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IFAC PapersOnLine 55-24 (2022) 279–284

Cooperative Navigation Strategy for Connected Autonomous Vehicle Operating at Smart Intersection

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Abstract:
This paper focuses on the cooperative navigation strategy for connected autonomous vehicles operating at smart intersections. The goal of this work is a cooperative navigation system to achieve cooperative collision avoidance for enhancing the safety and capacity of the intersection. This work considers cooperative connected autonomous vehicles operating simultaneously with non-cooperative autonomous vehicles. This work uses beyond visual range scenarios to reduce the vulnerable situations. Beyond visual range, information is implemented by using the data from the roadside units, autonomous intersection management system, smart traffic lights, and onboard units. The efficacy of this work is validated in MATLAB/Simulink environment. The simulation results show the separation time within the set upper and lower bounds. That ensures that the ego vehicle does not collide with others at the intersection. The cooperative collision avoidance algorithm guides the ego vehicle as soon as the ego vehicle comes in the range of the intersection service area, which increases the safety and capacity of the intersection. This strategy is comfortably used for both an unsignalized and signalized intersection. In an unsignalized intersection scenario, the ego vehicle uses an onboard unit. In signalized intersection scenario, the ego vehicle uses a roadside unit, onboard unit, autonomous intersection management system, and smart traffic lights. As no such framework is found in the literature. The proposed framework is the near-future requirement where the connected autonomous vehicle utilizes the information from smart infrastructure devices.

Keywords: Navigation, guidance, control, Smart intersection, Collision avoidance, Connected autonomous vehicle, Cooperative navigation.

1. INTRODUCTION

Recent advancements in the automotive industry focus on autonomous vehicles. Technology innovations such as Vehicle to Vehicle (V2V) communication, Vehicle to Infrastructure (V2I) communication, Vehicle to Cloud (V2C), Vehicle to Pedestrian (V2P) communication, and guidance, navigation, and control system continue to propagate to provide a safe environment for Connected Autonomous Vehicles (CAVs) and all road users. Government agencies are creating investment opportunities for automotive manufacturers, technology companies, and research institutes in this area for better future perspectives Khayatian et al. (2020). Smart Columbus is one of the major projects supported by the U.S. Department of Transportation (USDOT) to develop Columbus as a model smart connected city for CAVs to improve people's quality of life, economic growth, sustainability, and safety Cocks and Johnson (2021). Researchers and scientists are making remarkable efforts to develop a secure and highly reliable autonomous system for smart cities. These systems categorize into two major domains, (i) infrastructure development approach and (ii) vehicular control approach for connected autonomous vehicles.

Technological development in infrastructure related to the automobile industry is focusing on roadside computing and communication devices called Road Side Unit (RSU), Smart Traffic Lights (STL), Smart Traffic Signs (STS), Autonomous Intersections Management (AIM) system, Cloud Storage and Connectivity, and Automated Traffic Management (ATM) System. RSU is an edge computing device that establishes the connection of communication between vehicles and infrastructure. RSU uses the Dedicated Short Range Communication (DSRC) channel to exchange information between infrastructure and vehicles. Researchers have proposed different management strategies for Automated Intersection Management (AIM) systems in past few years. However, vehicular control approach-based navigation had many subsystems of the automatic driving systems (way-points positioning system, path planning system, lane-keeping system, etc.) that make vehicles smart enough to operate safely in a vulnerable environment. All subsystems are crucial to converting a vehicle into Highly Automated Vehicles (HAVs) and Highly Smart Vehicles (HSVs) to operate in vulnerable environments or situations.

In Pourmehrab et al. (2017), the authors developed the algorithm for the smart intersection that can minimize

Peer review under responsibility of International Federation of Automatic Control.
10.1016/j.ifacol.2022.10.297

the headway time and increase the throughput. It is based on the assumption that the lead vehicle was exempt from optimization of headway. In Barzilai et al. (2018), the author proposed the algorithm that controls the SPaT information and prioritizes the signal information or signal phase according to the need for urgency. This work does not discuss the challenges faced by CAVs at the intersection. In Milo (2020), the authors present the autonomous traffic management system that can safely route the connected autonomous vehicle across the intersection without collision. In Arizala et al. (2021), the authors developed the testing framework at CARLA for path following and collision avoidance of connected autonomous vehicles. The path-following and collision avoidance using a non-linear model predicted controller in a straight road driving scenario was developed in Bifulco et al. (2021). The vehicle level control strategy for collision avoidance and path following are presented and demonstrated in Martinsen (2021). From the above discussion, it is concluded that the efforts were made in the direction of (i) infrastructure development approach, which is developed only for the smart intersection, and (ii) vehicular control approach, which only works for the un-signalized intersection using V2V communication. Intersection management strategies use a reservation approach for CAVs, compromising the intersection's capacity. On the other hand, the vehicular navigation strategies mostly use the game theory approach for CAVs at the intersection which compromises safety where beyond visual information is not available Khayatian et al. (2020).

To the best of the authors' knowledge, No cooperative navigation algorithm that uses infrastructure information is found in the literature. Hence, there is a need to develop a novel framework that can eliminate the cons and combine the pros of the above-mention two research directions. The proposed framework utilizes the V2I and V2V information to decide the efficient realization of systems in the smart intersection and non-smart intersections. It will reduce the hazards due to hacking and system failure in the vulnerable environment and enhance the safety, and capacity of CAVs operating at smart intersections. The rapid development of smart cities required the proposed cooperative navigation strategy for CAVs operating at the smart intersection. The main contribution of the proposed work is in the domain of safety and capacity of the smart intersections. Where:

- Safety is achieved using infrastructure devices and vehicle sensors simultaneously by a cooperative navigation framework.
- Capacity and safety are achieved by velocity optimization in a cooperative collision avoidance algorithm.

The paper consists of five sections: section 2 discusses the problem formulation and mathematical modeling of the CAVs. Section 3 presents the cooperative navigation strategy to avoid collisions for CAVs. Section 4 details the results of the cooperative collision avoidance algorithm, followed by the concluding remarks in section 5.

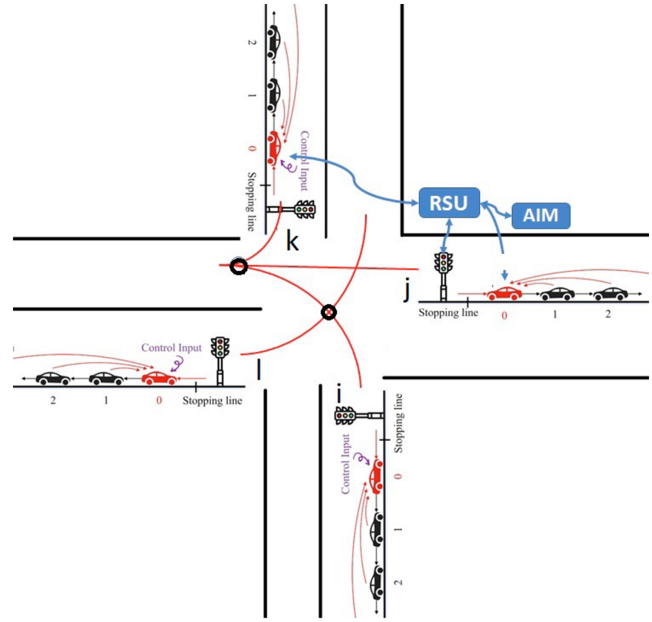

Fig. 1. Overview of simulation Scenario of smart intersection contains RSU, AIM, and STL. If any actor vehicle does not follow SPaT or AIM, the ego vehicle will collide at the highlighted conflict points.

2. PROBLEM FORMULATION

Operations over intersections are the core interest for the researchers as it contains the maximum number of merge, diverge and cross conflict points. The focus of the presented work is to develop a cooperative position, navigation, and timing (PNT) solution for the ego vehicle based on other vehicles operating at the same intersection. It is accomplished keeping in view the navigation strategy to realize the collision avoidance at the smart intersection. The realization of the proposed work is assumed that the smart intersection is equipped with RSU, AIM, and STL. Due to the presence of the mentioned devices, the SPaT, intersection parameters, MAP, time-slots, and other lane vehicle information are available for the ego vehicle. All actor vehicles are non-cooperative vehicles. Actor vehicles only share their velocity profiles and do not respond to the other vehicle's actions. Ego vehicle uses the information from all other vehicles. Actor vehicles' velocity profile and distance are used to generate the ego vehicle velocity profile. Hence, this information is used to calculate the other vehicle's future path with the time of arrival at the conflict point to find potential conflicting situations. Problem formulation has been done based on conflict points, intersection parameters, and CAV's future path. Fig. 1 shows the intersection scenario that has the three vehicles in each lane and all have different directions to move that is straight, right, and left turn. The leading vehicle in the i lane is the ego CAV that has to follow the left turn path. A vehicle in the j lane is another CAV that has to follow the straight path. CAV in the k lane has to follow the right turn, and CAV in l lane has to follow the left turn. This specific scenario generates two conflict points concerning the latitude and longitude positions of the ego vehicle, while in the time frame, there are three conflicting situations. The actor vehicles are connected and automated, but they do not have beyond visual range cooperativeness. The vehicle shares information such as forward and rear lengths of the GPS receiver point, turn indication, the width of the vehicle, the height of the vehicle, the current position of the vehicle in terms of latitude and longitude, the velocity at which its approaching intersection, and heading angle of the vehicle. It assumed that all perception sensors were performing well and generating relative positioning and speed information of other vehicles and their surrounding obstacles. The scenario simulation only deals with the leading vehicles in lanes, but the proposed solution can be implemented for other vehicles in each lane.

2.1 CAVs Mathematical model

The dynamic model of the vehicle has been taken into account while developing the simulation framework. The tire modeling is used to depict the nonlinear behavior of the vehicles Bian et al. (2014). The effects of tire slip with steering angle also considered for the evaluation. (1) is the $3DOF$ mathematical modeling of CAVs operating at the intersection. Dynamic modeling is referred and modeled according to the SAE J670e standards Code (1995).

$$\begin{cases} I\ddot{\phi} = aP^n_{if}\delta + bF^n_{ilf} - bF^n_{ilr} \\ m(\dot{V}^n_{iy} + V^n_{ix}\dot{\phi}) = \delta P^n_{if} + F^n_{ilf} + F^n_{ilr} \\ m(\dot{V}^n_{ix} + V^n_{iy}\dot{\phi}) = P^n_{if} + P^n_{ir} + F^n_{ilr}\delta \\ \dot{x}^n_i = V^n_{ix}cos\phi - V^n_{iy}sin\phi \\ \dot{y}^n_i = V^n_{iy}cos\phi + V^n_{ix}sin\phi \end{cases} \tag{1}$$

Where I is the inertia of the vehicle, ϕ is the yaw angle, a and b are the forward and rear length of the vehicle from the center of gravity, P_f and P_r are longitudinal forces on the front and rear tires, F_{lf} and F_{lr} are lateral forces on the front and rear tires, m is the mass of the vehicle, V_x and V_y are longitudinal and lateral velocities, x and y are longitudinal and lateral positions and δ is the steering angle. $'i'$ represents the lane ID of the intersection, and 'n' represents the vehicle ID. Similar indexes were used for other actors vehicle dynamics, such as j, k, and l for different lanes and $n = 1, 2, 3.., n$ for different vehicles. The terms δP^n_{if} and δF^n_{ilf} in (1) represent the effect of vehicle side-slip. It is necessary because the vehicle operating at the intersection needs to take a 90-degree turn. Since side-slip is the product of lateral force with steering angle as shown in (1). Therefore, as the velocity of the vehicle increases the side slip also increases Kim and Ryu (2011). Precise steering command signals depend on the side-slip of vehicle.

2.2 Intersection Mathematical Model

The intersection is modeled in terms of conflict points for each lane and path taken by the vehicle. The selection of the way-points is crucial for the accurate calculation of conflicting situations. As shown in Fig. 1, if the selected consecutive way-points are far apart, there is a high probability that system not calculate highlighted conflict points. Since all vehicles are connected, ego CAV can develop a set of way-points for each leading vehicle that can create a conflicting situation. Hence, every next-way point is spaced by the length of the vehicle. (2) shows the number of conflict points in a path for a particular vehicle.

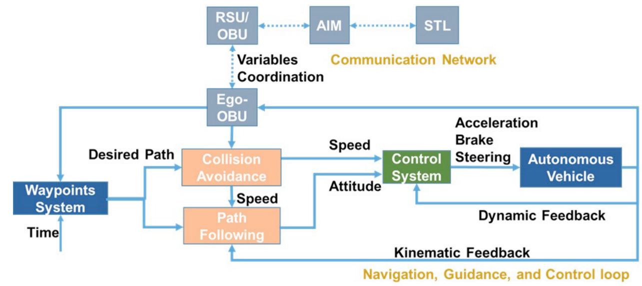

Fig. 2. Cooperative Navigation, Guidance and Control framework, communication network contains all edge devices and shared actor vehicle and environmental data to provide beyond visual range information.

$$\begin{cases} q = \dfrac{R_l\theta}{L^n_i} \\ C^i_q = \Gamma^0_i + qL^n_i \end{cases} \tag{2}$$

Where R_l is the left turn radius of the intersection. Γ^n_i is a position where the intersection starts. L^n_i is the length of the vehicle, and C^i_q is the set of waypoints generated to follow the path. q is the number of conflict points for the vehicle. As soon as the vehicle leaves one conflict point, it will enter the next conflict point. This strategy provides all possible conflicting points in a path. Whereas other strategies found in the literature [Milo (2020)], and [Cocks and Johnson (2021)] use a maximum of 7 conflict points in any of the paths across the intersection. (2) can generate conflict points for any configuration of intersection. The value of the θ range for the path is from 0 to 90^o. Therefore, the modeled intersection is in a perfect cross configuration. This ensures that the proposed system will work for any type of intersection with the ability to avoid collision.

3. COOPERATIVE NAVIGATION SYSTEM

Navigation based on smart infrastructure relies on devices that share data using the DSRC communication channel. This type of guidance is prone to cyber security threat issues. While navigation using onboard sensors does not provide beyond visual range information. However, both pieces of information are necessary for operations at the smart intersection. The proposed cooperative navigation strategy using both (i) AIM, STL, and RSU information and (ii) Feedback from sensors simultaneously, to provide safe and effective cooperative navigation at the intersection of smart cities. Signalized intersection scenario is discussed in this paper that has a single incoming lane on each side of the intersection as shown in Fig. 1. The number of vehicles in each lane is represented by a different group of vehicles as shown in Fig. 1 that is "i", "j", "k", and "l". The formulation is done to maintain a safe distance within the same group of vehicles and simultaneously avoid conflicts between different groups of vehicles. Fig. 1 shows the potential conflict points over the signalized intersection of the simulation scenario highlighted by a circle. Fig. 2 shows an overview of cooperative navigation, guidance, and control system that depicts the flow and type of information that can be exchanged between RSU and OBUs of the vehicle. the cooperative collision avoidance block uses all actor vehicles, ego vehicle, and environmental parameters to calculate optimized velocity for the ego vehicle which avoids conflict in the vulnerable scenario. Velocity is used by the path following block to generate actuation command to vehicle dynamics block. Current state values are feedback to path following and send to OBU for cooperation with other vehicles. The cooperative collision avoidance algorithm uses other vehicle information such as position, velocity, length, width, heading angle, lane identity, and turn indication of vehicle. The cooperative collision avoidance algorithm resolves the conflict point between all leading vehicles from each lane and within the lane vehicle.

3.1 Collision Avoidance

There are several collision avoidance algorithms available in literature Huang et al. (2021), Bifulco et al. (2021), and Wang et al. (2021) which address the collision avoidance at unsignalized intersection, also address cooperative scenario but not at signalized intersection. In this work, the collision avoidance algorithm will be part of the onboard computing system. It has capabilities of accessing the information from the modern developed technology such as AIM, RSU, and STL available at the smart intersection. If two of the vehicles have a common $3D$ positioning such as [lat, long, time] at any timestamp they will collide. The cooperative collision avoidance system calculates the desired velocity to avoid conflicts. Once algorithm optimized the velocity, it will share the velocity to the path following algorithm and repeat the process throughout the simulation. This will generate the velocity profile at which the vehicle follows its path across the intersection. The surrogate optimization fulfills the two basic requirements of real-time optimization in automotive applications. Surrogate consumes less time to optimize the solution and can find the optimal solution for the problem. In the proposed framework, SPaT information from STL, P_i, and turn indication I_i^n from the vehicle is the standard requirement to optimize the ego vehicle velocity. Surrogate optimizes the function within a bounded range defined by the scenario. The algorithm constructs a surrogate as an interpolation of the objective function by using a radial basis function (RBF) interpolator Xu et al. (2018). RBF interpolation has several convenient properties that make it suitable for constructing a surrogate. Evaluating an RBF interpolator takes little time. Which is an essential requirement for an automotive system.

The objective function defines in terms of the time of arrival, traveling time, and phase time of the signal. In (3) "T_i^n" is the time vehicle takes to travel from its current position to the next waypoint.

$$\left\{ T_i^n = \frac{C_q^i - x_{i1}^n}{V_i^n} + \tau_i^n \right. \tag{3}$$

Where x_i^n, V_i^n, τ_i^n represent the current position, velocity and minimal separation time of CAV respectively. τ_i^n is also the function of vehicle parameters as a vehicle having a larger size in length needs more separation time than a shorter vehicle. So the conflict situation arises when $C_q^i = C_q^j$ at any particular timestamp.

Let ζ be the difference in time of arrival from ego vehicle to another vehicle at the intersection. Therefore, the objective function in Eq. (4) is used to minimize the ζ for

Algorithm 1 Cooperative Collision Avoidance Algorithm

for $Lane = 1 : S_t$ **do**
  Scan lane ID 'i', 'j', 'k', and 'l'
  Scan number of vehicles in each lane
  Scan AIM information ${f_i}^n$
  Scan SPaT information P_i,P_j, P_k, P_l
  for $Vehicles = 1 : n, \ldots,$ **do**
    Initialized vehicles parameters ${V_x}^n$,${V_y}^n$, δ^n, ϕ^n, a^n, b^n, x^n, y^n, I^n, f^n
    if $P_i = I_n$ **then**
      Calculate ${C_q}^i$, ${C_q}^j$, ${C_q}^k$, and ${C_q}^l$, based on vehicle parameters
      if ${C_q}^i = {C_q}^j$ or ${C_q}^k$ or ${C_q}^l$ **then**
        Optimize surrogate ${\zeta_i}^n$, ${\zeta_j}^n$, ${\zeta_k}^n$, ${\zeta_l}^n$ wrt. v
        Share optimized solution to path following algorithm
      end if
    end if
  end for
end for

all the vehicles at the intersection by using information from AIM, RSU, and OBUs.

$$\begin{cases} \zeta_i^n = |e^{|I_i^n - P_i|}(f_i^n + T_i^n) - e^{|I_i^{n+1} - P_i|}(f_i^{n+1} + T_i^{n+1})| \\ \zeta_j^n = |e^{|I_i^n - P_i|}(f_i^n + T_i^n) - e^{|I_j^n - P_j|}(f_j^n + T_j^n)| \\ \zeta_k^n = |e^{|I_i^n - P_i|}(f_i^n + T_i^n) - e^{|I_k^n - P_k|}(f_k^n + T_k^n)| \\ \zeta_l^n = |e^{|I_i^n - P_i|}(f_i^n + T_i^n) - e^{|I_l^n - P_l|}(f_l^n + T_l^n)| \end{cases} \tag{4}$$

Where f_i, f_j, f_k, f_l is the assign time for the vehicle generated by AIM system. $e^{|I_i^n - P_i|}$ is the conditional check on the vehicle to follow the intersection SPaT information. If $T_i^n = T_j^n$ or $T_i^n = T_k^n$ or $T_i^n = T_l^n$ or $T_i^n = T_i^{(n+1)}$ the ego vehicle will collide with any of the four vehicles. Ego CAV velocity is one control variable to avoid collision and following path. (4) contains all the parameters that are received by another vehicle in V2V communication. However, this cost function has an upper and lower bound to prevent unwanted delay and excessive speed while CAVs operate at the intersection. (5) shows the formulation of upper and lower bound constraints.

$$\left\{ \frac{D_{min}}{V_{max}} \leq \zeta_i^n \leq \frac{D_{max}}{V_{min}} \right. \tag{5}$$

Where $D_{min} = 1m$ and $D_{max} = 7m$ is the separation distance and V_{min} and V_{max} is the upper and lower limit of ego velocity.

4. RESULTS AND DISCUSSION

The cooperative navigation, guidance, and control strategy are implemented on Ego Vehicle using MATLAB/Simulink environment. Five vehicles simulated one actor vehicle in each lane and one ego vehicle in lane 'i', as shown in Figure 1. ζ is the separation time between ego vehicle and actor vehicles. The Separation time shown in Fig. 3, 4, and 5. Different color bar represents different actor vehicle in a scenario. Since the ego vehicle is the reference, therefore its bar height is zero and does not appear on the graph. Fig. 3 shows V2V cooperation, Fig. 4 shows V2V and AIM cooperation, and Fig. 5 shows V2V, AIM, and STL cooperation. Simulation results show the

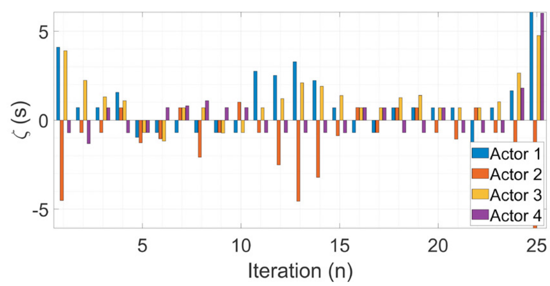

Fig. 3. Cooperative Collision avoidance results where only V2V cooperation is available. Non zero value of actor vehicle shows that at any instant, ego vehicle and actor vehicle do not collide based on velocity profile followed by actor and ego vehicle.

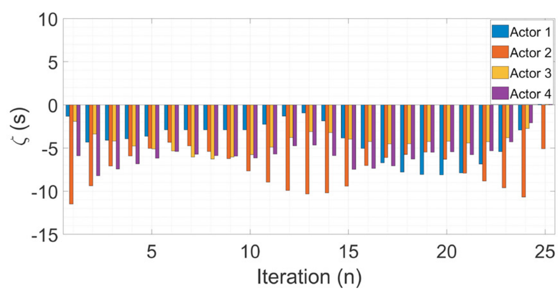

Fig. 4. Cooperative collision avoidance results with V2V and AIM devices are available. All actor vehicles pass after the ego vehicle as the time stamp provided to the ego vehicle is much earlier than the actor vehicle.

effectiveness of the proposed optimization and control framework by ensuring the values of the upper and lower bound constraints as defined in Eq. (5). Fig. 3 shows the plot for the cooperative collision avoidance result discussed in a scenario where only V2V cooperation is available. The vertical axis shows the separation time concerning the ego vehicle at the conflict point identified by the cooperative collision avoidance algorithm. The horizontal axis is the sample for each second during the simulation. Non zero value of actor vehicle shows that at any instant, ego vehicle and actor vehicle do not collide based on velocity profile followed by actor vehicle and optimized velocity followed by ego vehicle. Negative value shows that the actor vehicle passes before the ego vehicle at a potential conflict point. The high bars in the figure between 10 to 18 show that the ego vehicle crosses the conflict point much earlier than the actor vehicle. Ego vehicle tries to maintain the least possible separation distance that also ensures the increase in intersection's capacity with safety. Fig. 4 shows cooperative collision avoidance result discussed in a scenario where V2V and AIM cooperation is available. As a result, all actor vehicles pass after the ego vehicle as the time stamp provided to the ego vehicle is much earlier than the actor vehicle. Fig. 5 shows the cooperative collision avoidance result discussed in a scenario where V2V, AIM, and STL cooperation is available. More separation time between each actor vehicle and ego vehicle shows that SPaT information also provides collision avoidance to CAV.

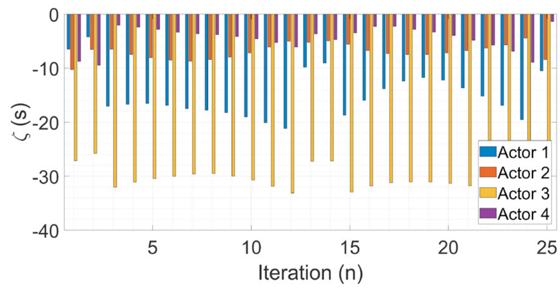

Fig. 5. Cooperative collision avoidance results where V2V, AIM, and STL cooperation are available. SPaT information also provides collision avoidance to channel CAV according to phase and time information.

Table 1. Qualitative analysis of actor 1

	X(m)	Y(m)	Time (s)
Actor 1	-110	3	12
Ego (Nc)	-110	3	12
Ego (V2V,AIM,STL)	-111	-101	12
Ego (V2V,AIM)	-106	-49	12
Ego (V2V)	-107	-32	12

Since vehicles enter and leave the intersection at a much faster speed, therefore, time spent by the vehicle at the intersection is less than the scenario where vehicles use V2V communication only. This in turn increases the throughput of the intersection. Table 1, 2 and 3 shows the quantitative analysis for actor 1, 2, and 3 respectively. The time column in the tables shows the reference time when actor vehicles collide with ego vehicles in a scenario where no cooperation is done between vehicles. The rows of the table show the level of cooperation of the ego vehicle. In the position column, Different position at the same time stamp at different cooperation level shows that the ego vehicle mange to avoid collision and move faster than when there is no cooperation. Where actors 1, 2, and 3 had conflicting situations at simulation times of 12, 18, and 16 seconds respectively. Actor 4 is in the same lane as the ego vehicle, therefore, it maintains a safe distance throughout the trajectory.

The efficacy of the path following algorithm is shown in Fig. 6. As the path following algorithm receives guidance from the cooperative collision avoidance algorithm, it starts tracking the desired velocity. It is vivid from Fig. 6 that the ego vehicle is following the reference velocity profile while crossing the intersection. Velocity tracking results show that cooperative collision avoidance algorithms provide different velocity profiles in different scenarios. Cooperative collision avoidance reference velocity provided by V2V cooperation only is the slowest velocity profile to operate safely at the intersection and avoid the collision. The reference velocity profile provided by V2V and AIM Cooperation slightly increases the velocity of the ego vehicle within the bounds of safety limits provided by AIM which gives an ego vehicle an edge to move faster than it is moving in V2V cooperation. The reference velocity is at its maximum value when all V2V, AIM, and STL cooperation is available, hence giving maximum throughput. Therefore proposed cooperative navigation, guidance, and control strategy increase the throughput with safety.

Table 2. Qualitative analysis of actor 2

	X(m)	Y(m)	Time (s)
Actor 2	-111	-16	18
Ego (Nc)	-111	-16	18
Ego (V2V,AIM,STL)	-104	-224	18
Ego (V2V,AIM)	-106	-100	18
Ego (V2V)	-107	-71	18

Table 3. Qualitative analysis of actor 3

	X(m)	Y(m)	Time (s)
Actor 3	-111	0	16
Ego (Nc)	-111	0	16
Ego (V2V,AIM,STL)	-104	-192	16
Ego (V2V,AIM)	-106	-85	16
Ego (V2V)	-107	-57	16

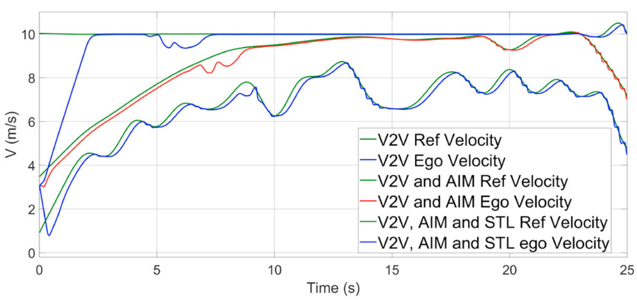

Fig. 6. Velocity tracking results are shown in different cooperation scenarios: (i) V2V cooperation, (ii) V2V and AIM cooperation, and (iii) V2V, AIM, and STL cooperation.

5. CONCLUSION

The proposed framework enables CAV to behave intelligently and cooperate with other vehicles while passing through the smart intersection. Simulation of the suggested framework of the cooperative navigation algorithm used infrastructure information with sensor feedback. The cooperative navigation Algorithm improved safety and intersection capacities while operating at the smart intersection. The efficacy of the proposed framework was evaluated and validated by static environmental parameters, which will be extended to the dynamic environment in the future. This work can also be extended to explore the action of CAVs in presence of threats. In the future, this work continues to evaluate the performance in different scenarios for the threat and vulnerabilities associated with CAVs having cooperative navigation technology.

ACKNOWLEDGEMENTS

I thank the Center for Automotive Research (CAR), The Ohio State University (OSU), allow me to work on this project. The U.S. Department of Transportation (USDOT) sponsored this project under Grant 69A3552047138 for the CARMEN University Transportation Center (UTC).

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