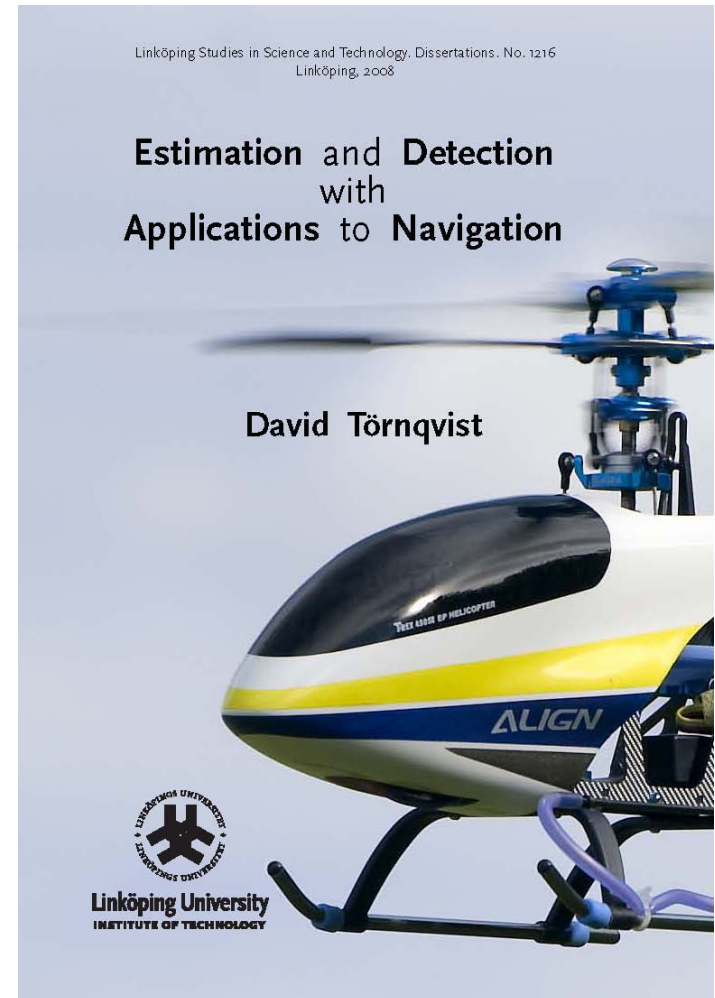


# An Overview of My Thesis

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# Content Summary

## ■ Estimation

- Estimate position and map (SLAM) with particle filter
- Estimate target position (using positive and negative information)
- Use of sensors with different update rate in the particle filter

## ■ Detection

- Extension of the parity space method
- Detect disturbances/fault (eg magnetometer disturbances)
- Detection of spurious features



# Background



- SLAM – Simultaneous Localization and Mapping
- There is a large need in the UAV industry to have a backup navigation system, independent of GPS



# Particle Filter SLAM

- Typically, the SLAM-problem has been addressed for ground vehicles with a low dimensional vehicle model  $(x, y, \theta)$
- We want to make full 3D SLAM with a particle filter and use a high dimensional vehicle model
- This allows us to:
  - Make better predictions of the vehicle position and orientation.
  - Filter measurements of accelerations and angular velocity rather than just integrating them.



- Make the following partition of the states  $x = \begin{pmatrix} x^v \\ m \end{pmatrix}$
- Estimate the vehicle model  $x^v$  with a particle filter
- For each particle, estimate the map  $m$  with a Kalman filter

$$p(x_{1:t}^v, m_t | y_{1:t}) = p(x_{1:t}^v | y_{1:t}) \underbrace{p(m_t | x_{1:t}^v, y_{1:t})}_{\prod_i \mathcal{N}(\hat{m}_{i,t}, \Sigma_i)}$$

- The last factorization lowers the complexity from quadratic to linear in the number of map entries!



# Extra Rao-Blackwellizing

- An extra Rao-Blackwellizing is made for the vehicle model
- Observe that the Kalman filter is partitioned
  - One covariance matrix for the linear states in the vehicle model (blue)
  - One covariance matrix for each map entry (black)

$$p(x_{1:t}^p, x_t^k, m_t | y_{1:t})$$
$$= \underbrace{p(x_{1:t}^p | y_{1:t})}_{\text{particle filter}} \underbrace{p(x_t^k | x_{1:t}^p, y_{1:t}) \prod_{j=1}^{M_t} p(m_{j,t} | x_{1:t}^p, x_t^k, y_{1:t})}_{\text{(extended) Kalman filter}}$$



# Flight Campaign

- Helicopter, Yamaha RMAX
- Revinge, Sweden



# Results



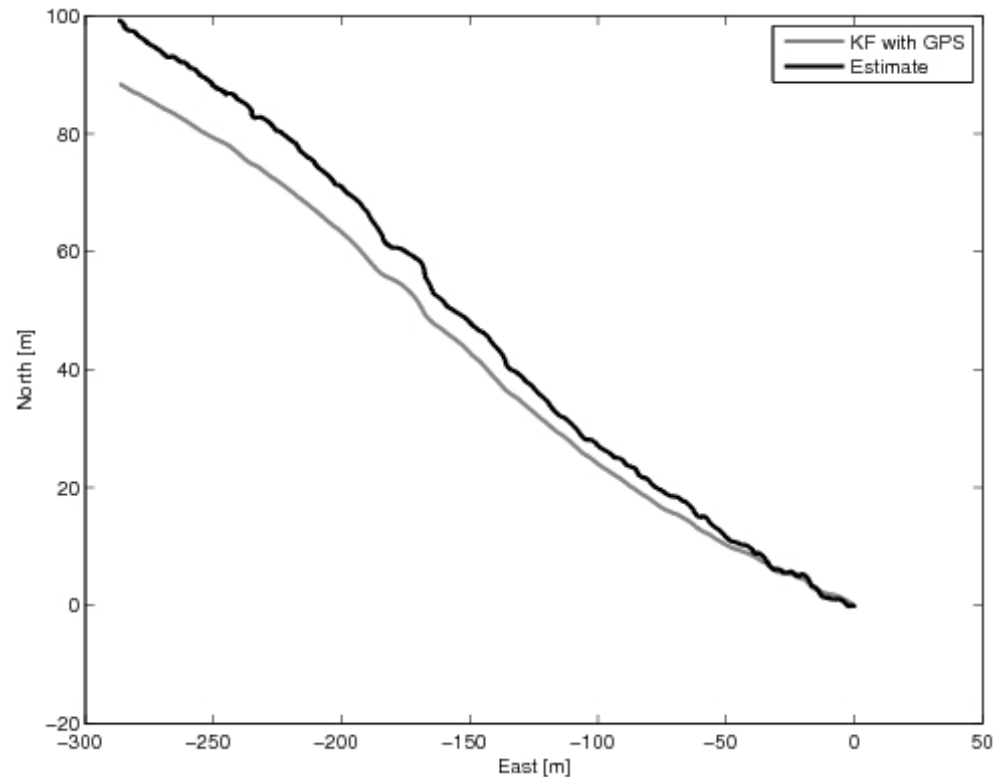
- New map entry
- + Measured map entry
- Particle for position





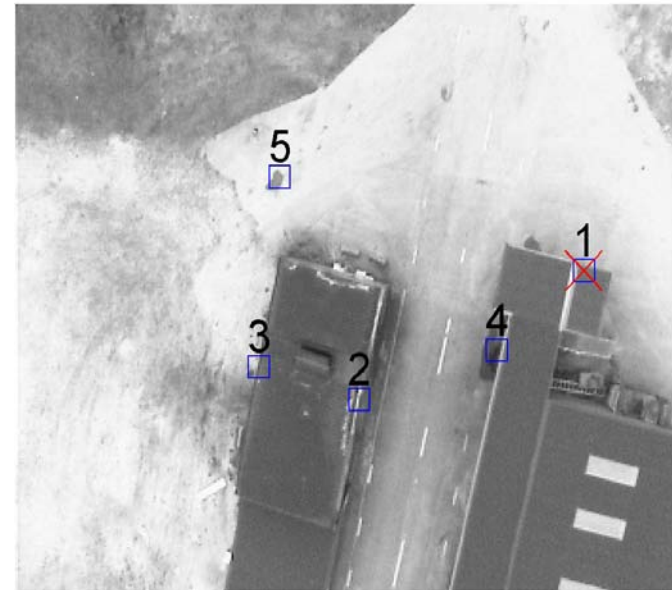
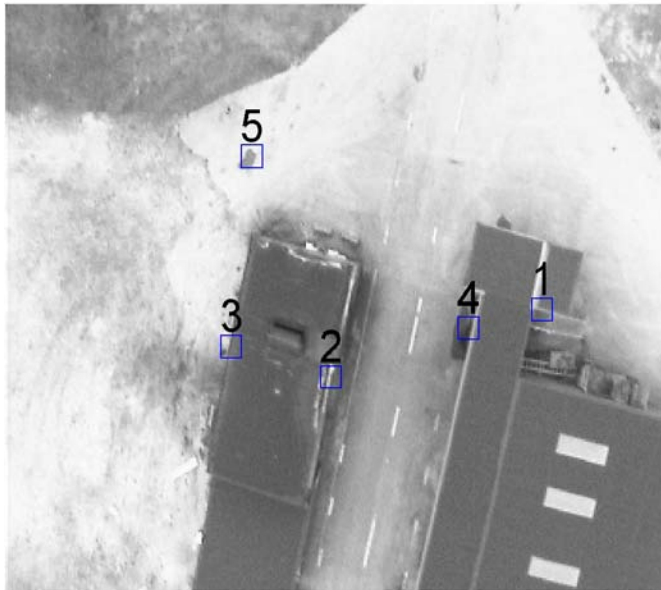
# Results

- Low drift in position over a 300m distance.



# Feature Detection for SLAM

- Features are detected in the image
- Corresponding features should be found in the next image



- Correspondence sometimes faulty, must be detected!

# Parity Space – Idea

- Is output data consistent with the model over a time-window?
- Algorithm:
  - A projection removes outputs consistent with the model
  - Only noise and faults are left
  - GLR-test determines if there are faults



# Parity Space – Projection

- Eliminate influence of the initial state by projection, standard method (Chow and Willsky, 1984).

- Model description over time-window

$$\mathbb{Y} = \mathcal{O}x + \bar{H}_f\mathbb{F} + \bar{H}_v\mathbb{V} + \mathbb{E}$$

$x$  is the initial state, can also include unknown parameters.

- The residual is formed as

$$r = \mathcal{P}_{\mathcal{O}\perp}\mathbb{Y} = \mathcal{P}_{\mathcal{O}\perp}(\bar{H}_f\mathbb{F} + \bar{H}_v\mathbb{V} + \mathbb{E})$$



# Parity Space – GLR Test

- Form the following hypothesis test

$$\mathcal{H}_0 : r \sim N(0, S),$$

$$\mathcal{H}_1 : r \sim N(\mathcal{P}_{\mathcal{O}^\perp} \bar{H} f \mathbb{F}, S).$$

- If the noises are Gaussian a Chi-square variable results from the GLR-test

$$L = \bar{r}^T \mathcal{P}_{W^T \bar{H} f} \bar{r} \sim \chi_\nu'^2(\lambda)$$

- Central or non-central Chi-square distribution determines if a fault is present or not.



# Feature Modeling

- Model with stationary features
- Pinhole camera model
- The measurement model is linearized

“Unknown” parameters

$$m_{i,t+1} = m_{i,t}$$

$$y_{i,t} = \frac{1}{z_{i,t}^c} \begin{pmatrix} x_{i,t}^c \\ y_{i,t}^c \end{pmatrix} = \frac{1}{z_{i,t}^c} \begin{pmatrix} I & 0 \end{pmatrix} R_t(m_{i,t} - p_t) + e_{i,t}$$

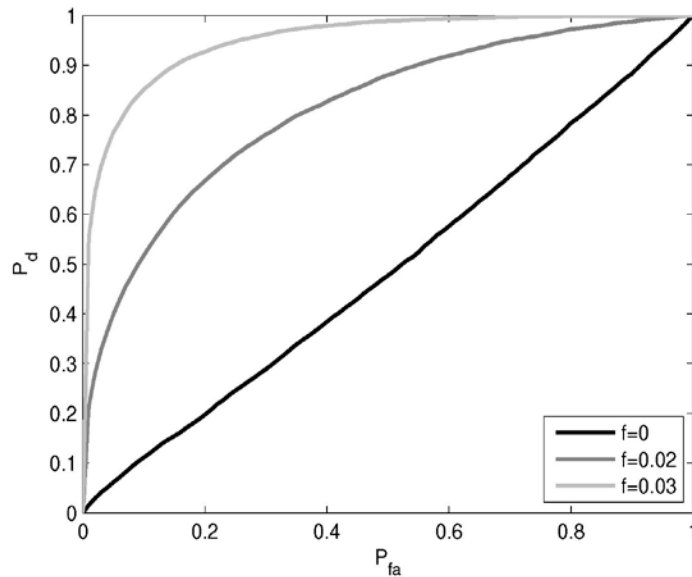
where  $m_{i,t}^c = \begin{pmatrix} x_{i,t}^c \\ y_{i,t}^c \\ z_{i,t}^c \end{pmatrix} = R_t(m_{i,t} - p_t).$



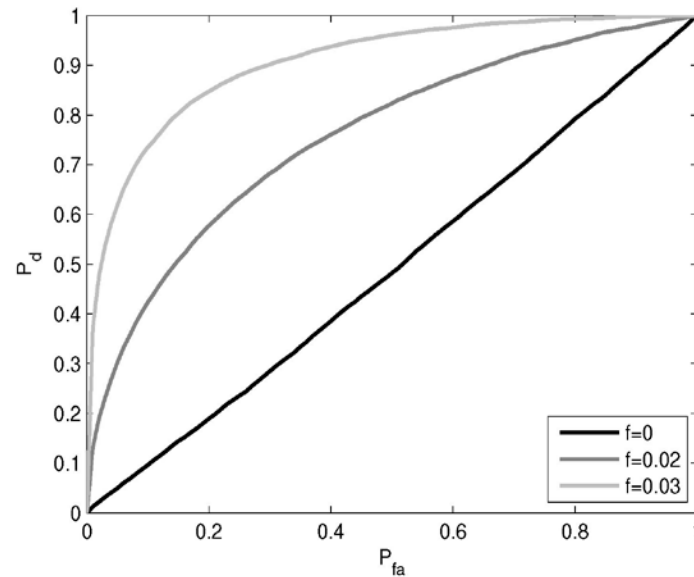
# Simulation Example –

## Detection Performance

- Receiver Operation Characteristics (ROC)
- More powerful test when the position is accurately estimated



Position estimated

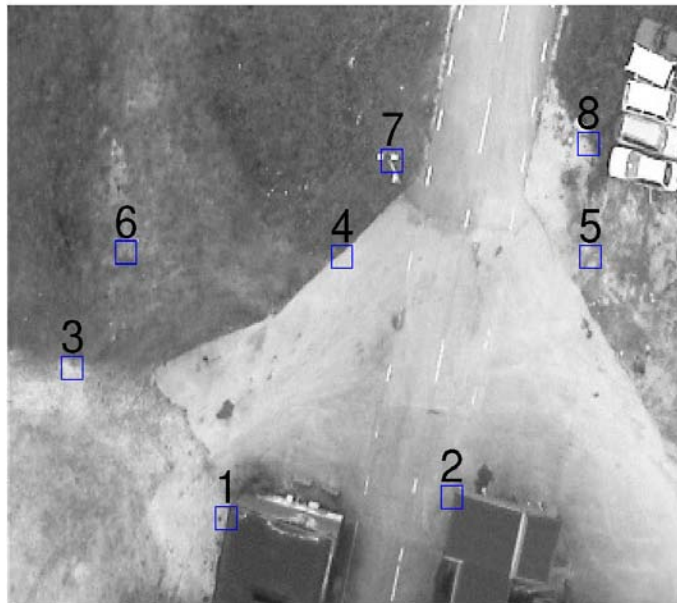


Position projected away



# Real-World Example – Autonomous Helicopter

- Simultaneous Localization and Mapping (SLAM)
- Flying a 300m distance at 60m altitude
- Divergence without spurious feature detection





# Advantages with this Method



- Rejects spurious features with *statistical methods*
- A *combination* of IMU and camera is used
- A time window of *several images* can be used
- Successful implementations



# Thank you for listening!

## Questions?

