IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received December 20, 2019, accepted January 6, 2020, date of publication January 10, 2020, date of current version January 22, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.2965552

Data Redundancy Mitigation in V2X Based Collective Perceptions

HUI HUANG[1], HUIYUN LI[1,2], (Member, IEEE), CUIPING SHAO[1], TIANFU SUN[1], (Member, IEEE), WENQI FANG[1], AND SHAOBO DANG[1]

[1]Automotive Electronics Research Center, Shenzhen Institute of Advanced Technology, Chinese Academy of Sciences, Shenzhen 518055, China
[2]Shenzhen College of Advanced Technology, University of Chinese Academy of Sciences, Shenzhen 518055, China

Corresponding author: Huiyun Li (hy.li@siat.ac.cn)

This work was supported in part by the National Natural Science Foundation of China (NSFC) under Grant 61672512 and Grant 51707191, in part by the Shenzhen S&T Funding under Grant JCYJ20160510154531467, Grant JCYJ20180507182628567, Grant JCYJ20170818164527303, and Grant JCYJ20180507182619669, in part by the CAS Key Laboratory of Human–Machine Intelligence-Synergy Systems, and in part by the Shenzhen Engineering Laboratory for Autonomous Driving Technology.

ABSTRACT Collective perception is a new paradigm to extend the limited horizon of individual vehicles. Incorporating with the recent vehicle-2-x (V2X) technology, connected and autonomous vehicles (CAVs) can periodically share their sensory information, given that traffic management authorities and other road participants can benefit from these information enormously. Apart from the benefits, employing collective perception could result in a certain level of transmission redundancy, because the same object might fall in the visible region of multiple CAVs, hence wasting the already scarce network resources. In this paper, we analytically study the data redundancy issue in highway scenarios, showing that the redundant transmissions could result in heavy loads on the network under medium to dense traffic. We then propose a probabilistic data selection scheme to suppress redundant transmissions. The scheme allows CAVs adaptively adjust the transmission probability of each tracked objects based on the position, vehicular density and road geometry information. Simulation results confirm that our approach can reduce at most 60% communication overhead in the meanwhile maintain the system reliability at desired levels.

INDEX TERMS Collective perception, connected and autonomous vehicles, V2X communications, data redundancy.

I. INTRODUCTION

Autonomous driving and advanced driving assistant systems (ADAS) in development rely on onboard sensors to build a local dynamic map of a vehicle's road environment [1]. However, these sensors naturally are only capable of detecting light-of-sight (LOS) road objects, therefore providing limited perception coverage especially in dense traffic, where the sensors' field of view (FoV) might suffer from heavy blockage effects resulting from other vehicles on the road [2].

With the introduction of vehicle-2-x (V2X) communications, the limited horizon of vehicles could be extended by V2X based collective perceptions (i.e. crowd sensing in other literatures) [3]. The term V2X incorporates multiple types of wireless technologies enabling V2I (vehicle-to-infrastructure), V2V (vehicle-to-vehicle), V2P (vehicle-to-pedestrian) and V2D (vehicle-to-device) communications [4]. In such a system, connected and autonomous vehicles (CAVs) collect real time information of the environment, and share it with other vehicles on the road.

Specifically speaking, V2X based collective perceptions could be further classified into V2I and V2V based. In the former case, vehicles periodically upload their sensory information to a remote traffic management centre (TMC) using V2I communications. On the other hand, V2V based collective perceptions allow vehicles directly exchange their sensory information by periodic broadcasting, enabling more timely usage of essential data [5]. In order to reduce communication overhead, CAVs only transmit the descriptions of their tracked objects instead of raw sensory data [6], [7].

A large body of works emerged in recent years show that V2X based collective perceptions have the potential to improve traffic safety and efficiency by supporting a rich set of vehicular applications, e.g., congestion avoidance, path

The associate editor coordinating the review of this manuscript and approving it for publication was Tie Qiu.

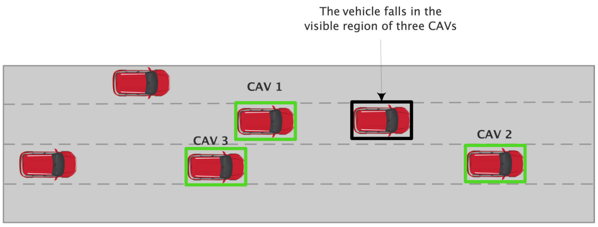


FIGURE 1. The data redundancy issue in V2X based collective perception.

planning and safety applications. However, a source of inefficiency of this new paradigm comes from the fact that the same object could be detected and tracked by several CAVs on the road, resulting in redundant data transmissions over the network. As illustrated in Fig. 1, the vehicle with black border can be tracked by three CAVs (e.g. CAV1, CAV2 and CAV3), and each CAV share the sensory information of their tracked objects with others by V2X communications. Since the sharing frequency for collective perception messages should be at least 5 to 10 Hz so that the vehicle velocity vector does not change too much between updates [3], without any coordinations, three observations for the same object will be frequently transmitted over the network. The increased load on the network could lead to increased transmission delay, which ultimately hurts the usability of collective perception messages. Thus, data redundancy mitigation is necessary to improve the efficiency and reliability of collective perceptions.

Eliminating data redundancy in the meanwhile maintaining the system reliability is a challenging task. Because a wide class of applications supported by V2X based collective perceptions are safety related, the sensory information from the network should provide high perception coverage over the road environment. An intuitive solution to the data redundancy issue in V2V based collective perception is to implement an overhearing mechanism. That is, a CAV should compare its tracked objects with the sensory information received from the network, and only broadcast these who have not been shared for a given interval. However, this method is unreliable because the packet reception rate in vehicular environment suffers from adverse multipath fading channels and collisions due to hidden terminals [8], [9], particularly when the density of vehicles is high and the communication traffic is relatively heavy. In addition, the data association among sensory information from multiple sources is still an open problem, especially when the raw sensory data is not available because of the limited wireless resources in V2X networks. The matching procedure involves complicated computations and time-consuming filtering due to different angles of observations and the inaccuracy of localisation equipments [10]–[12].

Indeed, the data redundancy issue has also been studied in the context of mobile ad hoc networks (MANETs) [13]–[15], these approaches do not map well to V2X based collective perceptions as they focus on multi-hop message dissemination in intermittently connected networks. It is also noticeable that a few recent works have been established to remove data redundancy in floating car data (FCD) collections and disseminations [16]–[18]. Their approaches create clusters of vehicles having common features and apply in-network aggregations to reduce communication overhead. Nevertheless, the applications supported by V2X based collective perception are safety related. Clustering based approaches do not fit because data aggregations will hurt the granularity of perception messages.

In this paper, we restrict our study in highway scenarios to address the data redundancy issue in V2X based collective perceptions. We first propose an analytic model of collective perceptions that takes road geometry, CAV penetration rate and vehicular density into consideration. Our analysis shows that even though highway scenarios do not suffer from blockage effects resulting from buildings, the blockages from other vehicles still have significant impacts on sensors' field of view, and it is insufficient to overcome this problem by increasing the sensing range. On the other hand, employing collective perception can greatly improve the perception coverage of vehicles even in the early stage of the market, however, with the price of heavy transmission redundancy; the expected number of redundant data transmissions could be as high as around 6.5 folds.

In order to relieve the data redundancy issue, we then propose a probabilistic data selection scheme that is suitable for both V2I and V2V based collective perceptions. The scheme does not require any coordinations between CAVs and allows them distributively determine the transmission probability of their tracked objects based the observed environments. The main challenge of designing such a scheme is to effectively reduce communication overhead in the meanwhile maintain the system reliability at the required level.

Our contributions could be summarised as follows:

- We build an analytic model to study the data redundancy issue and validate it through extensive simulations. The proposed model provides understanding of the benefits and limits of V2X based collective perceptions, as well as yield insights in how the application requirements could be possibly satisfied. To the best of our knowledge, this is the first attempt to analytically study the performance of V2X based collective perceptions in different traffic scenarios.
- We propose a novel data selection scheme, called p-consistence, which can balance the tradeoff between communication overhead and system reliability. The proposed scheme allows CAVs to adaptively change the transmission probability of their tracked objects based on the local vehicular density, CAV penetration rate and road geometry.
- We compare the performance of p-consistence against state-of-the-art using real maps and microscopic simulations. The results confirm that our algorithm reduces at most 60% communication overhead, while maintaining the system reliability at the required level.

The rest of the paper is organised as follows. In Section II and III, we discuss the related work and details the system model of V2X based collective perception. We then propose a comprehensive analytic model to study the data redundancy issue in Section IV, followed by the proposed redundancy control approach in Section V. Our analytic model and proposed scheme are validated and evaluated in Section VI by extensive simulations. Finally, we conclude our work in Section VII.

II. BACKGROUND AND RELATED WORKS

Sharing sensory information between network nodes has been an active topic of research in the field of wireless sensor networks (WSNs). For example, several nodes equipped with different types of sensors can exchange their sensory information to provide surveillance of large areas [19]. Due to the specific requirements and relatively static network topology, these approaches do not map well to vehicular applications. Instead of focusing on low energy consumption, the collective perception in road environments usually requires accurate position information and high update frequencies [7].

The work presented in [20] is the first attempt to exchange sensor information between vehicles, in which the CarSpeak is implemented enabling autonomous vehicles to share their 3D-point clouds. In this work, the raw sensory data is encoded by an octree scheme, and vehicles actively propagate their regional requests over the networks. Other vehicles can response the received requests to provide additional field of view that is invisible to the requestors. Similarly, the authors in [21] propose a multimodal cooperative perception system providing see-through views to drivers by sharing vision-based data between vehicles. The experiment results show that such a system can improve the reaction time in many scenarios such as forward collision warning and overtaking/lane-changing.

Since exchanging raw sensor data would consume enormous network resources, especially in dense traffic. The authors in [6] propose to realise collective perception by asking vehicles periodically broadcast the descriptions of their tracked objects only. They later introduce a new message format called environmental perception message (EPM) in the context of European Telecommunications Standards Institute (ETSI) intelligent transport system (ITS) G5 communication [7]. However, the simulation results show that apart from the benefits, leveraging collective perception still can overload the network in dense traffic due to the coexistence of other vehicular applications.

Another challenge of realising collective perception in vehicular networks is the data association from different sources, as these data usually comes with high temporal and spatial errors [22]. This aspect, therefore, receives many attentions from the community. For example, the authors in [10] propose a high-level fusion architecture where the V2X interface is treated as a virtual sensor. The objects perceived from the network is then fused with the local sensory information using the popular iterative closest point (ICP) algorithm. In [11], the authors address the problem of collaborative object tracking based on the Gaussian mixture probability hypothesis density (GM-PHD) filter. The recent work in [12] proposes a track-based association algorithm using an interacting multiple model estimator with a sequential multiple hypothesis test (IMM-SMHT). The experimental results show the proposed algorithm outperforms the traditional point matching algorithm in term of accuracy.

In summary, most of the existing works focus on prototyping the collective perception systems or addressing the issue of distributed sensory fusion. There still lacks understanding of the data redundancy issues in V2X based collective perceptions.

III. SYSTEM MODEL

Consider a highway scenario where vehicles on the road consist of a set of CAVs and the rest of them are plain vehicles (PVs). The CAVs are equipped with various sensors for localisations and environment perceptions, and wireless devices enabling V2X communications. Each CAV performs data fusion on the raw sensory data, and then generates a standardised track list for every detected road participants and peripherals that of potential interest to the vehicular applications. As suggested in [6], the detailed descriptions of each sensed object, including position, velocity and acceleration vectors, are then periodically encoded into an environmental perception message (EPM), and transmitted over the V2X network. According to the ETSI standards, we also assume that CAVs periodically broadcasts their travelling status in small *beacon* messages called cooperative awareness messages (CAMs) [23]. The transmission frequency for EPMs and CAMs should be at least 5 to 10 Hz to meet the safety requirements in vehicular environments [3].

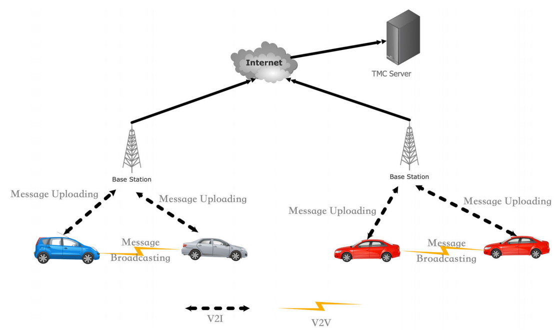


FIGURE 2. Network structure of V2I and V2V based collective perceptions.

Fig. 2 shows the typical network structure of V2X based collective perceptions. The base stations (e.g. RSUs or eNodeB) can provide network access for vehicles, allowing them to communicate with remote servers in the cloud by the V2I interface. On the other hand, the V2V interface enables vehicles to communicate with their one-hop neighbours directly. Based on the network structure, we consider the following two collective perception schemes:

1) V2I Based Collective Perception: CAVs on the road periodically upload the list of tracked objects to the remote TMC through V2I communications.

2) V2V Based Collective Perception: CAVs on the road periodically exchange the list of tracked objects with their proximity vehicles through single hop V2V broadcasting.

Since a wide range of applications supported by V2X collective perceptions are safety related, both V2I and V2V based collective perceptions require a certain level of system reliability. Ideally speaking, if an object is tracked by some CAVs on the road, at least one of them should share the object over the network. Therefore, we define the following metric to measure the system reliability of V2X based collective perceptions.

*Definition 1: The **share ratio** is the fraction of objects tracked by all CAVs on the road that are transmitted over the network.*

By definition, the share ratio is 100% in naïve approach such that CAVs simply encapsulate all tracked objects into EPMs. Our target is then to design a fully distributed approach that can effective suppress redundant data transmissions while maintain the share ratio at required levels.

IV. MODELLING V2X BASED COLLECTIVE PERCEPTION

We model the road as a wrapped strip $\mathcal{WS}$ of width h to remove border effects. A vehicle (CAV or PV) on the road is modelled as a simple rectangle $v_i = (c_i, l_i, w_i)$, where c_i is the geometric centre of the rectangle, l_i and w_i denote its length and width, respectively. For simplicity, we do not take the height of vehicles into consideration as most of existing CAVs install the sensors around their bodies for reducing air drags during travelling. Because the transmission interval for EPM takes a very short time (fraction of a second), the vehicle mobility is negligible and does not need to be taken into consideration in our model. The key notations and assumptions in our analyses are summarised as follows.

- Let $\Phi = \{c_i\}$ be the set containing the centres of all vehicles on the road. We assume that Φ form a homogeneous Poisson point process (P.P.P.) in $\mathcal{WS}$ with density λ, where λ denote the spatial density (in $vehs/m^2$) of vehicles. Note that the studies in [24] and [25] show that the inter-arrival time of vehicles in free-flow highway scenarios could be approximated by exponential distribution, which only implies that their locations along the road is a P.P.P. Therefore, this assumption would cause certain errors in our model because vehicles tend to drive within lanes. Through simulations, we show that the errors are acceptable.
- Denote α as the CAV penetration rate, and let $\lambda_c = \alpha\lambda$ be the spatial density of CAVs on the road. It is easy to see that the centres of all CAVs is a partition of Φ, therefore is also a homogeneous P.P.P. in $\mathcal{WS}$ with density λ_c.
- The lengths l_i and widths w_i of vehicles are independent and identically distributed (i.i.d.) according to some probability density functions $f_L(l)$ and $f_W(w)$. Note that the assumption about independence allows the overlapping of vehicles, but the error due to overlap is negligible especially in sparse vehicular density.
- Unlike complex urban scenarios, a line-topology highway scenario usually does not suffer from blockage effects resulting from buildings. In this regard, instead of modelling the maximum sensing region as a circle originated at the centre of the tagged vehicle, we assume it is a rectangle $\mathcal{S}$ that covers the road segment of length $2\times s$. This assumption is unrealistic but provides tractability in the analysis. Through simulations, we show that it only incurs minor errors.

TABLE 1. Notation summary.

Notation	Description
$\mathcal{WS}$	A wrapped strip modelling the road
h	The width of the road $\mathcal{WS}$
c_i	The location of the centre of the ith vehicle
l_i	The length of the ith vehicle
w_i	The width of the ith vehicle
$f_L(l)$	The PDF of vehicles' length
$f_W(w)$	The PDF of vehicles' width
$\Phi = \{c_i\}$	A P.P.P. Modelling the spatial locations of vehicles
λ	The spatial density $(vehs/m^2)$ of vehicles
λ_c	The spatial density $(vehs/m^2)$ of CAVs on the road
$\alpha = \frac{\lambda_c}{\lambda}$	The CAV penetration rate

Table 1 lists notations for the proposed analytical model. Based on the above models, we define the following metrics:

*Definition 2: The **effective field of view** (eFoV) Ψ of a CAV is the set of locations in $\mathcal{S}$ that have LOS links with the centre of the vehicle.*

*Definition 3: The **coverage probability** P_c of a point in $\mathcal{WS}$ is defined as the probability that the location falls in the **effective field of view** of at least one CAV on the road.*

According to the above definitions, Ψ reflects the impacts of blockage effect on the visible region of an individual vehicles. Since many applications supported by V2V based collective perceptions are safety-related, it is desired that the sensory information from the network can provide high perception coverage over the road environment. The **coverage probability** P_c is therefore a key metric reflecting the system reliability of V2V based collective perceptions. Now, let Γ be a random variable denoting the number of CAVs whose eFoV covers a given location on the road. We are interested in deriving the probability distribution of Γ.

A. LOS PROBABILITY

We start our analysis from the LOS probability between a pair of locations in the $\mathcal{WS}$. Define $\mathcal{V}(l, w) = \{v_i : l_i \in (l, l + \mathrm{d}l), w_i \in (w, w + \mathrm{d}w)\}$ such that $\mathcal{V}(l, w)$ contains the vehicles whose lengths and widths fall in the small intervals $(l, l + \mathrm{d}l)$ and $(w, w + \mathrm{d}w)$, respectively. Let $\Phi(l, w)$ be the point process that is formed by centres of vehicles in $\mathcal{V}(l, w)$.

Lemma 1: $\Phi(l, w)$ is a P.P.P. with density of $\lambda_{l,w} = \lambda f_L(l)\mathrm{d}l f_W(w)\mathrm{d}w$. If $(l_i, w_i) \neq (l_j, w_j)$, then $\Phi(l_i, w_i)$ and $\Phi(l_j, w_j)$ are independent P.P.P..

Proof: It is easy to see that $\Phi(l, w)$ is a partition of the point process Φ. Since Φ is a P.P.P., and l_i, w_i are i.i.d. distributed, according to the *independent thinning theorem*, $\Phi(l, w)$ is also a P.P.P. of density $\lambda_{l,w} = \lambda f_L(l)\mathrm{d}l f_W(w)\mathrm{d}w$. If $(l_i, w_i) \neq (l_j, w_j)$, $\Phi(l_i, w_i)$ and $\Phi(l_j, w_j)$ are disjoint sets of points, therefore are independent P.P.P.. $\square$

Extending the works in [26], we have the following Theorem.

Theorem 1: Choose a random location in $\mathcal{WS}$ as the origin of the coordinate system, and let Ω be the random variable denoting the number of vehicles that block the LOS from the origin $(0, 0)$ to another location (x, y) in $\mathcal{WS}$. Ω is a poisson variable with mean $\lambda(\mathbb{E}[w]|x| + \mathbb{E}[l]|y| + \mathbb{E}[w]\mathbb{E}[l])$.

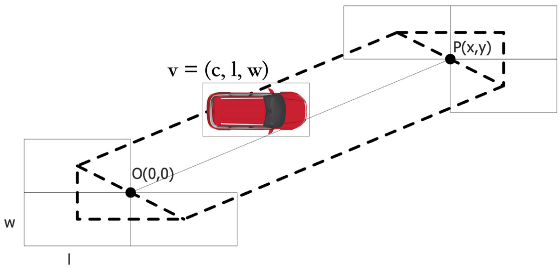


FIGURE 3. A vehicle blocks the line ***OP*** if and only if its centre falls in the dashed polygon.

Proof: Consider the scenario as shown in Fig. 3, in which the grey boxes represent the limiting positions such that a vehicle with length l and w will not block the line OP joining two points $(0, 0)$ and (x, y). Suppose that a vehicle $v = (c, l, w)$ blocks the line OP, it is easy to see that the centre of the vehicle must fall in the dashed polygon formed by connecting the centres of these grey boxes. Let $\mathcal{A}(l, w)$ denote the area of the dashed polygon, by simple geometry, we have:

$$\begin{aligned}\mathcal{A}(l, w) &= \sqrt{w^2 + l^2}|OP|(\frac{|y|}{|OP|}\frac{l}{\sqrt{w^2 + l^2}} \\ &\quad + \frac{|x|}{|OP|}\frac{w}{\sqrt{w^2 + l^2}}) + wl \\ &= w|x| + l|y| + wl \end{aligned} \tag{1}$$

Let $\Omega(l, w)$ be the random variable denoting the number of vehicles in $\mathcal{V}(l, w)$ blocking OP. By the Lemma 1, $\Omega(l, w)$ equals to the number of points in $\Phi(l, w)$ that fall in the dashed polygon in Fig. 3. Consequently, $\Omega(l, w)$ is a Poisson variable with mean $\lambda(l, w)\mathcal{A}(l, w)$.

Note that $\Phi(l_i, w_i)$ and $\Phi(l_j, w_j)$ are independent P.P.P. if $(l_i, w_i) \neq (l_j, w_j)$. By the superpositions law of independent Poisson random variables, the expected number of vehicles that blocks OP is the sum of the expectation of each random variable, then:

$$\begin{aligned}\mathbb{E}[\Omega] &= \sum_{l,w} \mathbb{E}[\Omega(l, w)] \\ &= \int_l\int_w \lambda(w|x| + l|y| + wl)f_L(l)f_W(w)\mathrm{d}l\mathrm{d}w \\ &= \lambda(\mathbb{E}[w]|x| + \mathbb{E}[l]|y| + \mathbb{E}[w]\mathbb{E}[l]) \end{aligned} \tag{2}$$

$\square$

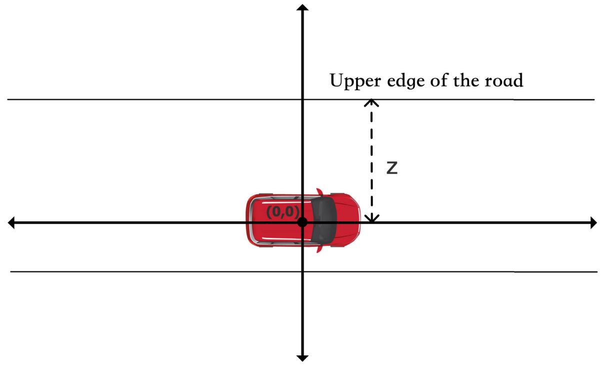


FIGURE 4. The variable ***z*** is introduced to denote the distance between the tagged location and the upper edge of the road.

The LOS between O and P exists in the case of $\Omega = 0$. Because Ω follows the Poisson distribution, we have the following Corollary:

Corollary 1: The LOS probability P_l from a location (x, y) in $\mathcal{WS}$ to the origin of the coordinate system is:

$$e^{-\lambda(\mathbb{E}[w]|x|+\mathbb{E}[l]|y|+\mathbb{E}[w]\mathbb{E}[l])} \tag{3}$$

The above analysis matches the intuition that the longer the distance between two locations is, the more vehicles are likely to block the LOS link. In order to simplify our notation, in the following sections, we use $\bar{w}$ and $\bar{l}$ to denote $\mathbb{E}[w]$ and $\mathbb{E}[l]$, respectively.

B. THE BLOCKAGE EFFECTS

Next, we study the impact of blockages from other vehicles on the LOS obstruction. The expected size of the eFoV of a tagged CAV can be calculated by using the following theorem:

Theorem 2: Let z be the distance of the tagged CAV from the upper edge of the road, and denote $\Psi(z)$ as the size of the eFoV. Then $\mathbb{E}[\Psi(z)]$ equals to:

$$\frac{2e^{-\lambda\bar{l}\bar{w}}}{\lambda^2\bar{w}\bar{l}}(e^{-\lambda s\bar{w}} - 1)(e^{-\lambda\bar{l}z} + e^{-\lambda\bar{l}(h-z)} - 2) \tag{4}$$

Proof: As shown in Fig. 4, let the centre of the tagged CAV be the origin of the coordinate frame and denote z as the distance from the CAV to the upper edge of the road. Now divide the strip $\mathcal{WS}$ into a lattice of small cubes of area $\Delta c = \Delta x\Delta y$. Assume that a cube at the location $(x, y) \in \mathcal{S}$ is visible if there exists a LOS link between the centre of the CAV $(0, 0)$ and (x, y), then $\mathbb{E}[\Psi(z)]$ can be calculated as the following:

$$\begin{aligned}\mathbb{E}[\Psi(z)] &= \sum_{\mathcal{S}} P_l(c)\Delta c \\ &= \sum_{z-h}^{z}\sum_{-s}^{s} e^{-\lambda(\bar{w}|x|+\bar{l}|y|+\bar{w}\bar{l})}\Delta x\Delta y \end{aligned} \tag{5}$$

As $\Delta c \to 0$, we have:

$$\begin{aligned}\mathbb{E}[\Psi(z)] = 2\{&\int_0^z\int_0^s e^{-\lambda(\bar{w}x+\bar{l}y+\bar{w}\bar{l})}\mathrm{d}x\mathrm{d}y \\ &+ \int_0^{h-z}\int_0^s e^{-\lambda(\bar{w}x+\bar{l}y+\bar{w}\bar{l})}\mathrm{d}x\mathrm{d}y\}\end{aligned}$$

$$
\begin{aligned}
&= \frac{2}{\lambda^2 \bar{w}\bar{l}}\{e^{-\lambda \bar{l}\bar{w}}(e^{-\lambda s\bar{w}}-1)(e^{-\lambda \bar{l}z}-1) \\
&\quad + e^{-\lambda \bar{l}\bar{w}}(e^{-\lambda s\bar{w}}-1)(e^{-\lambda \bar{l}(h-z)}-1)\} \\
&= \frac{2e^{-\lambda \bar{l}\bar{w}}}{\lambda^2 \bar{w}\bar{l}}(e^{-\lambda s\bar{w}}-1)(e^{-\lambda \bar{l}z}+e^{-\lambda \bar{l}(h-z)}-2) \quad (6)
\end{aligned}
$$

□

We are also interested in the expected size of the eFoV for a random CAV on the road, which can be calculated by the following Corollary:

Corollary 2: The expected size of the eFoV for a random CAV on the road is:

$$
-\frac{4e^{-\lambda \bar{l}\bar{w}}}{\lambda^3 \bar{l}^2 \bar{w}h}(e^{-\lambda s\bar{w}}-1)(\lambda h\bar{l}+e^{-\lambda h\bar{l}}-1) \quad (7)
$$

Proof: Since the centres of vehicles form a homogenous P.P.P., the location distribution of CAVs in term of z is uniform. The expected size of the eFoV for a random CAV on the road then could be derived by simply integrating Equation (6) in term of z from 0 to h, and is omitted. □

Note that for mathematical tractability, our derivation implies that the LOS probabilities between any pair of points are independent. Indeed, this assumption does not always hold as the same vehicle could block lines within a specific region; hence the LOS probabilities between these endpoints are correlated. However, simulations show that ignoring this correlation only causes a minor loss in accuracy.

Due to the fact that $\lim_{\lambda\to 0}(e^{-\lambda s\bar{w}}-1)(e^{-\lambda \bar{l}z}+e^{-\lambda \bar{l}(h-z)}-2) = \lambda^2 \bar{l}\bar{w}sh$, equation (6) approaches to the maximum sensing range $2sh$ at $\lambda = 0$. Theorem 2 and Corollary 2 show that the eFoV of a CAV drops quickly with the increase of vehicular density. In other words, CAVs, even in simple highway scenario, could also suffer from heavy LOS blockages from other vehicles on the road.

C. DATA REDUNDANCY ANALYSIS

Now armed with the LOS probability and eFoVs of CAVs on the road, we are ready to investigate the data redundancy issue in V2X based collective perceptions. Toward this end, we first analyse the eFoV overlaps among CAVs on the road, deriving the coverage probability, P_c, as defined in Definition 3.

Theorem 3: Let z be the distance between a tagged location to the upper edge of the road, then the coverage probability, $P_c(z)$, of the tagged location is:

$$
1 - e^{-\lambda_c \mathbb{E}[\Psi(z)]} \quad (8)
$$

Proof: Following the same setting on deriving Theorem 2, and let the tagged location be the origin of the coordinate frame. Assume that each small cube c can only contain one vehicle's centre. Since the centres of CAVs also form a P.P.P., the probability that a CAV's centre fall in a cube at (x, y) is therefore $\lambda_c \Delta c + o(\Delta c)$. Then the probability that the tagged location falls in the eFoV region of a CAV at c is simply $\lambda_c p_l(c)\Delta c$.

The LOS condition implies that if A is visible to B, then B is also visible to A. Because we assume CAVs have identical perception range, $\mathcal{S}$ can also be interpreted as maximum region in which a CAV's eFoV covers the tagged location. Therefore, the probability that none of CAVs can see this location is:

$$
p_n(z) = \prod_{\mathcal{S}}\{1-\lambda_c P_l(c)\Delta c\} \quad (9)
$$

As $\Delta c \to 0$:

$$
\begin{aligned}
p_n(z) &= \lim_{\Delta c\to 0}\prod_{\mathcal{S}}\{1-\lambda_c P_l(c)\Delta c\} \\
&= \lim_{\Delta c\to 0} exp\{\sum_{\mathcal{S}} log[1-\lambda_c P_l(c)\Delta c]\} \\
&= \lim_{\Delta c\to 0} exp\{-\sum_{\mathcal{S}}[\lambda_c P_l(c)\Delta c]\} \\
&= exp\{-\lambda_c \int_{-s}^{s}\int_0^h e^{-\lambda(\bar{w}|x|+\bar{l}|y|+\bar{w}\bar{l})}\mathrm{d}x\mathrm{d}y\} \quad (10)
\end{aligned}
$$

Replacing the exponent of equation (10) with (6), we have:

$$
P_c(z) = 1 - e^{-\lambda_c \mathbb{E}[\Psi(z)]} \quad (11)
$$

□

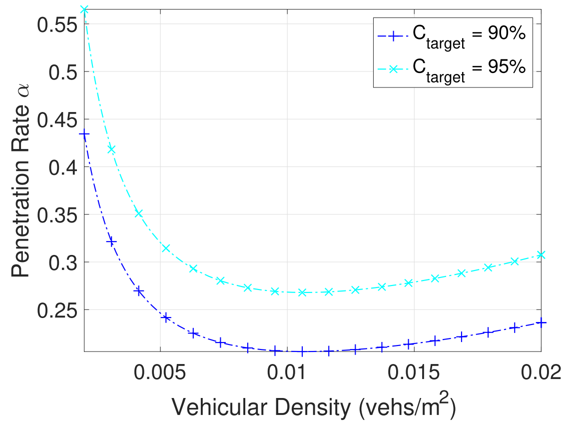


FIGURE 5. The required penetration rate α to achieve different target coverage probability C_{target}.

The coverage probability P_c is a key metric to evaluate the reliability of V2V based collective perceptions. Incorporating with $\alpha = \frac{\lambda_c}{\lambda}$, the required penetration rate to achieve a desired coverage probability, C_{target}, could be calculated by taking the logarithm on both sides of equation (8):

$$
\alpha = -log(1 - C_{target})/\lambda * \mathbb{E}[\Psi(z)] \quad (12)
$$

Note that, α solved by the above equation could be larger than 1 for vary small λ, which indicates that the C_{target} can never be achieved even if all vehicles on the road are CAVs. Fig. 5 plots the numeric results of equation 12 for $C_{target} = 90/95\%$, $s = 100m$, $z = h/2$, and $h = 15m$ representing typical width of 4 lanes roads. It can be seen from the figure that the curves decrease with the increase of λ and then slightly increase when the traffic becomes dense due to heavy blockage effects. For $C_{target} = 95\%$,

α stays at around 25% to 30% starting from the density of 0.005 $vehs/m^2$.

According to Equation (11), the coverage probability P_c of a location in $\mathcal{WS}$ is exponential. Therefore, we have the following immediate Corollary:

Corollary 3: Let $\Gamma(z)$ denote the number of CAVs whose eFoVs cover a tagged location at z, then $\Gamma(z)$ is a Poisson random variable with mean $\lambda_c \mathbb{E}[\Psi(z)]$.

Corollary 3 provides a mean to analyse data redundancy issue by leveraging collective perception. That is, assume that a CAV can detect and track an object (e.g. vehicles, pedestrians or obstacles) if its centre falls in the eFoV. Then for an object at z, the expected number of CAVs that transmit this object is simply $\lambda_c \mathbb{E}[\Psi(z)]$.

Observing that Equation 6 also depends on z, we have:

Lemma 2: $\Gamma(z)$ satisfies:

$$\lambda_c \mathbb{E}[\Psi(0)] \leq \Gamma(z) \leq \lambda_c \mathbb{E}[\Psi(\frac{h}{2})] \tag{13}$$

Proof: We begin by observing that $\mathbb{E}[\Psi(z)]$ is linear in $e^{-\lambda \bar{l} z} + e^{-\lambda \bar{l}(h-z)} - 2$, hence the maximum and minimum values of $\mathbb{E}[\Psi(z)]$ can be determined by taking the partial derivative with respect to the variable z:

$$\frac{\partial (e^{-\lambda \bar{l} z} + e^{-\lambda \bar{l}(h-z)} - 2)}{\partial z} = \lambda \bar{l}(e^{-\lambda \bar{l}(h-z)} - e^{-\lambda \bar{l} z}) \tag{14}$$

It is easy to see that the following inequalities hold:

$$\begin{cases} \lambda \bar{l}(e^{-\lambda \bar{l}(h-z)} - e^{-\lambda \bar{l} z}) < 0 & \text{if } 0 \leq z < \frac{h}{2} \\ \lambda \bar{l}(e^{-\lambda \bar{l}(h-z)} - e^{-\lambda \bar{l} z}) = 0 & \text{if } z = \frac{h}{2} \\ \lambda \bar{l}(e^{-\lambda \bar{l}(h-z)} - e^{-\lambda \bar{l} z}) > 0 & \text{if } \frac{h}{2} < z \leq h \end{cases} \tag{15}$$

Therefore, Equation (6) monotonically increases in the interval $[0, \frac{h}{2})$, and decreases in the interval $(\frac{h}{2}, h]$. We then have the following inequality:

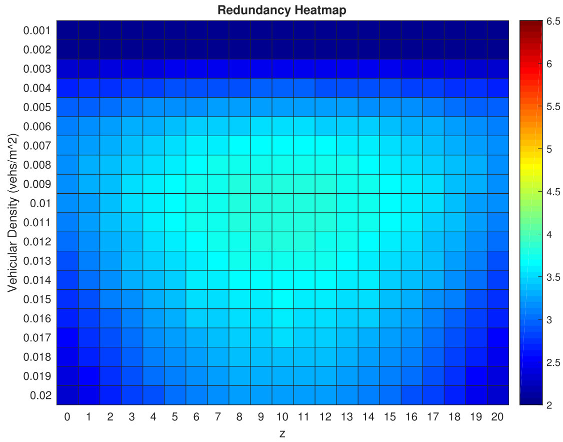
$$\mathbb{E}[\Psi(0)] \leq \mathbb{E}[\Psi(z)] \leq \mathbb{E}[\Psi(\frac{h}{2})] \tag{16}$$

$\square$

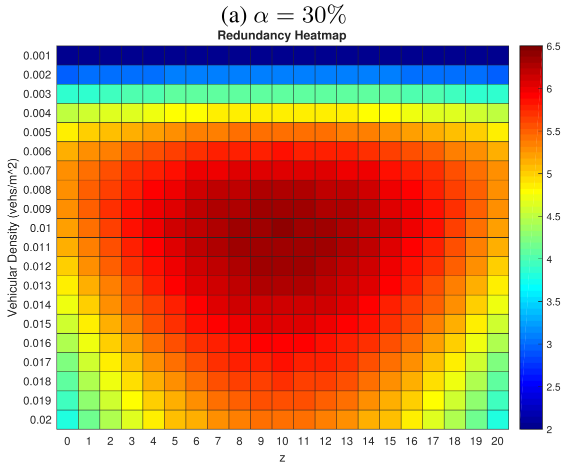
Lemma 2 shows that for any object on the road, the expected number of redundant transmissions is lower bounded by $\lambda_c \mathbb{E}[\Psi(0)]$ and upper bounded by $\lambda_c \mathbb{E}[\Psi(\frac{h}{2})]$. Fig. 6 shows the heat map of $\Gamma(z)$ as a function of z and λ. The results confirm that object located at the centre of the road has more chance to be detected by those who located at the edge of the road. The transmission redundancy could be as high as 6.5 for $\alpha = 50\%$.

V. REDUNDANCY CONTROL

As shown in the previous section, V2X based collective perceptions could result in heavy data redundancy. In this section, we propose a fully distributed redundancy control scheme to suppress redundant transmission for V2I and V2V based collective perceptions.



(a) $\alpha = 30\%$



(b) $\alpha = 50\%$

FIGURE 6. The heat map of $\Gamma(z)$ as a function of z and λ. The numeric results are obtained by setting $s = 100$, $h = 20$, $w = 2$ and $l = 4.5$.

A. THE ALGORITHM OVERVIEW

A simple and effective way to suppress data redundancy is to let CAVs transmit their sensory information probabilistically. That is, for each object ob_i in the track list, the CAV selects the object with a probability p_i, which is computed using a predefined probability assignment function $f_p(ob_i)$. Only the selected objects are encapsulated into the EPM and transmitted over the network at each transmission interval. The pseudo-code of the data selection algorithm is illustrated in Algorithm 1.

Algorithm 1 The Data Selection Algorithm

Data: *TrackList*
Result: Determine the set of tracked objects for transmission
for ob_i *in TrackList* **do**
  Compute a transmission probability p_i according to $f_p(ob_i)$
  Encapsulate the sensory information of ob_i into the EPM with probability p_i
end
Transmit the EPM via the chosen interface.

With a properly defined probability assignment function, the main advantage of the probabilistic approach is that CAVs can solely determine their transmission policy without any coordinations. However, the main challenge is how to effectively reduce redundancy in the meanwhile still guarantee the share ratio of the collective perception. Assigning an overly high transmission probability will result in excessive redundant transmissions for the same object. On the other hand, if the probability is too small, some tracked objects might not be shared in the network. The key idea of our redundancy control scheme is to give a higher transmission probability to objects having lower probability being detected by other CAVs on the road.

B. P-CONSISTENCE ASSIGNMENT SCHEME

In order to meet the required share ratio in both V2I and V2V based collective perception, we propose the *p-consistence* assignment scheme as the following:

Definition 4: In p-consistence assignment scheme, CAVs assign the same probability to the same object in their track list.

By this way, assume that an object falls in the eFoV of n CAVs. If they all transmit the object with a probability p, the expected number of transmissions then could be reduced to $n \times p$, and the probability that none of them share the object is simply $(1-p)^n$. Unfortunately, CAVs on the road cannot easily get n without any coordinations. The transmission probability could be estimated by incorporating Theorem 3, leading to the following Proposition:

Proposition 1: Assume that a tagged CAV has detected an object whose distance to the upper edge of the road is z, and let λ'_c be the local density estimation of other CAVs on the road (e.g. not including the tagged CAV). In p-consistence assignment scheme, the probability that the object is not transmitted over the network is: $(1-p)e^{-\lambda'_c p \mathbb{E}[\Psi(z)]}$.

Proof: Following the same setting in deriving Theorem 3, assume that each small cube c can only contain one vehicle's centre point. By the definition of p-consistence scheme, the probability of a CAV at c will detect and broadcast the object is $p\lambda'_c p_{los}(c)\Delta c$. Using the same technique in deriving Theorem 3, the probability that none of CAVs (exclude the tagged CAV) will share the object is $e^{-\lambda'_c p \mathbb{E}[\Psi(z)]}$. Because the tagged CAV also share the object with probability p, then the probability that the object will not be shared by any CAV is simply $(1-p)e^{-\lambda'_c p \mathbb{E}[\Psi(z)]}$, which completes the proof. □

Given the above proposition, we then propose a threshold based probability assignment function. Let θ denoting the desired share ratio in V2X based collective perception. The selection probability p_z for a tracked object at z could be computed by taking the numeric inverse of the following equation:

$$(1-p_z)e^{-\lambda'_c p_z \mathbb{E}[\Psi(z)]} = 1-\theta \tag{17}$$

Fig. 7 plots the numeric results of p_z for $\theta = 0.95/0.99$, $h = 20$ meters and $z = 10$. It can be seen that the data selection probability adaptively changes according to the CAV penetration rate and vehicular densities, and the curves reach to their minimum at around $\lambda = 0.006$ $vehs/m^2$. In general, sparse traffic and low penetration rate lead to higher selection probability in order to meet the sharing ratio requirement, on the other hand, the curves increase for dense traffic and higher penetration rate to compensate the heavy blockage effects.

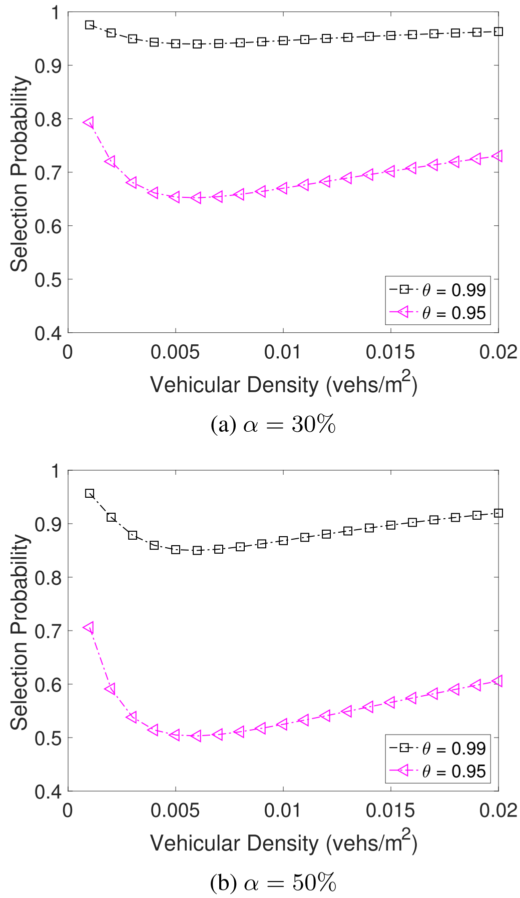


FIGURE 7. The numeric results of p_z for $\theta = 0.95/0.99$, $h = 20$, $z = 10$, $s = 100$, $w = 2$ and $l = 4.5$.

By definition, θ could be arbitrarily close to 1. However, the tradeoff between reliability and redundancy in our proposed schemes needs to be carefully considered. As shown in Fig. 7, the selection probability increases at most 40% from $\theta = 0.95$ to $\theta = 0.99$, which implies that the ability of suppressing redundant transmissions will be greatly compromised in order to further improve just 4% share ratio. Considered that the update frequency of EPMs is relatively high (e.g. 5-10 Hz), the temporal missing of a small number of sensed objects could be dealt with the object tracking modules, which can predict the future position of road objects when their sensing information is unavailable for short time. In this paper, we take $\theta = 0.95$ to balance the tradeoff between data redundancy and system reliability.

C. LOCAL DENSITY ESTIMATION

The proposed scheme relies on two local observations, λ_c' and λ, to determine the transmission probability of each tracked object. These two values can be locally estimated based on the information in received CAMs, which contain the travelling status, such as velocities and locations, that are of importance to prevent traffic accidents. Since traffic density estimation using network information has been an active research topic in the community [27], in this section, we present possible solutions in the literature that are suitable for the considered highway scenarios.

The CAV density λ_c' can be estimated by counting the number of unique CAMs received within a density estimation interval (i.e., 1s). The simulation results in [28] confirm that this simple CAM counting approach maintains a good accuracy; the estimation errors are lower than 10% even in dense traffic (e.g., 2700 CAVs per hour) with the most frequent CAM broadcasting (e.g., 10Hz). The overall vehicular density λ, in the meanwhile, can be estimated by applying well-established models for the relationship between traffic density and speed on the kinematic information collected from CAMs. For example, the Drew and Pipes-Munjal model shows that the average velocity v is related to the density k by the following equation:

$$v = v_f(1 - (\frac{k}{K_j})^n) \tag{18}$$

where v_f is the free-flow road speed, K_j is the jam density in vehicles per meter and n is the model parameter.

Each CAV then could calculate the average travelling speed using the received CAMs within an estimation interval and feed it to the Drew and Pipes-Munjal formula to estimate the local vehicular density. The authors in [29] report that this approach can achieve a high level of accuracy with low CAV penetration rate: by receiving CAMs from around 30% neighbouring vehicles, the accuracy is higher than 90% from sparse to dense traffic. Note that our scheme is not limited to the above method, other vehicular network based density estimation approaches can also be applied when the environment changes. Interesting readers could refer to [27] for more details.

D. DISCUSSIONS

By definition, CAVs in p-consistence scheme have the same opportunity to be the transmitter of a road object, therefore are naturally suitable for V2I based collective perceptions. Due to the broadcast nature of V2V communications, it is more reasonable to assign higher broadcast priority to CAVs that is farther away from the tracked object to provide larger broadcast coverage, as suggested in many geo-casting protocol in VANETs [30].

For example, the irresponsible forwarding (IF) proposed in [14] relegates the responsibility of forwarding a geo-casting message to the downstream vehicles in order to achieve higher forward progress. In the context of V2V based collective perceptions, a modified version of IF could be implemented by assigning a probability to a tracked object based on the probability of *having other CAVs that is farther way who also detect the object*. If the chance of finding another CAV is high, then the selection probability should be set to a small value, and vice versa. By Theorem 3 the probability assignment function could be defined as the following:

$$e^{-\lambda_c' \mathbb{E}[\Psi^k(z)]} \tag{19}$$

where k is the distance between the tagged CAV and the object, and

$$\mathbb{E}[\Psi^k(z)] = \int_0^h \int_s^k e^{-\lambda(\bar{w}|x|+\bar{l}|y|+\bar{w}\bar{l})} \mathrm{d}x\mathrm{d}y \tag{20}$$

However, we argue that this consideration is not necessary in the context of V2V based collective perception. According to our analytic model, CAVs could experience heavy blockage effects due to other vehicles as obstructions, the eFoV is therefore much smaller than the V2V communication range, especially for dense traffic. In Section VI, we compare the p-consistence with a modified IF, showing that ignoring the broadcast coverage factor only has negligible impacts on the performance of V2V based collective perceptions.

VI. EVALUATIONS

In the previous sections, we analytically investigate the data redundancy issues of V2X based collective perceptions by simplifying the physical environment for mathematical tractability. Based on our model, we then proposed a redundancy control approach that is suitable for both V2V and V2I based collective perceptions. In this section, we present the simulation results to evaluate our proposed model and algorithm, as well as gain insights into a range of other parameters not captured by the models.

A. SIMULATION SETUP

The simulations are conducted using three interconnected tools, OpenStreetMap, SUMO and Matlab. OpenStreetMap is used for obtaining real-world maps. This map is imported to SUMO [31] to generate realistic vehicle traces using microscopic vehicular mobility models. The traces are then sent to the Matlab-based simulator via the *TraCI* interface. In the analytical models, we assume that the maximum sensing region is a rectangle for mathematic tractability. In our simulations, this aspect is modelled as a circle originated at the centre of the CAV of radius $s = 100/150\ m$. We also assume that a CAV can detect an object if its eFoV covers the centre of the object.

Since our work focuses on investigating the data redundancy issue due to eFoV overlaps and propose a data selection scheme to reduce generated network traffic, the Matlab program accurately simulate the blockage effects resulting from other vehicles on the road using the computational geometry toolbox, on the other hand, the V2V communications are simplified as the disk model. Ignoring the details of the network layer might compromise our results as network loads could affect the accuracy of real time traffic density estimations, however, it is not overly optimistic either. In our simulations, we carefully choose the parameters according to [28] and [29], such that the estimation errors are lower than 10% from sparse to dense traffic by using the methods as outline in Section V-C. In addition, CAMs should be transmitted over a dedicated control channel (e.g., G5-CCH) with the highest priority (e.g., AC0 in 802.11p) to avoid competing resources with other applications [32], the network traffic generated by the collective perceptions has small impacts on the accuracy of density estimations by shifting the transmissions of EPM to a service channel in heterogeneous multi-radio vehicular networks [33].

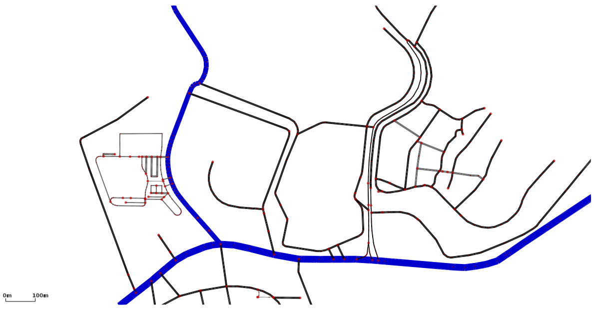


FIGURE 8. The map used for the performance evaluation and comparison.

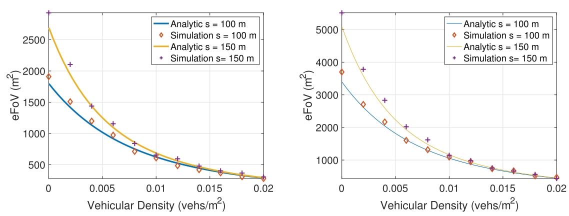
The considered scenarios are two urban roads, Xueyuan avenue and Orchid road, in Shenzhen, P.R.China, as highlighted blue in Figure 8. The Xueyuan avenue is a 4 lanes bidirectional urban highway and the Orchid road has 2 lanes in both directions. For each scenario, vehicles with three different dimensions, $1.8 \times 4.4\ m^2$, $1.95 \times 4.8\ m^2$ and $2.4 \times 10\ m^2$, are inserted at the road segments with the percentages of 30%, 60% and 10%, respectively. Therefore the average vehicle dimension is $1.95 \times 5.2\ m^2$. The vehicles' mobility is defined by the default *carFollowing-Krauss* model. Three CAV penetration rates are evaluated, 10%, 30% and 50%, and the traffic density varies from 0 to 75 $vehs/lane/km$, corresponding to around 0 to 0.02 $vehs/m^2$. The simulation parameters are summarised in Table 2.

TABLE 2. Simulation parameters.

Parameter	value
Traffic density	0 to 75 $vehs/lane/km$ (0 to 0.02 $vehs/m^2$)
Average vehicle width	1.95 m
Average vehicle length	5.2 m
Maximum sensing range	100/150 m
CAV penetration rates	30% and 50%
CAM frequency	$5Hz$
Density estimation interval	$1s$
Critical density K_j	$1/6$ vehs/meter
Density model parameter n	0.6

Following the work in [7], we let each CAV maintains a perceived object container (POC) storing tracked objects (e.g. other vehicles in our case) at every time step. The EPM then can be generated by applying the proposed p-consistence with $\theta = 95\%$. For comparison purpose we use the *naïve* and *fixed-p* scheme as base lines. The former one refers to the case where CAVs simply transmit all tracked objects over the network, while the fixed-p allows CAVs transmit their tracked objects with a pre-defined probability (e.g. 60% for Orchid road and 50% for Xueyuan avenue). We also implement a modified IF formulated in Section V-D to compare with the p-consistence in V2V based collective perceptions. In addition to the primary metric share ratio, as defined in Section III, we collect the following statistics from our simulations:

- *Payload size*: the payload size is defined as the number of tracked objects that are encapsulated into the EPM, which measures the network overhead of V2I and V2V based collective perceptions.
- *Number of detections*: for each vehicle on the road, we count the average number of CAVs who detect the tagged vehicle over its simulation time.
- *Transmission probability*: it is defined as the transmission probability assigned to a tracked objects.
- *V2V awareness*: the V2V awareness of a CAV is defined as the number of objects shared by CAVs within the V2V communication range. By definition, the naive policy achieves the maximum V2V awareness.
- *Forwarder distance*: for a given object, the forwarder distance is defined as the distance to a CAV who transmit the sensory information of the object via V2V interface.



(a) Orchid road (b) Xueyuan avenue

FIGURE 9. The analytic and simulation results of eFoV.

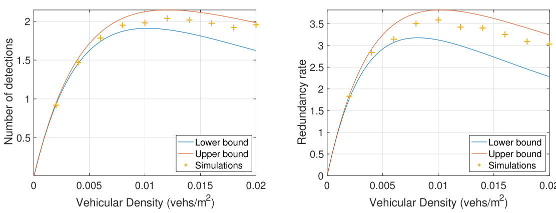
B. MODEL VALIDATIONS

For all scenarios, Fig. 9 shows the eFoV results obtained as a function of vehicular density, where the analytic results are obtained using Theorem 2. For the simulation results, we consider two maximum perception ranges of $s = 100m$ and $s = 150m$. We observe that our analytic model shows a good fit with the simulation results but the matches for the intervals of $\lambda = [0, 0.001]$ are slightly worse. This is because we assume the maximum perception region $\mathcal{S}$ is a rectangle rather than a circle.

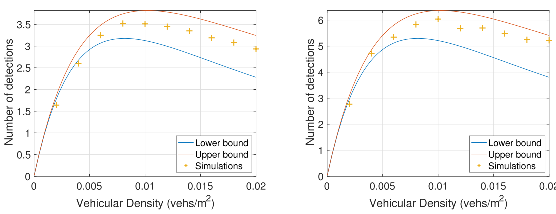
We also observe that CAVs suffer from heavy blockage effects due to other vehicles on the road. The results show that the eFoV drops quickly with the increase of vehicular density λ. The expected size of the visible region halves at around 0.0047 $vehs/m^2$, corresponding to just around

17.6 $vehs/lane/km$. Note that this level of vehicular density is very common for urban highway scenario. For example, the authors in [34] show that the traffic volume on all road types in Sydney urban region would be higher than 800 $vehs/hour$ from 6 AM to 12 PM, which translates to a traffic flow of around 13.3 $vehs/km$ if the average vehicle speed is 60 $km/hour$. Similarly, the real traffic data presented in [35] shows that the average traffic flow of the backbone road networks in Beijing is higher than 20 $vehs/km$ for more than 16 hours per day.

The results also suggest that simply increasing the sensor perception range s only provide limited benefits, and it is insufficient to extend the eFoV of individual CAVs for most of the traffic situations: for all cases, starting from 0.01 $vehs/km^2$, the eFoVs of the two settings, $s = 100m$ and $s = 150m$, are almost the same due to other vehicles as obstructions.



(a) Orchid road, $\alpha = 30\%$ (b) Orchid road, $\alpha = 50\%$



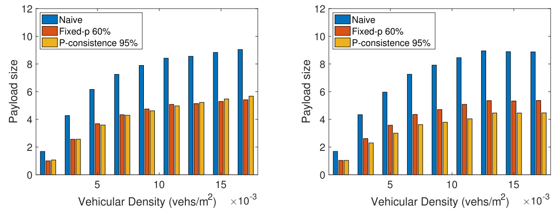
(c) Xueyuan avenue, $\alpha = 30\%$ (d) Xueyuan avenue, $\alpha = 50\%$

FIGURE 10. The average number of detections for the same object for $s = 100$ *m*.

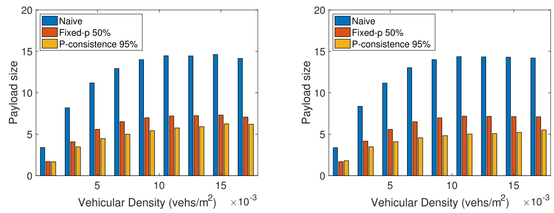
Next we validate our redundancy analysis. Fig. 10 plots the average number of detections over the vehicle population for $s = 100m$ and $\alpha = 30\%/50\%$ (i.e., the results for $s = 150m$ are not reported due to the space constraints). As shown in the figures, the simulation results are bounded by Lemma 2. Unlike the eFoV results as presented in Fig. 9, the number of detections for the same vehicle increase almost logarithmic fast from sparse to medium densities, the curves reach to their maximum at around $\lambda = 0.009$ $vehs/m^2$. For dense traffic, even though the eFoVs of individual CAVs drop quickly, redundant detections only decreases slowly because there are more CAVs on the road.

C. PERFORMANCE OF P-CONSISTENCE

For all scenarios, Fig. 11 compares the average payload sizes obtained as a function of the vehicular densities for naive, fixed-p and p-consistence schemes. We observe that both fixed-p and our proposed scheme can significantly reduce the payload size, the p-consistence with $\theta = 95\%$ scheme



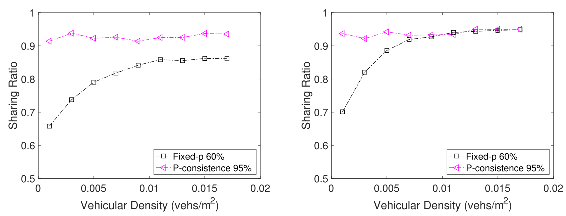
(a) Orchid road, $\alpha = 30\%$ (b) Orchid road, $\alpha = 50\%$



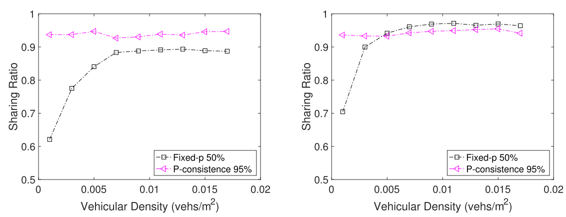
(c) Xueyuan avenue, $\alpha = 30\%$ (d) Xueyuan avenue, $\alpha = 50\%$

FIGURE 11. V2I duplicates comparison.

can reduce at most around 60% communication overhead for medium to dense traffic. The results also show that the p-consistence performs slightly worse than fixed-p for Orchid road with $\alpha = 30\%$, but it overwhelm fixed-p for the rest of scenarios.



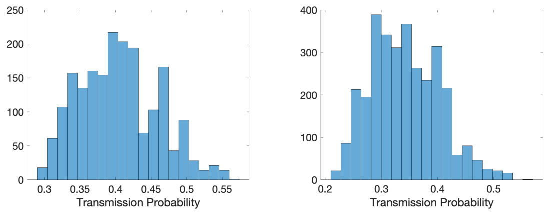
(a) Orchid road, $\alpha = 30\%$ (b) Orchid road, $\alpha = 50\%$



(c) Xueyuan avenue, $\alpha = 30\%$ (d) Xueyuan avenue, $\alpha = 50\%$

FIGURE 12. Share ratio comparison between fixed probability assignment scheme and p-consistence scheme.

From Fig. 11, one might conclude that our proposed scheme does not show significant improvements over the simple fixed-p scheme. However, the main advantage of the p-consistence scheme is that CAVs can adaptively change the transmission probability to maintain the overall share ratio at a required level. Fig. 12 compares the share ratio of p-consistence and fixed-p scheme for all scenarios, it can be seen that the performance of fixed-p highly depends on the traffic parameters; the share ratio generally increase with the increase of vehicular density. For Orchid road with $\alpha = 30\%$, $p = 60\%$ is overly low as the share ratio can never reach to 85%, on the other hand, $p = 50\%$ will be overly hight for Xueyuan avenue with $\alpha = 50\%$, especially under dense traffic. In contrast, the share ratio of p-consistence scheme stabilises at the desired threshold θ for all scenario. The results confirm the success of our proposed p-consistence scheme as it can maintain the reliability of V2V based collective perception at all time.



(a) Xueyuan avenue $\alpha = 30\%$ (b) Xueyuan avenue, $\alpha = 50\%$

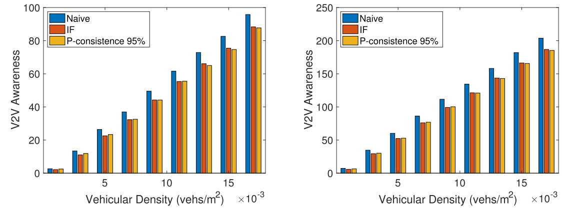
FIGURE 13. **Transmission probability histogram of p-consistence for $\theta = 95\%$ and $\lambda = 0.011$ *vehs/m*^{2}.**

Fig. 13 compliments the picture by showing the transmission probability histogram of p-consistence for Xueyuan avenue of $\lambda = 0.011$ $vehs/m^2$. Since the probability assignment function is designed based on our redundancy model, unlike the simple fixed-p scheme, the selection probability of a tracked object is calculated by the local estimations of the environments. For sparse local vehicular density and low CAV penetration rate, CAVs transmit the tracked objects with higher probability to prevent unexpected losses of sensory information. If there are more CAVs around, the transmission probability reduces accordingly to suppress unnecessary transmissions. Therefore, even though p-consistence achieves higher share ratio in Xueyuan avenue with $\alpha = 30\%$, but the average payload size is still lower than that of fixed-p.

D. P-CONSISTENCE IN V2V BASED COLLECTIVE PERCEPTIONS

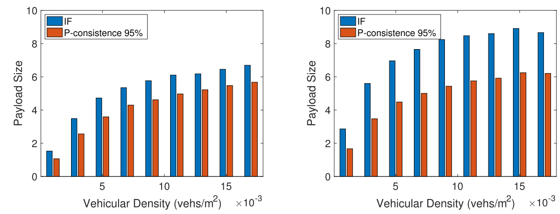
As mentioned in Section V-D, the proposed p-consistence scheme, at the first glance, might not be suitable for V2V based collective perceptions as it does not give higher broadcast priority to CAVs that are farther away from the tracked objects. In this section, we investigate the performance of p-consistence in V2V based collective perceptions.

By definition, the best case V2V awareness is achieve in naive approach as CAVs simply encapsulate all objects in their tracked list. Fig. 14 compares the V2V awareness for naive, IF and p-consistence for $\alpha = 30\%$. It is clear to see that even though IF takes the broadcast coverage into consideration, the benefits are negligible as both IF and p-consistence achieve around 92% V2V awareness when compared with the naive policy. However, the payload size results presented in Fig. 15 shows that p-consistence is more efficient than IF in term of communication overhead. The payload size of IF is around 30% larger than that of p-consistence, but it only achieves similar performance in V2V awareness.



(a) Orchid road (b) Xueyuan avenue

FIGURE 14. **The V2V awareness for $\alpha = 30\%$.**



(a) Orchid road (b) Xueyuan avenue

FIGURE 15. **The payload size comparison between IF and p-consistence for $\alpha = 30\%$.**

TABLE 3. **The downstream maximum forwarder distance in meters comparisons between IF and p-consistence.**

Scenario	$\lambda(vehs/m^2)$	**0.001**	**0.005**	**0.009**	**0.013**	**0.017**
Orchid road	P-consistence	5.83	16.97	19.19	17.32	17.87
	IF	9.43	24.20	24.10	23.41	22.88
	Diff	*3.59*	*7.22*	*7.91*	*6.09*	*5.01*
Xueyuan avenue	P-consistence	6.44	24.37	26.37	23.46	21.78
	IF	10.04	30.76	35.63	35.02	30.19
	Diff	*3.60*	*6.39*	*9.26*	*11.56*	*8.41*

Table 3 compares the maximum forwarder distance at downstream for IF and p-consistence. It can be seen that IF can only provide slightly higher broadcast coverage toward downstream traffic. This is because the eFoVs decrease quickly due to the blockage effects of other vehicles on the road, the CAVs who detect the same road object, therefore, tend to stay close with each other. Even the broadcast priority is intentional assigned to CAVs that are farther away from the object, the difference is still insignificant considered that the V2V communication range is much larger.

VII. CONCLUSION

In this paper, we address the data redundancy issue in V2X based collective perceptions by proposing a lightweight, fully distributed redundancy control approach. In this regard, we first analytically study the eFoV and coverage probability of CAVs in different traffic scenarios, showing that employing V2X based collective perceptions could result in heavy communication overhead due to redundant transmissions of sensory data. Based on our model, we propose p-consistence to suppress unnecessary data transmissions taking the vehicular density, CAV penetration rate and road geometry into consideration. The simulation results show that p-consistence can significantly reduce the communication overhead in the meanwhile maintain the share ratio at desired level for both V2V and V2I based collective perceptions.

ACKNOWLEDGMENT

(Hui Huang, Cuiping Shao, and Tianfu Sun contributed equally to this work.)

REFERENCES

[1] J. Levinson, J. Askeland, J. Becker, J. Dolson, D. Held, S. Kammel, J. Z. Kolter, D. Langer, O. Pink, V. Pratt, M. Sokolsky, G. Stanek, D. Stavens, A. Teichman, M. Werling, and S. Thrun, "Towards fully autonomous driving: Systems and algorithms," in *Proc. IEEE Intell. Vehicles Symp. (IV)*, Jun. 2011.

[2] L. Hobert, A. Festag, I. Llatser, L. Altomare, F. Visintainer, and A. Kovacs, "Enhancements of V2X communication in support of cooperative autonomous driving," *IEEE Commun. Mag.*, vol. 53, no. 12, pp. 64–70, Dec. 2015.

[3] *Technical Specification Group Services and System Aspects: Study on Enhancement of 3GPP Support for 5G V2X Services*, document TR 22.886, 3GPP, 2017.

[4] S. Chen, J. Hu, Y. Shi, Y. Peng, J. Fang, R. Zhao, and L. Zhao, "Vehicle-to-everything (v2x) services supported by LTE-based systems and 5G," *IEEE Commun. Standards Mag.*, vol. 1, no. 2, pp. 70–76, 2017.

[5] K. Bian, G. Zhang, and L. Song, "Toward secure crowd sensing in vehicle-to-everything networks," *IEEE Netw.*, vol. 32, no. 2, pp. 126–131, Mar. 2018.

[6] H.-J. Gunther, O. Trauer, and L. Wolf, "The potential of collective perception in vehicular ad-hoc networks," in *Proc. 14th Int. Conf. Telecommun. (ITST)*, Dec. 2015.

[7] H.-J. Gunther, B. Mennenga, O. Trauer, R. Riebl, and L. Wolf, "Realizing collective perception in a vehicle," in *Proc. IEEE Veh. Netw. Conf. (VNC)*, Dec. 2016.

[8] A. Bazzi, B. M. Masini, A. Zanella, and I. Thibault, "On the performance of IEEE 802.11p and LTE-V2V for the cooperative awareness of connected vehicles," *IEEE Trans. Veh. Technol.*, vol. 66, no. 11, pp. 10419–10432, Nov. 2017.

[9] B. Toghi, M. Saifuddin, H. N. Mahjoub, M. O. Mughal, Y. P. Fallah, J. Rao, and S. Das, "Multiple access in cellular V2X: Performance analysis in highly congested vehicular networks," in *Proc. IEEE Veh. Netw. Conf. (VNC)*, Dec. 2018.

[10] A. Rauch, S. Maier, F. Klanner, and K. Dietmayer, "Inter-vehicle object association for cooperative perception systems," in *Proc. 16th Int. IEEE Conf. Intell. Transp. Syst. (ITSC)*, Oct. 2013.

[11] M. Vasic and A. Martinoli, "A collaborative sensor fusion algorithm for multi-object tracking using a gaussian mixture probability hypothesis density filter," in *Proc. IEEE 18th Int. Conf. Intell. Transp. Syst. (ITSC)*, Sep. 2015.

[12] T. Yuan, K. Krishnan, Q. Chen, J. Breu, T. B. Roth, B. Duraisamy, C. Weiss, M. Maile, and A. Gern, "Object matching for inter-vehicle communication systems—An IMM-based track association approach with sequential multiple hypothesis test," *IEEE Trans. Intell. Transp. Syst.*, vol. 18, no. 12, pp. 3501–3512, Dec. 2017.

[13] S. Busanelli, G. Ferrari, and S. Panichpapiboon, "Efficient broadcasting in IEEE 802.11 networks through irresponsible forwarding," in *Proc. IEEE Global Telecommun. Conf. (GLOBECOM)*, Nov. 2009.

[14] S. Panichpapiboon and L. Cheng, "Irresponsible forwarding under real intervehicle spacing distributions," *IEEE Trans. Veh. Technol.*, vol. 62, no. 5, pp. 2264–2272, Jun. 2013.

[15] X. Zhang, G. Mao, X. Tao, and Q. Cui, "Uncoordinated cooperative forwarding in vehicular networks with random transmission range," in *Proc. IEEE Global Commun. Conf. (GLOBECOM)*, Dec. 2015.

[16] W. Drira, K. Ahn, H. Rakha, and F. Filali, "Development and testing of a 3G/LTE adaptive data collection system in vehicular networks," *IEEE Trans. Intell. Transp. Syst.*, vol. 17, no. 1, pp. 240–249, Jan. 2016.

[17] I. Turcanu, C. Sommer, A. Baiocchi, and F. Dressler, "Pick the right guy: CQI-based LTE forwarder selection in VANETs," in *Proc. IEEE Veh. Netw. Conf. (VNC)*, Dec. 2016, pp. 1–8.

[18] K. Abboud and W. Zhuang, "Stochastic modeling of single-hop cluster stability in vehicular ad hoc networks," *IEEE Trans. Veh. Technol.*, vol. 65, no. 1, pp. 226–240, Jan. 2016.

[19] G. Anastasi, M. Conti, M. Di Francesco, and A. Passarella, "Energy conservation in wireless sensor networks: A survey," *Ad Hoc Netw.*, vol. 7, no. 3, pp. 537–568, May 2009.

[20] S. Kumar, L. Shi, N. Ahmed, S. Gil, D. Katabi, and D. Rus, "Carspeak: A content-centric network for autonomous driving," in *Proc. ACM SIGCOMM*, Aug. 2012.

[21] S.-W. Kim, B. Qin, Z. J. Chong, X. Shen, W. Liu, M. H. Ang, E. Frazzoli, and D. Rus, "Multivehicle cooperative driving using cooperative perception: Design and experimental validation," *IEEE Trans. Intell. Transp. Syst.*, vol. 16, no. 2, pp. 663–680, Apr. 2015.

[22] A. Rauch, F. Klanner, R. Rasshofer, and K. Dietmayer, "Car2X-based perception in a high-level fusion architecture for cooperative perception systems," in *Proc. IEEE Intell. Vehicles Symp.*, Jun. 2012.

[23] *Intelligent Transport Systems (ITS), Framework for Public Mobile Networks in Cooperative ITS (C-ITS)*, ETSI Technical Committee Intelligent Transport System, Standard 102 962 (2012), Sophia Antipolis, France, 2012.

[24] M. Gramaglia, P. Serrano, J. A. Hernandez, M. Calderon, and C. J. Bernardos, "New insights from the analysis of free flow vehicular traffic in highways," in *Proc. IEEE Int. Symp. World Wireless, Mobile Multimedia Netw.*, Jun. 2011.

[25] G. S. Thakur, P. Hui, and A. Helmy, "Modeling and characterization of vehicular density at scale," in *Proc. IEEE INFOCOM*, Apr. 2013.

[26] T. Bai, R. Vaze, and R. W. Heath, "Analysis of blockage effects on urban cellular networks," *IEEE Trans. Wireless Commun.*, vol. 13, no. 9, pp. 5070–5083, Sep. 2014.

[27] J. Wang, Y. Huang, Z. Feng, C. Jiang, H. Zhang, and V. C. M. Leung, "Reliable traffic density estimation in vehicular network," *IEEE Trans. Veh. Technol.*, vol. 67, no. 7, pp. 6424–6437, Jul. 2018.

[28] S. Bastani, L. Libman, and S. T. Waller, "Impact of beaconing policies on traffic density estimation accuracy in traffic information systems," in *Proc. IEEE Int. Symp. World Wireless, Mobile Multimedia Netw.*, Jun. 2014.

[29] L. Libman, S. Bastani, and S. T. Waller, "Real-time traffic monitoring using wireless beacons with the cell transmission model," in *Proc. 17th Int. IEEE Conf. Intell. Transp. Syst. (ITSC)*, Oct. 2014.

[30] S. Panichpapiboon and W. Pattara-Atikom, "A review of information dissemination protocols for vehicular ad hoc networks," *IEEE Commun. Surveys Tutr.*, vol. 14, no. 3, pp. 784–798, 3rd Quart., 2012.

[31] D. Krajzewicz, J. Erdmann, M. Behrisch, and L. Bieker, "Recent development and applications of SUMO-Simulation of Urban MObility," *Int. J. Adv. Syst. Meas.*, vol. 5, nos. 3–4, pp. 128–138, 2012.

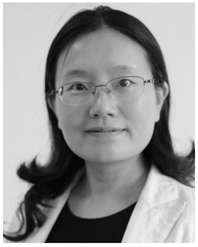
[32] *Intelligent Transport Systems (ITS); Access Layer Specification for Intelligent Transport Systems Operating in the 5 GHz Frequency Band*, Standard 302 663 (v1.2.1), ETSI, Sophia Antipolis, France, 2012.

[33] W. Huang, L. Ding, D. Meng, J.-N. Hwang, Y. Xu, and W. Zhang, "QoE-based resource allocation for heterogeneous multi-radio communication in software-defined vehicle networks," *IEEE Access*, vol. 6, pp. 3387–3399, 2018.

[34] N. Orthongthed, B. Wang, and J. Legaspi, "Estimating cost expansion factors in the Sydney urban and NSW rural road networks for economic evaluation of road projects," in *Proc. Australas. Transp. Res. Forum (ATRF)*, 2013.

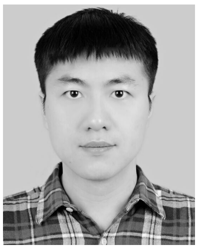
[35] B. Jing, L. Wu, H. Mao, S. Gong, J. He, C. Zou, G. Song, X. Li, and Z. Wu, "Development of a vehicle emission inventory with high temporal–spatial resolution based on NRT traffic data and its impact on air pollution in Beijing—Part 1: Development and evaluation of vehicle emission inventory," *Atmos. Chem. Phys.*, vol. 16, no. 5, pp. 3161–3170, 2016.

HUI HUANG received the M.Sc. degree in computing science from the University of Glasgow, U.K., in 2013, and the Ph.D. degree from the University of New South Wales, Australia, in 2018. He is currently a Research Associate with the Shenzhen Institutes of Advanced Technology, Chinese Academy of Sciences. His research interests include V2X communications, autonomous driving, and intelligent transportation systems.

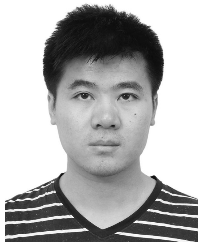


HUIYUN LI (Member, IEEE) received the M.Eng. degree in electronic engineering from Nanyang Technological University, in 2001, and the Ph.D. degree from the University of Cambridge, U.K., in 2006. She is currently a Professor with the Shenzhen Institutes of Advanced Technology, Chinese Academy of Sciences, and The Chinese University of Hong Kong. Her research interests include automotive electronics, autonomous driving, V2X, and so on.

CUIPING SHAO received the B.S. degree from the Xi'an University of Technology, China, in 2009, the M.S. degree from the Xi'an Microelectronics Technology Research Institute, China, in 2012, and the Ph.D. degree from the University of Chinese Academy of Sciences, China, in 2019. She is currently an Engineer with the Shenzhen Institutes of Advanced Technology, Chinese Academy of Sciences. Her research interests include integrated circuit reliability design and testing, and AI hardware implementation.



TIANFU SUN (Member, IEEE) was born in China. He received the B.Eng. degree in mechanical engineering and the M.Sc. degree in civil engineering from the Dalian University of Technology, Dalian, China, in 2009 and 2012, respectively, and the Ph.D. degree in electrical and electronic engineering from The University of Sheffield, Sheffield, U.K., in 2016. From 2016 to 2017, he was with the Department of Electronic and Electrical Engineering, The University of Sheffield, U.K., where he was a Postdoctoral Research Fellow. He is currently working as an Associate Professor of electric drives with the Shenzhen Institutes of Advanced Technology, Chinese Academy of Sciences, Shenzhen, China. His current research interests include connected and automated vehicles, power electronics, and the motor drives.



WENQI FANG received the B.S. degree in applied physics from the Zhejiang University of Technology, China, in 2012, and the Ph.D. degree in theoretical physics with the Institute of Physics, Chinese Academy of Sciences. He is currently a Research Associate with the Shenzhen Institutes of Advanced Technology, Chinese Academy of Sciences. During the Ph.D., his research focuses on quantum information and quantum computing. His research interests include optimization method, data analysis with Bayesian methodology, Gaussian process, and so on.

SHAOBO DANG received the Ph.D. degree from the University of New South Wales, in 2018 and the Graduate degree from the Northwestern Polytechnical University, in 2014. He is currently a Postdoctoral Researcher with the Shenzhen Institution of Advanced Technology (SIAT), Chinese Academy of Science (CAS). His research interests include data mining, machine learning, and technologies in autonomous vehicle.