the available variables/parameters of the vehicle system.

The MPC controller is an advanced control technique in which the system model is used to predict the output at future times, capable of generating a control strategy that optimizes several selected quadratic criteria [14]. This

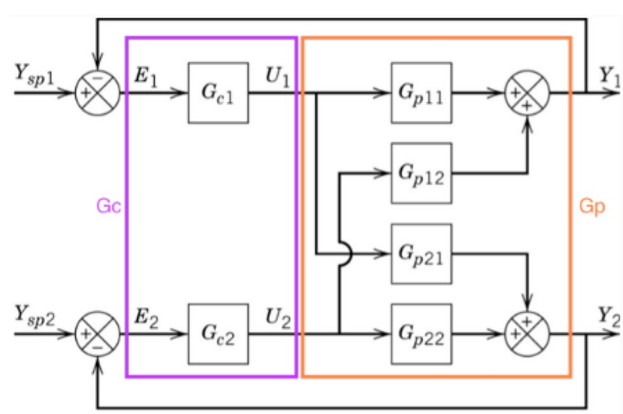

Fig. 1 Multivariable system with feedback control

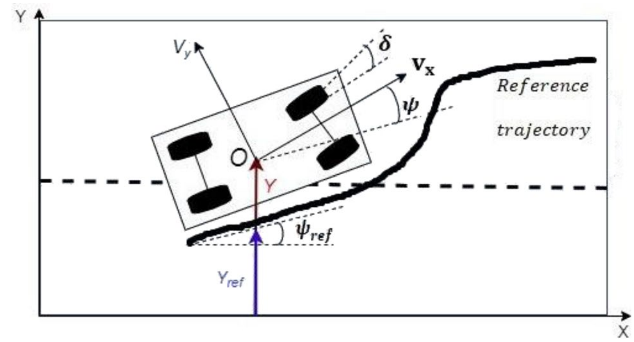

Fig. 2 Cartesian reference and supposed dynamic variables of a vehicle

Table 1 Vehicle dynamic variables

Variable	Description
V_y	Lateral velocity
V_x	Longitudinal velocity
X, Y	Vehicles global position
ψ	Yaw angle
δ	Front steering angle
Y_{ref}	Reference lateral position
ψ_{ref}	Reference yaw angle

Table 2 Variables that influence the vehicle system

Variable	Description	Unit
m	Total vehicle mass	kg
I_z	Moment of inertia of the vehicle	mNs^2
L_f	Longitudinal distance from the center of gravity to the front tires	m
L_r	Longitudinal distance from center of gravity to the rear tires	m
C_f	Cornering stiffness of the front tires	N/rad
C_r	Cornering stiffness of the rear tires	N/rad

technique can be implemented in both continuous and discrete systems [15, 16].

Figure 2 shows the vehicle and its dynamic variables without the MPC controller.

The dynamic variables are described in detail in Table 1 below.

The variables that influence the vehicle system are highlighted in Table 2.

In this paper, only the lateral controller (lateral dynamics) is validated, however the longitudinal velocity (longitudinal dynamics) is considered constant [17, 18]. It is possible to represent the lateral dynamics from an Linear Time-Invariant (LTI) system associated with state, input and output variables. As show the Table 3.

Table 3 Variables of the vehicle's lateral dynamics

1. State variables	2. Input variables	3. Output variables
V_y-lateral velocity ψ-yaw angle r-yaw angle rate Y-global position	δ-front steering angle	Y-global position ψ-yaw angle

The state-space representation is defined by the input $\left(\dot{X}_{(t)}\right)$ and output $\left(Y_{(t)}\right)$ matrices of an LTI system [18, 19]. The input matrix is defined by Eq. 1.

$$\dot{X}_{(\mathrm{t})} = A_{x(t)} + B_{u(t)}. \tag{1}$$

The output vector is defined by Eq. 2.

$$Y_{(t)} = C_{x(t)} + D_{u(t)}. \tag{2}$$

However, the input matrices are considered in relation to the lateral dynamics of the vehicle according to Eq. 3.

$$\frac{d}{dt}\begin{Bmatrix} \dot{y} \\ \psi \\ \dot{\psi} \\ y \end{Bmatrix} = \begin{bmatrix} -\frac{2(C_f+C_r)}{m/V_x} & 0 & -V_x - \frac{2(C_fL_f-C_rL_r)}{m/V_x} & 0 \\ 0 & 0 & 1 & 0 \\ -\frac{2(C_fL_f-C_rL_r)}{I_z/V_x} & 0 & -\frac{2(C_fL_f{}^2+C_rL_r{}^2)}{I_z/V_x} & 0 \\ 1 & V_x & 0 & 0 \end{bmatrix} \begin{bmatrix} \dot{y} \\ \psi \\ \dot{\psi} \\ y \end{bmatrix} + \begin{bmatrix} \frac{2C_f}{m} \\ 0 \\ \frac{2C_fL_f}{I_z} \\ 0 \end{bmatrix} \delta. \tag{3}$$

The output matrix in relation to the lateral dynamics of the vehicle is described by Eq. 4.

$$C_{x(t)} = Y_{(t)} - D_{u(t)}. \tag{4}$$

Punctually, the works [20, 21] describe the global position Y as the dynamics associated the relation of the longitudinal velocity V_x (constant) multiplied by the yaw angle ψ, added by the lateral velocity V_y. As described in Eq. 5.

$$\dot{\mathrm{Y}} = V_x\psi + V_y. \tag{5}$$

The longitudinal velocity V_x is adapted according to each project during vehicle displacement to evaluate lateral dynamics in relation to curves and complex maneuvers that require more efforts from the vehicle's dynamic variables (robust system). The state, input and output matrices are converted from linear to discrete (nonlinear) systems [22].

MPC Controller Functional Project

During the computational simulations, the structure of the MPC diagram was based on the input and output variables as shown in Fig. 3 [23]. The functional project of the MPC controller associated with the autonomous/intelligent

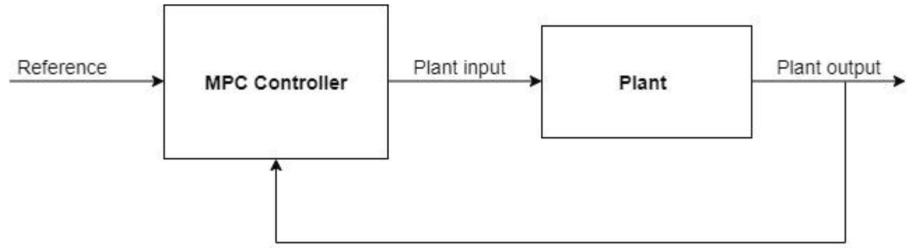

Fig. 3 Diagram of the MPC Controller applied to autonomous vehicles

vehicle factory considers a feedback system with principal references:

Based on the lateral position reference (Y_{ref}) and yaw angle reference (ψ_{ref}), the driving scenario (project developed from Matlab-Simulink software) where the trajectory points are parameterized so that the vehicle moves and varies its steering angle at each actual curve of the trajectory, the longitudinal velocity (V_x) must be constant. The input variable of the vehicle system is the forward steering angle (δ), the output of the vehicle system is characterized by the overall lateral position (Y), yaw angle (ψ) and other variables can be considered according to its project [24, 25]. The block diagram of the MPC controller is parameterized using the predictive control toolbox (Matlab-Simulink software).

In this implantation the MPC controller (Model Predictive Control) for the steering system of an autonomous vehicle is validated, whose representation in diagram of the multivariable closed-circuit system of the MPC controller is shown in Fig. 4 [26, 27].

This block diagram (MPC controller closed-loop multivariable system) comprises the following topology:

1. Identify the environment in which the vehicle circulates (Road Environment Informations);
2. Generation of physical signals from the velocity reference (Longitudinal Controller (MPC) used to control the vehicle velocity) and the trajectory reference (Lateral Controller (MPC) used to control the angle of the vehicle's steering);
3. The dynamic behavior of the vehicle (longitudinal position) depends on the vehicle velocity (u_{th}) and the desired velocity (u_{br}), this comparison is possible because it is a closed-loop/feedback system;
4. The dynamic behavior of the vehicle (lateral position) depends on the vehicle's steering angle (δ_{sw}) this comparison is possible because it is a closed- loop/feedback system;
5. Longitudinal controller and lateral controller can be run at the same time;
6. Implanted in robust multivariable systems.

The representation of the MPC controller implanted in the process/plant can be represented by simple block diagrams or by the more detailed representation such as that of the multivariable system. In technological and scientific research the MPC controller can be applied to the longitudinal and lateral control of a vehicle even when considering the robust system [28, 29].

Parameters Used in the Simulations

Values were assigned that contribute significantly to the simulations and validation of the vehicle system, described in Table 4.

As described in Eqs. 3 and 4 respectively, the input $\left(\dot{X}_{(t)}\right)$ and output $\left(Y_{(t)}\right)$ matrices of the LTI system can be calculated based on Table 4. Replacing the values in Table 4

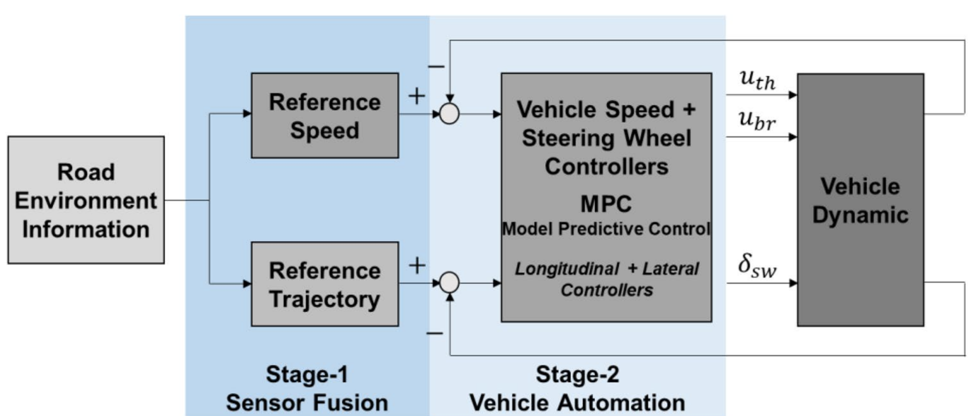

Fig. 4 MPC controller closed loop multivariable system

Table 4 Vehicular system parameters

Variable	Value	Unit
m	1565	kg
I_z	2875	mNs^2
L_f	1.2000	m
L_r	1.6000	m
C_f	19000	N/rad
C_r	33000	N/rad

with Eq. 3, the values of the input matrices (A and B) are obtained according to Eq. 6.

$$\frac{d}{dt}\begin{Bmatrix} \dot{y} \\ \psi \\ \dot{\psi} \\ y \end{Bmatrix} = \begin{bmatrix} -4.4021 & 0 & -12.4603 & 0 \\ 0 & 0 & 1 & 0 \\ 1.3913 & 0 & -5.1867 & 0 \\ 1 & 15 & 0 & 0 \end{bmatrix}\begin{bmatrix} \dot{y} \\ \psi \\ \dot{\psi} \\ y \end{bmatrix} + \begin{bmatrix} 24.1269 \\ 0 \\ 15.8608 \\ 0 \end{bmatrix}\delta. \tag{6}$$

From Eq. 2, the output matrix was calculated with the help of the Matlab/Simulink software giving rise to Eq. 7.

$$\mathrm{Y}_{(t)} = \begin{bmatrix} 0 & 0 & 0 & 1 \\ 0 & 1 & 0 & 0 \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \end{bmatrix}. \tag{7}$$

This equation characterizes the output of the system, (D) being considered a scalar of zero (0) value. The tuning of the MPC controller was based on the parameters described in Table 5.

Discussions and Results

The feedback controller reduces the effect of noise and disturbances in the vehicle system excess cross-wind can disturb the position of the vehicle during its displacement on the highway as shown in Fig. 5 [30]:

If there whereby it requires that the lateral and longitudinal control acts immediately on the steering system compensation the feedback controller ensures that the output

Table 5 Parameters used for tuning the MPC controller

Description	Variable	Value	Unit
Sample time	T_s	0.1	s
Prediction horizon	P_h	10	m
Control horizon	C_h	3	m
Constraints input	C_i	−0.5236to0.5236 −0.2617to0.2617[rate]	rad
Constraints output	C_o	−2to6 −0.2000to0.2000	m rad
Weights input	w_i	0 0.1[rate]	dimensionless
Weights output	w_o	1to0.1	dimensionless

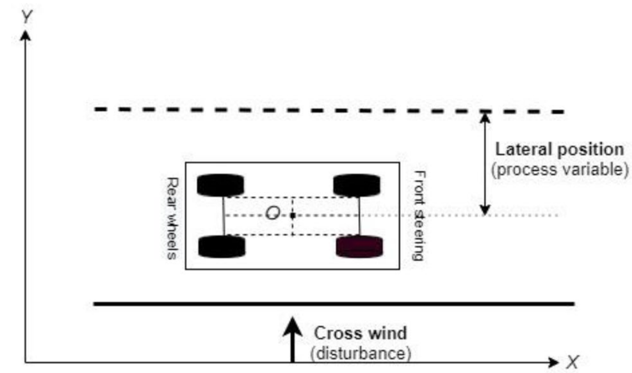

Fig. 5 Projection of noise and disturbance

variables of the vehicle system are controlled the inaccurate reading of the vehicle sensing system induces the controller to produce the noise [31–34].

To approximate the real context mentioned above; the input and output constraints/limitations of the MPC controller were considered in the simulations to test and validate its robustness.

In the block diagram of the MPC controller a reference input (δ-front steering angle) is configured which is connected to the vehicle plant by which it anticipates two output variables of the vehicle plant (Y-global position and ψ -yaw angle). After defining the sampling time $\left(T_s = 0.1\mathrm{s}\right)$ a linearization is defined for the vehicle plant, the horizontal prediction is defined as $\left(P_h = 10\mathrm{m}\right)$ and horizontal control defined as $\left(C_h = 3\mathrm{m}\right)$. For the input restrictions/limitations of the steering angle (δ) it has its movements defined in the minimum (−0.5236) and maximum (0.5236), as well as its direction dynamics (rate) has its minimum (−0.2617) and maximum dynamics (0.2617) for both cases it is defined as scalar (1). The exit restrictions/limitations of the global lateral position (Y) have their positions defined in minimum (−2) and maximum (6), as well as their yaw angle (ψ) has their minimum (−0.2617) and maximum (0.2617) for both cases it is defined as scalar (1). Closed-loop performance is tuned to robust and somewhat aggressive. For w_i (input weight) it is considered(0), its dynamics (0.1) and for w_o (weight exits) 1 to 0.1 was considered, both cases dimensionless values. The behavior of the input signal (δ-front steering angle) of the vehicle's plant considers a linear MPC controller, as shown in Fig. 6.

The behavior of the output signal (Y-global position) or lateral position of the vehicle's plant considers a linear MPC controller, as shown in Fig. 7.

The output signal (ψ-Yaw angle) or lateral angle of the vehicle's plant considers a linear MPC controller, as shown in Fig. 8.

In the vehicle plant scenario, a ramp excitation signal of (0.5) in time ($1s$) is introduced to the lateral position

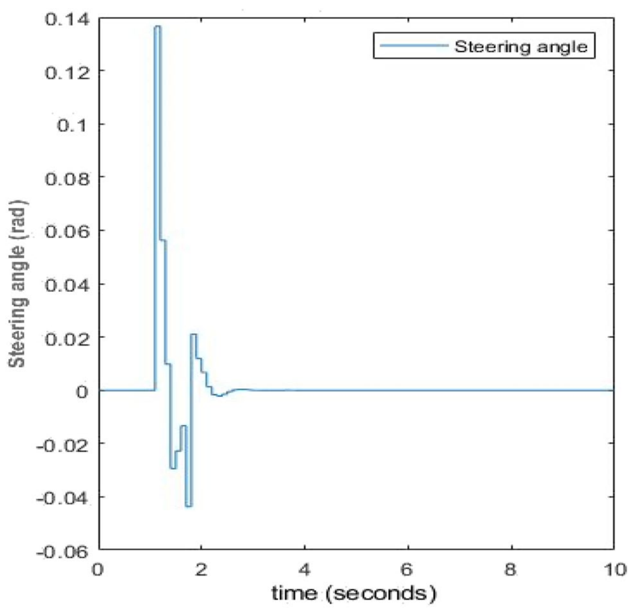

Fig. 6 Steering angle input signal from the linear MPC controller in the vehicle plant

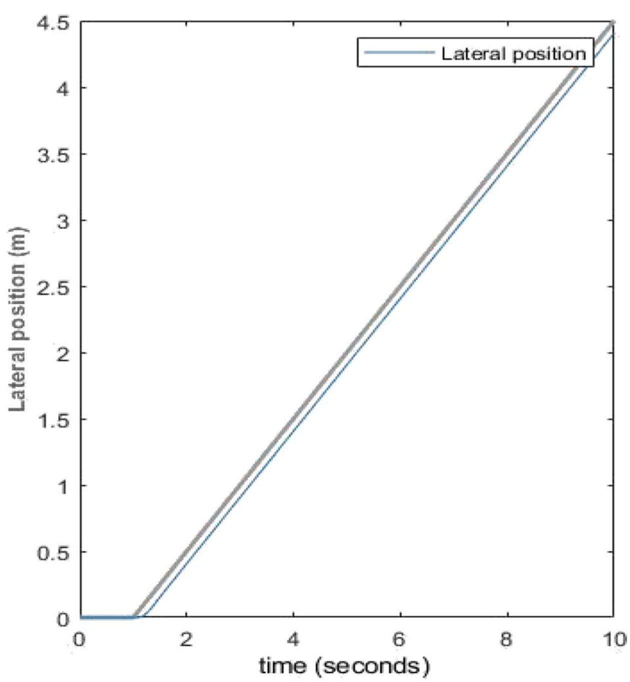

Fig. 7 Lateral position output signal from the linear MPC controller in the vehicle plant

reference (Y_{ref}) and for the yaw angle reference signal (ψ_{ref}) is considered constant. The system outputs (Y-global position and ψ-yaw angle) are constant and the simulation time of (10s) is standardized. As a response to the vehicle plant prediction the response of the nonlinear (discrete) MPC

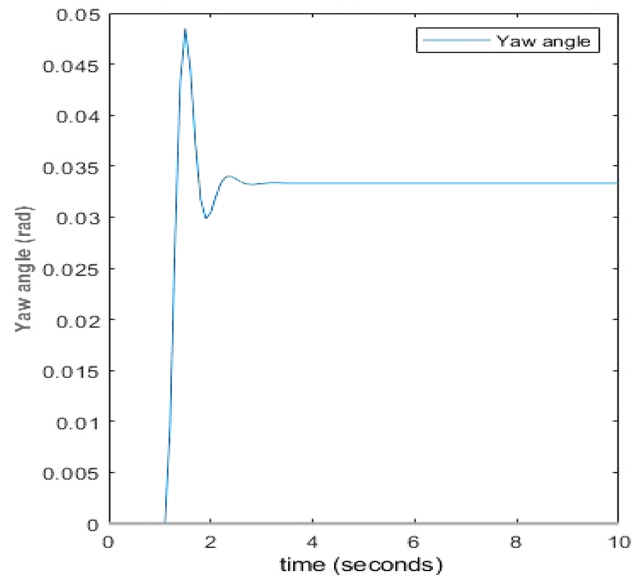

Fig. 8 Yaw angle output signal from the linear MPC controller in the vehicle plant

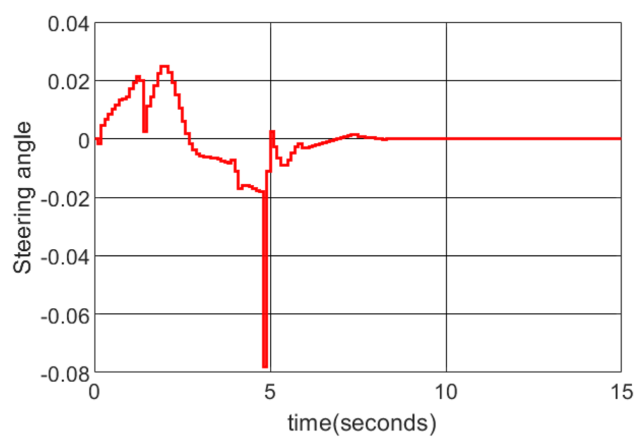

Fig. 9 Steering angle input signal from the discrete MPC controller in the vehicle plant

controller is shown, it is ensured that it will control the lateral output (Y) and yaw angle (ψ) with higher precision and a more precise correction in the output. The behavior of the input signal (δ-forward steering angle) of the nonlinear (discrete) MPC controller is shown in Fig. 9.

The behavior of the output signal of the (Y-lateral position) of the non-linear (discrete) MPC controller, is shown in Fig. 10.

The output signal (ψ-Yaw angle) or lateral angle considers a non-linear (discrete) MPC controller, is shown in Fig. 11.

If compared to other controllers, the MPC has the advantage of being applied to both linear and non-linear plants, its cost of application can be high but as shown in the Figures

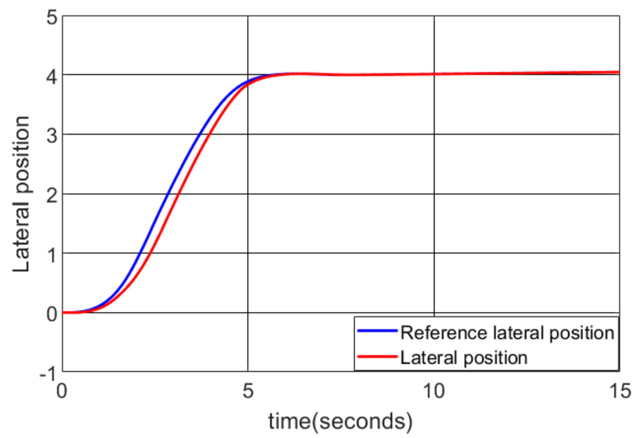

Fig. 10 Lateral position output signal from the discrete MPC controller in the vehicle plant

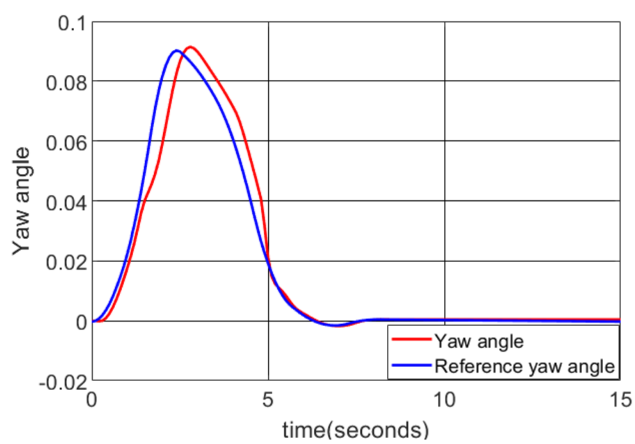

Fig. 11 Yaw angle output signal from the discrete MPC controller in the vehicle plant

above, its ability to control a given system is accurate and secure. Especially when it is a complex and robust system.

Final Considerations

The respective outputs of the vehicle system represented in the Figures, show the importance of the MPC controller for the longitudinal and lateral control of a vehicle. The precision shown in each curve when following the trajectory determined from the longitudinal (x) and lateral (y) position, the control of the vehicle system was performed from the steering which classifies the complex dynamic system. Based on a linearization of the plant, was possible to estimate the future exit from the system, and correct as soon as possible and easily approach the values applied in the totally complex system, since the feedback control to the feedforward. However, has been determined a constant longitudinal velocity (15m/s) to facilitate estimate the outputs and relative dynamics of the system (δ-frontal steering angle, Y-lateral position, ψ-yaw angle). After optimizing of the parameters such as safety restrictions/constraints along the displacement of the vehicle, the system was determined as robust or aggressive to ensure that any maneuvers or lateral movements performed, the controller has the absolute power of decision in order to avoid obstacles. The applied MPC nonlinear lateral controller has been validated to take over the steering and braking of an autonomous vehicle in situations of sudden or interrupted movements.

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Declarations

Conflict of Interest The authors declares that there is no conflict of interest regarding the publication of this paper.

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