Archives of Photogrammetry, Cartography and Remote Sensing, Vol. 22, 2011, pp. 117-129
ISSN 2083-2214

A COOPERATIVE POSITIONING ALGORITHM FOR DSRC ENABLED VEHICULAR NETWORKS

Mahmoud Efatmaneshnik [1], Allison Kealy [2], Nina Alam [3], Andrew G. Dempster [4]

[1, 2]Department of Infrastructure Engineering, University of Melbourne, 3010, Australia
(mahmoude, a.kealy)@unimelb.edu.au
[3,4] School of Surveying and Spatial Information Systems, University of New South Wales, 2052, Australia
(a.dempster, nima.alam)@unsw.edu.au

KEY WORDS: DSRC, VANET, Cooperative Positioning, Ranging, Time of Arrival, CRLB, Kalman Filtering, Robust Positioning

ABSTRACT: Many of the safety related applications that can be facilitated by Dedicated Short Range Communications (DSRC), such as vehicle proximity warnings, automated braking (e.g. at level crossings), speed advisories, pedestrian alerts etc., rely on a robust vehicle positioning capability such as that provided by a Global Navigation Satellite System (GNSS). Vehicles in remote areas, entering tunnels, high rise areas or any high multipath/ weak signal environment will challenge the integrity of GNSS position solutions, and ultimately the safety application it underpins. To address this challenge, this paper presents an innovative application of Cooperative Positioning techniques within vehicular networks. CP refers to any method of integrating measurements from different positioning systems and sensors in order to improve the overall quality (accuracy and reliability) of the final position solution. This paper investigates the potential of the DSRC infrastructure itself to provide an inter-vehicular ranging signal that can be used as a measurement within the CP algorithm. In this paper, time-based techniques of ranging are introduced and bandwidth requirements are investigated and presented. The robustness of the CP algorithm to inter-vehicle connection failure as well as GNSS dropouts is also demonstrated using simulation studies. Finally, the performance of the Constrained Kalman Filter used to integrate GNSS measurements with DSRC derived range estimates within a typical VANET is described and evaluated.

1. INTRODUCTION

1.1 Dedicated Short Range Communication

DSRC (Dedicated Short Range Communications) is an emerging technology that can facilitate the rapid development and deployment of global Intelligent Transportation Systems (ITS). Currently, the main implementations of DSRC are in the areas of electronic toll collection and access control applications. However, the robust attributes of 5.9GHz DSRC in terms of fast, accurate and timely data transfers between vehicles combined with the fact that it supports roadside to vehicle communications, makes it a critical infrastructure for future ITS.

The primary mission of DSRC is to increase the road safety. Safety applications of DSRC predominantly are subcategorized into (CAMP-Vehicle-Safety-Communications-Consortium, 2005):

- Collision Avoidance applications such as Traffic Signal Violation Warning, Left Turn Assistance and Intersection Collision Warning
- Public Safety applications such as Approaching Emergency Vehicle Warning and Post Crash Warning
- Sign Extension applications such as Curve Speed Warning and Low Bridge Warning
- Vehicle Diagnostics and Maintenance applications such as Just-In-Time Repair Notification
- Cooperative Applications use information from other vehicles such as Cooperative Adaptive Cruise Control, Cooperative Collision Warning, Lane Change Warning, Blind Spot Warning etc.

1.2 Position Requirements for DSRC Safety Applications

All DSRC's safety related Cooperative Applications rely on accurate position information, both of the vehicles location and the relative location of other vehicles. For example, Cooperative Collision Warning System (CCWS) is a very important application of DSRC, the vehicle receives data regarding the position, velocity, heading, yaw rate, and acceleration of other vehicles in the vicinity. Using this information along with its own position, dynamics, and roadway information (map data), the vehicle will determine whether a collision with any vehicle is likely. In addition, the vehicle will transmit its own position, velocity, acceleration, heading, and yaw rate to other vehicles.

The promise of DSRC for improving road safety heavily relies on the accuracy of the employed positioning technologies. Almost all the safety applications require continual position estimation and for the most important applications, such as collision avoidance, position must be estimated at a frequency of 10Hz with an accuracy of no less than 0.5m (CAMP-Vehicle-Safety-Communications-Consortium, 2005).

However, the expectation that Global Navigation Satellite System (GNSS) will provide accurate and reliable positioning for vehicular environments, and DSRC applications, poses a significant challenge to realising the benefits of DSRC application. Typically, a GPS receiver with a conventional low cost L1 single frequency antenna, often used for vehicular positioning, has a Circular Error Probability (CEP) of 10m and a directional error of 7m. Moreover, extensive tests show that GNSS alone is not reliable in the city centres where urban canyons are ubiquitous.

1.3 Frequency of GPS Outages in Urban Areas

Within urban and other difficult environments, the position estimation from GNSS can be biased due to multipathing effects and poor satellite geometry and in the worse case complete satellite obstruction. A set of GPS data collected on 25/11/2009 in the Sydney CBD with a typical GPS receiver, Ublox showed a maximum error of 90m from the centre line of the road. In addition, the high rise buildings create interruptions in the GPS measurements, because they can totally mask the satellite. Figure 1 shows the frequency of the masked area, i.e. where the number of observable satellites has been less than four.

Most of the masked areas are segments of the road of less than 25m length with only a few more that 25m long. The total distance of the travelled path used for these tests is 2.7km. Most of the outages cover very short lengths of the streets, and the longer the length of the masked area the lower is its likelihood. The total number of outages that have lengths greater than 15m are 25 which means there are roughly 10 outages of those lengths in every kilometre of the CBD area. This level of unreliability is disastrous for DSRC safety applications. Based on these observations, the reliability and integrity of GNSS positioning is quite dubious. However in areas where the line of sight of satellites is always clear (e.g. in highways out of the city area) GNSS can be relied upon from the availability perspective, higher accuracy, though, is yet another issue.

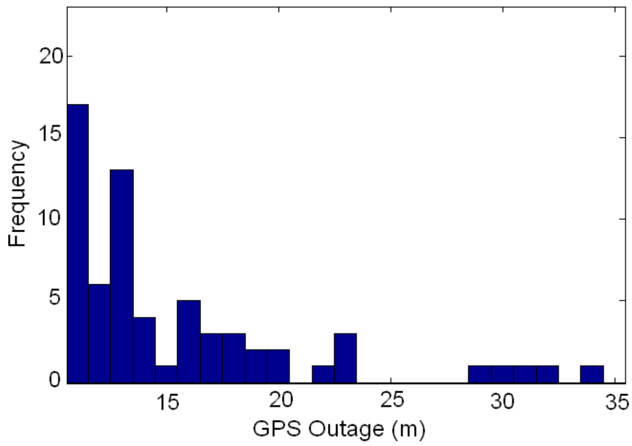

Fig. 1. The length of the masked areas and their frequencies.

1.4 Cooperative Positioning (CP)

CP is an idea originating from Wireless Sensor Networks research where each node (or even a central unit) uses range information between nodes to localize the network of nodes as a whole. CP is based on three fundamentals: data resources, data communication, and data fusion. One advantage of CP is that the localization accuracy is expected to increase with the node density (number of neighbour vehicles used in collective localization). In a Vehicular Ad-hoc Network (VANET), CP utilizes distance measurements between nodes with partially known or unknown positions. This is the case when all or some of the nodes (vehicles) are equipped with GPS. The network collective positioning is done once the ranges and the position information are exchanged between the nodes. The reliability of the positioning with this technique to some great extents is dependent on accurate ranging between vehicles. In CP the communication system (DSRC) may be involved in the creation of required data.

In Figure 2, vehicles are represented by nodes in a VANET and the infrastructure nodes are called anchors. The nodes do not necessarily have the same knowledge about the outside world and data fusion is identified for each node. Data from different sources are shared among the nodes.

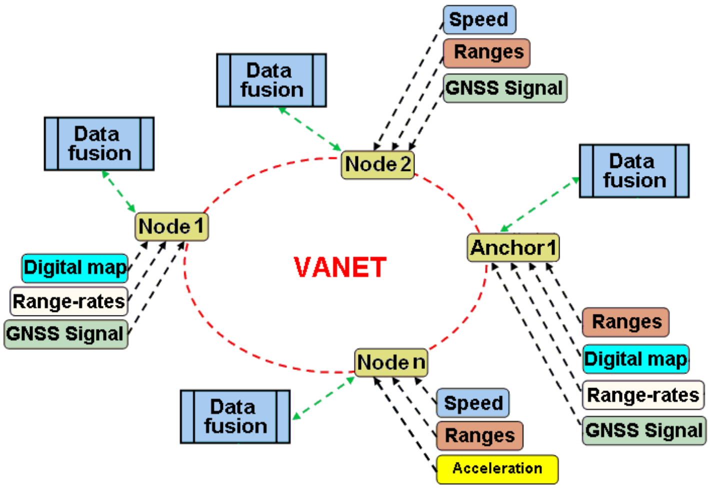

Fig. 2. Modern CP system architecture

1.5 Overview of the Paper

The goal of this paper is to show that CP improves different aspects of positioning such as accuracy, availability, and latency. In the next section a brief review of different radio ranging techniques are discussed, and the performance of Time of Arrival technique is demonstrated via simulation. Then the performance of CP as a kind of loose DSRC/GPS integration is discussed. The Cramar Rao Lower Bound is derived for CP. In the end a Kalman Filter for CP estimation is presented and its performance is evaluated via simulation.

2. RANGING BETWEEN VEHICLES WITH DSRC

There are several different methods of radio ranging for positioning including Received Signal Strength (RSS), Time of Arrival (TOA), Time Difference of Arrival (TDOA), and Round Trip Time (RTT). Angle of Arrival (AOA) is a technique to determine the bearing of coming signal. It is not considered for CP due to high levels of error due to multipath channels in urban areas, and the extra size and complexity required of the antenna (Sakagami, et al., 1992). For DSRC-based vehicular communication, three main challenges exist: synchronization, limited bandwidth, and environment noise. An analysis of ranging and range-rating techniques shows that there are limited feasible choices for radio ranging in a vehicular environment with a suitable accuracy for CP purposes (Alam, et al., 2009).

Ranging with RSS is very popular due to its simplicity and lower deployment costs compared to other methods but it is very inaccurate. RSS accuracy for rough street conditions can be as low as 100-500m error (Alam, et al., 2009). In a vehicular network, providing synchronization between nodes may be technically very difficult and expensive (Alam, et al., 2009). Avoiding the necessity of synchronization, RTT is a solution for ranging between transmitter and receiver based on round trip signal propagation time. In this method, one node, say node1, transmits a packet at time t_1 to another one, say node

2, and waits for acknowledge which is received at time t_2. A drawback of RTT-based ranging is the necessity of the numerous measurements for achieving better ranging resolutions through averaging the estimates. This results in latency of the distance estimation and more bandwidth occupation. The first leads to the ranging error for mobile nodes and the other decreases the number of nodes which can use a common channel.

2.1 Time of Arrival (TOA) and Time Difference of Arrival (TDOA)

Time-based techniques measure signal propagation time between transmitter and receiver. For TOA, synchronization between the transmitter and receiver is necessary. In TDOA, the difference between the arrival times at a receiver of signals from two synchronized transmitters is considered for distance estimation. Also, the difference between the arrival times of a signal in different synchronized receivers from a single source can be used for TDOA. Time based methods are more complex and expensive than RSS because of the synchronization requirement. Figure 3 shows the best achievable performance for TOA-based ranging in a multipath-free channel in terms of bandwidth and Signal to Noise Ratio (SNR). As can be seen, higher SNR and wider bandwidth results in more accurate ranging. Also, sub-meter ranging accuracy is achievable, provided the nodes are synchronized and there is not any multipath. Note that for TDOA, assuming independent estimates of the arrival time of the received signals, ranging variance will be twice that of the TOA-based. Thus TOA has performance advantage over TDOA, but it needs synchronized nodes.

The achieved ranging accuracy achieved with TOA is promising. The effect of ranging error on the performance of a CP algorithm is explained more in section 3.

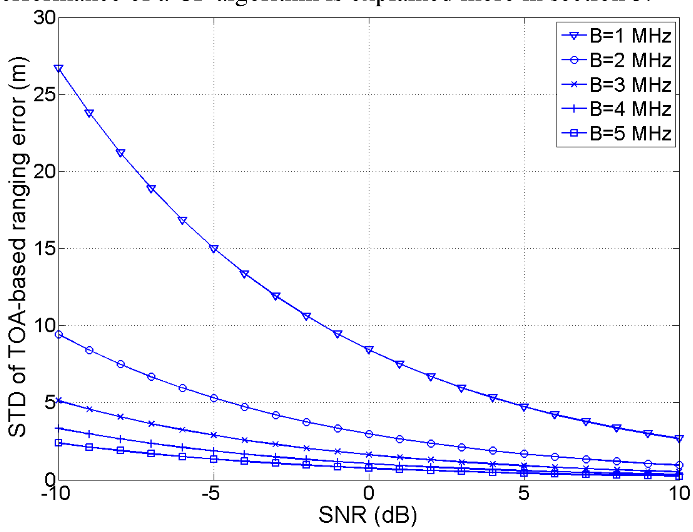

Fig. 3. Effect of bandwidth and SNR on TOA ranging error.

3. COOPERATIVE POSITIONING PERFORMANCE

3.1 Cramar Rao Lower Bound (CRLB)

The CRLB sets the minimum variance of any unbiased estimation of a random variable, and is the inverse of the Fisher Information matrix. Thus, CRLB is a means of estimating the performance of the cooperative positioning technique as well as benchmarking the performance of any localization algorithm. The CRLB has been derived for the general case of Adhoc Networks in (Savvides, et al., 2003). Consider a vehicle with n-1 other vehicles in its neighbourhood. The position of the vehicles can be unknown or partially known with known accuracy. Assume the ground truth positions of vehicles are $x = \{[X_i \quad Y_i]\}_{i=1}^{n}$ for localization in a two dimensional plane. Let $\hat{\delta}_{i,j} = \delta_{i,j} + e_{i,j}$ be the inter-node range measurements between pairs of n nodes with a standard noise $e_{i,j} \sim N(0, \sigma_{i,j}^2)$, all stacked in a column matrix δ which has n×(n-1) elements. Under the normality assumption, $f_\delta(\delta \mid x)$ is a normal distribution with $\sigma_{i,j}^2$ on its diagonal covariance matrix Σ which underlines the assumption of inter-nodes measurements independence, then:

$$f_\delta(\delta \mid x) = N(\delta, \Sigma) \tag{1}$$

The Fisher Information matrix $F(X \mid \delta)$ for the estimation of position vector *X* is:

$$F(x \mid \delta) = E\left[(\nabla_X f_\delta(\delta \mid x)) \times (\nabla_X f_\delta(\delta \mid x))^T\right] \tag{2}$$

Where ∇_X denotes the gradient with respect to elements of vector *X*. The inverse of $F(X \mid \delta)$ in its current form gives the CRLB for the case when only the range measurements are used without the a priori information about the node locations. Assuming that Σ_P is the covariance matrix of the a priori position information *X* (e.g. provided by GPS), a hybrid CRLB for cooperative positioning can be introduced as:

$$P = \left(\Sigma_P^{-1} + F(x \mid \delta)\right)^{-1} \tag{3}$$

where $\sum p$ is the a priori covariance matrix of ***X*** that is a diagonal matrix with σ_{GPS}^2 (about 7 meters) on the diagonal

3.2 CRLB for VANET

For mobile networks such as VANET, the motion information of the nodes and their likely routes can be used to refine the position estimates. A computational algorithm that facilitates tracking and fusion of spatial information across time is referred to as a filter. By the filtering mechanism the position estimation at each instant *k* in time is refined by the estimation at instant *k-1* based on a mobility model. Assume the velocity based mobility:

$$x_{k+1} = x_k + T_k u_k + T_k \xi_k \tag{4}$$

Where

$$\begin{aligned} x_k &= [X_1^k, X_2^k, \cdots, X_n^k, Y_1^k, Y_2^k, \cdots, Y_n^k] \\ u_k &= [U_1^k, U_2^k, \cdots, U_n^k, V_1^k, V_2^k, \cdots, V_n^k] \end{aligned} \tag{5}$$

U is velocity in X direction and V in Y. T_k is the time interval between measurements. ξ_k is a standard error with zero mean and variance of σ_v^2. Thus the hybrid CRLB for mobile networks becomes:

$$P_{k+1} = \left((P_k + T_k \Sigma_v)^{-1} + \Sigma_P^{-1} + F(x \mid \delta) \right)^{-1} \tag{6}$$

Where P_{k+1} and $\boldsymbol{P_k}$ are the hybrid CRLB matrices at instants $k+1$and k, T_k is the scalar elapsed time, Σ_v is the diagonal covariance matrix of the measured velocity of vehicles. It is clear that noisier velocity measurements, thus larger σ_v^2, lead to a smaller contribution from the previous instant's position information and if it is too large filtering has no effect on the accuracy. An indicator of cooperative positioning error for each node over a period of time (K) can be readily obtained based on Circular Error Probability (CEP):

$$C = \left(\sum_{k=1}^{K} \frac{\sigma_{x\,i}^{k\,2} + \sigma_{y_i}^{k\,2}}{K} \right)^{\frac{1}{2}} \tag{7}$$

Where $\sigma_{x\,i}^{k\,2}$ and $\sigma_{y_i}^{k\,2}$ respectively are the estimated error variance of node i at time k in directions x and y.

3.3 Simulation of Performance

A simulation study was conducted to demonstrate the performance of CP with the cluster topology when fused with a velocity sensor. Using Netlogo™, an agent-based and Java-based programming platform, a street traffic network was simulated. Figure 4 is a snapshot of the Netlogo traffic network. The length of the horizontal road was set at *2 km*. From this simulation, only the ground truth values of the vehicles' positions were obtained. The rest of the calculations, such as obtaining the noisy GPS measurements and DSRC range measurements were performed in the Matlab™ environment. The traffic condition was set at *1200 v/h* that corresponds to heavy/slow traffic. A target vehicle was set to travel a particular path of about *2 km*. The simulation time was about 550s. The DSRC range was set at *250 m*. The underlying assumptions for this test and all the following tests are that the inter-node ranging error has a mean of zero and co-variance of σ_{ij}, which was changed from *1 m* to *10 m*. The GPS standard error was set at *10 m*.

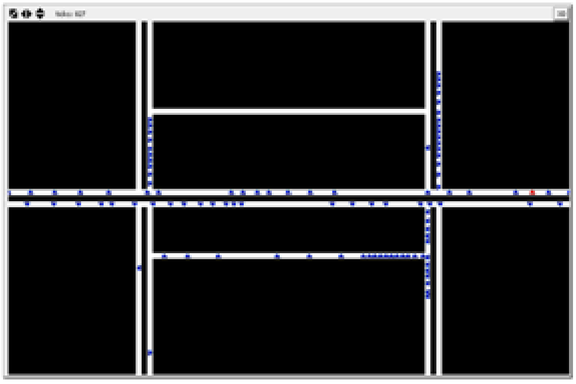

Fig. 4. The road network of traffic simulation.

Figure 5 shows the expected error for CP based on CRLB analysis for heavy traffic conditions. The errors obtained from Equation 7 are averaged over the simulation run time. The ranging standard deviation varied between *1 m* and *10 m* as shown on the curves; the standard deviation of velocity measurement varied from *0.1 m/s* to *2.1 m/s*. It can be seen that CP error has high sensitivity to the velocity error. Better than *1 m* accuracies are typical when the velocity measurement has an error standard deviation of about *0.1 m/s*. This velocity error margin can be met with ABS-based odometers (Bonnifait, et al., 2001; Stephen, 2000).

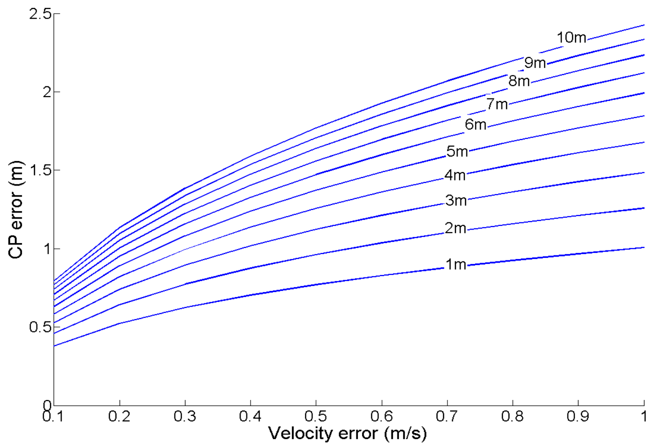

Fig. 5. Error bounds for various conditions.

3.4 CP Robustness to GPS Outage

A second simulation was set up to demonstrate the robustness of CP to GPS outages already demonstrated to be widespread in the CBD areas. In this simulation, twenty outages that correspond travelled distances of 15m to 35m long were randomly allocated in every kilometer of the simulated road network. If a vehicle entered the outage zones, its position error deviation was set at infinity (or a very large number), which literally means the absence of position information in those zones. In Figure 6, the error bounds for two cases as well as the GPS drop out times are shown. Case 1 is the worst case scenario for CP performance. Also the ranging and velocity errors are set at their highest, $\sigma_R = 10m$ and $\sigma_v = 1m/s$. Case 2 has same ranging error as case 1 but better velocity measurements $\sigma_v = 0.1m/s$. This figure shows that in case 1, CP error has some sensitivity in the form of sharp short spikes to the outages. However, case 2 has a very smooth error even during the outages. The smoothness particularly is due to better velocity measurements. The figure illustrates the important positive impact of the velocity accuracies on both smoothness of the CP solution as well as its accuracy. Thus CP is proved to be an effective system to gap GPS outages.

4. CP ALGORITHM

A localization algorithm is a computational procedure or an estimation engine that addresses the problem formulation, robustness, estimation accuracy, coordination and computational complexity, given some measurement information. Monte Carlo Localization, Convex Optimization, Iterative Multilateration, Multidimensional Scaling (MDS) and Kalman Filter (KF) for mobile networks are the most popular network localization algorithms. A perfectly efficient CP algorithm is one that has the same errors as CRLB over many trials. In this research the KF was selected as already having demonstrated as a computationally simple and efficient algorithm for combining disparate measurements. As it is anticipated that this algorithm will need to run on devices with limited computation power (such as in-car navigation system), the KF was deemed by the authors as having the least computational complexity.

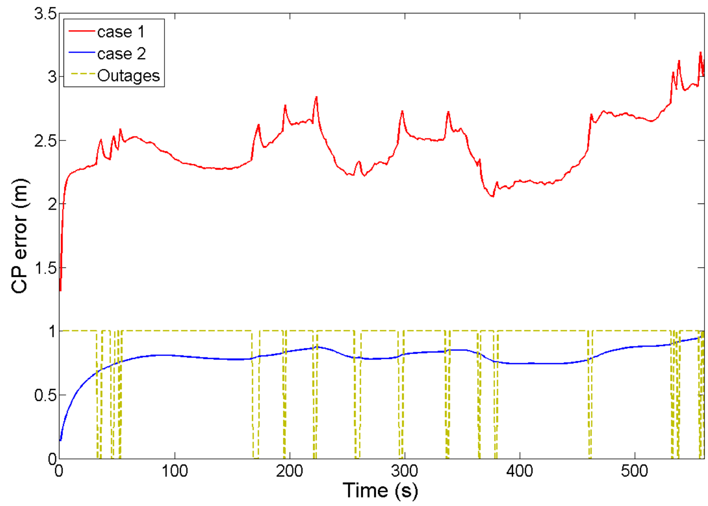

Fig. 6. CP error for two cases. The green dashed lines show the outages. A value of 1 indicates GPS availability and 0 the GPS unavailability.

4.1 Kalman Filtering

KF is an optimal state least squares recursive estimation process applied to a stochastic dynamic system such as a vehicular network. KF is a linear, unbiased, and minimum error variance recursive estimation algorithm for the state of a dynamic system that uses noisy measurements taken at discrete real-time intervals. Consider the velocity mobility model in Equation 5 as the dynamic state model. The range measurements then are considered in a measurement model:

$$\begin{cases} X_{k+1} = A_k X_k + \Gamma_k \xi_k \\ Z_k = g(X_k) + \eta_k \end{cases} \tag{8}$$

where X_k is a vector containing the position coordinates of all nodes in a cluster and Z_k is the vector of measured ranges at instant k. The process noise ξ_k and measurement noise η_k are independent zero mean Gaussian white noise with covariance matrices respectively described by Q_k and R_k. Since for CP the relationship between Z_k and X_k is not linear, a linear Taylor transformation is required:

$$C_k = \frac{\partial g}{\partial X_k}(X_{k|k-1}) \tag{9}$$

The Kalman then solution is:

$$\begin{aligned} X_{k|k-1} &= A_{k-1} X_{k-1|k-1} \\ P_{k|k-1} &= A_{k-1} P_{k-1|k-1} A_{k-1}^T + \Gamma_{k-1} Q_{k-1} \Gamma_{k-1}^T \\ G_k &= A_{k-1} C_k^T (C_k P_{k|k-1} C_k^T + R_k)^{-1} \\ X_{k|k} &= X_{k|k-1} + G_k (v_k - C_k X_{k|k-1}) \\ P_{k|k} &= (I - G_k C_k) P_{k|k-1} \end{aligned} \tag{10}$$

Comparing Equation 5 and Equation 8 indicates that A_k and Γ_k are the unity matrices. The process noise Q_k in this case becomes a diagonal matrix with variances of velocity measurements on its diagonal. If we consider two sources of measurement (the GPS and DSRC ranges) then the measurement vector contains the GPS positions of all vehicles, and the measured ranges between pairs of vehicles. The measurement noise matrix R_k is then a diagonal matrix with variance of GPS measurements and ranges on its diagonal. The heading of the vehicles obtained from the digital map of the vehicles' in-car navigation system is, however, another source of information that can be added to the measurement vector. Additionally the outcome of the KF, $X_{k|k}$, can be adjusted to make sure it locates within the road boundaries.

4.2 Map Fusion

Map matching algorithms themselves commonly fall into two categories, termed geometric and topological (Kealy, et al., 2004). The two main map-matching rules are the more commonly used; the first one is based on the geometry of the road (Bétaille & Bonnifait, 2000; Taylor, et al., 2001) and the other based on the heading or bearing of the road (Bernstein & Kornhauser, 1996; Greenfeld, 2002). The first rule makes the assumption that the vehicle is traveling on a road (which is typically the case) and adjusts the position to the center-line of the road (or lane). This simple constraint immediately improves the accuracy of the computed position of the vehicle. This simple algorithm is effective when the nearest road/lane to the estimated position (from GPS or other sources) is in fact the road being traveled. However, when approaching intersections or when two roads are close to each other, the nearest road may not be the road being traveled. In these situations, searching for the nearest road can downgrade the position solution. To overcome this problem, a second map- matching rule applied in parallel takes into account the direction of the road on which the vehicle is traveling. This second rule requires that the nearest road to which the vehicle's position is corrected (using the first map matching rule) must have a similar bearing to the direction of travel that is available from GPS, meaning the heading of the vehicle must be the same as the bearing of the road.

Applying the first rule to the estimated state $X_{k|k}$ requires adjustment of the estimated covariance of the state $P_{k|k}$, that will be used in KF equations in the next instance, $k+1$. Here a scaling diagonal matrix is required to put the one-sigma errors ellipses within the road boundaries. The scaling matrix must have the sine and cosine of the heading of the vehicles on its diagonal. With this scaling the estimated covariance of vehicle i, σ_i is adjusted to τ_i as follows:

$$\begin{cases} \tau_{x_i}^k = \sigma_{x_i}^k \sin(h_i^k) \\ \tau_{y_i}^k = \sigma_{y_i}^k \cos(h_i^k) \end{cases} \tag{11}$$

Applying the second rule to the KF is achieved by adding a third set of measurements, the headings, to the measurement vector, knowing that the heading of node i at instant k is related to the position of the vehicle at moments k and $k-1$:

$$h_i^k = a\tan\left(\frac{y_i^k - y_i^{k-1}}{x_i^k - x_i^{k-1}}\right) \tag{12}$$

The variance associated with this measurement must be considered as a very small number close to zero, since the heading measured from the digital map is very accurate.

4.3 KF Performance Simulation

A simulation study was carried out to demonstrate the performance of the presented KF. The Netlogo traffic simulation for *1200 v/h* traffic rate was used. Figure 7 shows the performance of KF without any of the map matching rules (KF1), and KF with only the first map matching rule (KF2), snap-to-the-centerline, and KF with both map-matching algorithms (KF3). The simulations run for about *220 s*. The ranging standard deviation was set at *3 m* and that of GPS (in terms of CEP) was *10 m*. The average of error over the number of simulation runs was used as the overall estimation error. The simulation was repeated *500 times* at which point the increase of number of iterations didn't have any effect on the outcome. One can argue that the simulation trail number is dependent on many subtle characteristics such the topography of the road network, the maximum and minimum velocity of nodes etc. The performance of KF1, KF2 and KF3 are compared together and with the hybrid CRLB. KF1 performs slightly above the hybrid CRLB that shows the superior performance of KF for cooperative positioning. The performance of KF2 and KF3 are well below (better than) the hybrid CRLB, because the map matching add more information to the estimation process than was used in the CRLB evaluation. Thus the accuracy of the final estimation is much better than hybrid CRLB.

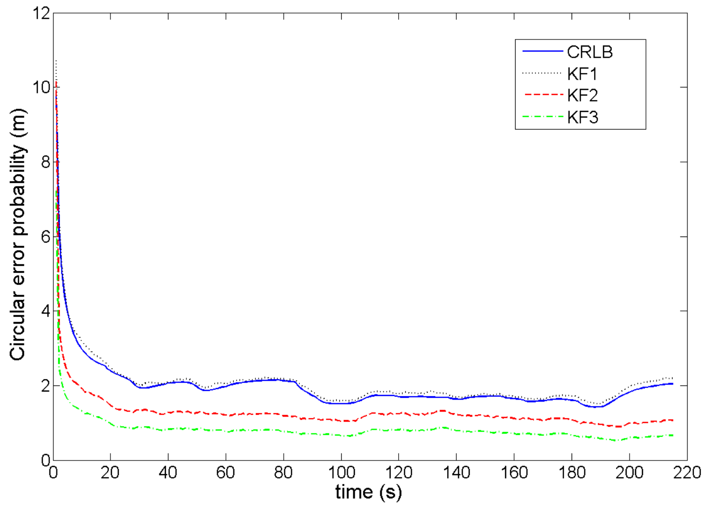

Fig. 7. The performance of three Kalman Filters compared to the hybrid CRLB.

5. CONCLUSIONS

The emergence of infrastructure such as DSRC allows us to establish ad hoc vehicular networks in which range measurements between the moving vehicles can be quantified and included as part of the integrated positioning solution. This new information source together with GNSS system forms a platform for robust position estimation that can meet the strict performance requirements of a range of road safety systems and services. CP is an important application of DSRC that has a crucial role for the reliability of safety-related applications; because it can provide consistent below meter positioning accuracy. A range-based CP was analyzed and proved competent and reliable for the position information in vehicular environments. CP is a positioning solution at no extra cost and with no major implications to DSRC system developers. CP can potentially lead to reliable and consistent below 1-meter positioning accuracy. There are of course, challenges with ranging such as Synchronization of DSRC boards that need further research.

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