Safe Intersection Coordination with Mixed Traffic: From Estimation to Control ⋆

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Abstract: In this paper, we propose an integrated framework for safe intersection coordination of connected and automated vehicles (CAVs) in mixed traffic. An intelligent intersection is introduced as a central node to orchestrate state data sharing among connected agents and enable CAV to acknowledge the presence of human-driven vehicles (HDVs) beyond the line of sight of onboard sensors. Since state data shared between agents might be uncertain or delayed, we design the intelligent intersection to safely compensate for these uncertainties and delays using robust set estimation and forward reachability analysis. When the intersection receives state data from an agent, it first generates a zonotope to capture the possible measurement noise in the state estimate. Then, to compensate for communication and processing delays, it uses forward reachability analysis to enlarge the set to capture all the possible states the agent could have occupied throughout the delays. Finally, using the resulting set as the initial condition, a distributed model predictive control onboard the CAV will plan an invariant safe motion by considering the worst-case behavior of human drivers. As a result, the vehicle is guaranteed to be safe while driving through the intersection. A prototype of our proposed framework is implemented using the Small-Vehicles-for-Autonomy (SVEA) platform. The effectiveness of our framework is evaluated in experiments based on a challenging scenario where the collision would have occurred without efficient coordination.

Keywords: Intelligent Transportation Systems, Autonomous vehicles, Multi-vehicle systems, Sensor integration and perception, Decentralized control and systems.

1. INTRODUCTION

In recent years, great progress has been made in the development of connected and automated vehicles (CAVs). Utilizing vehicle-to-everything (V2X) communication and vehicle automation, the CAV technology is expected to drastically improve traffic safety and efficiency (Contreras-Castillo et al. (2018); Bajpai (2016)).

In particular, the safe coordination of CAVs in intersections is a promising research direction with many ongoing works (Khayatian et al. (2020)). With the help of wireless communication, CAVs approaching an intersection can access the state information of others that are beyond the line of sight of the onboard sensors and form inter-vehicle cooperation in advance. This enables CAVs to automatically adjust their motion into the intersection with increased safety and efficiency by minimizing stop-and-go traffic and avoiding collisions in general. In light of these benefits, coordination strategies based on both centralized (Müller et al. (2016); Nor and Namerikawa (2019); Chen and Mårtensson (2021)) and distributed (Zhang and Cassandras (2018); Chen and Mårtensson (2022); Katriniok et al. (2022)) approaches have been proposed. In centralized approaches, a coordination node gathers state information on all approaching CAVs and designs a conflict resolution plan for every vehicle. For improved scalability, distributed approaches allow CAVs to resolve individual motion planning problems through mutual information sharing. Safety and traffic efficiency benefits can be witnessed in both approaches and the results are mainly obtained through extensive simulation studies. Most coordination studies work under the idealized assumption of homogeneous CAV traffic. In addition, relying on vehicular communication for intersection coordination heavily depends on the quality of communication. Although the applicability of both the distributed and the centralized approach has been experimentally demonstrated (Katriniok et al. (2022); Hult et al. (2019)), performance degradation is to be expected without rigorous treatment of the communication delay and measurement uncertainty (Liu et al. (2021)). In this paper, we study the intersection coordination problem of CAVs with potentially occluded human-driven vehicles (HDVs). Due to the occlusion, there is a need to complement the perception of CAVs with external information through V2X communication. Such a concept is often referred to as shared situational awareness (Narri et al. (2021)). To compensate for measurement noise, set-based methods for shared situational awareness provide better safety guarantees in comparison to point-based methods (Rego et al. (2018)). Among set-based estimation methods, the set-membership estimator (Alanwar et al. (2020)) has proven to

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be effective in providing situational awareness for CAVs in our previous work Narri et al. (2021). In this work, we extend the use of our method and propose an integrated framework for the safe coordination of CAVs. For shared situational awareness, We design a central node to provide reliable estimation using the set membership method. In addition, to deal with communication and processing delay, we propose the use of reachability analysis (Althoff (2010)) to compute state variation over the delay period to further enlarge the set estimation for safety guarantee. Using the resulting set estimation as the initial condition, a distributed model predictive control (DMPC) (Chen and Mårtensson (2022)) is integrated onboard the CAV to plan a safe motion by considering the worst-case behavior of the human driver. As a result, the integrated framework is designed to counteract the presence of measurement errors, communication, and processing delays, making it more resilient against points of failure and offering a higher degree of safety for in-vehicle implementation in a mixed-traffic scenario.

To summarize, the contributions of this paper include the following:

(1) We extend our previous works Narri et al. (2021), Chen and Mårtensson (2022) and propose an integrated framework to deal with the safe coordination task of CAVs in mixed traffic through shared situational awareness.
(2) We provide a systematic way of dealing with measurement uncertainties, communication, and processing delays for enhanced safety.
(3) A prototype of our integrated framework is implemented using SVEA platform Jiang et al. (2022) and evaluated in experiments.

The remainder of the paper is outlined as follows. In Section 2, we explain the problem formulation together with the basic intersection scenario considered in this paper. In Section 3, we outline the proposed system architecture and describe in detail each module of the system and their integration. A prototype of our proposed system is implemented and the experimental setup and results are presented in Section 4. Finally, we provide some concluding remarks in Section 5.

2. PROBLEM FORMULATION

In this paper, we consider a simple four-way intersection of crossing conflict between one CAV and one HDV to simplify the formulation and analysis. Here we denote the CAV as vehicle A and the HDV as vehicle H as can be seen in Fig. 1. Our framework is not restricted by the scenario and can be extended to handle general intersections with multiple vehicles in a similar fashion. Here the HDV is occluded from the sensing range of the CAV. To assist the CAV with state information of the HDV, we assume that an edge device denoted as an intelligent intersection with potential sensing capability is installed to support shared situational awareness.

Given the maximal effective communication range of the intelligent intersection, We define the control zone as the area covered under the communication range. Within the control zone, we introduce two coordinate frames: A fixed global frame (x, y) common for all vehicles and a road-aligned local frame (s_i, d_i) for each vehicle $i \in \{A, H\}$ individually along the center line of the road it occupies. Here s_i is the distance traveled measured from the entry of the road into the control zone and d_i is the lateral deviation from the road center line as

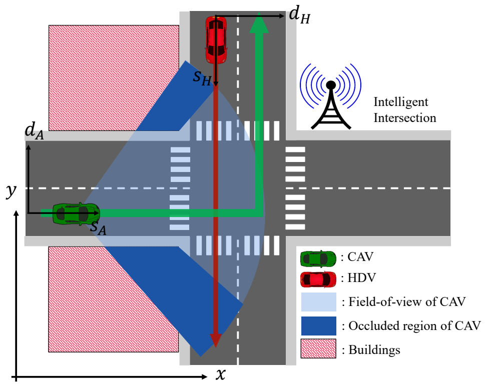

Fig. 1. Intersection scenario of occlusion with one CAV and one HDV.

can be seen in Fig. 1. The translation between the two frames is done through a mapping function

$$\mathcal{M}_i : (x, y) \rightarrow (s_i, d_i) \tag{1}$$

In this paper, we make the following reasonable assumptions for the intersection scenario:

Assumption 1. The state of the HDV inside the control zone can be measured and communicated to the intelligent intersection by the HDV itself or by the intelligent intersection or Both.

Assumption 2. All communication delays and processing time are upper-bounded and can be measured and acquired by the intelligent intersection.

3. METHODOLOGY

3.1 Integrated System Architecture

In this section, we describe the proposed integrated framework in detail. The communication architecture that connects all entities and the corresponding information flows can be seen in Fig. 2. The proposed framework can be scaled to multiple vehicles by adding them in a similar fashion as described below.

The intelligent intersection is assigned the task as the central node to orchestrate communication and provide situational awareness to the CAV. The overall framework consists of 2 main modules:

- Robust Set Estimation Module: Provide reliable set estimation of HDV to the CAV
- Safe Vehicle Coordination Module: Provide an invariant safe motion plan for CAV using the given set estimation

As can be seen in Fig. 3. The robust set estimation module resides on the intelligent intersection. Once the HDV enters the control zone, it gathers the state estimation of the HDV together with measurement uncertainty in terms of covariance. To compensate for the measurement uncertainty, first, a set membership estimator is implemented to fuse state estimation from potentially multiple sources (HDV and Intelligent Intersection). As a complement to the robust set estimation module, we use reachability analysis to compute a forward reachable set to capture potential state variation during the interval of communication and processing delay. This is viable since the intelligent intersection as the central node can measure communication delay to and from it. In addition, it measures the internal process time for the robust estimation module and

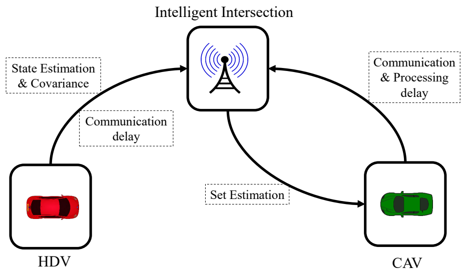

Fig. 2. Integrated system architecture: communication layer

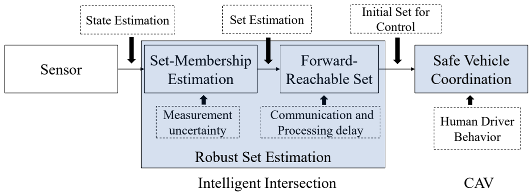

Fig. 3. Integrated system architecture: estimation and control layer

acquires the processing time of the safe vehicle coordination module onboard the CAV. The remaining uncertainty of the scenario is unpredictable human behavior. For the safe vehicle coordination module, we implement a DMPC by using the received set estimation as the initial condition and perform an invariant safe motion plan according to the worst-case behavior of the human driver.

3.2 Robust Set Estimation

The robust set estimation module is designed to compensate for the uncertainty caused by measurement noise, communication and processing delay to form the set of initial state for safe vehicle coordination module.

First, to handle measurement noise and model error, a set membership estimator based on our previous work Narri et al. (2021) is designed to generate a set representation using zonotopes (Kühn (1998)). The true state of the vehicle is guaranteed to belong to the set given that the state estimation and covariance of the HDV are obtained, see Fig. 2.

We use a discrete-time linear time-varying system (2) to describe the state model for the HDV.

$$z_{k+1} = F_k z_k + B_k u_k + \epsilon_k, \tag{2}$$

where $z_k \in \mathbb{R}^n$ is the state vector defined in the global coordinate frame (x, y) at time $k = 1, 2, \dots, N$, where N is the horizon. F_k and B_k are time-varying state and input matrix. $u_k \in \mathcal{U}$ is the input with the corresponding bounded input set $\mathcal{U}$ and ϵ_k is the model error to the system.

An observable discrete-time linear time-varying system (3) is used as the measurement model

$$\phi_k = H_k z_k + \omega_k, \tag{3}$$

where $\phi_k \in \mathbb{R}^p$ is state estimation in the global frame obtained by intelligent intersection see Fig. 3. This is assumed to be generated by the sensors of HDV or intelligent intersection or both. H_k is the measurement matrix and ω_k is the measurement noise.

Both the model error and measurement noise in (2), (3) are assumed to be unknown but bounded by zonotopes: $\epsilon_k \in \mathcal{Z}_{Q,k} = \langle 0, Q_k \rangle$, and $\omega_k \in \mathcal{Z}_{R,k} = \langle 0, R_k \rangle$. Here the measurement noise zonotope is generated using the received covariance matrix from state estimation.

Given state estimation and covariance, the set-membership estimator uses Definitions 1, 2 and 3 to compute a set of reachable states that encloses the true state of system (2) in an iterative fashion.

Definition 1. (**Predicted State Set**). Given system (2) – (3) with initial set $\mathcal{Z}_0 = \langle c_0, G_0 \rangle$, the predicted reachable set $\hat{\mathcal{Z}}_k$ is defined recursively as:

$$\hat{\mathcal{Z}}_k = F_k \hat{\mathcal{Z}}_{k-1} \oplus \mathcal{Z}_{Q,k}, \quad \hat{\mathcal{Z}}_0 = \mathcal{Z}_0 \tag{4}$$

Definition 2. (**Measurement State Set**). Given system (2) – (3), the measurement state set $\mathcal{S}_k$ is the set of all possible solutions z_k which can be reached given ϕ_k and noise zonotope $\mathcal{Z}_{R,k}$ where $R_k = \text{diag}([r_k^1, \dots, r_k^{m_s}])$.

$$\mathcal{S}_k = \left\{ z_k \middle| |H_k z_k - \phi_k| \leq r_k \right\}. \tag{5}$$

Definition 3. (**Corrected State Set**). Given system (2) – (3) with initial set $\mathcal{Z}_0 = \langle c_0, G_0 \rangle$, the reachable corrected state set $\bar{\mathcal{Z}}_k$ is defined as:

$$\left(\hat{\mathcal{Z}}_k \cap \mathcal{S}_k \right) \subseteq \bar{\mathcal{Z}}_k. \tag{6}$$

Set-membership estimator intersects the set of states consistent with the model (predicted state set), $\hat{\mathcal{Z}}_{k-1}$ with the set consistent with the measurements (measurement state set), $\mathcal{S}_k$ to obtain the corrected state set, $\bar{\mathcal{Z}}_k$. We denote the final corrected state set after iteration as $\bar{\mathcal{Z}}_f$. Given that the error bounds $\epsilon_k \in \mathcal{Z}_{Q,k}$, and $\omega_k \in \mathcal{Z}_{R,k}$ hold, $\bar{\mathcal{Z}}_f$ will enclose the true state of system (2).

The time difference between the instance when the state estimation is generated and when the CAV applies the control is considered as a delay denoted δ_{sum}. To guarantee safety, potential state variation during the delay δ_{sum} needs to be captured. As indicated in Fig. 2, the intelligent intersection gathers the communication delay δ_{com} from HDV to CAV. In addition, the internal process time δ_{set} for the robust set estimation module and the computation time δ_{MPC} for the vehicle coordination module onboard CAV are measured and notified by the intelligent intersection. The total delay is then obtained as:

$$\delta_{sum} = \delta_{com} + \delta_{set} + \delta_{MPC} \tag{7}$$

To capture the state variation during the delayed time interval $[0, \delta_{sum}]$, we introduce the definition of a forward reachable set as follows:

Definition 4. (**Forward Reachable Set**). Given the initial set of vehicle state $\mathcal{X}_0$ at t_0, a forward reachable set at time t_h, denoted as $\mathcal{R}(\mathcal{X}_0, t_h)$, is defined as

$$\mathcal{R}(\mathcal{X}_0, t_h) = \left\{ \chi(t_h, x_0, u([t_0, t_h])) \middle| x_0 \in \mathcal{X}_0, u([t_0, t_h]) \in \mathcal{U} \right\} \tag{8}$$

where $\chi(t_h, x_0, u([t_0, t_h]))$ denote the solution of (2) given the initial state x_0 and a input trajectory $u([t_0, t_h])$ between time t_0 and t_h

We use the CORA toolbox (Althoff (2015)) based on reachability analysis (Althoff (2010)) to compute the reachable set $\mathcal{R}([0, \delta_{sum}])$ in the time interval $[0, \delta_{sum}]$ as the union of reachable sets computed at N discrete time instances within that interval:

$$\mathcal{R}([0,\delta_{sum}]) = \bigcup_{k=0}^{N-1} \mathcal{R}(\bar{\mathcal{Z}}_f, k\delta t), \tag{9}$$

where $(N-1)\delta t = \delta_{sum}$. Notice here we use $\bar{\mathcal{Z}}_f$ from the set membership estimator as the initial set. As a result, $\mathcal{R}([0,\delta_{sum}])$ will capture uncertainty caused by both measurement noise and the total delay. For simplicity, in what follows, we denoted $\mathcal{R}([0,\delta_{sum}])$ as $\mathcal{R}_{H,0}$ since it will serve as the initial set for HDV in the safe vehicle coordination module.

3.3 Safe Vehicle Coordination

For vehicle coordination, the remaining uncertainty is the human behavior of HDV. Here, we restrict to the longitudinal vehicle motion on the road-aligned coordinate frame (s,d). The dynamic model considered for each vehicle $i \in \{A, H\}$ is a second-order linear differential equation given as follows:

$$\begin{aligned}\dot{s}_i(t) &= v_i(t),\\ \dot{v}_i(t) &= u_i(t),\end{aligned} \tag{10}$$

where $s_i(t)$ is the distance traveled of vehicle i measured from its road aligned coordinate frame. $v_i(t)$ is the velocity and $u_i(t)$ is the input acceleration.

Both $v_i(t)$ and $u_i(t)$ are restricted by the following constraints

$$\begin{aligned}0 \le v_i(t) &\le v_{max}\\ u_i^{min} \le u_i(t) &\le u_i^{max},\end{aligned} \tag{11}$$

We denote $D(s_A(t), s_H(t))$ as the distance measure between CAV A and HDV H, which is a function of $s_A(t)$ and $s_H(t)$.

Assuming $s_H(t)$ is known at time t, to ensure safety, we require that

$$D(s_A(t), s_H(t)) \ge d_{safe} \tag{12}$$

where d_{safe} is the safety distance. Since the model is restricted to the longitudinal direction, safety constraint (12) is valid given that vehicles perfectly follow the road center line. For HDV, there is a potential to deviate from the path due to the uncertainty of human control. Such lateral deviation from the road center line needs to be considered when forming the safety constraints. For this, we propose the following safety constraint:

$$D(s_A(t), s_H(t)) \ge \min\big(d_H(t) + d_{safe}, d^{max} + d_{safe}\big) \tag{13}$$

Here $d_H(t)$ is the lateral deviation of HDV, and d^{max} is the maximal lateral deviation due to the road layout that is bounded by the distance between the road center line and the road boundary.

To guarantee the safety of vehicles in mixed traffic, we use the invariant safe DMPC formulation proposed in our previous work Chen and Mårtensson (2022). Given the initial set $\mathcal{R}_{H,0}$ for HDV obtained from robust set estimation, We formulate a safe state set for CAV based on the forward reachable set of the HDV in the following fashion:

Definition 5. (**Safe State Set**). The set of safe states for CAV A at time t against HDV H with initial set $\mathcal{R}_{H,0}^{\mathcal{M}}$ is denoted as $\mathcal{F}(\mathcal{R}_{H,0}^{\mathcal{M}}, t)$ which is the set of state $[s_A(t)\ v_A(t)]^T$ in which safety constraint (13) is satisfied for all $s_H(t), d_H(t) \in \mathcal{R}^{\mathcal{M}}(\mathcal{R}_{H,0}^{\mathcal{M}}, t)$ and $v_A(t) \in [0, v_{max}]$.

Here superscript $\mathcal{M}$ over the reachable sets indicates the fact that a mapping from the global frame to the local road-aligned frame is done. e.g., $\mathcal{M} : \mathcal{R}_{H,0} \to \mathcal{R}_{H,0}^{\mathcal{M}}$

To impose safety at all times, a maximal invariant safe set is defined and later used in the MPC to form the terminal constraint.

Definition 6. (**Maximal Invariant Safe Set**). The maximal invariant safe set for CAV A at time t against HDV H with initial set $\mathcal{R}_{H,0}^{\mathcal{M}}$ denoted as $S(\mathcal{R}_{H,0}^{\mathcal{M}}, t)$ is defined as the set of all state $z_A(t) = [s_A(t)\ v_A(t)]^T$ such that at time t, $z_A(t) \in \mathcal{F}(\mathcal{R}_{H,0}^{\mathcal{M}}, t)$ and $\forall \tau \ge t$, $\exists u_A([t,\tau]) \in [u^{min}, u^{max}]$ s. t. $\chi(\tau, z_A(t), u_A([t,\tau]) \in \mathcal{F}(\mathcal{R}_{H,0}^{\mathcal{M}}, \tau)$.

Here $\chi(\tau, z_A(t), u_A([t,\tau])$ denote the solution of (10) given the initial state $z_A(t)$ and a input trajectory $u_A([t,\tau])$ between time t and τ

For the exact calculation of the maximal invariant safe set, we refer the interested reader to our previous work Chen and Mårtensson (2022).

We consider a planning horizon of N steps with a discretization of Δt for each step. At any planning time instance t_p, given the initial set $\mathcal{R}_{H,0}$ of HDV, we formulate the MPC problem for CAV as follows:

$$\begin{aligned}
\min \quad & \sum_{k=0}^{N-1} g_k(u_{A,k}, z_{A,k}) + g_N(z_{A,N}) && \text{(14a)}\\
\text{s. t.} \quad & z_{A,k+1} = Az_{A,k} + Bu_{A,k},\ k = 0, ..., N-1 && \text{(14b)}\\
& z_{A,0} = z_A^0, && \text{(14c)}\\
& u_{A,k} \in [u_A^{min}, u_A^{max}],\ k = 0, ..., N-1 && \text{(14d)}\\
& z_{A,k} \in \mathcal{F}(\mathcal{R}_{H,0}^{\mathcal{M}}, k),\ k = 1, ..., N && \text{(14e)}\\
& z_{A,N} \in S(\mathcal{R}_{H,0}^{\mathcal{M}}, N) && \text{(14f)}
\end{aligned}$$

Here $z_{A,k} = [s_{A,k}\ \ v_{A,k}]^T$ and $u_{A,k}$ are the state and input of CAV A at discrete time instance k with the initial condition $z_{A,0} = z_A^0$. The objective function (14a) is designed to minimize control effort and maximize control progress. The constraint (14b) is the discrete-time dynamics obtained by the discretization of (10). Constraint (14e) is the safety constraint to ensure that $z_{A,k}$ is in the safe state set within the planning horizon. The terminal constraint (14f) ensures that the terminal state $z_{A,N}$ will stay in the maximal invariant safe set to guarantee invariant safety at all times.

As an integrated framework, the system is robustified against measurement uncertainty, communication, and processing delay. It results in safe intersection coordination regardless of the uncertain behavior of the human driver which is due to the recursive feasibility and invariant safety property of (14)

Remark 7. The recursive feasibility property of (14) is true under the condition that the error bound assumed for the measurement noise holds. In practice, the slack variable needs to be added to (14) since measurement noise is unbounded and it can drift away due to bad localization.

Remark 8. For the initial condition z_A^0 of CAV, a time delay δ_{MPC} is present due to processing time for solving the optimization problem (14). To compensate for δ_{MPC}, the previous optimal input sequence can be applied to forecast the actual initial state at $t_p + \delta_{MPC}$. It is a safe approach since the input sequence is invariant safe against all conditions. A more rigorous approach is to apply the constraint-tightening technique which is not done in this paper.

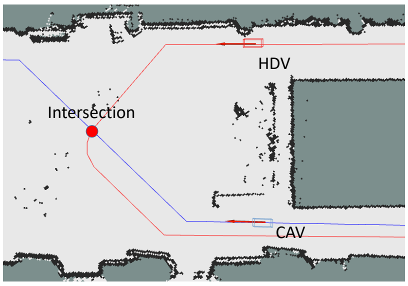

Fig. 4. Intersection layout for experiment

4. EXPERIMENTAL RESULTS

4.1 Experimental Setup

To evaluate our proposed integrated framework, a prototype of the system is implemented using two 1:10 scale miniature platforms SVEA developed at KTH see our previous work Jiang et al. (2022). Here, one SVEA is acting as HDV, the proposed safe vehicle coordination module is implemented onboard the second SVEA acting as CAV. A laptop PC is used as the intelligent intersection where the robust set estimation module is implemented. Both the SVEAs and PC are connected through a local WiFi network using ROS and a tailored communication protocol to support the required data sharing. For implementation, we use Matlab and Cora Tool Box for the robust set estimation while the MPC (14) is implemented in python and the resulting MIQP problem is formulated using CasADi and solved with the default Bonmin solver.

The layout of our experimental scenario is shown in Fig. 4. The HDV and CAV are placed in separate corridors with complete occlusion until the vicinity of the crossing. We initiate the scenario with a configuration that would lead to a collision without coordination. To demonstrate the effectiveness of our proposed framework, we choose two-speed settings: a low-speed setting at $v_{max} = 0.5\ m/s$ and a high-speed setting at $v_{max} = 0.8\ m/s$. For the MPC, we set the horizon to $N = 8$ and time step to $\Delta t = 0.5$ for both speed settings. A video of the experiments can be found at https://bit.ly/ifac_intersection.

4.2 Experimental Results

For the experiment, we measured the worst case communication delay δ_{com}, processing delay δ_{set} of robust set estimation and processing delay δ_{MPC} of MPC. The results are gathered in Table. 1.

Table 1. Worst case delay measurement

	δ_{com} (s)	δ_{set} (s)	δ_{MPC} (s)
Worst Case Delay	0.2	0.2	0.6

The experimental results for both speed setting $v_{max} = 0.5\ m/s$ and $v_{max} = 0.8\ m/s$ are shown in Fig. 5 and Fig. 6. For the result in Fig. 5, the longitudinal distance traveled is shown in Fig. 5a, the intersection is located at $18.43\ m$. here the HDV measurement is shown to be within its upper and lower bound as a result of the robust set estimation. The CAV successfully anticipate the variation caused by both measurement and delay and slows down before the intersection to avoid collision. More specifically, as the upper bound of the distance traveled for the HDV reached the intersection point, the CAVs reacts by slow down at about $16\ s$ in Fig. 5a. The same result can be clearly seen in Fig. 5b, here the relative distance between CAV and HDV is shown to be above the computed maximal safe distance at all time, this is the safety constraitn required to be fulfilled. In Fig. 5c we demonstrate the fact that the HDV velocity is within its bound as a result of the set estimation, and CAV approaches the intersection by slowing down until a full stop. In summary, the experimental result indicates that the CAV travels through the intersection safely without collision under noisy measurement and delays. A similar result is shown in Fig. 6, with the high speed setting. The CAV avoids collision with the HDV in a similar fashion as in the low speed setting.

5. CONCLUSION

In this work, we have developed an integrated framework for safe intersection coordination of CAVs in mixed traffic with occluded HDVs. To enable shared situational awareness to the CAV, an intelligent intersection is introduced. As the central node, a robust set estimation module is designed on the intelligent intersection to provide a set estimation capturing measurement noise, and various delays using the set-membership method and reachability analysis. A safe vehicle coordination module is designed onboard the CAV to use the given set estimation as the initial condition and plans an invariant safe motion for the vehicle.

With the experiment results, we demonstrate that our proposed framework is feasible for in-vehicle implementation and results in safe coordination of CAV in mixed traffic with occluded HDV under noisy measurement and real communication and processing delays.

For future work, we would like to verify our proposed framework in a multi-vehicle experiment with the addition of an RSU and study in detail how the network property can affect the coordination performance on a large scale. Another direction is to integrate hardware-in-the-loop using the proposed framework with real-time traffic data in an integrated testbed.

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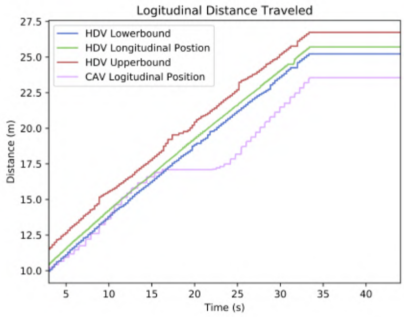
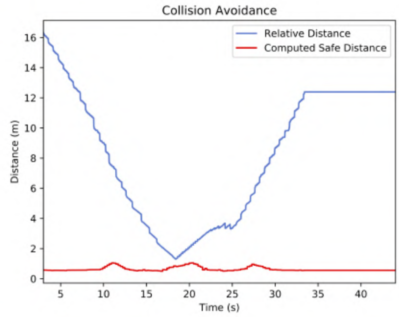
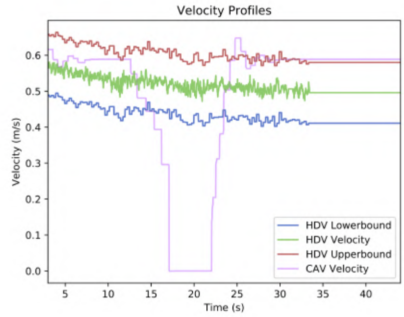


(a) Distance travel for CAV and HDV

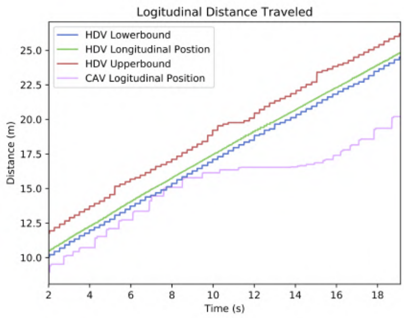


(b) Relative distance between CAV and HDV

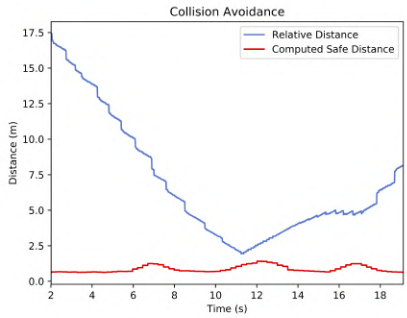


(c) velocity profile for CAV and HDV

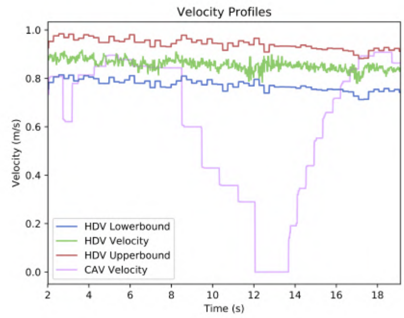
Fig. 5. Experiment result for speed setting $v_{max} = 0.5\ m/s$



(a) Distance travel for CAV and HDV



(b) Relative distance between CAV and HDV



(c) velocity profile for CAV and HDV

Fig. 6. Experiment result for speed setting $v_{max} = 0.8\ m/s$

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