2021 IEEE Intelligent Transportation Systems Conference (ITSC)
Indianapolis, USA. September 19-21, 2021

CIM: Constraint-based Intersection Management in Mixture of Non-Connected Vehicles

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2021 IEEE International Intelligent Transportation Systems Conference (ITSC) | 978-1-7281-9142-3/21/$31.00 ©2021 IEEE | DOI: 10.1109/ITSC48978.2021.9564997

***Abstract*— While traffic control systems for connected autonomous vehicles (CAVs) are expected to provide multipurpose mobility services in the upcoming Mobility as a Service (MaaS) era, non-connected vehicles (NCVs) must also be considered when expanding MaaS service areas. Accordingly this paper proposes constraint-based intersection management (CIM) as a traffic control system that utilizes spatiotemporal constraints to ensure that CAVs can safely negotiate intersections with poor visibility, even in the presence of NCVs. To handle such mixed environments, it is important that CAVs be able to utilize both information from traffic control systems and data collected from their on-board sensors. To accomplish this, our CIM system utilizes local dynamic maps (LDMs) to obtain NCV information and then sends spatiotemporal constraint data to the CAVs via the traffic control system. The use of spatiotemporal constraint data provides robustness against uncertainty in both NCV behavior predictions and LDM sensing errors. Through the simulation experiments conducted in this study, we confirmed that the proposed method is both efficient and robust, and that it enables CAVs to negotiate traffic intersections safely despite any potential NCV predictive uncertainties and/or position measurement errors.**

I. INTRODUCTION

As part of what has come to be collectively referred to as Mobility as a Service (MaaS) [1], there has a growing movement towards utilizing the traffic control systems of connected autonomous vehicles (CAVs) whose automatic driving capability are "Level 4" [2] to facilitate multipurpose mobility in logistics, sales, and public transportations. The ability to operate effectively in densely populated urban areas is important if MaaS is to be integrated into established markets, but traffic flows in those areas also include numerous non-connected vehicles (NCVs) and pedestrians. Additionally, those areas are often home to numerous intersections, including many with poor visibility.

In low visibility intersections, such as those where walls prevent drivers from seeing around corners, it is difficult for CAVs to operate safely using just their on-board sensors (*e.g.*, cameras and light detection and ranging (LiDAR)), or to detect other traffic participants and predict their movements before making their own navigation decisions, as shown in Fig.1. However, by employing roadside sensors, traffic control systems can provide CAVs with important information on other participants (*e.g.*, their positions and speeds) in the form of a common data structure, such as a local dynamic map (LDM) [3].

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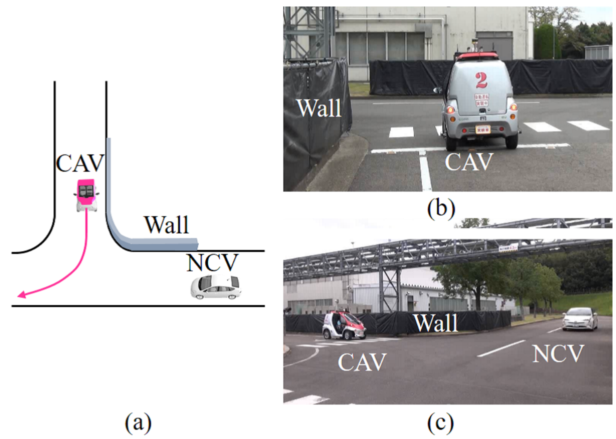

Fig. 1. Intersection with poor visibility: (a) top-down view, (b) CAV view, and (c) overall view.

To facilitate smooth traffic flows at an intersection, the following traffic control system requirements must be satisfied:

1) To prevent collisions, the system must be capable of mediating between CAVs and other traffic participants based on appropriate criteria.
2) The traffic mediation criteria must be efficient and robust against sensor detection errors and system prediction uncertainties.

In general, CAVs plan and drive under appropriate constraints such as speed limits, etc. We have reported a system implementation that extends CAV to accept additional spatiotemporal constraints to avoid collisions between traffic participants [4]. In this study, we focus on the concept of this implementation, namely "Constraint-based Intersection Management (CIM)". The advantage of CIM is that the visibility level at the intersection as seen from the CAV doesn't affect the quality of intersection management because its spatiotemporal constraint takes into account predictive uncertainties. The detail of CIM and spatiotemporal constraint will be described in section III.

In an earlier study involving the use of an actual CAV and two real NCVs at a small T-intersection with poor visibility, it was found that using an LDM implementation with appropriate spatiotemporal constraints as criteria could achieve an acceptable level of mediation [4][5]. The resulting CIM system allowed the CAVs to safely negotiate intersections despite the presence of NCVs. However, its effectiveness has been verified at an intersection consisting of a single lane. When this CIM system was applied to an intersection with multiple lanes, simulations confirmed a few cases where CAVs stopped in the intersection to block other vehicles from driving.

In this paper, we report on improved spatiotemporal constraints that have been introduced into previously proposed CIM system to adapt it to general intersections, as well as on simulations aimed at producing a realistic traffic control system that employs hundreds of vehicles. The contributions of this paper are as follows:

1) The spatiotemporal constraint improvements allow CAVs to pass through intersections consisting of multiple lanes with hundreds of vehicles.
2) Numerical experiments show that the traffic efficiency and robustness of the proposed method are better than those of a conventional traffic signal.

The rest of this paper is organized as follows. Section 2 describes related work, while Section 3 provides an overview of the spatiotemporal constraints. Section 4 describes the simulation environment, and Section 5 presents the obtained experimental and analytical results. Finally, we conclude the paper in Section 6.

II. RELATED WORK

In recent years, a variety of intersection management (IM) models have been proposed for CAVs as part of studies into intersection crossing strategies [6]. These IM approaches can be classified into two types: decentralized and centralized.

For a decentralized approach, a vehicle-to-vehicle (V2V) interface is most commonly used, and various methods such as sending and receiving symbol-based commands between CAVs [7] and adopting request-response negotiation-based protocols [8] have been proposed.

Centralized approaches are further classified into query-based intersection management (QB-IM) and assignment-based intersection management (AM-IM) approaches. Of these, autonomous intersection management (AIM) [9] is a typical QB-IM method. In this system type, when the CAV queries the IM regarding whether or not it can enter the intersection, the IM predicts the potential for collisions and sends a yes/no answer to the CAV. Separately, Xi *et al.* [10] proposed an IM model for mixed traffic transportation systems that combines IM and intersection traffic signals to coordinate intersection entry permissions for connected human-driven vehicles (CHVs) and CAVs. In contrast, the AM-IM approach assigns permissions and trajectories for each vehicle. In a separate method proposed by Wang[11], once an autonomous crossing strategy has been determined at intersections without signal lights, trajectories are optimized by road segments and then assigned to the CAVs.

However, these approaches assume that all vehicles are CAVs and that the IM can perfectly predict the time at which each vehicle will enter the intersection, which means the IM does not require CAVs to plan when they will make their individual transits. In other words, CAVs only need to follow the symbol-based driving commands (*e.g.*, passable/not passable) or the trajectory sent by the IM. However, IM approaches will be ineffective if the traffic environment includes a mixture of CAVs and NCVs because the system has no control over traffic participants other than CAVs or CHVs. Additionally, it would be difficult for CAVs that are strictly following symbol-based driving commands to avoid accidents resulting from sudden changes that an IM cannot predict, such as the sudden rogue acceleration of a CHV. Furthermore, while some studies have addressed the problems related to mixed CHVs and NCV environments [12], those studies did not address the predictive uncertainties of NCV behaviors nor the possibilities of NCV position measurement errors that were discussed above.

In response to the above-mentioned problems, we introduced a prototype of the abovementioned CIM in an earlier study and showed how it can allow CAVs to pass through the intersection of an actual experimental road in the presence of several moving NCVs [4]. In this study, we report on improvements to the spatiotemporal constraints of the system that were made to adapt it to general intersections, and the results obtained by applying the revised system to simulation experiments employing hundreds of vehicles.

III. TRAFFIC CONTROL SYSTEM WITH SPATIOTEMPORAL CONSTRAINTS

The CIM manages intersections by spatiotemporal constraints as additional planning constraints for CAVs that enable CAVs to avoid collisions with NCVs. The spatiotemporal constraint is imposed on a conflict point that is an intersection of paths of two vehicles. Since a conflict point is a place where two vehicles can potentially collide, the spatiotemporal constraint can be used to shift the timing of the passage to avoid the collision. Assigning priorities for each vehicle at the conflict point allows all CAVs to pass through it safely. Here, it should be noted that both safety and efficiency are achieved by taking both predictive uncertainties and measurement errors into consideration when setting the spatiotemporal constraints.

Figure 2 shows a system overview of the traffic control system, which consists of three major modules, the LDM, the traffic controller, and the CAVs. The role of LDM is to estimate driving information (*e.g.*, the position and speed) of NCVs from roadside sensor data. However, as mentioned above, such driving information may include sensing errors. The role of the traffic controller is spatiotemporal constraint computation for all CAVs through path predictions for both the CAVs and the NCVs. The traffic controller also computes global paths for all CAVs in the proposed system since it is natural for a MaaS application to assume that goal and CAV routes are provided by traffic controllers. After receiving both their global paths and spatiotemporal constraints from the traffic controller, local path planning is computed in the CAVs in order to ensure they conform to the global path and satisfy the provided spatiotemporal constraints. It should be noted that we assume that all modules share a vector map that consists of road segments such as lanes and links. The global path indicates a route, which is an array of road segments, from start to goal. However, the global path does

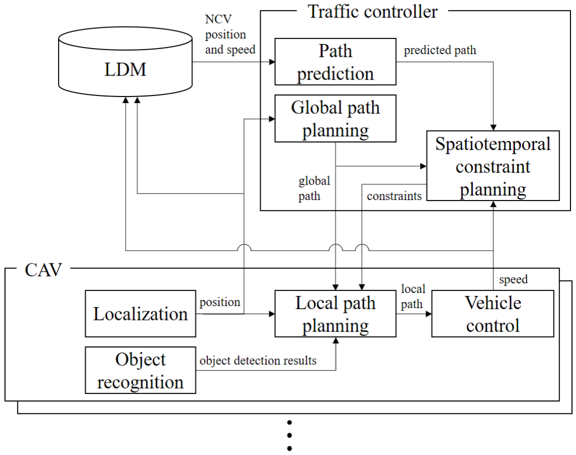

Fig. 2. Architecture of CIM system.

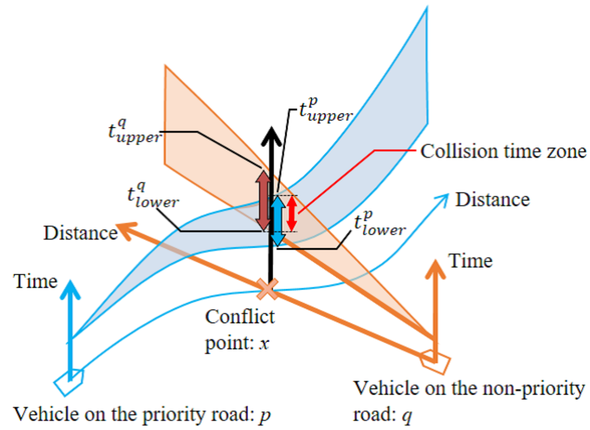

Fig. 3. Spatiotemporal constraint schematics [4]. Copyright(C)2021 IEICE.

not contain the following information needed to control the vehicle: timestamp, speed, and curvature at each waypoint. The local path planner computes this missing information for vehicle control as a local path.

A. Traffic Controller

The traffic controller generates spatiotemporal constraints at potential conflict points that facilitate efficient traffic control between the related vehicles by using the following submodules: path prediction, global path planning, and spatiotemporal constraint planning.

1) Path prediction for NCVs: When the system is in operation, the traffic controller assumes that NCVs travel on the centerline of the vector map along a predicted path, which is a sequence of waypoints that start from the waypoint closest to the NCV's current position on the vector map. Those waypoints extend ahead of the vehicle in the lane's travel direction and end at the waypoint whose cumulative distance exceeds L_{prd}, which is the predicted path length. L_{prd} is calculated by the following equation:

$$L_{prd} = v_{ncv} T_{prd}, \tag{1}$$

where v_{ncv} is the NCV speed and T_{prd} is the prediction time. When a branch is identified during pathfinding, a predicted path is generated for each branch destination.

2) Global path planning for CAVs: Once given a destination, the traffic controller generates a global path for a CAV based on the vector map waypoints. As in the NVC path prediction, the waypoint closest to the measured CAV current position is used as the start position. Global paths are planned and distributed to all CAVs with goals set.

3) Spatiotemporal constraint planning for CAVs: Spatiotemporal constraints are time-limited entry prohibitions that apply only to specified CAVs under traffic control guidance. Here, the generation of spatiotemporal constraints is formulated as the problem of determining the priorities of vehicles passing through a conflict point. Next, the method of generating spatiotemporal constraints for multiple conflict points and vehicles is explained. A schematic of the proposed method is shown in Fig 3. In order for a priority vehicle to proceed through a conflict point safely without being affected by a non-priority vehicle, the non-priority vehicle must be prevented from entering the intersection at the time the priority vehicle passes through it. When the travel paths of two vehicles p and q intersect at a conflict point x, the s_x state at the conflict point x is

$$s_x \in \{0 : \text{vehicle } p \text{ has priority}, \\ 1 : \text{vehicle } q \text{ has priority}\}. \tag{2}$$

Here, the vehicle traveling on the priority road is referred to as p, and the vehicle traveling on the non-priority road is referred to as q.

The time $\boldsymbol{t}$ when the vehicle is expected to pass through the conflict point x is given by Eq. (3), by considering the predictive vehicle behavior uncertainties and potential vehicle position measurement errors.

$$\boldsymbol{t} = [t_{lower}, t_{upper}) \tag{3}$$

where t_{lower} and t_{upper} are the earliest and latest times the vehicle will pass the conflict point, respectively. When calculating t_{lower}, it is assumed that the vehicle would accelerate from its current position and then travel at a constant speed. Similarly, when calculating t_{upper}, it is assumed that the vehicle travels at a constant speed after decelerating from the current position.

To find the spatiotemporal constraints at the multiple conflict points, it is first necessary to find the $\boldsymbol{S} = (s_1, s_2, ..., s_N)$ state of the N conflict points that minimize the objective function $C(\boldsymbol{S})$.

$$\begin{aligned} C(\boldsymbol{S}) \;=\; & \omega_{\text{time}} C_{\text{time}}(\boldsymbol{S}) + \omega_{\text{dist}} C_{\text{dist}}(\boldsymbol{S}) \\ & + \omega_{\text{type}} C_{\text{type}}(\boldsymbol{S}) + \omega_{\text{cons}} C_{\text{cons}}(\boldsymbol{S}) \\ & + \omega_{\text{rule}} C_{\text{rule}}(\boldsymbol{S}) + \omega_{coord} C_{coord}(\boldsymbol{S}) \end{aligned} \tag{4}$$

where ω_{time}, ω_{dist}, ω_{type}, ω_{cons}, ω_{rule}, and ω_{coord} are positive constants that refer to the weight of each cost. Each cost function is represented by the following equation:

$$C_{\mathrm{time}}(\boldsymbol{S}) = \sum_{i=1}^{N} C_{\mathrm{time}}(s_i; \boldsymbol{t}^p, \boldsymbol{t}^q), \quad (5)$$

$$C_{\mathrm{dist}}(\boldsymbol{S}) = \sum_{i=1}^{N} C_{\mathrm{dist}}(s_i; d^p, d^q), \quad (6)$$

$$C_{\mathrm{type}}(\boldsymbol{S}) = \sum_{i=1}^{N} C_{\mathrm{type}}(s_i; \varphi^p, \varphi^q), \quad (7)$$

$$C_{\mathrm{cons}}(\boldsymbol{S}) = \sum_{i=1}^{N} C_{\mathrm{cons}}(s_i^{(T)}, s_i^{(T-1)}), \quad (8)$$

$$C_{\mathrm{rule}}(\boldsymbol{S}) = \sum_{i=1}^{N} C_{\mathrm{rule}}(s_i), \quad (9)$$

$$C_{\mathrm{coord}}(\boldsymbol{S}) = \sum_{i=1}^{N} \sum_{j=i+1}^{N-i} C_{\mathrm{coord}}(s_i, s_j) \quad (10)$$

where $\boldsymbol{t}^p$ and $\boldsymbol{t}^q$ are the expected passage time of the vehicle p, q, $s_i^{(T)}$ is state of the i-th conflict point at time T, d is distance from conflict point to the vehicle, and φ is the vehicle type (CAV or NCV).

$C_{\mathrm{time}}(\boldsymbol{S})$, $C_{\mathrm{dist}}(\boldsymbol{S})$ are the cost for the priority passage of vehicle q on a non-priority road. $C_{\mathrm{time}}(\boldsymbol{S})$ allows vehicle q to pass first when the interference between the expected passing times of the two vehicles is short and there is a high probability that vehicle q will pass the conflict point before vehicle p arrives. $C_{\mathrm{dist}}(\boldsymbol{S})$ prevents vehicle q from stopping near the conflict point and instructs it to pass through the conflict point when vehicle q reaches the near side of conflict point before vehicle p. $C_{\mathrm{type}}(\boldsymbol{S})$ is the cost associated with the vehicle type, which allows an NCV to pass before a CAV. $C_{\mathrm{cons}}(\boldsymbol{S})$ is the cost related to consistency in the time direction, which suppresses the frequent state switching between priority and non-priority at the conflict points. $C_{\mathrm{rule}}(\boldsymbol{S})$ is the cost related to the lane priority, which directs vehicle p on the priority road to pass first. $C_{\mathrm{coord}}(\boldsymbol{S})$ is the cost of coordinating the states of neighboring conflict points, which encourages the neighboring conflict points to be in the same state. $C_{\mathrm{coord}}(\boldsymbol{S})$ is a further addition to $C(\boldsymbol{S})$ in our earlier study [4] in order to allow CAVs to pass through an intersection consisting of multiple lanes.

By finding the $\boldsymbol{S}$ that minimizes the objective function, it can be determined whether vehicle p or q should be given priority. The traffic controller prohibits non-priority vehicles from entering the conflict point during the time when the priority vehicle is expected to pass through that point.

B. CAVs

As stated above, each CAV receives a global path and spatiotemporal constraints from the traffic controller, and then performs local path planning to avoid collisions. A local path consists of a curvature path and a speed profile that satisfies the spatiotemporal constraints and the regulatory information (*e.g.*, speed limit) obtained from the vector map.

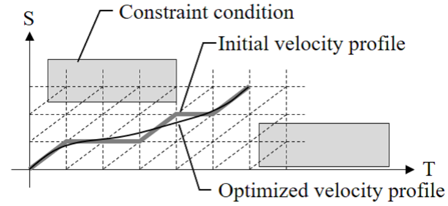

Fig. 4. Speed planning schematics. Copyright (C)2021 IEICE.

The curvature path, which is computed based on the global path, is computed in a manner that ensures the CAV can follow it smoothly. The speed profile is determined through dynamic programming and optimization calculations that satisfy the spatiotemporal constraints and regulatory information in the T-S coordinate system based on time T and the distance S along the curvature path (Fig.4).

IV. EXPERIMENTS

The following simulation experiments were conducted to confirm that the proposed method achieves both efficient and robust operation at an intersection without signal lights.

Experiment 1:
To verify the resulting traffic efficiency under conditions of predictive uncertainty without NCV position errors, we measured the passage throughput, travel time, and congestion lengths of NCVs during the CAV's intersection passage.

Experiment 2:
To investigate the effect of NCV position measurement errors on the proposed method, we evaluated the CAV travel times in relation to the NCV position errors.

A. Evaluation Environment

We conducted a simulation in which CAVs passed through an intersection without signal lights, where priority and non-priority roads intersect (Fig. 5). Each road has one lane in each direction. NCVs travel in each lane of the priority roads according to the pre-set traffic volumes, while CAVs repeatedly travel one-by-one between start point S and goal point G in one lane of the non-priority road. The speed limit for the CAVs was set at 22 [km/h].

B. NCVs

Since it is assumed that there are no interactions between the NCVs and CAVs, NCV driving data is generated in advance using the Vissim ver. 2020 [13] traffic simulator and then sent to the traffic controller for use as LDM data. Vissim parameters are shown in Table I.

The NCVs travel on each lane according to predetermined traffic volumes (100, 200, 300, 400, 500, and 600 vehicles per hour). Figure 6 shows the case of 500 vehicles per hour recorded over a one-hour period. To simulate NCV predictive uncertainty, the speed limit was varied from 18 to 20 [km/h]

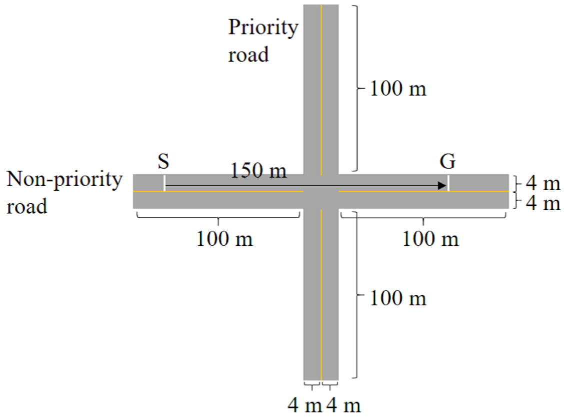

Fig. 5. Intersection environment.

TABLE I
VISSIM PARAMETERS

Parameters	Setting
Priority road vehicle speed limit	18-22 [km/h]
Number of vehicles in one priority lane per hour	100-600
Recorded time	1 [hour]

for each vehicle, and the NCVs were set to accelerate and decelerate while traveling.

The NCVs travel according to the Wiedemann 99 driver behavior model with Vissim parameters set as the defaults. NCV lengths were selected based on the probabilities shown in Table II, after which the simulation results were converted to the Robot Operating System (ROS) [14] file format, *i.e.* rosbag file, and used as traffic controller input. Realtime simulation for CAV was conducted using this bag file. The details are presented in the next section.

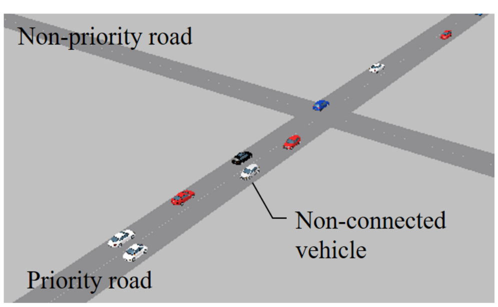

Fig. 6. Example of traveling NCVs in one lane at 500 vehicles per hour.

TABLE II
NCV OCCURRENCE RATIO

Vehicle length [m]	3.75	4.01	4.21	4.36	4.61	4.64	4.76
Occurrence ratio	0.1	0.14	0.24	0.02	0.18	0.16	0.16

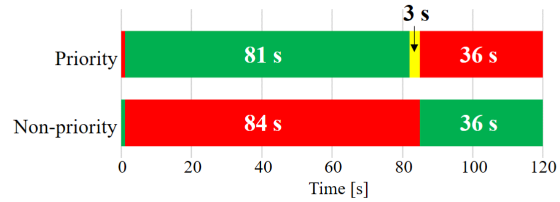

Fig. 7. Traffic signal settings.

C. CAVs and Traffic controller

The control system of CAV and the traffic controller were implemented in the ROS and each module has a common vector map that was composed via Lanelet2[a] [15] . The traffic controller receives the NCV driving data recorded in the bag file as input from the LDM.

Each CAV is configured to travel from point S to point G. When a CAV reaches point G, the next CAV starts traveling from point S. Spatiotemporal constraints and the global path are sent from the traffic controller to the CAVs at 10 Hz and 2 Hz, respectively.

The optimal $\boldsymbol{S}$ is obtained by a brute-force method, which enumerates all possible combinations of s_x and evaluates them all. In this method, it costs 2^N of time for this evaluation where N is the number of conflict points. However, the maximum N in this experiment was 8, which is within the range that can be calculated in a realistic time.

In the traffic controller, the prediction time T_{prd} in the Eq. (1) was set to 10 [sec]. The weight coefficients of Eq. (4), which are ω_{time}, ω_{dist}, ω_{type}, ω_{cons}, ω_{rule}, and ω_{coord}, were set to 1000, 1000, 10, 100, 1, and 10000, respectively.

D. Comparison with intersections with traffic signal lights

We also simulated traffic control at intersections with traffic signal lights for comparison with the proposed method. In this comparison, referring to [12], we generated driving NCV data according to the 120-second signal cycle shown in Fig.7. Note that the yellow signal is not applied to CAVs in this study.

V. RESULTS

A. Travel efficiency

In this experiment, we found that CAVs were able to pass through the intersection without collisions regardless of the preset traffic volumes. Figure 8, which shows the number of transited CAVs, demonstrates that the CAV throughput of the proposed method is higher than that of the traffic signals at volumes up to 400 vehicles per hour, while Figure 9 shows that the median travel time of the proposed method is shorter than that for intersections with traffic signal lights at volumes up to 400 vehicles per hour. These results show that the proposed method improves traffic efficiency in conditions of up to 400 vehicles per hour on the priority road when compared to intersections with traffic signal lights.

[a]A C++ handling map data library compiled for use in automated driving applications.

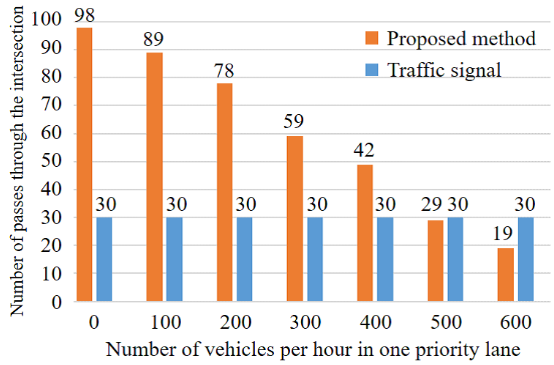

Fig. 8. The number of times the CAV passed through the intersection.

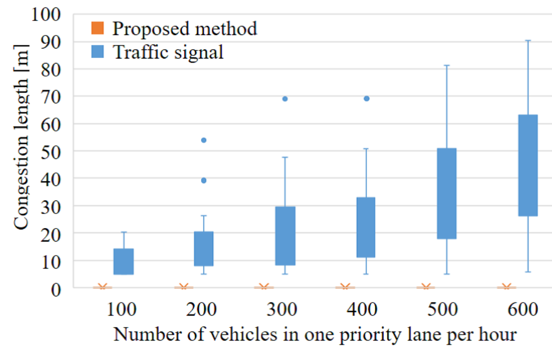

Fig. 10. NCV congestion lengths.

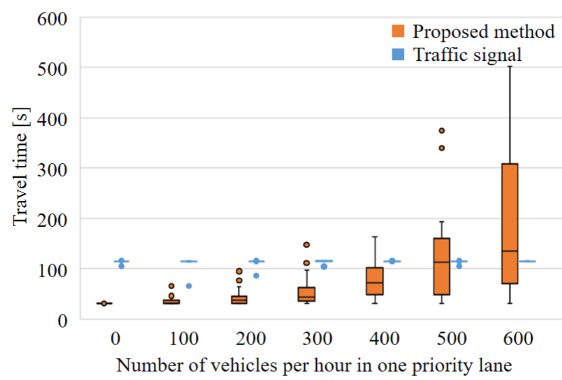

Fig. 9. Elapsed CAV travel time(s) from the starting point to the goal

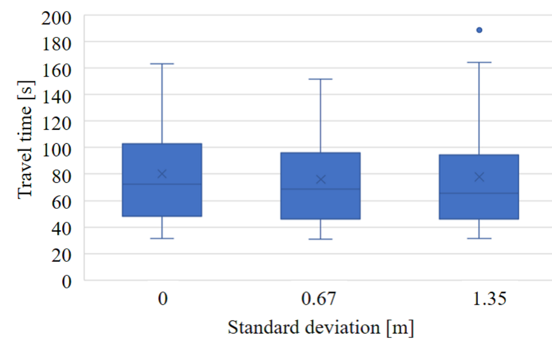

Fig. 11. NCV position error robustness.

Next, we compared traffic efficiency of NCVs for both the proposed method and the traffic signal. Traffic efficiency is evaluated by measuring the congestion length defined as the length of the NCV queue stopped by a red signal that is waiting for the signal to turn green. Figure 10 shows NCV congestion lengths in relation to NCV traffic volumes. It is clear that the congestion length of the proposed method is zero since NCVs are not stopped by the traffic controller. In contrast, the traffic signal makes congestion and larger traffic volume results in longer congestion length. The results shows that the proposed method achives higher traffic efficiency than the traffic signal for both CAVs and NCVs when traffic volume are less or equal than 400 vehicles per hour.

B. NCV position error robustness

Since NCV position is estimated by the LDM, it should be necessary for the proposed method to confirm robustness against position error of NCV. We evaluated travel time of CAV to confirm smoothness of the traffic at the intersection because the position error may affect decisions of the traffic controller and traffic smoothness can be suffered by unstable decisions. NCV positions from Vissim are modified by adding position error, which follows a normal distribution and whose standard deviations (SDs) are σ = 0.0, 0.65, and 1.35 [m]. It should be noted that 1.35 [m] in SD means that 95% of the position errors are within 2.7 [m] equevalent to the position error of the LDM [4].

The simulation results are shown in Fig.11 where it can be seen that there were no significant changes in CAV travel time even when the SD increased. The results shows that position error doesn't affect traffic smoothness in the proposed method bacause both $C_{\text{cons}}(\boldsymbol{S})$ and $C_{\text{coord}}(\boldsymbol{S})$ in traffic controller suppress unnecessary decision changes.

VI. CONCLUSION

In this paper, we proposed the traffic control system with CIM adapted to general intersections. Numerical experiments showed that the proposed method is more efficient than traffic signals for facilitating CAV passage through an intersection in conditions of up to 400 vehicles per hour on the priority road. In addition, we found that the proposed method was robust to the NCV measurement position errors.

In this study, a simple intersection passage was used as an example for verification, and more case studies will be added in the future to show the validity of the proposed method. For example, verification of the case where there is interaction between CAV and NCV, or the trade-off between safety and efficiency due to the predicted range of time $\boldsymbol{t}$. It is hoped that the results of this study will help traffic managers and urban planners cope with traffic situations in which CAVs and NCVs must travel together in multi-intersection road networks.

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