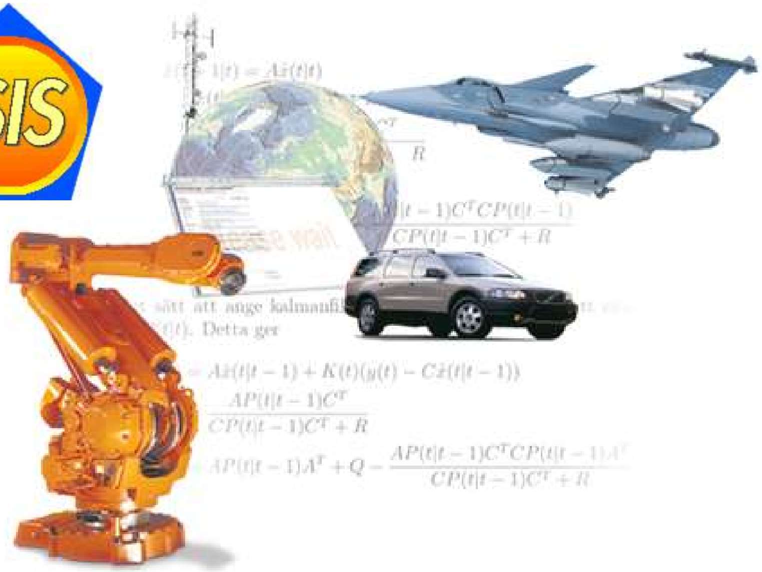
Particle Filtering in Practice

Sensor fusion, Positioning and Tracking



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Particle Filtering within ISIS from my perspective

Agenda

- **Positioning**
  - Robot positioning
  - Map-Aided navigation
    - Underwater Navigation
    - Surface Navigation

- **Analysis**
  - Quantization
  - Complexity Analysis -- Marginalization POSTER

Particle Filtering in Practice

- General model

$$x_{t+1} = f(x_t, w_t)$$

$$y_t = h(x_t, e_t)$$

Process noise

Measurement noise

- Common models for tracking and navigation

$$x_{t+1} = A_t x_t + w_t$$

$$y_t = h(x_t) + e_t$$

Bayesian Recursions

$$p(x_t|Y_t) = \frac{p(y_t|x_t)p(x_t|Y_{t-1})}{p(y_t|Y_{t-1})}$$

$$p(y_t|Y_{t-1}) = \int_{\mathbb{R}^n} p(y_t|x_t)p(x_t|Y_{t-1})dx_t$$

Particle Filter

Extended Kalman Filter

Robot Positioning & Sensor Fusion

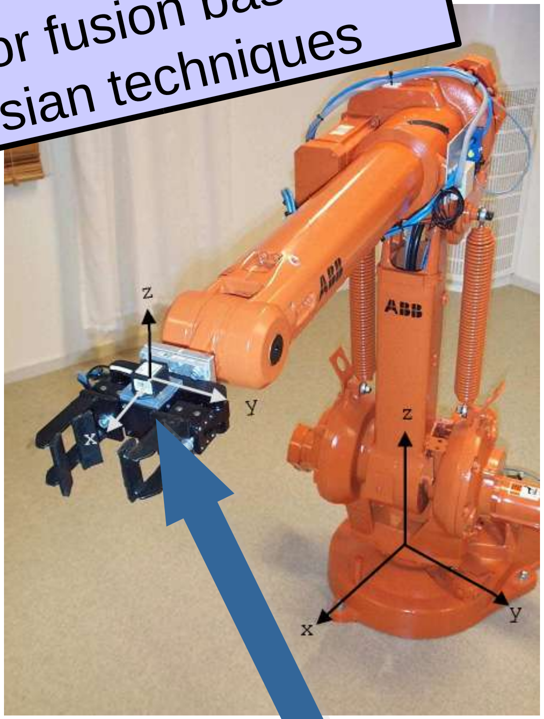
R. Karlsson & M. Norrlöf

Estimation Model

Sensor fusion based on Bayesian techniques

$$x_t = \begin{pmatrix} q_{a,t} & \dot{q}_{a,t} & \ddot{q}_{a,t} \end{pmatrix}$$

$$x_{t+1} = F_t x_t + G_{u,t} u_t + G_{w,t} w_t$$
$$y_t = h(x_t) + e_t$$



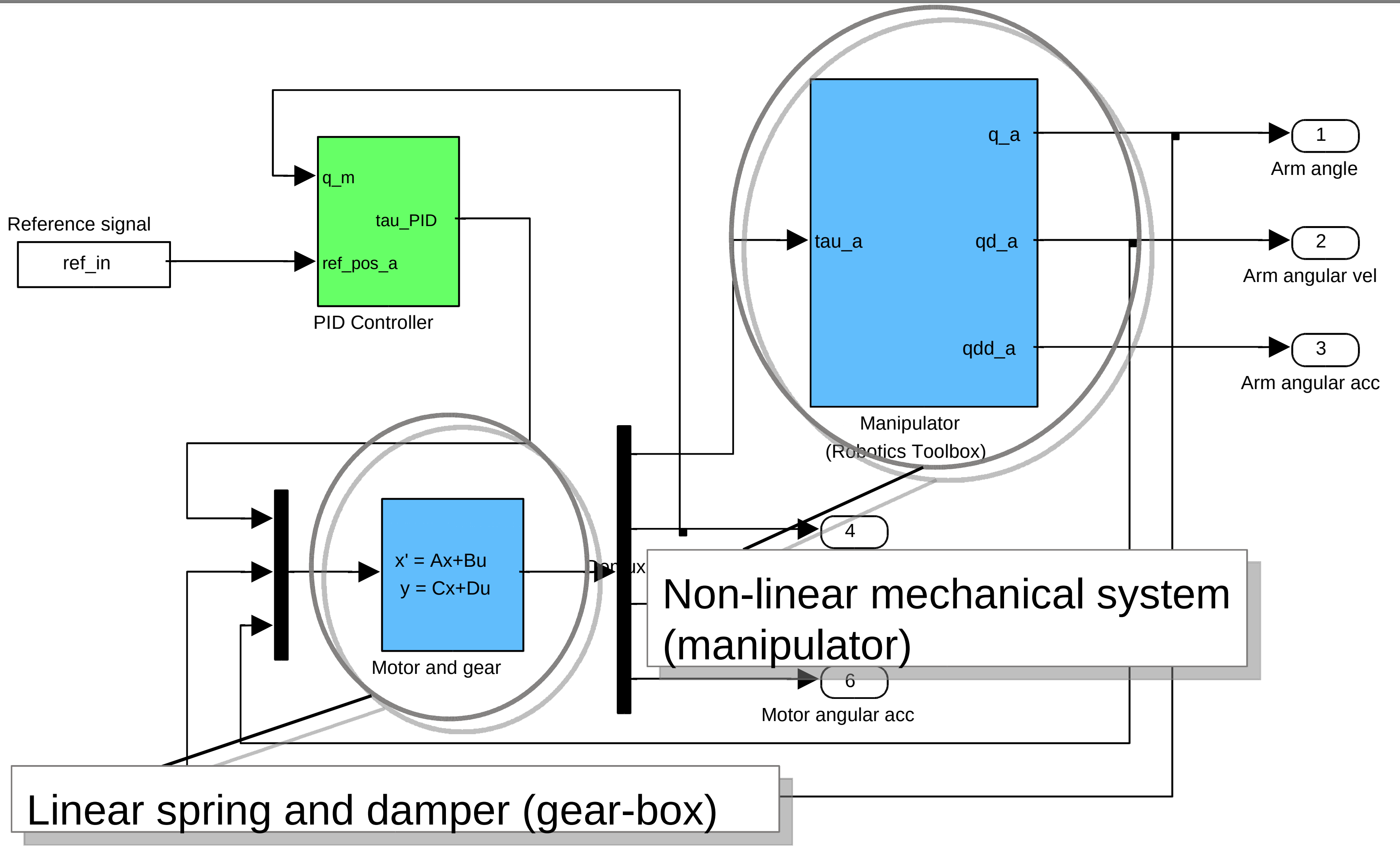
Accelerometer

$$h(x_t) = \begin{pmatrix} q_{m,t} \\ \ddot{\rho}_t \end{pmatrix}$$

Motor angle

Cartesian acceleration

The “True” System



Motivation: state estimation

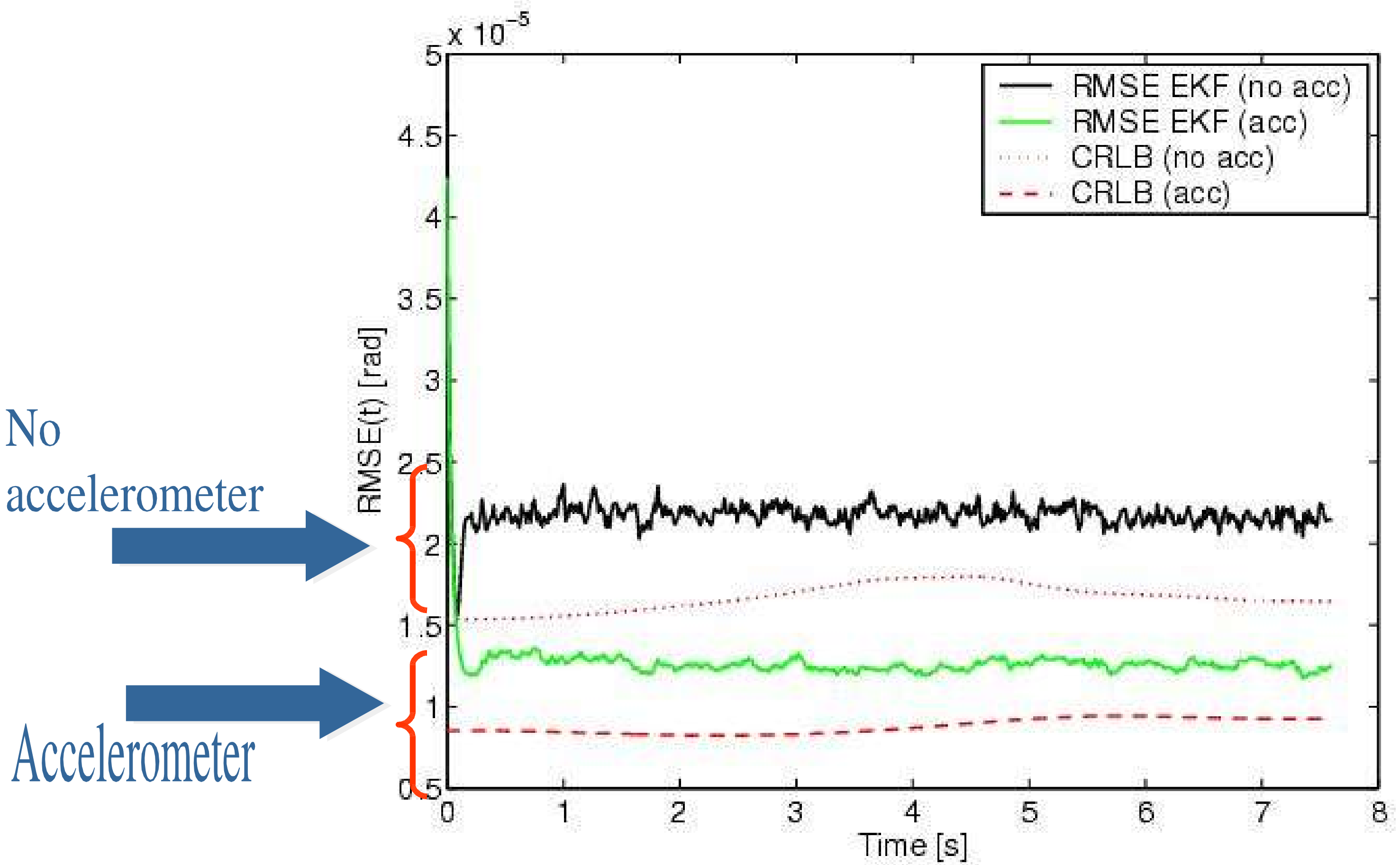
$$q_m = \frac{1}{r_g}\left(q_a + \frac{1}{k}(M_a(q_a)\ddot{q}_a + C(q_a, \dot{q}_a)\dot{q}_a + g(q_a))\right)$$

Inertia Coriolis Gravity

Arm estimates needed!

$$\widehat{q}_{a,t}, \widehat{\dot{q}}_{a,t}, \widehat{\ddot{q}}_{a,t}$$

EKF: RMSE and Cramér-Rao Lower Bound



Underwater Navigation

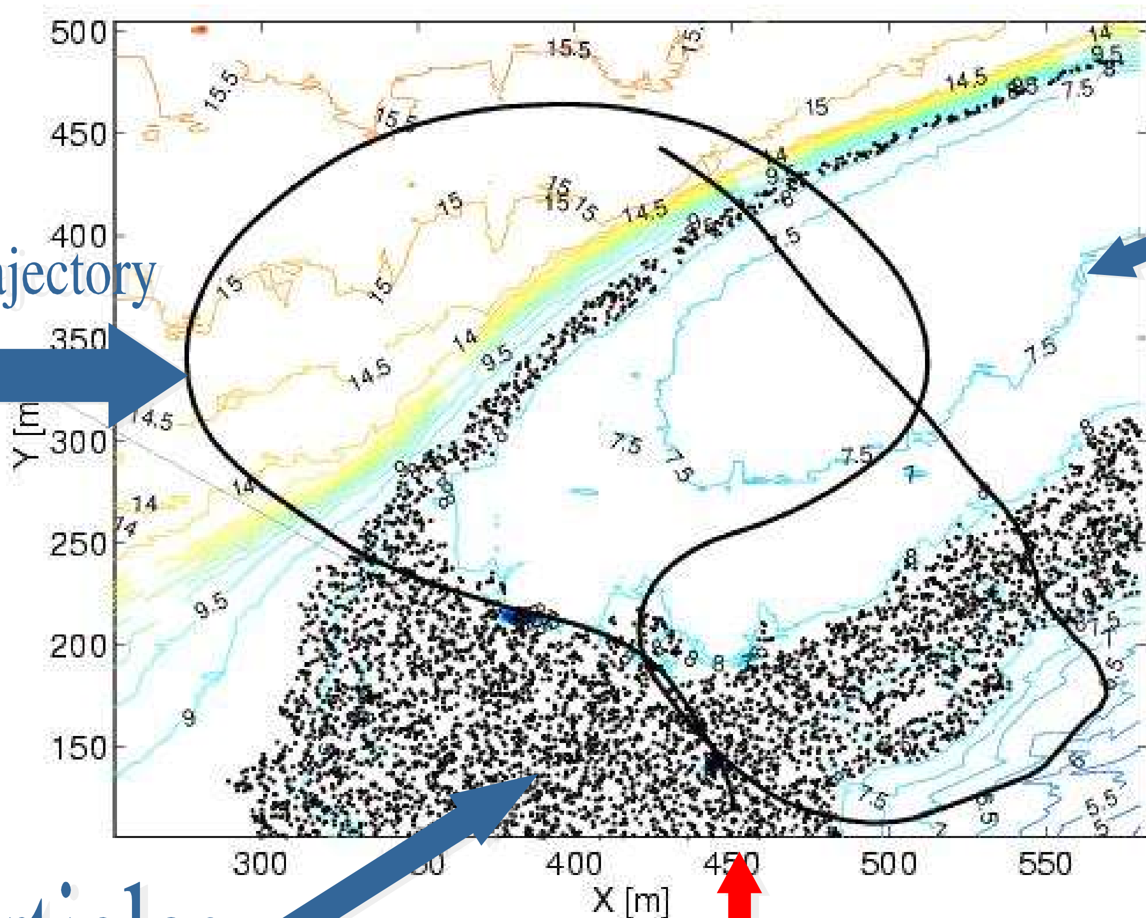
R. Karlsson & F. Gustafsson

Underwater Navigation

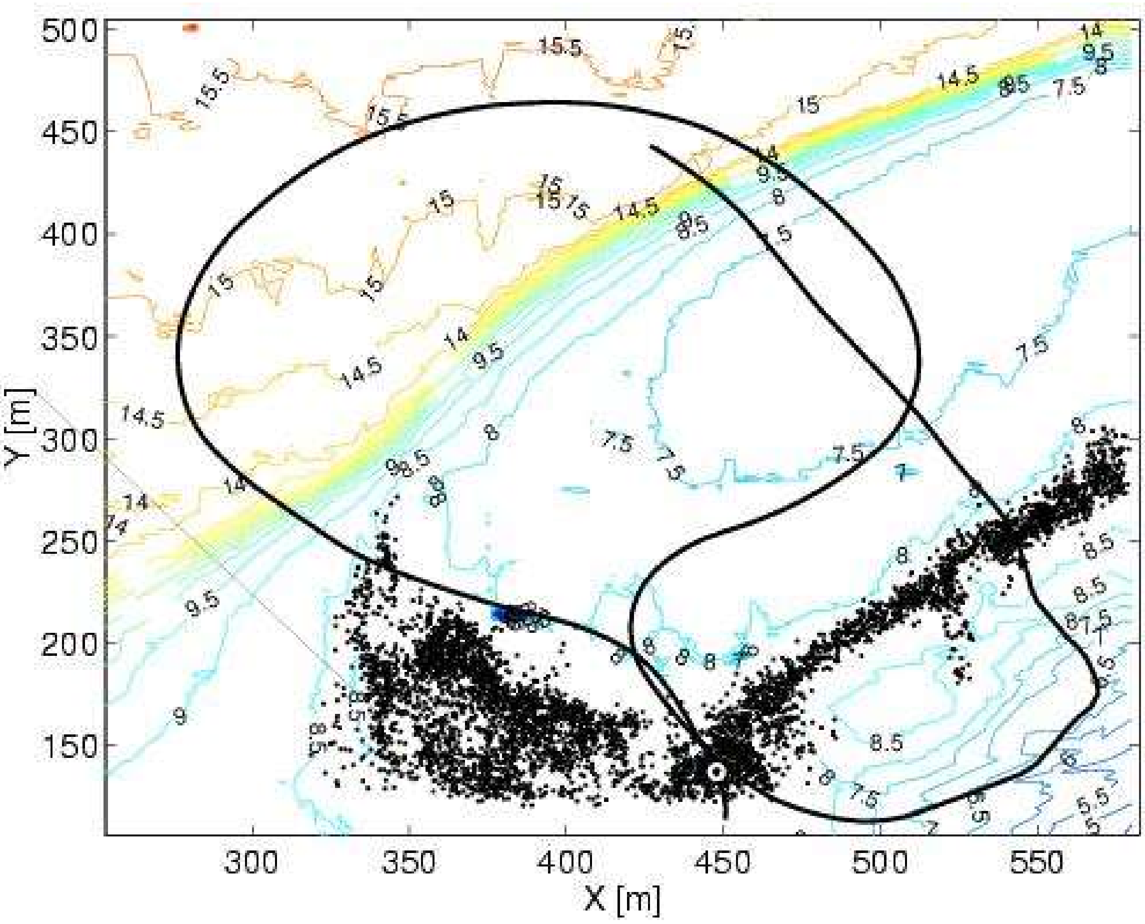
Saab Bofors Underwater Systems

- Sonar depth sensor
- Depth map
- INS

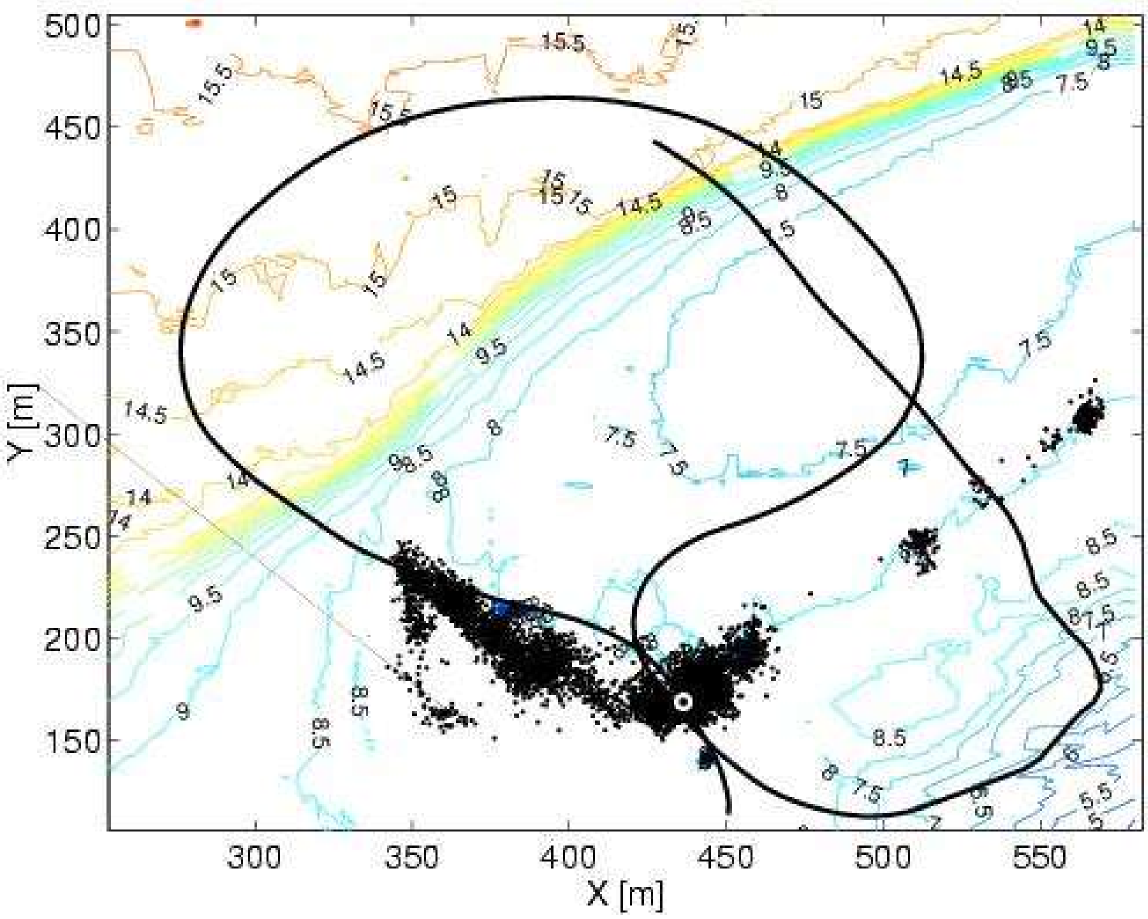
Particle Filter: t=1



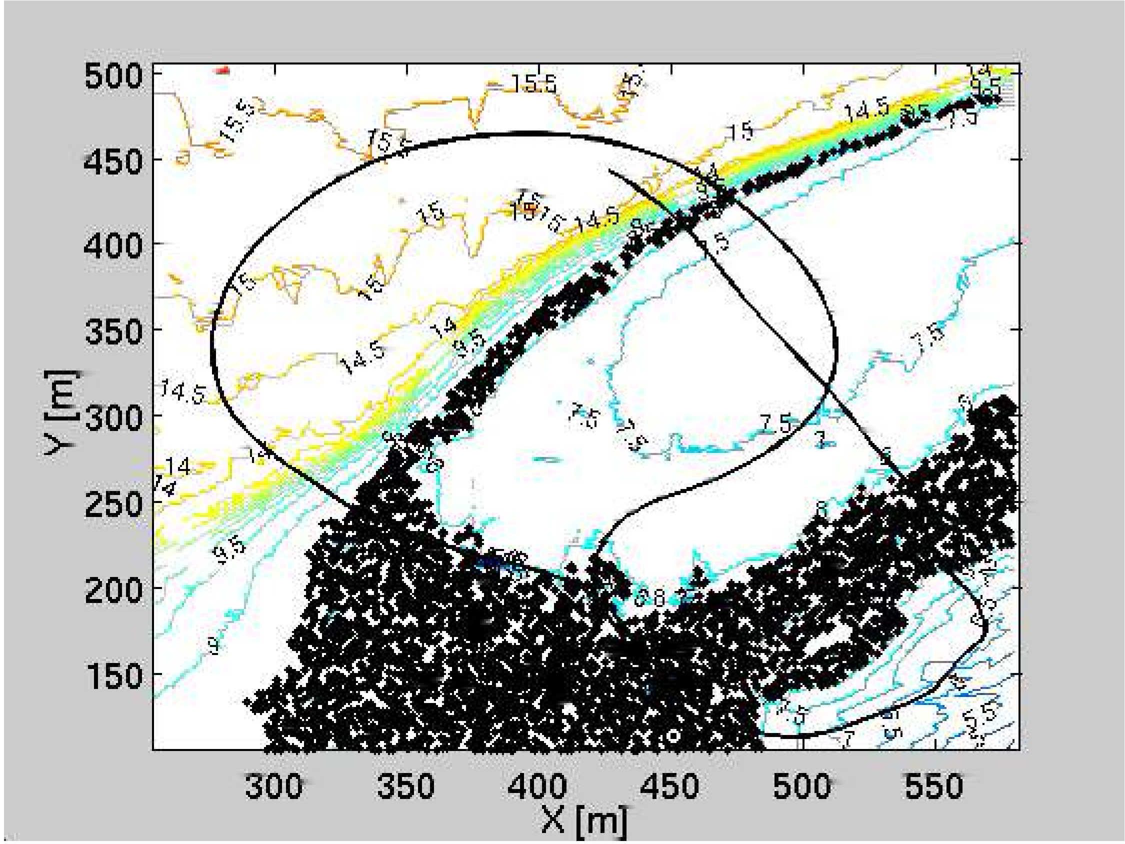
1. Likelihood:
   $\gamma_t^{(i)} = \gamma_{t-1}^{(i)} p_e(y_t - h(x_t^{(i)}))$
2. Normalize
3. Resample
4. $x_{t+1}^{(i)} = f(x_t^{(i)}, u_t, w_t^{(i)})$



Y [m]
X [m]


Y [m]
X [m]

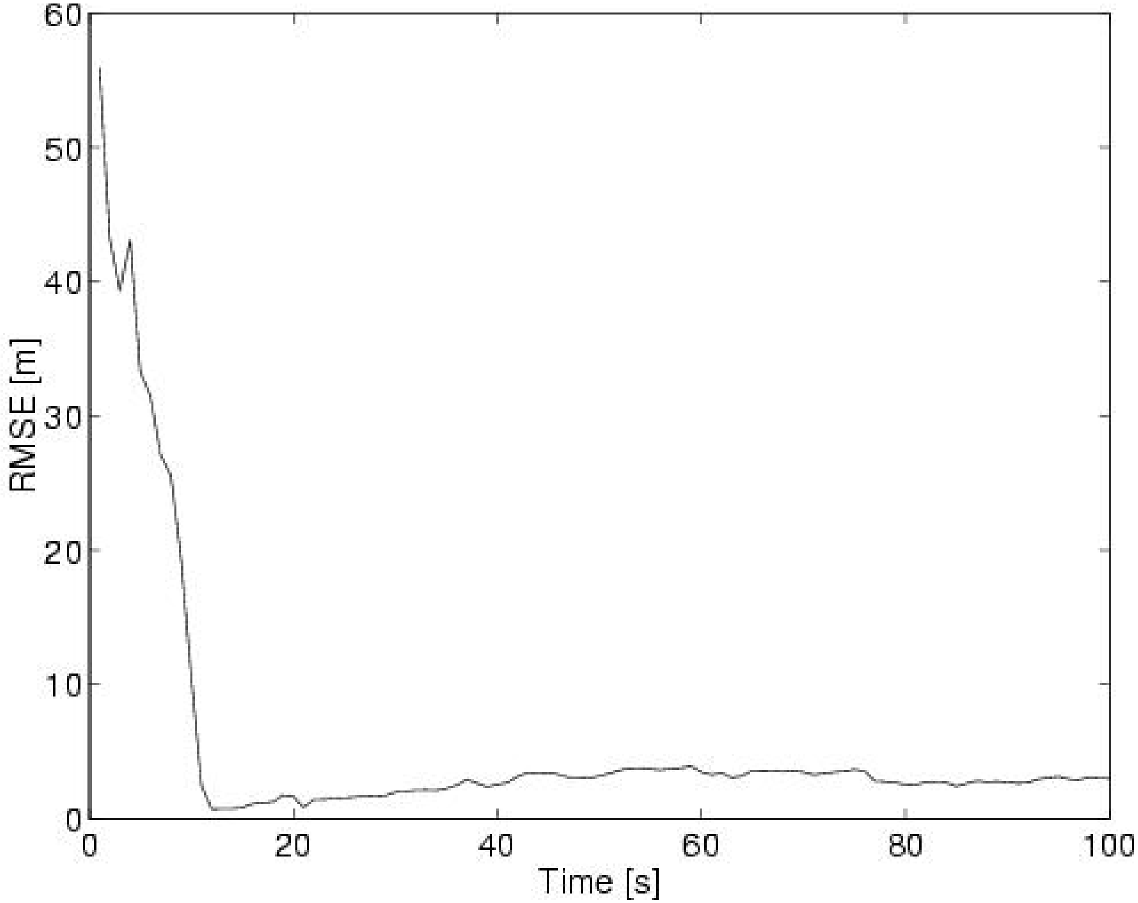
UW Animation (experimental data)



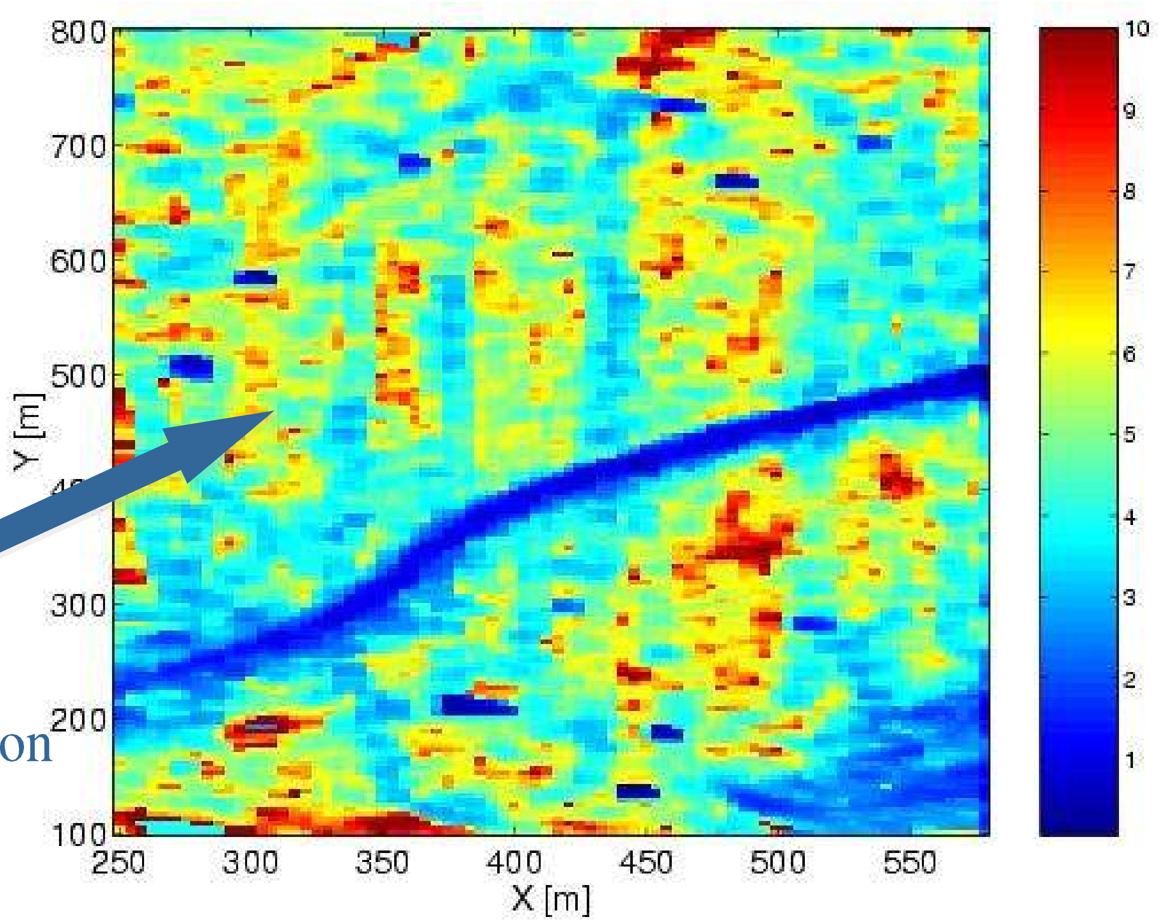
RMSE about 2-10 m

RMSE

50 Monte Carlo Simulations



CRLB: An Analytic Expression



CRLB for each position

Map-Aided Surface Navigation

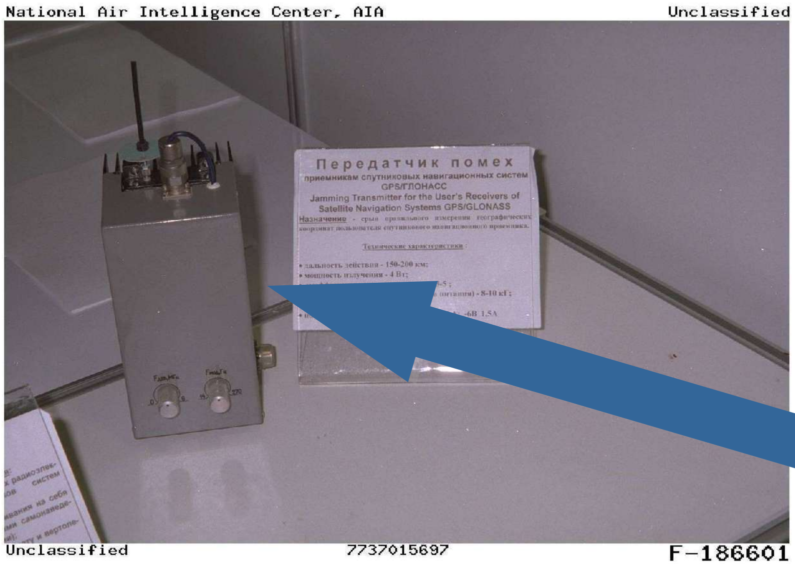
R. Karlsson & F. Gustafsson

Navigation at Sea using the GPS

- Main positioning sensor at Sea: GPS

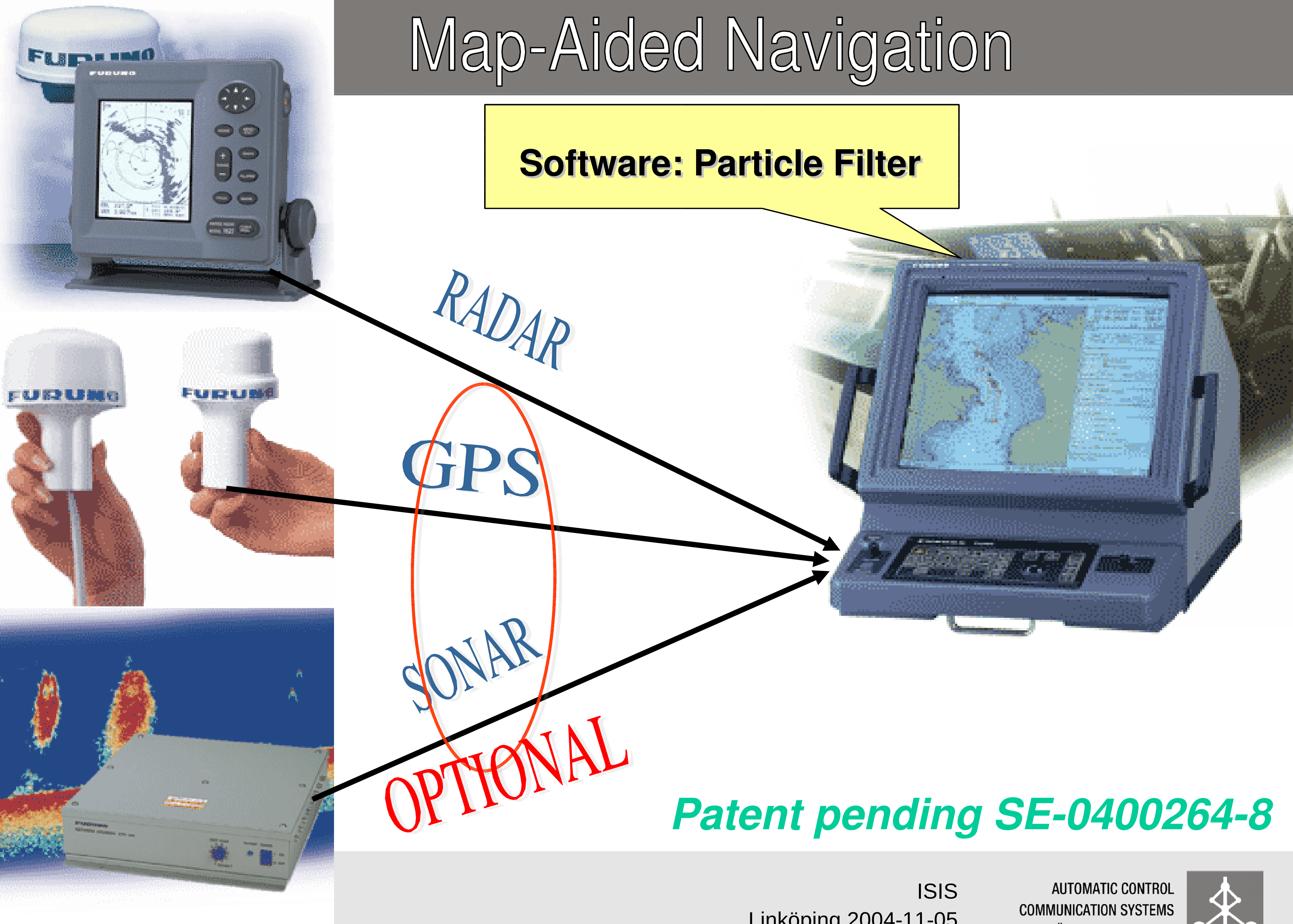
- American and European authorities have recently published reports on the need for backup systems

- Problems: jamming and spoofing



Commercial jammer
range 150-200 km

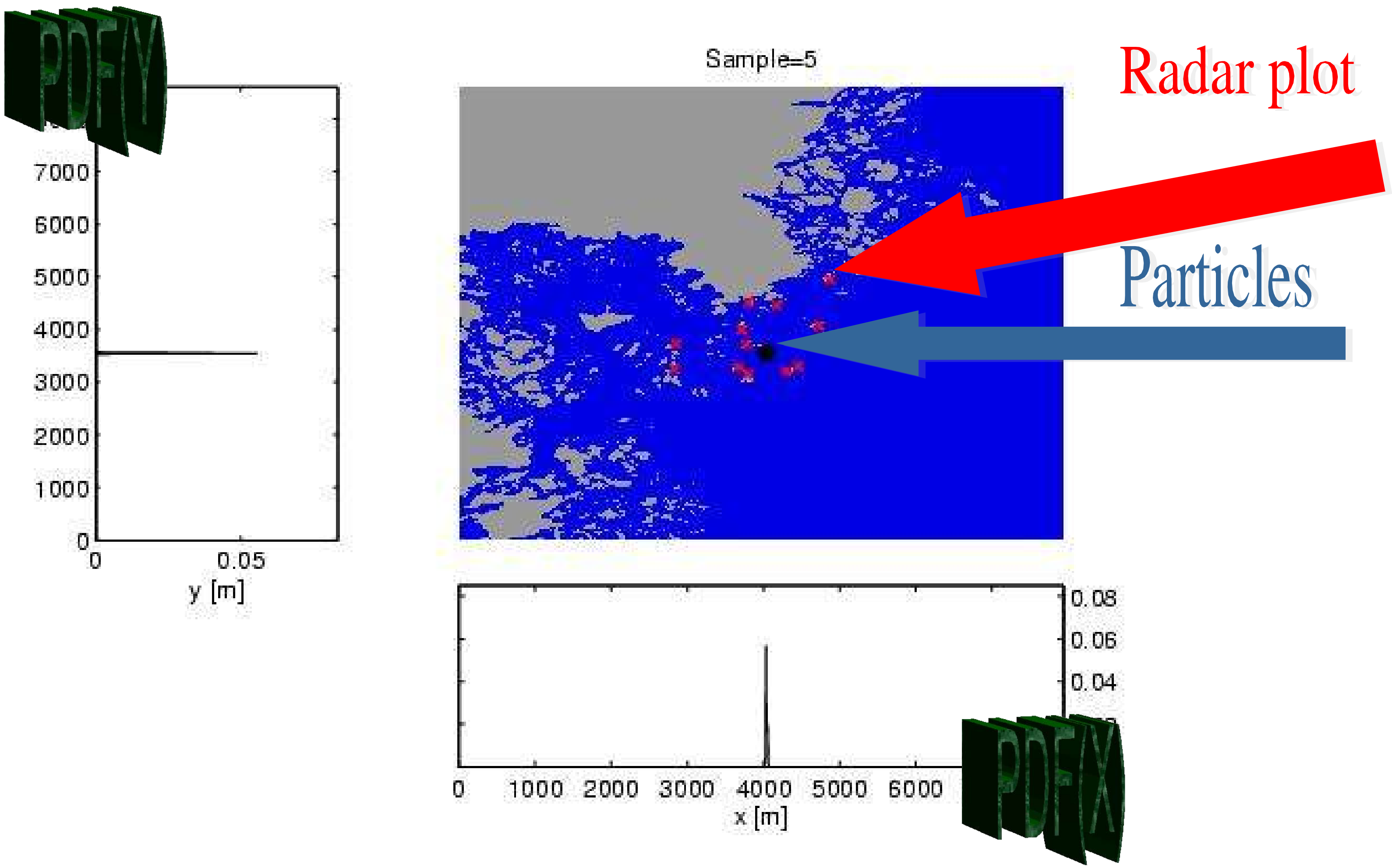
Map-Aided Navigation



Patent pending SE-0400264-8

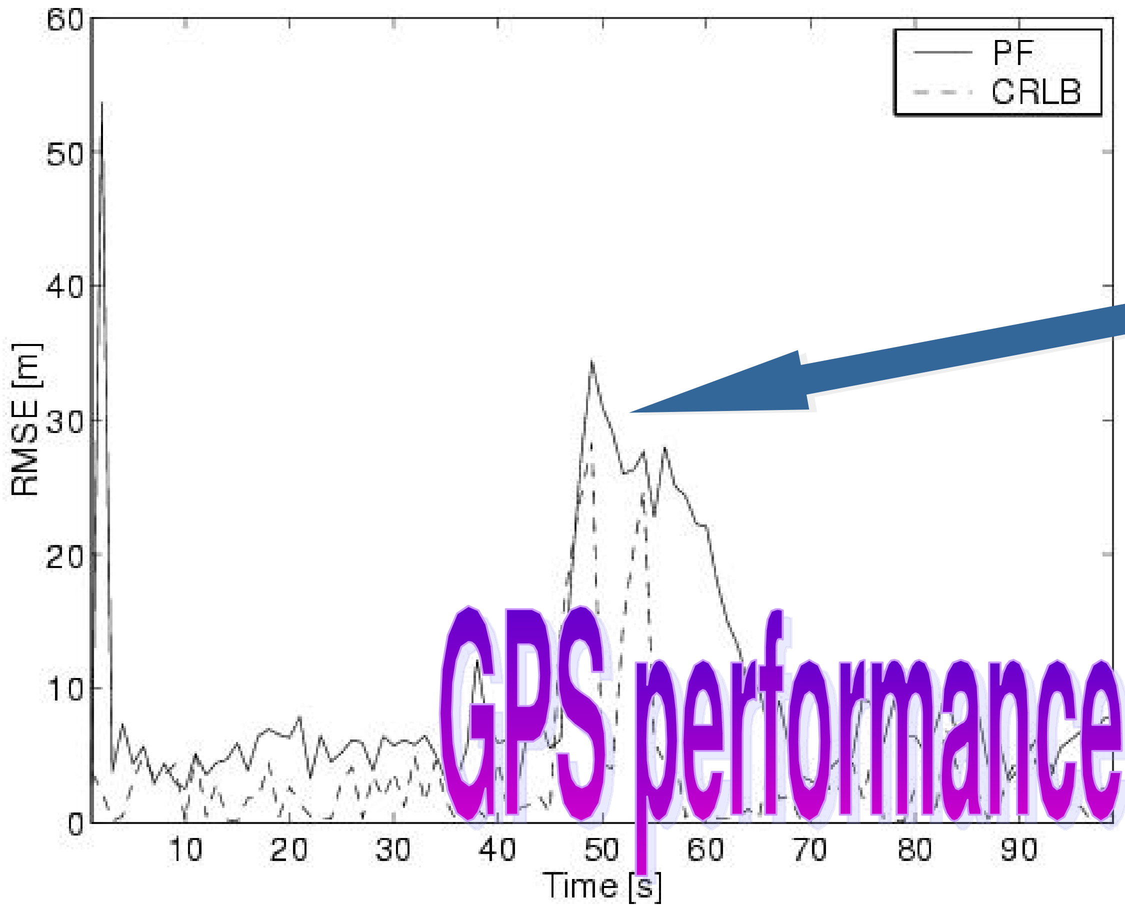
Surface Navigation

Surface Navigation: Scenario



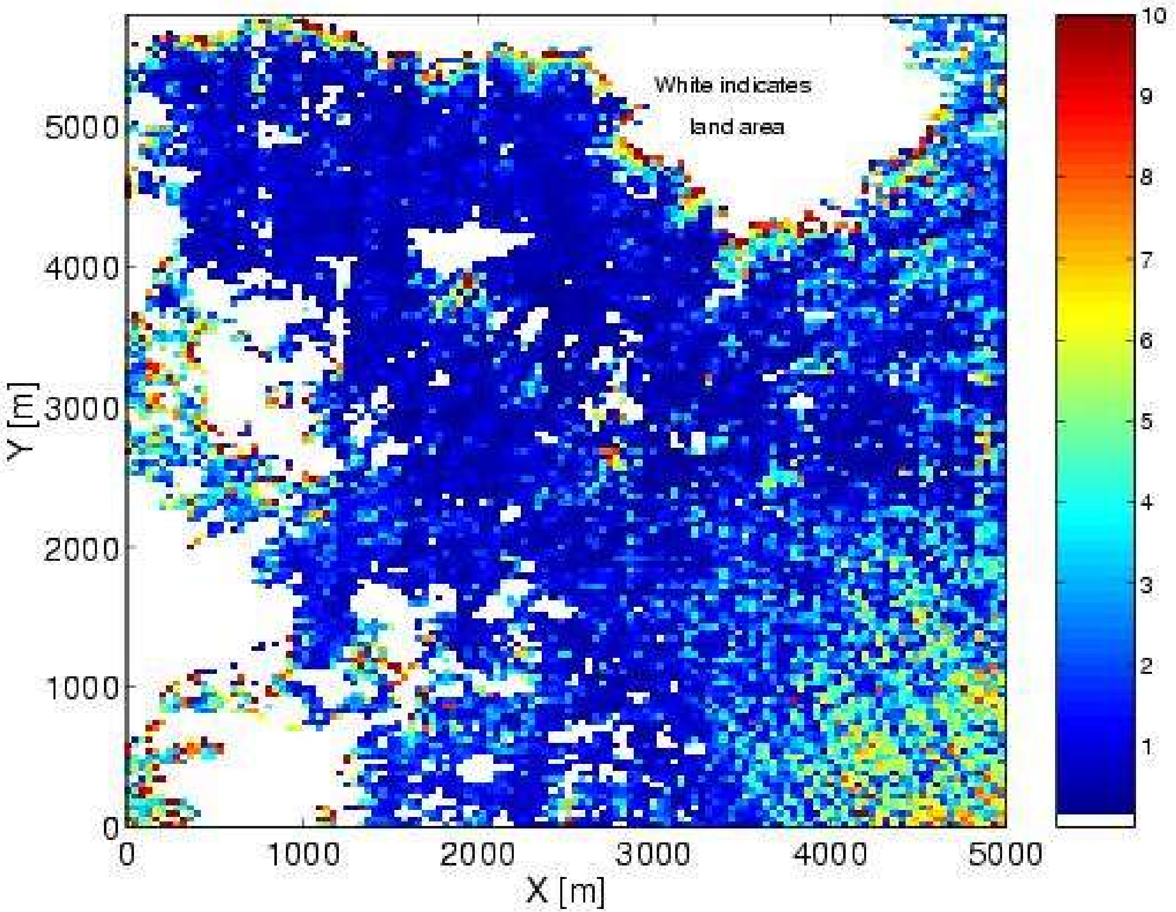
RMSE

50 Monte Carlo Simulations



No radar meas. available

CRLB: The Analytic Expression



Quantization

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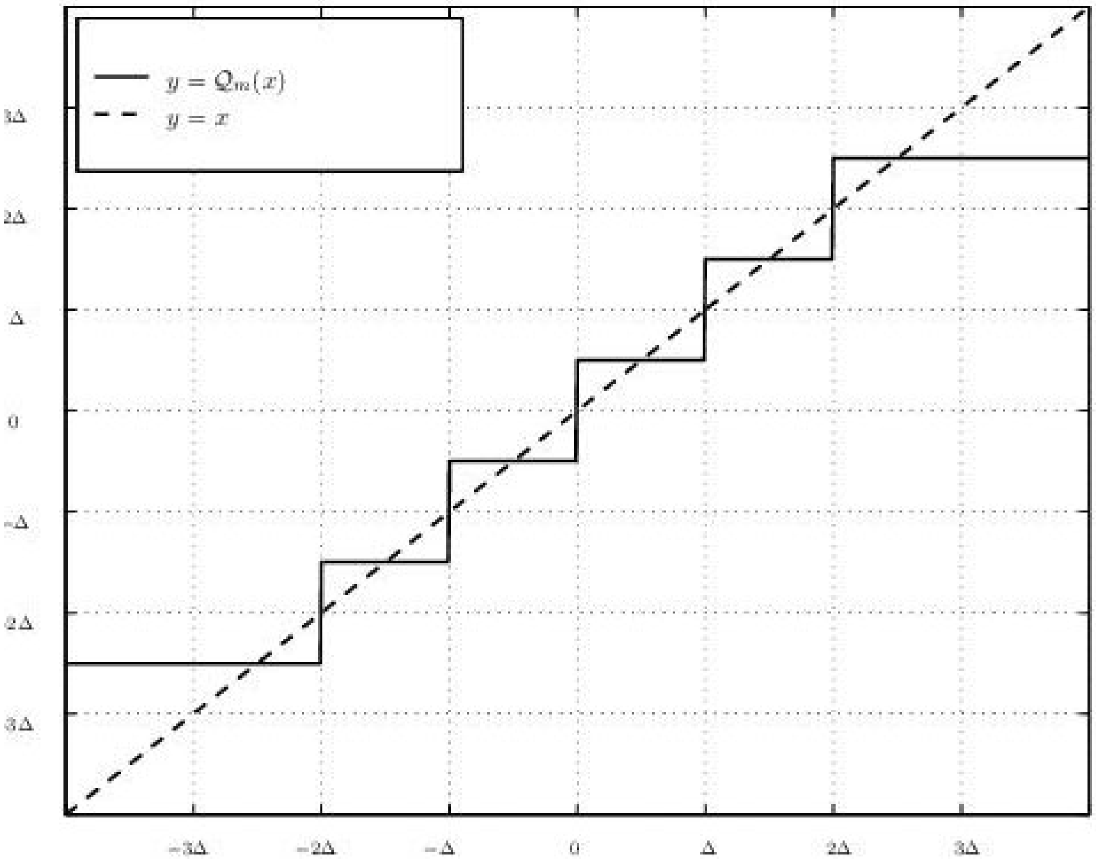
Quantization



Motivations

- Inexpensive hardware
  Integer, fix-point
- Sensor Networks

$$y_t = Q(x_t + e_t)$$

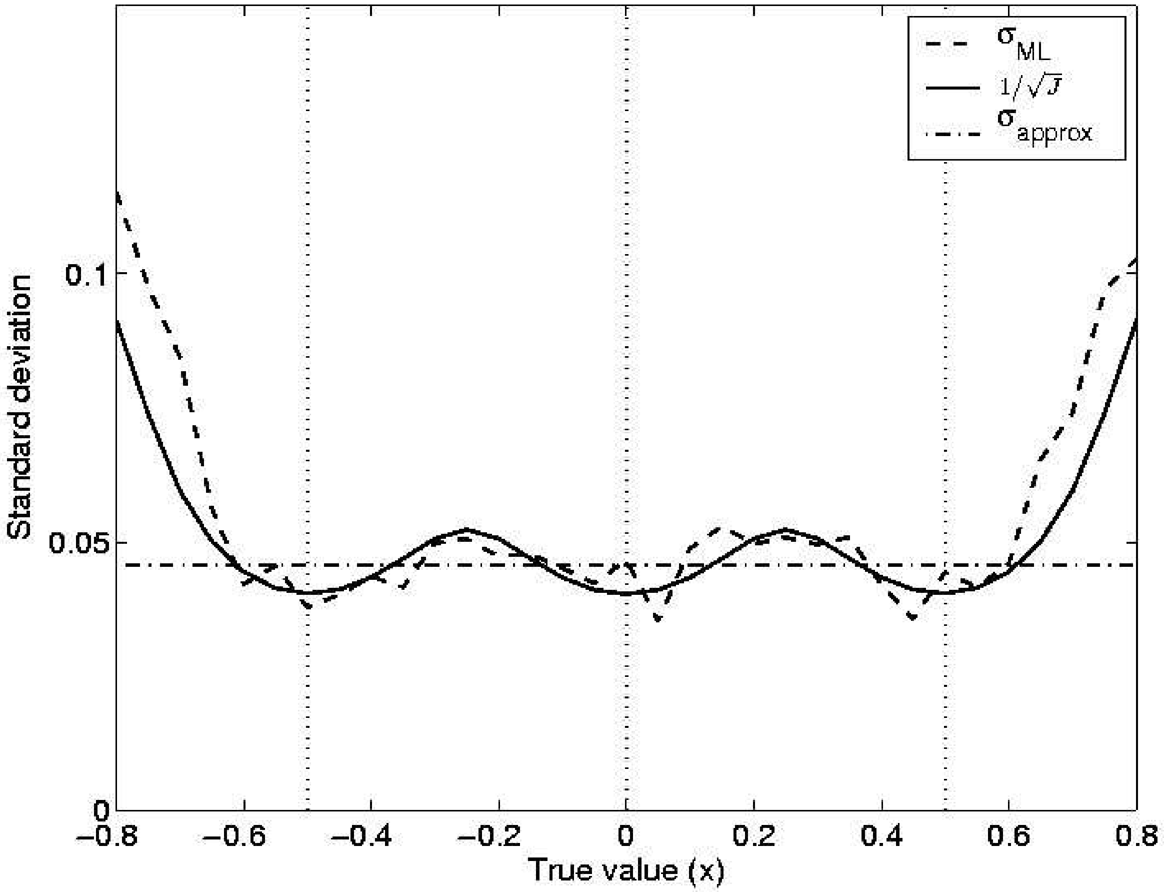
What’s done, some results

- Analytical Results (one-bit, multi-level quantization)
  - ML-estimate
  - CRLB

- Static System

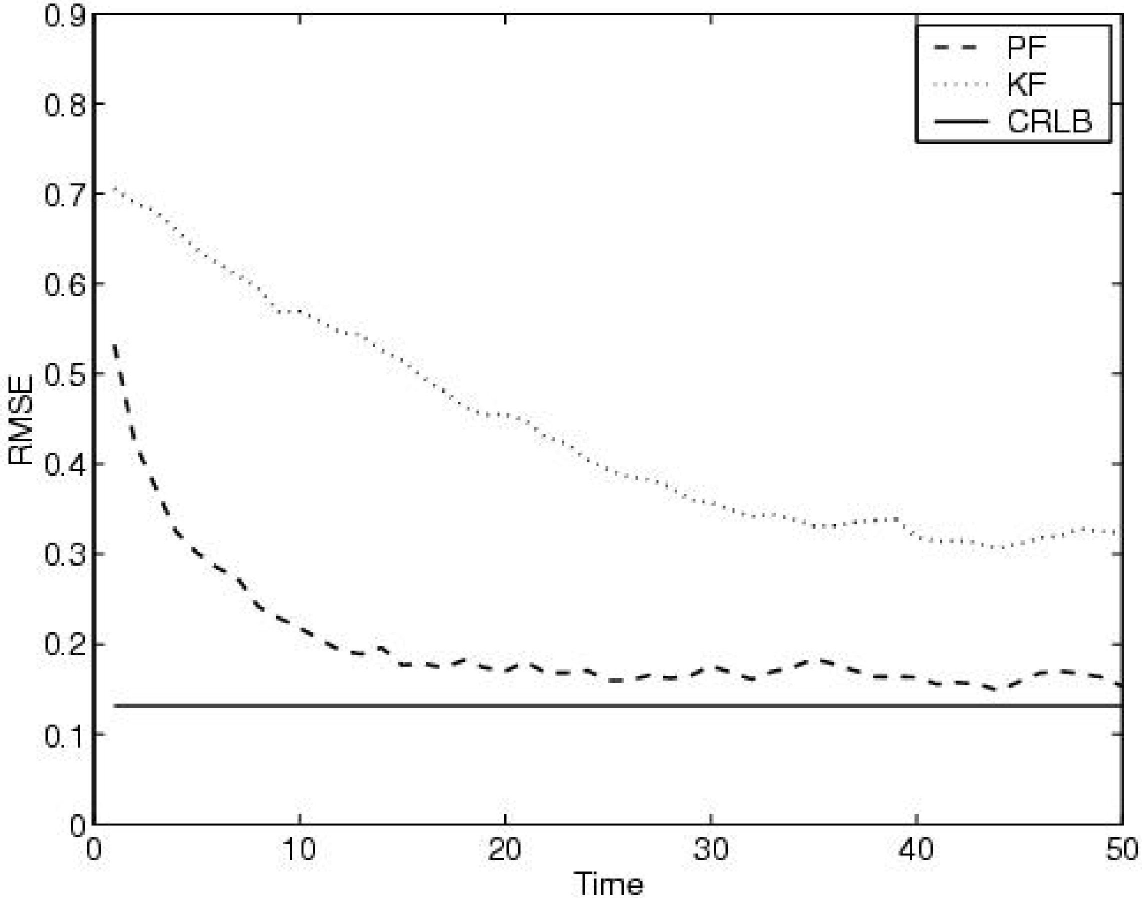
- Dynamic System

Static: Multi-Level Quantization



- $m = 3$ Levels
- $\Delta = \frac{1}{2}$
- MC runs: 20
- Measurements $N = 20$
- $\sigma^2 = \frac{\Delta^2}{12} = 0.14^2$

Dynamic: One-bit Quantization



Using 5 measurements/time

$$y_t = sign(x_t + e_t)$$

PF: correct likelihood

KF: approx. likelihood


The End
ISIS
Target Tracking
Collision Avoidance
Positioning
Analysis