Congestion Control Algorithms for Collective Perception in Vehicular Networks

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Invited Paper

Congestion Control Algorithms for Collective Perception in Vehicular Networks

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Abstract: By exchanging information on objects on the road detected by in-vehicle sensors through inter-vehicle communication, vehicles can detect objects that cannot be detected directly by their own sensors. This enables the connected vehicles (CVs) to provide more appropriate safe driving support and automatic driving even in the environment where connected and non-connected vehicles are mixed. Such a system is called a Collective Perception System, and has been actively researched in recent years. However, if individual CVs simply transmit information on the objects they have detected frequently, the wireless communication channel will be congested, and the data originally intended to be sent will not reach the destination, making it difficult for each vehicle to detect other objects quickly. Therefore, appropriate congestion control technology for sensor information transmission is necessary. This paper introduces recent techniques for congestion control in the transmission of vehicle and sensor information in inter-vehicle communication. In addition, we introduce a congestion control technique we have designed based on the relative positions of vehicles.

Keywords: vehicular networks, ITS, collective perceptions, decentralized congestion control, IEEE802.11p

1. Introduction

With Vehicle-to-vehicle (V2V) communication, vehicles exchanges beacon messages (called Basic Safety Message (BSM) or Cooperative Awareness Message (CAM)), including the information of the sender, such as their position, speed, and direction of travel via direct wireless communication links between vehicles. Thus they can recognize the existence of other vehicles. However, this mechanism can work effectively only when a sufficient number of vehicles on the road have the V2V communication function. Sharing not only the information of CVs themselves but information on surrounding conditions will solve the problem.

Today, the development of Advanced Driver Assistance System (ADAS) technology is underway to enable vehicles to assess the surrounding traffic conditions using their onboard sensors accurately, warn the driver, and control the vehicle on behalf of the driver to avoid collisions with approaching objects. Vehicles equipped with ADAS functions acquire positional information on surrounding objects, i.e., other vehicles, pedestrians, etc., from sensors such as LiDAR (Light Detection and Ranging), millimeter-wave radar, and stereo cameras, provide driving assistance to the driver. Much work on 3D object detection methods for autonomous driving applications is summarized in Ref. [1], which presents the potential of cooperative perception to improve the vehicle's perception beyond the sensor's range and obstacles.

The standardization of Collective Perception, in which a communicating vehicle shares with other communicating vehicles information on vehicles detected by its onboard sensors, in addition to information on its position, speed, and direction of travel, is underway by ETSI [2] and SAE [3]. **Figure 1** presents the overview of collective perception and definitions of terminologies used in this paper. Collective perception makes it possible for connected vehicles (CV) to identify surrounding vehicles even if CVs and non-connected vehicles (NCVs) coexist on the road. Suppose an NCVis in a blind spot of a remote CV as shown in Fig. 1. In that case, the CV can detect the NCV by receiving a Collective Perception Message (CPM), including the information about detected objects (vehicles, pedestrians, and other objects on the road) based on sensor data from other remote CVs. In Fig. 1 ego vehicle can detect NCV Z by receiving a CPM from CV Y. However, the size of messages carrying sensor data can be larger than that of general beacon messages that include only the sender CV's information (BSM/CAM). Thus, when the density of vehicles in an area is high and the message transmission rate is high, the radio communication channel for V2V communication will be congested, and necessary information may not be delivered to surrounding vehicles. In addition, multiple CVs may detect the same object and broadcast CPMs containing information about

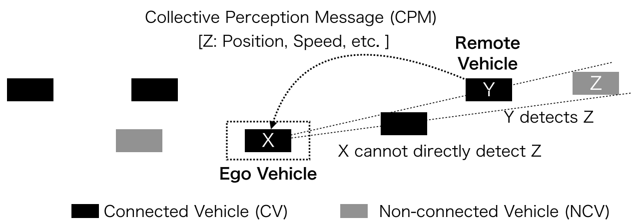

Fig. 1 Collective perception.

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the same object. Thus messages including redundant such information lead to channel congestion.

To tackle the congestion problem of V2V links, many researchers have been working on congestion control algorithms that contol the traffic caused by BSMs/CAMs and CPMs. This paper reviews decentralized V2V congestion control algorithms focusing on classic beacon messages (BSM/CAM) and collective perception messages (CPMs) in DSRC and ITS-G5 networks that works on IEEE802.11p [4]/ETSI ITS-G5 CSMA/CA-based MAC and also introduces our recent work on congestion control based on the relative position of vehicles. Though 3GPP defined a framework for access-layer congestion control, e.g., packet dropping, MCS adaptation, in Ref. [5], this is out of the scope of this paper.

The remainder of this paper is organized as follows. In Section 2, we firstly introduce the state of the art of standardization of V2X congestion control algorithms, ETSI DCC and SAE DCC. Section 3 introduces congestion control algorithms for collective perception, including our relative position-based congestion control algrorithm (RRP). Section 4 describes the detail of the RRP. Finally, Section 5 concludes this paper.

2. Standardized Congestion Control Methods

2.1 ETSI DCC

2.1.1 Architecture

ETSI decentralized congestion control (DCC) architecture consists of multiple components; i) DCC_ACC located in the access layer, ii) DCC_NET located in the networking & transport layer, iii) FCC_FAC located in the facilities layer, and iv) DCC_CROSS located in the management layer that covers access, networking & transport layer, and facilities layer. DCC_ACC specified in Ref. [6] is the core component that directly controls parameters that affect the channel congestion. The DCC_ACC uses the local channel busy ratio (CBR) as the input to evaluate the congestion level of the channel. CBR is calculated as follows:

$$\mathrm{CBR} = \frac{T_{\mathrm{busy}}}{T_{\mathrm{CBR}}} \tag{1}$$

T_{CBR} is 100 msec. T_{busy} is the period of time when the strength of the received signal overs a period T_{CBR} exceeds −95 dBm.

Based on the congestion level evaluated using CBR, DCC_ACC controls one or several techniques in the following.

Transmit power control (TPC) alters the transmission power to adjust the channel load. Low output power reduces the channel load, but CVs further away are hard to receive the transmitted messages.

Transmit rate control (TRC) regulates T_{off}, the time between two consecutive packets from a CV. By using a lower transmission rate, T_{off} becomes longer, and the channel load is mitigated.

Transmit datarate control (TDC) configures the modulation and coding scheme (MCS) to control the datarate. With a high datarate, the air time of a packet T_{on} becomes short, and channel congestion is mitigated. However, CVs far away from a packet sender CV are hard to receive the packet.

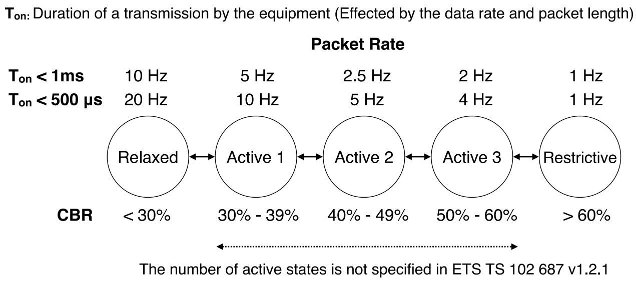

Fig. 2 ETSI DCC reactive algorithm.

In the earlier version of DCC_ACC [7], two control techniques, i) DCC sensitivity control and ii) Transmit access control, are included. However, they are removed in the new version. Though specification of DCC_ACC [6] does not specify the detail of each technique, possible parameters to control T_{on} and T_{off} that are configured through TRC and TDC are introduced in the document.

Reference [6] specifies either of the following two algorithms shall be implemented; i) Reactive algorithm, and ii) Adaptive algorithm. The latter is introduced in the new version.

2.1.2 Reactive Algorithm

The reactive algorithm consists of several states corresponding to the current CBR. Every T_{CBR}, CBR is evaluated, and one state is reached according to the CBR. One state can be reached by a neighboring state. Depending on the current state, the congestion level is controlled by using one or several techniques presented before. **Figure 2** presents an example of the states and possible parameters introduced in Ref. [6].

2.1.3 Adaptive Algorithm

Adaptive algorithm is based on LIMERIC, a linear adaptive control algorithm proposed by Bansal et al. in Ref. [8]. In this algorithm, each CV updates a smoothed CBR value, u_s, when UTC time modulo 200 msec. is zero using the following equation.

$$u_s = 0.5 \cdot u_s + 0.5 \cdot (u(k) + u(k-1))/2, \tag{2}$$

where $u(k)$ and $u(k-1)$ stand for the two recent local measurement values of CBR. Then, based on the difference between the target CBR (= u_{target}) and u_s, δ_{offset} is calculated, and the maximum fraction of time that the CV is allowed to transmit on the channel, δ, is calculated.

$$\delta_{\mathrm{offset}} = \begin{cases} \min(\beta \cdot (u_{\mathrm{target}} - u_s), G^{+}_{\max}) & (u_{\mathrm{target}} > u_s) \\ \max(\beta \cdot (u_{\mathrm{target}} - u_s), G^{-}_{\max}) & (u_{\mathrm{target}} \leq u_s) \end{cases} \tag{3}$$

$$\delta = \min(\max((1-\alpha) \cdot \delta + \delta_{\mathrm{offset}}, \delta_{\min}), \delta_{\max}) \tag{4}$$

Table 1 shows the basic parameter setting of the adaptive algorithm. To satisfy the δ channel occupancy limit, DCC_ACC implements a gate-keeping function at the MAC layer. The gate is closed when the access layer cannot accept a packet due to δ value.

Reference [9] surveys existing methods and algorithms for congestion mitigation foucusing on ETSI DCC and its variants.

2.2 SAE DCC

SAE J2945/1 specifies the congestion control mechanism for DSRC [10]. The SAE DCC controls the transmission of BSMs

Table 1 Parameter values of adaptive algorithm

Parameter	Value
α	0.016
β	0.0012
u_{target}	0.68
$\delta_{\max}$	0.03
$\delta_{\min}$	0.0006
$G^{+}_{\max}$	0.0005
$G^{-}_{\max}$	−0.00025
T_{CBR}	100 msec.

by means of the message rate, transmission timing of additional messages sent so that other CVs can correctly track the position of the ego CV in case of significant vehicle dynamics (e.g., lane change, acceleration, deceleration), and transmission power. Multiple metrics, Vehicle Density in Range, Channel Busy Percentage (CBP), and Packet Error Ratio (PER), are used as inputs of the DCC algorithm.

Vehicle Density in Range is used to control the message rate. Each vehicle periodically measures the number of CVs, $N(k)$, in the range of 100 m based on the number of unique CV IDs at the end of each 1,000 ms-interval k. Then the smoothed number of vehicles $N_s(k)$ is calculated as follows:

$$N_s(k) = \lambda_{\text{N}} \cdot N(k) + (1 - \lambda_{\text{N}}) \cdot (N_s(k-1)), \tag{5}$$

where $\lambda_{\text{N}} = 0.05$ is the weight factor. Then the system calculates the message generation interval T as follows:

$$T = \begin{cases} T_{\min} & (N_s(k) \leq B) \\ T_{\min} \cdot N_s(k)/B & (B < N_s(k) < BT_{\max}/T_{\min}) \\ T_{\max} & (BT_{\max}/T_{\min} \leq N_s(k)) \end{cases}, \tag{6}$$

where $B = 25$ is the density co-efficient, and $T_{\max}$ and $T_{\min}$ are 600 msec. and 100 msec., respectively.

CBP is used for transmission power control. Each CV measures the current CBP, $U(k)$% every 100 msec. Then calculates the smoothed CBP, $U_s(k)$ as follows:

$$U_s(k) = \lambda_{\text{U}} U(k) + (1 - \lambda_{\text{U}}) U_s(k-1), \tag{7}$$

where $\lambda_{\text{U}} = 0.5$ is the weight factor. Then the CV calculates its transmission power $P(k+1)$ as follows:

$$P'(k) = \begin{cases} P_{\max} & (U_s(k) < U_{\min}) \\ P_{\max} - (U_s(k) - U_{\min}) \frac{P_{\max} - P_{\min}}{U_{\max} - U_{\min}} & (U_{\min} < U_s(k) < U_{\max}) \\ P_{\min} & (U_{\max} \leq U_s(k)) \end{cases}, \tag{8}$$

$$P(k+1) = P(k) + \lambda_{\text{P}}(P'(k) - P(k)), \tag{9}$$

where $P_{\max} = 20$ dBm, $P_{\min} = 10$ dBm, $U_{\max} = 80\%$, $U_{\min} = 50\%$, and $\lambda_{\text{P}} = 0.5$.

PER is used to determine the timing of additional messages transmitted so that the surrounding CVs can accurately track the dynamics of the ego CV. Each CV measures PER $E_i(k)$ for each of the other CVs in the range of 100 m every 1 s. $E_i(k)$ is calculated as the ratio of the number of missed BSMs from CV i and the expected number of BSMs from i during the last 5 s., which is calculated from DE_MsgCount in the last and first BSMs received from i in the period. Then, each CV calculates Channel Quality Indicator ($\Pi(k)$) as follows:

$$\Pi(k) = \min\left(\Pi_{\max}, \sum_{i \in \mathbf{N}} \frac{E_{i(k)}}{|\mathbf{N}|}\right), \tag{10}$$

where $\mathbf{N}$ is the set of CVs in range of 100 m and $\Pi_{\max} = 0.3$. By using $\Pi(k)$, the ego CV estimates the 2D position tracking error e at CVs in $\mathbf{N}$ every 100 msec. Then it calculates the probability of message transmission on dynamics p as follows:

$$p = \begin{cases} 1 - \exp\left(-\alpha|e - T|^2\right) & (T \leq e \leq S) \\ 1 & (e \geq S) \\ 0 & (\text{otherwise}) \end{cases}, \tag{11}$$

where $T = 0.2$ m, $\alpha = 75$, and $S = 0.5$ m.

In Ref. [11], the authors evaluate the performance of SAC DCC in IEEE802.11p DSRC and LTE-V2X PC5 mode 4.

3. Congestion Control for Collective Perception

3.1 ETSI Collective Perception Message Generation Rule

ETSI is currently in the process of standardizing the Collective Perception Service (CPS). Based on mainly on the earlier work by Günther et al. [12], [13], [14], ETSI released technical report 103 562 [2], [15], which includes a proposal of collective perception message (CPM) format and the message generation rule. Since an object on the road can be detected by multiple CVs, redundant CPMs that include information about the same object may be generated without any countermeasures. Also, clearly frequent message generation about stable objects will waste the channel capacity. Thus, designing an effective CPM generation rule is important.

In the ETSI generation rule, each vehicle attempts transmission of a CPM periodically. For every $T_{\text{Gen}_\text{C}\text{PM}}$, the minimum time duration between two consecutive message generation attempts, each vehicle selects which object information is included in a CPM. The range of the value of $T_{\text{Gen}_\text{C}\text{PM}}$ is between 0.1 sec. and 1 sec. and may be set by DCC or other entities of the communication. The information about an object detected by onboard sensors of the ego vehicle is included in a CPM when at least one of the following conditions are satisfied.

Novelty The object has not been selected for transmission before.

Distance The object has moved more than 4 m from the position of the object included in a CPM.

Speed The object's speed has changed by more than 0.5 m/s from the last speed value of the object included in a CPM.

Age The object has not been included in a CPM for more than 1 s.

The threshold values of the distance, speed and age are derived from the cooperative awareness (CA) service [16].

References [2] and [15] reports simulation study results of the generation rule in two scenarios, i) the Luxembourg SUMO Traffic (LuST) scenario [17] and ii) Spider scenario, which consists of 20 concentric circular two-lane roads evenly spaced at 50 m with each lane being occupied with opposing traffic, using Artery V2X simulation framework [18], which supports ETSI ITS-G5 protocols, CAMs [16], and Decentralized Notification (DENMs) [19] and uses SUMO [20].

3.2 Improvement of ETSI CPM Generation Rules

Some improvemnet methods for ETSI CPM generation rule have been proposed. Thandavarayan et al. have conducted a simulation evaluation of the impact of different CPM transmission strategies on channel load and situation awareness [21]. Their results showed that CPMs tend to be sent at a high transmission rate (10 Hz) even when the transmitter is configured to be adaptive in its message generation frequency due to dynamically changing conditions. The same authors propose an extension to the ETSI CPM generation rule [22]. In the extension, a vehicle includes additional objects in a CPM. Even if an object is not selected by the ETSI CPM generation rule, if it satisfies one of the following conditions, it is selected to be included in a CPM. Let v and a is the current speed and acceleration.

- The sum of the difference of the position of the object with regard to the last position included in a CPM and $vT_{\mathrm{Gen_CPM}} + 0.5aT_{\mathrm{Gen_CPM}}$ is larger than 4 m.
- The sum of the difference of the speed of the object with regard to the last speed included in a CPM and $aT_{\mathrm{Gen_CPM}}$ is larger than 0.5 m/s.
- The sum of the elapsed time from the last time the object was selected for transmission and $T_{\mathrm{Gen_CPM}}$ is larger than 1 s.

This extension is designed to avoid many CPMs containing small number of objects are transmitted.

Delooz et al. have proposed a similar extension to reduce the number of small CPMs [23]. In their extension, if an object is not selected to be included in a CPM according to the ETSI generation rule, it is selected if including the object in the CPM does not affect the frequency of sending CPMs. That is, if the size of the CPM size does not exceed the maximum packet length, even if additional object information is included, the information is included. One interesting feature of their work is that they evaluate the performance of the proposed extension using LIMERIC-based (adaptive approach) DCC introduced new ETSI DCC standard [6], while most of the other studies use the old reactive approach DCCdescribed in the old DCC standard [7].

Thandavarayan et al. propose another improvement for ETSI CPM generation rule [24], in which an object is not selected if the difference of the object's position, speed, or elapsed time with regard to the last CPM sent from other vehicles or the ego vehicle is less than a threshold. That is, if the information about the same object has been reported by other vehicles recently and the status difference is small, the object is not included in a new CPM. This will reduce messages containing redundant information about objects detected by multiple vehicles.

3.3 Other Approaches

3.3.1 Probability-based Method

Higuchi et al. have proposed a probability-based strategy to reduce redundant messages caused by multiple CVs that detects the same object [25]. In their method, when a CV generates a CPM, it anticipates the value of the information of a detected object for potential receivers based on the estimated history of the reception of CPMs. Their method uses the packet reception probability estimated from the number of CVs in proximity. Then the CV estimates the gain of knowledge that other CVs obtain from the new CPM containing the information of the object. If the gain is larger than the predefined threshold, it includes the information in a new CPM. The evaluation of their method is evaluated by using a simplified communication model, in which packet loss probability is given as a function of the density of CVs. Though their communication model is simplified and the correctness of the network performance seems insufficient, their approach opens a new direction of reduction of redundant CPMs.

3.3.2 Reinforcement Learning-based Approach

Aoki et al. have proposed a reinforcement learning-based strategy [26]. They have made a simulation environment that consists of SUMO traffic simulator [20], CARLA vehicle simulator [27], YOLO-based object classifier [28], V2X communication simulator, and a deep reinforcement learning-based cooperative perception simulator. By using this environment, they trained the Convolutional Neural Network in the system. The reinforcement learning consists of three main concepts, State, Action, Reward. The action space in their system is $\{Transmit, Discard\}$ the information of a detected object. Their reward model is designed so that CVs can reduce redundant CPMs. One binary reward included in the model becomes 1 when an object sent by the sender CV has not been detected by the receiver CV. Three penalties included in the system correspond to i) the number of recently received CPMs about the same object, ii) the elapsed time from the last time the receiver CV has detected the object by itself, and iii) the network congestion level.

3.3.3 Position-based Approach

Some methods leverage information of the positions of CVs and objects to control the traffic of CPMs [29], [30], [31]. Gani et al. propose a strategy to select objects included in CPM messages depending on the distance between the ego CV and the object. Their proposed method gives higher priority to objects that are farther away from the ego CV but closer to the edge of the local sensor's range [29]. This strategy is based on the idea that if a CV moving at the head of a group of vehicles transmits information about an object close to the edge of the sensor range, the follower CVs in the group will be able to know about the presence of the object farther away.

The vehicle density is used to control the transmission of CPMs in Ref. [30]. The authors develop an analytic model of collective perceptions that considers road geometry, CV penetration rate, and vehicular density. Based on the analysis with the model, they propose a method to control the probability of including an object in a CPM. For a case with very low CVs density, the method is highly likely to select objects included in a CPM to share more data. As the density increases, the method reduces the probability of selecting an object, but as the density increases further, it increases the probability to compensate for the heavy blockage effects.

In Ref. [31], we have proposed a method for controlling the frequency of beacon message transmissions based on the relative positions of a CV in its surrounding CVs and the road structure. In the next section, we introduce this method and present some simulation results. Hereafter, we refer to this method as *Relative Position-based Priority* (RRP) method.

3.3.4 RSU-based CP

So far, we have discussed methods that focus on the transmission of messages from vehicles. However, roadside units (RSU) can be used for collective perception. Since road objects can be observed by RSUs even no CVs are in the vicinity of the object, CPMs from RSU can improve the awareness of the object. Tsukada et al. propose Grid Proxy CAM [32]. Under Grid Proxy CAM, roadside sensors detect vehicles, and the information is gathered via a high-speed infrastructure network and broadcast from roadside transmitters. Reference [33] reports the effectiveness of using RSUs for collective perception through analytical and simulation studies. Garlichs et al. present that aggregating cooperative awareness information sent from vehicles at an RSU places at an intersection significantly improves the drivers' reaction time [34].

4. Relative Position-based Congetion Control Algorithm

In this section, we introduce the RRP method proposed in Ref. [31]. This method reduces traffic of CPMs by using a simple rule based on the relative position of a CV itself among its surrounding vehicles. In Ref. [31], the term, a beacon, was used to describe a CPM that contains information of a sender CV itself and detected objects. Thus, in the following, we use the same word. This method assigns a higher transmission frequency of beacons containing the information of both the sender CV itself and detected objects to CVs that have a wider field of view than other CVs and assigns lower transmission frequencies to other CVs. Each CV knows its relative position to the surrounding CVs and the road structure, such as a road merging point, calculates its priority for sending beacons based on its relative position, and increases or decreases the frequency of beacon transmissions according to the priority. In Ref. [31], we confirmed that vehicles can detect surrounding vehicles, including hidden ones due to occlusion, with a small amount of communication even in congested environments through simulations using a simplified vehicle mobility model, in which vehicles do not change the inter-vehicular distance and do not overtake. In the following, we introduce the overview of the method focusing on the method to determine the beacon transmission frequency based on the relative position of a CV in surrounding CVs and present detailed simulation results obtained with a realistic vehicle traffic simulator (SUMO) [20].

4.1 RRP Method

Figure 3 shows the detectable range of each vehicle's onboard sensors. In this figure, vehicles that send beacons at a high frequency are shown in blue. Most of the regions that a blue car can cover with its sensor cannot be seen by red cars because of occlusion. The view of each red car mostly covers the region covered by other red cars. By giving a high frequency of sending beacons containing detected objects (= CPMs) to the blue cars, the surrounding cars can obtain information on the blind spots of their

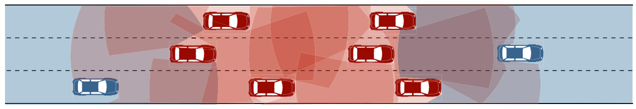

Fig. 3 RRP method - Control strategy.

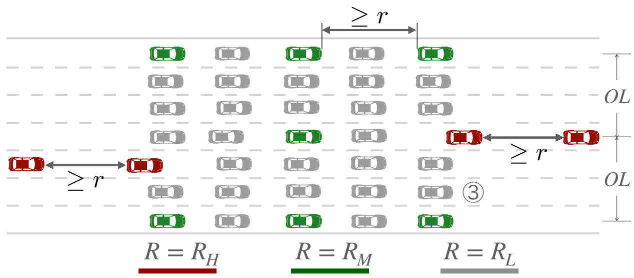

Fig. 4 Categorization of relative positions in a cluster.

sensors with high frequency even if red cars send their beacons at a low frequency. To realize this idea, we designed the RRP method.

In the RRP method, CVs behave as follows. Each CV estimates its relative position to its surrounding CVs. Based on the relative position, each CV obtains a priority of sending beacons at a high frequency, $R \in (0, 1]$. Then, it determines its beacon transmission interval based on R as Eq. (12)

$$I = \min\left(\frac{I_{\min}}{R \cdot S}, I_{\max}\right) \tag{12}$$

Here, $I_{\min}$, $I_{\max}$ are minimum and maximum transmission intervals, respectively. A CV with a high priority has a beacon transmission interval close to $I_{\min}$, resulting in a high beacon transmission frequency. On the other hand, a CV with a low priority has a beacon transmission interval close to $I_{\max}$ and a low beacon transmission frequency.

R is given according to the relative position of a CV to its surrounding CVs moving in the same direction. From now on, we refer to such a group of vehicles as a cluster. We assume both CVs and NCVs are in a cluster and they are moving on a multilane road. According to the relative position of a CV in a cluster, the CV is categorized into one of the following categories: H) Head/Tail, M) Head/Tail supporter or Middle supporter, L) others. **Figure 4** shows the overview of the categorization.

The rule of categorization is as follows. One of R_H, R_M, and R_L is given to each CV according to its category. Here, $1 > R_H > R_M > R_L > 0$. Let OL be the number of lanes corresponding to the lateral sensor range of CVs, and let r be the longitudinal sensor range. We also assume that beacon messages sent from each CV include at least the sender CV's location, lane ID, moving direction, and category (H, M, and L).

H) Head/Tail A CV that has no CVs in the same direction within r[m] of its front/rear. $R = R_L$.

M) Head/Tail supporter or Middle Supporter CVs at the head/tail of CVs in a lane that is OL apart from the lane where an H CV exists and CVs moving on a lane where an H or L CV exists and are r apart from the H or L CV. $R = R_M$.

L) Others Other CVs. $R = R_L$.

Figure 5 shows the transmission interval of the beacon for each

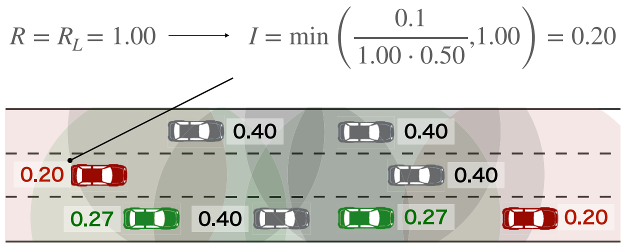

Fig. 5 Example of calculating beacon transmission interval.

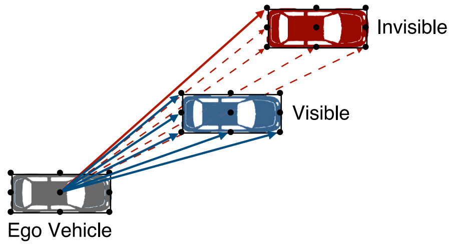

Fig. 6 Vehicle detection model in simulation.

Table 2 Setting values in Fig. 5.

r [m]	OL	$R_{\max}$	R_{mid}	$R_{\min}$	S	$I_{\min}$ [s]	$I_{\max}$ [s]
100	3	1.00	0.75	0.50	0.50	0.1	1.0

CV when each value is set as in **Table 2**. As shown in the figure, the transmission interval is longer for CVs that have much overlap of sensor range with other CVs. Also, CVs that have less sensor range overlap have short transmission intervals.

4.2 Simulation Model

We conducted the simulation of the RRP method using a vehicle behavior model created using the traffic flow simulator SUMO [20] and Scenargie wireless network simulator [35]. In Ref. [31], the vehicular mobility model was simplified; the relative positions between vehicles did not change during a scenario, and only single type vehicles were on the road. In this paper, we used a realistic vehicle mobility model; vehicles change their moving speed, overtaking happens, and two different types of vehicles (car and bus) are on the road.

Each CV updates the beacon transmission interval every 0.1 seconds. Before calculating the transmission interval, a CV evaluates its relative position according to the information it has recently received from other CVs. Then, it identifies its relative position in a cluster and updates its beacon transmission interval. The information received from other CVs is valid during Δt. Thus, even if some beacons are lost, a CV can update its relative position in a cluster using valid information it has recently received.

Each beacon message includes the beacon sender CV's location, ID, the relative position in a cluster (H, M, and L), beacon transmission time, and the ID and position of vehicles it has detected. We assume that CVs sense other vehicles every 0.1 seconds. IDs of other vehicles detected within the last 0.1 seconds before sending a beacon message are included in the message.

CVs are assumed to be equipped with a sensor capable of detecting the position of a vehicle within a 360-degree radius of 100 m. The sensor is capable of detecting a vehicle in a position where the sensor has a clear line of sight within the detectable range. Only if two or more of the vertices and the midpoints of each side of a rectangle representing a vehicle shape are in a line of sight, the vehicle is detected (**Fig. 6**). **Table 3**, **Table 4**, **Table 5**, and **Table 6** show detailed simulation parameters.

Table 3 Vehicle model configuration.

	Car	Bus
Max. Speed	100 km/h	80 km/h
Max. Acceleration	2.9 m/s	1.2 m/s
Max. Deceleration	7.5 m/s	4.0 m/s
Body Size	4.7 m × 1.7 m	12 m × 2.5 m
Antenna Height	1.5 m	3.8 m
Initnai Lane Prob.	0.2/0.2/0.2/0.2/0.2	0.4/0.3/0.2/0.07/0.03
Min. Distance between vehicles	2.5 m	

Table 4 Parameters of LC2013 lane change model.

lcStrategic	1.0
lcCooperative	1.0
lcSpeedGain	Car: 1.0, Bus: 0.6 to 1.0
lcKeepRight	1.0
lcOvertakeRight	0
lcOpposite	1.0
lcLookaheadLeft	2.0
lcSpeedGainRight	0.1
lcSpeedGainLookahead	0
lcAssertive	1
lcSigma	0.0

Table 5 Simulation parameters.

PHY / MAC	IEEE 802.11p at 5.9 GHz
Data rate	6 Mbps
Propagation model	free space
TX power	20 dBm
Preamble detection power threshold	−85 dBm
Carrier sense level	−65 dBm
Packet size	1,500 bytes
Detectable range	100 m
Detection interval	0.1 sec.
Simulation Setup time	100 sec.
Execution time	200 sec.
Execution count	50
Δt	0.1, 0.15, 0.2, and 0.5 sec.
Road	5 lanes/2,000 m (Only the second half section is monitored.)

Table 6 Configuration of RPP method.

OL	r	R_H	R_M	R_L	S	$I_{\min}$	$I_{\max}$
3	100 m	1.00	0.75	0.50	0.50	0.10 sec.	1 sec.

4.3 Simulation Results

We conducted simulations of RPP method and periodic beacon transmission (5 Hz and 10 Hz). We used *Awareness Ratio* as a performance metric. The awareness ratio is defined as the ratio of the number of vehicles recognized by communication and the ego CV's sensors to the number of vehicles existing within 300 m of the evaluation area per unit time. We measured the awareness ratio of each CV every 0.1 seconds. **Figure 7** shows the CDF of the awareness ratio with different densities of vehicles. It can be seen that in all scenarios, the awareness rate becomes large as the data validity period Δt increases. This is because the longer the validity period, the fewer chances the information of surrounding vehicles is discarded.

In a low-density scenario with only cars, more than 50% of all CVs achieve a high awareness ratio of 80% in all methods.

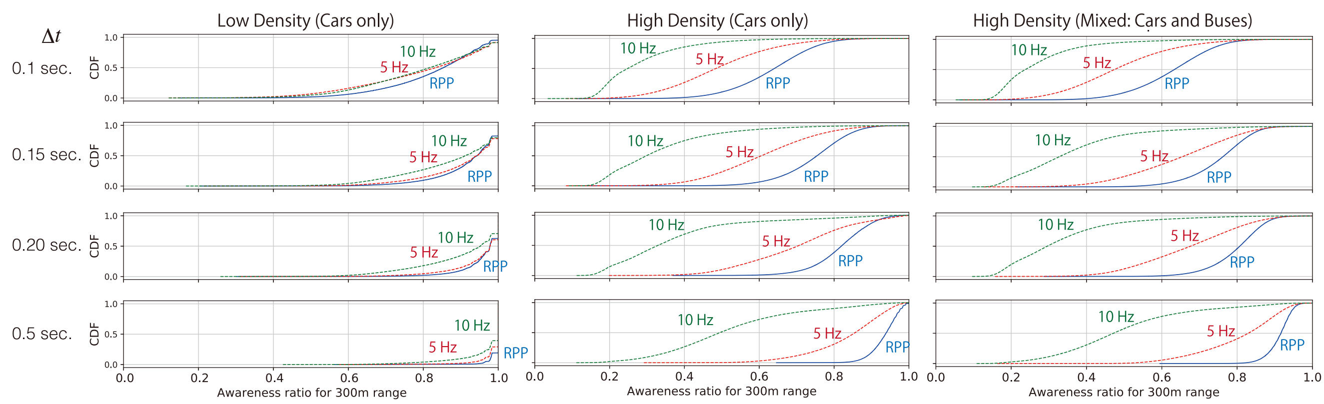

Fig. 7 CDF of awareness ratio.

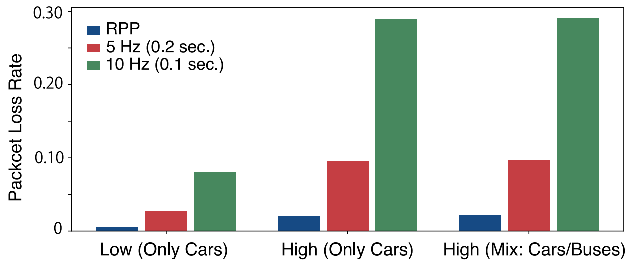

Fig. 8 Packet loss ratio.

The number of beacon transmissions and the packet loss rate are low for all the methods. RPP method has a higher awareness ratio with all Δt than periodic beacon cases. About 65.3% of the CVs recognize more than 80% of the surrounding vehicles even at $\Delta t = 0.1$ seconds.

In the high-density scenario with only cars, the awareness ratio of periodic beaconing cases severely becomes worse. With periodic beaconing of 5 Hz and 10 Hz, only about 20% and 70% CVs achieve the awareness ratio of 0.8 even at long Δt, respectively. On the other hand, RPP method achieves a higher awareness ratio. When Δt is 0.5 sec, about 100% CVs achieve an awareness ratio of 0.8 and much higher awareness ratios with shorter Δt compared with periodic beaconing.

The CDF of awareness ratio in the high-density scenario with cars and busses mixed scenario is similar to the car only high-density scenarios, though the awareness ratio in the mixed scenario is slightly worse than car-only scenario due to the increase of occlusions caused by a large body of busses. However, the impact of the existence of buses is smaller with RPP method than periodic beacon cases.

Figure 8 shows the packet loss rate. It is cleary observed that RPP method significantly decreases packet loss without decreasing the awareness ratio.

5. Conclusions

We introduced recent work on congestion control for cooperative awareness and cooperative perception systems and our work on congestion control in cooperative perception, RPP method. Under RPP method, CVs control the frequency of transmission of beacon messages containing detected objects based on their relative positions among neighboring vehicles. The core idea of the method can be combined with other strategies, such as the current ETSI CPM generation rule and its variants. Though cooperative awareness has already been standardized, the details of the congestion control are not specified in the standard and need further studies. The standardization of cooperative perception is underway in both ETSI and SAE. Further investigations focusing on both the efficiency in the wireless channel and the performance of applications depending on the exchanged detected object information are needed. Proposals on the control of transmission of detected objects in the application level tend to lack simulation with detailed V2X communication models, while studies using a detailed V2X communication simulation model tend to lack the analysis of redundant information from multiple CVs. Simulation studies that focus on both communication, DSRC and cellular V2X, and higher-level message redundancy will be needed.

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