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COOPERATIVE POSITIONING IN VANET

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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 underdense traffic conditions, these protocol improvements achieve a twofold reduction in packet loss rates and increase the positioning accuracy of CP by 40%.Vehicle localization is an important task for intelligent vehicle systems and vehicle cooperation may bring benefits for this task.In the proposed method, each vehicle maintains an estimate of a decayed group state and this estimate is shared with neighboring vehicles; the estimate of the decomposed group state is updated with both the sensor data of the ego-vehicle and the estimates sent from other vehicles; the covariance intersection filter which yields consistent estimates even facing unknown degree of inter-estimate correlation has been used for data fusion. A comparative study based simulations demonstrate the effectiveness and the advantage of the proposed cooperative localization method.**

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 commercialgrade 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]. 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.

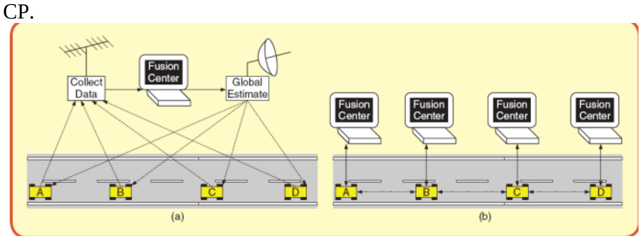
• It is demonstrated that exchanging range information using simple protocols that basically collect range measurements within a safety interval and transmitting these measurements in the next interval achieves small accuracy gains but results in high packet collision rates. Protocol improvements are 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. vehicle localization (ground vehicles) is an important task for intelligent vehicle systems. Traditionally, for a vehicle, the localization process is only based on its own sensor data, such as GPS data camera data, or laser scanner data etc. On the other hand, the rapidly developed inter-vehicle communication technology which enables information sharing among multiple vehicles stimulates research interests in cooperative multi-vehicle localization (“cooperative localization” for short) , where multiple vehicles perform localization tasks cooperatively by taking advantage of information sharing. It is believed that cooperative localization methods will outperform traditional single-vehicle localization methods. If the size of a group of vehicles in cooperation is small,then a *centralized architecture*, in which only one fusion center maintains a single global state vector for the whole group, might be a possible solution. However, in real traffic scenarios, thousands of vehicles will operate in the same district at the same time. It is unlikely for a single fusion center to fulfill the task of cooperative localization, due to limited computational ability as well as limited vehicle communication ability. Instead of a centralized architecture,a *decentralized architecture*, where multiple fusion centers exist and each of them handles only local information, turns out to be a desirable solution, because of comparatively low computational burden for each fusion center and the flexibility for dealing with dynamic vehicle networks.

II.RELATED WORK

Several range-independent CP techniques have been proposed for vehicular localization, e.g., differential Global Positioning System (DGPS) , RTK positioning , Assisted Global Positioning System (A-GPS) , a satellite-based augmentation system (SBAS), and a ground-based augmentation system (GBAS). 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 .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). 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) . 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 propose a distributed CPmethod that relies on the ranging information between a targetvehicle 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 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) . 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*. 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 . 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 , 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.



Cooperation architecture: (a) centralized architecture,
(b) decentralized architecture.

III.COOPERATIVE LOCALIZATION ARCHITECTURE:

Cooperative localization is realized in decentralized (distributed) manner. From the perspective of an intelligent vehicle, the localization procedures are as follows

- At each period, the vehicle evolves its state estimate(including covariance) using its motion measurements.
- When the vehicle has an absolute positioning measurement of its own, it updates its state estimated.
- When the vehicle receives data from a neighboring vehicle, it updates its state estimated.

As we can see, this decentralized cooperative localization architecture is rather simple: when the vehicle has some new data from itself or from another vehicle, it canuse the new data to evolve or update its state estimate; no monitoring or controlling of the data flow within vehicle networks is needed. Despite of the simplicity of this architecture, the risk of over-convergence can be essentially removed, because the risk is removed directly by the split covariance intersection filter during estimates fusion.

Single Vehicle Localization Method (SL)

Each ego-vehicle performs localization using only its ownsensor data and using the EKF for data fusion. More specifically, at each period, the ego-vehicle evolves its state estimate using its motion measurements; when the egovehicle has an absolute positioning measurement of its own, it updates its state estimate according to the EKF. Naïve Cooperative Localization Method (NCL).Each ego-vehicle performs single vehicle localization as described above; besides, when the ego-vehicle receives the data from a neighboring vehicle, it treats the received data as new independent information and it updates its state estimate also using the EKF.

State Exchange Based Cooperative Localization Method (SECL).

Each ego-vehicle maintains two state estimates. The first estimate is maintained as in single vehicle localization. When the ego-vehicle receives the data from neighboring vehicles, it forms the second estimate by using the EKF to fuse its first estimate and the received data. The second estimate (i.e., the fusion result of the data of the ego-vehicle and other vehicles) will neither be further used in the localization process of the ego-vehicle nor shared with other vehicles.

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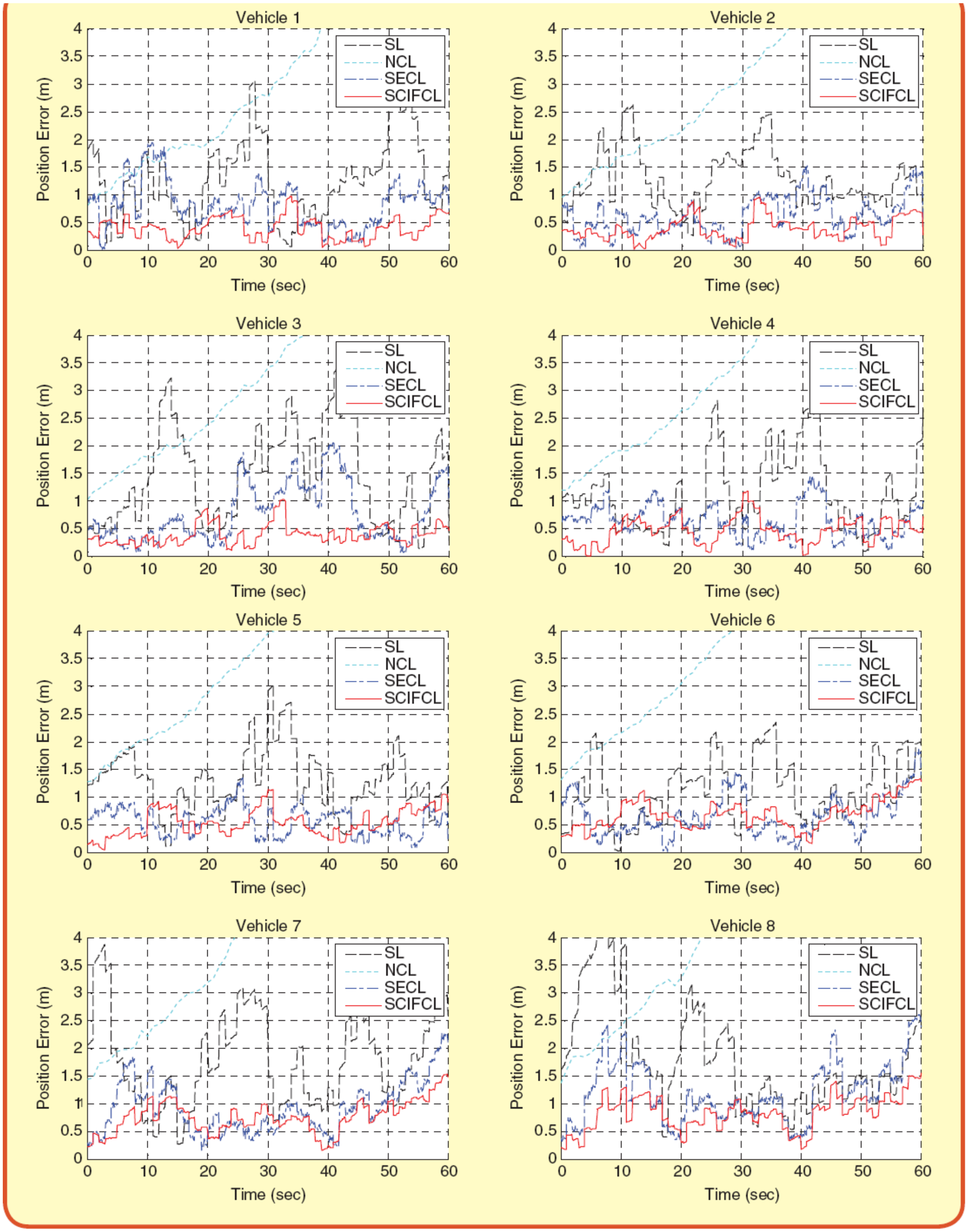
IV.COOPERATIVE POSITIONING IN VEHICULAR AD HOC NETWORKS

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 . 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 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).



Performance of the SL method, the NCL method, the SECL method and the SCIFCL method (homogeneous absolute positioning ability).

V.DISCUSSION:

Two kinds of experiments have been described in previous sub-sections. The experiment for homogeneous systems is intended to demonstrate the statistical advantage of cooperative localization using the SCIFCL method. In reality, each vehicle usually has few neighboring vehicles to cooperate with (for example, just the front one and the following one);as a consequence, this statistical advantage might be quite limited (yet existing) for intelligent vehicles with homogeneous absolute positioning ability in practical applications. On the other hand, cooperative localization is more valuable and practical for intelligent vehicles with heterogeneous absolute positioning ability, as demonstrated in the experiment for heterogeneous systems. A prominent advantage of the SCIFCL method is that it enables good localization results to be naturally spread within a vehicle network in connection while always keeping a reasonable confidence for the state estimate of each vehicle.The significance of cooperative localization demonstrated by the experiment for heterogeneous systems can be interpreted as follows: Suppose there are several vehicles in neighborhood; each vehicle might randomly lose their accurate absolute positioning ability. During cooperative localization, if only one vehicle can possess accurate absolute positioning ability, then other vehicles can also obtain rather accurate localization results. From statistical viewpoint, at a certain time, although some vehicles might temporarily lose their accurate absolute positioning ability, it is very UNLIKELY that all the vehicles lose their accurate absolute positioning ability.

VI.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 wellknown 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. The cooperative localization method has been tested in simulation and a comparative study (among the single vehicle localization method, the naïve cooperative localization method, the state exchange based cooperative localization method and the proposed method) has been carried out.

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