

# A Microscopic Human-Inspired Adaptive Cruise Control for Eco-Driving

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## I. INTRODUCTION

Adaptive Cruise Controls (ACCs) are nowadays becoming a reality thanks to the effort dedicated to their development in the last decades (see [1], [2], [3]). The objective of ACCs is to offer a safe and comfortable transportation with reduced congestion, emissions and travel time. Since the first works on ACCs, human factors such as comfort or safety perception in a control-oriented framework (see [4]) were taken into account. The controllers were first designed according to some performance or stability-based criteria and secondly adapted to human characteristics by parameter modifications. More recently, there has been a paradigm shift and the main criterion for the design of ACCs tools is the correct human driving representation. Our work lies in this research line, and extends some previous results presented in [5], where a human-inspired hybrid automaton (see [6]) for ACC was proposed. Moreover, we address the problem of computing the optimal speed, acceleration and fuel consumption (also known as eco-driving, as in [7], [8]) in a single-lane car-following scenario, in a Vehicle-to-Vehicle (V2V) communication framework.

## II. MODELING

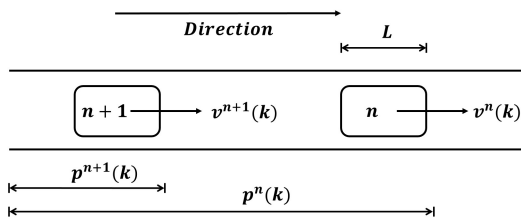


Fig. 1. Reference framework.

We consider  $N$  vehicles with length  $L \in \mathbb{R}^+$  ( $\mathbb{R}^+ = (0, +\infty)$ ) on a single lane road (see Fig.1), sorted by location and indexed by  $n \in \{1, \dots, N\}$ , where  $n = 1$  denotes the first vehicle on the lane. We suppose that each vehicle can be described by a triple integrator, discretized with sampling time  $\tau$ , where the control input is the acceleration variation (jerk), that allows for a smoother acceleration profile. If  $k\tau$ ,  $k \in \mathbb{N}$  denotes the  $k$ -th sampling time, then the variables

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describing the evolution of vehicle  $n$ , are the longitudinal position ( $p^n(k) \geq 0$ , [m]), speed ( $0 \leq v^n(k) \leq v_{\max}$ , [m/s]) and acceleration ( $|a^n(k)| \leq a_{\max}$ , [m/s<sup>2</sup>]).

Let the pair  $(n, n + 1)$ ,  $n = 1, \dots, N - 1$ , denote leader vehicle ( $n$ ) and follower vehicle ( $n + 1$ ). Then the follower's state vector is defined as

$$x^{n+1}(k) = \begin{bmatrix} x_1^{n+1}(k) \\ x_2^{n+1}(k) \\ x_3^{n+1}(k) \\ x_4^{n+1}(k) \end{bmatrix} = \begin{bmatrix} p^n(k) - p^{n+1}(k) \\ v^n(k) - v^{n+1}(k) \\ a^{n+1}(k) \\ v^n(k) \end{bmatrix} \quad (1)$$

In the following we omit the index  $n + 1$ , for notational simplicity. For the first vehicle of the cluster we assume that there exists a virtual leader  $n = 0$ , such that  $v^0(k) = v_{\max}$  and  $a^0(k) = 0 \forall k \in \mathbb{N}$ .

Physical and legal limits lead to the following constrained set  $X \subseteq \mathbb{R}^4$  of feasible states for  $x(k)$ :

$$X = \{x \in \mathbb{R}^4 : x_1 \geq s, |x_2| \leq v_{\max}, |x_3| \leq a_{\max}, 0 \leq x_4 \leq v_{\max}\} \quad (2)$$

with  $v_{\max}, a_{\max} > 0$  and where  $s$  is the minimum distance to be kept in order to avoid collision.

The discrete-time evolution of the continuous state is described by

$$x(k + 1) = Ax(k) + B_u u(k) + B_d d(k) + Ee(x(k)) \quad (3)$$

where

$$A = \begin{bmatrix} 1 & \tau & 0 & 0 \\ 0 & 1 & -\tau & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, B_u = \begin{bmatrix} 0 \\ 0 \\ \tau \\ 0 \end{bmatrix}, B_d = \begin{bmatrix} 0 \\ \tau \\ 0 \\ \tau \end{bmatrix}, E = \begin{bmatrix} 0 \\ \tau \\ 0 \\ 0 \end{bmatrix},$$

$|u(k)| \leq u_{\max}$ ,  $u_{\max} > 0$ , is the jerk of vehicle  $n + 1$ ;  $e(x) = c_1 + c_2(x_4 - x_2)^2$ ,  $c_1, c_2 > 0$ , is a nonlinear term representing friction (see [9]);  $d(k) = a^n(k)$  is the acceleration of the vehicle ahead modeled as a bounded disturbance  $|d(k)| \leq a_{\max}$ .

Following the framework established in [5], we define the functions  $T_E : \mathbb{R}^4 \rightarrow \mathbb{R}$ ,  $T_R : \mathbb{R}^4 \rightarrow \mathbb{R}$  and  $T_S : \mathbb{R}^4 \rightarrow \mathbb{R}$ , that represent different time headways needed to stop the vehicle in different scenarios, to partition the set  $X$  with respect to the human perception [10], [11], [5]. Then, for each pair  $(n, n + 1)$  a simplified microscopic hybrid model [6] is developed, whose discrete states are associated with the partition of  $X$ . In particular, this partition is used to define domain and transition conditions of the discrete states, that are listed in the following:

- 1)  $q_1$ : Free driving. The leader vehicle is either too far away or faster or both.
- 2)  $q_2$ : Following I. The follower is closing in on the vehicle.

- 3)  $q_3$ : Following II. The speed difference is large and the distance is not.
- 4)  $q_4$ : Closing in. The distance from vehicle  $n$  is close to the unsafe one.

The continuous dynamics (3) is associated to each discrete state.

### III. CONTROL DESIGN

For a generic vehicle  $n$ , the control action  $u(k)$  is the acceleration variation (jerk). Given a fixed prediction horizon  $\mathcal{N}_j \in \mathbb{N}$  for every  $q_j \in \mathcal{Q}$ , at each time  $k$ , the control law is determined by implementing an MPC algorithm to solve an optimization problem that depends on the current discrete state  $q_j$ . The cost function  $J_j$  associated to  $q_j$  is defined as:

$$J_j = \frac{1}{2} \left[ \tilde{y}^T(\mathcal{N}_j) P_j \tilde{y}(\mathcal{N}_j) + M_j \sum_{h=0}^{\mathcal{N}_j} \exp(w^T(h) P_j^C z(h)) \right] \quad (4)$$

$$+ \frac{1}{2} \left[ \sum_{h=0}^{\mathcal{N}_j-1} (\tilde{y}^T(h) G_j \tilde{y}(h) + u^T(h) R_j u(h)) \right]$$

where  $\tilde{y} = y - y^r$ ,  $y = [x_1 \ x_2 \ x_3 \ x_4 - x_2]^T$  and  $y^r = [\Delta S \ 0 \ 0 \ v_{des}]$ ,  $\Delta S$  and  $v_{des}$  are the desired distance and velocity.  $z$ ,  $w$ ,  $\exp(w^T(h) P_j^C z(h))$ ,  $P_j^C \in \{P_j^{C+}, P_j^{C-}\}$  are operators that describe fuel-consumption/emission [12], [13]. Matrices  $P_j$  and  $G_j$  are semidefinite positive and  $R_j, M_j \geq 0$ .

### IV. SIMULATIONS AND CONCLUSIONS

Simulations have been performed using Matlab-Simulink and the optimization toolbox Yalmip (see [14]). Two cases of leader-follower scenario have been considered which differ for the fact that in one (named *case 1*) the consumption is optimized and in the other it is not (named *case 2*). The initial conditions are  $x_1(0) = 60$ ,  $x_2(0) = -10$ ,  $x_3(0) = 0$ ,  $x_4(0) = 5$  and  $u(0) = 0$ . In figure (2) we show the speed profile of the leader and the resulting profiles of the follower in both cases, while in figure (3) we report the distance profile evolution between the two vehicles. Our results show that in both cases the follower is able to satisfy safety conditions. Moreover, with the introduction of the emission term, a smoother profile and a lower fuel consumption are obtained. Future research will address the combination of the MPC algorithm with the proposed hybrid automaton. Moreover, the proposed approach will be extended by including macroscopic quantities.

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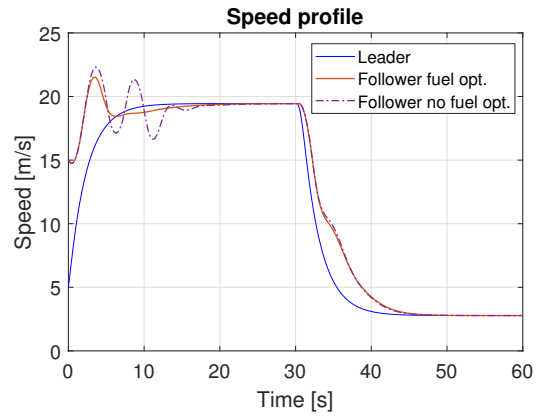


Fig. 2. Speed profile of the leader (blue line), of the follower in the case 1 (red line) and in the case 2 (dotted line)

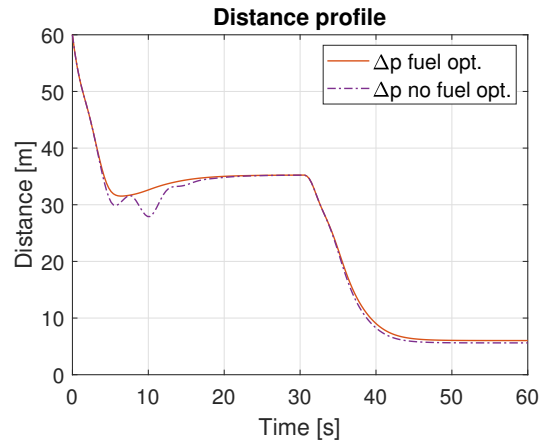


Fig. 3. Inter-vehicular distance in case 1 (red line) and case 2 (dotted line)

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