# Improving Cooperative Positioning for Vehicular Networks

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*Abstract*—Cooperative positioning (CP) can potentially improve the accuracy of vehicle location information, which is vital for several road safety applications. Although concepts of CP have been introduced, the efficiency of CP under real-world vehicular communication constraints is largely unknown. Our simulations reveal that the frequent exchange of large amounts of range information required by existing CP schemes not only increases the packet collision rate of the vehicular network but reduces the effectiveness of the CP as well. To address this issue, we propose simple easily deployable protocol improvements in terms of utilizing as much range information as possible, reducing range broadcasts by piggybacking, compressing the range information, tuning the broadcast frequency, and combining multiple packets using network coding. Our results demonstrate that, even under dense traffic conditions, these protocol improvements achieve a twofold reduction in packet loss rates and increase the positioning accuracy of CP by 40%.

*Index Terms*—Cooperative positioning (CP), positioning accuracy improvement, range information exchange, vehicular networks.

## I. INTRODUCTION

THE AUTOMOTIVE industry has been working on an advanced crash warning system for drivers, which will use direct wireless communication between vehicles to periodically exchange the location, speed, and other kinematic information for predicting potential crashes. Accurate positioning information is the key to the success of such warning systems, because inaccuracy will cause either false alarms or failure to warn a driver during an emergency. The initial plan to obtain positioning information in each vehicle was to use commercial-grade Global Positioning System (GPS) receivers. However, it was later established that the 5–10-m accuracy of commercial GPS will not be very effective for crash warning or other safety applications [1]. On the other hand, the centimeter-level accuracy of professional-grade receivers, e.g., real-time kinematic (RTK), cannot readily be delivered in an urban environment [2]. This case has sparked research in developing solutions that can improve commercial GPS positioning accuracy in vehicular networks.

Radio-ranging-based cooperative positioning (CP) has been considered one of the promising approaches for improving GPS positioning accuracy [3]. Such CP is attractive for vehicular networks, because the required ranging (or the intervehicle distance) information can readily be measured from the periodic exchange of location information that is used for the crash warning system. If a group (cluster) of vehicles can share with each other their intervehicle distance measurements through the Dedicated Short-Range Communications (DSRC) [4] links, they can then use existing CP algorithms based on multilateration or trilateration principles [5] to further improve their current position estimates.

One issue with CP in vehicular networks is that the frequent exchange of large amounts of range information over a shared DSRC control channel can cause significant packet collisions, hence reducing the probability of a packet, which also shares the same channel that is successfully received. This condition will not only affect the performance of safety applications but also reduce the effectiveness of CP algorithms. The communication overhead of CP may not be an issue in light-traffic scenarios, but it cannot be ignored for dense traffic conditions, where a large number of vehicles are within their communication ranges and can potentially interfere with each other's transmissions.

Some researchers acknowledge the problem of communication overhead for CP in vehicular networks [3], but a detailed investigation of this issue seems not to exist in the literature. The objective of this paper is to examine the impact of range information exchange overhead and identify mechanisms for optimizing CP in dense vehicular networks in terms of improving the positioning accuracy and reducing the packet collision rates. This paper makes the following two key contributions.

- It is demonstrated that the framework that is used by existing distributed CP algorithms are limited, because they cannot make use of all range information that is received by a vehicle due to the strict *clustering rule*. An extension to the existing CP framework is proposed to make more efficient use of all exchanged range information, therefore improving the performance of CP.
- It is demonstrated that exchanging range information using simple protocols that basically collect range measurements within a safety interval and transmitting these

measurements in the next interval achieves small accuracy gains but results in high packet collision rates. Protocol improvements are proposed, which are shown not only to reduce the packet collision rate but to improve the positioning accuracy at the same time as well.

The rest of this paper is organized as follows. We discuss the related work in Section II. In Section III, we briefly present an overview of CP for vehicular networks. In Section IV, we conduct simulations to investigate the effectiveness and identify the potential issues of CP in realistic communication channels. Sections V and VI present a series of techniques for improving the performance of CP. This paper concludes in Section VII.

## II. RELATED WORK

Several range-independent CP techniques have been proposed for vehicular localization, e.g., differential Global Positioning System (DGPS) [6], RTK positioning [2], Assisted Global Positioning System (A-GPS) [7], a satellite-based augmentation system (SBAS), and a ground-based augmentation system (GBAS) [6]. These techniques commonly involve communications between vehicles and fixed or mobile reference nodes with known positions. These reference nodes provide augmentation information such as the measured common positioning error at or near a location. Through communications with the reference nodes, a vehicle uses the augmentation information to improve its own position estimate. However, these range-independent CP approaches heavily rely on the support from infrastructure. In addition, these techniques commonly have stringent requirements on the received GPS signal quality, e.g., low multipath errors and the visibility of multiple (at least four or five) GPS satellites, which are not viable in dense urban areas. Other possible ways of mitigating the GPS error include using a Kalman filter that fuses the GPS and the vehicle's kinematics information and the inertial navigation system (INS)/GPS integration [8]. However, the accuracy improvement that is provided by these techniques is still not sufficient for robust crash warning or other vehicular safety applications [1].

In a mobile ad hoc network (MANET) and a wireless sensor network, the localization problem with range measurements is often tackled by trilateration and multilateration to some fixed or mobile beacons (nodes with known location such as GPS satellites) [5]. The internode distance are commonly measured using radio-ranging or range-rating techniques such as the time of arrival (TOA), time difference of arrival (TDOA), received signal strength (RSS), Doppler shift, carrier-frequency offset (CFO), and round-trip time (RTT) [9]. Because a vehicular ad hoc network (VANET) is a special form of MANET, prior works have proposed to adopt the range-based CP techniques into VANETs. In this paper, we focus on the range-based CP schemes and simply refer to these schemes as CP.

To reduce the multipath effects to the GPS positioning accuracy, Drawil and Basir [10]–[12] propose a distributed CP method that relies on the ranging information between a target vehicle and its neighbors. In their scheme, a vehicle requiring a more accurate position estimate sends request messages to its neighbors. Each neighbor responds with its GPS position reading and the associated uncertainty of the estimate. The target vehicle measures the distance to all the neighbors (ranging information) upon receiving the response messages. Finally, the target vehicle's position is trilaterated using the neighbor vehicles' GPS estimates and range information in an algorithm that considers the associated GPS error uncertainties. A similar work is proposed in [13] to locate the vehicles without GPS or that experience outage of GPS signals. However, the focus of these approaches is to allow each individual vehicle to achieve more accurate positioning for itself. These approaches were not designed to improve the position estimations of the *neighbor vehicles* at the same time.

In a fast-moving VANET environment, the instant acquisition of positions of neighbor vehicles is particularly important for safety applications, e.g., cooperative collision warning (CCW) [1]. For example, when an impending hazard ahead is reported, CCW needs the surrounding vehicles' positions and kinematics information to make the decision to warn the driver to change lane or apply brakes [3]. In wireless sensor and ad hoc networks, there are several works [5], [14]–[16] that address the problem of simultaneously localizing a group of nodes that form a *cluster*. The cluster-based CP methodology has been extended to VANET localization [3], [17]–[21]. The cluster-based CP approach is also based on intervehicle distance measurements. Each vehicle constantly measures the distances to their neighbors using radio-ranging techniques. Then, vehicles exchange their own *states*, i.e., vehicle kinematics, GPS measurements, and intervehicle range estimates, in the neighborhood. Based on this information, each vehicle executes CP algorithms to estimate the positions for the entire cluster of vehicles using popular data fusion techniques such as least mean square error (LMSE), Kalman filter, extended Kalman filter, and particle filter [22]. Although the aforementioned works propose various potential CP algorithms in VANETs, the communication effects of exchanging the range information that is required by CP are often neglected. In a preliminary work [23], we highlighted the effect of packet loss on CP performance. In this paper, our focus is to comprehensively evaluate the CP efficacy with respect to realistic communication constraints and propose protocol improvements to improve the practical performance of CP.

## III. COOPERATIVE POSITIONING IN VEHICULAR AD HOC NETWORKS

CP was originally proposed as an approach for location determination within wireless ad hoc and sensor networks. Contrary to non-CP approaches, where each node individually estimates its own location, the goal of CP is to allow neighbor nodes to work together to collectively improve the accuracy of their positions. The ad hoc nature of vehicular communications makes it natural to extend existing CP techniques into VANETs. The popular CP framework [3] in vehicular networks is shown in Fig. 1. The CP process relies on the following two pieces of information: 1) the unknown or rough estimated positions (e.g., from the GPS) and 2) the kinematics information of the neighbor vehicles and intervehicle distance measurements among these vehicles. In general, applying CP in VANETs is a three-step distributed process, including range and kinematics
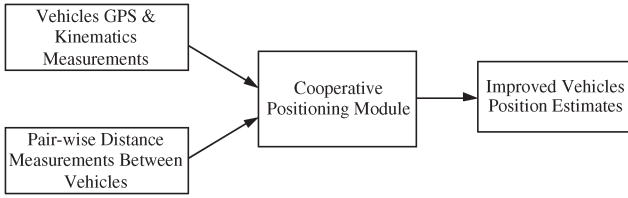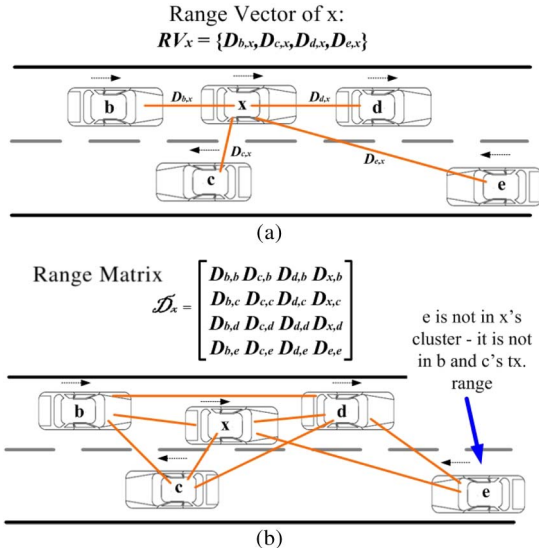
Fig. 1.   CP framework.



Fig. 2.   Measurement and exchange of range information. (a) Maintaining the range vector. (b) Creating the range matrix after the RV exchange.

information measurements, information exchange, and the final localization. In the following sections, we briefly discuss the fundamentals of using CP in vehicular communications. Next, we derive the positioning accuracy bound of VANET CP using the Cramer–Rao lower bound (CRLB) [24].

### A. Measurement Phase

The primary task in the measurement phase is for each vehicle to collect the following data: 1) its kinematics information and 2) distance measurements to its one-hop neighbors. A vehicle can readily measure its kinematics information, such as position estimates, heading, velocity, and acceleration, from the GPS or onboard kinematics sensors. For the distance measurements, the radio-ranging and range-rating techniques, e.g., TOA, TDOA, RSS, Doppler shift, CFO, and RTT, can be exploited. The feasibility and applicability of these techniques are investigated in [5] and [9] and are not the focus of this paper. In this paper, we assume that the range measurements can be made available with a suitable method. Upon receiving a packet from a neighbor, vehicles can estimate the distance to the neighbor using these ranging techniques. For example, vehicle $x$ in Fig. 2(a) estimates the distances between itself and neighbors $b$, $c$, $d$, and $e$ after receiving the packets from them. The outcome of the measurement phase is the range vector (RV), which consists of the collection of the range information to all neighbors.

### B. Exchange Phase

In this phase, each vehicle broadcasts its own RV and kinematics information to its one-hop neighbors through DSRC links. The local kinematics information is natively embedded in the periodic safety message broadcast. To share range information in the neighborhood, each vehicle periodically broadcasts its RV. The received RVs and kinematics information form the inputs to the localization process.

### C. Localization Phase

In the localization phase, a distributed CP algorithm [25] is employed to generate more accurate position estimates of neighbor vehicles within a *cluster*. A cluster is a set of vehicles in which all intervehicle distance measurements are known. Each vehicle learns its own cluster from the received RVs. Fig. 2(b) shows a typical example of the clustering. Assume that vehicles $b$, $c$, $d$, and $x$ are within each other's transmission range. During the measurement phase, each vehicle learns the distance between itself and other vehicles. Thus, after the exchange phase is done, $x$ receives all RVs from each of the neighbors. Because all range measurements between $b$, $c$, $d$, and $x$ are known to $x$, it identifies the cluster of four vehicles. Similarly, $b$, $c$, and $d$ can identify the same four-vehicle cluster. Note that, in this example, although $x$ can receive the RV from the extra vehicle $e$, $e$ is not in $x$'s cluster, because $e$ is outside the transmission ranges of vehicles $b$ and $c$. For $e$, the cluster that is detected only consists of the following three vehicles: 1) $e$; 2) $d$; and $x$. After the cluster has been determined, the range measurements within the cluster form the range matrix $\mathcal{D}$. The range matrix and the reported vehicles' kinematics are then fed as inputs into the CP algorithm. The idea is to improve the position estimates of each vehicle using these inputs based on multilateration or trilateration principles [26]. Various such CP algorithms have been proposed in the literature [3], [13], [17]–[21].

### D. Discussions

The idea of CP is particularly attractive in vehicular networks, because the accuracy of positioning is expected to increase when the vehicle density increases [3]. Nevertheless, the high-speed movements of vehicles create a challenging environment for employing CP. The highly dynamic environment leads to frequent network fragmentation, rapid topology evolution, and short wireless link life [25]. Hence, to allow the CP algorithms to track the updated network topology in real time, range information needs to frequently be exchanged among the vehicles. However, the intensive range information exchange over the shared DSRC control channel naturally introduces significant communication overhead into the VANET. This case inevitably deteriorates the congestion conditions and impacts the reliability of the exchange of safety packets that are transmitted over the shared control channel. This condition can ultimately adversely affect the reliability and performance of safety vehicular applications [1]. Furthermore, when the wireless channel is congested, the RV packets are also prone to loss. This case potentially reduces the cluster size and leads to degraded CP accuracy. In the next section, our simulation

study will show that frequent range information exchange has a significant impact on not only the reliability of safety communications but on the CP performance as well.

In addition, the strict cluster-based CP algorithms rely on the full range matrix, where all pairwise range information between vehicles within a cluster is recorded. The range information from vehicles that do not belong to the cluster is simply discarded from the calculations [21]. For example, in Fig. 2(b), the RV from $e$ is discarded by $x$, because $e$ is not considered in the cluster. In this case, $x$ misses the potential opportunity to further improve the positioning accuracy by leveraging the extra range information that is available from $e$. In Section V, we will investigate how using the extra range information can effectively improve the CP performance in VANETs.

### E. Positioning Accuracy Bounds for CP in VANETs

The accuracy of the CP is primarily dictated by the errors from GPS position and intervehicle ranging estimates. The technique for estimating the position in CP can also affect the CP accuracy. However, the evaluations and discussions on the applicability, advantage, and disadvantage on specific estimation techniques are beyond the scope of this paper. To evaluate the accuracy of CP in general, the standard approach in ad hoc networks is to calculate the CRLB [24]. The CRLB is the inverse of the Fisher information matrix (FIM) [27] and represents the lower bound for the variance of any unbiased estimations. Thus, the CRLB can be used as the benchmark for evaluating the CP performance, regardless of the position estimation technique that is used. This metric is used in this paper. In the following discussion, we derive a CRLB model that can be used to evaluate the CP performance in VANETs.

In the following discussion, we assume a simple zero-mean normal distribution for GPS-based positioning and radio-ranging errors [3]. The normality assumption on GPS error is practical in the cases of highway and open-space scenarios. We acknowledge that this assumption may not be always applicable in urban areas due to the time- and location-varying multipath, interference, and dilution-of-precision (DOP) effects on the GPS signal [12], [28]. For example, the real-world distribution of position error in urban scenarios may be better modeled as a Gaussian mixture model (GMM) [29]. However, the precise modeling and analyzing of the effect of GPS measurement error is beyond the scope of this paper. Recall that the primary goal of this paper is to investigate the CP performance under the effects of DSRC channels. Hence, assuming a simple normal GPS error model allows us to simplify the analysis without being affected by the adverse effects of the GPS receiver vulnerabilities. In our future work, we plan to extend the CRLB model using more advanced realistic GPS error models that are more appropriate for urban scenarios.

We denote $\sigma_P$ as the standard deviation of GPS-based positioning error along the $x$- and $y$-axes and $\sigma_R$ as the standard deviation of ranging measurements error between two vehicles. Consider a scenario with a total of $n$ vehicles in a cluster. We define $W = \{x_1, y_1, \dots, x_n, y_n\}$ as the vector of true 2-D positions of vehicles and $Z = \{\breve{x}_1, \breve{y}_1, \dots, \breve{x}_n, \breve{y}_n, \breve{D}_{1,1}, \dots, \breve{D}_{1,n}, \dots, \breve{D}_{n,n}\}$ as the vector that consists of the measured GPS positions and range information. Furthermore, we define $\eta = \{x_1, y_1, \dots, x_n, y_n, D_{1,1}, \dots, D_{1,n}, \dots, D_{n,n}\}$ as the combined vector of true positions and ranges, and $\sum$ is the diagonal covariance matrix of the position and range measurements,[1] i.e., $\sum = \mathrm{diag}(\sigma_{P_{x1}}, \sigma_{P_{y1}}, \dots, \sigma_{P_{xn}}, \sigma_{P_{yn}}, \sigma_{R_{1,1}}, \dots, \sigma_{R_{1,n}}, \dots, \sigma_{R_{n,n}})$. Thus, the conditional joint probability density function (pdf) of the measurements $Z$, given the true states $W$ of vehicles, is

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

where $N_Z$ is the size of vector $Z$. Note that there are $2n$ position entries (in 2-D) in $Z$. In addition, the number of entries for ranging information in $Z$ is $\binom{n}{2}$. Hence, $N_Z = 2n + \binom{n}{2} = n(n+3)/2$. The corresponding FIM $F$ of the measurements is listed in[2]

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

Let us denote $i, j = \{1, \dots, n\}$, $x_i$, and $y_i$ as the coordinates of vehicle $i$ and $r_{ij}$ as the real distance between vehicles $i$ and $j$. Assuming that $i \neq j$, then the entries of FIM are

$$F_{kk} = \begin{cases} \frac{1}{\sigma_P^2} + \sum\limits_{j=1, j\neq i}^{n} \frac{(x_i-x_j)^2}{\sigma_R^2 r_{ij}^2}, & k=2i-1 \\ \frac{1}{\sigma_P^2} + \sum\limits_{j=1, j\neq i}^{n} \frac{(y_i-y_j)^2}{\sigma_R^2 r_{ij}^2}, & k=2i. \end{cases} \tag{3}$$

$$F_{kl} = \begin{cases} -\frac{(x_i-x_j)^2}{\sigma_R^2 r_{ij}^2}, & k=2j-1, l=2i-1, i\neq j \\ -\frac{(y_i-y_j)^2}{\sigma_R^2 r_{ij}^2}, & k=2j, l=2i, i\neq j \\ -\frac{(x_i-x_j)(y_i-y_j)}{\sigma_R^2 r_{ij}^2}, & k=2i-1, l=2j, i\neq j \\ \sum\limits_{j=1, j\neq i}^{n} \frac{(x_i-x_j)(y_i-y_j)}{\sigma_R^2 r_{ij}^2}, & k=2i-1, l=2i. \end{cases} \tag{4}$$

$$F_{kl} = F_{lk}. \tag{5}$$

Note that $F$ is a $2n \times 2n$ matrix. The CRLB $C$ is simply the inverse of the FIM, i.e., $C = F^{-1}$. The variance of the CP localization error for each vehicle in the cluster resides on the diagonal of $C$. Hence, the positioning errors $Err$ of the entire cluster is defined as the square root of the mean of the diagonal elements of $C$, i.e.,

$$Err = \sqrt{1/(2n) \times trace(C)}. \tag{6}$$

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

$$PAG = \frac{\sigma_P - Err}{\sigma_P} \times 100. \tag{7}$$

PAG shows the accuracy gain (as a percentage) of CP compared to unassisted GPS positioning.

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[1] Recall that we assume that $\sigma_{P_{xi}} = \sigma_{P_{yj}} = \sigma_P$ and $\sigma_{R_{i,j}} = \sigma_R$ for $i, j = 1, \dots, n$.

[2] $E$ in (2) represents the expectation operator.

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 |



Fig. 3.    Map of the loop road used in the simulation.

## IV. CHARACTERIZATION OF COOPERATIVE POSITIONING IN VEHICULAR AD HOC NETWORKS

In this section, we characterize the performance of CP through simulation experiments. We first present the simulation setup in Section IV-A. Next, we evaluate the efficacy of CP under ideal and realistic communication channels in Section IV-B and C, respectively. Performance issues that are related to CP are identified and discussed in Section IV-D.

### A. Simulation Setup

Our simulations are run using the ns-2 simulator. To simulate realistic wireless communications, we have used the latest version (v2.34) of ns-2 with the recent overhaul on the IEEE 802.11 physical- and medium access control (MAC)-layer implementations [30]. To simulate the use of DSRC radio, we used the parameter settings recommended in [31]. The primary parameters are listed in Table I. To simulate a realistic urban radio propagation environment, we used the *Nakagami* propagation model with the configurations suggested in [31]. The DSRC transmission range is set to 240 m.

The simulated road topology is shown in Fig. 3. We simulated a triangular-shaped loop road with three lanes on both clockwise and counterclockwise directions. The lane width is set to 3.5 m. The loop road allows the number of vehicles in the network to be consistent during each simulation run. In addition, the particular triangular shape of the road enables us to observe the aggregate CP performance under various road conditions. For example, we can collect results not only on straight roads (highway linear topology), e.g., during the middle section of Grand River Ave., but at intersections and corners of the roads as well. 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 average vehicle speed is 60 km/h. In the simulations, we
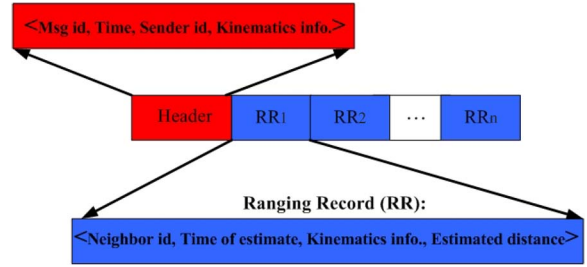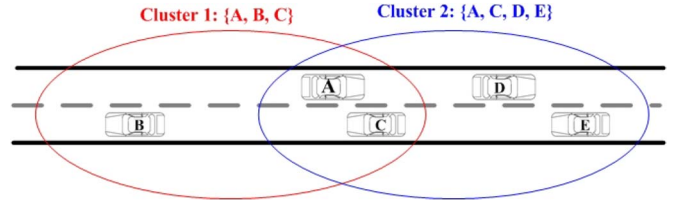


Fig. 4.    Details of a RV packet.



Fig. 5.    Vehicle can belong to multiple clusters at the same time.

varied the number of vehicles that circulate the road from 30 to 210. This approach corresponds to different traffic densities, where 12.5–87.5 veh/km represent light- to heavy-traffic conditions. The simulation time for each run is 100 s.

We assume that the clocks on all vehicles are synchronized (e.g., through a GPS clock [6]). Each 1-s interval is partitioned into ten synchronized intervals (SIs) of 100 ms. Within each SI, each vehicle randomly selects a time to broadcast its safety messages to its neighbors, resulting in a broadcast rate of 10 Hz [32]. Note that each broadcast packet consists of the kinematics and control information of a vehicle, including the instantaneous GPS location measured [33]. The size of safety broadcast packets is assumed to be 200 B [34].

During each SI, we assume that a vehicle "detects" a neighbor if the vehicle receives a packet from that neighbor. We assume that the distance between the vehicle and the neighbor can be estimated using the ranging techniques discussed in Section III-A. Thus, each vehicle updates its RV at the end of each SI. To share the RV with other neighbors, we have implemented a *baseline* broadcast protocol, where each vehicle periodically broadcasts its current RV (collected in the last SI) within each SI. The details of a RV packet are shown in Fig. 4. The RV packets consist of necessary header information and a set of ranging records (RRs) of all detected neighbors. The information that is contained in the RV packet header is similar to a safety packet; hence, we assume that the header size of a RV packet is 50 B [33]. Considering the content, the size of each RR is assumed to be 20 B [33]. Note that the size of an RV packet proportionally increases when the number of detected neighbors increases. An RV can be fragmented into multiple MAC frames when the number of RRs that are carried is large (i.e., greater than 72) due to the 1500-B maximum transmission unit (MTU) constraint of the IEEE 802.11 MAC.

After receiving the RV packets from other neighbor vehicles, each vehicle constructs its range matrix to run the CP algorithm. For this approach, a vehicle first needs to identify to which cluster it belongs. Recall that a cluster is a group of vehicles in which all pairwise intervehicle distance measurements are

known. Note that a vehicle may simultaneously belong to multiple clusters, as shown in Fig. 5. Depending on the number of vehicles and the relative positions of the vehicles within a cluster, the positioning accuracies provided by different clusters are different. Hence, to select the cluster that achieves the best positioning performance, all candidate clusters need to be identified and compared. The pseudocode of a simple algorithm to identify the clusters used in our simulations is listed in Algorithm 1. After identifying all available clusters, the positioning accuracy that is achieved by each cluster is evaluated (as discussed in Section III-E) and compared. The best positioning accuracy is recorded for the vehicle.

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**Algorithm 1**: Pseudocode for identifying clusters of vehicle $x$.

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1: Input: The neighbor set $NS_x$ and the set of received ranging vectors $\mathbf{RV}_i$, $i \in NS_x$.
2: Output: The set of identified clusters $\mathcal{C}$.
3:
4: Initialization:
5: $\mathcal{C} = NULL$;
6: $n = \#$ of neighbor vehicles detected by $x$;
7: The index $n + 1$ is used to represent $x$ itself;
8:
9: /*Finding the neighbor vector for each vehicle.*/
10: **for** $i \in \{1, 2, \ldots, n + 1\}$ **do**
11:     $V_i = NULL$;
12:     **for** $j \in \{i + 1, \ldots, n + 1\}$ **do**
13:         **if** $D_{i,j} \in \mathbf{RV}_j$ or $D_{j,i} \in \mathbf{RV_i}$ **then**
14:             Add $j$ to $V_i$;
15:             Add $i$ to $V_j$;
16:         **end if**
17:     **end for**
18: **end for**
19:
20: /*For each neighbors, find the largest cluster to which it belongs.*/
21: **for** $i \in \{1, 2, \ldots, n\}$ **do**
22:     $initSet = V_i \cap V_{n+1}$;
23:     $Cluster_{temp} = initSet$;
24:     **for** Each vehicle $k$ in $initSet$ **do**
25:         **if** $k \in Cluster_{temp}$ **then**
26:             $Cluster_{temp} = V_k \cap Cluster_{temp}$;
27:         **end if**
28:     **end for**
29:     **if** $Cluster_{temp} \notin \mathcal{C}$ **then**
30:         Add $Cluster_{temp}$ to $\mathcal{C}$;
31:     **end if**
32: **end for**

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We report the packet delivery ratio (PDR) of broadcast transmissions to evaluate the impact of RV exchange on safety communication reliability. The PDR of each broadcast packet is calculated as the ratio between the number of neighbor vehicles that receive the packet and the total number of neighbors that exist in a vehicle's transmission range. To evaluate the
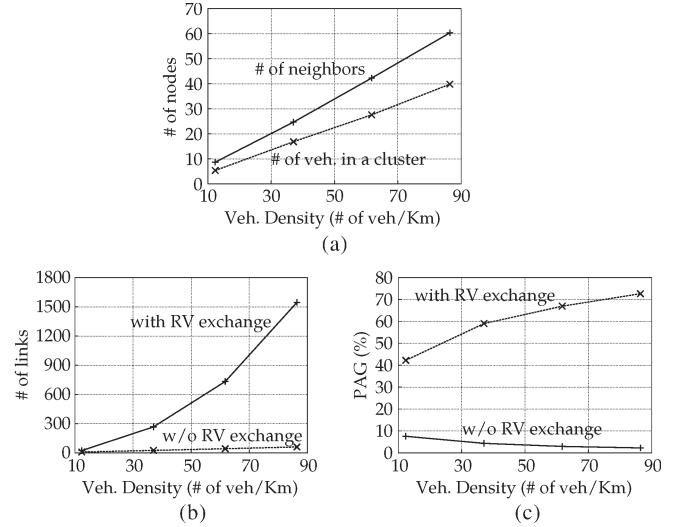


Fig. 6. Effect of range information exchange under ideal communication channels. (a) Number of nodes. (b) Number of available links. (c) Accuracy improvement.

positioning performance, we calculate the PAG (as discussed in Section III-E) for each vehicle for each SI. The PAG is calculated using MATLAB after each simulation run has been finished. To calculate the PAG, based on (3)–(5), we feed the ground-truth positions $W$ of vehicles in the cluster, the ranging error standard deviation $\sigma_R$, and the GPS positioning error standard deviation $\sigma_P$ into the CRLB model. In our simulations, we assume that $\sigma_R = 5m$ and $\sigma_P = 7m$, which is consistent with state-of-the-art ranging and GPS performance [3]. All our results reported are averaged over all vehicles and over the entire simulation duration. The standard error achieved is less than 5% of the mean value reported.

### B. CP Under Ideal Communication Channels

As a benchmark, we first study how using CP can effectively improve the positioning accuracy in a vehicular network under an ideal communication channel, i.e., without packet collisions and loss. In this case, a vehicle can always successfully detect all neighbors and receive their RVs. For this approach, we only simulated the vehicle mobility and disabled the communications between the vehicles in ns-2. Thus, we process the neighbors and clusters and calculate PAG results based on only the positions of the vehicles and the transmission range assumed.

Fig. 6(a) plots the number of neighbors and the number of vehicles that form the cluster as a function of the traffic density. Although the number of vehicles in a cluster linearly increases when the traffic density increases, a cluster only consists of around 50%–60% of the neighbors. This case is because not all the neighbors of a vehicle can overhear each other due to the limited transmission range. For example, $b$ and $e$ are both $x$'s neighbor, but they cannot overhear each other, as shown in Fig. 2. Next, we show the number of available links with range estimates that can be used in CP in Fig. 6(b). As evident, with RV exchange, the number of available links with range information rapidly grows with the increase in traffic density. This case is due to the increasing number of vehicles in the
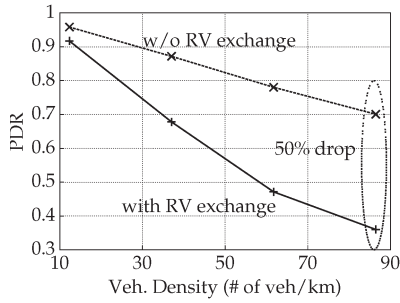
Fig. 7. Effect of range information exchange on the PDR under realistic communication channels.
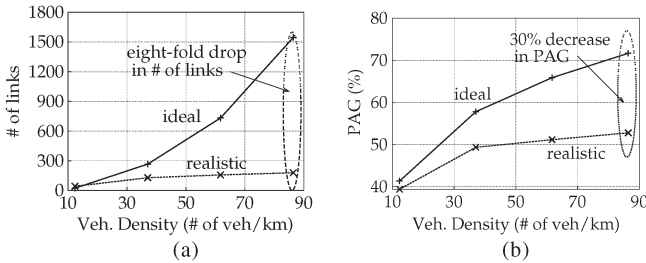


Fig. 8. CP performance under realistic communication channels. (a) Number of available links. (b) Accuracy improvement.

cluster, as observed in Fig. 6(a). As a result, Fig. 6(c) shows that, through RV sharing, the positioning accuracy of the whole cluster can readily be improved by more than 40%, even under low traffic density. The accuracy gain of CP becomes more pronounced when the traffic density increases, exceeding 70% under the heavy traffic density. On the contrary, without RV sharing, each vehicle can only access its own RV and improve the estimate accuracy of its position. In this case, improving position estimates on neighboring vehicles is not possible. Hence, the PAG over the entire neighborhood is marginal, as shown in Fig. 6(c). Furthermore, the PAG decreases with the increase in the traffic density, because more neighbors (without improved position estimates) are involved in the calculations under heavier traffic densities.

## C. CP Under Realistic Communication Channels

In the previous section, we have shown the usefulness of CP under ideal communication channels without considering any packet loss. In this section, we investigate the actual CP performance under realistic vehicular communications. For this case, we have enabled the IEEE 802.11 MAC, the radio propagation model, the safety message broadcasts, and the RV broadcasts. Hence, packet loss and collisions happen in this set of simulations. The corresponding results are presented and discussed as follows.

Fig. 7 shows the PDR results of CP (with RV exchange) under various traffic density scenarios. For comparison, we also plot the results when only safety information is exchanged in the network (without RV exchange). As observed, the extra RV exchange overhead results in significant reduction in the PDR by up to 50% under heavy-traffic conditions. The impairment to the PDR can seriously affect the reliability of the safety applications. Furthermore, as evident in Fig. 8(a),

the real-world communication constraints significantly reduce the number of available links with the range information used in CP compared with ideal conditions. This difference under heavy-traffic-density conditions is nearly eightfold. The limited range information seriously affects the positioning accuracy, as shown in Fig. 8(b). We see that, unlike the ideal case, the improvement in PAG from realistic communication quickly tapers off when the traffic density increases. Under heavy traffic density, the PAG drops by about 30% from the ideal case due to the excessive packet loss.

## D. Summary

In the aforementioned analysis, we have investigated the performance of CP under both ideal and realistic communication channels. Under ideal conditions, we have shown that CP can achieve significant improvements in positioning accuracy, even under light-traffic conditions. In addition, we have shown that the efficacy of CP rapidly increases when the vehicle density increases. However, we found that the packet collisions under real-world communication constraints significantly affect the achievable performance of CP. In summary, we identify two major issues of applying CP in vehicular networks. First, the strict clustering constraint of the existing CP algorithms is not efficient in lossy wireless communication environments. Recall that the range information that is received from the nodes that do not belong to the cluster is excluded from the CP process and is discarded. Our results show that this inefficient use of range information makes it impossible to achieve a large cluster and further improve positioning accuracy, even with a large number of neighbors available. Second, the communication overhead that is generated by the range information exchange significantly aggravates the network congestion conditions. This case inevitably affects the reliability of safety applications, which contradicts the incentive of employing CP in vehicular communications.

Our observations suggest that, to make CP a viable technique for vehicular networks, improvements on the various aspects of CP need to be investigated. In the following sections, we address this issue in two distinct ways. First, in Section V, we investigate an enhanced CP data fusion approach to improve the efficiency of the cluster-based approach in utilizing the available range information. Furthermore, in Section VI-A, we propose a series of protocol improvement techniques to reduce the impact of communication overhead that is introduced by range information exchange in CP.

## V. EFFICIENT DATA FUSION IN COOPERATIVE POSITIONING

In the previous section, we have shown that the strict cluster approach does not achieve significant PAG under real-world communication constraints. One reason is attributed to the limited size of the cluster that is found by a vehicle. The amount of range information that is received by a vehicle can significantly be larger than the range information that is used in the cluster-based CP process. For example, recall that, in Fig. 2(b), the extra range information $D_{x,e}$ and $D_{e,d}$ that is available to $x$

$$\mathscr{D}_x = \begin{bmatrix} D_{b,b} & D_{c,b} & D_{d,b} & D_{x,b} & n/a \\ D_{b,c} & D_{c,c} & D_{d,c} & D_{x,c} & n/a \\ D_{b,d} & D_{c,d} & D_{d,d} & D_{x,d} & D_{e,d} \\ D_{b,x} & D_{c,x} & D_{d,x} & D_{x,x} & D_{d,x} \\ n/a & n/a & D_{d,e} & D_{x,e} & D_{e,e} \end{bmatrix}$$

Fig. 9.  Extended range matrix.

is discarded from the cluster-based CP algorithm. However, it may be possible to achieve better CP positioning accuracy by exploiting the *extended range matrix*, which includes the range estimates $D_{x,e}$ and $D_{e,d}$, as shown in Fig. 9. Compared with the range matrix of the strict cluster in Fig. 2(b), the extended matrix contains several *n/a* entries, because some of the link distance measurements are not available. To incorporate all available range information in the extended matrix, a CP algorithm can use the existing data fusion techniques, such as the Kalman filter [3], particle filter [21], [22], and least mean square error (LMSE) [35]. Although exact implementation details of such CP algorithms are beyond the scope of this paper, in this section, we derive the potential gain of such algorithms through CRLB analysis. In the following discussion, we refer to the proposed CP algorithm using the extended range matrix as *extended cluster*.

The CRLB calculation over the extended-cluster scheme only requires minimal modifications to the models discussed in Section III-E. Aside from the vector of true vehicle locations $W$, $\sigma_P$, and $\sigma_R$, the modified model takes an additional input auxiliary matrix $I$, i.e.,

$$I_{i,j} = \begin{cases} 1, & D_{i,j} \text{ exists} \\ 0, & D_{i,j} = \text{n/a} \end{cases} \quad (8)$$

where $i$ and $jj$ are two vehicle indices in the matrix. Then, the covariance of range measurements between any pair of vehicles is defined as

$$\sigma_{R_{i,j}}^2 = \begin{cases} \sigma_R^2, & I_{i,j} = 1 \\ \text{inf}, & I_{i,j} = 0. \end{cases} \quad (9)$$

Then, the CRLB and the corresponding PAG results can accordingly be calculated following (3)–(7).

To understand the potential PAG due to the extended-cluster scheme, we first conduct studies, assuming ideal communication conditions. The performance of the extended-cluster scheme and the strict cluster are plotted against traffic density in Fig. 10. Observe that, for both schemes, the number of available links with range information that is used in CP rapidly grows with the increase in traffic density. However, the extended cluster constantly leads to more available links than the cluster, because it exploits the extra link information that is discarded by the cluster. As a result, Fig. 10(b) shows that the extended cluster constantly outperforms the cluster in positioning accuracy by roughly 10%.

Next, we study the actual performance of the extended-cluster scheme under realistic communication constraints in Fig. 11. We also plot the results from the cluster scheme for comparison. Furthermore, the performance of the extended
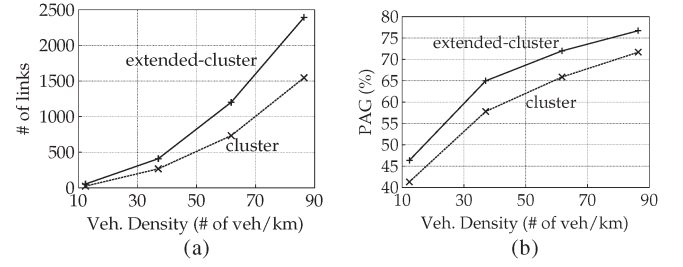


Fig. 10.  Performance of the extended-cluster CP scheme under ideal conditions (lossless communications). (a) Number of available links. (b) Accuracy improvement.
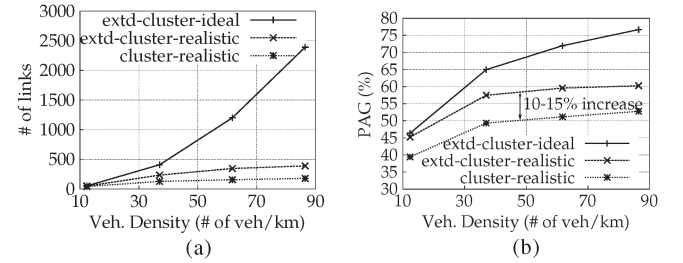


Fig. 11.  Performance of the extended-cluster CP scheme under realistic communication conditions. (a) Number of available links. (b) Accuracy improvement.

cluster for the ideal channel is shown as the benchmark. In Fig. 11(a), we can see that the number of available links used by the extended cluster is clearly larger than the number of available links used by the cluster. Fig. 11(b) shows that, because of the efficient utilization of all received range information, the extended cluster constantly achieves a 10%–15% improvement in positioning accuracy compared with the cluster.

Nonetheless, we observe that, even with the extended-cluster scheme, the number of available links that are usable by the CP process is only a small portion of the ideal. Accordingly, the positioning accuracy is noticeably lower than the ideal case. This condition is clearly the effect of excessive packet loss that is caused by RV exchanges. Moreover, as discussed in Section IV-C, excessive packet loss also significantly affects the reliability of safety communications. This case highlights the need to improve the RV broadcast protocol to both reduce the communication overhead and enhance the RV exchange reliability. Therefore, we further discuss possible improvements on RV exchanges in the next section.

## VI. EFFICIENT RANGE INFORMATION EXCHANGE

In the previous section, we proposed an extension of the existing CP algorithm to improve the efficiency of range information utilization. In this section, we seek to further improve the performance of CP by improving the baseline communication protocol used in the previous sections. Our enhancements are twofold. In Section VI-A, we first propose to incorporate a series of schemes to reduce the overhead that is caused by the RV exchange. Next, we further improve the reliability of the range information exchange by employing network coding techniques in Section VI-B.
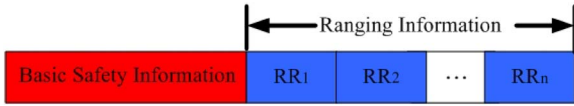
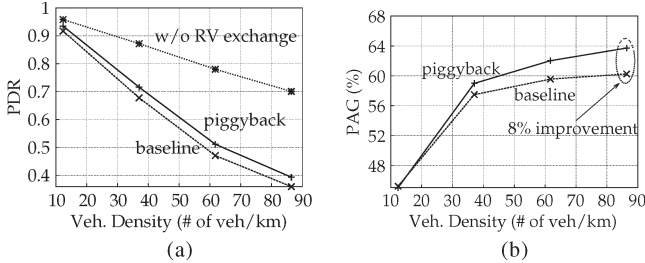Fig. 12.    Using the safety packet to piggyback the RV.



Fig. 13.    Effect of incorporating piggyback into the RV exchange on the CP performance. (a) PDR. (b) Accuracy improvement.



Fig. 14.    Effect of incorporating compression into the RV exchange on the CP performance. (a) PDR. (b) Accuracy improvement.

### A. Reducing the Communication Overhead

In this section, we present various schemes to reduce the communication overhead in RV exchanges. In the following discussion, we present each of these schemes and individually evaluate their performance against the baseline communication scheme discussed in Section IV-A.

*1) Piggyback:* The piggyback scheme is shown in Fig. 12. Instead of individually sending each RV packets (see Fig. 4), an RV is directly appended to the end of a safety packet. The simple piggybacking can reduce the amount of information that is transmitted in the network, because it reuses the header information in the safety packet and eliminates the need for the extra header that is required when an RV is transmitted separately. In addition, it reduces the number of packets that are exchanged in the network, hence alleviating the channel contention conditions. We have implemented the piggyback scheme and evaluated its performance in our simulations. Fig. 13 plots the PDR and PAG results as a function of traffic density. We observe that, in Fig. 13(a), due to the alleviated congestion conditions, piggyback constantly improves the PDR compared with the baseline scheme. The improved PDR clearly has a positive effect on positioning accuracy, as shown in Fig. 13(b). This case is because the higher the PDR, the more the information that is available in the CP process. For heavy traffic density, we observe that the simple piggyback scheme can readily result in about 8% improvement in PAG compared with the baseline scheme.

*2) Compression:* Another possible way of reducing the communication overhead in CP is to minimize the size of the RVs that are exchanged. Intuitively, it may be possible to reduce the size of an RV by compressing its content. In data communication, compression has been a viable technique for improving the transmission efficiency, e.g., Transmission Control Protocol/Internet Protocol (TCP/IP) header compression [36] and Hypertext Transfer Protocol (HTTP) content compression [37]. In the following discussion, we investigate the possibility of incorporating a compression technique to improve the communication in CP.

To preserve all information in the RV, lossless compression techniques [38], e.g., Lempel–Ziv (LZ) [39] and GNU zip
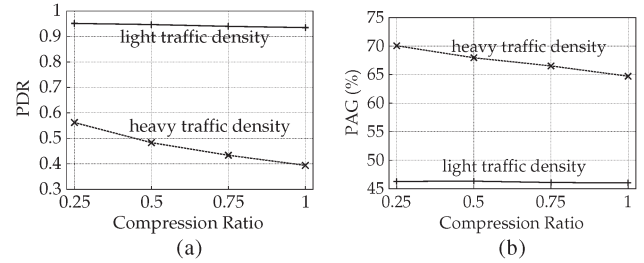
(gzip) [40], can be used. The efficiency of a compression technique is generally defined by the compression ratio (CR), i.e., the ratio between the size of the compressed and the uncompressed data. Depending on the type of information that is compressed, some schemes can result in up to 0.25 in the CR. Note that compression also introduces delays due to the computation overhead. Because the size of each RV is not significant, the compression delays can be considered negligible compared with an SI. In the following discussion, we evaluate the effect of compression on the performance of CP through simulations, assuming different CRs. To emulate the effect of applying compressions on RVs, for a given RV of size $S_o$, the number of bytes that are transmitted $S_a$ is calculated as $S_a = S_o \times CR$ in our simulations.

In Fig. 14, we plot the results under both light and high traffic densities as a function of CR. Note that a CR of 1 represents the baseline scheme without applying compression. Fig. 14(a) shows the PDR results. We observe that compression is particularly helpful under dense traffic scenarios. For example, under high traffic density, compression (with 0.25 CR) can improve the PDR by nearly 50% compared to the baseline scheme. Furthermore, the reduced packet loss increases the amount of information available to the CP process, hence improving the PAG by 10% under heavy traffic density. Nevertheless, the compression technique shows no significant effect under the light-traffic-density scenario. This case is expected, because the packet loss is not significant when the vehicle density is low.

*3) RVBI:* Recall that, in the baseline scheme, the ranging vector broadcast interval (RVBI) is set to be the same as the safety message interval SI. This frequent broadcast is necessary, because each vehicle requires constant updates on its neighbors' positions. However, our results have shown that this intense range information exchange conversely deteriorates the network congestion conditions. One possible solution for this issue is to reduce the rate of RV broadcast. However, this approach means increasing the delay between subsequent CP updates. This delay may have reverse effects on the positioning accuracy. Hence, there may exist an optimal RVBI setting that can maximize the positioning accuracy while achieving reasonable PDR. In this section, we explore this issue under different traffic scenarios through simulation studies.

We assume that the RVBI is always a multiple of the SI. At the start of an RVBI, each vehicle updates its own RV for sharing, as discussed in Section III-A. Within each RVBI,
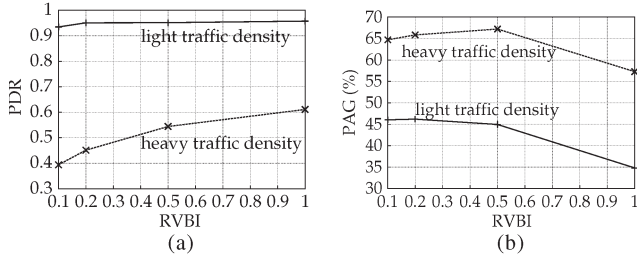
Fig. 15. Effect of varying RVBIs on the CP performance. (a) PDR. (b) Accuracy improvement.



Fig. 16. Correlation between the PAG and the PDR under different RVBI settings. (a) Heavy traffic density. (b) Light traffic density.

each vehicle randomly selects the time to broadcast its own RV. At the end of each RVBI, each vehicle processes its collection of RVs and invokes the CP process (the extended-cluster CP scheme discussed in Section V) to improve the estimates on the positions of neighbor vehicles. Note that, due to the transmission delay of the RVs, the outputs of the CP process are the improved vehicle position estimates at the previous RVBI. To infer the current vehicle positions, we can use the dead reckoning [22] techniques, which have widely been used in addressing the vehicle localization problem during intermittent GPS outages. The idea is to estimate a vehicle's current position based on the last known vehicle location and kinematics information. For example, assume that the initial vehicle position estimate $p_i$ and the speed measurement $v$ are known. Then, the vehicle position after time $t$ can roughly be estimated as $p(t) = p_i + t \times v$. Assuming that the initial estimation errors of vehicle positions and the vehicle's speed are normally distributed with the standard deviation of $\sigma_{p_i}$ and $\sigma_v$, the standard deviation of the error of the positioning estimates that are inferred from the initial estimates after $t$ is

$$\sigma_{p(t)} = \sqrt{\sigma_{p_i}^2 + t^2 \times \sigma_v^2}. \qquad (10)$$

Clearly, $\sigma_{p(t)}$ is a monotonic increasing function of $t$ with given $\sigma_{p_i}$ and $\sigma_v$. To evaluate the impact of RVBI in our simulations, we compute the initial positioning error $Err_i$ at the end of each RVBI as in (6). Hence, for the $k_{th}$ ($k = \{0, \ldots, RVBI/ SI - 1\}$) SI before the end of the next RVBI, $Err$ is calculated as in (10), where $t = RVBI + k \times SI$. The $\sigma_v$ is assumed to be 10 km/h.

Fig. 15 plots the CP performance for light and heavy traffic densities against different RVBI values. We first focus on the results for heavy traffic density. Fig. 15(a) shows the pronounced improvement on PDR by increasing the RVBI for heavy traffic density. This case shows that a reduction in the RV exchange rate effectively relieves the congested wireless channel. Recall that, in the previous piggyback (see Section VI-A1) and compression (see Section VI-A2) analysis, we observed that the increase in PDR generally has a positive effect on the PAG. However, in Fig. 15(b), we only observe this trend for the heavy-traffic-density scenario when the RVBI is moderate, i.e., smaller than 500 ms. The PAG noticeably decreases when a 1-s RVBI of is used. This observation suggests a tradeoff when selecting the RVBI under dense traffic conditions. For better understanding, we consider the correlation between the PAG and the PDR for the heavy traffic density plotted in Fig. 16(a). Note that, when increasing the RVBI, the improved
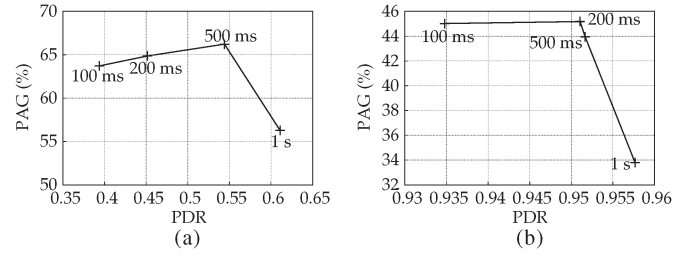
PDR warrants extra range information available in the CP process, which helps improve the positioning accuracy. On the other hand, the delay in RV exchange impairs the accuracy of the positioning at the same time. Fig. 16(a) shows that, when the RVBI is small, the PAG from the improved PDR overpowers the loss that is caused by the RV exchange delays, hence resulting in the increase in the PAG. However, when the RVBI increases beyond 500 ms, the effect of the delay in RV exchange becomes dominant, which leads to the sharp drop in the PAG. We found that a 500-ms RVBI appears to be a balanced choice, which achieves both good PAG and PDR for heavy-traffic conditions.

On the other hand, for light-traffic conditions, the increase in the PDR is marginal by tuning the RVBI, as shown in Fig. 15(a). Hence, the positioning accuracy is mainly affected by the delay in RV exchange. This case is evident in Fig. 16(b), where we can observe that the increasing RVBI does not result in a positive effect on the PAG. Hence, in the light-traffic scenario, where the network is not congested, using a smaller RVBI is preferable to avoid the positioning delay.

*4) Combined Improvement:* In this section, we cross compare the aforementioned improvement techniques and investigate the performance of combining them together. Fig. 17 shows the performance of different schemes as a function of the traffic density. The PDR results are shown in Fig. 17(a). We compare various communication schemes, i.e., baseline, piggyback, compression (assuming 0.25 CR), RVBI (assuming $RVBI = 500$ ms), and the combined approach, which combines all three (piggyback, compression, and RVBI) techniques. Last, the communication scheme without RV exchange is shown as the PDR upper bound. Comparing the three standalone improvement techniques, we can see that compression and RVBI significantly improve the PDR performance compared to the baseline, whereas the improvement from piggyback is relatively smaller. Furthermore, by combining the three techniques together, we observe that the PDR increases to fairly close to the upper bound, i.e., without RV exchange. This case shows that the series of improvements effectively reduce the communication overhead that is caused by CP.

Fig. 17(b) compares the PAG results of the different schemes. For comparison, we also show the ideal scheme (with the extended-cluster CP data fusion scheme as shown in Section V), which corresponds to the upper bound of the PAG under certain traffic densities. We observe that the ranking of the schemes is the same as in Fig. 17(a). Recall that, in Fig. 17(a), we observe similar PDR results between compression and RVBI.
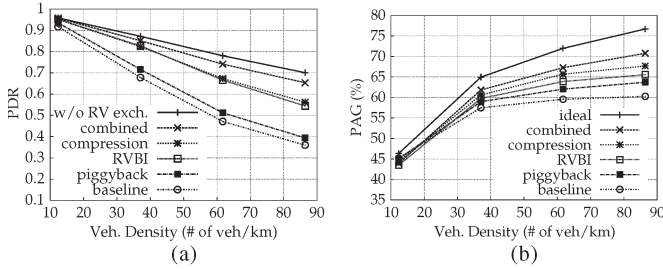
Fig. 17. Combined effect of using piggyback, compression, and RVBI on the CP performance. (a) PDR. (b) Accuracy improvement.

However, the PAG difference between the two approaches is more pronounced in Fig. 17(b). This case is because, under similar PDR conditions, the positioning accuracy of the RVBI scheme is also affected by the delay in RV exchange, as highlighted in Section VI-A3. Combining all three techniques clearly achieves further improvements.

### B. Coding Improvement

In the previous section, we showed the efficacy of several techniques in reducing the communication overhead that is introduced by RV exchanges. Although these techniques effectively improve the PDR, the PAG that is achieved is still noticeably lower compared to the ideal scheme, as shown in Fig. 17(b). Note that, in the lossy DSRC channel, the CP performance is significantly affected by the loss of range information. In this section, we propose to incorporate a simple network coding scheme into the previously proposed schemes to improve the reliability of range information exchange and the positioning accuracy of CP.

Our idea is summarized in Fig. 18. At the start of each RVBI, an original RV is partitioned into $N$ equal-size data segments. Next, an extra coding segment is generated through exclusive OR (XOR) operations over the all $N$ data segments. Consequently, an RV results in a total of $N + 1$ data and coding segments. Each of the $N + 1$ segments is piggybacked by the safety packets that are sent in a different SI during the same RVBI. Hence, the duration of an RVBI needs to accordingly be a minimum of $(N + 1) \times SI$. During an RVBI, the receiver keeps collecting the segments that are sent by the sender. At the end of an RVBI, the receiver tries to recover any lost segments of an RV by implementing an XOR operation on the segments received.

The usefulness of coding lies in its ability to recover lost segments. For example, whenever a receiver receives any $N$ segments out of the $N + 1$ segments, it can readily reconstruct the missing segment from the $N$ segments received. Hence, the entire RV can be reconstructed. If the number of successfully received segments is less than $N$, the missing segments cannot be recovered. In this case, the receiver can only record the range information that is available from the received segments. Recall that the CP accuracy is closely related to the amount of range information available and the more reliable RV exchange can potentially boost the performance of CP. To better understand the efficacy of the coding process, we first analyze the coding gain as follows.
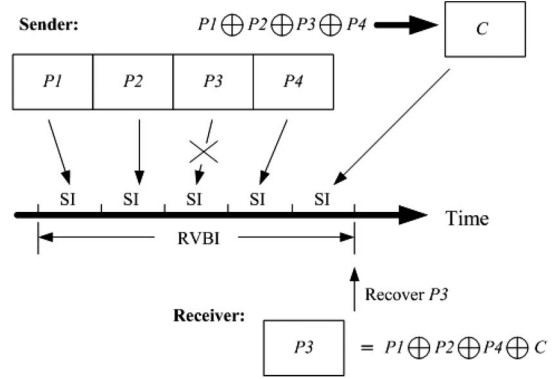


Fig. 18. Using coding in the RV exchange.

Let us denote $Pr$ as the expected packet loss probability (assuming independent packet loss) in the network and $L_s$ as the average number of RRs in an RV. We assume that the size of a RVBI is $(N + 1) \times SI$. Then, the probability that $n$ packets are lost within a RVBI $P_n$ can be defined as

$$P_n = \binom{N+1}{n} \times Pr^n \times (1 - Pr)^{N+1-n}. \quad (11)$$

Without any coding enhancement, each RV is piggybacked on one of the safety packets that are sent within a RVBI. Thus, the RV is lost only when the reception of the corresponding safety packet fails. Assume that $L_n$ is the number of RRs that can be received when $n$ safety packets are lost within an RVBI. When $n = 0$, no safety packet is lost; thus, the RV must successfully be received, and $L_n$ is equal to $L_s$. In case that all safety packets are lost, $L_n$ is 0. When $1 \leq n \leq N$, the RV is received when the corresponding safety packet that carries it is received. The associated probability for this case is $\binom{N}{n} / \binom{N+1}{n}$. Hence, $L_n$ is equal to $L_s \times \binom{N}{n} / \binom{N+1}{n}$. Equation (12) summarizes the calculations of the aforementioned $L_n$

$$L_n = \begin{cases} L_s, & n = 0 \\ L_s \times \dfrac{\binom{N}{n}}{\binom{N+1}{n}}, & 1 \leq n \leq N \\ 0, & n = N+1. \end{cases} \quad (12)$$

As a result, the expected total number of received RRs without coding enhancement $L_r$ is

$$L_r = \sum_{n=0}^{N+1} P_n \cdot L_n. \quad (13)$$

When coding is in use, an RV is partitioned into $N$ segments; thus, the number of RRs contained in each data segment is $L_{seg} = L_s / N$. Note that the size of the coding segment is the same as $L_{seg}$. In case that all safety packets are lost ($n = N + 1$) within an RVBI, the number of RRs that can be recovered $L_n^c$ is 0. When one or less safety packet is lost, the entire RV can be recovered; thus, $L_n^c$ is $N \times L_{seg}$. In case that $2 \leq n \leq N$, the size of $L_n^c$ depends on whether the coding packet is lost. If the coding packet is not lost, the number of RRs that can be recovered is $(N + 1 - n) \times L_{seg}$. The associated probability of this case is $\binom{N}{n-1} / \binom{N+1}{n}$. When the coding packet is lost, the
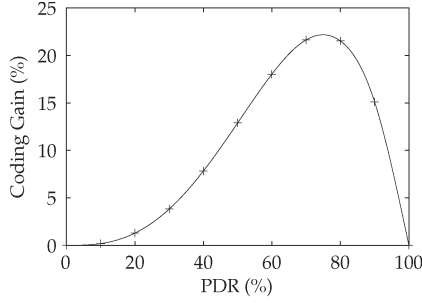
Fig. 19.    Coding gain as a function of the PDR.

number of recoverable RRs is $(N - n) \times L_{seg}$. The probability of this case is $\binom{N}{n} / \binom{N+1}{n}$. The aforementioned calculations are summarized as follows:

$$
L_n^c = \begin{cases} N \times L_{seg}, & \text{n} = \{0, 1\} \\ (N - n + 1) \times L_{seg} \times \frac{\binom{N}{n-1}}{\binom{N+1}{n}} & \\ \quad + (N - n) \times L_{seg} \times \frac{\binom{N}{n}}{\binom{N+1}{n}}, & 2 \leq \text{n} \leq N \\ 0, & \text{n} = N + 1. \end{cases} \tag{14}
$$

Accordingly, (15) lists the expected number of RRs that can be achieved using coding

$$
L_r^c = \sum_{n=0}^{N+1} P_n \cdot L_n^c. \tag{15}
$$

To compare the theoretical range information gain from coding, we define the coding gain $(G)$ by normalizing the $L_r^c$ with respect to $L_r$, i.e.,

$$
G = (L_r^c - L_r) / L_r. \tag{16}
$$

We use $N = 4$, because we have observed that a RVBI of 500 ms (five SIs) yields the reasonable performance in Section VI-A3. Fig. 19 plots the coding gain results calculated using (16) as a function of the PDR, i.e., $1 - Pr$. We observe that, when the PDR is around 70–80%, the coding gain is the most pronounced. Recall that our simulation results in Section IV-C show that, under heavy traffic density, the corresponding PDR falls within this range. This case shows that, by using coding, it is possible to effectively increase the amount of range information that is successfully exchanged. Note that, as shown in Fig. 19, the coding gain diminishes when the PDR approaches 0% or 100%. This case is expected, because it is not possible to reconstruct any information when all segments are lost, whereas it is impossible to further improve through coding when there is no packet loss.

Note that the aforementioned analysis assumes the same $Pr$ between the coding and noncoding schemes. However, in reality, the coding is expected to cause a higher $Pr$ compared with a noncoding approach due to the additional coding segment transmitted. To investigate the actual effect of coding, we implement the proposed idea in ns-2 for evaluation. The PDR results of coding are plotted as a function of traffic density in Fig. 20(a). For comparison, we also show the combined approach (the combination of piggyback, compression, and RVBI, as discussed in Section VI-A4), the baseline cluster
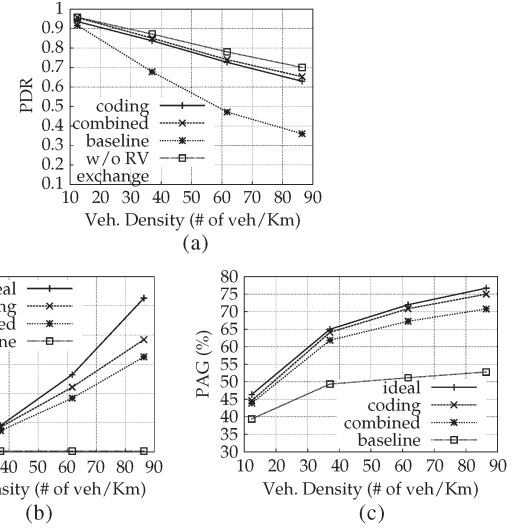


Fig. 20.    Effect of using coding in improving the RV exchange reliability. (a) PDR. (b) Number of links. (c) Accuracy improvement.

(i.e., the cluster-based CP algorithm with the baseline range information exchange scheme), and the scheme without any RV exchange. Fig. 20(a) shows that the PDR of the coding scheme is slightly lower than the combined approach. However, the margin is clearly small, which means that the coding overhead causes minimal effect on the PDR. Fig. 20(b) shows the number of available links with range estimates of various schemes and the scheme with an ideal channel. We observe that coding effectively increases the number of available links compared with the combined for all traffic densities. The improvement is up to about 20% improvement under high traffic density. Due to the increased distance information available in the CP process, the coding scheme further improves the positioning accuracy [as shown in Fig. 20(c)] compared with the combined. Note that the achieved PAG of coding is only slightly lower than the optimal ideal scheme. Furthermore, as evident in Fig. 20, a series of improvements (i.e., incorporating the extended-cluster CP algorithm, reducing the communication overhead, and using coding) effectively lead to a more than twofold improvement in PDR and more than 40% improvement in positioning accuracy compared to the baseline-cluster scheme.

In summary, the aforementioned results clearly demonstrate the practicability for CP to achieve a near-optimal positioning accuracy, which can be experienced under ideal communication channels, with minimal overhead by exploiting proper improvement techniques.

## VII. CONCLUSION

We have examined the issue of communication overhead for CP in vehicular wireless networks. We have found that, unless we find efficient ways of exchanging large amounts of range information over the congested vehicular communication channel, CP may not provide a viable option to increase positioning accuracy. We have demonstrated that simple well-known protocol improvements, e.g., information piggybacking, data compression, and network coding, can help address the range information exchange overhead issue for CP in vehicular networks.

In this paper, we have assumed a simple normal GPS error distribution with a constant standard deviation in our CRLB model. This approach allows the analysis to focus on the effect of DSRC channels on CP performance without being affected by the GPS receiver vulnerabilities in urban environments. In our future work, we plan to extend the current CRLB model using more advanced realistic GPS error models that are more appropriate for urban scenarios.

## REFERENCES

[1] S. E. Shladover and S. K. Tan, "Analysis of vehicle positioning accuracy requirements for communication-based cooperative collision warning," *J. Intell. Transp. Syst.: Technol., Plan., Oper.*, vol. 10, no. 3, pp. 131–140, 2006.

[2] B. Hofmann-Wellenhof, H. Lichtenegger, and J. Collins, *Global Positioning System Theory and Practice*, 5th ed. Wien, Austria: Springer-Verlag, 2001.

[3] R. Parker and S. Valaee, "Vehicular node localization using received-signal-strength indicator," *IEEE Trans. Veh. Technol.*, vol. 56, no. 6, pp. 3371–3380, Nov. 2007.

[4] *Standard Specification for Telecommunications and Information Exchange Between Roadside and Vehicle Systems—5.9 GHz Band Dedicated Short Range Communications (DSRC) Medium Access Control (MAC) and Physical Layer (PHY) Specifications*, ASTM E2213 - 03(2010), 2003.

[5] I. Amundson and X. D. Koutsoukos, "A survey on localization for mobile wireless sensor networks," in *Proc. 2nd Int. Conf. Mobile Entity Localization Tracking GPS-Less Environ., MELT*, 2009, pp. 235–254.

[6] E. D. Kaplan and C. J. Hegarty, *Understanding GPS Principles and Applications*, 2nd ed. Norwood, MA: Artech House, 2006.

[7] F. V. Diggelen, *A-GPS: Assisted GPS, GNSS, and SBAS*. Norwood, MA: Artech House, 2009.

[8] C. Hide, T. Moore, and M. Smith, "Adaptive Kalman filtering for low-cost INS/GPS," *J. Navig.*, vol. 56, no. 1, pp. 143–152, 2003.

[9] N. Alam, A. Tabatabaei, and A. Dempster, "Range and range–rate measurements using DSRC: Facts and challenges," in *Proc. IGNSS Symp.*, Gold Coast, Australia, 2009.

[10] N. Drawil and O. Basir, "Vehicular collaborative technique for location estimate correction," in *Proc. IEEE 68th Veh. Technol. Conf.*, Calgary, AB, Canada, 2008, pp. 1–5.

[11] N. Drawil and O. Basir, "Toward increasing the localization accuracy of vehicles in VANET," in *Proc. IEEE ICVES*, Nov. 2009, pp. 13–18.

[12] N. Drawil and O. Basir, "Intervehicle-communication-assisted localization," *IEEE Trans. Intell. Transp. Syst.*, vol. 11, no. 3, pp. 678–691, Sep. 2010.

[13] A. Benslimane, "Localization in vehicular ad hoc networks," in *Proc. Syst. Commun.*, Montreal, QC, Canada, 2005, pp. 19–25.

[14] H. Wymeersch, J. Lien, and M. Z. Win, "Cooperative localization in wireless networks," *Proc. IEEE*, vol. 97, no. 2, pp. 427–450, Feb. 2009.

[15] D. Moore, J. Leonard, D. Rus, and S. Teller, "Robust distributed network localization with noisy range measurements," in *Proc. 2nd Int. Conf. Embedded Networked Sens. Syst., SenSys*, 2004, pp. 50–61.

[16] R. Iyengar and B. Sikdar, "Scalable and distributed GPS free positioning for sensor networks," in *Proc. IEEE Int. Conf. Commun.*, 2003, pp. 338–342.

[17] R. Parker and S. Valaee, "Vehicle localization in vehicular networks," in *Proc. IEEE 64th Veh. Technol. Conf.*, Montreal, QC, Canada, 2006, pp. 1–5.

[18] T. S. Dao, K. Y. K. Leung, C. M. Clark, and J. P. Huissoon, "Markov-based lane positioning using intervehicle communication," *IEEE Trans. Intell. Transp. Syst.*, vol. 8, no. 4, pp. 641–650, Dec. 2007.

[19] N. Karam, F. Chausse, R. Aufrere, and R. Chapuis, "Cooperative multi-vehicle localization," in *Proc. IEEE Intell. Vehicles Symp.*, Tokyo, Japan, 2006, pp. 564–570.

[20] N. Karam, F. Chausse, R. Aufrere, and R. Chapuis, "Localization of a group of communicating vehicles by state exchange," in *Proc. IEEE Int. Conf. Intell. Robots Syst.*, Beijing, China, 2006, pp. 519–524.

[21] M. Efatmaneshnik, A. Balaei, N. Alam, and A. Dempster, "A modified multidimensional scaling with embedded particle filter algorithm for cooperative positioning of vehicular networks," in *Proc. IEEE Int. Conf. Veh. Electron. Safety*, Pune, India, 2009, pp. 7–12.

[22] A. Boukerche, H. A. B. F. Oliveira, E. F. Nakamura, and A. A. F. Loureiro, "Vehicular ad hoc networks: A new challenge for localization-based systems," *Comput. Commun.*, vol. 31, no. 12, pp. 2838–2849, Jul. 2008.

[23] M. Efatmaneshnik, A. T. Balaei, A. Dempster, and J. Marczyk, "A channel capacity perspective on cooperative positioning algorithms for VANET," in *Proc. ION-GNSS*, Savannah, GA, 2009, pp. 1034–1041.

[24] A. Savvides, W. Garber, S. Adlakha, and M. B. Srivastava, "On the error characteristics of multihop node localization in ad hoc sensor networks," in *Proc. 2nd Int. Conf. Inf. Process. Sens. Netw.*, Palo Alto, CA, 2003, pp. 317–332.

[25] J. J. Blum, A. Eskandarian, and L. J. Hoffman, "Challenges of intervehicle ad hoc networks," *IEEE Trans. Intell. Transp. Syst.*, vol. 5, no. 4, pp. 347–351, Dec. 2004.

[26] J. A. Farrell, *The Global Positioning System and Inertial Navigation*. New York: McGraw-Hill, 1998.

[27] H. L. V. Trees, *Detection, Estimation, and Modulation Theory*. New York: Wiley-IEEE, 2003.

[28] S. Syed and M. E. Cannon, "Fuzzy-logic-based map matching algorithm for vehicle navigation system in urban canyons," in *Proc. ION Nat. Tech. Meeting*, Jan. 2004, pp. 982–993.

[29] A. Giremus, J. Tourneret, and V. Calmettes, "A particle filtering approach for joint detection/estimation of multipath effects on GPS measurements," *IEEE Trans. Signal Process.*, vol. 55, no. 4, pp. 1275–1285, Apr. 2007.

[30] Q. Chen, F. Schmidt-Eisenlohr, D. Jiang, M. Torrent-Moreno, L. Delgrossi, and H. Hartenstein, "Overhaul of IEEE 802.11 modeling and simulation in NS-2," in *Proc. MSWiM*, Chania, Greece, Oct. 2007, pp. 159–168.

[31] The Project of Overhaul of IEEE 802.11 in NS-2. [Online]. Available: http://dsn.tm.uni-karlsruhe.de/english/Overhaul_NS-2.php

[32] T. ElBatt, S. K. Goel, G. Holland, H. Krishnan, and J. Parikh, "Cooperative collision warning using dedicated short-range wireless communications," in *Proc. VANET*, Los Angeles, CA, 2006, pp. 1–9.

[33] Dedicated Short Range Communications (DSRC) Message Set Dictionary, Soc. Automotive Eng., SAE J2735, 2009.

[34] X. Ma, X. Chen, and H. H. Refai, "Performance and reliability of DSRC vehicular safety communication: A formal analysis," *EURASIP J. Wireless Commun. Netw.*, vol. 2009, pp. 1–13, Jan. 2009.

[35] K. W. Cheung, H. C. So, W.-K. Ma, and Y. T. Chan, "A constrained least squares approach to mobile positioning: Algorithms and optimality," *EURASIP J. Appl. Signal Process.*, vol. 2006, pp. 1–23, 2006.

[36] V. Jacobson, "Compressing TCP/IP Headers," IETF, RFC 1144, 1990. [Online]. Available: http://tools.ietf.org/html/rfc1144

[37] R. Fielding, J. Gettys, J. Mogul, H. Frystyk, L. Masinter, P. Leach, and T. Berners-Lee, "Hypertext Transfer Protocol—HTTP/1.1," IETF, RFC 2616, 1999. [Online]. Available: http://tools.ietf.org/html/rfc2616

[38] M. F. Carreto-Castro, J. M. Ramirez, J. L. Ballesteros, and D. Baez-Lopez, "Comparison of lossless compression techniques," in *Proc. 36th Midwest Symp. Circuits Syst.*, 1993, pp. 1268–1270.

[39] J. Ziv and A. Lempel, "A universal algorithm for sequential data compression," *IEEE Trans. Inf. Theory*, vol. IT-23, no. 3, pp. 337–343, May 1977.

[40] P. Deutsch, "GZIP File Specification Version 4.3," IETF RFC1952, 1996. [Online]. Available: http://tools.ietf.org/html/rfc1952

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