Cooperative Vehicle Position Estimation

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Outline

- Introduction
- Related work and background information
- Problem definition
- Vehicle position estimation
- Analysis
- Experimentation results
- Conclusions

Introduction

- The cooperative collision warning system will work by vehicles cooperatively sharing information(location, speed, heading, acceleration, etc)
- In order to enable the operation of such a system , it is required that a vehicle build a map of the relative location of neighboring vehicles, in an accurate and reliable way

Introduction

- GPS-based
  - Global positioning system (GPS)
    - 10 meters error
  - Differential GPS
    - 3-7 meters error
  - Bridges , tunnels , skyscrapers
- Radio based ranging techniques

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Related work

- Radio based ranging techniques
  - Stationary sensor network
- Mobility makes localization much more difficult and that position estimation errors increase with speed
- Robust quads algorithm (unambiguous)
- Mobile sensor network (arbitrary direction, speed bound)

Radio based ranging techniques

- Signal strength indicator
- Time-of-flight
- Angle-of-arrival

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Problem definition

- *Consider a cluster of n vehicles labeled 1,2,…n*
  - $\boldsymbol{A} = [x_1, x_2 \ldots x_n , y_1 .. y_n]$
- Three main vectors
  - Inter-vehicle distance (radio based ranging)
  - Velocity information (onboard sensors)
  - Road map (road boundaries)

Information collected

1. Inter-vehicle distance measurements are made by each vehicle using a radio ranging technology to estimate their relative distance
2. Vehicles will read their own speed information
3. Standard multicast
4. n*(n-1) inter-vehicle distance and n velocity readings

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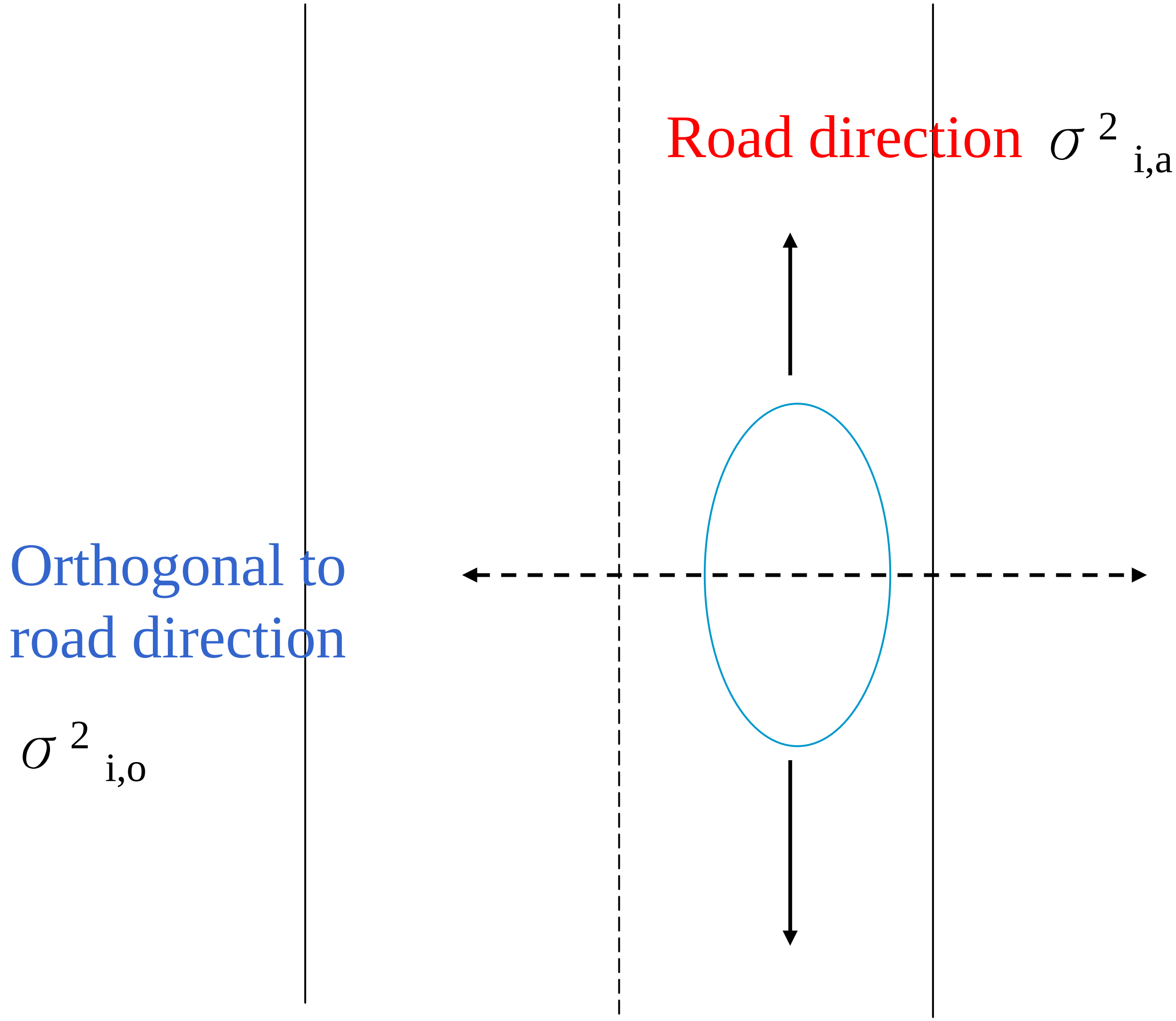
Motion model

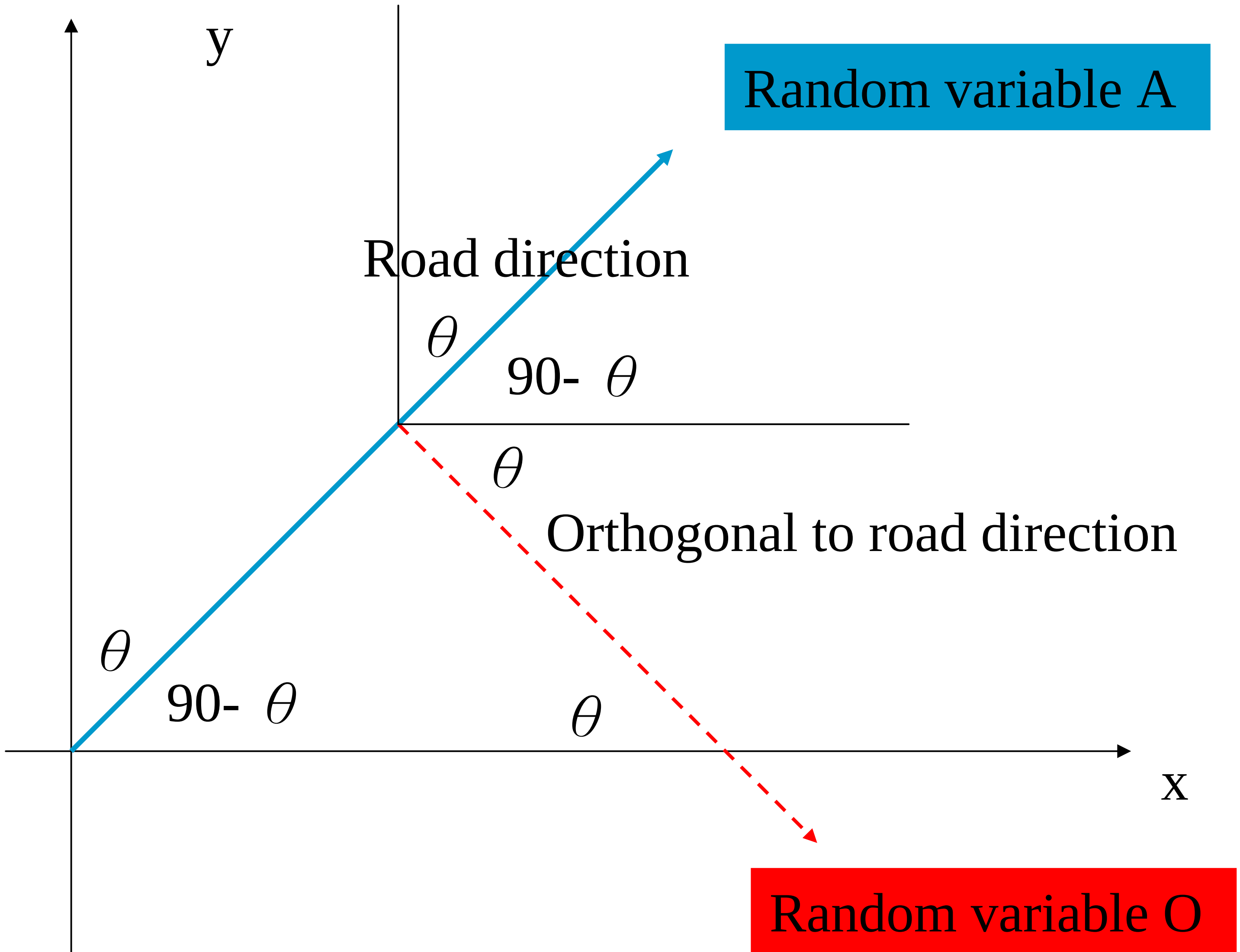
- $\boldsymbol{A}_k = \boldsymbol{A}_{k-1} + T_s\mathbf{u}_{k-1} + T_s\mathbf{w}_{k-1}$ (2)
- $\boldsymbol{A}_k = [x_{1,k}, x_{2,k}\ldots x_{n.k}, y_{1,k}\ldots y_{n,k}]^T$ (3a)
- $\mathbf{u}_{k-1} = [v_{x1,k-1}, \ldots v_{xn,k-1}, {}_{vy1,k-1\ldots}v_{yn,k-1}]^T$ (3b)

T_s: sampling interval

$\boldsymbol{A}_k$: the position of vehicle at time k

$\mathbf{w}_{k-1}$:mobility variations


Road direction $\sigma^2_{i,a}$
Orthogonal to road direction
$\sigma^2_{i,o}$



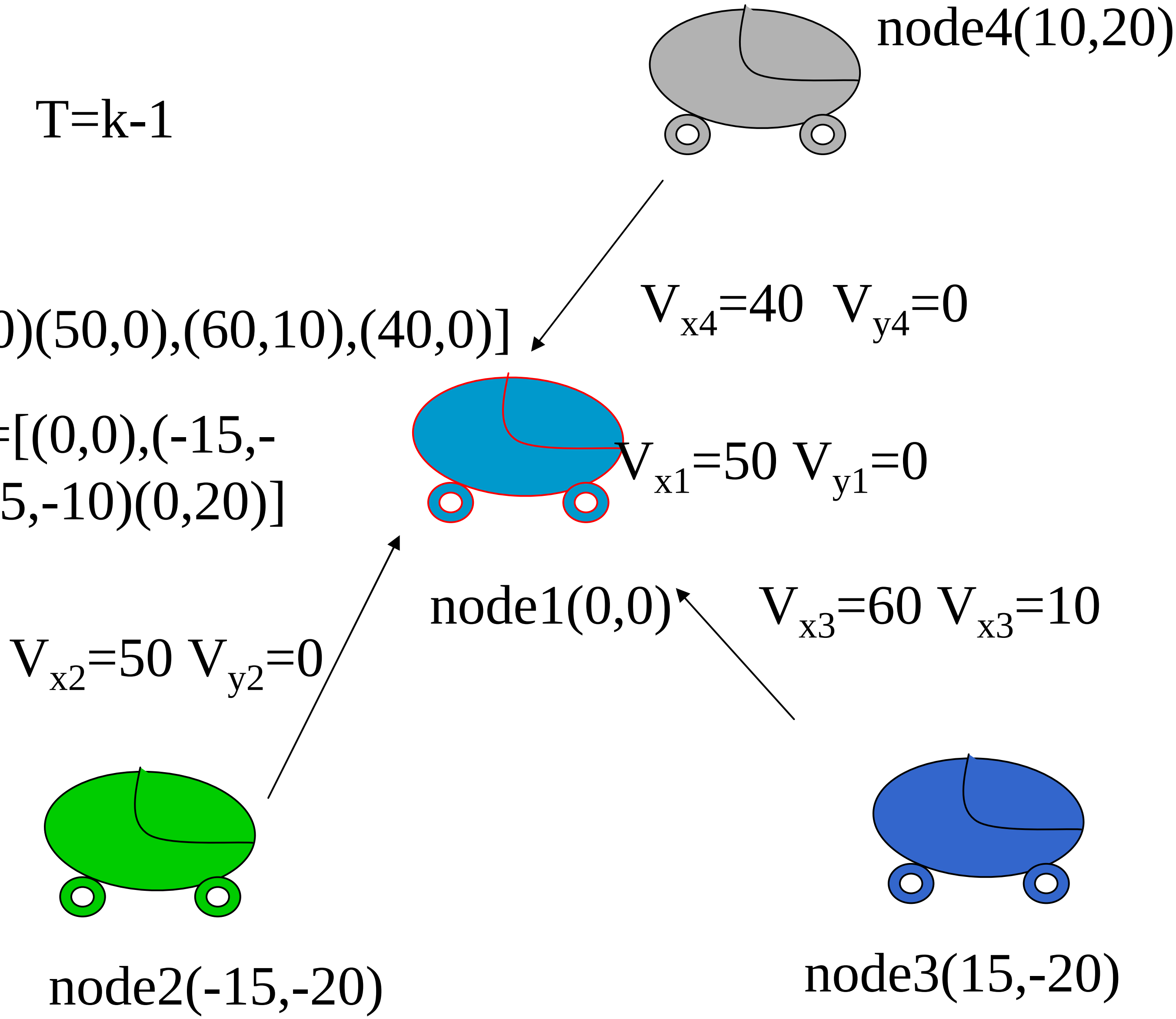
$$Xi = O\cos\theta + A\sin\theta$$

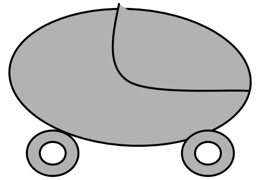
$$\sigma^2_{Xi} = \sigma^2_{i,o}\cos^2\theta + \sigma^2_{i,a}\sin^2\theta$$

T=k-1

u_{k-1}=[(50,0)(50,0),(60,10),(40,0)]

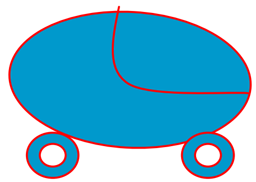
$A_{k|k-1}$=[(0,0),(-15,-20),(25,-10)(0,20)]



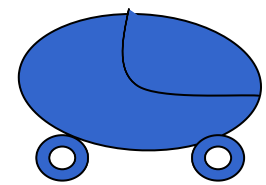


node4(0,20)

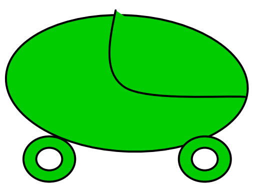
$A_{k|k-1}$=[(0,0),(-15,-20),(25,-10)(0,20)]



node1(0,0)



node3(25,-20)



node2(-15,-20)

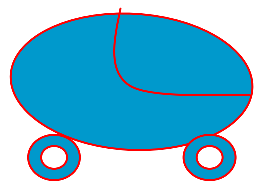
Kalman filter gain

- $K_k = P_{k|k-1} H_k^T (H_k P_{k|k-1} H_k^T + R_k)^{-1}$
- If R_k(noise) is large , Kalman filter gain is small
- If R_k(noise) is small , Kalman filter gain is large
- $Z_k = h_k(A) + V_k$

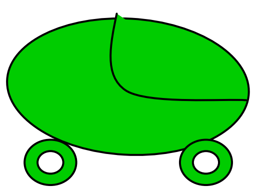
Assume that Kalman filter gain between node1 and node2 = 0.8

Time= k value z_k = 26 value $h_k(A_{k|k-1})$= 25 $z_k - h_k(A_{k|k-1})$= 1

Then node2(-10+ 0.8*1 , -20 + 0.8*1) = (-9.2 , -19.2)



node1(0,0)



node2(-10,-20) → node2(-9.2,-19.2) $A_{k|k}$

Vehicle position estimation

1. Each vehicle performs inter-vehicle distance measurement, and take a reading of its own velocity The information is then shared with all vehicles within the cluster
2. Update the prediction function (9)(10)
3. Incorporate the measurements from step 2 to update (11)(12)
4. Repeat step 1-4, at the update rate ,Ts

Algorithm performance bound

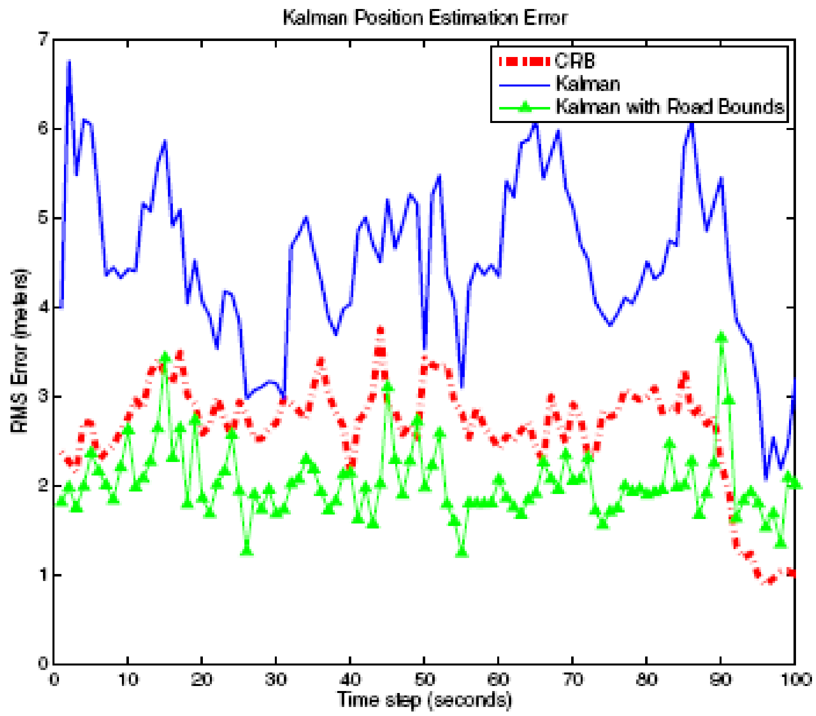


Fig. 1. Cramér-Rao bound for position estimates versus our Kalman filter based solution, lower curve shows performance gain by forcing the position estimate to be within the confines of the road

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Simulation environment

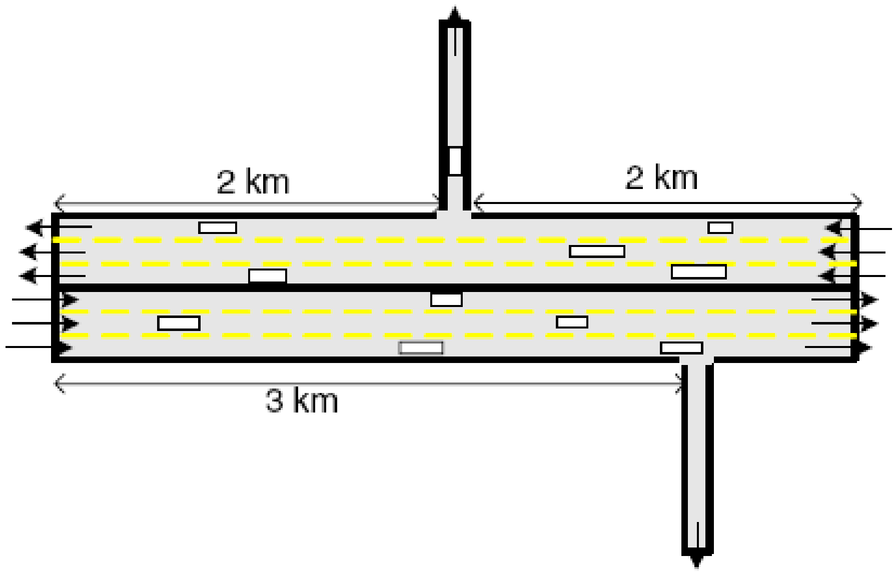

Fig. 2. Roadway for simulated vehicular environment

Performance Metrics

- Root-mean-square error (RMSE)

$$\sigma_{\text{final}} = \sqrt{\sum_{i=1}^{n} \frac{(x_{\text{final est. i}} - x_{\text{actual i}})^2 + (y_{\text{final est. i}} - y_{\text{actual i}})^2}{n}} \quad (21)$$

$$\sigma_{\text{d}} = \sqrt{\sum_{i,j=1}^{M} \frac{(\hat{d_{i,j}} - d_{i,j})^2}{M}}$$

Performance comparisons with other algorithms

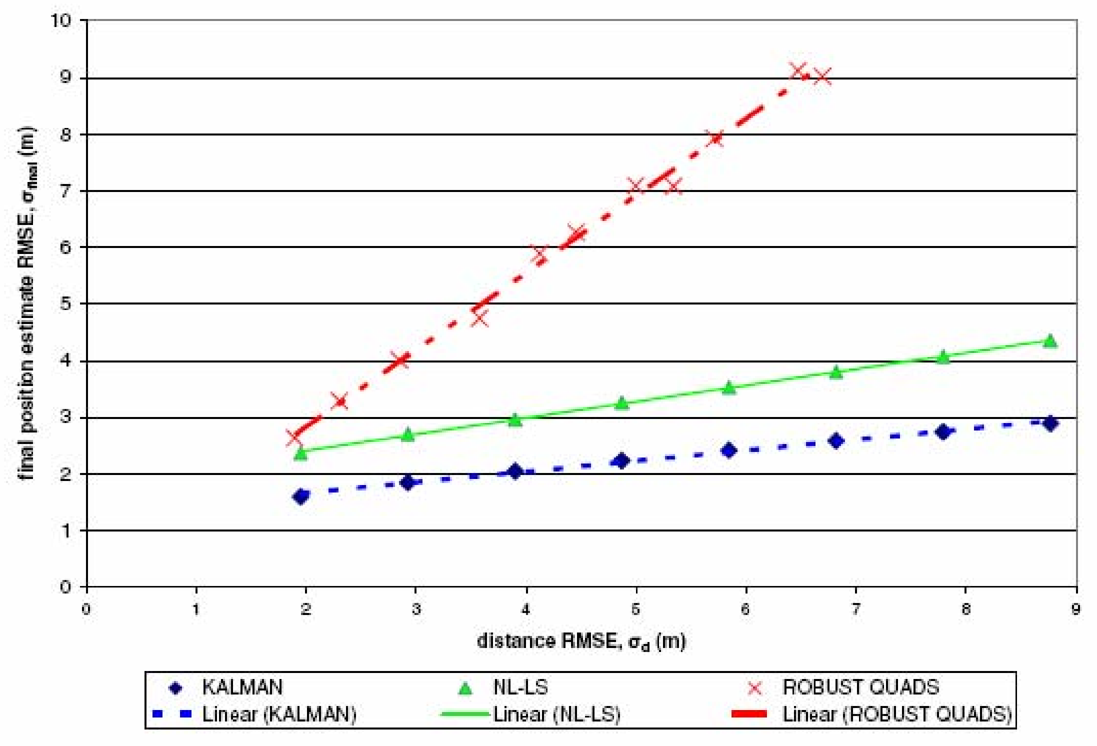

Fig. 3. Showing effect on performance when the inter-vehicle distance estimation error is varied

Performance comparisons with other algorithms

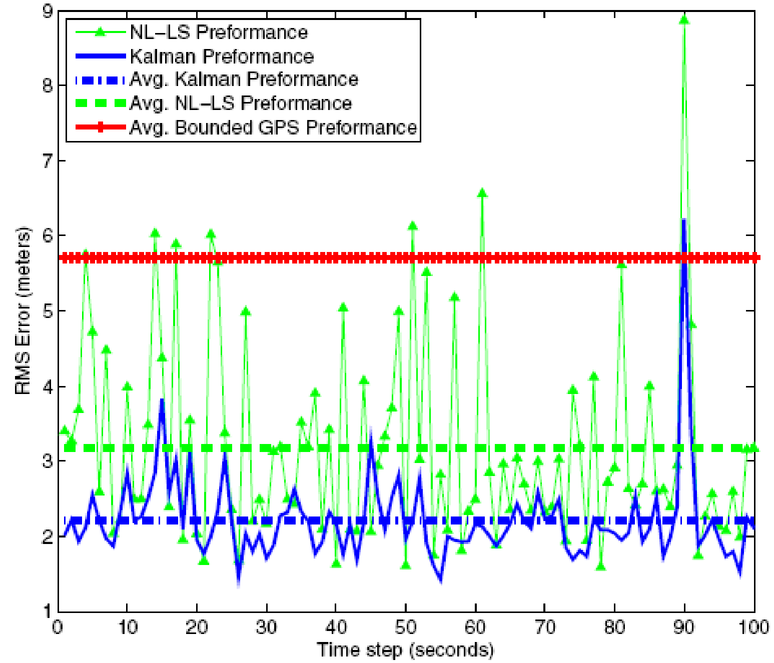

Fig. 4. Comparison of Nonlinear Least of Squares approach to our Kalman filter based approach, also the performance of using GPS with a mapping module is shown for reference

Conclusions

- The accuracy of previously proposed radio ranging based localization can be improved by taking into account extra information that is available to vehicles
- It is practical for future vehicle safety applications