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An Identification of Performance Accuracy Gain under Realistic Scenario

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***Abstract*— Cooperative Positioning (CP) in VANET is mainly for road safety applications such as cooperative collision warning system etc. CP is an approach for location determination within wireless adhoc sensor networks. The goal of CP is to allow neighbor nodes to work together to collectively improve the accuracy of their positions. Although this technique is well known, the efficiency of CP under real world scenario is not considerable. So in our paper, we propose a technique to increase the efficiency of CP. This technique includes the formation of range vector, extended range matrix and also calculates the accurate position of a vehicle using the trilateration method. 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 10-15%.**

Keywords- Cooperative Positioning (Cp), Positioning Accuracy Improvement, Range Vector, Extended Range Matrix.

I. INTRODUCTION

Nowadays we are facing more road accidents due to lack of predicting near-by vehicles range. The industry is developing its idea on advanced crash warning system for drivers to give alert messages. This system exchanges the speed, location and other kinematic informations periodically for predicting potential crashes. Accurate positioning is the key element in these systems because inaccuracy will cause either false alarms or failure to warn a driver during an emergency.

Radio-ranging-based Cooperative Positioning (CP) has been considered as one of the promising approaches for improving GPS positioning accuracy. 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) links, they can then use existing CP algorithms based on multilateration or trilateration principles to further improve their current position estimates. The objective of this paper is to improve the positioning accuracy. The key contribution is as follows, 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.

II. RELATED WORK

In our scheme, a vehicle requiring more accurate position has to broadcast its own position to all its neighbours. Then each vehicle calculates the intervehicle distance to its one-hop neighbours. Using this information each vehicle forms a range vector and broadcast it. Then each vehicle has to identify the cluster to which it belongs. Further an extended range matrix is build and a vehicle's accurate position is calculated by using the trilateration method. 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). 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. In wireless sensor and ad hoc networks, there are several works that address the problem of simultaneously localizing a group of nodes that form a cluster [10]. The cluster-based CP methodology has been extended to VANET localization. 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.

III. COOPERATIVE POSITIONING IN VEHICULAR ADHOC NETWORKS

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 neighbour vehicles and inter vehicle distance measurements among these vehicles. The CP framework in vehicular networks is shown in Fig. 1.

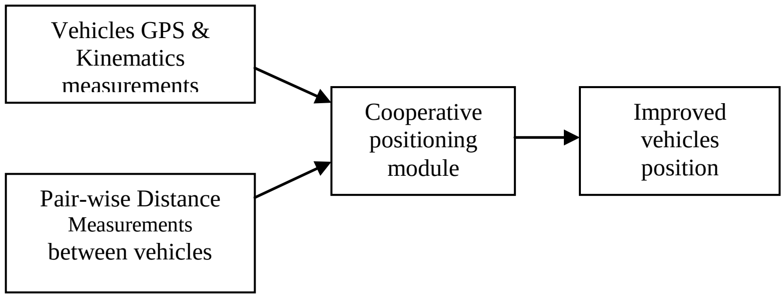


Figure 1. CP framework

CP in VANETs is a three-step distributed process, including range and kinematics information measurements, information exchange, and the final localization.

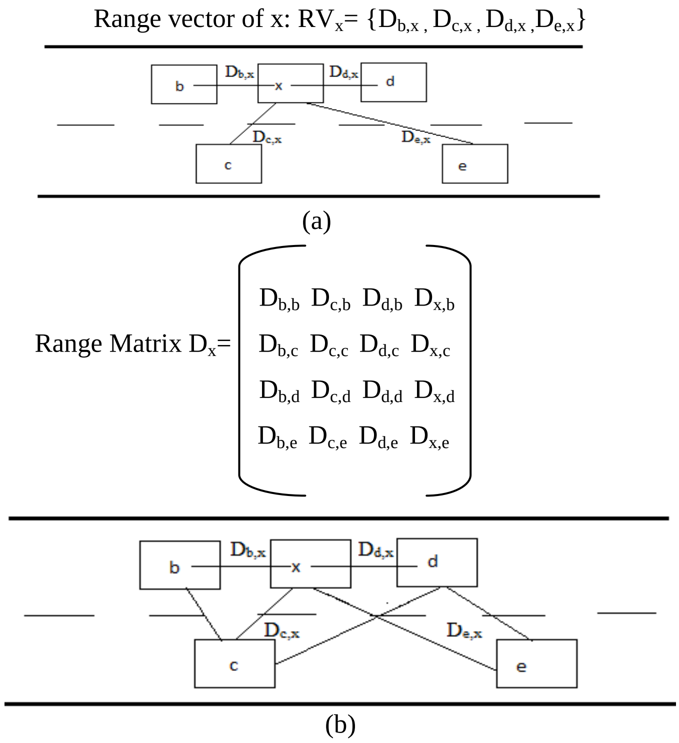


Figure 2. Measurement and exchange of range information. (a) Maintaining the range vector. (b) Creating the range matrix after the RV exchange.

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 distance measurements 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 neighbours. To share range information in the neighborhood, each vehicle periodically broadcasts 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 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 extended range matrix D as shown in Fig. 3.

$$
D_x = \begin{pmatrix}
D_{b,b} & D_{c,b} & D_{d,b} & D_{x,b} & n/a \\
D_{b,c} & D_{c,c} & D_{d,c} & D_{x,c} & n/a \\
D_{c,d} & D_{d,d} & D_{x,d} & D_{e,d} & \\
D_{b,x} & D_{e,x} & D_{d,x} & D_{x,x} & D_{d,x} \\
n/a & n/a & D_{d,e} & D_{x,e} & D_{e,e}
\end{pmatrix}
$$

Figure 3. Extended range matrix.

The extended 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.

IV. SIMULATION SCENARIO

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. We simulated a triangular shaped loop road with three lanes consist of 30 nodes. At the beginning of the simulation each node will be at a particular position and starts to move towards the destination at 0.5s. We assume that vehicles will not change their lanes and directions during the simulations. The simulation time for each run is 240s. In Fig. 4 Each node broadcast its own range range vector to its one-hop neighbour. 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 as shown in the Fig. 5.

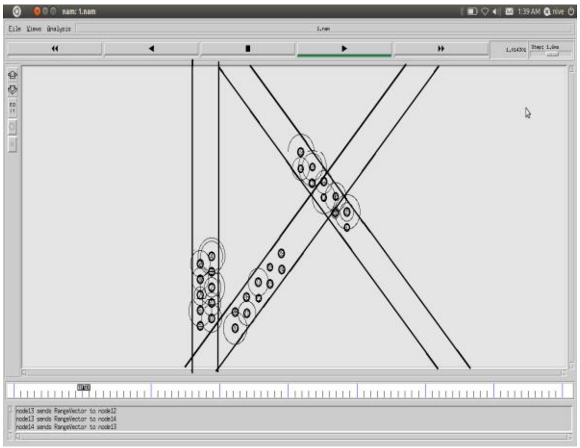


Figure 4. Broadcasting range vector

The pseudo code 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.

Algorithm 1: Pseudo code for identifying clusters of vehicle *x*.

```
Input: The neighbour set NSx and the set of received ranging
  Vectors RV_i, i ∈ NS_x.
Output: The set of identified clusters C.
Initialization:
C = NULL;
n = #of neighbor vehicles detected by x;
The index n + 1 is used to represent x itself;
/*Finding the neighbour vector for each vehicle.*/
for i ∈{1, 2, . . . , n + 1} do
V_i = NULL;
for j ∈{i + 1, . . . , n + 1} do
if D_{i,j} ∈RV_j or D_{j,i} ∈RVi then
Add j to V_i;
Add i to V_j ;
end if
end for
end for
/*for each neighbours, find the largest cluster to which it belongs.*/
for i ∈{1, 2, . . . , n} do
initSet = V_i ∩ V_{n+1};
Clustertemp = initSet;
for each vehicle k in initSet do
if k ∈Clustertemp then
Clustertemp = V_k ∩ Clustertemp;
end if
end for
if Clustertemp =∈C then
Add Clustertemp to C;
end if
end for
```

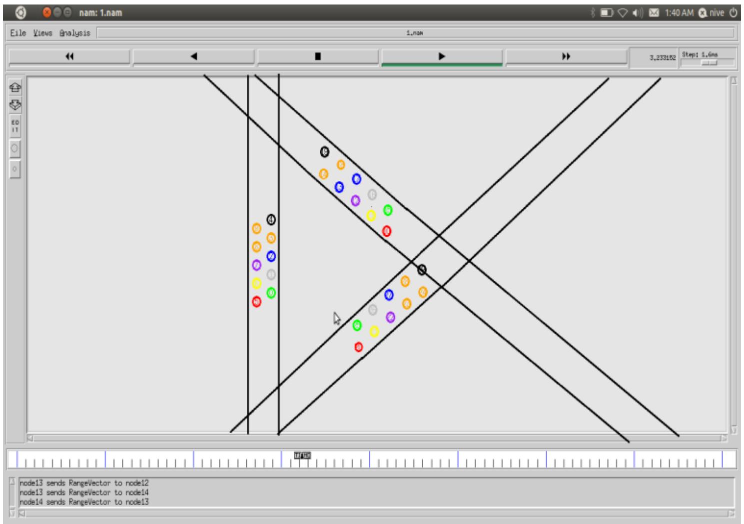
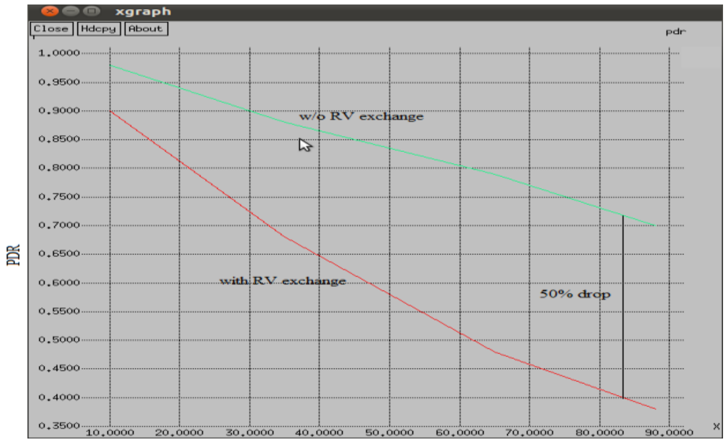


Figure 5. Cluster identification

V. SIMULATION RESULTS

Fig. 6 shows the Packet Delivery Ratio (PDR) when each node broadcast its own range vector. PDR is the ratio of sent and received packets. 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 neighbours that exist in a vehicle's transmission range.



Vehicles Density

Figure 6. PDR during RV exchange

Normally, the Performance Accuracy Gain (PAG) reaches peak at the ideal conditions. (loss-less communication) . Our aim is to achieve that gain level.

Fig. 7 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. The graph shows the Performance Accuracy Gain (PAG) under Extended-cluster-ideal, Extended-cluster-realistic and cluster realistic.

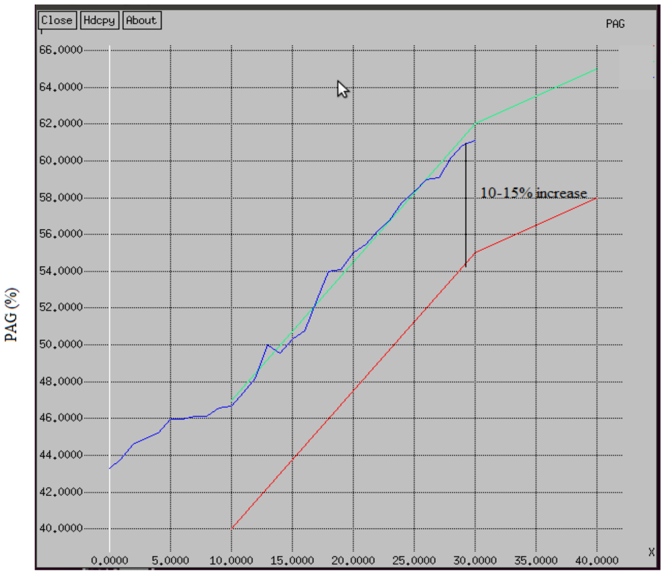


Figure 7. Performance of Extended-cluster-realistic

VI. CONCLUSION

We have examined the issue of CP in vehicular wireless network. As mentioned, we have increased the efficiency of CP by 10% - 15%. 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. So to overcome the issues of communication overhead simple protocol improvements like piggyback, compression and network coding can be done as the further enhancement.

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