Vehicle Localization in Vehicular Networks

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***Abstract*— We propose a distributed algorithm that uses inter-vehicle distance estimates, made using a radio-based ranging technology, to localize a vehicle among its neighbours. Given that the inter-vehicle distance estimates contain noise, our algorithm reduces the residuals of the Euclidean distance between the vehicles and their measured distances, allowing it to accurately estimate the position of a vehicle within a cluster. In this paper, we show that our proposed algorithm outperforms previously proposed algorithms and present its performance in a simulated vehicular environment.**

***Index Terms*— Localization, position estimation, wireless communication, DSRC, vehicular networks.**

I. INTRODUCTION

THE motivation for this work stems from recent advances in the area of intelligent transportation systems (ITS) with the advent of dedicated short range communication (DSRC), which is designed to support high speed, low latency vehicle-to-vehicle and vehicle-to-infrastructure communication using the IEEE 802.11p and Wireless Access in Vehicular Environments (WAVE) standards [1]. In the future, vehicles will likely be equipped with DSRC devices. DSRC will support critical safety communications, such as collision avoidance and road hazard warnings, and other ITS applications such as electronic toll collection, real-time traffic advisories, and digital map updates [2].

One of the most promising vehicular safety applications is the development of an advanced cooperative collision warning system. It is envisioned that this system will use vehicle-to-vehicle radio communications to create a cooperative collision warning system, where vehicles — equipped with DSRC devices — cooperatively share information (i.e. location, speed, heading, acceleration, etc.) for collision anticipation. By sharing this information between peers, each vehicle is able to predict potential hazards. For example, consider a vehicle at the head of a platoon[1], which encounters an emergency event and is forced to stop suddenly. Typically, drivers rely on the brake lights of the vehicle immediately ahead of them to decide on their own braking action. However, if the emergency event is triggered several cars ahead, by the time the car immediately ahead brakes, it may be too late to safely stop in time. The time for the driver to process the brake light ahead and step on the brake (typically 0.75 to 1.5 seconds) compounds the problem, potentially leading to a single emergency event causing a multi-vehicle accident. However, if instead vehicle's use vehicle-to-vehicle communication to cooperatively share information (i.e. location, speed, heading, acceleration, etc.) this type of collision can be reduced in severity or prevented altogether. Tatchitkou et al. [3] showed that sending safety warning messages with position information can substantially reduce the probability of collision within a platoon.

Currently, the global position system (GPS) can be used to estimate a vehicle's position. In GPS, a mobile unit locates itself by comparing the signal received from four or more GPS satellites. GPS can generate relatively precise position estimates in flat open areas where line-of-sight to multiple satellites is possible. In flat open areas, regular GPS has an average accuracy of approximately 10 meters [4] and some of it's improved variants such as differential GPS (DGPS)[4] and assisted GPS (A-GPS) [5] can achieve an average accuracy between 3-7 meters. However, since GPS requires line-of-sight, between the satellites and the receiver, the GPS signal can often become degraded or blocked when the vehicle is traveling through tunnels, in downtown areas where skyscrapers are present, in mountainous or canyon areas, in areas of dense vegetation or foliage. Also, vehicles can suffer sustained GPS outages during periods of high solar activity or due to terrestrial interference. To combat some of the availability issues with GPS, some vehicles are equipped with a dead reckonings system, which uses a vehicles velocity, distance and acceleration information to extrapolate the GPS position estimate, during short GPS outages. However, dead-reckoning is prone to error accumulation. Even during short-outages (e.g. 30 seconds or less) the position estimate can become inaccurate by as much as 10-20 meters, if the vehicle is traveling at 100km/h [6]. Therefore, GPS can provide relatively accurate position estimates for flat open areas, however it's potential lack of availability and degraded operation, where line-of-sight to multiple satellites is not possible, means that GPS — in its current state — alone cannot be used for vehicle safety applications relying on position information. It has been recently argued that a combined solution using GPS — or one of its improved variants — and the use of radio based ranging techniques (such as the received signal strength indicator (RSSI)) to determine distance estimates between vehicles in a cluster, can be used to increase the reliability and accuracy of the location estimator [6].

The use of RSSI for distance estimation between vehicles presents a number of challenges. First, the distance measurements are inherently noisy as a result of a number of factors including: limitations of the measurement device, multipath fading, shadowing and non-line-of-sight errors. Second, mo-

[1]We define a platoon as a grouping of vehicles heading the same direction.

bility complicates the handling of noise, since outliers and noisy measurements can be misconstrued as observed motion and the effects of fading becomes more prevalent. Therefore, it is critical for a position estimation algorithm to be robust and to attempt to mitigate these errors.

In this paper, we present a distributed vehicle position estimation algorithm that locates a vehicle by reducing the residuals of the Euclidean distance between the vehicles and their measured distances. At a high level, our localization algorithm works as follows. Each node estimates the distances to the neighbouring vehicles, using a radio ranging technology (e.g. RSSI), then shares this information with its one-hop neighbours. Based on this one-hop information, each vehicle runs our algorithm to create a map of the relative position of its neighbours[2].

The remainder of this paper will present how accurate vehicle position estimates can be made using the inter-vehicle distance estimates. First, we will provide a review of related radio based localization algorithms and the techniques. Then, we will provide a detailed description of how our algorithm works and present its performance characteristics.

II. Background and Related Work

The majority of existing research using radio ranging technologies for position estimation has been done for wireless sensor network applications, since having GPS on all sensor nodes is not feasible (see [7] for a survey). Generally, previously proposed localization schemes fall into two categories: *course grain* and *fine grain*. Within each of these schemes there are distributed and centralized approaches. Course grain localization typically uses mere connectivity radio between nodes and requires a central node in the network to establish position estimates for the nodes and works well when only a rough estimate of a node's position is sufficient (e.g. [8], [9]). Conversely, fine grain localization schemes provide a relatively accurate node position estimates — typically operating in either a distributed or centralized approach. The distributed fine grain localization approaches are most closely related to our work, so the remainder of this section will focus on a review of the existing approaches.

In [10], a GPS-free positioning algorithm for mobile adhoc networks was proposed where each node runs a self-positioning algorithm that computes the angles between the one-hop neighbours using the inter-node distance measurements to establish a local coordinate system. Once the local coordinate systems are established, the nodes orient their coordinate system to a common coordinate system such that all nodes' x, y coordinates point in the same direction. However, as pointed out by Iyengar and Sikdar [11] the GPS-free algorithm [10] is expensive in terms of the number of messages that need to be exchanged between nodes — resulting in the algorithm not scaling well. Iyengar and Sikdar [11] derived an improved version of [10], to tackle these issues, by creating an algorithm that improves scalability and convergence times.

Kukshya et al. [6] made use of the results from [11] to create a scheme for localizing neighbouring vehicles based on radio range measurements. Their goal was to establish an accurate map of the relative positions of all neighbouring vehicles. Under the assumption that vehicle did not have access information from GPS or dead-reckoning system (e.g. operating in conditions where GPS did not have line of sight). They use trilateration for estimating a vehicles position, however noise in the range measurements can quickly cause error to propagate as the coordinate systems are aligned to a common coordinate system.

In [12], a "DV-hop" method is proposed where each node uses the average number of hops to anchors with known locations. Then, anchors calculate the average number of hops between them, so the number of hops can be converted distances and trilateration can be preformed. This method works well for dense topologies, but degrades significantly for sparse and hard network topologies (i.e. cases where whole or parts of the network can be rotated or flipped given the same set of distance measurements.) Savarese et al. [13] use a method similar to [12], but the author's propose a heuristic to detect networks with hard network topologies. They consider a node uniquely localizable only if a node has three disjoint paths to three distinct beacons and suggest using a least-squares optimization to reduce the effects of measurement errors. However, [14] disprove this heuristic and derive a theoretical framework for determining nodes that have a unique localization in terms of graph rigidity theory.

Moore et al. [15] use this theoretical framework to derive a *robust quads* algorithm to determine the nodes positions in the presence of noisy range measurements. They identify two scenarios which prevent a localization from being unique: (i) a flip ambiguity where all the distance measurements are the same but parts of the graph can become mirror reflections; or (ii) flex ambiguities where the distance constraints remain the same, but the graph is sheared. They derive a heuristic to detect nodes which have a high probability of having a unique position, given a set of distance constraints. The objective of their algorithm is to only localize those nodes with unique realization, therefore minimizing the propagation of localization error when coordinate systems are aligned to a common orientation.

In [15], the majority of results discussed the case of stationary nodes however, in one experiment they showed if a single node had mobility, it could be tracked within the network. Of the algorithms surveyed, the *robust quads* algorithm [15] shows the most promise for use in vehicular networks. Therefore, we will compare our method to it.

III. Problem Definition

Consider a cluster of n vehicles labeled 1, 2,...n at distinct unknown locations in some physical region. Distance measurements are made between all vehicles within a cluster — using a radio ranging technology (such as received signal

[2]We define a node's neighbours as those nodes that have direct bidirectional communication and ranging capabilities, and a cluster as a node and its neighbours.

strength indictor (RSSI)) — and shared with all vehicles within that cluster. Our objective is for each vehicle to establish relative Euclidean positions for each of neighbours, such that the estimated Euclidean position of each neighbour closely resembles the actual (or ground truth) Euclidean position of each vehicle up to a global translation and rotation.

IV. Approach

Each vehicle builds its own local coordinate system. Setting itself as the centre of its own coordinate system with position (0,0). Then its objective is to estimate the relative (x,y) coordinates of all its neighbours. Once the location of all vehicles is estimated, a mapping of the vehicular network is known to that vehicle. Our distributed vehicle localization algorithm can be broken down into three phases, as follows.

Phase 1: Initialization

- Each vehicle measures the distance to all its neighbours, then exchanges this information with them. Allowing each vehicle to establish a matrix of distance measurements for its one hop neighbours.
- Rough initial estimates of the relative (x, y) coordinates of the vehicle's neighbours are made.

These initial estimates can come from a number of possible sources: GPS; or GPS used in combination with a dead reckoning system; or GPS used in combination with a road mapping module, which places vehicles on map within the confines of the road; or making use of the inter-vehicle distance estimates to perform trilateration.

If trilateration is used, there is the possibility of a flip ambiguity. To prevent this ambiguity, trilateration can be preformed multiple times, each time using a new set of inter-vehicle distance estimates, then taking the most probable location estimates. Since, the vehicles are moving it is unlikely two consecutive iterations will yield the same flip ambiguity.

Phase 2: Refinement:

Each vehicle refines the initial estimates to provide a final estimate of its neighbours location. The objective is to minimize the residuals of the Euclidean distance between the vehicles and the measured distance. Let $f_{i,j}$ be defined as:

$$f_{\text{i,j}} = \hat{d_{i,j}} - \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}. \tag{1}$$

where (x_i, y_i) and (x_j, y_j) are the location estimates of nodes i and j, respectively, and $\hat{d_{i,j}}$ is the measured distance between vehicle i and vehicle j. Using (1), each vehicle can create an $n \times n$ matrix (where n is the number of nodes in the cluster), which takes the form:

$$\begin{bmatrix} 0 & f_{1,2} & f_{1,3} & \cdots & f_{1,\text{n}} \\ f_{2,1} & 0 & f_{2,3} & \cdots & f_{2,\text{n}} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ f_{\text{n-1},1} & f_{\text{n-1},2} & \cdots & f_{\text{n-1,n-1}} & f_{\text{n-1,n}} \\ f_{\text{n},1} & f_{\text{n},2} & \cdots & f_{\text{n,n-1}} & 0 \end{bmatrix}$$

Then location estimates (x_i, y_i) are selected to minimize:

$$min \sum_{i=1}^{n} \sum_{j=1}^{n} f_{\text{i,j}}^2. \tag{2}$$

This equation is of the form of a non-linear least-squares problem and can be solved using gradient descent methods [16].

Using the knowledge that vehicles generally travel within the confines of roads, and in general within lanes, we can reduce the search space of (2); thus, reducing the complexity and improving the accuracy of our algorithm. We can also compare the final position estimates from the previous iterations to the current position estimate to ensure the change in a vehicle's position is consistent with velocity and acceleration constraints. This also provides the benefit of being able to smooth out any irregularities that exist from one round of position estimation to the next, therefore reducing the probability of error in a vehicle position estimate.

Phase 3: Iteration

In a mobile environment phases 1 and 2 are repeated every T seconds. The final estimated position from phase 2 plus a correction based on how far the vehicles and what direction the vehicle would have traveled in the last T second can act as the initial position estimate of the subsequent interval.

V. Simulation Results

We have evaluated the performance of our algorithm under three scenarios. First, we examined the theoretical accuracy gains of our algorithm over traditional GPS based positioning approaches. Second, we examined how error in the initial position estimate affects the resulting final position estimate at the output of our algorithm. Third, we studied the effects of noise in the inter-vehicle distance measurements and its impact on the final position estimate. Also, we have compared our algorithm to the *robust quad* algorithm proposed by Moore et al. [15].

The *robust quads* algorithm implemented by Moore et al. [15] works as follows. Each node estimates the relative location of its neighbours that have a low probability of being subject to a flex or flip ambiguity (i.e. nodes that can be unambiguously localizable with high probability), where the chance of a node being subject to an ambiguity is determined by heuristics derived in [15]. With the set of unambiguously localized nodes, robust quadrilaterals within a cluster are identified and formed. Then node position estimates within a cluster are incrementally computed by trilateration and chaining the quadrilaterals with 3 or more nodes in common. Finally, all nodes coordinate systems are aligned to a common orientation.

A. Performance Metrics

To measure the accuracy of the initial position estimates, made in phase 1 of our algorithm, we compare the initial vehicle position estimate to the actual position. We define the root-mean-square error (RMSE) in the initial position estimate as:

$$\sigma_{\text{initial}} = \sqrt{\sum_{\text{i}=1}^{n} \frac{(x_{\text{int. est. i}} - x_{\text{actual i}})^2 + (y_{\text{int. est. i}} - y_{\text{actual i}})^2}{n}} \tag{3}$$

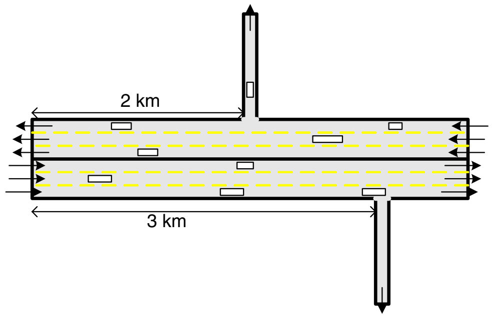

Fig. 1. Setup for simulated roadway

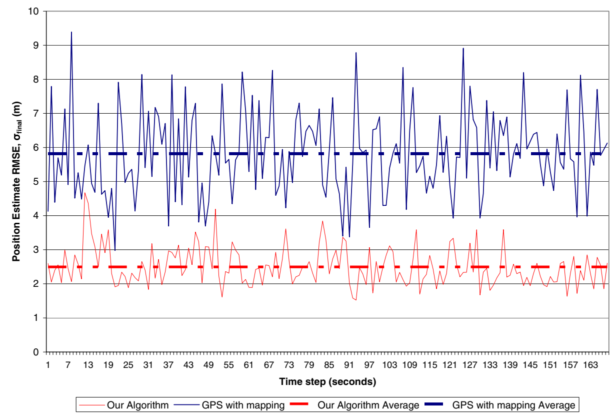

Fig. 2. Our algorithm is shown as the lower curve, indicating the accuracy of the location estimate has the potential to be improved using inter-vehicle distance constraints.

where $(x_{\text{int. est. i}}, y_{\text{int. est. i}})$ iis the initial position estimate of vehicle i and $(x_{\text{actual i}}, y_{\text{actual i}})$ represents the true position of vehicle i. This can be thought of as the average distance the initial position estimate deviates from the true position.

Similarly, we have defined the RMSE of the final position estimate as:

$$\sigma_{\text{final}} = \sqrt{\sum_{i=1}^{n} \frac{(x_{\text{final est. i}} - x_{\text{actual i}})^2 + (y_{\text{final est. i}} - y_{\text{actual i}})^2}{n}} \tag{4}$$

where $(x_{\text{final est. i}}, y_{\text{final est. i}})$ are the final position estimate of vehicle i.

To examine the amount of noise present in the distance, we define the RMSE in the distance measurements as:

$$\sigma_{\text{d}} = \sqrt{\sum_{i=1}^{M} \frac{(\hat{d}_i - d_i)^2}{M}} \tag{5}$$

where M is the number of inter-vehicle distance measurements, $\hat{d}_i$ is the measured distance to vehicle i, and d_i is the actual distance to vehicle i.

B. Accuracy Study: GPS versus our algorithm

In this experiment, we studied the accuracy of GPS versus our algorithm in a simulated vehicular environment. We have used a microscopic transportation simulator CORSIM (CORridor SIMulator) developed in the United States by the Federal Highway Administration to model vehicle movement. We modeled a 2.5 mile (4 km) road with 3 east bound and 3 west bound lanes with vehicles entering into the east and west end of system at the rate of 1200 vehicles per hour (see Figure 1). The speed limit for the road was set to 60 mph (97 km/h).

For the experiment, have assumed that the position estimated by GPS differs from the true position according by a Gaussian distributed random variable with standard deviation of 6 meters, which is consistent with real GPS error levels of $3-10$ meters [4].

Figure 2 shows the results of how well a single vehicle was able to localize its neighbours at each time step as it traveled through the system. We have assumed that each vehicle has a communication range of 150 meters, so throughout the course of the simulation, vehicles will often enter and exit a vehicles communication range. In general, for this simulation between 8 and 14 vehicles were within communication range of a vehicle at each time step.

The upper curve, in Figure 2, shows the error in the position estimates of a vehicle's neighbours when GPS is used in combination with a mapping module and dead-reckoning system. The mapping module is used to correct the GPS position estimate, to ensure a vehicle's position estimate is within the confines of the road. The dead reckoning system is used to verify, that two consecutive GPS position estimates obey a vehicles velocity and acceleration constraints. The lower curve is the implementation of our algorithm, we have used the same road and velocity constraints as we did for the GPS case and assumed the inter-vehicle distances have Gaussian error with a 6 meter standard deviation. Also, we have assumed that during phase 1 of our algorithm (the initialization phase) GPS was used to make an initial estimate, and in subsequent localization rounds the previously estimated position plus a correction for the expected distance traveled was used. Note that on average, our algorithm yields a 3 meter improvement in the position estimate.

C. Inaccurate initial position estimate study

In this study, we examined the effects of poor initial estimates at the initialization phase of our algorithm. We considered a cluster of 9 vehicles randomly distributed over a 200×200 square-meter section of road, at a single time instant to determine the effects of error in the initial position estimates on the final position estimate (see Figure 3 for the results). Each of the data points shown in Figure 3 is the average result after 30 runs of our algorithm; each run has a different vehicle positions, to average out the effects of poor network topologies, and the distance measurement error is set to 1 meter.

Our algorithm is shown to preform well even if the initial position estimate has RMSE of 9.5 meters, on average our

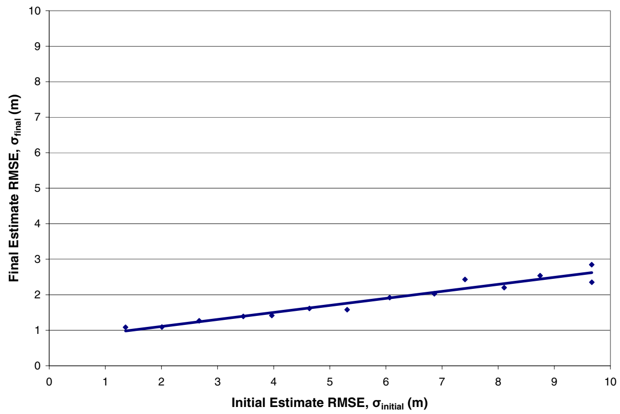

Fig. 3. Show relationship between initial position estimates and final position estimates.

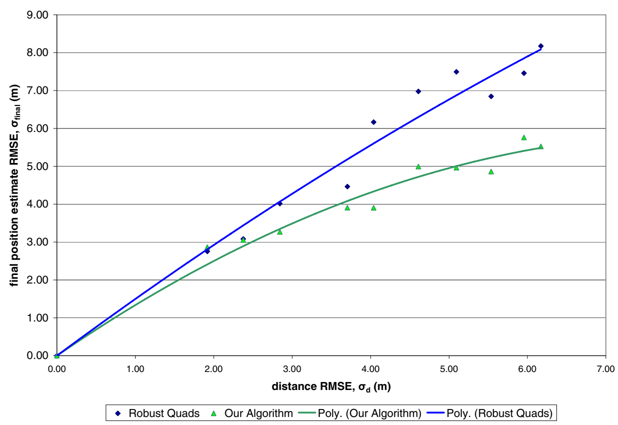

Fig. 4. Implementation of our algorithm showing the accuracy of the final position estimates given noise in the distance measurement

algorithm can reduce the RMSE to approximately 3 meters.

D. The effects of noisy range measurements study

In this set of experiments, we consider a cluster of 9 vehicles randomly distributed over a 200×200 square-meter section of road. The RMSE in the distance measurements were varied leaving the other parameters constant. We set the (x,y) coordinates of the initial position estimate to deviate from the actual position according to a Gaussian distribution with standard deviation of 5 meters. The results of this experiment are shown in Figure 4 (our algorithm shown as the lower line). From this figure, it can be seen that the plot of the root-mean-squared error in the final position versus the RMSE in the distance has a second-order exponential distribution.

Also in Figure 4, we have compared our algorithm to the *robust quads* algorithm [15] through a set of identical scenarios, using the same input data set. Notice how our algorithm, yields a better accuracy average position estimate as the noise in the distance measurement increases.

VI. Conclusion

We have presented a novel distributed solution for localization in vehicular networks that can be used as a complement to GPS. We have shown through simulations that estimating the inter-vehicle distances, using a radio based ranging technology (such as RSSI), and feeding these inter-vehicle distances into our optimization algorithm we can improve upon the accuracy of GPS. We have shown that even with high levels of error in initial vehicle position estimates (e.g. if GPS provides a poor position estimate) that our algorithm converges toward the actual position, with relatively high accuracy. Therefore, GPS combined with our algorithm can provide an accurate and reliable means of determining a vehicles — as is required for future applications in vehicular networks.

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