Framework for Cooperative Perception of Intelligent Vehicles: Using Improved Neighbor Discovery

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***Abstract*—Neighbor discovery, providing neighbor information by broadcasting discovery message, is a promising solution for cooperative perception of intelligent vehicles. However, a frequent discovery sacrifices due to the highly dynamic mobility and channel randomness of vehicle environments, which induces a superabundant overhead. In this paper, we propose a new framework for cooperative perception of intelligent vehicles by novelly introducing an improved neighbor discovery. Considering the highly mobility and channel randomness of intelligent vehicle environments, we first investigate the inherent issue of neighbor discovery in the environments through modeling and analyzing the performance of the classic neighbor discovery method. Specifically, a closed-form expression of the key performance parameter, i.e., the hitting probability, respecting to the discovery interval, network mobility and channel randomness, is derived for the improved neighbor discovery, which enables the discovery method to control the discovery accuracy and overhead. Motivated by the analysis, we then discuss the process of cooperative perception using the improved neighbor discovery. At last, simulation results in three common channel conditions verify the accuracy of the analysis.**

I. INTRODUCTION

More than 1.2 million people die annually and up to 50 million injuries occur on the world's road. $160 billion are costed by traffic congestion in the U.S. every year. In addition, 31% of the global CO2 emissions were caused by vehicles tailpipes [1]. The growing threats from the traffic crash, roadways congestion and vehicle pollution are driving transportation system towards more efficient, eco-friendly and intelligent. Enhanced with perception, reasoning and actuating devices, intelligent vehicles enable the automation of driving tasks such as safe lane following, obstacle avoidance, avoiding dangerous situations, and determining the optimal route, and makes motoring safer, and more convenient and efficient, which is one of the most helpful solution of Intelligent Transportation System (ITS) [2].

As the basic and essential ability of intelligent vehicles, driving environment perception, providing information on state of the vehicle (i.e., position and speed) and surrounding (i.e., range and vision), is executed by sensors, radars and cameras, which relies on the sensing devices. However, the performance of perception cannot guaranteed due to the heavy interference and statistical noise in transportation system [3]. Furthermore, the high price of some special devices, such as the laser radar also impedes the development of intelligent vehicles. A new low price and efficient assist sensing method is required, while neighbor discovery is a promising method.

The neighbor discovery scheme denotes the process of discovering all neighbors in a device's communication range, which is widely used in many peer-to-peer communications [4], [5]. Here, we novelly propose to use neighbor discovery for driving environment perception of intelligent vehicles. Following a neighbor discovery scheme, an intelligent vehicle broadcasts a special discovery message every discovery interval. Meaningful Information of the vehicle including the location, speed and time are contained in the message [6]. Through receiving and exacting information of neighbors, vehicles can cognize the neighbor information and realize the driving environment perception cooperatively.

The scheme is initially conceived as a means to deal with energy issues at deployment in wireless sensor networks, where the main objective is to acquire information about network topology for subsequent communication [7]. While applying in vehicle networks, minimizing the discovery time and overhead become the goal. However, it is still a challenging task due to the impact of traffic environments. Firstly, a highly dynamic feature exists due to the rapid variation of vehicle velocity, short lifetime of link connection and quick change of mobile environment. Accordingly, a vehicle needs a small discovery interval to inform its neighbors its presence in time, which arouses a high discovery overhead. Furthermore, mass data including the safety message, transportation status news, and HD map shares the stringently restricted network resource with the neighbor discovery message in intelligent vehicles. Thus, the little the resource is used for neighbor discovery the better the network service is, which calls for a large discovery interval. However, the discovery time can not be guaranteed. In addition, wireless connections are random, time-varying and space-varying, caused by the uncertainty of available spectrum band, shadowing and fading. This wireless channel randomness induces a frequent changing of the discovery performance, which calls for an channel adaptive discovery method. In general, although neighbor discovery is a promising solution for cooperative perception of intelligent vehicles, it still has the contradiction of the discovery efficiency and overhead while it is applied in vehicle environments.

Meaningful works have been presented to address the issue of neighbor discovery in vehicle networks. The most popular discovery scheme is periodic method, in which the discovery interval is constant [6]. Then, the reactive method using the request-reply mechanism and the event-based method are proposed for latency tolerant traffic [8]. Recently, considering the feature of traffic, Zouina et. al [9] design the discovery method under 802.11p frame while David et. al [10] present a work in LTE networks. Focusing on the issue of fair, Esteban and Pablo [11] present a series of works on discovery rate adaption, and Lin et. al [12] make neighbor discovery using directional antennas. However, most of the works focus on the network mobility while impact of the channel randomness is rarely considered.

In this paper, we address the inherent issues of neighbor discovery in vehicle environments, and propose a new framework for cooperative perception of intelligent vehicles by novelly introducing the improved neighbor discovery into perception. We consider a scenario that all intelligent vehicles can broadcast and receive discovery messages for perception. They need discover their neighbors in time while the overhead is as low as possible in the highly dynamic, channel randomness and resource limited environments. Targeting at the metric of time and overhead, we first derive a closed-form expression of the key performance parameter, i.e., the hitting probability, respecting to the discovery interval, network mobility and channel randomness. Using the expression, the presented improved neighbor discovery enables to control the discovery accuracy and overhead. Depending on the analysis, we discuss the process using neighbor discovery for the cooperation perception of intelligent vehicles. In the end, simulation results in three common channel conditions verify the accuracy of the analysis. Specifically, the novelty and contributions of this paper are summarized as follows.

1) The proposed perception framework is a low-cost, because we novelly utilize a soft method, i.e., neighbor discovery, for perception without none of the expensive hardwares.

2) By a comprehensive analysis of discovery process under vehicle environments, we give a closed-form expression which can be utilized to address the inherent issues of neighbor discovery in vehicle environments. Thus, our framework is also an efficient assistant method with the improved neighbor discovery.

The remainder of this paper is organized as follows. We describe the analytical model and problem formation in Section II. The analysis results are introduced in Section III, while the framework of cooperative perception is discussed in Section IV. Then, we conduct simulations and give corresponding results in Section V. At last, we conclude this paper.

II. System Model

To address the issue of neighbor discovery in vehicle environments, we first model the discovery process. As illustrated in Fig.1, we consider a traffic scenario that intelligent vehicles moving on highway. All vehicles can communicate with its neighbor vehicles by one-hop. Then, each vehicle advertises its existence by broadcasting its discovery message, and sense its neighbors by receiving their message. Useful information,

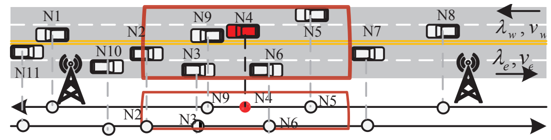

Fig. 1. Illustration of the vehicular network.

such as the location, speed and direction of the node, is contained in the message. Thus, the cooperative perception is achieved by the discovery process. The reciprocal of the broadcasting frequency defines the discovery interval, marked by I. However, a channel access delay exists influenced by the channel access delay, which means that the time interval between two discovery message of a node is $\tau = I + T_s$, where T_s is the average channel access delay. We make the following assumptions to study neighbor discovery.

1) Mobility model: Two mutually independent traffic lanes exit without lane changing. We ignore the road-width based on the analysis in [13]. All nodes access the west (east) lane following the poisson distribution with density λ_w (λ_e). We assume that all node on the same lane have the same constant speed, i.e., v_w and v_e respectively, because all drivers tend to maintain a constant spacing with their leader car by the car-following regime. Therefore, the distribution of the nodes follows a homogenous poisson process.

2) Communication model: We consider three popular radio propagation models which are the unit disk model (UDM), lognormal model (LM) and Nakagami-m lognormal composite model (NLM). Subjecting to shadowing and fading, we adopt the variable radio range in our analysis [14]. Assume that two nodes can communicate iff the distance between them is smaller than the radio range. The range is constant under UDM, which is r_0.

3) Problem definition: Without loss of generality, we choose $Node_s$ on the west lane as the reference and establish a location coordinate. Then, a new metric, i.e., hitting probability, is defined by the stable ratio between the number of discovered nodes and the number of real neighbors. Obviously, it will increase with more frequent discovery. Furthermore, the probability can reflect the performance of efficiency and overhead of a neighbor discovery scheme. On one hand, when the probability is smaller than 1, the notification and discovery are not in time, because some neighbors are omitted. On the other hand, the value of the hitting probability always equals to 1 with an increasing discovery interval. At this time, almost all neighbors have discovered the reference, while abundance packets are consumed. Here, two steps are required to investigate the neighbor discovery in vehicle environments.

- We first analyze the relation between the hitting probability and discovery interval by focusing on the periodic discovery method subjected to the network mobility and channel randomness. Assume that all vehicles broadcast a discovery message every τ seconds from time 0 to time T, where τ is constant in periodic method. We can solve the problem by calculating the function of hitting

probability (p_h) when T approaches infinity.
- Motivated by the hitting function, we try to propose our improved neighbor discovery to balance the efficiency and overhead of discovery. The difficulty lies in counting the critical point where hitting probability goes to 1.

III. On statistic analysis of classic neighbor discovery

In this section, the target is the stable hitting probability for periodic discovery in different channel scenarios.

A. General case

We first analyze the general case in which the radio range is denoted by a general random variable. According to the definition, we have $\lim\limits_{T\to\infty} E\left[p_h\right] = \lim\limits_{T\to\infty} E\left[N_D\left(T\right)/N_R\left(T\right)\right]$, in which $N_D\left(T\right)$ and $N_R\left(T\right)$ are the number of discovered nodes and the number of real neighbors during T seconds. Then, we use Lemma 1 to turn the stable probability into a new form.

Lemma 1. *Suppose that $Node_s$ broadcasts W discovery packets in T seconds, where $T = W\tau + \delta, \delta \in [0, \tau)$ is a positive integer, then, the stable hitting probability satisfies*

$$\lim_{T\to\infty} E\left[p_h\right] = \lim_{W\to\infty} E\left[\frac{N_D\left(W\tau\right)}{N_R\left(W\tau\right)}\right]. \tag{1}$$

Proof. Neighbor discovery is a continuous discrete process, as shown in Fig. 2. At time $i\tau$, $Node_s$ broadcasts a discovery packet with radio range R_i, where i is a positive integer. Obviously, we have that $N_D\left(T\right) = N_D\left(W\tau + \delta\right) = N_D\left(W\tau\right)$, because $Node_s$ broadcasts at $i\tau$ only. According to the feature of homogeneous Poisson Process, $N_R\left(T\right) = N_R\left(W\tau + \delta\right) = N_R\left(W\tau\right) + N_R\left(\delta\right)$. When T goes to infinity, the stable hitting probability satisfies

$$\begin{aligned}
\lim_{T\to\infty} E\left[p_h\right] &= \lim_{W\to\infty} E\left[\frac{N_D\left(W\tau+\delta\right)}{N_R\left(W\tau+\delta\right)}\right] \\
&= \lim_{W\to\infty} E\left[\frac{N_D\left(W\tau+\delta\right)}{N_R\left(W\tau\right)+N_R\left(\delta\right)}\right] \\
&= \lim_{W\to\infty} E\left[\frac{N_D\left(W\tau\right)}{N_R\left(W\tau\right)}\right].
\end{aligned} \tag{2}$$

□

The value of $N_D\left(W\tau\right)$ is difficult to calculate due to the channel randomness. Thus, we need Lemma 2 to analyze the function of the probability.

Lemma 2. *Suppose that $N_G\left(W\tau\right)$ is the number of neighbors receiving 0 discovery message from $Node_s$ in $W\tau$ seconds, then, the stable hitting probability satisfies*

$$\lim_{W\to\infty} E\left[\frac{N_D\left(W\tau\right)}{N_R\left(W\tau\right)}\right] = 1 - \lim_{W\to\infty} E\left[\frac{N_G\left(W\tau\right)}{N_R\left(W\tau\right)}\right], \tag{3}$$

where $E\left[N_G\left(W\tau\right)/N_R\left(W\tau\right)\right]$ is denoted by Eq. 8.

Proof. Due to the existing of two lanes, there are two cases to analysis.

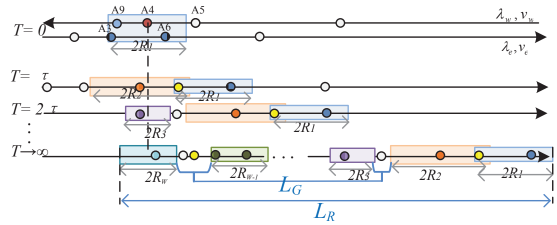

Fig. 2. System model.

Firstly, we focus on the west lane where the reference node locates. All nodes on the road have the same velocity with the reference. Thus, nodes in range $[-R_{max}, R_{max}]$ have been the real neighbors of $Node_s$, as well as the discovered neighbors of $Node_s$, in which $R_{max} = max\{R_i\}, i = 1, 2...W$. Taken the number of discovered neighbors and the number of real neighbors on west lane as $N_D^w\left(W\tau\right)$ and $N_R^w\left(W\tau\right)$, we have that both $N_D^w\left(W\tau\right)$ and $N_R^w\left(W\tau\right)$ follow a homogenous Poisson process with density $\lambda_w 2R_{max}$.

However, nodes on east lane have a relative velocity $\Delta v = v_e + v_w$ respecting to $Node_s$. In $W\tau$ seconds, it seems that nodes on the lane move towards east with a displacement $\Delta v\left(W\tau\right)$. Thus, the real neighbor of $Node_s$ are nodes locating in range $[-R_W, W\Delta v\tau + R_1]$, and its number $N_R^e\left(T\right)$ follows the homogenous poisson process with density $\lambda_e\left(R_1 + R_W + \Delta vT\right)$. During the process, only nodes in discrete ranges $\bigcap\limits_{i=1}^{W} [(i-1)\Delta v\tau - R_i, (i-1)\Delta v\tau - R_i]$ have received discovery message from the reference, which are the discovered neighbors and its number is $N_D^e\left(W\tau\right)$. At this time, a gap with long L_G exists, in which nodes receive 0 packet from $Node_s$. Defining the node number by $N_G\left(W\tau\right)$, we have

$$\begin{aligned}
&\lim_{W\to\infty} E\left[\frac{N_D\left(W\tau\right)}{N_R\left(W\tau\right)}\right] = \lim_{W\to\infty} E\left[\frac{N_D^w\left(W\tau\right)+N_D^e\left(W\tau\right)}{N_R^w\left(W\tau\right)+N_R^e\left(W\tau\right)}\right] \\
&= 1 - \lim_{W\to\infty} E\left[\frac{N_R^e\left(W\tau\right)-N_D^e\left(W\tau\right)}{N_R\left(W\tau\right)}\right] \\
&= 1 - \lim_{W\to\infty} E\left[\frac{N_G\left(W\tau\right)}{N_R\left(W\tau\right)}\right].
\end{aligned} \tag{5}$$

Furthermore, we can derive the probability mass function of L_G, which is shown in Eq. 4. Using the feature of homogeneous Poisson spatial distribution, we have

$$\begin{aligned}
&E\left[\frac{N_G\left(W\tau\right)}{N_R\left(W\tau\right)}\right] \\
&= \sum_{m=0}^{\infty}\sum_{n=0}^{m}\frac{n}{m}\Pr\left\{N_G\left(W\tau\right)=n\left|N_R\left(W\tau\right)=m\right.\right\} \\
&\times \Pr\left\{N_R\left(W\tau\right)=m\right\} \\
&= \sum_{m=0}^{\infty}\sum_{n=0}^{m}\frac{n}{m}\sum_{p}C_m^n p^n(1-p)^{m-n}Pr\left\{\frac{\lambda_G}{\lambda_R}=p\right\} \\
&\times \Pr\left\{N_R\left(W\tau\right)=m\right\}
\end{aligned} \tag{6}$$

where λ_G and λ_R are the Poisson density for $N_G(W\tau)$ and $N_R(W\tau)$ respectively, and we have

$$\frac{\lambda_G}{\lambda_R} = \frac{\lambda_e L_G}{\lambda_e 2R_{\max} + \lambda_w (R_1 + R_W + \Delta v\tau (W-1))} \quad (7)$$

Substituting Eq.7 to Eq. 6, we can get

$$\begin{aligned} & E\left[\frac{N_G(W\tau)}{N_R(W\tau)}\right] \\ & = \sum_{m=0}^{\infty}\sum_{p} pPr\left\{\frac{\lambda_G}{\lambda_R} = p\right\}\frac{{\lambda_R}^m e^{-\lambda_R}}{m!} = E\left[\frac{\lambda_G}{\lambda_R}\right] \\ & = E\left[\frac{\lambda_e(\Delta v\tau - R_i - R_{i+1})(W-1)}{\lambda_e 2R_{\max} + \lambda_w(R_1 + R_W + \Delta v\tau(W-1))}\right. \\ & \left.\times \Pr\{\Delta v\tau > R_i + R_{i+1}\}\right], \end{aligned} \quad (8)$$

where R_i and R_{i+1} are two adjacent broadcasting range. □

Here, the stable hitting probability of classic neighbor discovery is derived by Theorem 1, when the radio range is denoted by a general random variable.

Theorem 1. *In periodic discovery method, the stable hitting probability satisfies*

$$\lim_{T\to\infty} E[p_h] = \frac{E[R_i + R_{i+1} | \Delta v\tau > R_i + R_{i+1}]}{\Delta v\tau}. \quad (9)$$

Proof. Using Lemma 1 and Lemma 2, we have

$$\begin{aligned} & \lim_{T\to\infty} E[p_h] = 1 - \lim_{W\to\infty} E\left[\frac{N_G(W\tau)}{N_R(W\tau)}\right] \\ & = \lim_{W\to\infty}\frac{\lambda_e(\Delta v\tau - R_i - R_{i+1})(W-1)}{\lambda_e(R_1 + R_W + \Delta v\tau(W-1)) + \lambda_w(2R_{\max})} \\ & \times \Pr\{\Delta v\tau > R_i + R_{i+1}\} \\ & = \frac{E[R_i + R_{i+1} | \Delta v\tau > R_i + R_{i+1}]}{\Delta v\tau}. \end{aligned} \quad (10)$$

□

B. Under unit disk model

The unit disk model(UDM) is the commonly-used radio propagation model in wireless communication systems, under which two nodes are directly connected iff the Euclidean distance between them is smaller than the radio range. In our analysis, we adopt r_0 for the range. Therefore, substituting the radio range $R_i = R_{i+1} = r_0$ into Eq. 6, the stable hitting probability is given by

$$\lim_{T\to\infty} E\left[p_h^{UDM}\right] = \begin{cases} \frac{2r_0}{\Delta v\tau} & 2r_0 < \Delta v\tau \\ 1 & 2r_0 \geq \Delta v\tau \end{cases} \quad (11)$$

C. Under lognormal model

Channel randomness is caused due to the reflection, refraction and scattering induced by various obstacles in the media. Thus, the received signals are characterized by small scale fading as well as large scale fading in vehicular networks. Normally, the variations of signal amplitude are modeled by lognormal distribution for large scale fading. In addition, a general model, i.e., Nakagami-m lognormal composite fading model, is well known statistical distribution to model the multipath fading and shadowing. Therefore, to modeling the channel randomness, we adopt both lognormal model and the Nakagami-m lognormal model for the variable radio range. Under lognormal model, the radio range follows a Gaussian distribution. Then, according to the radio range of UDM, the pdf of lognormal distribution (R_i and R_{i+1}) is given by

$$f_{LM}(r) = \frac{1}{r\sqrt{2\pi\sigma^2}} e^{-\frac{(\ln(r)-\mu)^2}{2\sigma^2}}, \quad (12)$$

where $\mu = \ln(r_0)$ and $\sigma =$ are mean and standard deviation respectively of random variable $ln(r)$. They can be expressed in decibels by $\sigma_{dB} = \xi\sigma$ and $\mu_{dB} = \xi\mu$, where $\xi = 10/\ln(10)$ [16]. Taking the radio range in Eq. 9, we get the stable hitting probability $\lim\limits_{T\to\infty} E\left[p_h^{LM}\right]$ under lognormal model.

D. Under nakagami-m lognormal composite model

The radio range under Nakagami-m lognormal composite model is expressed as

$$\begin{aligned} f_{NL}(r) = & \int_0^{\infty}\left\{\frac{m^m r^{m-1}}{\omega^m \Gamma(m)} e^{-\frac{mr}{\omega}}\right\} \\ & \times \left\{\frac{1}{\omega\sqrt{2\pi\sigma^2}} e^{-\frac{(\ln(\omega)-\mu)^2}{2\sigma^2}}\right\} d\omega \end{aligned} \quad (13)$$

It is difficult to calculate the result in close-form. Taking $\ln(\omega) = x$ in Eq. 13, and using the approach proposed by

$$L_G = \begin{cases} 0 & p_0 \\ \Delta v\tau - R_i - R_{i+1} & p_1, i \in [1, W-1] \\ (\Delta v\tau - R_i - R_{i+1}) + (\Delta v\tau - R_j - R_{j+1}) & p_2, i, j \in [1, W-1], i \neq j \\ \vdots & \vdots \\ \underbrace{(\Delta v\tau - R_i - R_{i+1}) + (\Delta v\tau - R_j - R_{j+1}) + \cdots + (\Delta v\tau - R_k - R_{k+1})}_{k} & p_k, i, j, k \in [1, W-1], i \neq j \neq k \\ \vdots & \vdots \\ \sum_{i=1}^{W-1}(\Delta v\tau - R_i - R_{i+1}) & p_{W-1} \end{cases} \quad (4)$$

where $p_k = \Pr\{\Delta v\tau > R_i + R_{i+1}\}\Pr\{\Delta v\tau > R_j + R_{j+1}\}\cdots\Pr\{\Delta v\tau > R_k + R_{k+1}\}\prod\limits_{l=1, l\neq i,j,k}^{W-1}\Pr\{\Delta v\tau \leq R_l + R_{l+1}\}$.

Holtzman [15], [16], the finally pdf under Nakagami-m lognormal composite model is given by

$$\begin{aligned} f_{NL}(r) = \frac{2}{3}\psi(r;\mu) + \frac{1}{6}\psi\left(r;\mu+\sigma\sqrt{3}\right) \\ + \frac{1}{6}\psi\left(r;\mu-\sigma\sqrt{3}\right) \end{aligned} \tag{14}$$

where $\psi(r;x) = \frac{m^m r^{m-1}}{e^{xm}\Gamma(m)} \mathrm{e}^{-\frac{mr}{e^x}}$.

Then, using Eq. 14 in Eq.9, we can have the stable hitting probability $\lim_{T\to\infty} E\left[p_h^{NL}\right]$ under Nakagami-m lognormal composite model.

IV. Framework for cooperative perception using improved neighbor discovery

In section III, the closed-form expression for stable hitting probability is derived, which is related to discovery performance, discovery interval, network mobility and channel randomness. Motivated by the expression, we design an improved neighbor discovery, and propose the perception framework in this section.

Generally, the highly mobility and complex radio environments are main features of the environment of intelligent vehicles. However, the discovery scheme gets poor performance if the discovery interval holds. For instance, a vehicle moves from a sparse and high-speed avenue to a dense but low-speed street. According to Eq. 9, the hitting probability reduces if the discovery interval is constant. Therefore, a mobility-aware and adaptive discovery scheme is necessary, while we use the neighbor discovery for cooperative perception. Depending on theorem 1, we propose an improved neighbor discovery containing three steps.

Step1. Initially, all nodes in the network send discovery packets every τ seconds, in which $\tau = g^{-1}\left(\overline{p_h}\right)$ and $\overline{p_h}$ is the expected threshold of the stable hitting probability. The discovery packet contains node ID, current location, local speed, time stamp, and a few necessary data.

Step2. In step 2, every node records all information in the discovery packet receiving from other nodes. At the same time, they calculate a new speed difference Δv. A node will move to step 3 if it perceives a variation of mobility or channel.

Step3. Every node will calculate a new discovery interval depending on $\tau' = g^{-1}\left(\overline{p_h}\right)$ in step 3. Then, nodes follow the new patten to broadcast discovery packets.

Following the discovery process, an intelligent vehicle can obtain information of the neighbor while it receives a discovery message from the neighbor. Accordingly, the intelligent vehicle can deliver all information it owned by broadcast a discovery message. With these steps, cooperative perception is finished in an low cost and easy way.

V. Simulation

In this section, we make Monte-Carlo simulations on Matlab. The simulation is conducted on a bidirectional street (as shown in Fig.1). The street contains three continuous segments, i.e., the low mobility segment, medium mobility segment and high mobility segment. Due to the velocity restriction, values of velocity on east lane and west lane are taken as 10m/s and 20m/s for low mobility segment, 20m/s and 40m/s for medium mobility segment, and 40m/s and 40m/s for high mobility segment. In addition, the node density on west lane and east lane are given by $\lambda_w = 0.06$ and $\lambda_e = 0.04$ (typical density for sparse scenarios in VN [13]). The expected radio range is defined by $r_0 = 50$m, $r_0 = 100$ and $r_0 = 150$. Specifically, m takes value 0.5 and 4. Value of σ is defined as 0.806 for heavy shadowing, 0.391 for average shadowing, and 0.161 for light shadowing [14].

Based on our assumption, each vehicle in the network travels at a constant speed in one segment until it moves to the next segment. Passing and lane changing do not exist in our simulation. Further, an open system model where vehicles who exit the network do not re-enter into the network. New vehicles are generated and get reinserted into the network based on the assumed Poisson process. Since we are only interested in performance of neighbor discovery in the network-layer, we adopt a ideal MAC and PHY layers in the simulation.

We depict results relating to the analysis of periodic discovery method in Fig. 3, Fig.4, Fig.5 and Fig.6. The simulation results match very closely with our analysis results, which verifies that results of Theorem 1 are in fact quite accurate.

In Fig. 3, all nodes moves in low mobility segment, in which $\Delta v = 30$m/s. In addition, we set $r_0 = 50$, $\sigma = 0.161$ and $m = 4$. Under the assumption, we analyze the value of stable hitting probability under three radio models. Firstly, the curve of the hitting probability is a segmental line under UDM. The probability linearly increases with $1/\tau$, and the slope is $2r_0/\Delta v$ and the threshold value is $1/\tau = 0.3$. Then, it is identically equal to 1. This reflects that the ratio of the discovered neighbors linearly increases when nodes broadcast discovery messages more quickly. All neighbors can be discovered once the discovery frequency is bigger than the threshold. At this time, larger discovery interval means waste of network resource. Then, focusing on the probability under LM and NLM, we have that the thresholds are different although the trend of the curves are same. The threshold is 0.42 under LM and almost 1.25 under NLM. This reflects that to discover all neighbors, nodes should make discovery more frequently under LM and NLM. Therefore, more network resource should be used for neighbor discovery with the channel randomness.

We investigate the impacts of shadowing factors on neighbor discovery by focusing on lognormal model. The corresponding results are shown in Fig. 4. In this scenario, all nodes moves in low mobility segment, in which $\Delta v = 30$m/s, and $r_0 = 50$. We analyze the value of stable hitting probability when the variation factor σ changes. The figure reveals two results. Firstly, targeting at $p_h \lim 1$, the thresholds is 0.23, 0.42 and 0.67 under $\sigma = 0.161$, $\sigma = 0.391$ and $\sigma = 0.806$ respectively. Thus, to discover all neighbors, nodes should broadcast more frequently under heavy shadowing scenarios. In addition, the stable hitting probability for $\sigma = 0.806$ is

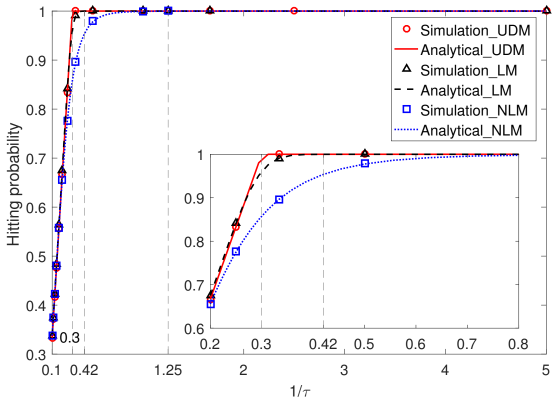

Fig. 3. Hitting probability under three models.

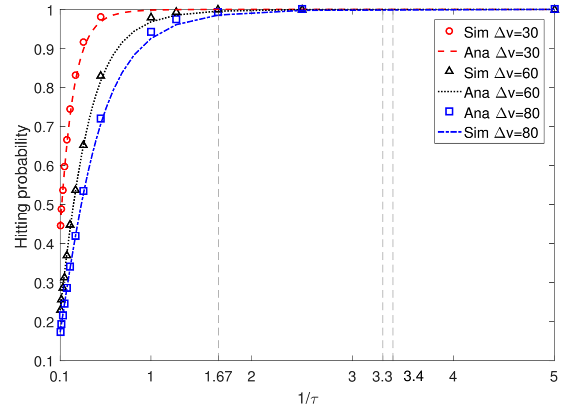

Fig. 5. Hitting probability varies with velocity.

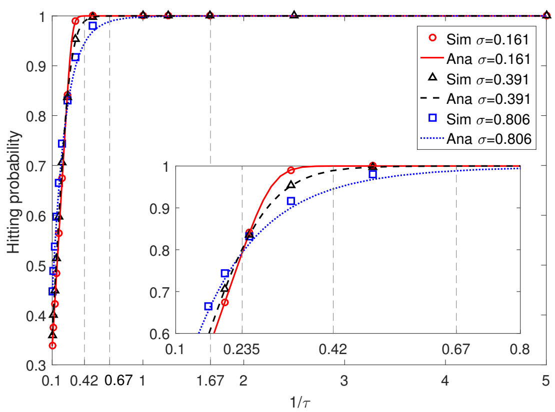

Fig. 4. Hitting probability under different shadowing.

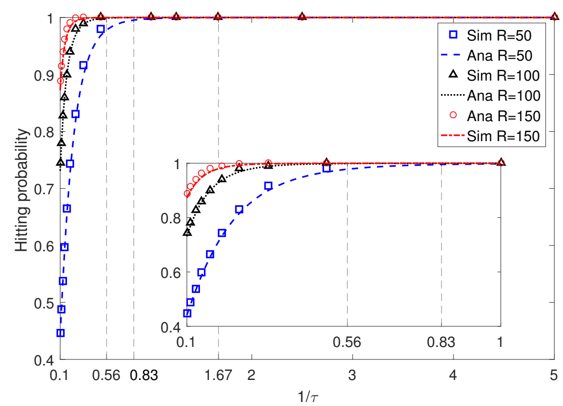

Fig. 6. Hitting probability varies with radio range.

always the largest when $1/\tau < 0.235$, which means that larger variation of radio range brings more chance to discover more neighbors. Thus, compared with small shadowing variation scenarios, smaller discovery interval can be adopted when the requirement of discovery ratio is low.

Fig. 5 depicts the hitting probability varying with the relative velocity. In this scenario, we consider that all nodes moves in the low mobility segment with $\Delta v = 30$m/s, the medium mobility segment $\Delta v = 60$m/s, and the high mobility segment $\Delta v = 80$m/s. In addition, we set $r_0 = 50$ and $\sigma = 0.806$. In the figure, the curve for $\Delta v = 30$m/s is always higher than the other two. The reason is that the stable hitting probability is inversely proportional to the relative velocity, which is revealed by Theorem 1. Targeting at $p_h \lim 1$, the threshold is 1.67, 3.3 and 3.4 in the low mobility segment with $\Delta v = 30$m/s, the medium mobility segment $\Delta v = 60$m/s, and the high mobility segment $\Delta v = 80$m/s, respectively. Therefore, more discovery packets needed for higher discovery ratio.

In Fig. 6, we study the stable hitting probability varying with the expectation radio range r_0. In this scenario, all nodes move in the low mobility segment, in which $\Delta v = 30$m/s, and $\sigma = 0.161$. We set the range by $r_0 = 50$m, $r_0 = 100$ and $r_0 = 150$. Obviously, the larger the range is, the higher the stable hitting probability is. The phenomenon agrees with results of Theorem 1. Furthermore, the threshold is 0.56, 0.83 and 1.67 for $r_0 = 50$m, $r_0 = 100$ and $r_0 = 150$ targeting at $p_h \lim 1$. Thus, nodes should broadcast discovery packets more frequently to discover all neighbors when the radio range is small.

VI. Conclusion

Neighbor discovery is the fundamental step of all peer-to-peer communication. In this paper, we investigated the method and novelly proposed to use it in cooperative perception of intelligent vehicles. To address the inherent issue of neighbor discovery, we first made an in-depth analysis of the popular periodic discovery method. By defining a new metric, i.e., hitting probability, related to time and overhead, we derived the stable hitting probability function, and gave the results under three radio models. Motivated by the analysis results, we proposed an improved neighbor discovery, in which nodes change the discovery interval adaptively according to the network status. In addition, we introduced the improved discovery into cooperative perception. At last, our simulation results verified the analysis results.

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