Human-Inspired Mesoscopic Hybrid Automaton for Longitudinal Vehicle Control

A. Iovine, D. Bianchi, E. De Santis, M. D. Di Benedetto

***Abstract*— In this paper a mesoscopic hybrid automaton is introduced in order to obtain an human-inspired based adaptive cruise control: such controller processes other vehicles information and take decisions regarding to the brake or throttle actions. The proposed control law fits the design target to replace and imitate an human driver behaviour. A microscopic hybrid automaton model for longitudinal vehicle control based on human psycho-physical behavior is first presented. Advantages of using hybrid automaton are that all possible driver behavior depending on next vehicle are considered. Then a rule for changing time headway depending on macroscopic quantities is used to describe importance of interaction among all next vehicles and their impact on driver performance. The resulting mesoscopic vehicle model has a set of possible behaviors that contains more real-life situations than the purely microscopic one.**

I. Introduction

Nowadays traffic control is one of the most studied problems in engineering. This is due to its high impact in human life: progressing the knowledge and control over traffic systems means to raise life quality [1]. The main purpose of traffic control is to improve the traffic management depending on a variety of different goals: congestion, emissions and travel time reduction, safety increments etc.... Over the time a multitude of traffic control systems have been generated (see [2], [3], [4], [5]). A classification can be done regarding the utilized description level (macroscopic, microscopic or mesoscopic) or the adopted control strategy (centralized or decentralized).

Focus of this paper is a decentralized mesoscopic control approach. Microscopic models representing human-drivers will be used to the purpose to imitate a safe human behavior: to better represent human-style, a macroscopic value dependence will be added to the final model. The idea is to control the single vehicle dynamics through an automatic controller that will process other vehicles information and take decisions regarding to the brake or throttle actions in order to take the place of the human driver. It will not present human weaknesses as mistakes or distractions but strengths as adaptability to various conditions or comfort. To the best authors knowledge, no hybrid automaton has been presented as a description of a microscopic human-driven vehicle. Furthermore, the consideration of macroscopic quantities is an important step-ahead.

This paper is organized in 6 sections. Section II introduces the adopted control strategy. In Section III the model of the microscopic hybrid automaton of a single vehicle will be described. Then in Section IV a variance-driven time headway mechanism will be introduced into the hybrid automaton. Section V provides simulation results about automaton behaviour, while summary and conclusions are outlined in Section VI.

II. Problem definition

In this paper a car-following situation on a single road is analyzed. The purpose is to develop a model able to control a generic $n+1$ vehicle, which is "follower" respect to its "leader" vehicle, n, with $n \in \{1, 2, ...N-1\}$ where N is the total number of vehicles taken into account, $N > 1$. The dynamical model of each vehicle is stated as:

$$\dot{x}_i(t) = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} x_i(t) + \begin{bmatrix} 0 \\ 1 \end{bmatrix} u_i(t) \tag{1}$$

where $x_{1_i}(t)$ is the position $p_i(t)$ and $x_{2_i}(t)$ is the speed $v_i(t)$, $i \in \{n, n+1\}$. In the following the time dependence will be omitted for sake of notation.

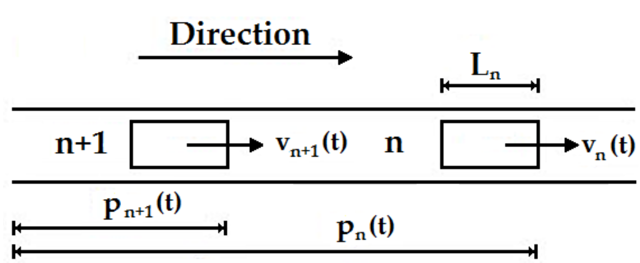

Fig. 1. n is the leader vehicle and $n+1$ the follower one. L_n is the vehicle length (all vehicles are supposed to be identical) and p_n, p_{n+1} are the covered distances by vehicles n and $n+1$ respectively.

Vehicles interactions will be based on $x_N - ... - x_{n+1} - x_n$ space, which has $2N$ dimension.

When $N = 2$ the simplest situation is presented: a leading car and a following one. Assuming there is no cooperation between them, in order to properly control $n+1$ vehicle the motion of the leading car needs to be taken into account because it influences behaviour of the following one. In fact, the n vehicle motion can be seen as a disturbance acting on it from the $n+1$ vehicle perspective; it is clear that control input u_{n+1} will be function of such a disturbance.

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D. Bianchi, E. De Santis, M. D. Di Benedetto, A. Iovine are with the Dipartimento di Ingegneria e Scienze dell'Informazione e Matematica, Center of Excellence DEWS, Università degli Studi dell'Aquila, 67100 L'Aquila, Italy. E-mail: {domenico.bianchi, elena.desantis, mariadomenica.dibenedetto}@univaq.it, alessio.iovine@graduate.univaq.it.

A reduction of space order can be allowed by introducing interaction quantities:

$$\Delta x_1 = \Delta x_{1_{n,n+1}} = x_{1_n} - x_{1_{n+1}} \tag{2}$$

$$\Delta x_2 = \Delta x_{2_{n,n+1}} = x_{2_n} - x_{2_{n+1}} \tag{3}$$

The considered dynamical model for a generic $n+1$ follower vehicle will then be:

$$\begin{cases} \Delta \dot{x}_1 = x_{2_n} - x_{2_{n+1}} \\ \dot{x}_{2_{n+1}} = u_{n+1} \\ \dot{x}_{2_n} = d_n \end{cases} \tag{4}$$

where Δx_1 is the distance, $x_{2_{n+1}}$ and x_{2_n} are the $n+1$ and n vehicle speed, respectively; d_n is an unknown bounded disturbance and u_{n+1} is the control law:

$$u_{n+1} = g(\Delta x_1, x_{2_{n+1}}, x_{2_n}) = g(x) \tag{5}$$

It is chosen a-priori; the system is autonomous because control law is state feedback.

Moreover, the function $g : \Delta x_1 \times x_{2_{n+1}} \times x_{2_n} \to U$ is such that $g(z) = h_i(z)$, $z \in \mathcal{Z}_i$ with sets $\mathcal{Z}_i$, $i \in \mathcal{I}$, that are partitions of the space $\Delta x_1 \times x_{2_{n+1}} \times x_{2_n}$:

$$\Delta x_1 \times x_{2_{n+1}} \times x_{2_n} = \bigcup_{i \in \mathcal{I}} \mathcal{Z}_i \tag{6}$$

These partitions are needed because the selected $u_{n+1}(t)$ function will not be unique, but it will depend on circumstances: different regions with different control laws can be defined. No data exchange are necessary because x_{n+1} is supposed to know x_n state model: only the d_n disturbance is unknown and it is equal to n vehicle acceleration, $u_n = d_n$.

In case of $N > 2$, all the N vehicles will constitute a platoon. The calculation of all possible cases in the original $2N$ dimensional space is very complicated and not practical: furthermore too many information need to be exchanged. For sake of computational cost an α_T aggregation parameter is introduced and for using less information each vehicle is modeled as an agent that can share information with its follower. A calculation of the parameter is done based on data coming from leader vehicle; it is utilized for varying regions borders in the simple $X = \mathbb{R}^3$ space. That makes the defined $\mathcal{Z}_i$ regions explicitly function of time because they can vary during the time: $\mathcal{Z}_i(t)$.

Thanks to its skills to include in a unique mathematical model different control actions, hybrid systems theory has been chosen for representing vehicle dynamics and its variety of control inputs: a follower vehicle will be modeled as an hybrid automaton controlled agent. Then properties as determinism or non-blocking can be exploited in order to analyze the model and its feasibility.By adding the aggregation parameter the used microscopic model will become mesoscopic because it will take into account macroscopic quantities such as mean speed and variance.

III. Microscopic Hybrid Model

Microscopic models describe traffic flow dynamics in terms of single vehicles. In this section, a microscopic traffic model based on classical car-following literature models is introduced for the l vehicle, where $l = n + 1$.

We used two different types of microscopic models: stymulus-response and psycho-physical. The former models type describes vehicle continuous dynamics depending on the stymulus (i.e. the continuous dynamics) of the ahead vehicle [4], [5], [13]. The latter models type uses thresholds in order to decide which continuous dynamics the vehicle will use [10]. As stated in Section II, the leading car is represented by the number n and the follower by $n + 1$. A first assumption that leader dynamical model is known by the follower is considered in this paragraph; it is given by equation (1). A second one is that leader state is correctly estimated by the follower.

The hybrid system describing the generic vehicle l will be the tuple

$$\mathcal{H} = (Q, X, f, Init, Dom, \mathcal{E}, \mathcal{G}, \mathcal{R}) \tag{7}$$

where:

- Q is a finite set of N discrete states;
- $X \subseteq \mathbb{R}^n$ is the continuous state space;
- $f(\cdot,\cdot) : Q \times X \to \mathbb{R}^n$ is a vector field that associates to each discrete state $q \in Q$ the continuous time-invariant dynamics
$$\dot{x} = f_q(x), \tag{8}$$
and the output map $y = g_q(x)$.
- $Init \subseteq Q \times X$ is the set of initial discrete and continuous conditions;
- $Dom(\cdot) : Q \to 2^X$ is a domain;
- $\mathcal{E} \subseteq Q \times Q$ is a set of edges;
- $\mathcal{G} : \mathcal{E} \to 2^X$ is a map associating to each transition $e \in \mathcal{E}$ a set $\mathcal{G}(e)$ called guard;
- $\mathcal{R}(\cdot,\cdot) : \mathcal{E} \times X \to 2^X$ is a reset map:

The automaton state is defined as $(x, q) \in X \times Q$.

A. Continuous dynamics

The dynamical model of a generic $l = n + 1$ follower vehicle will be given by $X = \mathbb{R}^3$, where state variables are described by equation (4).

$$x_l = \begin{bmatrix} x_{l_1} \\ x_{l_2} \\ x_{l_3} \end{bmatrix} = \begin{bmatrix} \Delta x_1 \\ x_{2_{n+1}} \\ x_{2_n} \end{bmatrix} \tag{9}$$

B. Discrete states

Also discrete states depend on vehicles interaction. A partially modified version of Fritzsche's psycho-physical Car-Following model (see [10]) is used for setting discrete states of the hybrid automaton. The Fritzsche's model accounts for human perception in the definitions of the model regimes. The space is divided in different regions; for each one thresholds are defined accordingly to some human characteristics. The model represents in $\Delta x_1 - x_{2_{n+1}} - x_{2_n}$ plane two thresholds for perception of speed differences (PTN,

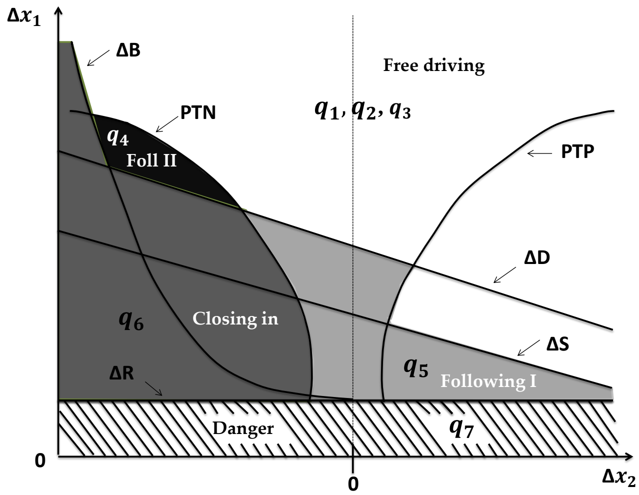

Fig. 2. The different thresholds and regimes in Fritzsche car-following model. There are two main areas; one is related to the so-called "leader phase" (q_1, q_2, q_3) where the vehicle does not take into account its ahead vehicle, and the other one related to the "follower phase" (q_4, q_5, q_6, q_7) where vehicle dynamic depends on its ahead vehicle. Automaton discrete states correspond to the different thresholds and regimes. The case where $x_{2_{n+1}} = v_{des}$ is not included into the figure: it is supposed to lie more to the left respect to the presented diagram.

negative, and PTP, positive) and four thresholds for the followers space headway to its leader (the risky distance ΔR, the safe distance ΔS, the desired distance ΔD and the braking distance ΔB) (see Figure 2). These thresholds are:

$$PTN = \{x \in \Re^3 : (\Delta x_1 > 0) \wedge (x_{2_n} < x_{2_{n+1}}) \wedge \\ (x_{2_n} - x_{2_{n+1}} = -k_{PTN} \cdot (\Delta x_1 - s_n)^2 - f_x)\} \tag{10}$$

$$PTP = \{x \in \Re^3 : (\Delta x_1 > 0) \wedge (x_{2_n} > x_{2_{n+1}}) \wedge \\ (x_{2_n} - x_{2_{n+1}} = k_{PTP} \cdot (\Delta x_1 - s_n)^2 + f_x)\} \tag{11}$$

$$\Delta R = \{x \in \Re^3 : (\Delta x_1 > 0) \wedge (\Delta x_1 = s_n + T_r x_{2_n})\} \tag{12}$$

$$\Delta S = \{x \in \Re^3 : (\Delta x_1 > 0) \wedge (\Delta x_1 = s_n + T_s x_{2_{n+1}})\} \tag{13}$$

$$\Delta D = \{x \in \Re^3 : (\Delta x_1 > 0) \wedge (\Delta x_1 = s_n + T_d x_{2_{n+1}})\} \tag{14}$$

$$\Delta B = \{x \in \Re^3 : (\Delta x_1 > 0) \wedge \\ (\Delta x_1 = s_n + T_r x_{2_n} + \frac{(x_{2_n} - x_{2_{n+1}})^2}{|b_{min}| + a_n^-})\} \tag{15}$$

where k_{PTN}, k_{PTP}, f_x, b_{min}, a_n^- are model parameters, $s_n = L_n + 1$ is the least distance from the ahead vehicle and T_r, T_s, T_d are time headways.

A graphical representation cannot be done because of space dimensions: for such reason, x_{2_n} is supposed constant and the Δx_2 combination of $x_{2_{n+1}}$ and x_{2_n} variables is considered. The $\Delta x_2 - \Delta x_1$ plane will then be utilized, that is a section of the 3 dimensional X space. It provides a clear problem's graphical visualization.

An hybrid model with 7 discrete states is formalized according to Fritzsche's cars interaction space definitions

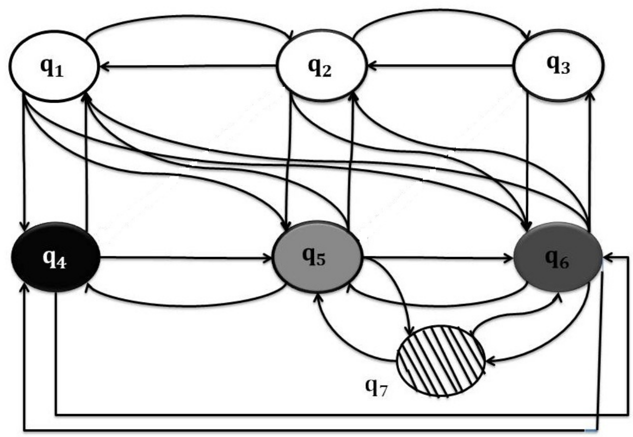

Fig. 3. The obtained hybrid automaton: discrete states colors are related to Fritzsche's model area divisions.

(see Figure 2).

$$Q = (q_1, q_2, q_3, q_4, q_5, q_6, q_7) \tag{16}$$

In each state the (4) dynamical model has a different control law u_{n+1} and bounds are considered for it;

$$u_{min} \leq u_{n+1} \leq u_{max} \tag{17}$$

There $u_{min} < 0$ is the maximum deceleration and $u_{max} > 0$ the maximum acceleration. In the following description α_1^+, α_3^-, α_4^- sensitivity parameters will be utilized, while v_{des} is the desired speed the driver wants to achieve. For sake of notation, Δx_2 will be utilized, while $M|_x$ represent the element of set M given by the current x state.

1) q_1: in the "Free driving" region the vehicle can run freely because the leader vehicle is either too far away or faster or both. The follower is "free", and he acts as a his own "leader": it means his behaviour is not related to $\Delta x_2 - \Delta x_1$ plane, but it depends on $v_{des} - x_{2_{n+1}}$ quantity. Three possibilities of acting will be possible, and they are described by three distinguished discrete states: in this one, the driver is supposed to accelerate because his speed is less than the desired one.
$$u_{n+1} = \alpha_1^+ \cdot (v_{des} - x_{2_{n+1}}) \tag{18}$$

2) q_2: as for q_1, the follower chose its action depending on$v_{des} - x_{2_{n+1}}$ quantity; the driver does not make any action, because the speed is more or less equal to the desired one.
$$u_{n+1} = 0 \tag{19}$$

3) q_3: as for q_1 and q_2, the $\Delta x_2 - \Delta x_1$ plane is not considered here; the driver is supposed to decelerate, because his speed is higher than the desired one.
$$u_{n+1} = \alpha_3^- \cdot (v_{des} - x_{2_{n+1}}) \tag{20}$$

4) q_4: in the "Following II" region the driver has noticed that he is closing in on the vehicle in front but the space headway is too large referred to ΔD threshold, so he keeps accelerating but with different parameters; this time acceleration will depend on relative speed and distance, following the model in [5].

$$u_{n+1} = \alpha_4^- \cdot \frac{\Delta x_2}{\Delta x_1} x_{2_{n+1}} \tag{21}$$

5) q_5: in the "Following I" region speed difference and distance are small; as consequence, in [10] the driver is supposed to take no conscious action. A sliding-mode control will be applied in order to let $n+1$ vehicle follow properly its leader, modifying the psycho-physical model in order to obtain a desired behavior.

$$u_{n+1} = \| \Delta x_1 - \Delta D|_x + \Delta R|_x \| \cdot sign(\Delta x_2) \tag{22}$$

6) q_6: in the "Closing in" region the speed difference is large and the distance is not, so the driver has to decelerate; he will do it depending on distance and relative speed, according to the model in [13].

$$u_{n+1} = \frac{x_{2_n}^2 - x_{2_{n+1}}^2}{2(\Delta x_1 + \Delta R|_x)} \tag{23}$$

7) q_7: in the "Danger" region the distance from the leading vehicle is very small and the driver uses his maximum deceleration.

$$u_{n+1} = u_{min} \tag{24}$$

C. Domains, edges and guard conditions

Discrete state domains come from the $x_{n+1} - x_n$ space using logic conditions and thresholds. As before, speed-position plane will be used for defining them. Edges set $\mathcal{E}$ can be defined in the same way too. For example, q_1 and q_5 domains are defined as follows:

$$\begin{aligned} Dom(q_1) = \{x \in \Re^3 : (0 \le x_{2_{n+1}} < v_{des}) \wedge \\ [((\Delta x_2 > PTP|_x) \wedge (\Delta x_1 > \Delta S|_x)) \vee \\ ((\Delta x_2 > PTN|_x) \wedge (\Delta x_1 > \Delta D|_x))]\} \end{aligned} \tag{25}$$

$$\begin{aligned} &Dom(q_5) = \{x \in \Re^3 : \\ &[(\Delta x_2 > PTN|_x) \wedge (\Delta x_2 \le PTP|_x) \wedge \\ &(\Delta x_1 \le \Delta D|_x) \wedge (\Delta x_1 > \Delta R|_x)] \vee \\ &[(\Delta x_2 > PTP|_x) \wedge (\Delta x_1 \le \Delta S|_x) \wedge (\Delta x_1 > \Delta R|_x)]\} \end{aligned} \tag{26}$$

The same reasoning will be adopted for guard conditions sets. Furthermore, they will be set to be mutually exclusive. For example

$$\begin{aligned} \mathcal{G}(q_1, q_2) = \{x \in \Re^3 : [(x_{2_{n+1}} > v_{des}) \wedge \\ [((\Delta x_2 > PTP|_x) \wedge (\Delta x_1 > \Delta S|_x)) \vee \\ ((\Delta x_2 > PTN|_x) \wedge (\Delta x_1 > \Delta D|_x))]]\} \end{aligned} \tag{27}$$

$$\begin{aligned} \mathcal{G}(q_1, q_4) = \{x \in \Re^3 : [(\Delta x_1 > \Delta D|_x) \\ \wedge (\Delta x_1 > \Delta B|_x) \wedge (\Delta x_2 \le PTN|_x)]\} \end{aligned} \tag{28}$$

For lack of space, all sets are not formally introduced (see Figure 2). For a complete description see [14].

D. Initial and reset conditions

Starting discrete state will depend on the position of the $n+1$ vehicle and on its relative speed respect to n vehicle.

$$Init = \bigcup_{i=1}^{7} \{q_i\} \times \{Dom(q_i)\}. \tag{29}$$

There will be no reset condition:

$$\mathcal{R}(q_i, q_j, X) = X \quad \forall (i,j) : e_{ij} \in \mathcal{E}. \tag{30}$$

E. Automaton properties

Proposition 1: The hybrid automaton $\mathcal{H}$ is non-blocking and deterministic.

Proof: Appropriate guard conditions $\mathcal{G}(q_i, q_j)$ area added to the q_i state when $Dom(q_i) \cap RT_{q_i} \neq \emptyset$; then Lemma 4.1 in [15] is satisfied and the sufficient condition for constructing non-blocking status and avoiding blocking property is respected. Examples of these guard conditions are (27) and (28). Mutual exclusion and domains utilization for guard definitions are the adopted tecniques for respecting determinism conditions of Lemma 4.2 in [15]. Then $\mathcal{H}$ is deterministic. ■

F. Equilibrium points

In order to calculate equilibrium points let the disturbance d_n be equal to 0 and the desired speed $v_{des} > x_{2_{n+1}}$. The obtained equilibrium points set is

$$\Delta x_e = \begin{pmatrix} \Delta x^* \\ 0 \\ 0 \end{pmatrix} \tag{31}$$

with $\Delta x^* \in (\Delta R|_x, \Delta D|_x]$. In Figure 4 a qualitative phase portrait of the hybrid model is presented and equilibrium set is depicted.

G. Car-following stability considerations

According to Figure 4, there is an attraction region in the $\Delta x_2 - \Delta x_1$ space. Suppose the acceleration of the leading vehicle is fixed to 0; the space would be a section of the 3 dimensional space X. The gray line in q_7 represents the trajectory that shows us the minimum point where no collision condition is satisfied; in fact, entering in the discrete state from a barrier point to the left of the one that generates the gray trajectory will lead the $n+1$ vehicle to impact the n one. The same reasoning will explain the dotted line in q_6. As a consequence of this, a delimitation of a starting no collision zone can be done; in order to not have collision, the initial set must be contained in this zone. If that happens, then the equilibrium point is reached in finite time and the state lies there. In case of bounded disturbance acting on the model ($d_n \neq 0$), if the perturbed system has a new initial state inside the collision free zone the previous consideration will again be valid.

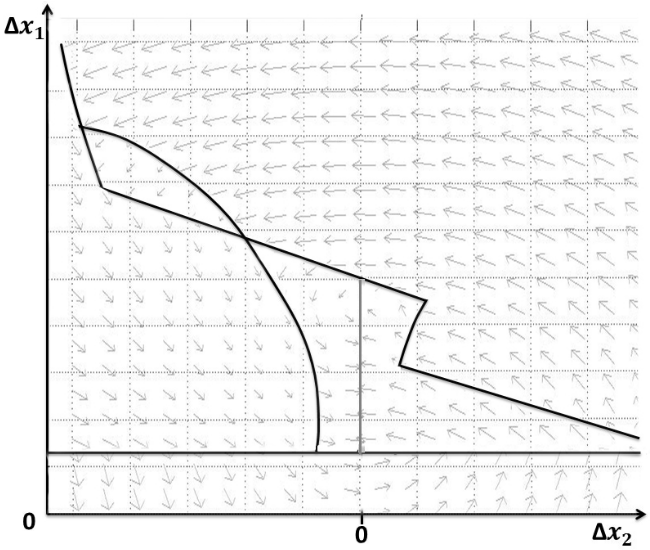

Fig. 4. Equilibrium points set (gray line) in a qualitative phase portrait.

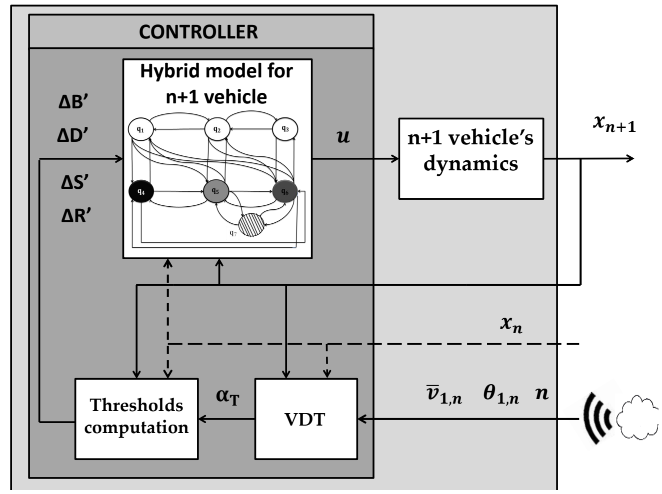

Fig. 5. The adopted architecture. Input data come from n vehicle and are x_n, n, $\bar{v}_{1,n}$, $\theta_{1,n}$: all information are used to compute local mean speed and local variance, which are needed to calculate the updated thresholds.

IV. MESOSCOPIC MODEL

In real life microscopic model parameters are related to macroscopic quantities, such as traffic density. Being variance a density-dependent function [11], a variance-driven adaptation mechanism is adopted for changing thresholds depending on the local mean speed value and local variance to improve the overall systems performance.

In this section the assumption that $n+1$ vehicle has information from n vehicle about its state x_n, n-th number into the platoon, calculated mean speed and variance is done. The needed values for variance and mean speed will be calculated iteratively based on data received from the leading car.

A. Variance-driven time headways model

In [16] authors formulate a variance-driven time headways (VDT) model in terms of a meta-model to be applied to any car-following model where a time headway T_0 for equilibrium traffic can be expressed by a model parameter or a combination of model parameters. They relate on the driver acting not only to his own leader, but also to the neighboring environment. A multiplication factor α_T that increases monotonously and is restricted to a maximum value is obtained.

$$\alpha_T = [\min(1 + \gamma V_N, \alpha_T^{max})] \tag{32}$$

Here γ is the sensitivity of the time headway for increasing velocity variations and α_T^{max} is the maximum value of the multiplication factor: these parameters can be determined from empirical data of the time-headway distribution for free and congested traffic (see [16]). Instead, the local variation coefficient V_N is defined as

$$V_N = \frac{\sqrt[2]{\theta_N}}{\bar{v}_N} = \frac{\sqrt[2]{\frac{1}{N-1}\sum_{i=0}^{N-1}\left(x_{2_{n+1-i}} - \left(\frac{1}{N}\sum_{i=0}^{N-1} x_{2_{n+1-i}}\right)\right)^2}}{\frac{1}{N}\sum_{i=0}^{N-1} x_{2_{n+1-i}}} \tag{33}$$

where $\bar{v}_N$ is the local velocity average, θ_N the local variance and N is the number of considered cars taken into account.

B. Hybrid model integration with VDT

On the basis of the VDT model, it is possible to include macroscopic parameters as average speed and variance changing thresholds definitions into the microscopic hybrid model defined in Section III. By multiplying T_r, T_s, T_d times α_T new thresholds $\Delta R'$, $\Delta S'$, $\Delta D'$ and $\Delta B'$ are defined. Now model considers also part of the environmental information. The α_T parameter will anticipate platoon caused actions, introducing a kind of future prediction in the model.

In this study N vehicles in a space of M meters in front of the $n+1$ vehicle are contemplated; each vehicle at each step calculates local mean speed and variance based on the data received from its leader (see Figure 5).

V. SIMULATION RESULTS

In this section two simulation sets are considered and the results of the proposed control technique are provided. First a comparison between the basic controller and one which uses the VDT mechanism when the desired speed is constant is done and an improvements in case of utilization of macroscopic data are shown. Later simulation results are outlined when vehicles platoon varies its speed. The values from empirical data are adopted for parameters γ and α_T^{max}. In this study we consider 5 vehicles on the segment road of 500 meters in front of the considered $n+1$ vehicle.

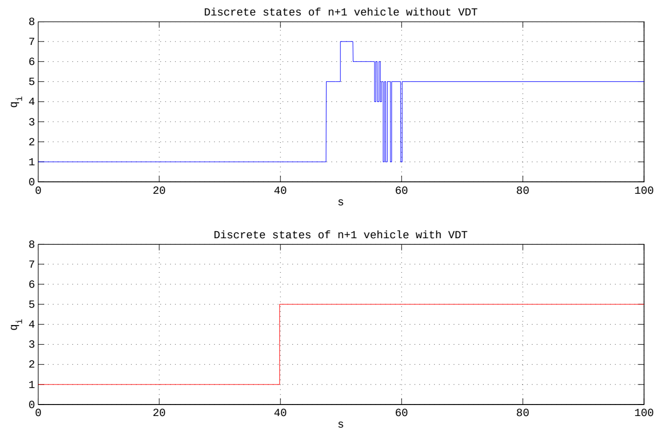

Fig. 6. Case I: Discrete states evolution. The blue line represent discrete evolution of $n+1$ vehicle in absence of α_T utilization, while the red one the discrete evolution when α_T is used.

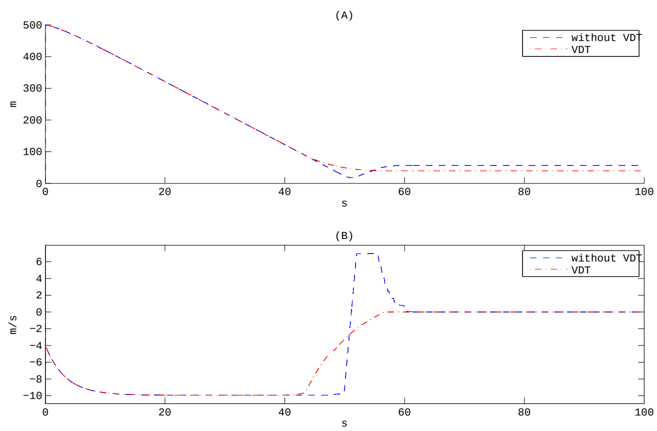

Fig. 7. Case I: Leader-Follower interaction: (A) Leader-Follower distance; (B) Leader-Follower speed difference. The dashed blue line represent the VDT absence case, the dashed red one the case where the VDT mechanism is implemented.

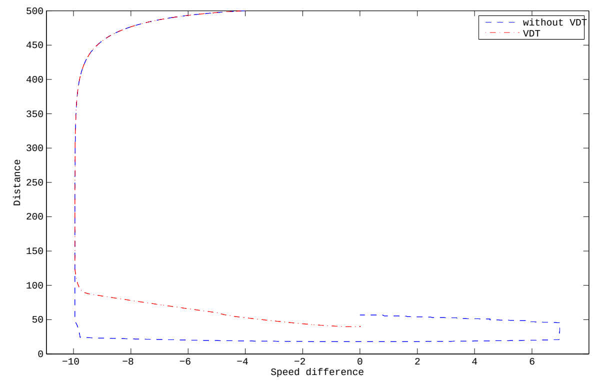

Fig. 8. Case I: Motion described in the $\Delta x_2 - \Delta x_1$ plane. The dashed blue line represent the VDT absence case, while the dashed red one the case where the VDT mechanism is implemented.

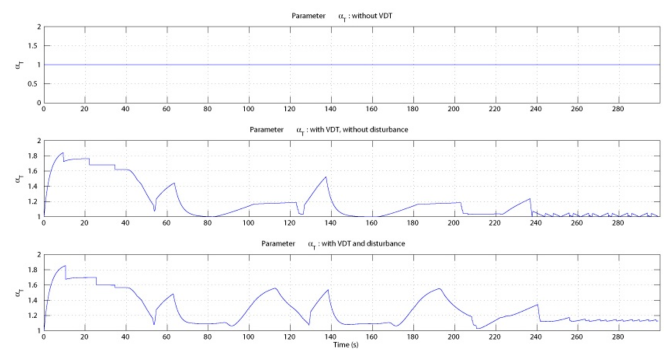

Fig. 9. Case II: α_T profiles in all different situations.

A. Case study I: Platoon approach

A stable platoon approaching situation is treated: vehicle $n+1$ has to decelerate because of the platoon and to tag along to it. Depending on the use of VDT mechanism different discrete evolutions take place. As the equilibrium set is contained in q_5 discrete state, it will be the critical one. Anticipatory action is depicted in Figure 6: the augmented thresholds force the system to exit in advance from q_4 discrete state and to enter in q_5 one (see around 40 s). As showed by Figures 7 and 8, also continuous dynamics are different: the system presents a better behavior when α_T is used. Taking into account platoon existence, the follower adapts its behavior in advance; that allows a smother maneuver. Indeed the introduced parameter provides a faster response and a shorter transient. DIRE QUALCOSA SUI PUNTI DI EQUILIBRIO DIFFERENTI???

B. Case study II: Platoon tracking

Vehicle $n+1$ accelerates trying to reach its desired speed of 30 m/s: after it does, it has to decelerate because of a platoon. Two possible platoon behavior are considered. In the first one, let us intend a string stable platoon without disturbance backward propagation; each vehicle holds the same shifted speed profile (see Figure 10). In the second case, we consider a platoon with speed disturbance propagation occurring on $n-1$ and $n-2$ vehicles. In order to make a good comparison, we suppose that the n vehicle behaves as in the no disturbance case: then the platoon could not be string stable anymore. We compare the use of VDT mechanism in these situations. From Figure 9 we can see that in the disturbance propagation case there is more information respect to one without VDT mechanism. Speed platoon profile is depicted in Figure 11. Because of the different vehicles with time-varying speed there will be an increase of car accident probability. Furthermore because of the disturbance collision probability will still augment. According to this, $n+1$ vehicle driver will keep a higher distance respect to the other case: the higher the probability VDT mechanism faces this situation in a better way because it keeps a bigger distance. collision increase the higher the distance augment. Figure 10 shows each vehicle speed profile in both cases. From Figure 11 it is possible to see that VDT mechanism faces the increase of car accident probability incrementing the distance. Hence the main advantage is given by an improved safety, thanks to augmented distance, and a non increased fuel consumption.

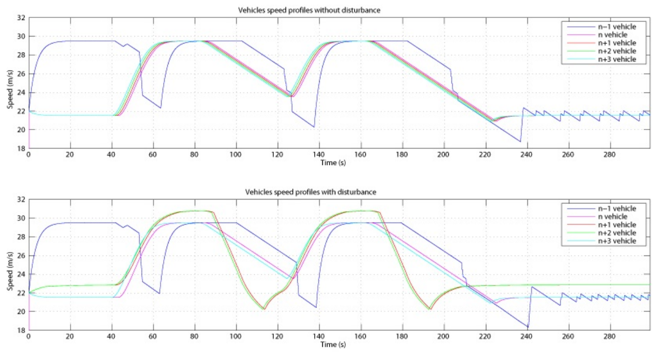

Fig. 10. Case II: Vehicles speed profiles.

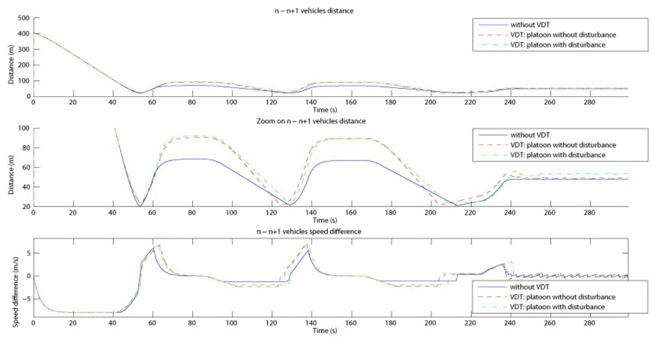

Fig. 11. Case II: Interaction between n and $n+1$ vehicles.

VI. Conclusions

The hybrid system presented in this paper describes different ways a car driver behaves. The automaton is able to introduce dynamical changes depending on next vehicle microscopic behavior and on macroscopic quantities too. Furthermore it similarly behaves as an human driver thanks to psycho-physical model. In an Automatic Cruise Control perspective it performs better from a comfort point of view.

Results described in Section V show multiple improvement. In fact they cover stuff as interaction distance or fuel consumption or more efficient system behavior.

Given the characteristic to take into account the different aspects related to the real behavior of a driver (comfort desired, acceptable risk of collision, etc.), the proposed model is suitable for being used in two ways: it can be used either as a driving support, which recommends a skillful performance to an human driver, either as a automatic control able to lead the progress as if a human being was driving.

Future work will extend this model for lane-change case. An interesting possibility would also be to take into account more macroscopic parameters. The focus could also be to try to produce a kind of "positive" shock wave for reducing (or totally neglecting) shock waves propagation.

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