Intelligent Traffic Based on Hybrid Control Policy of Connected Autonomous Vehicles in Multiple Unsignalized Intersections

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***Abstract*—Over the last decades, several advanced intersection control systems are built to alleviate traffic congestion. Connected Autonomous Vehicles (CAVs) can be more easily developed for cooperative navigation than regular traffic. Due to whole uncertainty in a transportation network, the conventional motion planning for local areas may lead to undesirable consequences in long term. In this context, this paper presents the Micro-Macro Flow Control (MiMaFC) strategy to explore CAVs' global navigation performance in a traffic network. In prior work, a separate management layer named local supervisor is constructed to control adjacent unsignalized intersections by considering traffic aggregated velocity and vehicle crossing priority. This paper extends the problem to multiple interacting road intersections. Correspondingly, a hybrid control policy is implemented in local areas to solve CAVs conflicts while improving the traffic flow. Further, enhanced intersection navigation protocols are exploited to deal with continued traffic streams. Simulations including a congested traffic network are presented to evaluate the proposed MiMaFC strategy. It is shown in the paper that the mobility in the urban network can be improved by the proposed motion planning framework compared to the non-supervised CAVs system in the same reference conditions.**

Keywords-Intersection Control System; CAVs; Cooperative Navigation; Flow Control

I. Introduction

Urban transport systems are expected to be enormously improved thanks to the connected intelligent vehicles [1], [2]. The efforts made by the academic institutions, car manufacturers and Big Tech companies permit to avoid the in-road hazards through Connected Automated Vehicles (CAVs) [3], improve fuel economy and reduce emissions [4] by more efficient cooperative navigation technologies. Under this circumstance, 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. In the core-level (first level) spectrum, the travel cost/choice and traffic capacity are emphasized for the near future. Obviously, CAVs may contribute in a better manner to boost the public transportation and the navigation in urban areas [1]. From this perspective, an important question arises: how can CAVs help to fulfill the increasing mobility demands in future? Therefore, developing novel mobility platforms, which are focusing on improving the arterial traffic performance, is attracting a considerable interest in the transportation systems community.

Conventionally, motion prediction and planning for road participants assume a significant role in upgrading the urban road traffic capacity [6], [7], [8]. In particular, the research work related to intersection management has received much attention in the past decade. 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 to overcome traffic congestion [11], [12]. Thanks to the new emergent vehicular communication technologies, a large range of unsignalized intersection management approaches are also introduced in the literature [13], [14]. Roughly, those methods may be classified into: cooperative resource reservation techniques, trajectory planning approaches and virtual traffic lights solutions [15]. The authors' previous works [16], [17] and [18] also addressed a trajectory-based method for cooperative navigation at signalized free intersection. Researchers in [19] presented a decentralized optimal control framework for CAVs crossing two urban unsignalized intersections based on minimizing fuel consumption. A similar work in [20] proposed a hierarchical distributed control strategy for multiple CAVs while exploiting Fast Model Predictive Control (F-MPC). A study, tackled in [21], described a Cooperative Eco-Driving (CED) in adjacent signalized corridors while using a role transition protocol. Despite their efficiency, the aforementioned approaches did not consider sufficiently several stochastic disturbances that may correspond to various hazards such as unexpected behavior of other vehicles. Besides, motion planning is crucial to adapt traffic fluctuation whereas it is constrained by different control granularity. Therefore, there is still a need for further investigations in complex intersection environments.

In this paper, a Multi-layer Hybrid Control Policy and Motion Planning (MHCPMP) framework is developed to improve traffic efficiency by applying Micro-Macro Flow Control (MiMaFC) strategy. To address the problem of unexpected traffic disturbances, a macroscopic flow model is proposed to compute the aggregated speed to harmonize the crossing stream. Simultaneously, cooperative CAVs are assigned with corresponding priority to speed up the leaving of the considered intersection. To ensure the hybrid control policy, a local supervisor is designated in this paper for the overall proposed navigation framework. Furthermore, a microscopic Autonomous Intersection Management (AIM) model for a single vehicle, in presence of other CAVs at an unsignalized intersection, is introduced to optimize its trajectory with upgraded navigation protocol.

This paper is organized as follows: Section II details the studied problem while introducing the overall proposed MHCPMP framework. Section III presents the proposed macroscopic flow model. Section IV explains the overall suggested safe and efficient intersection navigation scheme. The hybrid control policy from the macro-level are implemented in the CAVs optimization. Section V performs and interprets the obtained simulation results. The paper contributions and future work are summarized in Section VI.

II. An overview of traffic framework

Consider a scenario that only includes CAVs equipped with Vehicle-to-Vehicle (V2V) communication. Vehicles coming from different entries of urban network are assigned with determined paths. A module named local supervisor S_{Loc_A} is located at the unsignalized intersection. The S_{Loc_A} is assumed to obtain the updated downstream road message without considering measurement errors and delays.

The proposed two-layer MHCPMP framework is shown in Fig. 1. For each intersection, two main layers of the MHCPMP framework are distinguished into macroscopic flow model and a trajectory-based optimization model for AIM. Local supervisors S_{Loc_A} observe the 4-ways downstream traffic flow status. Thus, the traffic aggregated speeds and the rights of passage are then disseminated for upstream vehicles in different directions. CAVs are therefore considered to have on-board system to retrieve the hybrid control policy from S_{Loc_A}. It is important to note that all the

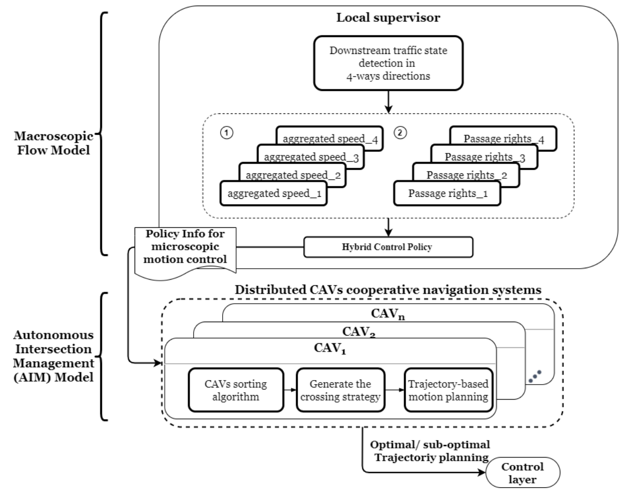

Figure 1. Basic schematic of the proposed Multi-layer Hybrid Control Policy and Motion Planning (MHCPMP) framework

approaching CAVs in the 4-ways upstream are considered as a distributed cooperative system based on their network topology structure. Additionally, the microscopic strategies and optimization solver are addressed by a previously introduced Probability Collective (PC) algorithm [16], [17] and [18]. In so doing, the CAVs system will guarantee an optimal (or sub-optimal) trajectories-based planning for lower control layer. Finally, the cooperative navigation for multiple CAVs systems is conducted regarding the traffic flow fluctuation while ensuring locally efficient and safe navigation. The main idea standing behind the proposed architecture is to construct a feasible link between the developed macroscopic flow strategy and the microscopic motion control as seen in the prior work [22]. In this paper, a more detailed explanations of the macroscopic flow model regarding urban network will be provided in Sections III. Next, the distributed CAVs optimization model for multiple intersections based on the proposed hybrid control policy is addressed in Sections IV.

III. Macroscopic flow model

The macroscopic flow model interprets the real-time state of the dynamic transportation network including multiple intersections. Firstly, a primitive car-following model is by ordinary difference equations as follows:

$$\begin{cases} \ddot{x}_i(t+T) = f(\Delta x_{i,i-1}(t), \Delta\dot{x}_{i,i-1}(t), \dot{x}_i(t)) + \varepsilon_i(t) \\ \dot{x}_i(t+T) = \dot{x}_i(t) + \ddot{x}_i(t+T)\cdot T \\ x_i(t+T) = x_i(t) + \dot{x}_i(t)\cdot T + \frac{1}{2}\ddot{x}_i(t+T)\cdot T^2 \end{cases} \tag{1}$$

In system (1), $x(t)$ is the displacement of the vehicle i at instant t. The acceleration $\ddot{x}_i(t+T)$ is addressed by the deterministic car-following policy function $f(\Delta x_{i,i-1}(t), \Delta\dot{x}_{i,i-1}(t), \dot{x}_i(t))$ after a time interval T. The corresponding subscript $\{i, i-1\}$ represents the ego vehicle and the vehicle ahead. $\varepsilon_i(t)$ is a random disturbance term that is related to perception and sensing error. By considering the space difference $\Delta x_{i,i-1}(t)$ and speed difference $\Delta \dot{x}_{i,i-1}(t)$ between two successive vehicles, the control law $u_i(t)$ (i.e., $u_i(t) = f(\Delta x_{i,i-1}(t), \Delta \dot{x}_{i,i-1}(t), \dot{x}_i(t))$) is adapted to the optional Cruise Control (CC) or Adaptive Cruise Control (ACC) system. For free road vehicles, the CC mode has to maintain a constant speed v_{con}. Hence $u_i(t)$ is expressed as (2):

$$u_i(t) = -k_0 \cdot (\dot{x}_i(t) - v_{con}) \tag{2}$$

When CAVs detect other traffic ahead, $u_i(t)$ in the ACC mode is defined as:

$$u_i(t) = k_1 \cdot (\Delta x_{i,i-1}(t) - d_{ref}(t)) + k_2 \cdot \Delta \dot{x}_{i,i-1}(t) \tag{3}$$

In equations (2) and (3) $\{k_0, k_1, k_2\}$ are the positive control gains. $d_{ref}(t)$ is the reference (bumper-to-bumper) distance which is linked to the preferred time headway th_i of vehicle i. It is further specified like the following:

$$d_{ref} = d_{safe} + th_i \cdot \dot{x}_i(t) \tag{4}$$

Where d_{safe} is the preset standstill safe distance. It is important to remark that the applied time headway th_i from road vehicles affect both: vehicles' distance headway and lane density for existing traffic flow. Therefore, the stochastic time headway is introduced to mimic human driving behaviors to exhibit the influence from time (space) gap policy which vehicle would like to perform by inconsistent feedback speed. Moreover, th_i is sampled based on a shifted log-normal distribution (i.e., $th_i \sim \text{Log-}N(\mu_v, \sigma_v)$) referring to previous research [23].

In this study, 9 neighborhood intersections are combined together as the urban road network such like in Fig. 2. The whole transportation network contains 48 links and 9 traffic junctions. The origins and destinations (O-D) are set to manage the flows in/out at the borders of the traffic network (see Fig. 2). Clearly, destinations points are located in 12 links which are not belong to any of the internal intersection areas (bounded by different colors in Fig. 2). In such neighborhood-sized sections of urban area, it is assumed that the traffic flow is homogeneously distributed. Further, the external conditions especially for the time-dependent traffic flow are supposed to change slowly. Thus, all the links to intersections may suffer from the congestion in same external flow rate. In addition, the traffic flow characteristics linking flow, speed and density can be uniformly defined and revealed by the Macroscopic Fundamental Diagram (MFD) existing in the completed road network.

There are many ways to interpret the value of fundamental traffic flow characteristics (flow, speed and density). Here, the measured space mean speed V, traffic density K and calculated travel flow Q are addressed in this paper. Generally, loop detectors collect vehicle number N_i and real-time

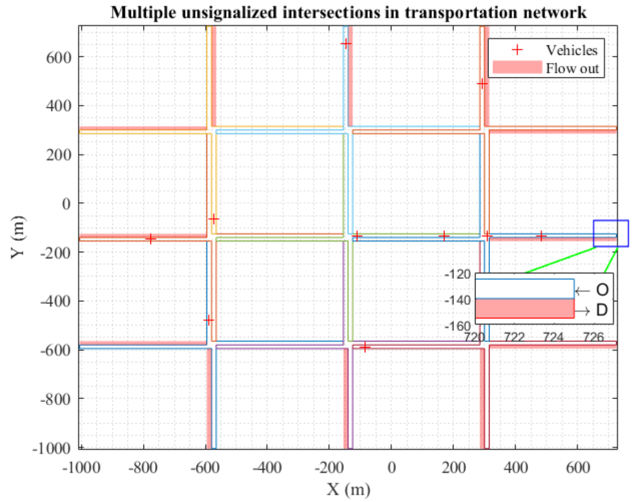

Figure 2. CAVs navigation in transportation network with Multiple unsignalized intersections

speeds V_i in a short period. Thus, the lane density at every instant for each link can be defined as follows:

$$K_i = \frac{N_i}{L} \tag{5}$$

Where L is the length of link. Accordingly, the intersection density is developed as given in equation (6):

$$K_s = \frac{\sum_1^{n_L} K_i}{n_L} \tag{6}$$

Where n_L is the number of the links in local area.

The space mean speed has been proved to be more accurate to reveal current traffic state than time mean speed which overestimates the influence of faster vehicles [24]. Hence, the harmonic mean of collected vehicle speed is used in this study as the space mean speed. Similarly, the fundamental speed for each lane and intersection area are respectively defined as:

$$\begin{aligned} V_L &= \frac{N_i}{\sum_1^{N_i}(1/V_i)} \\ V_s &= \frac{N_s}{\sum_1^{N_s}(1/V_i)} \end{aligned} \tag{7}$$

Where N_s is the vehicle number in whole intersection area.

In such a manner, the calculated flow rate can be also addressed as $Q_i = K_i \cdot V_L$ (for each lane) and $Q_s = K_s \cdot V_s$ (for each intersection area) at every instant. In so doing, we avoid to hourly measure flow rate which reflect the nearly equal traffic knowledge as calculated flow rate in the experimental intersection network.

The present work aims to develop proactive vehicle motion planning regarding the dynamic changes in the motorways between controlled intersections. The aforementioned traffic characteristics are firstly supposed to periodically widespread to the preassigned S_{Loc_A}. Secondly, the obtained traffic key factors are formulated to the macroscopic fundamental diagram by the notable Greenshields model [25] for every single lane as follows:

$$\begin{cases} \mathbb{V}_L = V_f(1 - \frac{K_i}{K_{jam}}) \\ \mathbb{Q}_i = V_f(K_i - \frac{K_i^2}{K_{jam}}) \end{cases} \tag{8}$$

where V_f and K_{jam} are respectively the free-flow speed and jam density regarding the current researched motorway's boundary conditions. $[\mathbb{V}_L, \mathbb{Q}_i]$ are the dependents on the measured traffic density in the proposed traffic fundamental diagram. It is worth acknowledge that the maximum road flow $\mathbb{Q}_i$ is theoretically defined at the vertex of the quadratic function in (8) when $\partial\mathbb{Q}_i/\partial K_i = 0$. If the vehicle number increasing consistently (while $\partial\mathbb{Q}_i/\partial K_i \leq 0$) till to the maximum road capacity, the flow rate will decrease and even collapse to zero at the jam density K_{jam}.

Ultimately, CAVs are supposed to adopt appropriate actions to ensure a proper spatial-temporal strategy at intersection areas w.r.t the policy info from S_{Loc_A} (see Fig. 1). When a car driving at the decision making points (bounds of a local area), the crossing policy is assigned for each one including the downstream aggregated speeds $[\mathbb{V}_1, \mathbb{V}_2, \mathbb{V}_3, \mathbb{V}_4]$ referring (8) and "road-weights" $[W_{r_1}, W_{r_2}, W_{r_3}, W_{r_4}]$ referring upstream density. An objective function will be presented subsequently for intersection crossing (cf. Subsection IV-B). Hence, the "road-weights" W_{r_i} for each approaching car from lane i can be addressed as:

$$W_{r_i} = (\frac{K_i}{K_s})^{\sigma_s} \times \varphi_{r_i} \tag{9}$$

Where:

$$\varphi_{r_i} = \begin{cases} \Pi^{e1}(t), \text{ if } \partial Q_i/\partial K_i > 0 \\ \Pi^{e2}(t), \text{ if } \partial Q_i/\partial K_i \leq 0 \end{cases} \tag{10}$$

Note that $[\sigma_s, \Pi^{e1}, \Pi^{e2}]$ are independent model parameters. σ_s is designed to amplify the "road-weights" impacts in the crucial intersection. The piecewise-defined function φ_{r_i} indicates the unblocked or congested traffic flow state w.r.t. the calculated traffic flow-density ratio $\partial Q_i/\partial K_i$. 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}.

IV. Microscopic AIM model

The systemic approach is implemented in this study to deal with consecutive vehicle's cooperative navigation at every single intersection. In order to provide a clearer idea about the microscopic layer of the MHCPMP, this latter is divided into two main parts in the sequel to highlight universal navigation protocol and local conflicts processing.

A. Universal intersection navigation protocol

Before entering the intersection decision points, a car approaching the intersection will decelerate at a specific distance (e.g., 50m to the bounds of local area). When CAVs at the decision points, S_{Loc_A} immediately update the local active vehicles memory. It should be noted also that if two or more vehicles accede S_{Loc_A} at the same time interval, a random service is applied for the concerned vehicles. The authors' previous work [22] addressing a sorting algorithm of local active CAVs, which calculates a sorting list of "collaborative agent" and "non-collaborative agent". The collaborative vehicles may perform a combined search of intersection crossing strategies based on a utility-maximizing decision model (cf. Subsection IV-B). However, the non-collaborative vehicle only broadcasts its self-interested intersection crossing trajectory without further support. Thus, other vehicles can only achieve a sub-goal of the navigation system by optimizing their own behaviors. Note that, S_{Loc_A} only conforms the active vehicles in the intersection and transmits policy messages when a new vehicle enters its area. As a result, the activated vehicle is organized as a distributed CAVs system to compute the optimal (sub-optimal) solutions to cross the intersection. Intuitively, vehicles in such a distributed system can independently carry out the same navigation protocol to deal with highly reproducible tasks. In this paper, an enhanced universal intersection navigation protocol is addressed like the following:

1) Firstly, a new vehicle added in CAVs system executes *Algorithm 1* to classify the collaborative and non-collaborative vehicles.
2) Secondly, the collaborative vehicle calculate its minimum Time-To-Collision which is a risk indicator to describe the remaining time for a probable collision between any two vehicles. The developed *2D TTC* in authors' prior work [16] is revisited to identify a car that has potential conflicts with other vehicles. Noting that, a threshold TTC_{min} is used to select the violated *2D TTC*.
3) If a collaborative vehicle has conflicts with any others, it will reschedule a new trajectory by the optimal control model (cf. Subsection IV-B). On the contrary, the collaborative vehicle will only keep the current speed if there are no conflicts after 2).
4) If the collaborative vehicles can not find feasible solutions to avoid a collision after 3), then conflicted vehicles will be listed as collaborative vehicle to re-execute the optimization.
5) If the vehicles remain in the intersection or still have conflicts after 4), it will be labeled as cooperative agent at 1) during the next time interval.
6) A "congestion mode" is reserved in which all the vehicles are labelled as collaborative agents to run a system optimization after 5).

Algorithm 1: Sorting algorithm for collaboration

Input: S_V, V_{opt}, $V_{conflict}$ and V_{rem}
Output: V_{Col}
if *vehicle in local area* **then**
  for *all* $i \in S_V$ **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};

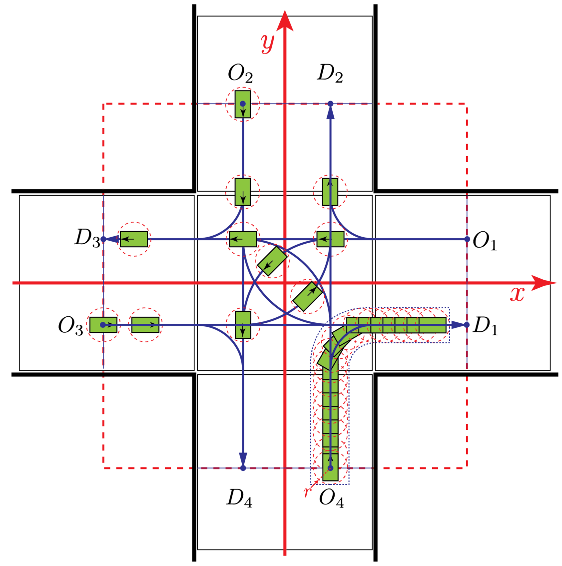

Figure 3. Illustration of the possible CAVs trajectories in an isolated intersection

Let us assume that the embedded motion planner of each vehicle in the distributed CAVs system S_V can update the coordination state at every instant. Then, the Boolean's values are correctly assigned for the labeled states such as: collaboration flag V_{Col}, optimization flag V_{opt}, conflict flag $V_{conflict}$ and remain in intersections flag V_{rem}, etc. The detailed steps to distinguish between the collaborative and non-collaborative vehicles are given in *Algorithm 1*. Particularly, the "congestion model" in 6) is toggled on when a conflict is repeatedly detected (more than a specific threshold $N_{conflict}$) between two vehicles after 5).

The synthesized protocol in this paper ensures its safe (non-conflict scene) and/or optimal (conflict scene) operation for consecutive vehicles to make decisions in an efficient way. With regard to the above mentioned, the CAVs system is required a deliberate effort on approximate optimal solutions integrating the S_{Loc_A} policy and the cooperative navigation utility. Therefore, the CAVs optimal control model running in 3) is proposed in the next section.

B. Local conflict processing

The detected conflict (cf. Subsection IV-A) between any two vehicles will be mastered immediately referring to current system states. The designed conflict resolutions process should provide a low complexity and fast optimization in the addressed intersection network.

In this paper, a trajectory planning-based optimization problem for CAVs is formulated. In fact, the vehicle's path is supposed to be fixed during the movement in the local area. Therefore, the only degree of freedom to re-plan a conflict-free trajectory is the speed for each of the collaborative agents. As seen in Fig. 3, the vehicles (e.g., the green rectangles) have assigned paths (e.g., the blue line) with origins O_i and destination D_i before crossing the intersection. To simplify, a red circle of radius r is defined to surround the car during movement. Any two circles in the 2D graph can not violate a center distance less than $2r$ when a vehicle follows its path. In so doing, the formulated problem only uses the information of the displacements in the path without concerning the path topology. It is worth noting that the algorithm is also independent of the topology of the intersection as long as some paths are defined. Our previous work in [16], [17] and [22] used a version of PC algorithm to search feasible solutions with sampled speed profiles in such a single (or adjacent) intersection(s). However, the bounded conditions (e.g., the initial speed) are quite different for CAVs system in the proposed road network. Accordingly, the strategy of sampled speed profiles is refined in this work.

As mentioned before, a car will decelerate until reaching the decision points (bounds of S_{Loc_A}) to identify whether participation in the optimization process. As illustrated in Fig 4 upper plot, the collaborative vehicle can firstly choose the actions at decision points 1. If it can not find any feasible solution at decision point 1, the vehicle will go on decelerating regarding previous speed during a specified interval (a few short seconds). Thus, the vehicle reruns the optimization at decision point 2 and generate a set of N_s possible speed profiles in a time horizon $T_{horizon}$ with lower initial speed. Generally, as seen in Fig 4, the speed profiles (blue line) have a constraint (red dotted line) of the acceptable range and final target speed (red line). The addressed downstream aggregated speed $[\mathbb{V}_1, \mathbb{V}_2, \mathbb{V}_3, \mathbb{V}_4]$ are defined as the final target speed in each direction. Addition-

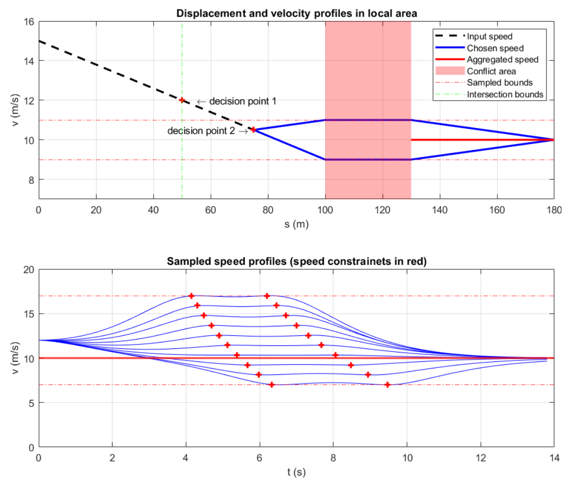

Figure 4. A representation of sampled speed profiles in searching space

ally, the sampled speed be kept constants when entering the conflict area to reduce the system complexity. Therefore, the sampled interval can be counted by different constant speed v_{ref} within the upper/lower bounds (see the bottom plot in Fig 4). The generation of the predefined strategies is inspired by the algorithms given in [26]. Indeed, a usual minimize quadratic problem can be formulated with the cost to the reference speed v_{ref}. Consequently, the repeated solution (i.e., the possible speed profiles) is given under the demanded sampled intervals.

Considering the search space including the whole obtained speed profiles for CAVs, the proposed objective function in this paper for implementing S_{Loc_A} policy in such a distributed system can be formulated as:

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

In equation (11), W_{sep}, W_{speed} and W_{cross,i_v} are respectively characterized as weights for the vehicle's separation d_k, deviation for reference exit speed v_{end,i_v} and local area crossing time T_{i_v}. k is the interval indicator computed by the discretization step of a predefined time horizon. v_k is the ego vehicle's speed at instant k. Moreover, the S_{Loc_A} policy is considered by the second term (v_{end,i_v}) and the third term (W_{cross,i_v}) in relation with downstream aggregated speed $[\mathbb{V}_1, \mathbb{V}_2, \mathbb{V}_3, \mathbb{V}_4]$ and "road-weight" W_{r_i} (cf. Section III) for each vehicle like:

$$\begin{cases} v_{end,i_v} = min\{\mathbb{V}_L, v_{upper}\} \\ W_{cross,i_v} = W_{r_i}^{i_v} \\ \mathbb{V}_L \in [\mathbb{V}_1, \mathbb{V}_2, \mathbb{V}_3, \mathbb{V}_4] \end{cases} \tag{12}$$

Where, $W_r^{i_v}$ is defined by equation (9) in the lane of vehicle i_v and v_{end,i_v} is defined corresponding to the aggregated speed $\mathbb{V}_L$ in the targeted direction. It is worth noting that the first term in equation (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 achieve the proposed MiMaFC strategy. As a result, the exit speed of the vehicle either towards to the maximum allowed speed v_{upper} in the intersection or reach the traffic aggregated speed (if $\mathbb{V}_L < v_{upper}$). To do that, the upstream vehicle can acquire a consensus speed at the beginning of entering to the downstream traffic flow. Furthermore, the third term in equation (11) is specified to alleviate the congestion upstream. $W_r^{i_v}$ will be significant increase if the upstream (the corresponding downstream of the previous adjacent intersection) traffic flow falls in unstable state. Under such a situation, the vehicles i_v in higher density road will ensure more efforts to have a short crossing time. Therefore, the collaborative vehicles in CAVs will reserve the preferred trajectory making vehicles i_v own priority to cross the intersection. Finally, the density in the congestion road can be mastered.

V. Simulation Results

To demonstrate the efficiency of the proposed two-layer MHCPMP framework, the simulations in Matlab considering multiple unsignalized intersections are executed within a computer of Core i7-10750H, 2.60GHz and 16GB RAM. The main parameters adopted in the tackled scenario are summarized in Table I.

Table I
PARAMETERS AND INITIAL STATES

Notation	Value	Notation	Value
T_{end}	$200[s]$	$\{k_0, k_1, k_2\}$	$\{1,1,3\}$
T_{sample}	$0.2[s]$	$\{\mu_v, \sigma_v\}$	$\{0.73, 0.52\}$
R	$65[m]$	d_{safe}	$6[m]$
TTC_{min}	$10[s]$	R_w	$30[m]$
r	$3[m]$	N_s	10
L	$410[m]$	$T_{horizon}$	$10[s]$
$[v_{min}, v_{max}]$	$[0,20][m/s]$	W_{sep}	10
$[a_{min}, a_{max}]$	$[-3,3]\left[m/s^2\right]$	W_{speed}	0.2
$[j_{min}, j_{max}]$	$[-2,2]\left[m/s^3\right]$	$\{\sigma_s, \Pi^{e1}, \Pi^{e2}\}$	$\{1,1,10\}$

The verified scenario can be seen in Fig. 5. The overall MHCPMP framework was running in this 4×4 urban road networks. The unidirectional flows arrive from outside of the network according to the Poisson distribution with parameter $\lambda = 1.5veh/s$. All the vehicles (safe radius r) were set up with the initial speed $10m/s$ in the velocity bounds $[0,20]$[m/s] (as Table I). Vehicles on the road were provided with in-vehicle embedded system for running cooperative navigation algorithm considering hybrid control policy from S_{Loc_A} (detection radius R). The Cruise Control (CC) and Adaptive Cruise Control (ACC) modes (detection range R_w) were adopted for maintaining a desired time headway

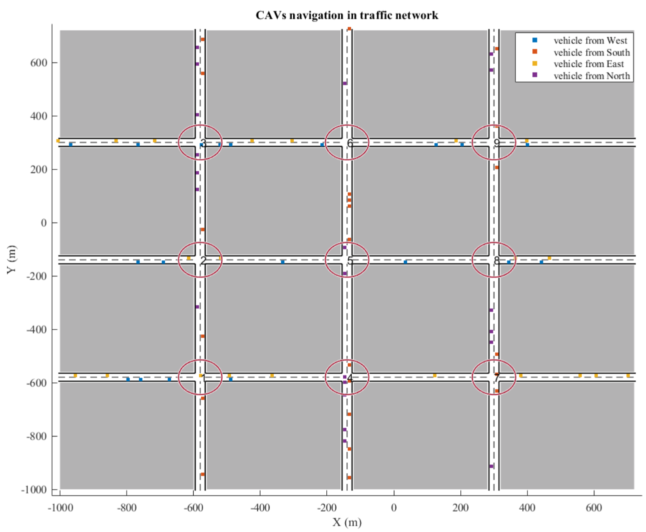

Figure 5. CAVs system navigation in traffic network (simulation video: https://bit.ly/3yVVLL1)

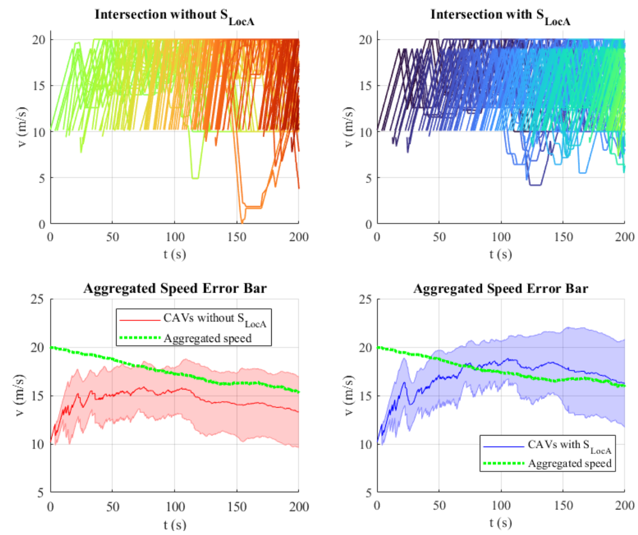

Figure 6. Comparison of CAVs velocities between MHCPMP framework and baseline method

regarding log normal distribution with predefined $\{\mu_v, \sigma_v\}$ (see Table I). To highlight the advantages of the proposed method, this paper performs a baseline model which did not include S_{Loc_A} and navigation protocols (cf. Subsection IV-A).

As seen in Fig. 6, the up-left and up-right velocity diagram graph give a global view of baseline model and the proposed method with S_{Loc_A}. Since there is no I2V communication in the intersections, the desired maximum speed is fixed to $20m/s$ for all CAVs to exit the intersection in the baseline approach. Nevertheless, due to the uncertain traffic flow speed, the velocity collapsed ($0m/s$ for minimum) when the vehicles increase. Additionally, the maximum vehicle to perform cooperative navigation is limited (4 in this case). Therefore, the remained CAVs in the local area have to slow down until permit to participate in cooperative optimization. In contrast, the proposed MHCPMP framework including S_{Loc_A} can adopt the I2V technology to improve the average velocity (blue) comparing with the whole distribute CAVs system's average speed (red). In addition, the traffic velocity can be adjusted for the traffic aggregated speed (green) in the same traffic congestion environments as shown in the bottom of Fig. 6. The CAVs protocol also cuts down the vehicle's deceleration time in synchronization area when performing the cooperative navigation at the signal-free intersection. In brief, it is able to apply consensus cooperation regarding the dynamic traffic stream fluctuation by the S_{Loc_A} in the proposed method.

The corresponding traffic fundamental diagram for each intersections and the exits of the whole urban network can be seen in Fig. 7 and Fig. 8. In order to get the boundary values, the Greenshield's model [27] is used with calibrated free flow speed $v_f = 72km/h$ and jam density $\rho_m = 133veh/km$ (optimum density $\rho_{opt} = 26veh/km$). Further, the average flow of the compared two CAVs systems is recorded in Table II. In general, the proposed approach with local supervisor S_{Loc_A} can guarantee relatively high traffic flow rates comparing the total distribute CAVs system without I2V technology in different intersections. Accordingly, the average traffic flow rate (around $300Vehs/hr$) out of the network with S_{Loc_A} is greater than the flow-out rate ($219Vehs/hr$) with non-supervised road network. It indicates that CAVs system in the signal-free intersection with S_{Loc_A} has the potential to improve traffic mobility. In addition, the color bar in scatter graphs Fig. 8 shows the traffic state shifting by time. It is interesting to note that the proposed MHCPMP framework can stay at the stable traffic region to avoid the traffic congestion during an increasing traffic flow rate and traffic density. Briefly, the designed intelligent local supervisor S_{Loc_A} can be beneficial as novel urban mobility management platforms to handle arterial traffic transportation.

Table II
AVERAGE FLOW IN LOCAL AREA

Intersection	Average flow $[Vehs/hr]$	
	Without S_{Loc_A}	With S_{Loc_A}
1	152.9609	155.4251
2	143.0535	151.8701
3	169.5117	173.3407
4	147.5074	148.6445
5	135.5132	126.5963
6	139.4899	151.8678
7	145.8927	154.1653
8	124.3480	132.0772
9	135.4521	138.3151
flow out	219.0017	300.5002

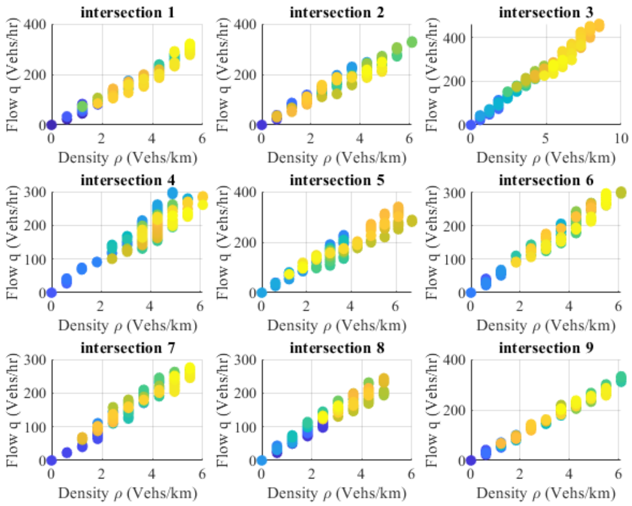

Figure 7. The traffic flow-density diagram for each intersections in urban traffic network

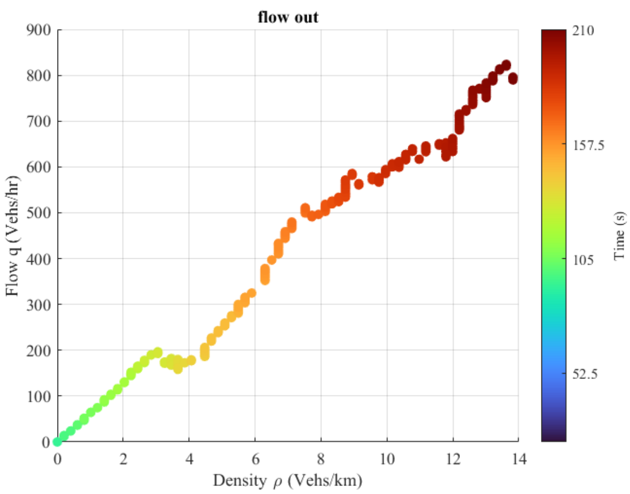

Figure 8. The traffic flow-density diagram for whole exits of traffic network

VI. CONCLUSION

In this paper, an overall MHCPMP framework is scheduled for efficient CAVs navigation in multiple unsignalized intersections. The proposed Micro-Macro Flow Control strategy has been tested in 9 neighborhood intersections. The major advantage of the present control architecture is improving the comprehensive traffic flow navigation performance by implementing the hybrid policy in local cooperative navigation optimization. More precisely, a macroscopic flow model is introduced to detect the traffic flow fluctuation, and then address the traffic right of passage with aggregated speed for CAVs. Hence, the undertaking distributed CAVs system navigation protocol is constructed for efficient intersection crossing. Furthermore, the CAVs optimization model for autonomous intersection management is augmented with the macroscopic hybrid control policy. To perform efficient collision-free trajectory planning for CAVs at an isolated intersection, the universal intersection navigation protocol is notably developed. Additionally, the local conflict resolution strategy depicted by sampled speed profiles is better designed in the optimization procedure. The PC algorithm is applied to find the optimal solution in the proposed searching space based on authors' previous works [16], [17] and [18]. Finally, simulations results show a remarkable improvement for traffic flow control. The assigned S_{Loc_A} at unsignalized intersection could harmonize the CAVs' average traffic speed with averaged traffic speed. Further work should extend the proposed method to involve wider traffic networks in more dense and complex urban environments.

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REFERENCES

[1] C. Legacy, D. Ashmore, J. Scheurer, J. Stone, and C. Curtis, "Planning the driverless city," *Transport reviews*, vol. 39, no. 1, pp. 84–102, 2019.

[2] L. Adouane, *Autonomous Vehicle Navigation: From Behavioral to Hybrid Multi-Controller Architectures*. Taylor & Francis CRC Press, ISBN: 9781498715584, 228 pages, April 2016.

[3] S. Glaser, B. Vanholme, S. Mammar, D. Gruyer, and L. Nouveliere, "Maneuver-based trajectory planning for highly autonomous vehicles on real road with traffic and driver interaction," *IEEE Transactions on intelligent transportation systems*, vol. 11, no. 3, pp. 589–606, 2010.

[4] J. B. Greenblatt and S. Shaheen, "Automated vehicles, on-demand mobility, and environmental impacts," *Current sustainable/renewable energy reports*, vol. 2, no. 3, pp. 74–81, 2015.

[5] D. Milakis, B. Van Arem, and B. Van Wee, "Policy and society related implications of automated driving: A review of literature and directions for future research," *Journal of Intelligent Transportation Systems*, vol. 21, no. 4, pp. 324–348, 2017.

[6] G. Karagiannis, O. Altintas, E. Ekici, G. Heijenk, B. Jarupan, K. Lin, and T. Weil, "Vehicular networking: A survey and tutorial on requirements, architectures, challenges, standards and solutions," *IEEE communications surveys & tutorials*, vol. 13, no. 4, pp. 584–616, 2011.

[7] C. Katrakazas, M. Quddus, W.-H. Chen, and L. Deka, "Real-time motion planning methods for autonomous on-road driving: State-of-the-art and future research directions," *Transportation Research Part C: Emerging Technologies*, vol. 60, pp. 416–442, 2015.

[8] H. Yao, J. Cui, X. Li, Y. Wang, and S. An, "A trajectory smoothing method at signalized intersection based on individualized variable speed limits with location optimization," *Transportation Research Part D: Transport and Environment*, vol. 62, pp. 456–473, 2018.

[9] E. Namazi, J. Li, and C. Lu, "Intelligent intersection management systems considering autonomous vehicles: A systematic literature review," *IEEE Access*, vol. 7, pp. 91 946–91 965, 2019.

[10] D. Elliott, W. Keen, and L. Miao, "Recent advances in connected and automated vehicles," *Journal of Traffic and Transportation Engineering (English Edition)*, vol. 6, no. 2, pp. 109–131, 2019.

[11] J. Yuan, M. A. Abdel-Aty, L. Yue, and Q. Cai, "Modeling real-time cycle-level crash risk at signalized intersections based on high-resolution event-based data," *IEEE Transactions on Intelligent Transportation Systems*, pp. 1–16, 2020.

[12] C. Dias, M. Iryo-Asano, M. Abdullah, T. Oguchi, and W. Alhajyaseen, "Modeling trajectories and trajectory variation of turning vehicles at signalized intersections," *IEEE Access*, vol. 8, pp. 109 821–109 834, 2020.

[13] Y. Xu, H. Zhou, T. Ma, J. Zhao, B. Qian, and S. Shen, "Leveraging multi-agent learning for automated vehicles scheduling at non-signalized intersections," *IEEE Internet of Things Journal*, pp. 1–1, 2021.

[14] X. Chen, B. Xu, X. Qin, Y. Bian, M. Hu, and N. Sun, "Non-signalized intersection network management with connected and automated vehicles," *IEEE Access*, vol. 8, pp. 122 065–122 077, 2020.

[15] B. Qian, H. Zhou, F. Lyu, J. Li, T. Ma, and F. Hou, "Toward collision-free and efficient coordination for automated vehicles at unsignalized intersection," *IEEE Internet of Things Journal*, vol. 6, no. 6, pp. 10 408–10 420, 2019.

[16] Z. Zhu, L. Adouane, and A. Quilliot, "Flexible multi-unmanned ground vehicles (mugvs) in intersection coordination based on ε-constraint probability collectives algorithm," *International Journal of Intelligent Robotics and Applications*, vol. 5, no. 2, pp. 156–175, 2021.

[17] C. Philippe, L. Adouane, A. Tsourdos, H.-S. Shin, and B. Thuilot, "Probability collectives algorithm applied to decentralized intersection coordination for connected autonomous vehicles," in *2019 IEEE Intelligent Vehicles Symposium (IV)*. IEEE, 2019, pp. 1928–1934.

[18] Z. Zhu, L. Adouane, and A. Quilliot, "A decentralized multi-criteria optimization algorithm for multi-unmanned ground vehicles (mugvs) navigation at signal-free intersection," *IFAC-PapersOnLine*, vol. 54, no. 2, pp. 327–334, 2021.

[19] Y. J. Zhang, A. A. Malikopoulos, and C. G. Cassandras, "Optimal control and coordination of connected and automated vehicles at urban traffic intersections," in *2016 American Control Conference (ACC)*. IEEE, 2016, pp. 6227–6232.

[20] Z. Du, B. HomChaudhuri, and P. Pisu, "Hierarchical distributed coordination strategy of connected and automated vehicles at multiple intersections," *Journal of Intelligent Transportation Systems*, vol. 22, no. 2, pp. 144–158, 2018.

[21] Z. Wang, G. Wu, and M. J. Barth, "Cooperative eco-driving at signalized intersections in a partially connected and automated vehicle environment," *IEEE Transactions on Intelligent Transportation Systems*, vol. 21, no. 5, pp. 2029–2038, 2019.

[22] Z. Zhu, L. Adouane, and A. Quilliot, "Hierarchical control for trajectory-based intelligent navigation in urban adjacent intersections," in *Intelligent Transportation Systems (ITSC'21),*. IEEE, 2021.

[23] L. Li and X. M. Chen, "Vehicle headway modeling and its inferences in macroscopic/microscopic traffic flow theory: A survey," *Transportation Research Part C: Emerging Technologies*, vol. 76, pp. 170–188, 2017.

[24] V. Knoop, S. P. Hoogendoorn, and H. van Zuylen, "Empirical differences between time mean speed and space mean speed," in *Traffic and Granular Flow'07*. Springer, 2009, pp. 351–356.

[25] B. Greenshields, J. Bibbins, W. Channing, and H. Miller, "A study of traffic capacity," in *Highway research board proceedings*, vol. 1935. National Research Council (USA), Highway Research Board, 1935.

[26] R. Hult, G. R. Campos, P. Falcone, and H. Wymeersch, "An approximate solution to the optimal coordination problem for autonomous vehicles at intersections," in *2015 American Control Conference (ACC)*. IEEE, 2015, pp. 763–768.

[27] T. Mathew and K. K. Rao, "Traffic stream models," *H Ttpnptel Ac Incourses105101008downloadscete*, vol. 3, 2014.