Characterizing Cooperative Positioning in VANET

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***Abstract*—Cooperative positioning (CP), a localization means that has been widely used in wireless sensor networks, is emerging as one of the promising solutions for improving the vehicular positioning in VANET. CP allows each individual node in the network to calibrate its own position, by leveraging distance measurements between neighbor nodes with unknown or estimated (e.g., from GPS) positions. While concepts of applying CP in VANET have been introduced, the actual performance of CP in real-world vehicular communication scenarios is largely unknown. In this paper, we bridge this gap by conducting a comprehensive simulation study to characterize the performance of CP in realistic VANET environments. We investigate the efficacy of CP under the effects of various communication factors exhibiting in VANET. Further, we analyze the performance of CP with respect to the constraints from underlying non-cooperative vehicular localization techniques.**

I. INTRODUCTION

To reduce road fatalities, road authorities around the world are looking for effective solutions. The IEEE 802.11p-based Dedicated Short Range Communication (DSRC) [1] has been identified as one of the promising technologies. With the advent of DSRC, each moving vehicle periodically broadcasts its current kinematic information to the neighbor vehicles within its transmission range. Safety related applications, such as collaborative collision warning (CCW), can make use of this information to help vehicles in avoiding traffic accidents.

However, recent studies [2] suggest that the current vehicular positioning systems, such as GPS, are not providing sufficient positioning accuracy to support the required reliability of vehicular safety applications. To address this issue, the idea of using cooperative positioning (CP) in VANET is attracting growing research interests. Through the periodical broadcasts on DSRC, each vehicle is able to collect the GPS information of the neighbors. Meanwhile, inter-vehicle distance can be measured using some radio-based ranging techniques [3]. Hence each vehicle may leverage the GPS and distance measurements of the neighbors to calibrate its own position, by using the CP localization algorithms [4].

Various concepts and ideas of applying CP in VANET have been extensively discussed in prior works [4]–[8]. These studies primarily focus on the localization algorithms of CP in VANET with the assumption of an ideal communication scenario, wherein each vehicle can always “detect” all its neighbors. However, due to the hidden node, signal fading and interference problems, packet transmissions in vehicular communications are known to be lossy [9]. Hence, a vehicle may fail to “detect” some of the neighbors when packets transmitted from them are lost. This reduces the amount of available neighborhood information, hence affecting the localization accuracy in CP. In [10], we have discussed the implications of packet loss on the accuracy of CP. However, the characterization of CP performance under realistic DSRC communication scenarios is still lacking in the literature. Our focus in this paper is to investigate this outstanding issue and provide insights on the future developments on CP protocols and algorithms for VANET.

The goal of this study is of two-fold: 1) We intend to characterize the efficacy of CP under realistic communication factors exhibiting in VANET, e.g., road traffic density, message broadcast pattern and DSRC radio transmission range; 2) We are interested to quantify the CP performance under the effect of the underlying non-cooperative localization constraints, e.g., the accuracies of GPS and radio-based ranging techniques. For this, we conduct realistic simulation experiments and evaluate the CP accuracy using the well-known metric Cramer Rao Lower Bound (CRLB). Our results demonstrate that CP can effectively reduce the vehicular positioning error by at least 40% as compared to the plain GPS approach, even under low traffic density scenarios. We find that, under communication constraints, the actual CP accuracy is noticeable less than that can be achieved in an ideal loss-less communication scenario. We also find that using CP is more beneficial when a larger DSRC transmission range is in use. Further, we show that, affected by the accuracy of the state-of-the-art underlying non-cooperative localization techniques, it is difficult for CP to achieve the stringent positioning requirements of safety applications (e.g., CCW requires position accuracy of 1 m [2]). However, our analysis reveals that CP can meet those requirements when incorporated with some augmentation techniques with improved positioning accuracy, e.g., using Inertial Navigation Systems (INS) [11] or Differential GPS (DGPS) [12]. To the best of our knowledge, this is the first attempt that comprehensively characterizes the CP performance in the context of VANET.

The rest of this paper is organized as follows. In Section II we review the application of CP in VANET and the positioning error bound in CRLB. Section III describes the simulation setup. Section IV analyzes the communication effects on the CP performance in VANET. In Section V, we discuss the implications of localization constraints on CP performance. Section VI concludes this paper.

II. Cooperative Positioning in VANET

A. Background

CP was originally proposed for location determination within wireless ad-hoc and sensor networks. Contrary to non-cooperative approaches, CP uses range measurements between neighbor nodes with unknown or estimated (e.g., from GPS) positions. The ad-hoc nature of vehicular networks makes it natural to apply the existing CP techniques in VANET.

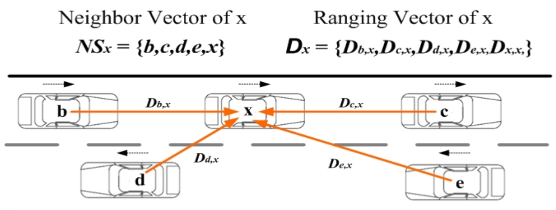


Fig. 1. A typical vehicular communication scenario

To achieve CP, a vehicle must acquire two pieces of information: 1) the estimated positions of its neighbors, and 2) the estimated distances between itself and each neighbor and, if available, the ranges between neighbors. With the advent of data communications over DSRC, vehicles can readily learn this information without supports from infrastructure. For example, let us consider the typical vehicular communication scenario shown in Fig. 1. Each vehicle periodically broadcasts its safety messages through DSRC. According to the latest DSRC specification [13], safety messages contain information, such as time, vehicle identities, kinematics and also the estimated position (e.g., from GPS). Thus, a vehicle (e.g., vehicle x in Fig. 1) can extract GPS positions of its neighbors (e.g., vehicles b, c, d and e) on receiving packets from them. Meanwhile, whenever a vehicle receives a packet from a neighbor, the distance between the vehicle and the neighbor can be estimated using radio-based ranging techniques, such as Time of Arrival (ToA), Time Difference of Arrival (TDoA), Received Signal Strength (RSS), Carrier Frequency Offset (CFO), and Round Trip Time (RTT). The principles and pros and cons of these techniques have been discussed in [3]. However, an accurate and efficient ranging solution is still an open question. Though the accuracy and feasibility of ranging techniques are not the focus of this paper, we will discuss the implications of the ranging accuracy on the performance of VANET CP in Section V-B. After collecting the neighbor vehicles' position estimates and the range measurements, each vehicle applies distributed CP algorithms to calibrate its own position. Depending on the amount of ranging information used, CP algorithms can be mainly classified as cluster- or star-based. In star-based schemes [5], [6], each vehicle only uses the measured distance between itself and its neighbors. The cluster-based [4], [7], [8] exploits the mesh of ranging information measured between all neighbors. Even though the cluster-based approach may provide more ranging information in the CP localization and achieve better accuracy, it attracts extra communication overhead as vehicles need to exchange their ranging information in the neighborhood. On the other hand, the star-based approach does not require additional ranging information exchanges. In this work, we focus on evaluating the performance of the simple star-based CP. We plan to extend our study to cluster-based schemes in the future.

B. Performance Bounds for Cooperative Positioning

The accuracy of the CP is primarily dictated by the errors from GPS positioning and ranging estimations between the nodes. To quantify the accuracy of CP, the standard approach in ad-hoc networks is to use the Cramer Rao Lower Bound (CRLB) [14]. CRLB is the inverse of the Fisher Information Matrix (FIM) [15], which sets the minimum variance of any unbiased estimation of a random variable. In the following, we briefly review the CRLB derived for the star-based CP in VANET, which has been previously proposed in [10].

Consider a scenario that a *target vehicle* has a total of n vehicles in its neighborhood (the target vehicle is the n_{th} node in the neighbor vector). We define W as the vector of unknown real 2D positions of vehicles, Z as the vector that consists of the measured GPS position and ranges (between the target vehicle and the neighbors), η as the vector of unknown real positions and ranges, and $\sum$ is the diagonal covariance matrix of the ranges and GPS position data. We assume a zero mean normal distribution for GPS-based positioning and radio ranging errors [4]. We denote σ_P as the standard deviation of positioning error along X and Y axes, and σ_R as the standard deviation of ranging measurements error between two vehicles. The conditional joint probability density function (PDF) of the measurements is:

$$f(Z|W) = \frac{(2\pi)^{(3n-1)/2}}{\sqrt{\det(\sum)}} \cdot \exp\left\{-\frac{1}{2}(Z-\eta)^T {\sum}^{-1}(Z-\eta)\right\}. \tag{1}$$

The corresponding FIM, F, of the measurements is:

$$F = -E\frac{\partial^2 ln(f(Z|W))}{\partial W^2}. \tag{2}$$

We refer readers to [10] for the detailed representations of the entries in F (omitted here due to space constraints). However, note that each entry in F is a function of σ_P and σ_R. The CRLB, C, of distance-based CP is the inverse of the FIM, e.g., $C = F^{-1}$. The CP localization error, E of the target vehicle is defined as the root mean squared (RMS) of C:

$$E = \sqrt{1/2 \times (C_{2n-1,2n-1} + C_{2n,2n})}. \tag{3}$$

To evaluate the efficacy of CP, we further define a metric called positioning accuracy gain (PAG):

$$PAG = \frac{\sigma_P - E}{\sigma_P} \times 100. \tag{4}$$

Note that, PAG shows the accuracy gain (in percentage) of CP as compared to the plain GPS positioning.

III. Simulation Setup

In this section, we present our simulation setup. We run our simulations using the *NS-2* simulator. To achieve realistic simulations, we used the latest version (v2.34) of NS-2 with the recent overhaul on 802.11 physical and MAC layers implementations [16]. To implement DSRC radio, we used the recommended parameter settings as in [17]. The primary parameters are listed in Table I. To simulate a realistic urban radio propagation environment, we have used the *Nakagami* propagation model with the configurations suggested in [17]. In most of the simulations, we have tuned the DSRC transmission range to 240 m. We will also investigate the impact of different transmission ranges on CP in Section IV-C.

TABLE I
DSRC radio parameters

Parameter	Value
Frequency	5.9 GHz
Channel Bandwidth	10 Mhz
Modulation	QPSK with 1/2 coding
Modulation Rate	6 Mbps

The simulated road topology is shown in Fig. 2. We simulated a triangular shape loop road with both clockwise and anti-clockwise directions. The lane width is 3.5 m. The loop road allows the number of vehicles in the network to be consistent during each simulation run. Also, the particular triangular shape of the road enables us to observe the aggregate CP performance under various road conditions. For example, we are able to collect results not only on straight roads (highway linear topology), e.g. during the middle section of Grand River Ave., but also at intersections and corners of the roads. At the beginning of each simulation, vehicles are randomly placed onto the road. We assume that vehicles will not change their lanes and directions during the simulations. The vehicle speed is randomly varied between 45 to 60 kmh. In the simulations, we varied the number of vehicle circulating in the network from 30 to 150. This corresponds to different traffic densities, e.g., 12.5 – 62.5 veh/km (light to heavy traffic conditions). The simulation time for each run is 100 seconds.

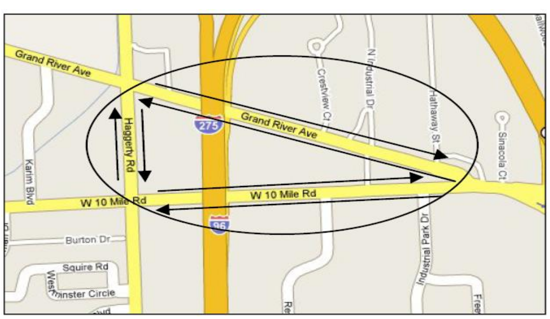


Fig. 2. The map of the loop road used in the simulation

We assume the clocks on all vehicles are synchronized (e.g., via GPS clock). We consider the typical scenario that each vehicle periodically broadcast the safety related messages to its neighbor vehicles at the rate of 10 Hz [9]. Note that, each broadcast packet consists of the kinematics and control information of a vehicle, including the instantaneous GPS location measured [13]. We assume the standard deviation of the GPS positioning error is $\sigma_P = 7m$. For implementing the broadcasts, we partition each 1 second interval into 10 Synchronized Intervals (SI) of 0.1 ms. Within each SI, each vehicle independently and randomly selects the time to broadcast its own safety message. In most of our simulations, we have used the basic broadcast scheme that each vehicle only broadcasts once within each SI. We will also study the effect of repeated broadcast in Section IV-B. We assume the size of each broadcast packet is 200 bytes.

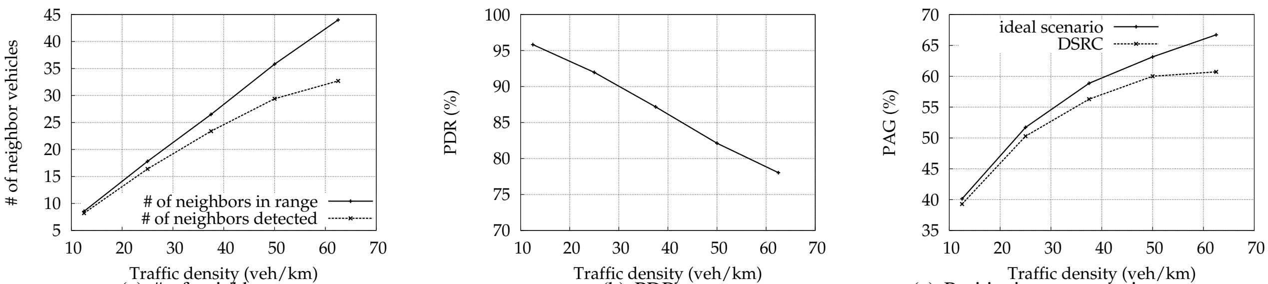
In each SI, we assume a vehicle "detects" a neighbor and hence estimates the distance between itself and the neighbor (using the ranging techniques discussed in Section II-A), if the vehicle can receive at least one broadcast packet from that neighbor. We assume the standard deviation of the ranging errors is $\sigma_R = 5m$. At the end of each SI, we assume each vehicle runs CP algorithms with the GPS positions and range estimates of the detected neighbors to calibrate its own location. We calculate the PAG (as discussed in Section II-B) for each vehicle on the road in each SI. In addition, we report the packet delivery ratio (PDR) of broadcast transmissions to evaluate the network congestion conditions. The PDR of each broadcast packet is calculated as the ratio between the number of neighbor vehicles receiving the packet and the total number of neighbors in a vehicle's transmission range. Note that all our results presented are averaged over all vehicles and over the entire simulation duration. The standard error achieved is less than 5% of the mean value that is reported.

IV. The Effect of Communication Constraints

The performance of CP in VANET largely depends on the amount of position and ranging information of neighbor vehicles that is available to a vehicle. The general intuition is that, the more neighbors that are in a vehicle's transmission range, the better positioning accuracy can be achieved by CP [4]. However, the increase in the number of neighbors may, at the same time, deteriorate the network congestion conditions over the DSRC wireless channel [16]. This in turn causes more transmission collisions and packet loss. Unlike wireless sensor networks, the network topology of VANET is highly dynamic, due to the high-speed vehicular mobility. To meet the real-time requirements of safety applications, such as CCW, each vehicle needs to constantly calibrate its position, e.g., for each SI. At a given SI, the packet loss may reduce the number of neighbors that a vehicle can actually detect, which can significantly impair the accuracy achieved by CP. In the following we intend to characterize the performance of CP under various DSRC communication scenarios.

A. Traffic Load

First, we show the effects of traffic density in Fig. 3. Fig. 3(a) shows that the number of neighbor vehicles within a vehicle's transmission range (labeled as "# of neighbors in range") linearly increases when the traffic density increases.



(a) # of neighbors (b) PDR (c) Positioning accuracy improvement

Fig. 3. The effect of traffic load on VANET CP

Ideally, a vehicle can receive the packets broadcasted from all its neighbors in each SI, when there is no packet loss. However, Fig. 3(b) highlights that PDR actually decreases linearly along with the increase in traffic density. Recall that each vehicle only broadcasts once in each SI. Thus, due to packet loss, our results in Fig. 3(a) show that a vehicle can only detect a portion of the neighbors in its vicinity. Note that, Fig. 3(a) shows that the difference between the numbers of detected neighbors and neighbors in range becomes more pronounced when the traffic density becomes higher, i.e., the difference is 25% when the traffic density is high.

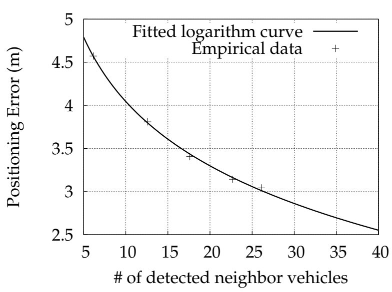


Fig. 4. The relationship between CP accuracy and # of detected neighbors

In Fig. 3(c), we plot the PAG achieved by CP in VANET as a function of traffic density. The curve labeled as “DSRC” corresponds to the actual CP performance under the packet loss effects observed above. We observe that, by using CP in VANET, the positioning accuracy can be effectively improved by nearly 40% even under low traffic density, i.e., 12.5 veh/km. Note that in this case, a vehicle can detect merely on average about 6 neighbor vehicles, as observed from Fig. 3(a). Further, the PAG increases along with the increase in traffic density. However, the increase in PAG tapers off even with more detected neighbors, under heavy traffic conditions. We attribute this to the constraints imposed by the accuracies of underlying non-cooperative positioning and ranging techniques. We will further discuss this in Section V. We also plot the “ideal” CP performance, wherein a vehicle is able to detect all neighbors in its transmission range. We observe that the actual positioning performance gain of CP in VANET is clearly lower as compared to the ideal scenario. The difference appears marginal under low traffic density, however it can be as large as 10% under dense traffic scenarios. This highlights the fact that the efficacy of CP is closely coupled with the real-world communication factors in VANET.

Further, we plot the raw positioning error archived by CP as a function of number of neighbor vehicles detected (as observed in Fig. 3(a)) in Fig. 4. We find the relationship between the CP error and the number of neighbors can be accurately fitted ($R^2 = 0.9979$) to logarithm functions, i.e.,

$$E = a \times ln(N_{neighbor}) + b, \quad (5)$$

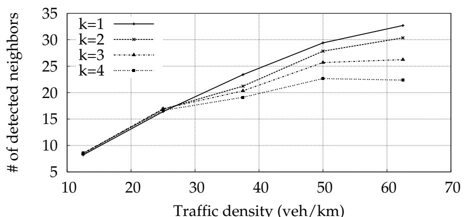
where the coefficient a and intercept b are two parameters determined by the accuracy of non-cooperative localization techniques, such as GPS positioning and radio ranging. Using the empirical functions, one may infer the number of detected neighbors required to achieve a positioning accuracy target. We list some examples in Table II. Observe that, with $\sigma_P = 7m$ and $\sigma_R = 5m$, a vehicle needs more than 150 neighbors to achieve the 1 m accuracy required by CCW. In Section V-C, we will further investigate how the improvements in GPS positioning and ranging accuracies can affect the number of neighbors required in achieving the same target accuracies.

TABLE II
THE NUMBER OF DETECTED NEIGHBOR VEHICLES REQUIRED TO MEET TARGETED POSITIONING ACCURACIES

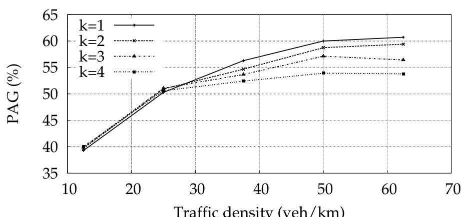
Targeted accuracy (m)	Req. # of detected neighbors
2.5	40
2	62
1.5	98
1	153

B. Repeated Broadcasts

The analysis shown in Fig. 3 was derived with the basic packet generation scheme, e.g., each vehicle only broadcasts once in each SI. It has been shown in prior works [9] that by repeating the broadcast multiple times within each SI, it may increase the broadcast reliability, i.e., the probability that a neighbor can hear at least once from a vehicle in a SI. Thus, using repeated broadcast may increase the number of neighbors that can be detected by a vehicle and improve the overall CP accuracy. To investigate this hypothesis, we conduct simulations with different number of broadcast repetition settings, denoted as k, in each SI. Fig. 5 shows the results with different values of k. Observe that, under light traffic densities, increasing the k only slightly increases the number of neighbors detected. Meanwhile, the improvements in the PAG results are marginal, as observed from Fig. 5(b). Further, we observe that repeated broadcasts actually lead to less number of neighbors detected and lower PAG, when the traffic density increases. In fact, we found that the basic broadcast scheme ($k = 1$) consistently achieves the best performance under higher traffic density scenarios. This shows that under high vehicle densities the repeated broadcasts pose extra burden on the congested communication channel and hence result in adverse effects on CP accuracy. The above results indicate that it is not feasible to improve CP accuracy by simply using repeated broadcasts in VANET.



(a) # of neighbors



(b) PAG

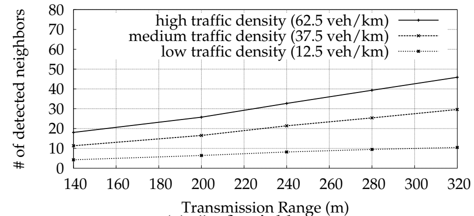
Fig. 5. The effect of repeated broadcast on VANET CP

C. Transmission Range

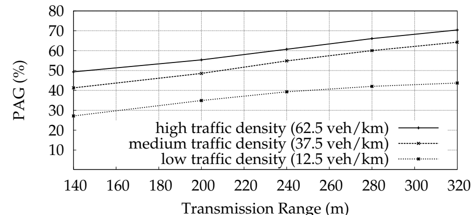
In the previous experiments, we have set the transmission range to 240m. Another dimension for increasing the number of neighbor vehicles is to increase the transmission range of vehicular communications. Hence, we now study the effect of transmission range on CP. In this set of simulations, we varied the DSRC transmission range of each vehicle by tuning the transmission power. Fig. 6 plots the number of detected neighbors and PAG results as a function of DSRC transmission range for different traffic densities, i.e., low (12.5 veh/km), medium (37.5 veh/km) and heavy (62.5 veh/km), respectively. Clearly the general trend observed is that the number of neighbors detected becomes higher when the transmission range increases. This correspondingly makes the CP accuracy more pronounced under larger transmission ranges. For example, when the transmission range is 320 m, CP can achieve over 70% in PAG as compared to plain GPS under the heavy traffic density. Note that, with the low traffic density and a small transmission range of 140 m, a vehicle can only detect on average only 4 neighbor vehicles. However, CP is still able to achieve over 25% in PAG as shown in 6(b). When the transmission range increases to 320 m, the PAG exceeds 40%.

V. The Impact of Localization Constraints

As discussed in Section IV-A, the CP performance can also be affected by the constraints imposed by the underlying non-cooperative localization technologies in use, e.g., GPS and radio-based ranging techniques. In the following, we fix the communication settings (TX_{range} = $240m$ and $k = 1$) in simulations and focus on quantifying the effect of the localization constraints on CP accuracy in VANET.



(a) # of neighbors



(b) PAG

Fig. 6. The effect of the transmission range on VANET CP

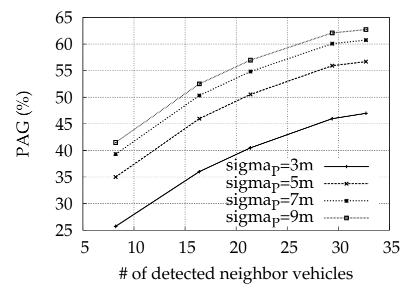


Fig. 7. The effect of σ_P on VANET CP ($\sigma_R = 5m$)

A. Constraints of Non-Cooperative Positioning

We first investigate the CP performance with respect to the accuracy of positioning accuracy (σ_P) of the non-cooperative positioning systems, e.g., GPS, installed on individual vehicles. To show the effect of σ_P, we fix the σ_R to be 5 m and vary the σ_P from 1 to 9 m. In Fig. 7, we plot the PAG results against the number of detected neighbors for different σ_P values. Observe that the CP can achieve significant accuracy improvement when the σ_P is large, which is the case of state-of-the-art GPS positioning. In particular, when a vehicle is cruising along city streets, the GPS accuracy can be even worse as satellite signals are blocked by the high-rise building in the city. Hence, our results imply that using CP is particularly beneficial in improving the positioning accuracy in such scenarios. Also, we observe the efficacy of CP remains even with the improved individual positioning accuracy (e.g., with INS). For example, when $\sigma_P = 3m$, we observe that CP is able to improve the positioning accuracy by up to 47%. These observations highlight the fact that CP is an effective complement to existing non-cooperative positioning systems. Note that, with a smaller σ_P, even though CP achieves better absolute positioning accuracy, Fig. 7 shows that the PAG generally decreases. This again highlights the fact that CP is more effective and efficient when the GPS accuracy is poorer.

B. Constraints of Ranging

To study the effect of ranging accuracy, we fix the σ_P to 7 m and calculate the PAG of CP for different σ_R configurations. Fig. 8 plots the PAG as the function of number of detected neighbor vehicles with various σ_R. We observe the efficacy of CP is pronounced even with poor ranging accuracy, which is the case of current radio based ranging techniques. For example, when $\sigma_R = 9m$, CP is still able to produce over 50% gain in positioning accuracy as compared to plain GPS. Further, Fig. 8 shows the improvements in σ_R has a positive effect on the performance of CP. Hence, to further improve the CP accuracy, efforts clearly need to be made in investigating more accurate ranging means in VANET environments.

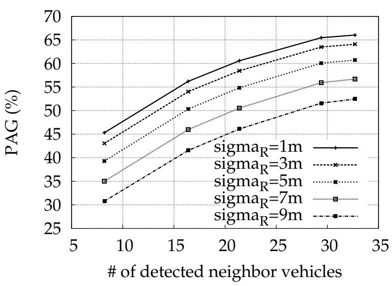


Fig. 8. The effect of σ_R on VANET CP ($\sigma_P = 7m$)

C. Combined Effects of Positioning and Ranging Constraints

Finally, we highlight the combined effects of improved GPS positioning and ranging accuracies on CP efficacy. We assume vehicles are equipped with INS assisted GPS, e.g., $\sigma_P = 3m$ and able to achieve accurate range measurements, e.g., $\sigma_R = 1m$. As in Fig. 4, we fitted the empirical data of raw CP errors and the number of detected neighbors to Eq.(5), and derived the corresponding values of a and b. Then we are able to infer the required number of detected neighbor vehicles in achieving the same accuracies targets shown in Table II. The comparisons of the results are listed in Table III. Observe that with the improved GPS positioning and ranging accuracies, CP can help vehicles to readily achieve 1 m accuracy with only 36 neighbor vehicles detected.

TABLE III
COMPARISONS OF CP PERFORMANCE UNDER DIFFERENT NON-COOPERATIVE LOCALIZATION ACCURACIES

Targeted accuracy (m)	Req. # of detected neighbors	
	$\sigma_P = 7m, \sigma_R = 5m$	$\sigma_P = 3m, \sigma_R = 1m$
2.5	40	2
2	62	5
1.5	98	12
1	153	36

VI. CONCLUSION

To gain better insights on the performance of CP in a VANET environment, we carried out a comprehensive characterization study through realistic simulations. Our results demonstrated that the CP is an effective and feasible technique in improving the vehicular positioning accuracy. However, we highlighted that the real-world constraints of DSRC communications can significantly affect the CP performance. The future developments on CP protocols and systems need to account for these factors. Further, we have shown that the performance of CP is also affected by the accuracies of underlying non-cooperative localization and ranging techniques. Our future work will seek to address these constraints in order to further improve the positioning accuracy in VANET.

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