Estimation of the Number of Obstacles Based on p-value for V2V Communications

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SUMMARY Vehicle-to-vehicle (V2V) communications have been continuously studied to realize reliable autonomous driving systems. Conventional works have clarified that multiple obstacle vehicles between a transmitter and a receiver have a strong effect on radio propagation characteristics. It is necessary to design communication parameters according to the number of obstacle vehicles for improving the robustness of V2V communications. This paper describes a method to estimate the number of obstacle vehicles using a small sample size based on a p-value, which is typically utilized in hypothesis testing. The cloud server first calculates the average received signal power for each number of obstacle vehicles assuming that each number is known. Subsequently, the number of obstacles is estimated by using newly reported samples. The simulation results reveal that the proposed method can accurately predict the number of obstacles using a small sample size.

key words: *V2V communications, obstacles, radio propagation, p-value*

1. Introduction

To realize reliable autonomous driving systems, many researchers are continuously studying vehicle-to-vehicle (V2V) communications [1, 2]. Vehicles communicate with each other and share safety information, such as approach of an emergency vehicle, in V2V communications. As the dedicated frequency for the V2V communications, 5.9 GHz band is assigned in the USA and Europe, meanwhile, 700 MHz band is utilized in Japan. Different from a wireless system with a fixed location of a transmitter (e.g., a cellular network), both transmitters and receivers dynamically move in the V2V communications. Hence, communication quality notably becomes poor owing to the fluctuation of radio propagation characteristics, such as a path loss. It is necessary to predict those characteristics with high accuracy to guarantee reliability of V2V communications.

A fundamental method of radio propagation estimation is an empirical propagation model (e.g. the Okumura–Hata model). Although this model enables us to roughly predict the median path loss, estimation accuracy against a true received signal power limits to around 8 [dB] owing to the shadowing [3].

We have considered utilization of a radio map [4–9] for V2V communications [10] to solve the above problem. In this method, distributed vehicles having sensing devices first observe radio propagation information in each location and upload measured samples to a cloud server. The cloud server divides the communication area into two-dimensional meshes and calculates the average received signal power in each mesh. Subsequently, the constructed statistical information is stored as the radio map in each transmission mesh on the cloud server. Radio maps enable us to accurately estimate the path loss and the shadowing in each mesh compared to the empirical propagation model [10].

However, the above method does not consider the situation that obstacle vehicles, such as a truck, exist between a transmitter and a receiver. Many researchers have conducted measurement campaign and theoretical analysis to survey effects of obstacle vehicles on radio propagation characteristics [11–20]. Especially, H. Nguyen *et al.* [20] have revealed that the shadowing loss linearly increases according to the number of obstacle vehicles. To improve the robustness of V2V communications, a transmitter must estimate the number of obstacle vehicles and design own communication parameters based on the estimation result. Although conventional works assume that the number of obstacle vehicles is known, a transmitter may not know this number due to a non-line-of-site in realistic V2V communications. Additionally, it is difficult to obtain enough number of samples in a fixed location owing to the dynamic mobility of a transmitter and a receiver.

Motivated by these facts, this paper describes a method for estimating the number of obstacle vehicles using a small sample size based on a p-value. The cloud server first calculates the average received signal power for each number of obstacle vehicles assuming that each number is known. Subsequently, the number of obstacles is estimated by using newly reported samples. The simulation results reveal that the proposed method can accurately predict the number of obstacles using a small sample size.

The remainder of this paper is organized as follows. Section 2 describes the system model. After Section 3 explains the proposed method, Section 4 shows the simulation results. Then, we conclude this paper in Section 5.

2. System Model

2.1 Measurement Model

Fig. 1 shows the system model. We consider a simple situation that the V2V communication is performed in the con-

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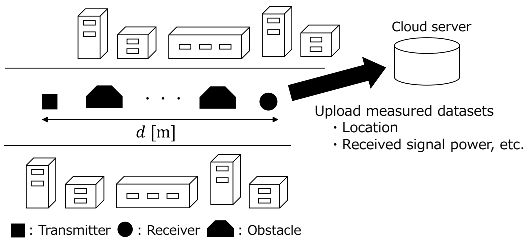

Fig. 1: The system model.

stant link distance d [m]. A transmitter sends a beacon signal, including own position information and the ID, to a receiver every 100 [ms] based on IEEE 802.11p. The receiver uploads these data in addition to the received position, the received signal power, and the center frequency to the cloud server after demodulating the transmitted beacon signal. Here, we assume that there are 0 to M obstacle vehicles (in the following, we call obstacle vehicles as *obstacles*) between the transmitter and the receiver, here, M is the maximum number of obstacles. The proposed method described in Section 3 calculates the p-value to estimate the number of obstacles using n_{ini} and n_{new} received signal power samples. Here, it is necessary to accumulate n_{ini} samples for each number of obstacles in advance assuming that the number of obstacles is known. Thus, each n_{ini} sample is assumed to be stored on the cloud server by pre-observation. After the accumulation, the receiver uploads n_{new} samples to the cloud server when the number of obstacles is unknown.

The cloud server estimates the number of obstacles using the proposed method and provides the estimation result to the transmitter. The transmitter adaptively designs communication parameters, such as the modulation format, according to the number of obstacles. For instance, a low order modulation is utilized if the number of obstacles is large to secure communication reliability. Here, we assume that the number of obstacles is constant until the transmitter sends the beacon signal using the provided estimation result.

Since the instantaneous received signal power contains the effect of the small-scale fading, the proposed method may not operate with high accuracy. Although such the fading variation can be mitigated by sharing enough datasets between several vehicles, the communication reliability degrades according to the surrounding environment. Thus, enough measured samples are accumulated in the cloud server.

If each obstacle mounts global positioning system (GPS), we may estimate the number of obstacles by accumulating GPS information on the cloud server. However, ordinary people driving obstacle vehicles may feel uncomfortable when their location information are known by the third party. Thus, we propose our method without using the GPS.

2.2 Shadowing Model

This paper assumes that the shadowing in each obstacle follows statistically independent the log-normal distribution. Here, it has been reported that the shadowing has the additivity of the mean in multiple obstacles environment [20]. Furthermore, we assume the additivity for the standard deviation. Thus, the mean and the standard deviation of the log-normal shadowing in multiple obstacles can be modeled as follows:

$$\mu_j = j\mu_1, \tag{1}$$

$$\sigma_j = \sqrt{j\sigma_1^2}, \tag{2}$$

where μ_j [dB] and σ_j [dB] are the mean and the standard deviation of the shadowing, respectively when the number of obstacles is j. μ_1 [dB] and σ_1^2 are the mean and the variance of the shadowing, respectively for $j = 1$.

3. Proposed Method

3.1 Preliminary Descriptions

A significant difference of the average received signal power may be inferred in multiple obstacles environment if the shadowing has the additivity. Under this condition, we can utilize the p-value of the hypothesis testing for estimating the number of obstacles. If the significant difference between two mean values is small, the p-value becomes large. Focusing on the property, the proposed method first calculates the p-value based on n_{ini} and n_{new} samples. Subsequently, the cloud server estimates the number of obstacles by searching the maximum p-value. As the hypothesis testing, we use Welch's t-test because this method enables us to accurately calculate the p-value compared to the general t-test and a non-parametric test.

3.2 Estimation Procedures

To calculate the p-value, the t-value t_j and the degree of freedom v_j when the number of obstacles is j are defined as follows:

$$t_j = \frac{\bar{X}_j - \bar{Y}}{\sqrt{\frac{S_j^2}{n_{\text{ini}}} + \frac{S^2}{n_{\text{new}}}}}, \tag{3}$$

$$v_j \approx \frac{\left(\frac{S_j^2}{n_{\text{ini}}} + \frac{S^2}{n_{\text{new}}}\right)^2}{\frac{\left(\frac{S_j^2}{n_{\text{ini}}}\right)^2}{n_{\text{ini}}-1} + \frac{\left(\frac{S^2}{n_{\text{new}}}\right)^2}{n_{\text{new}}-1}}, \tag{4}$$

where $\bar{X}_j$ [dBm] and S_j^2 are the average received signal power and unbiased sample variance when the number of obstacles is j, respectively. These values are calculated on the cloud server using n_{ini} samples in advance. $\bar{Y}$ [dBm] and S^2 are the average received signal power and unbiased sample variance using n_{new} samples. Here, the cloud server calculates each average received signal power as the logarithmic value rather than the true value. This is because the p-value cannot be accurately derived owing to the existence of outliers.

In Welch's t-test, the calculated t-value follows the Student's t distribution and its function is determined as

$$f(t_j, v_j) = \frac{\Gamma\left(\frac{v_j+1}{2}\right)}{\sqrt{\pi v_j}\,\Gamma\left(\frac{v_j}{2}\right)}\left(1+\frac{t_j^2}{v_j}\right)^{-\frac{v_j+1}{2}}, \tag{5}$$

where $\Gamma(\cdot)$ is the gamma function. It should be noted that, because v_j is required to be an integer, it is rounded off if it is a decimal. Under this condition, we can obtain the p-value by referring the tail of the Student's t distribution as follows:

$$p_j = \int_{-\infty}^{-t_j} f(\xi, v_j)\, d\xi + \int_{+t_j}^{+\infty} f(\xi, v_j)\, d\xi, \tag{6}$$

where ξ is an integral variable. This paper utilizes the two-sided test in which a rejection region exists in both tails of the Student's t distribution because the two-sided test is statistically recommended as compared with the one-sided test in most cases. Finally, the estimated number of obstacles $\hat{j}$ is derived using the following function:

$$\hat{j} = \underset{j=0,1,\cdots,M}{\arg\max}\ (p_j). \tag{7}$$

If d is not constant, the number of obstacles may be inaccurately estimated owing to the fluctuation of a path loss. Even in this situation, we can estimate the number of obstacles by removing the path loss effect from the average received signal power based on the linear regression. Due to space limitations, this task will be solved in future work.

In the realistic environment, if communication environment dynamically changes, the small-scale fading may drastically fluctuate owing to the static scatters, such as buildings. Hence, the assumed propagation models that will be described in Section 4.1 may not be suitable in the site-specific environment. As a result, the proposed method may not elaborately estimate the number of obstacles. Even in such the environment where the radio propagation is complicated, the accuracy of the proposed method may be guaranteed by increasing n_{ini} and n_{new} since the variation of fading can be mitigated.

If a height of an obstacle is lower than the heights of the transmitter and receiver, the proposed method may underestimate the number of obstacles compared to the actual numbers. However, in such the situation, we can consider that the obstacle having lowe height does not exist because no shadowing occurs by the obstacle.

4. Simulation Descriptions

4.1 Radio Propagation Model

We model the radio propagation model for calculating the instantaneous received signal power as follows:

Table 1: The simulation parameters

Transmission power P_{Tx} [dBm]	24
Path loss exponent γ	3
Maximum number of obstacles M	3
Communication distance d [m]	100
Reference distance d_0 [m]	10
Mean μ_1 [dB]	12.7 [18]
Standard deviation σ_1 [dB]	6.7 [18]
K-factors for $j = 0, 1$	30.9 [11], 1.19 [16]
F_j for $j = 2, 3$	Rayleigh fading
Center frequency [MHz]	760
The number of samples n_{ini}	100

$$P_j(d) = P_{\mathrm{Tx}} - L_0(d_0) - 10\gamma\log_{10}\left(\frac{d}{d_0}\right) - W_j + F_j, \tag{8}$$

where $P_j(d)$ [dBm] is the instantaneous received signal power when the number of obstacles is j. P_{Tx} [dBm] is the transmission power, γ is the path loss exponent, and d_0 [m] is reference distance. W_j [dB] is the log-normal shadowing when the number of obstacles is j. This random value is obtained from the log-normal distribution with μ_j and σ_j. Note that no shadowing occurs for $j = 0$. F_j [dB] is the small-scale fading for j. $L_0(d_0)$ [dB] is the free space path loss, and its function is given by

$$L_0(d_0) = 10\log_{10}\left(\frac{4\pi d_0}{\lambda}\right)^2, \tag{9}$$

where λ [m] is the wavelength.

4.2 Simulation Parameters

Table 1 represents the simulation parameters. The number of obstacles j is determined $[0, 3]$ on $d = 100$ [m]. μ_1 and σ_1 are based on the measured values [18]. Additionally, for $j = 0, 1$, the small-scale fading is modeled as the Nakagami–Rice fading by referring the measurements [11, 16]. We assume that F_2 and F_3 follow statistically independent the Rayleigh fading because the K-factor may be small owing to an increase in j. The simulation procedures are summarized as follows:

a). The instantaneous received signal power represented Eq. (8) is obtained for n_{ini} in each number of obstacles. Then, the cloud server calculates $\bar{X}_j$ and S_j^2.
b). Additionally, n_{new} samples are got based on Eq. (8) in each number of obstacles. Then, $\bar{Y}$ is derived using n_{new} samples. Subsequently, the cloud server estimates the number of obstacles based on Eqs. (5), (6), and (7).
c). We evaluate the average success rate that can correctly estimate the number of obstacles by performing the procedures from a). to b). for 1,000 times.

In the simulation, W_j and F_j are the random variable; thus, these realizations are random in each sample.

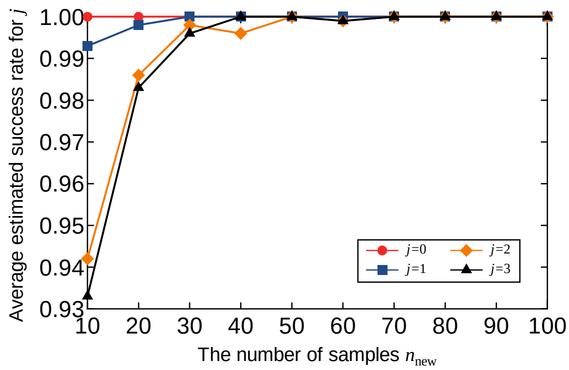

Fig. 2: The average estimated success rate for the number of obstacles.

4.3 Results

Fig. 2 shows the average estimated success rate in each j. These results revealed that the proposed method could accurately estimate the number of obstacles using the small number of samples (e.g. $n_{\text{new}} = 10$). However, the rate slightly became poor with an increase in j because variance of the received signal power was large owing to the additivity of variance. It is necessary to use enough samples in such a situation for improving the success rate. The proposed method will contribute to appropriately determine communication parameters, such as the transmission power and modulation format, according to the number of obstacles.

5. Conclusion

We have proposed the method for estimating the number of obstacles in V2V communications based on the p-value. Our method first accumulates the received signal power samples for the number of obstacles in advance. Then, the number of obstacles is calculated by searching the maximum p-value. The simulation results have clarified that the proposed method can accurately predict the number of obstacles. As future work, the performance evaluation using measured data in a real environment is considered.

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