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Hierarchical Control for Trajectory-based Intelligent Navigation in Urban Adjacent Intersections

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Abstract— **Autonomous Intersection Management (AIM) is of high importance to avoid traffic jams. Intelligent Vehicles (IVs) and cooperative navigation have received recently much attention in this context. More importantly, the local motion planning approaches for IVs may become impracticable due to traffic disturbances. To face this problem, this paper presents a two-layer Decision-Making and Motion Planning (DMMP) framework to perform trajectory-based IVs hierarchical control in multiple intersections. It includes a microscopic car-following model while taking into account the decisions made by the intersection management layer. This layer is ensured via a local supervisor that detects the vehicle flow rate of traffic downstream. Accordingly, the "road-weight" of each lane is designated to alleviate the traffic congestion. Simultaneously, an aggregated velocity is assigned for approaching IVs in the low-level motion planner layer. Hence, lane's priorities are specified by the local supervisor based on a predefined strategy to manage the distributed IVs system. The Probability Collectives (PC) algorithm is also adopted to ensure an optimal collision-free trajectory regarding the aggregated velocity. Simulations including two adjacent unsignalized intersections are presented to validate the DMMP coordination framework. The overall navigation performances and the traffic flow density are remarkably improved by the supervised AIM.**

I. Introduction

In the near future, urban transport systems are expected to be enormously improved thanks to the connected Intelligent Vehicles (IVs) [1], [2]. The efforts made by the academic institutions, car manufacturers and Big Tech companies permit to avoid the in-road hazards through IVs [3], improve fuel economy and reduce emissions [4] by more efficient cooperative navigation technologies. In this context, a review research work presented in [5] investigated the potential impacts of the automated/autonomous driving. It classified the implications of the autonomous navigation on three main levels. The first level consists of the travel cost/choice and traffic capacity. The second is the location choices, land use, road infrastructure and vehicle ownership. Finally, the third level refers to the social implications. Obviously, IVs may contribute in a better manner to boost the public transportation and the navigation in urban areas [1]. At this level, an important question arises: how can IVs help to fulfill the increasing mobility demands in future? Therefore, developing novel mobility platforms, which are focusing on improving the individual navigation, is attracting a considerable interest in the transportation systems community.

Conventionally, motion prediction and planning for road participants assume a significant role in improving the urban road traffic capacity [6] and [7]. In particular, the research work related to intersection management has received much attention in the past decade [8]. Interesting and comprehensive surveys in relation with this issue are reported in [9] and [10]. Several signal-based control approaches ensured a successful intersection management and helped in overcoming traffic congestion [11]. Thanks to the new emergent vehicular communication technologies, a large range of non-signalized intersection management approaches are also introduced in the literature [12], [13]. Generally, those methods may be classified into: cooperative resource reservation techniques, trajectory planning approaches and virtual traffic lights solutions [14]. The authors' previous works [15] and [16] also addressed a trajectory-based method for cooperative navigation at non-signalized intersection. The authors in [17] presented a decentralized optimal control framework for Connected Automated Vehicles (CAVs) crossing two urban unsignalized intersections. A similar work in [18] proposed a hierarchical distributed control strategy for multiple CAVs while exploiting the traffic density information. A study, tackled in [19], described a Cooperative Eco-Driving (CED) in adjacent signalized corridors. Despite their efficiency, the aforementioned approaches need to consider in a better way several stochastic disturbances that may correspond to various hazards such as unexpected behavior of other vehicles. Therefore, there is still a need for further investigations for IVs navigation in different intersection environments.

The study of the distributed coordination of multiple IVs was inspired from the successful application of the distributed computing, management sciences and statistical physics [20]. In the context of dynamic traffic environments, there are two main challenges that need to be addressed. First, since the high traffic demand and unexpected driver actions tend to create traffic disturbances, vehicles are prone to long delays and respectively slow traffic [21]. According to [22], vehicles are not able to react quickly and appropriately before that an incident triggers a downstream congestion. Then, undesirable hard breaks are performed by the concerned vehicles to avoid these problems [23]. Second, since the traffic density is not uniformly distributed, the motion planning solutions remain inaccurate and then not optimal. Hence, the trajectories, selected to avoid perturbation in dynamic traffic flows, may increase collision risks [24], [25]

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and fuel consumption [26].

In this paper, a Multi-layer Decision-Making and Motion Planning (DMMP) framework is developed to improve traffic efficiency both in the downstream traffic level and local intersection level. To address the problem of unexpected traffic disturbances, a Downstream Control Model is proposed to compute the road's right for passage and a suggested speed limit for assigned cooperative IVs for upstream vehicles. Furthermore, an Autonomous Intersection Management (AIM) model for a single vehicle, in presence of other IVs at an unsignalized intersection, is introduced to optimize its trajectory. Besides, a local supervisor is dedicated to improve the Decision-Making performance for the overall proposed navigation framework.

The remaining of this paper is organized as follows: Section II details the studied problem while introducing the overall proposed hierarchical control and coordination framework. Section III details the proposed Downstream Control Model. Section IV explains the overall suggested safe and efficient intersection navigation scheme. Section V performs and interprets the obtained numerical simulation results. The paper contributions and future work are summarized in Section VI.

II. System overview

The overview of the addressed adjacent intersections scenario is outlined in Fig. 1. Only IVs equipped with embedded system are considered in this work. The designated paths of IVs have been computed based on the stationary global information for each vehicle. A module named local supervisor (S_{Loc_A}) is located in an intersection. Additionally assume that downstream traffic information are provided by roadside sensors implanted along the mid-blocks between two intersections. For the sake of simplicity, the S_{Loc_A} is assumed to receive updated downstream information without considering measurement errors (and/or delays) induced from the Infrastructure-to-Infrastructure (I2I) communication.

The proposed two-layer DMMP framework is shown in Fig. 2. For each intersection, two main layers of the DMMP framework are distinguished into a Downstream Control

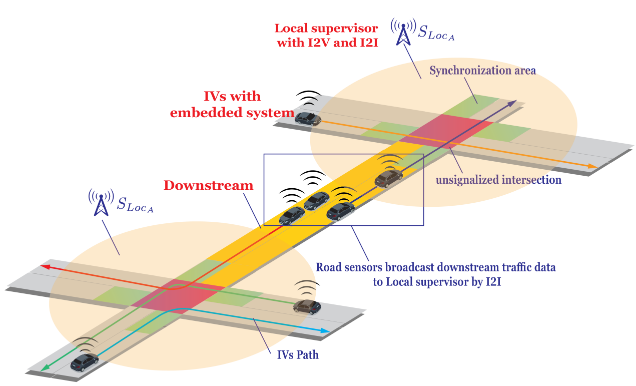

Fig. 1. Urban adjacent intersections road for IVs navigation

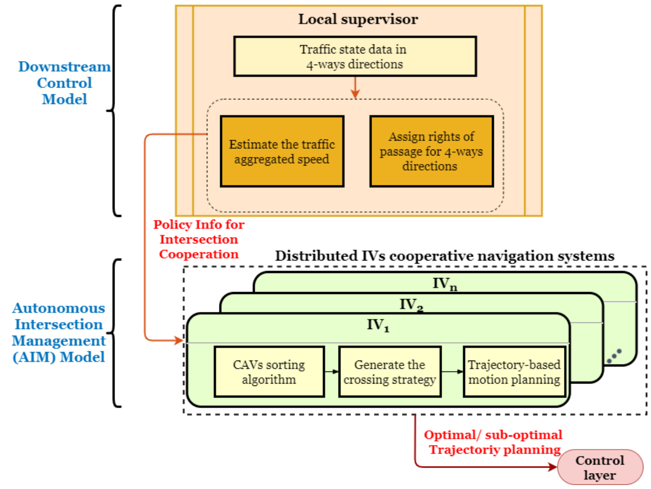

Fig. 2. Basic schematic of the proposed multi-layer Decision-Making and Motion Planning (DMMP) framework

Model (DCM) and an AIM model. S_{Loc_A} observe the traffic status and then disseminate the restrict speed and the right of passage for 4-ways approaching vehicles. IVs are therefore considered to have Infrastructure-to-Vehicle (I2V) communication to retrieve the policy information from S_{Loc_A}. It is important to note that all the approaching vehicles are regarded as a distributed cooperative navigation system. The developed system will run a protocol to decide whether to have overall cooperation or only calculate the self-preferred trajectory with acknowledging previous IVs system's motion planning. In addition, the corresponding cooperation algorithm are addressed by a previously introduced Probability Collectives (PC) method [15] and [27]. In so doing, the cooperative navigation for the IVs system is conducted to ensure optimal/sub-optimal performance while considering the downstream traffic status.

The main idea standing behind the proposed architecture is to construct a feasible link between the traffic downstream behaviors and the IVs intersection control. A detailed illustration of the DCM and IVs AIM model will be given respectively in Sections III and IV.

III. Downstream control model

The DCM is used to analyze the association between the intersection control and the demand of downstream traffic flow in the mid-block between two adjacent crossroads (cf. Figure 1). Firstly, a longitudinal car-following model is illustrated by ordinary difference equations as followings:

$$\begin{cases} \ddot{x}_i(t+T) = u_i(t) + \varepsilon_i(t) \\ \dot{x}_i(t+T) = \dot{x}_i(t) + \ddot{x}_i(t+T) \cdot T \\ x_i(t+T) = x_i(t) + \dot{x}_i(t) \cdot T + \frac{1}{2}\ddot{x}_i(t+T) \cdot T^2 \end{cases} \tag{1}$$

Where $x_i(t)$ and $\dot{x}_i(t)$ denote the displacement and velocity of the vehicle i at time instant t. $\ddot{x}_i(t+T)$ is the acceleration after a time interval T. Besides, $\ddot{x}_i(t+T)$ in (1) is addressed by the control input $u_i(t)$ and an uncertain disturbance factor $\varepsilon_i(t)$ which is related to perception and sensing errors. Thus, considering the relative distance $\Delta x_{i,i-1}(t) = x_{i-1}(t) - x_i(t)$ and relative speed $\Delta \dot{x}_{i,i-1}(t)$ between two successive vehicles (i.e., ego vehicle i and vehicle $i-1$ ahead). It assumes that IVs either perform Cruise Control (CC) to maintain a preset speed v_{ref} or Adaptive Cruise Control (ACC) when a vehicle ahead is detected within a distance $\Delta x_{i,i-1}(t) \leq d_{ref}$. The distance d_{ref} is defined as:

$$d_{ref} = d_{safe} + \Delta x^*_{i,i-1} \tag{2}$$

In (2), d_{safe} is the preset standstill safe distance. $\Delta x^*_{i,i-1}$ is the desired distance at current speed, which will be further discussed. Therefore, the control law $u_i(t)$ for vehicle i can be explicitly defined as (3) if $\Delta x_{i,i-1}(t) > d_{ref}$:

$$u_i(t) = -K_0 \cdot (\dot{x}_i(t) - v_{ref}) \tag{3}$$

else if $\Delta x_{i,i-1}(t) \leq d_{ref}$:

$$u_i(t) = K_1 \cdot (\Delta x_{i,i-1}(t) - d_{ref}(t)) + K_2 \cdot \Delta \dot{x}_{i,i-1}(t) \tag{4}$$

Where $\{K_0, K_1, K_2\}$ are the positive control grains. It is important to remark that $\Delta x^*_{i,i-1}$ represents the preferred distance for each vehicle in (2). IVs can be assigned with stochastic space policy like human driver applying invasive or conservative following strategy on road. In this paper, the desired distance $\Delta x^*_{i,i-1}$ is defined by the stochastic time headway th_i: $\Delta x^*_{i,i-1} = th_i \cdot \dot{x}_i(t)$. Further, it assumes that th_i is sampled based on a shifted log-normal distribution as [28]. Therefore, the ith vehicle is supposed to generate an i.i.d $t\hat{h}_i$ as self-preferred time gap (i.e., $th_i = t\hat{h}_i$). Thus, we have

$$t\hat{h}_i \sim \text{Log-}N(\mu_v, \sigma_v) \tag{5}$$

Where μ_v and σ_v are the predefined velocity dependent parameters in log-normal distribution. Statistical tests or high-quality datasets (as NGSIM used in Section V) can provide an estimation of the log-normal distribution.

In such a manner, local supervisor S_{Loc_A} is supposed to adopt appropriated policy to deal with traffic congestion by the previous car-following model in downstream. However, in macroscopic (or mesoscopic) view, the disturbance item such as an uncertain inflow rate and persistent stochastic disturbance (e.g., $\varepsilon_i(t)$ in (1) and th_i in (5)) in the proposed car-following model always disturb traffic. To address this problem, there is a strong intention in this work to establish a sound link between the microscopic IVs intersection control and the macroscopic (or mesoscopic) traffic downstream behavior. In according with the previous study based on macroscopic road traffic [29], the desired distance between consecutive vehicles can be defined as:

$$d^*_{ref} = 1/[\rho_m(1 - \frac{\dot{x}_i(t)}{v_f})] \tag{6}$$

Where ρ_m and v_f are respectively the traffic jam density and the maximum free flow speed in traffic theory. In such boundary conditions, the corresponding computed traffic aggregated velocity in downstream is $v(\rho) = v_f(1 - \rho(t)/\rho_m)$ with regarding to road density $\rho(t)$. It is noticing that $v(\rho)$ can be seen as a traffic propagation speed. To reduce the chance of braking, S_{Loc_A} in DCM enforced a restrained speed $v(\rho)$ for IVs to leave the intersection (cf. Subsection IV-B). Next, it assumes that $\{E[d_{ref}] \to d^*_{ref}, \dot{x}_i(t) \to v(\rho)\}$ at steady state for S_{Loc_A}. To better discuss the objectives, the traffic flow Q is obtained in (7):

$$Q(\rho) = v(\rho) \times \rho(t) = v_f(\rho(t) - \frac{\rho^2(t)}{\rho_m}) \tag{7}$$

In such a manner, a mapping function from the road segment density $\rho(t)$ to traffic flow rate $Q(\rho)$ is obtained. As shown in Fig. 3, the diagram of road traffic is divided into two regions to underline where the traffic flow is stable or unstable. Intuitively, it should be noted that if the number of vehicles in the road grows, a maximum traffic flow will be reached. After that, if the number of vehicles continues in increasing, the traffic flow will fall down (cf. Figure 3). The introduced local supervisor S_{Loc_A} can observe the down stream data (i.e., vehicles number N). Then, it computes at every instant the traffic flow $Q(t) = N/T$ and road density $\rho(t) = N/L$, wherein road length is L. Accordingly, the right of passage for upstream vehicles is designated for adjusting inflow rate to downstream. The "road-weight", therefore, is presented through (8):

$$W_r = \sum_{x=R_L}^{R_H} (\rho_x(t)/\rho_{m_x})^2 \times \varphi_x \tag{8}$$

Where:

$$\varphi_x = \begin{cases} \Pi^{e1}(t), \text{ if } \partial Q/\partial \rho \geq 0 \\ \Pi^{e2}(t), \text{ if } \partial Q/\partial \rho < 0 \end{cases} \tag{9}$$

Note that $x := [R_L, R_H]$ is the road length and $\rho_x(t)$ is the corresponding density in x. The piecewise-defined function $\varphi(x)$ indicates the stable or unstable traffic state w.r.t. the observed traffic flow density ratio $\partial Q/\partial \rho$. Every function $t \to \Pi^e$ is constant whereas Π^{e1} is significantly smaller than Π^{e2}. In consequence, the macroscopic flow model is established and joined to the proposed traffic policy implied by an intersection supervisor S_{Loc_A}, as shown in Fig. 2.

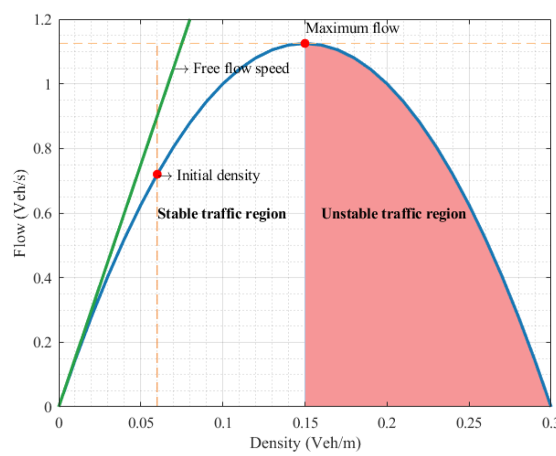

Fig. 3. The diagram of traffic density and traffic flow

IV. Autonomous Intersection Management Model

In order to provide a clearer idea about the microscopic layer of the DMMP, this later is divided into two main parts in the sequel to detail the proposed AIM strategy.

A. IVs system intersection navigation protocol

When IVs enter the intersection synchronization area (see Fig. 1), S_{Loc_A} will immediately activate the appropriate coordination mode according to the First Coming First Served (FCFS) fashion. However, if two or more vehicles accede the synchronization zone at the same time, a random service is applied for the concerned vehicles. As indicated in author's previous work [27], the connected IVs are labeled as "collaborative agent" and "non-collaborative agent". The collaborative IVs perform a combined search of coordinate intersection crossing strategies based on an utility-maximizing decision model (cf. Subsection IV-B). In contrast, the non-collaborative vehicle broadcasts its self-interested intersection crossing trajectory without further cooperation. Thus, other vehicles can only achieve a sub-goal by optimizing their own behaviors. Note that, S_{Loc_A} only conforms the active IVs in the intersection and transmits policy messages for a new entered vehicle. Further, the activated vehicles are regarded as a distributed IVs system to calculate the optimal/sub-optimal crossing strategy by an in-vehicle embedded system.

The proposed navigation protocol for all agents in IVs system can be summarized as follows:

1) Firstly, vehicles in IVs system execute *Algorithm 1* to classify the collaborative and non-collaborative vehicle. Previous vehicles that obtained optimized trajectories do not need to be involved in the re-optimization process unless steps 3 and 4 are met.
2) Secondly, the collaborative agents run the *PC algorithm* (cf. Subsection IV-B) to find the preferred trajectories w.r.t. the non-collaborative vehicles.
3) If the collaborative vehicles can not find feasible solutions to avoid a collision with the non-collaborative vehicles, then conflicted vehicles will be listed as collaborative vehicle to re-execute the optimization.
4) If the vehicles remain in the intersection after the previous motion planning, the vehicles need to run again the re-optimization process as collaborative agents.

Let assume that the embedded motion planner of each vehicle in an activated IVs system I_v can update the coordination state at every instant. Then, the Boolean values are correctly assigned for the labeled states such as: collaboration flag V_{Col}, optimization flag V_{opt}, conflict flag $V_{conflict}$ and remain flag V_{rem}, etc. The detailed steps to distinguish between the collaborative and non-collaborative vehicles is given in *Algorithm 1*. It should be noticed that in this study, a repeated motion planning is not necessary for non-collaborative vehicles that have their own safe trajectory. By following such a navigation protocol, the developed IVs system coordinate framework can avoid the time-consuming re-optimization process in a dynamic environment.

Algorithm 1: Sorting algorithm for collaboration

Input: I_v, V_{opt}, $V_{conflict}$ and V_{rem}
Output: V_{Col}

```
if vehicle in synchronization area then
    for all i ∈ I_v do
        if V_opt == 0 then
            V_Col = true;
        else
            V_Col = false;
            if V_conflict == 1 then
                V_Col = true;
            if V_rem == 1 then
                V_Col = true;
else
    V_Col = false
return V_Col;
```

B. Distributed PC algorithm: trajectory-based optimization

In this section, a trajectory planning-based optimization method for IV systems is presented to illustrate how vehicles cross the intersection with collision-free paths and optimal performances.

Fig. 4 shows a four-way intersection (with left-turn maneuver). Let denote by $T^a \in [0,T]$ the vehicle appearing time during the period $[0,T]$ at the intersection. The state space for single IV is formulated as $S \times V \subset \mathbb{R}^+$, where S is the vehicle's longitudinal displacement and V is its velocity. Let us define $(s_i, v_i) \in S \times V$ as the corresponding state vector

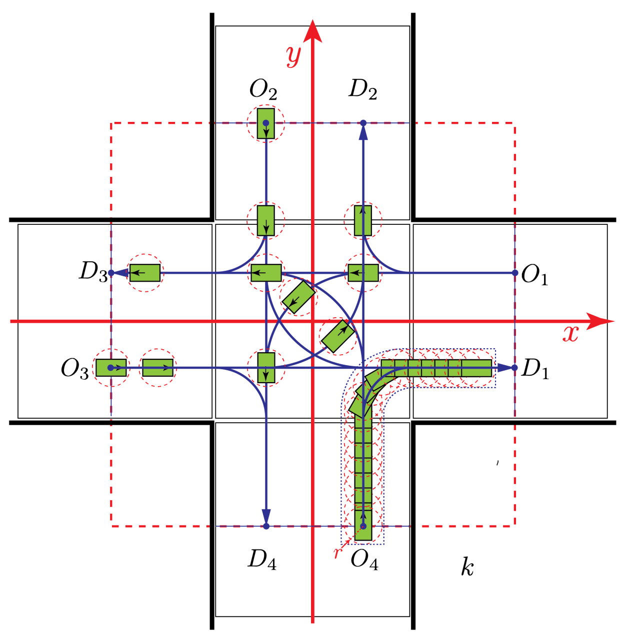

Fig. 4. Illustration of the possible IVs trajectories (bold blue line) in an isolated intersection

of vehicle i. Hence, a trajectory planning-based method is employed to address the non-signalized intersection IVs navigation problem based on the authors' previous works [15] and [16]. Let suppose that the vehicles approach to the intersection at $t = T^a$. There is only one lane for each direction of the upstream IVs. The vehicle is supposed to be a rectangle, surrounded by a red circle of radius r. The path of a single vehicle is also defined as a pair $\left(O_\xi, D_\xi\right)$ including its origin O_ξ and designation D_ξ in the 2D intersection graph (see Fig. 4). The subscript direction of indices $\{1,2,3,4\}$ corresponds respectively to the "east", "North", "West", and "South" in a counterclockwise direction.

Since the path is pre-scheduled during the IVs motion planning, henceforth a trajectory is separately presented by its assigned path and velocity. Rather than a single line, the predicted trajectory is bounded by considering the vehicle's safe radius r as depicted in Fig. 4 for the vehicle from O_4 to D_1. The speed strategies between all the involved vehicles will affect the interests of priority to leave the intersection. Thus, speed control strategies in a properly assigned time horizon Δt (e.g., $[T^a, T^a + \Delta t]$) will be sorted into three groups (i.e., accelerating, decelerating, and cruising). To reduce the complexity of the decision space, several pragmatic assumptions are presented as follows:

- All the vehicles aiming to cross the intersection have a limited number of strategies during $[T^a, T^a + \Delta t]$;
- Each strategy is denoted by a velocity profile, which is controlled by the input $u \in [u_L, u_H]$;
- The strategy should ensure a smooth curve of speed in the consecutive time intervals.

The generation of the predefined strategies is inspired by the algorithms given in [15] and [30]. Indeed, a quadratic cost function that considers cost on acceleration a_t, jerk u_t, and reference speed v_{ref} is formulated as follows:

$$\begin{aligned} min \quad & f(u) = \sum_{t=T^a}^{T^a+\Delta t} [Q_a a_t^2 + R u_t^2 + Q_v (v_t - v_{ref})^2] \\ subject\ to \quad & u_L \leq u_t \leq u_H \\ & 0 \leq v_{ref} \leq v_{ref}^{max} \end{aligned} \tag{10}$$

Where Q_a, Q_v, and R to minimize $f(u)$ with dynamic constrains: $(t,(a,v)) \to \ u_t \in [u_L, u_H]$. Thus, the selected strategies are generated by the optimal controls u_t^* corresponding to different v_{ref}. In this paper, one can define the $v_{ref}^{max} = min\{v_{max}, v(\rho)\}$ to ensure the fastest reference cross velocity v_{ref}^{max} so that it will not exceed the intersection speed limit v_{max} or traffic aggregated velocity $v(\rho)$ in the downstream (cf. Section III). Vehicle i can repeat the operation defined by (10) to find selective velocity profiles according to equally divided $v_{ref} \in [0, v_{ref}^{max}]$. If there are N_i velocity options for each vehicle in IVs system, the cooperative navigation issue is addressed as a combinatorial optimization problem. The major challenge is to optimize their self utilities and contribute maximum towards the cooperative objective. In this paper, the proposed objective function for IVs system can be formulated as:

$$\begin{aligned} J = & W_{sep} \sum_{i_v \neq i_{self}} \sum_{t=T^a}^{T^a+\Delta t} \frac{1}{d_k(i_v, i_{self})^2} \\ & + W_{speed} \sum_{t=T^a}^{T^a+\Delta t} (v_t - v_{ref}^{max})^2 + \sum_{i_v} W_{cross,i_v} T_{i_v} \end{aligned} \tag{11}$$

Where: W_{sep}, W_{speed} and W_{cross,i_v} are respectively weights for the vehicle's separation d_k, deviation for maximum reference speed v_{ref}^{max} and crossing time T_{i_v}. Moreover, the third term W_{cross,i_v} is in relation with DCM for each vehicle such like:

$$W_{cross,i_v} = W_r^{i_v} = \sum_{x=R_L}^{R_H} (\rho_x(t)/\rho_{m_x})^2 \times \varphi_x \tag{12}$$

In (12), $W_r^{i_v}$ is defined through (8) concerning traffic density from vehicle i_v approaching direction. It is worth noting that the first term in (11) is devoted to guarantee a safe spacing between vehicles in an isolated intersection. While the second and third terms are linked to the intersection policy from S_{Loc_A}. To satisfy the referenced maximum speed (i.e., $v_{ref}^{max} = min\{v_{max}, v(\rho)\}$), the exit speed of the vehicle either towards to the maximum allowed speed in the intersection or in the restrict traffic aggregated speed (if $v(\rho) < v_{max}$). To do that, the IVs can acquire a stable speed at the beginning of entering to the downstream traffic flow. Additionally the third term in (11) is specified to adjust output flow rate. One can derive that $W_r^{i_v}$ increase with the increasing inflow density. Under such situation, the vehicles i_v in the congestion road will ensure more efforts to have a short crossing time. Therefore, the collaborative vehicles in IVs will reserve the preferred trajectory making vehicles i_v own priority to cross the intersection.

V. Simulation Results

To illustrate the performance of the proposed two-layer DMMP framework, the Next Generation Simulation (NGSIM) data sets [31] are explored to characterize the stochastic headway distribution in (5). Next, simulations in Matlab considering two adjacent intersections are executed within a computer of Core i7-10750H, 2.60GHz and 16GB RAM. Main parameters adopted in the tackled scenario (see Fig. 5) are summarized in Table I:

TABLE I
PARAMETERS AND INITIAL STATES

Parameters	Value	Parameters	Value
T_{end}	40 [s]	$[v_{min}, v_{max}]$	$[0,20]$ [m/s]
T_{sample}	0.2 [s]	N_i	10
Syn length	50[m]	W_{sep}	1
(μ_v, σ_v)	$(0.422, 0.446)$	W_{speed}	1
$[j_{min}, j_{max}]$	$[-2,2]$ $[m/s^2]$	$\{\Pi^{e1}(t), \Pi^{e2}(t)\}$	$\{10,20\}$
$[a_{min}, a_{max}]$	$[-3,3]$ $[m/s^2]$	r	1.5 [m]

At first, the simulations verify the overall DMMP to reach the traffic aggregated speed with the intersection navigation protocol (cf. Subsection IV-A). In Fig. 5, the initial velocity for all IVs is set as $10m/s$ within the bounds $[0, 20m/s]$. IVs

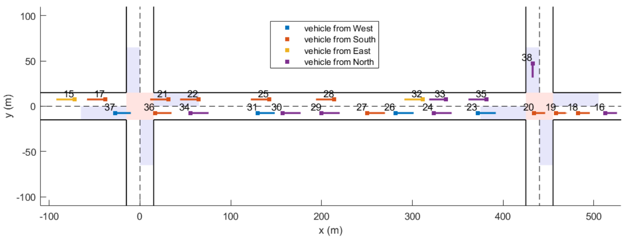

Fig. 5. IVs system navigation in two adjacent intersections (simulation video: https://bit.ly/3ef6XcE). The highlight green rectangles stands for the collaborative vehicles at the time instant

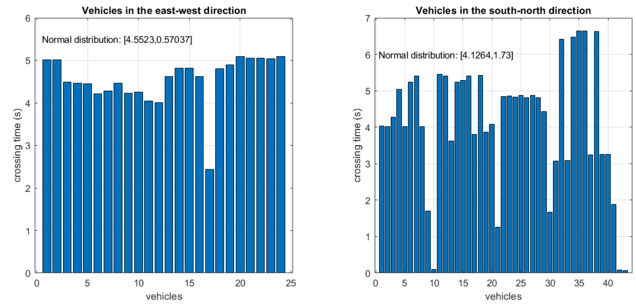

Fig. 7. A comparison of intersection crossing time for vehicles in the east-west direction and other direction

apply CC or ACC system (cf. Subsection III) before entering the synchronization area. Accordingly, the motion results are shown in Fig. 6, The speed profiles of IVs system in Fig. 6 give a global view of the varying traffic movement. The bottom speed diagram shows that traffic aggregated speed decrease with the increasing vehicles numbers. However, the proposed DMMP framework including local supervisor S_{Loc_A} can adopt I2V technology to assign timely traffic policy to adapt the traffic fluctuations. Therefore, the average traffic velocity (blue line) can be adjusted in according with traffic aggregated speed (green line) as shown in Fig. 6. The IVs protocol also propose an efficient cooperation to reduce waiting time (slow down) in synchronization area.

To verify road weights for 4-ways approaching vehicles, the crossing time are recorded in repeated batch simulations as see in Fig. 7. Because the main traffic stream is concentrated between two intersections in the east-west direction. Therefore, the increasing density will lead vehicles from west and east have more chance to leave the intersection by S_{Loc_A} policy. In Fig. 7, one can see that, although the average crossing time for vehicle in the east-west direction is close to the others directions around $4 \sim 5s$. Nevertheless, the variation of the east-west vehicle's crossing time is smaller than the other vehicles.

The corresponding traffic flow state is depicted in Fig. 8. The macroscopic baseline model is used with calibrated free flow speed $v_f = 72km/h$ and jam density $\rho_m = 320veh/km$ w.r.t. the previous scenario in Fig. 5. The corresponding relationship between traffic factors are highlight in Fig. 8 by the parabola. In general, the proposed approach with local supervisor S_{Loc_A} by the proposed DMMP framework can make overall traffic flow stay at the stable region. The traffic congestion is avoided during an increasing traffic flow rate and traffic density in this study. It indicates that IVs system in the signal-free intersection has the potential to improve traffic mobility and increase road capacity. The designed intelligent local supervisor S_{Loc_A} can be beneficial as novel urban mobility management platforms to handle arterial traffic transportation.

VI. Conclusion

In this paper, an overall hierarchical control and coordination framework for efficient IVs navigation in urban two adjacent intersections has been proposed. The major advantage of this work is the formulation of the trade-off between the made between the microscopic trajectory planning level and the downstream traffic flow level. In this sense, the proposed control architecture ensures efficiency, safety and optimize/sub-optimize the traffic flow. More precisely, this

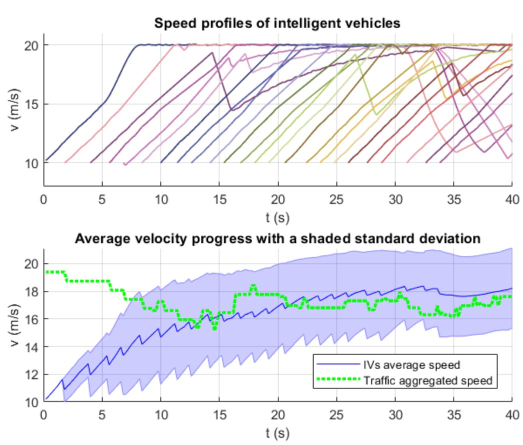

Fig. 6. The velocities of IVs system with policy message from S_{Loc_A}

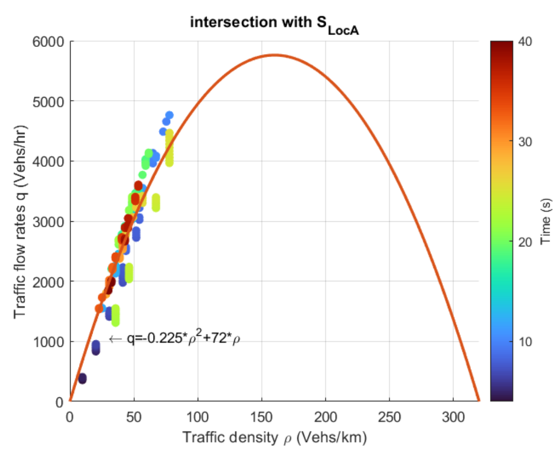

Fig. 8. Traffic flow-density diagram in DMMP framework

work builds on the authors' previous works [15] and [16] to perform a collision-free trajectory planning for IVs at an isolated intersection. Further, a two-layer Decision-Making and Motion Planning (DMMP) framework is introduced to integrate the traffic flow fluctuation into the control architecture. Hence, the IVs system intersection navigation protocol is undertaken to avoid the redundant re-optimization process. The simulations results show the efficiency of the proposed method to deal with traffic fluctuation. The proposed method should be later extended to involve wider urban traffic networks. Further work should also be carried out to evaluate the overall proposed approach in real-time urban environments.

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