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Performance Analysis of Vehicular Localization Accuracy With Non-Line-of-Sight Identification

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Abstract

Recently, vehicular localization has drawn a lot of attention due to increasing location-based applications in vehicular ad-hoc networks (VANETs). However, similar to the conventional localization problem, vehicular localization suffers from the biases caused by non-line-of-sight (NLOS) propagation. To reduce its impact, NLOS identification and mitigation are commonly used, where the accuracy of NLOS identification is crucial. This paper aims to investigate the relationship between localization performance and misidentification of NLOS. The impacts to vehicle localization accuracy of two types of NLOS misidentification, namely false and miss respectively, are analyzed. It is demonstrated with Monte Carlo simulations that those two factors have different impacts on localization accuracy. Furthermore, the dominating factor of localization for different scenarios with two types of localization strategies is concluded, which could be further used to chose the strategy leading to higher localization accuracy in different scenarios.

1 Introduction

In vehicular ad-hoc networks (VANETs), vehicle position information is indispensable for varieties of emerging applications, such as driverless car [1], speed advisory [2] and collision warning [3]. Especially with the conspicuous improvement of mmWave mobile-to-mobile (M2M) communications, larger amount of data can be transmitted in intelligent transportation systems (ITS) [4], which makes high-accuracy vehicle localization achievable. To further improve the accuracy and reliability of vehicular localization, some researches suggest using cooperative methods for vehicular localization. Ref. [5] estimates vehicle positions using an algorithm named distributed location estimate algorithm, which improves accuracy by sharing pesudorange measurements with neighboring vehicles. A cooperative localization paradigm called network localization and navigation is proposed in [6], where the mobile nodes could calculate the positions more precisely through spatiotemporal cooperation. Ref. [7] proposes a GPS-assisted cooperative localization algorithm named geometry-based localization for GPS outage in VCPS environments, in which vehicular dynamics and road trajectory are exploited during localization to weaken the impact of GPS outage.

Same to the conventional localization case, the performance of cooperative localization is also deteriorated by non-line-of-sight (NLOS) propagation. NLOS may occur at road crossing or blocked by other vehicles [8], adding bias to the measurements compared to LOS path [9], which eventually leads to poor localization performance. Such a problem can be resolved by detecting the NLOS status (i.e., NLOS identification) and eliminating the bias of measurement parameters (i.e., NLOS mitigation) [10]. NLOS identification aims to separate data contaminated by NLOS, and NLOS mitigation alleviates bias of NLOS data. In general, NLOS identification cannot always be correctly identified. There exists two types of mistakes of NLOS identification: *false* and *miss* [11], where *false* means the LOS status is identified as NLOS, and *miss* represents the case that NLOS status is identified as LOS. Those two cases are called NLOS misidentification. Even though many techniques of NLOS identification, such as hypothesis testing and machine learning based on features [10], have been proposed, the precision of NLOS identification, which is the key factor to improve localization accuracy, is not satisfying. Moreover, current research on the degradation of localization accuracy caused by NLOS misidentification is inadequate.

This article aims to investigate the specific relationship between them and improve localization accuracy. The impact of NLOS misidentification is analyzed by distinguishing the two cases: *false* and *miss*. It is demonstrated that *miss* has a greater impact on localization accuracy when both NLOS identification and mitigation are used. Whereas in the case that only NLOS identification is adopted, the dominating factor of localization may be *miss* or *false*, which depends on the vehicles' communication range.

2 System Model for Vehicular Localization

2.1 Error Model

In this paper, the target vehicles are located with TDOA algorithm, which does not introduce synchronization errors. This is because consistent time reference is not re-

Table 1. Parameters to Generate Excess Propagation Delay

Notation	Description	Value
T_1	The median value of τ_{rms} at $d = 1000$ m	1 μs
ε	An exponent parameter	0.5 dB
ξ	A lognormal distributed variable	-
σ_ξ	The standard deviation of ξ	4 dB

quired thereby precise synchronization between agents and anchors is unnecessary [12]. Here, the measurement distance $\hat{d}_{ij}$ between the i-th anchor and the j-th agent can be modeled as follows:

$$\hat{d}_{ij} = d_{ij} + m_{ij} + n_{ij} \tag{1}$$

where d_{ij} represents the actual distance, m_{ij} is the measurement error, n_{ij} is the error caused by NLOS propagation (henceforth called NLOS error). Parameter m_{ij} always exists and can be treated as a Gaussian random variable [13]. NLOS error n_{ij} usually depends on the surrounding environment of target vehicles, and equals to 0 when LOS propagation occurs. Two approaches are commonly used to generate the NLOS error: to treat it as constant or to treat it as variable [14], and the latter one is chosen in this paper. More specifically, assuming that the excess propagation delay τ is a random variable, the NLOS error $n_{ij} = c \cdot \tau$, where c is the speed of light. There have been several widely used random variable models for generating τ, including exponential distribution, uniform distribution and Gaussian distribution models, etc. [12]. In this paper, the exponential distribution model is chosen to generate the excess propagation delay, and its probability density function is given as [14]:

$$P_\tau = \begin{cases} \frac{1}{\tau_{\text{rms}}} e^{-\frac{\tau}{\tau_{\text{rms}}}}, & \tau > 0 \\ 0 & \text{, otherwise} \end{cases} \tag{2}$$

where τ_{rms} represents the delay spread caused by NLOS propagation and can be further expressed as follows:

$$\tau_{\text{rms}} = T_1 d^\varepsilon \xi \tag{3}$$

where d is the actual distance between agent and anchor, T_1 is the median value of τ_{rms} when $d = 1000$ m, ε is an exponent parameter lying between 0.5 to 1, ξ is a lognormal distributed variable with $10\log\xi \sim N(0, \sigma_\xi^2)$, and σ_ξ is its standard deviation. The setting values of the above environmental dependence parameters are listed in Table 1 according to [14].

According to [11], we definite P_{NLOS} to quantify the complexity of the communication environment. It indicates the statistical probability of NLOS propagation for each path. With known number of anchors N_{a} in a positioning system, the number of NLOS paths N_{NLOS} is binomial distributed with a probability of P_{NLOS} [11].

2.2 Localization Strategies

In this paper, two localization strategies based on NLOS identification and mitigation are used for analysis according to [11]:

(1) *Identification only*: This strategy only performs NLOS identification. The data identified as NLOS is discarded and only LOS data is used for localization. This may not work successfully when the number of LOS paths is less than 3 because at least 3 anchors are needed for TDOA based localization algorithm.

(2) *Mitigation after identification*: Though most NLOS mitigation can work successfully without involving identification, it is combined with NLOS identification in this strategy for a higher localization accuracy. This strategy first performs NLOS identification, then correct the data identified as NLOS status through adding a correction value, which is obtained with machine learning methods, to the measurement range to offset the ranging error caused by NLOS. After that, all data is used to estimate vehicle position.

It can be seen that both strategies are based on NLOS identification. Hence, the performance of NLOS identification influencing vehicle localization accuracy is crucial. Identification error rate is widely used to evaluate the NLOS identification performance. However, as is shown in this paper latter, error rate should not be the only criterion. Instead, NLOS misidentification should be further divided into two cases: identifying the NLOS path as the LOS path, and identifying the LOS path as the NLOS path, which are called *miss* and *false* cases respectively. Now define P_{F} and P_{M} as the probability of *false* and *miss* cases as follows:

$$P_{\text{F}} = \frac{S_{\text{F}}}{S} \tag{4}$$

$$P_{\text{M}} = \frac{S_{\text{M}}}{S} \tag{5}$$

where S is the number of all samples, S_{F} is the number of *false* samples, and S_{M} is the number of *miss* samples. Based these, the error rate of misidentification P_{E} could be written as follows:

$$P_{\text{E}} = \frac{1}{2}\left(P_{\text{F}} + P_{\text{M}}\right). \tag{6}$$

The impact of the two cases on vehicular localization accuracy will be analyzed later.

3 Simulations and Analysis

For localization simulations, we define the maximum allowable localization error as e_{th} (in units of meter). It is considered an "outage" occurs when the distance between the estimated position and the actual position exceeds e_{th}. That is, localization cannot be achieved. The probability of the outage is recorded as P_{out} and obtained by Monte Carlo simulations. Since P_{out} is able to represent the accuracy of localization in a statistical sense, it is used as the evaluation metric of vehicular localization performance.

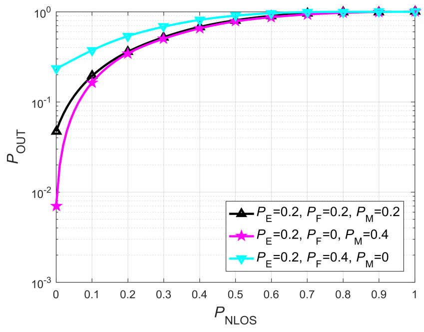

Figure 1. Result of vehicular localization with same P_E when using the strategy of *identification only* ($r = 200$).

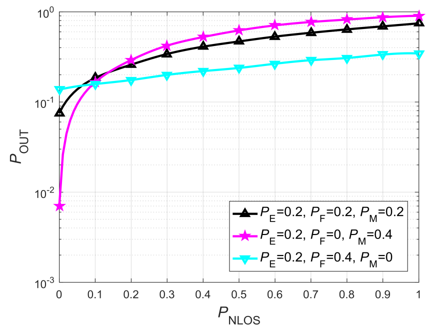

Figure 2. Result of vehicular localization with same P_E when using the strategy of *mitigation after identification* ($r = 200$).

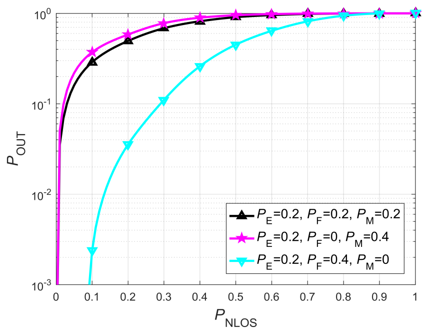

Figure 3. Result of vehicular localization with same P_E when using the strategy of *identification only* ($r = 500$).

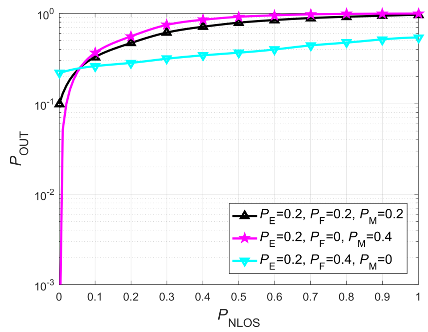

Figure 4. Result of vehicular localization with same P_E when using the strategy of *mitigation after identification* ($r = 500$).

Table 2. Simulation Parameters For Vehicular Localization

Notation	Description	Value
N_v	Number of vehicles	20
P_{gps}	Proportion of vehicles equipped GPS	0.5
S_w	Road width	25 m
S_l	Road length	500 m
e_{th}	Error threshold	20 m
r	Communication range of each vehicle	200 m

In the simulation, we assume that the road in the vehicular environment is a rectangle with length of S_l and width of S_w, and use a two-dimensional coordinate system to describe it. Then N_v non-overlapping points are randomly generate to represent vehicles, including both GPS-equipped and GPS-unequipped ones. The simulation parameters are given in Table 2.

We first set three groups of $[P_F, P_M]$ as $[0.2, 0.2]$, $[0, 0.4]$ and $[0.4, 0]$, and for each group, P_E always equals to 0.2. Then we conduct the simulations of localization using the parameters in Table 2. The simulation results with the two strategies are shown in Fig. 1 and Fig. 2, respectively. Fig. 1 shows that when using *identification only* as the localization strategy, though the total error rates of the three groups are the same with $P_E = 0.2$, P_{out} of each group is different. Specifically, P_{out} with $P_F = 0$ and $P_M = 0.4$ (i.e., the purple curve) is the smallest, and $P_F = 0.4$ and $P_M = 0$ (i.e., the cyan curve) is the highest. This means that the false misidentification has higher impact on accuracy on the sense of increasing outage probability. However, Fig. 2 indicates that with the strategy of *mitigation after identification*, only if P_{NLOS} is small (less than 0.1), P_{out} of the purple curve is the smallest. This is because NLOS mitigation introduces extra error to LOS data which is identified as NLOS, and such error is larger than NLOS error when P_{NLOS} is small. In other cases, it has worse performance compared to the cyan curve. Hence, it can be concluded that when the *identification only* strategy is chosen, the *false* misidentification is the dominant factor limiting the improvement of localization accuracy. Whereas using the strategy of *mitigation after identification*, the performance is more affected by the case of *miss*.

Table 3. The Dominating Factor of Localization Accuracy.

Strategy / r	*Identification only*	*Mitigation after identification*
200 m	*false*	*miss*
500 m	*miss*	*miss*

When communication coverage of vehicle r is increased, it is found that P_{out} changes as well. We consider the scenarios with large r, i.e., $r = 500$ m, and still set other parameters based on Table 2. Fig. 3 and Fig. 4 show the simulations of P_{out} for the two strategies. It can be observed that the simulation results of *mitigation after identification* do not change too much compared to Fig. 2, however, the results of *identification only* are significantly changed. As shown in Fig. 3, P_{out} with $P_{\text{F}} = 0.4$ and $P_{\text{M}} = 0$ (i.e., the cyan curve) is the smallest for $r = 500$. Whereas for $r = 200$, such case (i.e., the cyan curve in Fig. 1) shows the worst performance.

For the comprehensive analysis of the above results, localization outages are divided into two types: (i) it occurs when the localization error exceeds the allowed threshold e_{th}, (ii) it occurs when the available vehicles (anchor points) are less than three. When r is small, both (i) and (ii) exist in localization. In such case, for the strategy of *identification only*, the probability of (ii) is higher than (i), and the anchor will be abandoned if it is identified as NLOS status by mistake, hence *false* has significant impacts on the localization accuracy. Whereas using *mitigation after identification* can avoid that the number of available anchor points is less than three, thereby *miss* is the dominating factor of localization. In the scenarios where r is large, the probability of (ii) is small. Even if some anchor points in LOS status are abandoned by mistake, the usable vehicles are still more than 3. Therefore, no matter which strategy is adopted, the dominating factor impacting localization performance is *miss*. The observation results are summarized into Table 3.

4 Conclusion

This paper investigates the impact of NLOS identification on vehicular localization performance. Through the simulations, it is found that the LOS/NLOS misidentification significantly impacts localization accuracy, which shows the importance of precise NLOS identification for vehicular localization. The simulations show that the localization errors are not always the same even with identical total error rate of misidentification. It results from the impacts of the two types of misidentification, namely *false* and *miss*, respectively, which both affect the localization accuracy. It is found that in the scenarios where r is small, the dominating factor of localization accuracy is *false* for *identification only*, and *miss* for *mitigation after identification*. When r is large, *miss* is the dominating factor for the both strategies. Such conclusions can be utilized to improve cooperative vehicle localization accuracy.

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