High Precision Vehicle Positioning: Towards Cooperative Driving Based on VANET

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Abstract

High precision vehicle positioning is a crucial component for intelligent transportation systems. Current technologies based on the use of GPS signals have limitations in providing high precision positioning. Recently, dependence on roadside units (RSUs) has been introduced as alternative positioning methodology. Positioning errors are still encountered, however, due to lack of LOS signals among RSUs and vehicles, for dense traffic. This research proposes a GPS-free cooperative positioning method that considers signals from both RSUs as well as neighbor vehicles. A communication channel model in urban environment is developed based on IEEE 802.11p DSRC at 5.9 GHz. The model implements Wireless InSite ray-tracing tool, and is validated using published measurement results of path-loss and received power levels in urban roads. Accuracy is enhanced by estimating time-of-arrival (TOA) and direction-of-arrival (DOA) information of signals from neighbor RSUs and vehicles. Results show that the proposed method provides consistently less errors compared to other methods. In particular, the proposed framework with dependence on only three RSUs is found to improve accuracy by 92% compared to GPS based procedures, and by about 15% with respect to conventional techniques that depend on four RSUs.

Keywords: Cooperative vehicular positioning, Dedicated short-range communications (DSRC), Time-of-arrival (TOA), Direction-of-arrival (DOA).

1 Introduction

Traffic congestions and road accidents are increasing, especially in urban cities, due to population growth and increasing economic activities. Various efforts are directed towards improving traffic efficiency and reducing road accidents in dense-traffic urban environments. The concept of intelligent transportation systems (ITS) has thus risen to provide non-conventional resolutions to enhance road safety, reduce traffic congestion, and preserve the environment. The key element of ITS is based on a paradigm in which vehicles and installed roadside units serve as communicating nodes to exchange position information, safety warnings and traffic situations among each other. Direct communication is conducted among nodes by forming a vehicular ad-hoc network (VANET) [1]. Dedicated short-range communication (DSRC) at 5.9 GHz band has been developed in the US for wireless access in vehicular environments (WAVE), based on IEEE 802.11p standard amendment [2]. Analogous technology is developed in Europe as Cooperative ITS and the band is referred to as ITS-G5 band [3-4].

Realistic and efficient modeling of the signal propagation is the basis for successful evaluation of vehicular applications. Physical characteristics of the received signal directly affect the upper layers of the protocol stack. Accurate modeling of vehicular channels requires the consideration of the complex environment surrounding the communicating vehicles, including static objects (buildings, foliage, road-divider) as well as moving objects (vehicles on the road).

2 Literature Review

Vehicular channel models were developed and characterized based on DSRC at 5.9 GHz using simulation and experimental measurements [5-9]. However, these studies define the vehicular communication environments as uncrowded (LOS) or crowded (NLOS), based on vehicle density, without analyzing the impact that obstructing vehicles on the road and considers the outlines of objects (buildings and foliage) adjacent to the road. A more realistic channel model was developed in [10] based on extensive measurements performed in urban, highway and open-space environments at Porto in Portugal. We present an efficient vehicular communication channel model in urban environment that implements ray-tracing analysis. The model is validated by comparing the estimated results with the measurement data presented in [10] of path-loss and received power levels.

Accurate positioning is a key factor for enabling

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efficient VANET based ITS. Vehicular positioning is used in platooning, intersection warning, tolling applications, and car-park finding. With accurate information about own position as well as the locations of surrounding vehicles, a platoon of vehicles can move on the road while maintaining safe separation distances to achieve saving in travel time and mitigation of traffic congestions.

Global positioning system (GPS) provides coverage to most of the earth surface and exhibits low-cost devices, making it beneficial to be incorporated into vehicles [11]. But, GPS is unstable in urban environments, because of 'canyons' or obstructed line-of-sight (LOS) formed by high-rise buildings besides the roads [12]. GPS-based vehicle positioning suffers from the lack of ubiquitous availability and susceptible to higher positioning errors (5m to 30m). Therefore, this technique is not acceptable for vehicular safety applications.

Recently, vehicular positioning based on installed roadside units (RSUs) has emerged as more authentic alternative solution in GPS-denied environments [13]. However, current GPS-free positioning techniques consider the vehicle to interact with at least four roadside units for reference signal to obtain precise positioning. These techniques increase the system cost due to the requirement of more RSUs and delay the positioning decisions [14-16]. Furthermore, time-of-arrival (TOA) based vehicular positioning techniques that only depend on V2R communications suffer from the lack of line-of-sight (LOS) communications between vehicles and RSUs in urban scenarios. TOA positioning requires all RSUs and vehicle to be precisely synchronized. For proper synchronization, transmitted signal from roadside unit includes a time-stamp so that the on board communication unit of vehicle can obtain the time-stamp at which the signal is originated at the RSU. This additional time-stamp complicates the transmitted signal and results in an additional source of error.

In this research, we propose a GPS-free cooperative vehicle positioning technique based on TOA and DOA estimations of signal from three RSUs and cooperative vehicles on the road to achieve high-precision vehicle positioning. To overcome the LOS requirement of vehicle and RSU, we have incorporated V2V communications. In our approach, each vehicle performs position estimation independently using V2R communication, and cooperates with other vehicles to improve positioning accuracy. Enhanced accuracy depends on data fusion of positioning information estimated by various vehicles. Obtained results reveal that the accuracy of the proposed method depending on only three RSUs outperforms the conventional techniques that use V2R communications with four RSUs.

The remaining parts of the paper are organized as follows. Section 3 describes the vehicular channel model for urban road. Section 4 provides the experimental measurements and validation of the developed ray-tracing model. TOA and DOA estimation based vehicle positioning methods are described in Section 5. The proposed cooperative positioning method are described in section 6. Results and discussion have been provided in Section 7. Conclusions are then provided in Section 8.

3 Vehicular Urban Channel Model

The development of reliable vehicular communication system requires the accurate model of the propagation channel in vehicular environments and road scenarios. The motion of the transmitter and receiver and the frequency band operations make vehicular communication systems distinguished from the conventional cellular systems.

Figure 1 shows illustration of the ray-tracing simulation model for urban road. Simulation is conducted using Wireless InSite [17]. The time-variant nature of the propagation channel for vehicular communication is not only affected by the motion of the receiving and transmitting vehicles, but also by surrounding vehicles and objects along the road. Thus, to develop a realistic and efficient vehicular urban channel model, proper consideration of the scenario is necessary. The developed model considers common objects including buildings of different size and shape, road terrain, tree foliage along the road. The model also takes into consideration vehicles with communication unit and vehicles without communication unit as obstacles.

The model starts by designing various objects individually, which are characterized by relevant material properties. These objects are then integrated into a complete model. With realistic snapshots of road scenarios, the model is expected to provide accurate estimations of the performance of vehicular communication channel in urban environments. Simulation are then conducted in DSRC band at 5.9 GHz, considering estimations of path-loss and received power for varying distance between the communicating vehicles. The log-distance path-loss for distance d between transmitting and receiving vehicle is given by [10]

$$PL(d) = PL(d_0) + 10n\log_{10}\left(\frac{d}{d_0}\right) \quad \textbf{(1)}$$

where, n denotes the path-loss exponent and the term $PL(d_0)$ denotes the path-loss for a reference distance d_0.

The calculations are made by shooting rays from the transmitters and propagating them through the defined geometry. The rays interact with geometrical features as they make their way to receiver locations. Ray interactions include reflections from feature faces, diffractions around feature edges, and transmissions through features faces.

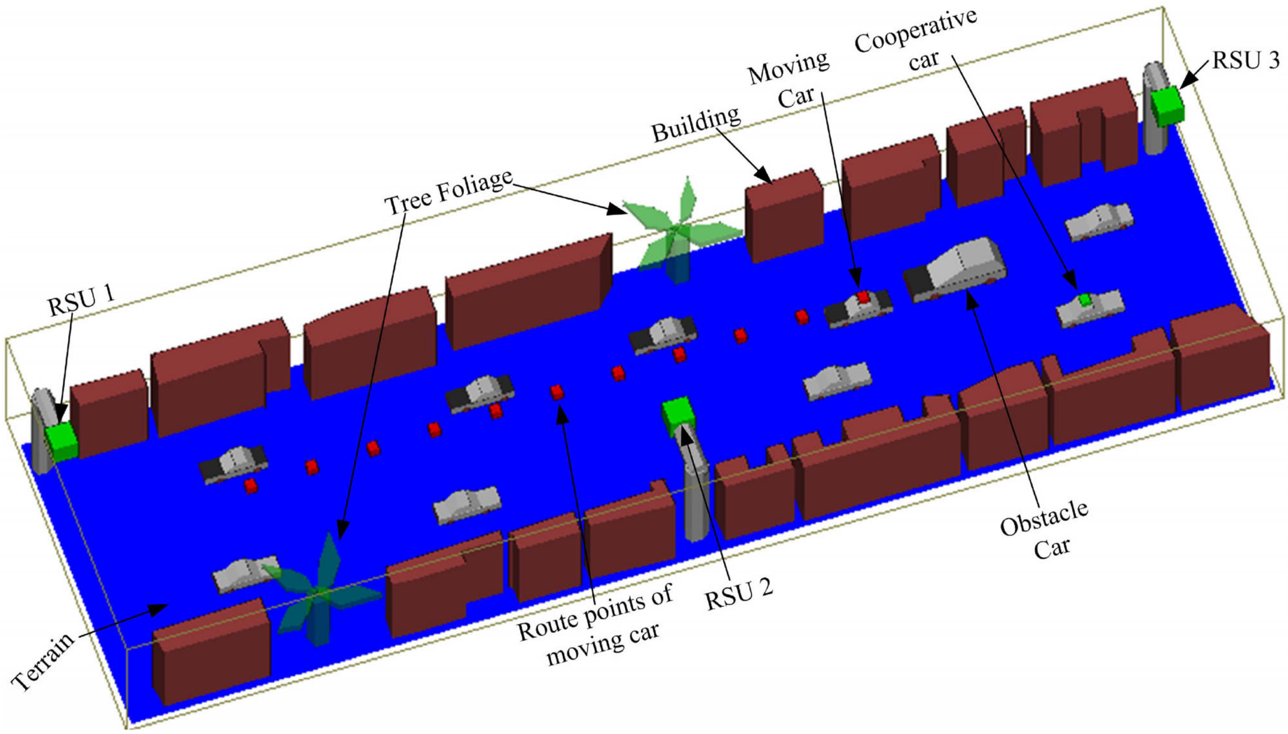

Figure 1. Developed vehicular channel model for urban road using Wireless InSite ray-tracing simulator

At each receiver location, contributions from arriving ray-paths are combined and evaluated to determine predicted values of received power, path-loss, TOA and DOA. The components of radio propagation are combined into the channel impulse response (CIR) between the transmitter position (r_{Tx}) and the receiver position (r_{Rx}). The CIR contains the contributions from all multipath components (MPCs) individually. The continuous time CIR based on 3D ray-tracing is given as

$$h\left(r_{Tx},r_{Rx},\tau,\phi,\psi\right)=\sum_{l=1}^{L}h_l\left(r_{Tx},r_{Rx},\tau,\phi,\psi\right) \quad \textbf{(2)}$$

$$h_l\left(r_{Tx},r_{Rx},\tau,\phi,\psi\right)=a_l\partial\left(\tau-\tau_l\right)\partial\left(\phi-\phi_l\right)\partial\left(\psi-\psi_l\right) \quad \textbf{(3)}$$

where, the variables, a_l, τ_l, φ_l and ψ_l denote the complex amplitude, time-delay, direction-of-departure (DoD) and the direction-of-arrival (DoA) respectively, related to the lth MPC. Furthermore, L is the total number of MPCs.

For vehicular *time-variant* channels, all multipath parameter components in equation (2) such as (a_l, τ_l, φ_l and ψ_l), transmitter position (r_{Tx}) and the receiver position (r_{Rx}), and the number of paths (L) become functions of time t. Thus, for vehicular channel, we can modify equation (2) as *time-variant* CIR given by

$$h\left(r_{Tx},r_{Rx},t,\tau,\phi,\psi\right)=\sum_{l=1}^{L}h_l\left(r_{Tx},r_{Rx},t,\tau,\phi,\psi\right) \quad \textbf{(4)}$$

4 Experimental Measurement and Validation

To validate the developed model, a comparison made with experiments performed in urban environment at Porto, Portugal [10]. The impact of both moving objects and static objects has been considered based on the received power and path-loss for varying distance. The experiment includes two vehicles equipped with DSRC devices. Each vehicle is equipped with a NEC LinkBird-MX, a custom-built development platform for vehicular communications. These DSRC devices operate at 5.85-5.925 GHz band and implement the IEEE 802.11p standard. The radios are connected to vertically polarized Mobile Mark ECOM6-5500 omnidirectional antennas, which measure 26 cm in height. Adding a GPS receiver to each communication system and taking advantages of the built-in beaconing functionality, the locations of the vehicles, and the received signal power are recorded throughout the experiments. Hardware configuration parameters based on IEEE 802.11p DSRC used in the experiments are summarized in Table 1.

Table 1. Hardware configuration parameters based on IEEE 802.11p DSRC

Parameter	Value
Center frequency	5.9 GHz
Bandwidth	10 MHz
Data rate	6 Mbps
Tx Power	10 dBm
Antenna Gain	5 dBi

Figures 2 and Figure 3 present a comparison of path-loss and received power level from the developed model and hardware measurements respectively. The path-loss and the received power based on the developed ray-tracing model using simulation are in good agreement with measurement results. It is also observed that the received power from the ray-tracing output meets the sensitivity threshold (-85 dBm) which is the requirements for DSRC receiver performance [10].

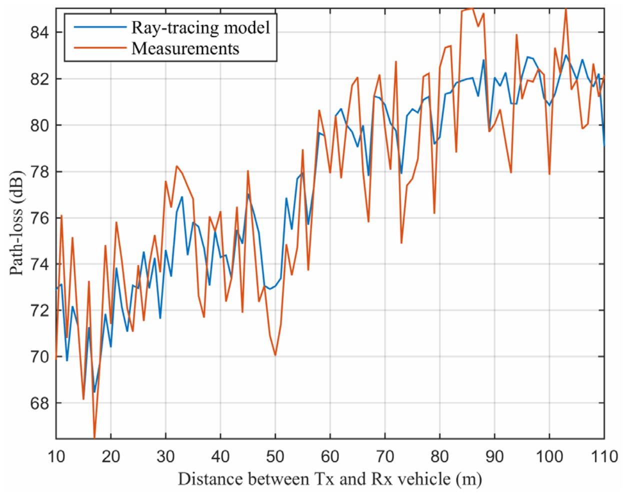

Figure 2. Path-loss from ray-tracing simulation model and measurements at DSRC band (5.9 GHz)

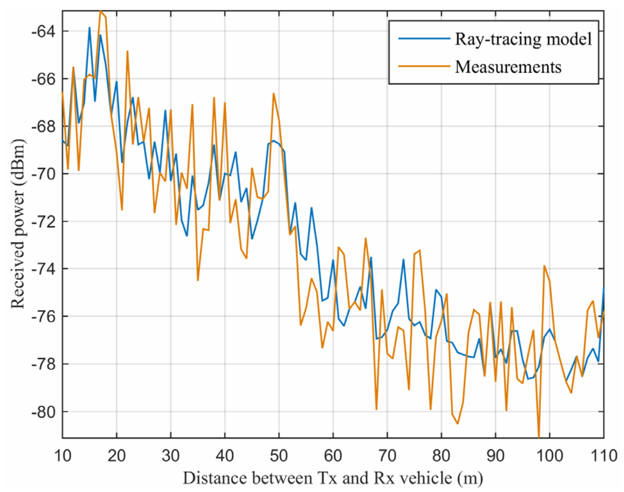

Figure 3. Received power from ray-tracing simulation model and measurements at DSRC band (5.9 GHz)

5 TOA and DOA based Vehicle Positioning

Time-of-arrival (TOA) is the propagation time of a radio signal traveling between transmitter and receiver. TOA information can be used to estimate the position of the vehicle based on the fact that the signal propagation time from RSUs or another cooperative neighbor vehicle to the candidate vehicle, which can be formulated as the distance between the two nodes as, $d = c\tau$, where, c denotes the speed of light and τ is the travel time of the signal between source and destination.

In practice, TOA data are subject to errors due to noise. TOA estimation can be formulated as

$$\mathbf{r}_{\mathrm{TOA}} = \mathbf{f}_{\mathrm{TOA}}(\mathrm{x}) + \mathbf{n}_{\mathrm{TOA}} \quad \mathbf{(5)}$$

where, n_{TOA} denotes the range error due to noise in r_{TOA}, which results from the TOA errors. The term $\mathrm{f}_{\mathrm{TOA}}$ denotes the actual TOA of the signal from RSUs or cooperative vehicles to receiving vehicle.

Direction of arrival (DOA) provides the direction from which the transmitted signal from RSU or cooperative vehicle arrives at the receiver of candidate vehicle. For each DOA of the received signal, we can consider a line of bearing (LOB) from the transmitter to the receiver. The intersection of at least two LOBs can provide the location coordinates (x, y). The z-coordinates can be obtained using the known height of the vehicle itself and height of the neighbor RSUs. The DOA estimation in presence of angle errors, can be given as

$$\mathbf{r}_{\mathrm{DOA}} = \mathbf{f}_{\mathrm{DOA}}\left(\mathrm{x}\right) + \mathbf{n}_{\mathrm{DOA}} \quad \mathbf{(6)}$$

where, the term n_{DOA} denotes the angle errors due to noises in $\mathrm{r}_{\mathrm{DOA}}$. The term $\mathrm{f}_{\mathrm{DOA}}$ is the DOA of the signal between receiving vehicle and RSUs or cooperative vehicles. We have considered both TOA and DOA based positioning estimations and analyze the trade-off of each method in terms of vehicle positioning.

6 Cooperative Vehicle Positioning

The proposed cooperative vehicle positioning is evaluated by combining the TOA and DOA data of the reference signal from RSUs with data provided by cooperative vehicles. Data fusion enhances the level of signal to noise ratio and enhances positioning accuracy. Figure 4 shows a scenario of the proposed cooperative positioning method that we introduce. Let us consider that the candidate vehicle V1 shown in the figure wants to estimate its position and V3 is a neighbor cooperative vehicle. Three roadside units periodically broadcast their position information and the time-stamp at which the signal is initiated. The candidate vehicle estimates its position using the time-stamp and TOA or DOA information of the LOS reference signal from three RSUs. The candidate vehicle needs to acquire at least three LOS signals for TOA based positioning and at least two LOS signals for DOA based positioning. However, vehicle V2 is not equipped with communication unit and it obstructs the LOS communication between V1 and RSU3. This causes positioning error for the candidate vehicle V1. We can overcome this problem by communicating and obtaining reference signal with position information from cooperative neighbor vehicle V3. Finally, the candidate vehicle estimates the own position by fusing the TOA or DOA data from roadside units and the cooperative vehicle.

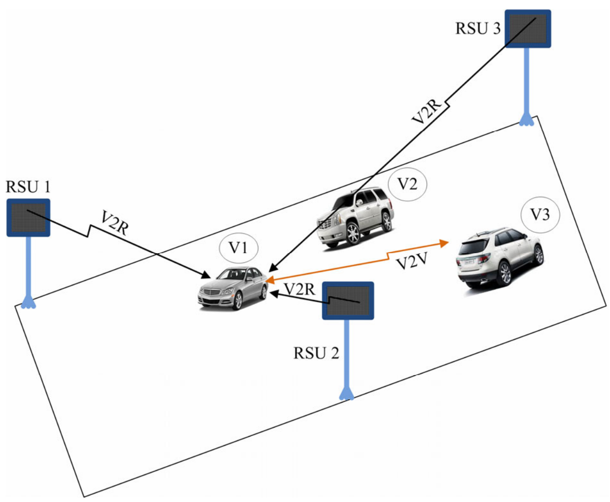

Figure 4. Cooperative vehicular positioning scenario

We can thus evaluate the positioning error by estimating m number of reference signal from RSUs and n number of reference signal from cooperative vehicles using TOA or DOA data that can be represented as,

$$\hat{x} = \arg\min_{x} \sum_{k=1}^{m+n} \frac{\left[r_n - d_k(x)\right]^2}{\sigma_{r_k}^2} \tag{7}$$

where, d_k is the actual distance and r_k is the estimated distance between candidate vehicle and RSU or cooperative vehicle. The term σ^2 denotes the variance of the estimated distance. Eq. (7) is equivalent to the minimization problem using maximum likelihood (ML) estimator. If we consider that the error distribution is known, the ML approach maximizes the PDFs of TOA or DOA estimations to obtain the vehicle position.

7 Results and Discussion

Figure 5 and Figure 6 show the position error considering RSU for reference signal as well as considering both RSU and cooperative vehicle for reference signal using TOA and DOA estimations respectively. GPS based vehicular positioning results has also been included for fair comparison with our proposed method.

The positioning error is determined using TOA or DOA estimated data from the ray-tracing simulation. The distances between vehicle and RSUs or cooperative vehicle is obtained from TOA or DOA data, which are then processed using tri-lateration or multi-lateration algorithm [18] to estimate the positions of candidate vehicle. Finally, positioning error is computed as absolute difference between the estimated positions and actual positions of the vehicle. It is observed that the proposed cooperative method exhibits consistently less positioning errors as compared other methods. Table 2 summarizes the average positioning error estimated by three different positioning approach.

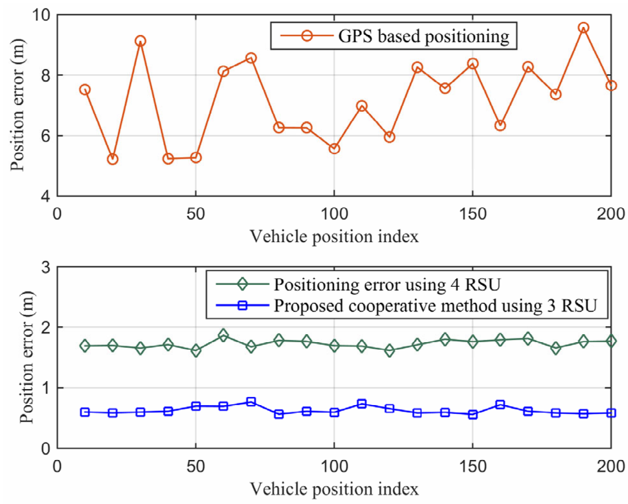

Figure 5. Positioning error based on GPS and VANET using TOA estimation

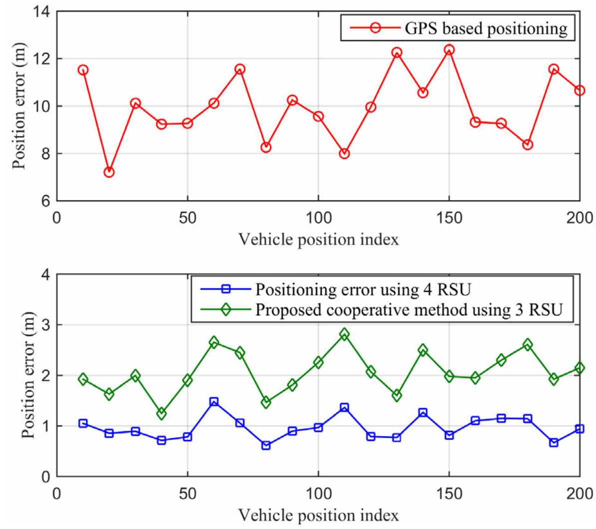

Figure 6. Positioning error based on GPS and VANET using DOA estimation

Table 2. Comparison of positioning error

Method	Average positioning error (meters)	
	TOA	DOA
GPS	7.19	10.17
V2R using 4 RSUs	1.61	1.96
Proposed Cooperative method using 3 RSUs	0.43	0.97

It is observed that DOA estimation exhibits higher positioning error than TOA estimation because a very small error in DOA angles results in higher positioning error. The trade-off between TOA and DOA estimation is that TOA provides lower positioning error than DOA, but TOA requires at least 3 RSUs while DOA requires only 2 RSUs for vehicle positioning.

We proceed to analyze the mean square error of position estimation. A lower bound on the variance obtainable by any unbiased estimator can be obtained using Cramer-Rao Lower Bound (CRLB) [19]. It is thus used here as a benchmark against which mean square position error (MSPE) performance is compared. CRLB can be obtained based on the corresponding Fisher information matrix (FIM). The diagonal elements of the inverse of FIM are the minimum achievable variances.

The FIM based on TOA estimation is given as

$$M_{TOA}(x)=\left[\frac{\partial f_{TOA}(x)}{\partial x}\right]^T C_{TOA}^{-1}\left[\frac{\partial f_{TOA}(x)}{\partial x}\right] \quad \textbf{(8)}$$

$$\text{where, } \left[\frac{\partial f_{TOA}(x)}{\partial x}\right]=\begin{bmatrix}\frac{x-x_1}{d_1} & \frac{y-y_1}{d_1}\\ \frac{x-x_2}{d_2} & \frac{y-y_2}{d_2}\\ \cdots & \cdots \\ \frac{x-x_L}{d_L} & \frac{y-y_L}{d_L}\end{bmatrix}$$

The covariance matrix C_{TOA} is given as

$$\begin{aligned}C_{TOA} &= E\left\{(r_{TOA}-d)(r_{TOA}-d)^T\right\}\\ &= E\left\{n_{TOA}n_{TOA}^T\right\}\\ &= \operatorname{diag}\left(\sigma_{TOA,1}^2\ \sigma_{TOA,2}^2\ \ldots\ldots\sigma_{TOA,L}^2\right)\end{aligned} \quad \textbf{(9)}$$

Employing equation (9), Equation (8) becomes

$$M_{TOA}(x)=\begin{bmatrix}\sum_{l=1}^{L}\frac{(x-x_1)^2}{\sigma_{TOA,l}^2 d_l^2} & \sum_{l=1}^{L}\frac{(x-x_1)(y-y_1)}{\sigma_{TOA,l}^2 d_l^2}\\ \sum_{l=1}^{L}\frac{(x-x_1)(y-y_1)}{\sigma_{TOA,l}^2 d_l^2} & \sum_{l=1}^{L}\frac{(y-y_1)^2}{\sigma_{TOA,l}^2 d_l^2}\end{bmatrix} \quad \textbf{(10)}$$

The CRLBs for TOA estimation are given by

$$CRLB_{TOA}(x)=\left[M_{TOA}^{-1}(x)\right]_{1,1}+\left[M_{TOA}^{-1}(x)\right]_{2,2} \quad \textbf{(11)}$$

Similarly, CRLB for DOA estimation can be derived using the FIM given by

$$M_{DOA}(x)=\left[\frac{\partial f_{DOA}(x)}{\partial x}\right]^T C_{DOA}^{-1}\left[\frac{\partial f_{DOA}(x)}{\partial x}\right] \quad \textbf{(12)}$$

$$\text{where, } \left[\frac{\partial f_{DOA}(x)}{\partial x}\right]=\begin{bmatrix}-\frac{y-y_1}{d_1^2} & \frac{x-x_1}{d_1^2}\\ -\frac{y-y_2}{d_2^2} & \frac{x-x_2}{d_2^2}\\ \cdots & \cdots \\ -\frac{y-y_L}{d_L^2} & \frac{x-x_L}{d_L^2}\end{bmatrix}$$

Analysis has been conducted to compare the mean square position error (MSPE) performance of the RSU-assisted positioning and the proposed cooperative positioning method. Cramer-Rao bound is also estimated for varying SNR values corresponding to TOA estimation. The results are presented in Figure 7. We observe that the ML estimations using proposed cooperative positioning method outperforms the RSU-assisted positioning method. In addition, the MSPE using the proposed method becomes very close to the CRLB at SNR above 25 dB.

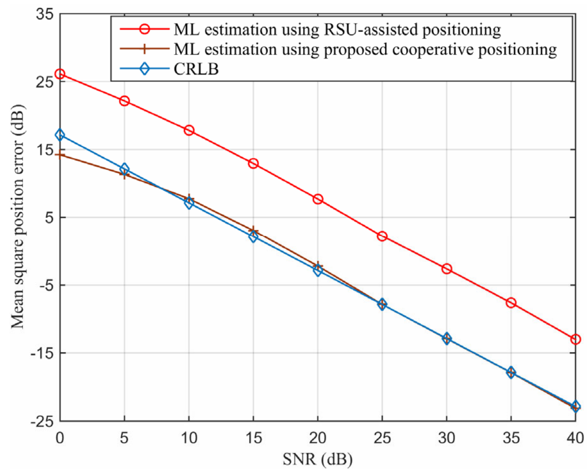

Figure 7. MSPE versus SNR for RSU-assisted positioning and proposed cooperative positioning

8 Conclusion

Vehicular channel model for urban road has been developed using Wireless InSite ray-tracing simulator. The developed model is validated with measurement results in terms of path-loss and received power for varying distances using DSRC band. Realistic urban traffic scenario is considered and vehicle positioning using TOA and DOA estimation has been addressed. Positioning accuracy is further improved by proposed cooperative positioning method combining the TOA or DOA measurements of RSUs and cooperative neighbor vehicles. Analysis of results shows that the proposed scheme outperforms conventional methods based on GPS or RSUs. In addition, the mean square position error is found to be closer to the lower bound determined by Cramer-Rao than other modalities.

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Biographies

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