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Cooperative Platooning with Mixed Traffic on Urban Arterial Roads

Zeyu Mu[1], Zheng Chen[2], Seunghan Ryu[3], Sergei S. Avedisov[4],
Rui Guo[4], B. Brian Park[1]

***Abstract*— In this paper, we showcase a framework for cooperative mixed traffic platooning that allows the platooning vehicles to realize multiple benefits from using vehicle-to-everything (V2X) communications and advanced controls on urban arterial roads. A mixed traffic platoon, in general, can be formulated by a lead and ego connected automated vehicles (CAVs) with one or more unconnected human-driven vehicles (UHVs) in between. As this platoon approaches an intersection, the lead vehicle uses signal phase and timing (SPaT) messages from the connected intersection to optimize its trajectory for travel time and energy efficiency as it passes through the intersection. These benefits carry over to the UHVs and the ego vehicle as they follow the lead vehicle. The ego vehicle then uses information from the lead vehicle received through basic safety messages (BSMs) to further optimize its safety, driving comfort, and energy consumption. This is accomplished by the recently designed cooperative adaptive cruise control with unconnected vehicles (CACCu). The performance benefits of our framework are proven and demonstrated by simulations using real-world platooning data from the CACC Field Operation Test (FOT) Dataset from the Netherlands.**

I. Introduction

Stop-and-go traffic caused by unconnected human-driven vehicles (UHVs) is one of the main reasons for traffic oscillations and crashes [1]. Connected automated vehicles (CAVs) provide a potential solution to address improper human driving behaviors at intersections [2], [3]. The emergence of vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) wireless communication enable CAVs to communicate with other connected vehicles, obtain information about traffic signal phase and timing (SPaT) at connected intersections, and control the CAVs' movements cooperatively. Therefore, compared to traditional UHVs, CAVs can use SPaT and motion information to further optimize their own motion with respect to safety, driving comfort, energy consumption and mobility. Existing research on optimizing CAV motion through connected intersections focuses on either controlling a single CAV, or the interactions between CAVs and connected infrastructure in a fully connected traffic environment.

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[1]Z. Mu, and B.B. Park are with the Link Lab and Department of Engineering Systems and Environment, University of Virginia, Charlottesville, VA 22904 USA (email: dwe4dt@virginia.edu; bp6v@virginia.edu).

[2]Z. Chen is with PCI TECHNOLOGY GROUP CO.,LTD, Guangzhou, China (email: zc4ac@virginia.edu).

[3]S. Ryu is with the Department of Planning, Piedmont Authority for Regional Transportation, NC 27409 USA (email: francisr@partnc.org).

[4]S. S. Avedisov and R. Guo are with Toyota Motor North America R&D - InfoTech Labs, Mountain View, CA 94043 USA (email: sergei.avedisov@toyota.com; endeavorui@gmail.com).

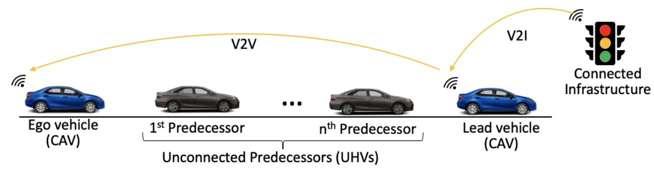

Fig. 1. Mixed traffic platoon composed of a a lead CAV, preceding CHVs, and an ego CAV. V2I and V2V communications are shown

Fig. 1 shows a mixed traffic platoon composed of UHVs and CAVs examined in this paper. The platoon is arranged with a leading CAV, followed by one or more UHVs, then followed by an ego CAV. The cooperation between the lead CAV and connected infrastructure at intersections by means of V2I SPaT messages allows the lead CAV to optimize its speed profile through the intersection. The cooperation yields benefits not only to the lead CAV but also to the rest of the platoon, as the UHVs and the ego CAV track the speed profile of the lead CAV. Such benefits in terms of energy efficiency and mobility are realized in a few previous studies. Research [4] examined a mixed traffic platoon consisting of a leading CAV and *n* following UHVs and showed that the mobility and fuel consumption of the entire platoon are improved by controlling the lead CAV. Similar research [5] developed frameworks for multiple CAVs to pass the intersection on a green phase and save fuel. Indeed most research on the interaction of mixed platoons with intersections focuses on fuel consumption, and does not account for the uncertain motion of UHVs.

While the V2I communication can be used to optimize the trajectory of the lead CAV, the V2V communication between the lead CAV and the ego CAV allows to optimize the performance of the ego CAV in the mixed platoon. In this case, the choice of control modes of the ego CAV needs to be investigated. Without connectivity, automated vehicles (AVs) may use adaptive cruise control (ACC) [6] where they use sensors to monitor the immediate predecessor. ACC typically improves safety over human-driven vehicles, but can not mitigate oscillations introduced by downstream vehicles [7]. This limitation can be overcome by Cooperative Adaptive Cruise Control (CACC) [8] which allows each CAV to obtain additional information about the predecessor (such as acceleration) via V2V communication. The main limitation of CACC is that all vehicles in the platoon must be CAVs. To reap the safety, driving comfort and energy efficiency benefits of CACC in mixed traffic, a cooperative adaptive cruise control with unconnected vehicles (CACCu) framework was developed [9]–[11]. In this paper two specific implementations of CACCu are considered; one that features a linear feedback controller (Linear-CACCu) [9], and one that uses an adaptive model predictive controller (A-MPC-CACCu) [10]. The latter accounts for uncertain factors such as signal phase change and number of unconnected vehicles in the platoon. While A-MPC-CACCu generally outperforms Linear-CACCu for systems with large uncertainty, A-MPC-CACCu requires more computation effort than Linear-CACCu. Previous research on the CACCu only focused on the control of the ego vehicle at the end of the platoon in a highway environment, without considering the behavior of the lead vehicle. Thus, it is necessary to investigate the synergy between optimizing the speed profile of the lead vehicle through V2I and using CACCu for the ego vehicle (see Figure 1).

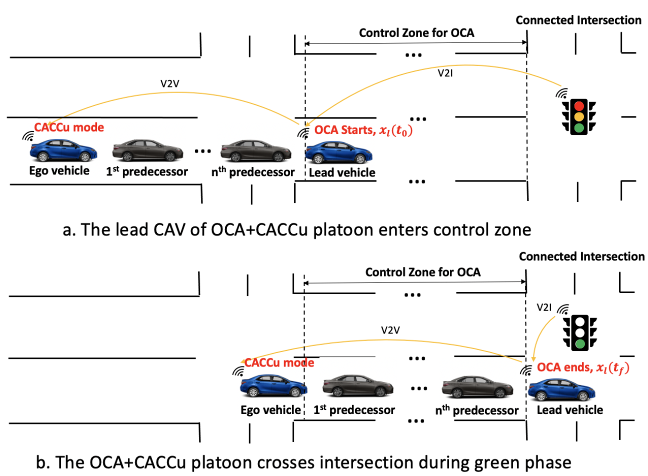

Fig. 2. Connected Signal and Control Zone for Mixed Traffic OCA+CACCu Platoon

We proposed a framework to realize cooperative control between the lead vehicle and ego vehicle as well as cooperation between the lead vehicle and the connected intersection for trajectory optimization, aiming at improving traffic efficiency (travel time) and energy efficiency, as well as ego vehicle performance in terms of safety and driving comfort in a mixed traffic platoon, as shown in Fig. 2. For cooperation between the lead vehicle and the connected traffic light, a sub-module of an optimal control algorithm (OCA) [12] was utilized to optimize the trajectory for the lead vehicle to pass during the green phase of the connected intersection. The OCA generates an optimal solution under the hard safety constraints of collision avoidance given the initial state and final state of the lead vehicle. The car following behaviors of following UHVs are given by the intelligent driver model (IDM) [13] for UHVs. The ego vehicle communicates with the lead vehicle through V2V communication and is controlled by CACCu.

The remainder of this paper is organized as follows: Modeling framework section explains trajectory optimization of the lead vehicle using OCA, model the motion of the unconnected predecessors, and describes the control modes for the ego vehicle. Simulation and performance comparison section describes the real-world urban arterial traffic data used for our simulation study, and evaluates the performance of the lead vehicle utilizing OCA and ego vehicles using ACC, Linear-CACCu, and A-MPC-CACCu. Finally, the findings and future work were summarized and discussed.

II. Modeling Framework

A. Mixed Traffic Platoon

A mixed traffic platoon on an urban arterial road with an intersection is shown in Fig. 2 a. The platoon consists of a lead vehicle (CAV), followed by one or more unconnected predecessors (UHVs), and then followed by a CAV referred to as an ego vehicle. As the mixed traffic platoon moves through urban arterial roads, the lead vehicle receives and reacts to Signal Phase and Timing (SPaT) messages from the connected traffic signals at the intersections. The lead vehicle utilizes this information to optimize its motion to pass the intersection in green phase in Fig. 2.b.

B. Lead Vehicle Trajectory Optimization

In the modeling framework, we make the following assumptions about the lead vehicle in a mixed platoon:

- The lead vehicle is a CAV that receives time-to-green information from connected traffic signals though V2I communication without packet loss and latency once it enters control zone.
- The lead vehicle passes through the signalized intersection without performing lane changes.
- The lead vehicle can follow the acceleration commands from the controller using Optimal Control Algorithm (OCA) without any error.
- The control zone spans the entire road segment between the two intersections. It is noted that the framework presented in this paper can be generalized to scenarios where the control zone is only part of the road segment between two intersections.

When approaching the intersection with a traffic signal ahead, a human-driven vehicle may behave according to two scenarios. In the With Signal Change (WSC) scenario, a human-driven vehicle enters the control zone and experiences traffic light turning from red to green. Thus, the vehicle decelerates and stops or almost stops at the stop bar, see Fig. 3a in the next section. In the Without Signal Change (WoSC) scenario, the vehicle enters the control zone and crosses the intersection in the green phase so that it does not need to decelerate to a stop and crosses the intersection relatively smoothly, see Fig. 3b in the next section.

Previous research has shown that WSC situations are in general more safety critical than WoSC situations due to acceleration fluctuations in the following vehicles [11]. To avoid the WSC case, an optimal control algorithm (OCA) [12] was proposed to optimize the trajectory of the lead CAV in the mixed platoon based on SPaT messages received from the connected traffic light. Compared with other trajectory optimization methods which utilize constant acceleration, the trajectory generated by OCA is optimal under safety

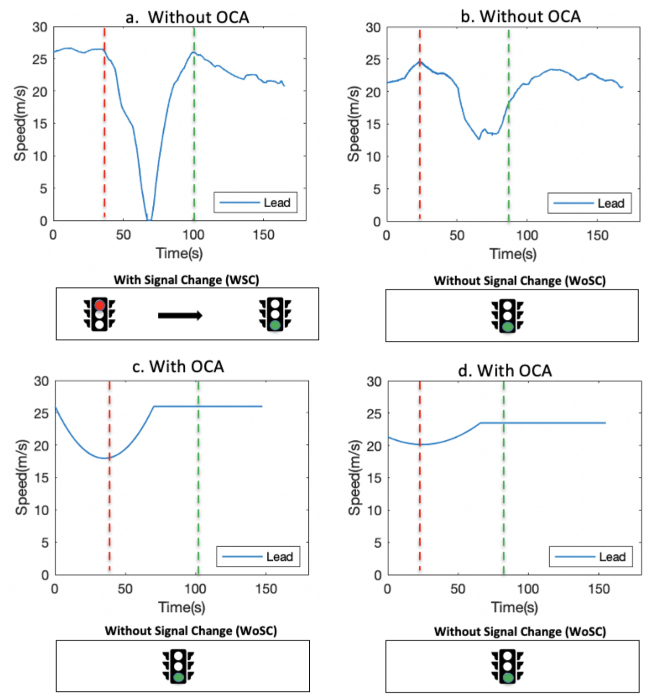

Fig. 3. Two Examples without (a,b) and with (c,d) Optimal Control Algorithm (OCA) Optimization (a, c or b, d are the same signal timing) : Speed Trajectory of the Lead Vehicle through Signalized Intersection

constraints given initial states and final states of the lead vehicle. We note that the benefits of this algorithm carry over to the following vehicles as they follow the speed profile of the lead vehicle through the intersection.

For the lead vehicle, the state within the control zone is given by

$$x_l(t) = \begin{bmatrix} d_l(t) \\ v_l(t) \end{bmatrix}, \quad \dot{x}_l(t) = \begin{bmatrix} v_l(t) \\ u_l(t) \end{bmatrix} \tag{1}$$

where $t \in \mathbb{R}^+$ is the time, x_l is the vector of position and velocity of lead vehicle and u_l is the control input (acceleration of the lead vehicle). We impose the constraints:

$$u_{min} \leq u_l(t) \leq u_{max}, v_{min} \leq v_l(t) \leq v_{max}, \forall t \in [t_0, t_f] \tag{2}$$

where $[t_0, t_f]$ is the time interval the lead CAV spends in the control zone; u_{min} and u_{max} are minimum and maximum values of the control input, and v_{min} and v_{max} are minimum and maximum speeds respectively. Combining functions (1) and (2), we define the optimization problem:

$$\begin{aligned} \text{minimize} \quad & \frac{1}{2}\int_{t_0}^{t_f} u_l^2(t)\,\mathrm{d}t \\ \text{subject to} \quad & (1), (2) \end{aligned} \tag{3}$$

The motion of the vehicle can be calculated by solving the constants of integration which are functions of time and states, please see [12] for details.

C. Unconnected Preceding Vehicle Maneuvers

For each platoon, there are n unconnected human-driven vehicles between the lead vehicle and the ego vehicle. We assume that they follow the lead vehicle through the intersection in the same signal phase and without lane changes. We modeled the UHV motion with the intelligent driver

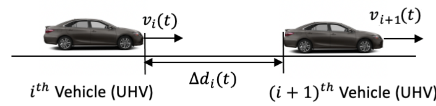

Fig. 4. Intelligent Driver Model

model (IDM) [13] in Fig. 4. where i represents i^{th} preceding vehicles. The acceleration of the preceding UHV i (where i ranges from 1 to n, see Fig. 2) is given by

$$u_i(t) = u_{i,max}\left[1 - (\frac{v_i(t)}{v_{i,d}})^{\sigma} - (\frac{\triangle d_{i,d}(v_i(t), \triangle v_i(t))}{\triangle d_i(t)})^2\right] \tag{4}$$

$$\triangle d_{i,d}(t) = s_0 + max\left(v_i(t) * T + (\frac{v_i(t) \cdot \triangle v_i(t)}{2\sqrt{u_{i,max} \cdot u_{i,d}}}), 0\right) \tag{5}$$

v_i, $v_{i,d}$ and u_i are the speed, desired speed and predicted acceleration of vehicle i; $\triangle v_i$, $\triangle d_i$ and $\triangle d_{i,d}$ are speed difference, gap and minimum desired gap between vehicle i and $i+1$; T is the time headway. The parameters used in this paper are listed as follows. Acceleration exponent σ is 4, jam distance s_0 is 5 m, desired deceleration $u_{i,d}$ is 3 m/s^2, maximum acceleration $u_{i,max}$ is 3 m/s^2.

D. Ego Vehicle Control Mode

We make the following assumptions about the ego vehicle

- The ego vehicle is a CAV equipped with sensors and receives motion information from the lead vehicle through V2V communication, see Fig. 2.
- The ego vehicle can utilize three control modes:
  - Adaptive Cruise Control (ACC)
  - Linear Cooperative Adaptive Cruise Control with unconnected vehicles (Linear-CACCu)
  - Adaptive MPC Cooperative Adaptive Cruise Control with unconnected vehicles (A-MPC-CACCu)
- The ego vehicle follows the preceding vehicles to pass the intersection in the same signal phase and without lane changes.

1) ACC mode: Without connected predecessors ahead, the ego vehicle is controlled by ACC which attempts to match the speed of the immediate predecessor whilst keeping a safe headway shown in Fig. 5.a. The high-level ACC controller utilizes proportional-derivative (PD) control, and the control input $u_e(t)$ can be written in terms of the spacing error $e(t)$:

$$u_e(t) = k_{e,p}e_e(t) + k_{e,d}\dot{e}_e(t) \tag{6}$$

where $k_{e,p}$, and $k_{e,d}$ are proportional and derivative gains, respectively. The spacing error $e_e(t) = d_{e,d}(t) - d_e(t)$ is the difference between desired gap from the immediate predecessor $d_{e,d}$ and the actual gap d_e. The desired gap $d_{e,d}(t) = v_e(t) \cdot T_e + d_0$ is defined by the time headway T_e, current speed v_e and standstill distance d_0. The low-level controller is modeled by a first-order lag τ to the acceleration command: $\dot{a}_{ia}(t) = -\frac{a_{ia}(t)}{\tau} + \frac{u_{ia}(t)}{\tau}$.

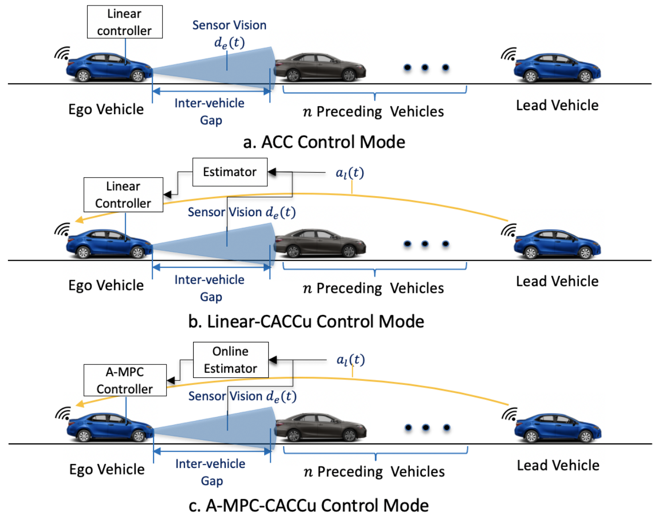

Fig. 5. Control Modes of the Ego Vehicle in Mixed Traffic Platoon

2) Linear-CACCu mode: The linear-CACCu [9] system extends the proportional-derivative (PD) controller of the ACC (6) with a feed-forward filter which utilizes the acceleration of the lead vehicle $a_l(t)$ to predict the motion of the immediately preceding unconnected vehicle. It applies the linearized optimal velocity model (OVM) [14] to estimate the car-following behavior of the preceding unconnected vehicles (Fig. 5 b). The control output $u_e(t)$ for the Linear-CACCu is defined as:

$$u_e(t) = k_{e,p}e_e(t) + k_{e,d}\dot{e}_e(t) + f(a_l(t)) \tag{7}$$

We note that the feedforward filter $f(\cdot)$ is calculated using Laplace transforms by setting the spacing error $e_e(t)$ to zero. For further details of this calculation see [11].

3) A-MPC-CACCu strategy: The rule-based design of linear-CACCu may limit performance benefits if the parameters of unconnected predecessors change significantly with time. To overcome this, A-MPC-CACCu [10] uses an adaptive model predictive controller to estimate the dynamic parameters of unconnected vehicles online (Fig. 5.c). A second-order model in Autoregressive Exogenous (ARX) structure is utilized to estimate the dynamics of unconnected predecessors in the mixed traffic platoon. A Kalman filter then used to predict the acceleration of the immediate predecessor every time step (which is 0.1s in our work). Afterwards, the model predictive control solves a rolling-horizon optimization problem at every time step. The objective function is designed to reduce spacing error e_e, speed difference e_v from the immediately preceding vehicle, and acceleration of the ego vehicle a_e:

$$\begin{aligned} \text{Minimize} \quad & \sum_{i=0}^{N}[w_p e_e^2(t+i\Delta t) + w_v e_v^2(t+i\Delta t) \\ & + w_a a_e^2(t+i\Delta t) + w_u u_e^2(t+i\Delta t) + \rho\varepsilon^2] \\ \text{subject to} \quad & e_{pmin} - \varepsilon \le e_p \le e_{pmax} + \varepsilon; \\ & u_{imin} - \varepsilon \le u_e \le u_{imax} + \varepsilon; \\ & u'_{imin} - \varepsilon \le u'_e \le u'_{imax} + \varepsilon; \end{aligned} \tag{8}$$

where w_p, w_v, w_a, and w_u are weights of spacing error e_e, speed error e_v, ego vehicle acceleration a_e, and acceleration command u_e, respectively, ε is a slack variable for the penalty term, ρ is the penalty weight, and N is the time horizon. In this paper, we set weights $w_p = 1$, $w_v = 3$, $w_a = 3$, $w_u = 9$, $\rho = 10000$. The maximum and minimum spacing error are 2 m and −2 m. The maximum commanded acceleration and deceleration are 3 $\mathrm{m/s^2}$ and −3 $\mathrm{m/s^2}$. The limitations on the jerk are 1 $\mathrm{m/s^3}$ and −2 $\mathrm{m/s^3}$, respectively. The time horizon N is 30, corresponding to 3 s. These parameters are derived from [10].

III. Simulation and Performance Evaluations

A. CACC Field Operation Test Dataset

The CACC Field Operation Test (FOT) dataset [15] was collected from the Province of Noord-Holland in the Netherlands. It consists of GPS coordinates and velocities of 3-vehicle and 7-vehicle platoons as well as the traffic signal phases and timing of the intersections. A 3 km straight road segment containing one intersection with a connected traffic signal from FOT dataset shown in Fig. 6 was used in this study. Five different scenarios based on ego vehicle control modes and SPaT information were recorded. We considered two scenarios for the unconnected preceding vehicles (UHVs) in the platoon. In the baseline data, the lead vehicles and preceding vehicles are human-driven.

Fig. 6. Selected Segment of CACC Field Operation Test Dataset [15]

B. Simulation Settings

The FOT dataset recorded human-driven platoons with 10 WoSC (without signal change) scenarios and 6 WSC (with signal change) scenarios shown in Fig. I. For each scenario, the platoon was simulated for different numbers ($n = 1, 2, 3$) of preceding vehicles. In all, the ego vehicles of human-driven platoons experienced 26 runs for the WSC scenario and 10 runs for the WoSC scenario shown in TABLE II.

The ego vehicle was simulated in Matlab with Simulink and PreScan [16] using an Audi A8 as the vehicle model. To obtain a high-fidelity response from controller commands, a lower-level controller received acceleration commands from ACC, CACC, and CACCu controllers and transformed these to throttle/brake commands for the PreScan vehicle model.

C. Lead vehicle performance

Previous research has shown that reducing fluctuations in the lead vehicle's acceleration benefits the safety of the following vehicles in the platoon [11]. With this in mind, we monitored the performance of lead vehicles in terms of RMS acceleration, minimum speed, travel time, distance and fuel consumption (see TABLE I)

The two examples of the lead vehicle behavior in WoSC and WSC scenarios are shown and compared in Fig.3. Human driven lead vehicle profiles for the WSC and WoSC scenarios taken from the FOT dataset are shown in Fig. 3a and b respectively. Fig. 3a shows the speed profile of the lead vehicle in WSC situation when the lead vehicle slowed down and stopped after the traffic light turn red (red dashed line) and then accelerated from a stop when the light turned green (green dashed line). If instead of a UHV we have a CAV that uses SPaT information and OCA (as in Fig. 3c) the CAV slows down pre-emptitively before the light turns red, and as a result can cross the intersection without stopping.

For the WoSC situation in Fig. 3b, the human driven vehicle arrives at the light after the light turned green, so in this scenario the human-driven vehicle decelerates to 15 m/s in the red phase. Here a CAV with OCA can also improve upon the human-drivers performance by decelerating preemptively (Fig. 3d.), and cross the intersection at over 20 m/s as a result.

TABLE I

PERFORMANCE COMPARISON OF LEAD VEHICLES IN TWO TRAFFIC SITUATIONS WITHOUT AND WITH OCA OPTIMIZATION

Lead Vehicle	Acceleration RMS	Speed Min $[m/s]$	Travel Time $[s]$	Distance $[m]$	Fuel Consumption $[ml]$
With Signal change (WSC, 10 scenarios)					
Human Driven	0.49	3.6	167	3200	169
OCA	0.19	15.7	148	3200	157
Without Signal change (WoSC, 6 scenarios)					
Human Driven	0.27	17.2	146	3309	171
OCA	0.08	20.8	136	3311	179

The performances of lead vehicles from mixed traffic platoons in two traffic situations with OCA optimization were compared with performances of the human-driven vehicles from the FOT dataset (without OCA optimization) in TABLE. I. For baselines which are real-world data, the fluctuation in acceleration of the lead vehicle was smaller in WoSC situation than that in WSC situation, which brought significant benefits to the travel time and distance. It is noted that the fuel consumption of the platoon with human-driven preceding vehicles in WoSC scenario was higher than that in WSC. The reason is that the human drivers in WoSC scenario drove a longer distance than in WSC scenario.

With OCA optimization, the lead vehicle was able to reduce its RMS acceleration by a factor of 2-3 compared to the experimental human-driven data. This applies to both WSC and WoSC scenarios. Besides, the minimum speed was improved by a factor of 2-3 with OCA in WSC cases and a factor of 1-1.5 in WoSC cases. We note that for our scenarios the minimum speed improved and OCA allowed the lead vehicle and its following vehicles pass through the intersection in a green phase. The travel time for OCA improved by 10% if there was a signal change, and by $5-7\%$ when there was no signal change. The fuel consumption improved by around 10% when there was a signal change, while in the scenarios where the signal did not change, the lead vehicle with OCA consumed more fuel than the human-driven vehicle. This is due to the lead vehicle typically keeping higher speed through the intersection to save travel time.

D. Ego vehicle performance

In this section, we assess the cumulative impacts of the OCA and CACCu strategies on the performance of the ego CAV at the end of the platoon (Fig. 1). We considered the spacing error RMS, acceleration RMS, and total fuel consumption of the ego vehicle which relate to safety, driving comfort and energy efficiency respectively.

TABLE II

EGO VEHICLE PERFORMANCE OF PLATOONS IN WITH AND WITHOUT SIGNAL CHANGE (WSC AND WOSC) SITUATIONS WITH OR WITHOUT OPTIMAL CONTROL ALGORITHM (OCA) OPTIMIZATION

Control Mode	Spacing Error RMS		Acceleration RMS		Fuel Consumption [ml]	
	OCA		OCA		OCA	
	W/O	W	W/O	W	W/O	W
WSC (26 scenarios; 10, 8, 8 runs for n*= 1, 2, 3, respectively)						
A-MPC-CACCu	0.82	0.63	0.69	0.24	174	153
Linear-CACCu	1.01	0.28	0.68	0.24	175	154
ACC	2.10	0.63	0.71	0.24	177	154
Human-driven	N/A	N/A	0.77	N/A	179	N/A
WoSC (10 scenarios; 6, 2, 2 runs for n = 1, 2, 3, respectively)						
A-MPC-CACCu	0.66	0.62	0.41	0.16	192	183
Linear-CACCu	0.67	0.28	0.41	0.18	193	184
ACC	1.17	0.45	0.43	0.18	196	184
Human-driven	N/A	N/A	0.45	N/A	196	N/A

* The number of preceding vehicles.

To investigate the ego vehicle performance in WSC and WoSC cenarios, the CACCu controlled ego vehicles were compared with real world data (human-driven vehicles) and ACC. The comparisons of ego vehicles in different control modes without OCA optimization in WSC and WoSC situations are shown in TABLE II. It is noted that results of human-driven vehicle are taken from the experiment. From Table II, in the WSC scenario, the CACCu algorithms outperformed ACC in all metrics. The most significant benefits occur in the scenario where OCA is not implemented on the leader vehicle, since the lead vehicle's speed changes dramatically as it passes through the intersection, see Fig. 3a. In the scenario where OCA is implemented, the linear CACCu provides significant benefits over ACC in spacing error, however the CACCu algorithms provide less benefit over ACC in this case since the leader's speed profile is smooth, as in Fig. 3c. Similarly, for the WoSC runs, the CACCu algorithms outperform the ACC algorithm when OCA is not used. In the case OCA is used, Linear CACCu performs best, while the A-MPC-CACCu performs worst in terms of spacing error, and both CACCu controllers outperform ACC in the rest of the metrics.

Overall we see that Linear-CACCu allows the ego vehicle to consistently outperform ACC regardless of whether the lead vehicle of the platoon is using OCA. Additional benefits for the ego vehicle can be extracted by A-MPC-CACCu when the lead vehicle is not running OCA.

E. Platoon performance

Apart from benefits gained by single vehicles in terms of safety, driving comfort and energy efficiency, the whole platoon performance (travel time and fuel consumption) was improved with trajectory optimization of lead vehicles. The travel time of the vehicles in the platoon for the three control modes (ACC, Linear-CACCu, A-MPC-CACCu) through the intersection decreased by 10% from 163 s to 146 s on average with introduction of OCA. Moreover, the fuel consumption of the vehicles in the platoon was reduced by around 13% on average when OCA was used (183 ml to 149 ml for A-MPC-CACCu, 183 ml to 160 ml for Linear CACCu and 184 ml to 160 ml for ACC).

IV. Conclusions and future work

In this paper, we improved the operation of mixed traffic vehicle platoons on sparse urban arterial roads by integrating an optimal control algorithm (OCA) and cooperative adaptive cruise control with unconnected vehicles (CACCu). In this framework, the lead connected automated vehicle (CAV) used signal phase and timing (SPaT) information from connected traffic lights to optimize its travel time and energy consumption using OCA. Then the ego CAV located at the end of the mixed platoon (Fig. 1), used basic safety message (BSM) information from the lead CAV to further optimize its motion by minimizing spacing error, acceleration, and energy consumption. Simulations using multiple runs of data collected in the Netherlands FOT dataset were used to show the performance benefits of OCA+CACCu algorithm, which carry over to the entire platoon, including the unconnected human-driven vehicles.

We note that the study considers platooning in urban arterial roads without accounting for surrounding traffic. In congested situations where multiple vehicles travel around the OCA+CACCu platoon, the behaviors of the lead vehicle (and in turn other members of the platoon) may be influenced by surrounding vehicles. In such situations it might not be possible for the entire platoon to pass the intersection during a green phase as dictated by the OCA algorithm. The size of the platoon will play a critical role in the platoon's ability to pass the intersection. We shall design decisions for the CAV to merge into platoons or split existing platoons. Such optimized decisions would increase the applicability and benefits of mixed traffic platoons.

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