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CONTROL ARCHITECTURE FOR AUTOMATED VEHICLES TO ENSURE OBSTACLE AVOIDANCE

BY

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Abstract. The automated vehicle concept is of great interest nowadays for researchers in both academia and industry. These intelligent vehicles can contribute to increase people’s safety, reduce travel cost and travel time, improve the comfort of the driver, reduce traffic jams, and maximize the traffic flow by maintaining a minimal safety gap between vehicles. Taking these into account, this paper proposes a control architecture for an automated vehicle that incorporates a trajectory planner and a trajectory follower for the lateral dynamics and a predictive controller for the longitudinal dynamics. The aim of the proposed solution is twofold: *i)* to plan and follow a path, both in the longitudinal and lateral directions and *ii)* to avoid possible collisions with fixed obstacles on the road. The obtained results illustrate that the trajectory planner succeeds to compute an obstacle free path for the automated vehicle, and the trajectory follower controls the vehicle to track the generated path.

Keywords: Automated vehicle; trajectory planner; obstacle collision avoidance; lateral control; longitudinal control; vehicle dynamics.

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1. Introduction

The researchers from academia and industry showed a great interest in automated vehicles, which lead to the development of advanced functionalities like adaptive cruise control, lane keeping, emergency braking. All of these have the purpose to ensure people's safeness by maintaining a safety distance between vehicles and avoiding collisions, aiming at the same time at improving driving comfort and reducing the travel costs. An automated vehicle must be able to detect its neighbour vehicles and the obstacles along the road, to plan its trajectory and to follow it. In literature there are many studies which offer solutions for automated vehicles. In (Keviczky *et al.*, 2006; Jiang and Astolfi, 2018; Lin *et al.*, 2019; Attia *et al.*, 2014; Falcone *et al.*, 2008) the authors propose algorithms to control the motion of vehicles along both longitudinal and lateral directions. These solutions ensure that the vehicle will follow the required path and velocity but, to obtain these, in literature different methodologies are proposed. In (Alirezaei *et al.*, 2016), the authors introduced an obstacle avoidance strategy for a vehicle platoon. The aim of the solution is to avoid the collision between vehicles when a vehicle wants to merge with the platoon. A solution designed to prevent the collisions between a platoon of vehicles and pedestrians is described in (Ferrara and Vecchio, 2007). A methodology based on a multi-agent system with the task of controlling a platoon to avoid obstacles is proposed in (Gechter *et al.*, 2011). In (Quirynen *et al.*, 2020), the authors present a hierarchical solution based on nonlinear model predictive control (NMPC) for a vehicle to avoid obstacles. In (Rios-Torres and Malikopoulos, 2017, a velocity planning method for the vehicles that want to merge on motorway is introduced. In (Pauca *et al.*, 2019), a solution for the longitudinal and lateral control of an automated vehicle is proposed without considering any obstacles that might appear on their path.

This paper proposes a control architecture with the tasks to plan and follow a safe trajectory that maintains the vehicle on the road and avoids collisions with fixed obstacles encountered along the way. The architecture also includes a longitudinal velocity controller which ensures that the vehicle is moving with the desired velocity. The trajectory planner has the task of maintaining the vehicle on the middle of the lane until the sensors of the vehicle detect an obstacle. When this situation occurs, the trajectory planner generates a trajectory for the vehicle to avoid a possible collision with the fixed obstacle. The trajectory follower is represented by a lateral predictive controller with the task of controlling the steering angle of the vehicle, so that that the vehicle follows the path generated by the trajectory planner. This lateral controller uses a linear bicycle model to predict the states of the vehicle, in order to compute the control law. Moreover, a longitudinal controller is proposed with the task of controlling the longitudinal velocity of the vehicle. Both controllers are formulated as optimization problems with constraints imposed on the lateral position of the vehicle, steering angle of the front tire for the bicycle model and on the longitudinal traction force, which represents the output of the longitudinal controller. The obtained simulation results illustrate that the trajectory of the vehicle was properly adapted to avoid the collision with a fixed obstacle. Also, the longitudinal controller ensures that the vehicle maintains the imposed velocity. The main difference between the solution proposed in this paper and the solution proposed in (Pauca *et al.*, 2019) is related to the introduction of the trajectory planner in the control architecture, while in (Pauca *et al.,* 2019) the trajectory is considered known beforehand.

2. Longitudinal Dynamics Model

To model the dynamics of a vehicle, it is considered that the motion of the vehicle is in a coordinate system denoted as *xOyz.* The movement along the *x* axis is called longitudinal movement, while the movement along the *y* axis is called lateral movement, and the rotation around the *z* axis is represented by the variation of the yaw angle.

The model of the longitudinal dynamics describes how the position of the vehicle along the *x* axis varies in time. Thus, the linear model for the longitudinal motion is represented by (Ulsoy *et al*., 2012):

$$\ddot{p}_x = -\frac{1}{T_x}\dot{p}_x + \frac{K_x}{T_x}(u_x + w_x) \tag{1}$$

$$T_x = \frac{m}{\rho A C_d(\dot{p}_{x0} - v_w)} \tag{2}$$

$$K_x = \frac{1}{\rho A C_d(\dot{p}_{x0} - v_w)} \tag{3}$$

$$w_x = mg(\mu_x \sin\varphi_0 - \mu_x mg\cos\varphi_0)\varphi \tag{4}$$

where p_x is the longitudinal position, $\dot{p}_x$ represents the longitudinal velocity, $\ddot{p}_x$ represents the longitudinal acceleration of the vehicle, T_x represents the time constant, K_x represents the gain factor, w_x models the disturbance, v_w represents the velocity of the wind and u_x is the longitudinal force, g represents the gravitational acceleration, φ is the road slope, ρ is the air density, C_d represents the drag coefficient, μ_x is the rolling resistance coefficient, *m* is the mass of the vehicle, and A is the vehicle frontal area. For controller design purposes, the linearization was performed considering a nominal operation point with $\dot{p}_x = \dot{p}_{x0}$ and $\varphi = \varphi_0$.

To obtain zero tracking error between the vehicle velocity and the imposed reference, an integrator was added in the model as:

$$\dot{\chi}_{\dot{p}_x} = v_{x-ref} - \dot{p}_x \tag{5}$$

This model will be used in the design phase of the longitudinal controller described in Section 5.

3. Lateral Dynamics Model

The lateral dynamics model of a vehicle describes how the position of the vehicle along the *y* axis changes when the steering angle of the tires is varied. The nonlinear bicycle model is represented by (Rajamani, 2006):

$$\begin{aligned} m\ddot{p}_y &= -m\dot{p}_x\dot{\theta} + 2F_{p_{yf}} + 2F_{p_{yr}} \\ I\ddot{\theta} &= 2\ell_1 F_{p_{yf}} - 2\ell_2 F_{p_{yr}} \end{aligned} \tag{6}$$

where p_y is the lateral position, $\dot{p}_y$ represents the lateral velocity, $\ddot{p}_y$ represents the lateral acceleration, θ is the yaw angle, ℓ_1 and ℓ_2 represent the distances from the center of gravity of the vehicle to the front and rear axles, respectively, $F_{p_{yf}}$ and $F_{p_{yr}}$ represent the lateral front and rear forces that depend on the front and rear steering angles, and *I* is the rotational inertia of the vehicle.

A linear bicycle model is obtained from Eq. (6) considering the following assumptions:

$$\begin{cases} \alpha_r = 0 \\ \alpha_f \le 0.174\ [rad] \\ \dot{p}_y \ll \dot{p}_x \\ \dot{p}_x = const \end{cases} \tag{7}$$

where α_r and α_f are the rear and front tire steering angles.

Applying the conditions from Eq. (7) for Eq. (6), a linear bicycle model is obtained (Rajamani, 2006):

$$\begin{bmatrix} \dot{p}_y \\ \ddot{p}_y \\ \dot{\theta} \\ \ddot{\theta} \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & -\frac{2C_1 + 2C_2}{m\dot{p}_x} & 0 & -\dot{p}_x - \frac{2\ell_1 C_1 - 2\ell_2 C_2}{m\dot{p}_x} \\ 0 & 0 & 0 & 1 \\ 0 & -\frac{2\ell_1 C_1 + 2\ell_2 C_2}{I\dot{p}_x} & 0 & -\frac{2\ell_1^2 C_1 + 2\ell_2^2 C_2}{I\dot{p}_x} \end{bmatrix} \begin{bmatrix} p_y \\ \dot{p}_y \\ \theta \\ \dot{\theta} \end{bmatrix} + \begin{bmatrix} 0 \\ \frac{2C_1}{m} \\ 0 \\ \frac{2\ell_1 C_1}{I} \end{bmatrix} \alpha_f \tag{8}$$

where C_1 and C_2 are the cornering stiffness coefficients of the front and rear tires, respectively.

Also, for reference-tracking purposes, an integrator is added in this model as:

$$\dot{\chi}_{p_y} = y_r - p_y \tag{9}$$

where y_r represents the lateral target position.

4. Trajectory Planning

In this section, a solution for trajectory planning that generates an obstacle-free path for a vehicle is presented. The trajectory planner uses a simple model for the lateral and longitudinal dynamics of the vehicle to predict the future position:

$$\begin{cases} \dot{y}_{pl} = a_y \\ \dot{x}_{pl} = \dot{p}_x \\ \dot{p}_x = constant \end{cases} \tag{10}$$

where y_{pl} represents the position of the point model along the y axis and a_y represents its lateral acceleration. Because this model neglects the dimension of the vehicle, the obstacle will be included in a parametrizable ellipse. The dimensions and center of the ellipse are chosen according to the center and dimension of the obstacle, but also to generate a smooth obstacle-free path. To obtain this path, at each sample time T_{s_pl}, a cost function must be minimized, (Gao, 2014):

$$\begin{aligned} J(a_y(k), a_y(k+1), ..., a_y(k+N_1-1)) = \sum_{i=1}^{N_1} \Bigg[& \beta_y (ref_y(k+i) - y_{pl}(k+i))^2 + \\ & \beta_{a_y}(a_y(k+i) - a_y(k+i-1))^2 + \frac{\beta_o \dot{p}_x(k+i)}{\Delta(k+i)+\delta} \Bigg] \end{aligned} \tag{11}$$

over a_y, subject to the constraints:

$$y_{\min} \le y_{pl}(k+i) \le y_{\max}, \; i = \overline{1, N_1} \tag{12}$$

where β_y, β_{a_y}, β_o represent tuning parameters, δ has a small value, ref_y is the lateral target position, N_1 is the prediction horizon, $y_{\min}$, $y_{\max}$ represent the minimum and the maximum values allowed for the lateral position and $\Delta(k)$ represents the distance between the vehicle and the obstacle that is computed with the relation:

$$\begin{cases} \Delta(k+i) = 0, if \; c-1 \le 0 \\ \Delta(k+i) = d, \; otherwise \end{cases} \tag{13}$$

where

$$\begin{aligned} c &= \frac{(x_{pl}(k+i) - x_{ce})^2}{L^2} + \frac{(y_{pl}(k+i) - y_{ce})^2}{h^2} \\ d &= \sqrt{(x_{pl}(k+i) - x_e)^2 + (y_{pl}(k+i) - y_e)^2} \end{aligned} \tag{14}$$

in which [x_{ce}, y_{ce}] represents the centre of the ellipse, L and h represent the parameters of the ellipse, [x_{pl}, y_{pl}] represents the position of the vehicle modelled by point model and [x_e, y_e] represents the closest point from the ellipse to the vehicle.

By minimizing the cost function given in Eq. (11), the optimal control command sequence yields as $[a_y^*(k), a_y^*(k+1), ..., a_y^*(k+N_1)]$, but only its first component is applied to the vehicle according to the receding horizon principle. The obstacle-free path is generated between the last future position and the present future position through which the vehicle should pass.

If the points $[p_{x1}^*,\; p_{y1}^*]$ and $[p_{x2}^*,\; p_{y2}^*]$ are the target position of the vehicle at the last sample time and the one for the present time, then the obstacle-free path, $P_{free} = [p_1,\; p_2\;, \;...,\; p_N]^T$, $p_i = [p_{xi},\; p_{yi}]$, $i = \overline{1, N}$, is obtained using:

$$\begin{aligned} p_{xi}(k) &= p_{x1}^* + i\dot{p}_x T_s \\ p_{yi}(k) &= p_{y1}^* + i\frac{(p_{y2}^* - p_{y1}^*)}{N}, \; i = \overline{1, N} \end{aligned} \tag{15}$$

where T_s represents the sample time used for the longitudinal and lateral controllers, with $N = T_{s-pl} / T_s$. Note that, the longitudinal velocity of the vehicle, *i.e.*, $\dot{p}_x$, is considered constant, while computing the planned trajectory.

5. Predictive Control

Since the control architecture uses model predictive control (MPC) algorithms for the lateral and longitudinal dynamics, in this section, the MPC design methodology is briefly described.

The main advantage of the MPC strategy concerns the implicit handling of constraints imposed for inputs, states and outputs directly in the optimization problem. The model of the system can by described as:

$$\begin{cases} \zeta(k+1) = A\zeta(k) + Bu(k) \\ z(k) = C\zeta(k) \end{cases} \tag{16}$$

where z represents the output of the system, ζ represents the state vector, u represents the input, the pair *(A, B)* is considered controllable and the pair *(C, A)* is considered detectable.

Knowing the initial state $\zeta_0 = \zeta(k)$, the MPC algorithm consists in determining a finite horizon input sequence $U = [u_0, ..., u_{N_{MPC}-1}]^T$ that minimizes the finite horizon cost function given by:

$$J(\zeta, U) = \zeta_{N_{MPC}}^T P \zeta_{N_{MPC}} + \sum_{j=0}^{N_{MPC}-1} (\zeta_j^T Q \zeta_j + u_j^T R u_j) \tag{17}$$

where N_{MPC} is the prediction horizon, $P \succeq 0$ and $Q \succeq 0$ are the weight matrices for the states of the system, $R \succ 0$ is the weight of the control command, ζ_j is the prediction of $\zeta(k+j)$, $j = \overline{1, N_{MPC}}$. Note that, the prediction horizon and the weight matrices influence the performances of the resulting closed-loop control system.

The matrix forms of the predictor and the cost function yield as:

$$\begin{aligned} \pi &= \Lambda \zeta_0 + \Upsilon U \\ J(\zeta, U) &= \zeta_0 Q \zeta_0 + \pi^T \Theta \pi + U^T \Psi U \end{aligned} \tag{18}$$

where: $\pi = [\zeta_1, ..., \zeta_{N_{MPC}}]^T$, $\Lambda = [A, ..., A^{N_{MPC}}]^T$, $\Theta = diag\{Q, ..., Q, P\}$

$$\Upsilon = \begin{bmatrix} B & 0 & \cdots & 0 \\ AB & B & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ A^{N_{MPC}-1}B & A^{N_{MPC}-2}B & \cdots & B \end{bmatrix}, \Psi = diag\{R, ..., R\},$$

size(Θ) =$[\tilde{n}N_{MPC}, \tilde{n}N_{MPC}]$, size($\Psi$)=$\tilde{m}N_{MPC}\tilde{m}N_{MPC}]$,
$\tilde{m}$ is the number of inputs and $\tilde{n}$ is the number of states.

The constraints imposed for the inputs and outputs, $u_{\min} \le u_j \le u_{\max}$, $z_{\min} \le z_j \le z_{\max}$, can be written using the following relation:

$$\Gamma\zeta_0 + \mathrm{K}\zeta + \varepsilon U \le \sigma \tag{19}$$

where:

$$\Gamma = [M_0 0...0]^T \quad , \quad K = \begin{bmatrix} 0 & \cdots & 0 \\ M_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & M_{N_{MPC}} \end{bmatrix} \quad , \quad \varepsilon = \begin{bmatrix} E_0 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & & E_{N_{MPC}-1} \\ 0 & \cdots & 0 \end{bmatrix} \quad ,$$

$M_i = [0\ 0 - C - C]^T$, $E_i = [I - I\ 0\ 0]^T$ $c = [b_0 ... b_N]^T$, $b_i = [-u_{l\min}\ u_{\max}\ - z_{\min}\ z_{\max}]^T$, $i = \overline{0, N_{MPC} - 1}$, $M_i \in \mathbb{R}_{(2\tilde{m}+2\tilde{p})\times\tilde{n}}$, $E_i \in \mathbb{R}_{(2\tilde{m}+2\tilde{p})\times 1}$, $\tilde{p}$ is the number of the outputs.

Now, to find the optimal control sequence, the following problem has to be solved:

$$\begin{gathered} \min_U \frac{1}{2} U^T G U + U^T F \zeta \\ JU \le \sigma + W\zeta \end{gathered} \tag{20}$$

with:

$$\begin{cases} G = 2(\Psi + \Upsilon^T \Theta \Upsilon) \succ 0, \ (\Theta \succ= 0 \ \mathit{and} \ \Psi \succ 0) \\ F = 2\Upsilon^T \Theta \Lambda \\ J = \mathrm{K}\Upsilon + \varepsilon \end{cases} \tag{21}$$

6. Experimental Results

The proposed control architecture, which is illustrated in Fig. 1, is composed of:

i) a longitudinal predictive controller that regulates the longitudinal velocity of the vehicle varying the traction force;

ii) a trajectory planner that generates an obstacle-free path for the vehicle in order to maintain it on the road and to avoid all the fixed obstacles encountered on the way;

iii) a trajectory follower, *i.e.*, a lateral predictive controller, that commands the steering angle of the front tire for the vehicle to follow the generated obstacle-free path.

The longitudinal predictive controller uses the model for the longitudinal dynamics given by Eqs. (1 - 4) and the integrator in Eq. (5). The constraint imposed for the input, *i.e.*, the longitudinal traction force, is expressed as $u_{x-\min} \le u_x < u_{x-\max}$. The controller computes the optimal command that minimizes the cost function in Eq. (17) and satisfies the imposed constraints, using the following control parameters determined heuristically:

$$P_{long} = 75I_3,\ Q_{long} = 75I_3,\ R_{long} = 0.00023529,\ N_{MPC_{long}} = 10.$$

The lateral predictive controller uses the model for the lateral dynamics of the vehicle given by Eq. (8) and the integrator in Eq. (9). The reference of the lateral position is computed by the trajectory planner, which finds it as an obstacle-free path for the vehicle. The controller has as output the steering angle of the front tire, which is constrained by $\alpha_{f-\min} \le \alpha_f < \alpha_{f-\max}$. The heuristically determined parameters of the trajectory planner are:

$$\beta_y = 1.5,\ \beta_{a_y} = 0.001,\ \beta_o = 0.85,\ L = 12\ [m],\ h = 1.5\ [m],\ N_1 = 10.$$

The parameters of the lateral controller were selected as:

$$P_{lat} = 8I_5,\ Q_{lat} = 8I_5,\ R_{lat} = 0.02,\ N_{MPC_{lat}} = 10.$$

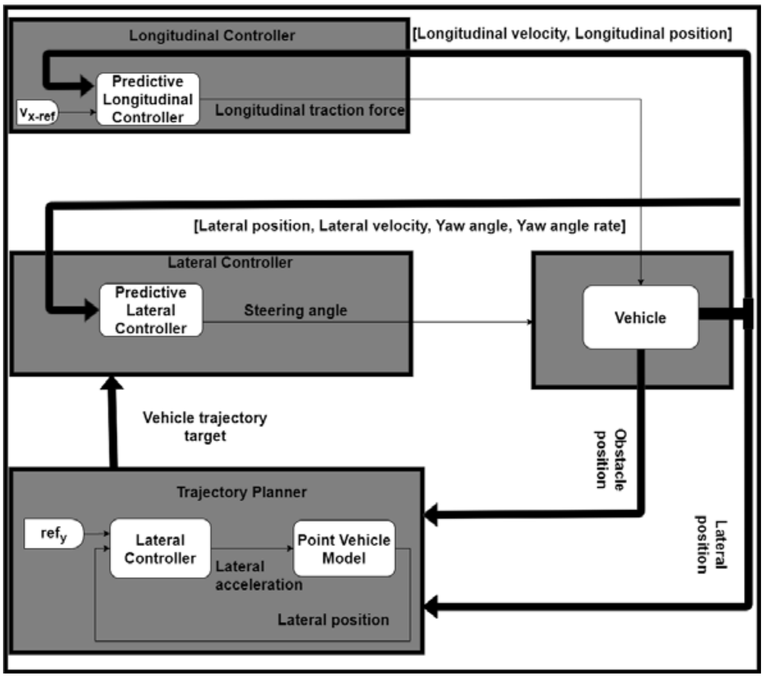

Fig. 1 – Control architecture of the automated vehicle.

Table 1
Vehicle Parameters

	Name	Value
m	*Vehicle mass*	1094 [Kg]
C_1	*Front tire cornering stiffness coefficient*	63291 [N·rad^{-1}]
C_2	*Rear tire cornering stiffness coefficient*	50041 [N·rad^{-1}]
ℓ_1	*Longitudinal distance from the center of gravity to the front tires*	1.108 [m]
ℓ_2	*Longitudinal distance from the center of gravity to the rear tires*	1.392 [m]
I	*Vehicle's rotational inertia*	1608 [kg. m^2]
$\alpha_{f-\min}$	*Minimum value of front wheel steering angle*	$-\pi/4$ [rad]
$\alpha_{f-\max}$	*Maximum value of front wheel steering angle*	$\pi/4$ [rad]
g	*The gravitational acceleration*	9.81 [m·s^{-2}]
$\dot{p}_{x0}$	*The initial velocity of the vehicle*	0 [m·s^{-1}]
φ	*The road slope*	0 [rad]
φ_0	*The initial road slope*	0 [rad]
ρ	*The air density*	1.202 [Kg·m^{-3}]
A	*The vehicle frontal area*	1.5 [m^{-2}]
C_d	*The drag coefficient*	0.5
μ_x	*The rolling resistance*	0.0015
v_w	*The wind speed*	2 [m·s^{-1}]
$u_{x-\min}$	*Minimum value of the longitudinal traction force*	0 [N]
$u_{x-\max}$	*Maximum value of the longitudinal traction force*	2000 [N]
$y_{\min}$	*Minimum value of the lateral position*	0 [m]
$y_{\max}$	*Minimum value of the lateral position*	4.5 [m]

The sampling periods of the lateral and longitudinal dynamics used for simulations are equal to $T_s = 0.01s$ and the sample time used by the trajectory planner is $T_{s\_pl} = 0.1s$. To simulate the dynamics of the vehicle, the nonlinear bicycle model from Eq. (6) is used. The parameters of the vehicle are presented in Table 1.

From Fig. 2 it can be noticed that the longitudinal velocity of the vehicle follows the desired reference, and from Fig. 3 it can be observed that the input, *i.e.*, longitudinal traction force, satisfies the imposed constraints. The steady – state error of the longitudinal velocity illustrated in Fig. 4 has small values which suggests that the controller has goods performances.

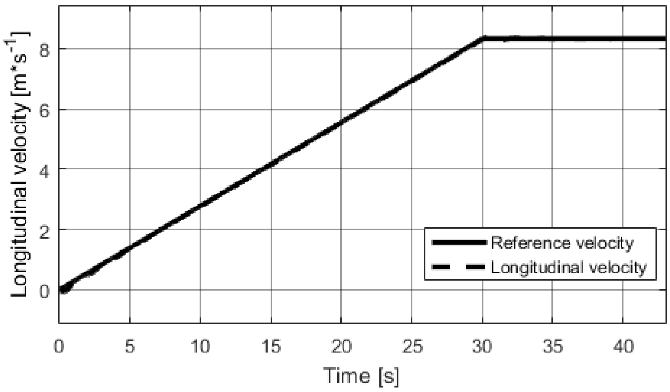

Fig. 2 – Longitudinal velocity.

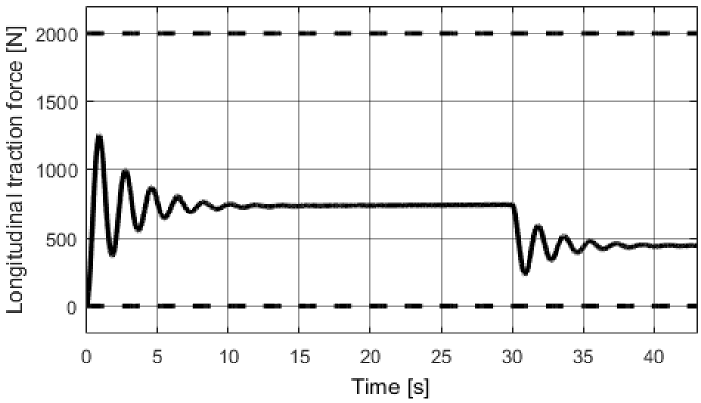

Fig. 3 – Longitudinal traction force (continuous line) and constraint limits (dashed).

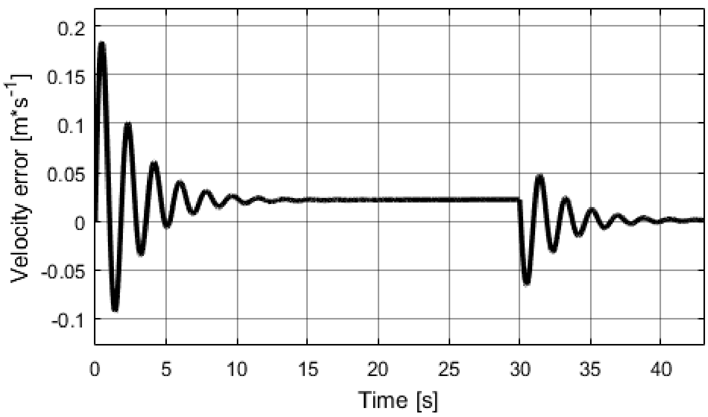

Fig. 4 – Longitudinal velocity error.

Also, from Fig. 2 it can be seen that the velocity reaches a constant value, $\dot{p}_x = 8.33\ [m \cdot s^{-1}]$, and from this moment the trajectory planner is active. It starts to plan the trajectory for the vehicle and the lateral controller starts to follow it.

In Fig. 5, the obstacle-free path obtained by the trajectory planner is illustrated with a dot-dashed line, and it can be observed that the path avoids the collision with the fixed obstacle and then returns on the initial lane. The reference position for the trajectory planner was set as $ref_y(k) = 0$. Note that the road has two lanes with the same direction for movement. Also, in Fig. 5, the trajectory of the vehicle is presented with continuous line, and the lateral error is illustrated in Fig. 6. The lateral controller commands the steering angle of the front tire, represented in Fig. 7, for the vehicle to follow the trajectory generated by the planner and it can be noticed that the obtained trajectory does not have oscillations which could affect the comfort of the passengers. Moreover, the control command satisfies the imposed constraints.

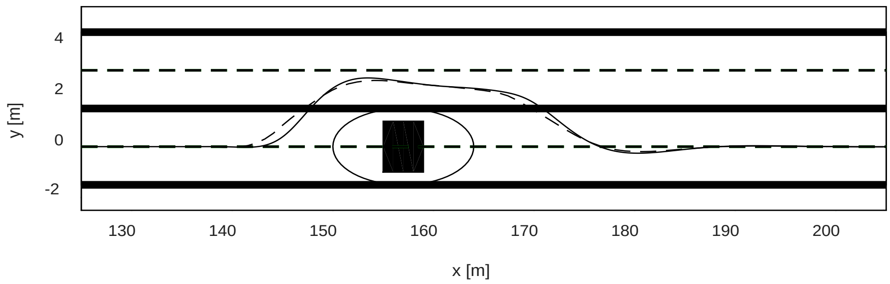

Fig. 5 – Obstacle avoidance use-case.

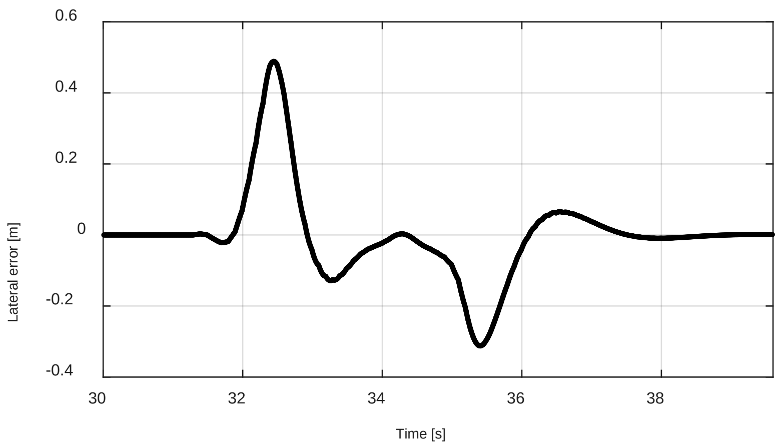

Fig. 6 – Lateral error.

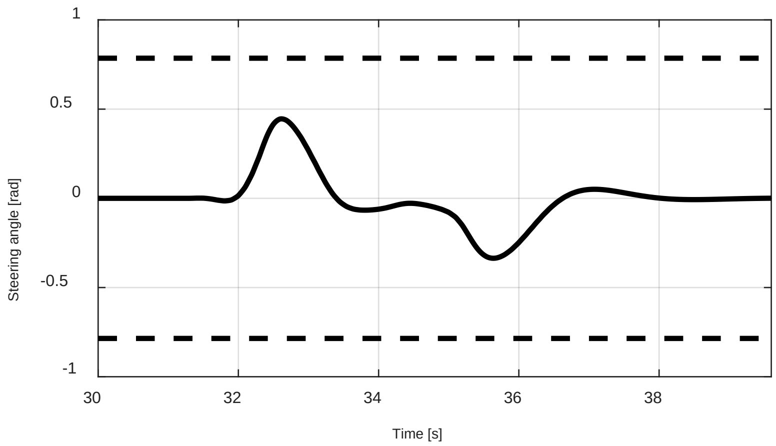

Fig. 7 – Steering angle of the front tire (continuous line) and constraint limits (dashed).

7. Conclusion

In this paper, a control architecture for an automated vehicle was proposed. This is composed of a longitudinal predictive controller that controls the velocity of the vehicle, a trajectory planner with the task of obtaining an obstacle-free path for the vehicle and a lateral predictive controller that commands the steering angle of the vehicle to follow the output of the trajectory planner. The results obtained in simulation illustrate the performances of the proposed architecture. Future work will focus to improve the trajectory planner and the lateral controller to handle moving obstacles.

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ARHITECTURĂ DE CONTROL PENTRU VEHICULELE AUTOMATE CARE ASIGURĂ EVITAREA OBSTACOLELOR

(Rezumat)

Ideea de vehicul automat este de mare interes atât pentru cercetătorii din mediul academic, cât și pentru cei din mediul industrial. Vehiculele inteligente contribuie la îmbunătățirea siguranței participanților la trafic, reducerea costurilor și a duratei călătoriilor, îmbunătățirea confortului pentru șofer și pasageri, reducerea ambuteiajelor din trafic și maximizarea fluxului de vehicule prin menținerea unei distanțe de siguranță minime între vehicule. Un vehicul automat trebuie să își poată detecta vecinii și obstacolele de pe carosabil, cu scopul de a-și planifica și urmări traiectoria astfel rezultată. Pornind de la aceste ipoteze, lucrarea de față propune o arhitectură de control pentru un vehicul automat care încorporează un planificator de traiectorie și un urmăritor de traiectorie pentru dinamica laterală a vehiculului și un regulator predictiv pentru dinamica longitudinală a acestuia. Scopul soluției propuse este de a planifica și urmări o traiectorie, atât pentru dinamica laterală, cât și pentru cea longitudinală, astfel încât să fie evitate posibilele coliziuni cu obstacolele fixe aflate pe carosabil. Planificatorul de traiectorie are rolul de a menține vehiculul pe mijlocul drumului până în momentul în care senzorii acestuia detectează un obstacol. În acest caz, planificatorul de traiectorie generează o traiectorie pentru vehicul pentru a fi evitată o posibilă coliziune cu acel obstacol fix. Urmăritorul de traiectorie este reprezentat de

un regulator predictiv pentru dinamica laterală, care este proiectat cu scopul de a controla unghiul de direcție al vehiculului astfel încât acesta să urmărească traiectoria generată de planificatorul de traiectorie. Regulatorul pentru dinamica laterală utilizează un model liniar de tip bicicletă pentru a prezice stările vehiculului cu scopul de a calcula mărimea de comandă. Regulatorul longitudinal propus are rolul de a controla viteza longitudinală a vehiculului. Ambele regulatoare sunt definite ca probleme de optimizare cu restricții impuse pentru poziția laterală a vehiculului, unghiul de direcție al roții din față și pentru forța de tracțiune longitudinală, care reprezintă mărimea de ieșire a regulatorului longitudinal. Rezultatele obținute arată că planificatorul reușește să genereze o traiectorie fără obstacole pentru vehiculul automat, iar urmăritorul de traiectorie controlează vehiculul astfel încât să fie urmărită traiectoria generată. De asemenea, regulatorul longitudinal asigură menținerea de către vehicul a vitezei de referință impuse.