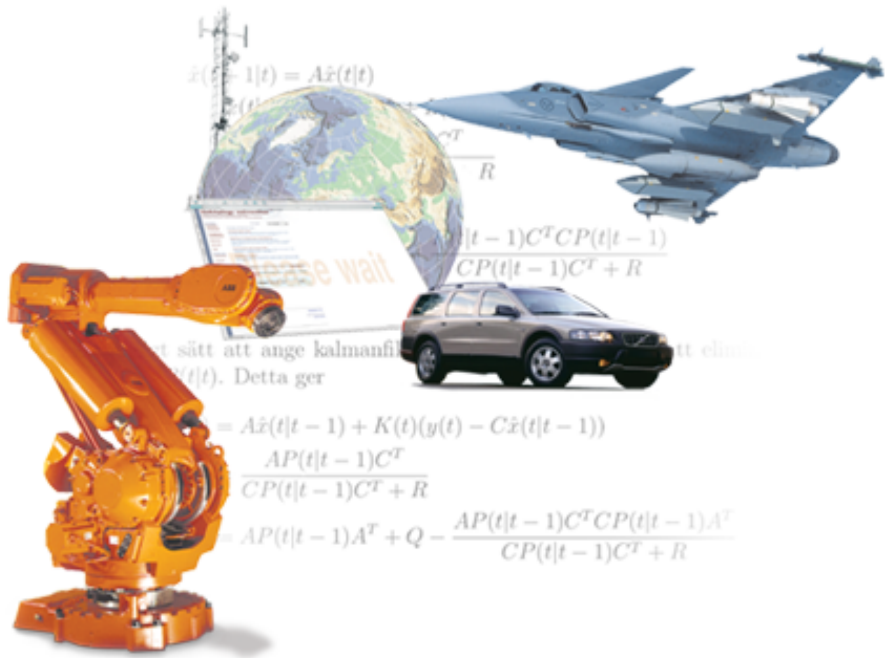
Sensor fusion in dynamical systems -

applications and research challenges



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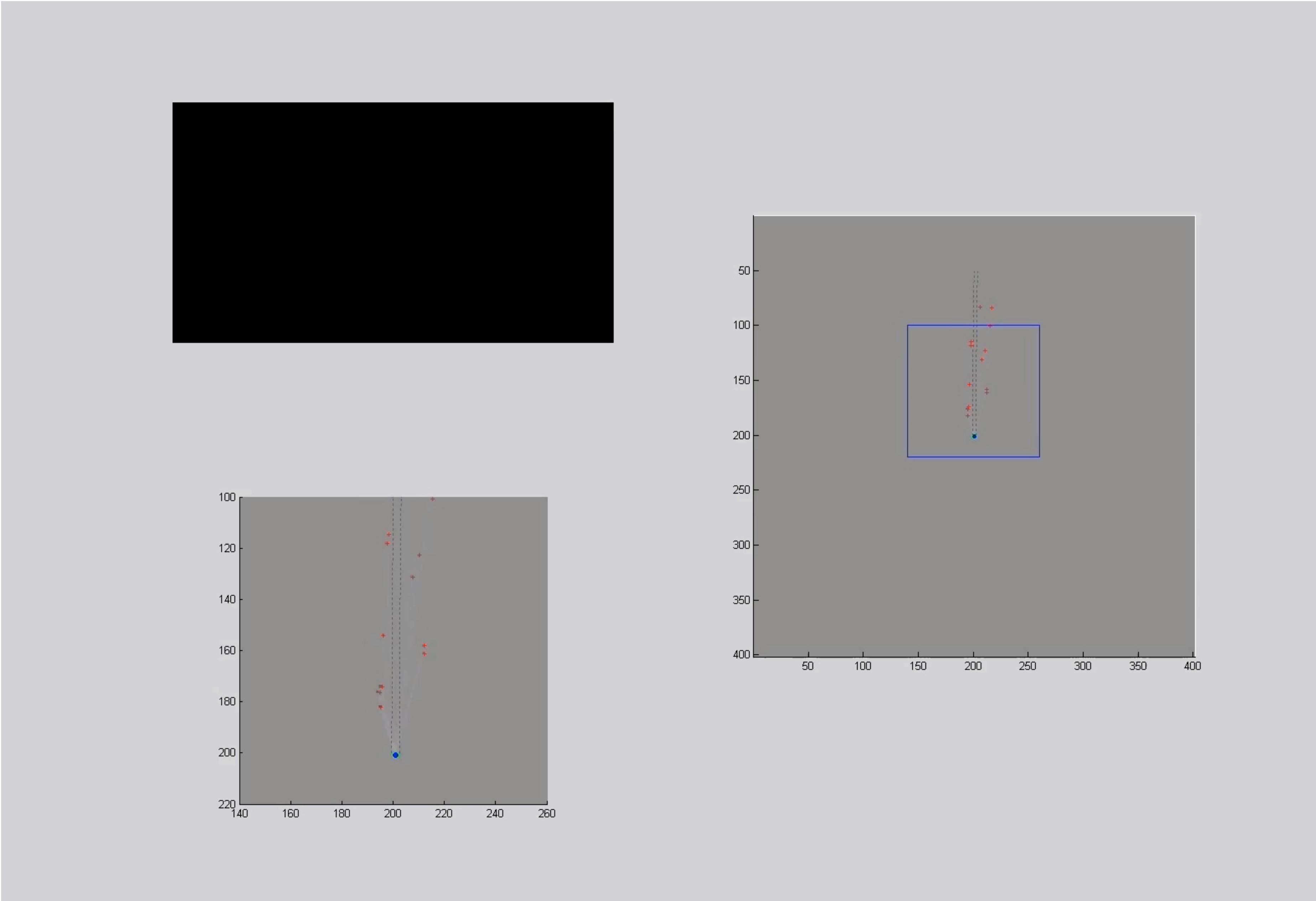
users.isy.liu.se/rt/schon

Joint work with (in alphabetical order): **Jonas Callmer** (*LiU*), **Andreas Eidehall** (*Volvo cars*), **David Forslund** (Autoliv), **Andreas Gising** (*Cybaero*), **Fredrik Gustafsson** (*LiU*), **Joel Hermansson** (*Cybaero*), **Jeroen Hol** (*Xsens*), **Johan Kihlberg** (*Xdin*), **Fredrik Lindsten** (*LiU*), **Henk Luinge** (*Xsens*), **Christian Lundquist** (*LiU*), **Johan Nordlund** (Saab), **Henrik Ohlsson** (*Berkeley*), **Jacob Roll** (*Autoliv*), **Simon Tegelid** (Xdin) and **David Törnqvist** (*LiU*).

A first example - automotive sensor fusion

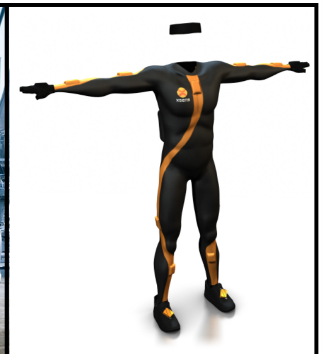


The sensor fusion problem

- Inertial sensors
- Camera
- Barometer

- Inertial sensors
- Radar
- Barometer
- Map

- Inertial sensors
- Cameras
- Radars
- Wheel speed sensors
- Steering wheel sensor



- Inertial sensors
- Ultra-wideband

How do we combine the information from the different sensors?

Might all seem to be very different problems at first sight. However, the same strategy can be used in dealing with all of these applications.

Outline

Sensor fusion

1. Dynamical systems
2. Sensors
3. World model
4. "Surrounding infrastructure"

Application examples

1. Vehicle motion estimation using night vision
2. Fighter aircraft navigation
3. Autonomous helicopter landing
4. Helicopter pose estimation using a map
5. Indoor positioning using a map
6. Indoor human motion estimation

1. Dynamical systems - probabilistic models

We are dealing with **dynamical** systems!

We model a dynamical system using **probability density functions (PDFs)**

State

Known input

$$x_{t+1} \mid x_t \sim f_\theta(x_{t+1} \mid x_t, u_t),$$ Dynamics

Measurements $\longrightarrow$ $$y_t \mid x_t \sim h_\theta(y_t \mid x_t, u_t),$$ Measurements

$$x_1 \sim \mu_\theta(x_1).$$ Initial state

$$\dot{x} = f(x, u, \theta)$$

Static parameters

Model = PDF

"The present state of a dynamical system depends on its history."

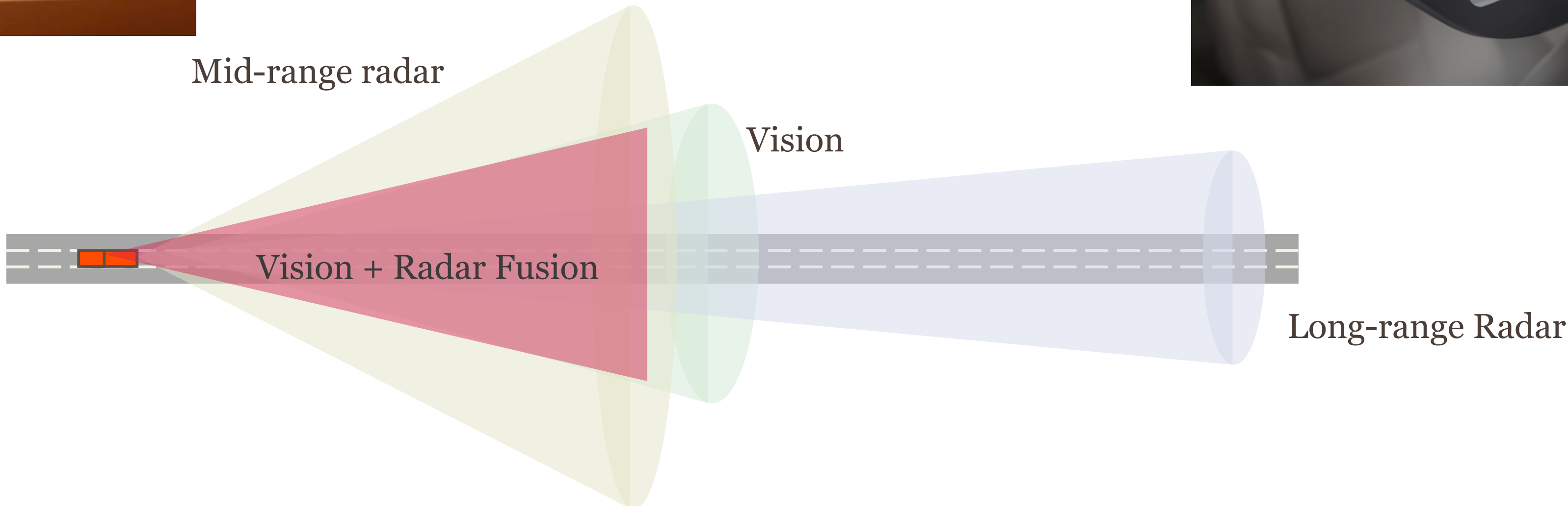
The state process is hidden (latent) and it is observed indirectly via the measurement process.

Often referred to as a **state space model (SSM)** or a **hidden Markov model (HMM)**.

2. Perception - sensors

The dynamical systems must be able to perceive their own (and others') motion, as well as the surrounding world.

This requires **sensors**.



Traditionally each sensor has been associated with its own field, this is now changing. Hence, you should not be afraid to enter and learn new fields!

Sensor fusion is multi-disciplinary

3. World model

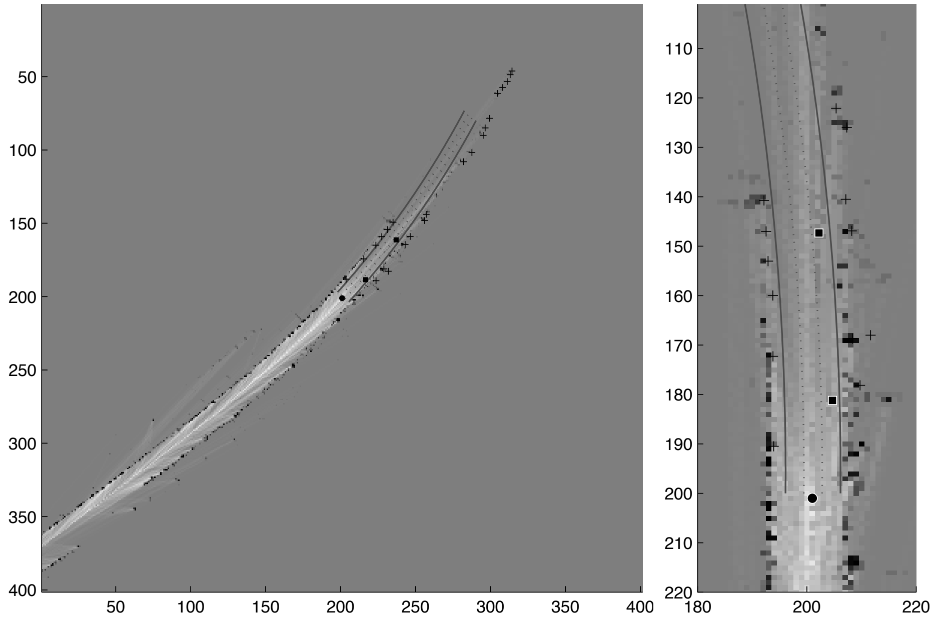
The dynamical systems exist in a context.

This requires a **world model**.

Valuable (indeed often necessary) source of information in computing situational awareness.

We will see two different uses of world models:

- Pre-existing world models, e.g., various maps
- Build world models on-line



(a) (b)


(c)

4. The “surrounding infrastructure”

Besides models for dynamics, sensors and world, a successful sensor fusion solution heavily relies on a well functioning “surrounding infrastructure”.

This includes for example:

- Time synchronization of the measurements from the different sensors
- Mounting of the sensors and calibration
- Computer vision, radar processing
- Etc...

An example:

Relative pose calibration:

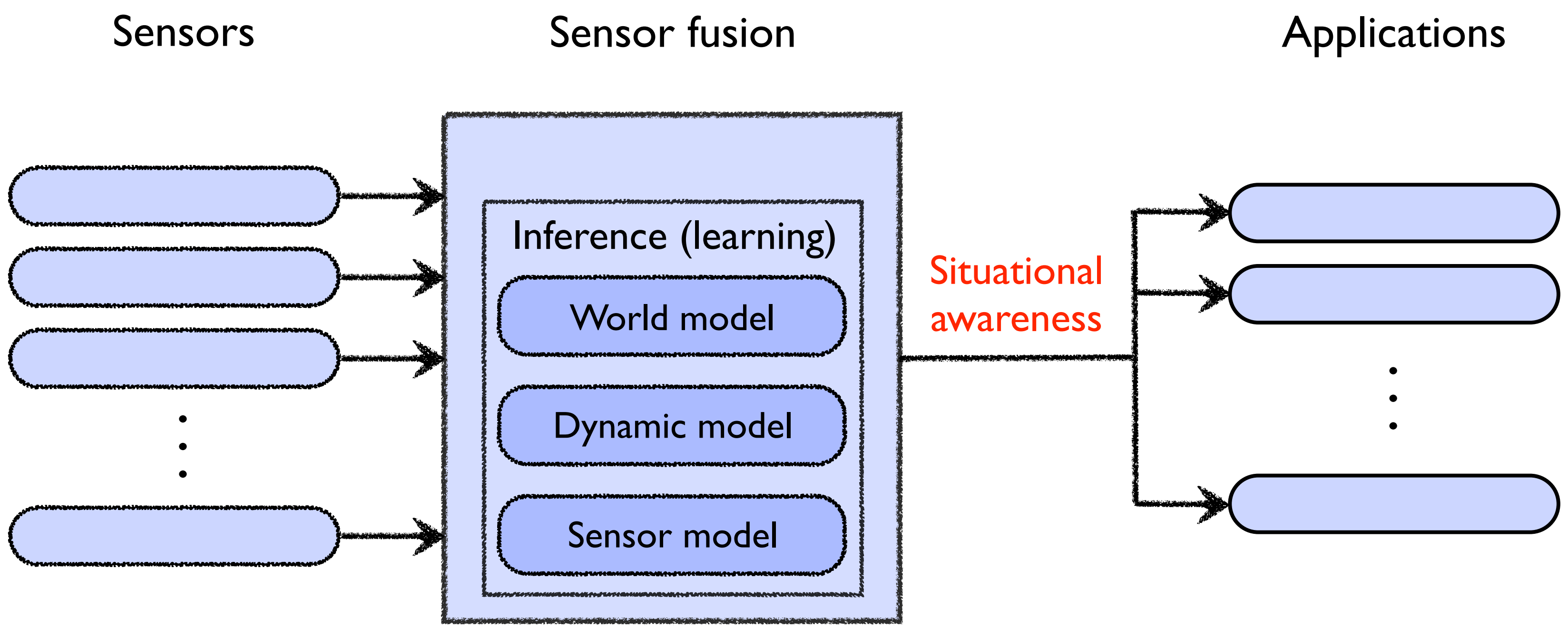
Compute the relative translation and rotation of the camera and the inertial sensors that are rigidly connected.

Jeroen D. Hol, Thomas B. Schön and Fredrik Gustafsson. **Modeling and Calibration of Inertial and Vision Sensors**. *International Journal of Robotics Research (IJRR)*, 29(2):231-244, February 2010.

Sensor fusion

Definition (sensor fusion)

Sensor fusion is the process of using information from **several different** sensors to **infer (learn)** what is happening (this typically includes states of various dynamical systems and various static parameters).



Inference

The inference problem amounts to **combining** the knowledge we have from the models (dynamic, world, sensor) and from the measurements.

The **aim** is to compute

$$p(x_{1:t}, \theta \mid y_{1:t})$$

and/or some of its marginal densities,

$$p(x_t \mid y_{1:t})$$
$$p(\theta \mid y_{1:t})$$

These densities are then commonly used to form point estimates, **maximum likelihood** or **Bayesian**.

- Everything we do rests on a firm foundation of probability theory and mathematical statistics.
- If we have the wrong model, there is no estimation/learning algorithm that can help us.

Inference - the filtering problem

$$p(x_t \mid y_{1:t}) = \frac{\overbrace{p(y_t \mid x_t)}^{\text{sensor model}} \overbrace{p(x_t \mid y_{1:t-1})}^{\text{prediction density}}}{p(y_t \mid y_{1:t-1})}$$

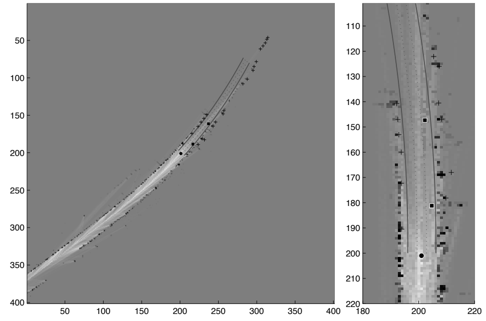
$$p(x_{t+1} \mid y_{1:t}) = \int \underbrace{p(x_{t+1} \mid x_t)}_{\text{dynamical model}} \underbrace{p(x_t \mid y_{1:t})}_{\text{filtering density}} dx_t$$

In the application examples these equations are solved using particle filters (PF), Rao-Blackwellized particle filters (RBPF), extended Kalman filters (EKF) and various optimization based approaches.

The story I am telling

1. We are dealing with dynamical systems

This requires a **dynamical model**.



2. The dynamical systems exist in a context.

This requires a **world model**.

3. The dynamical systems must be able to perceive their own (and others') motion, as well as the surrounding world.

This requires sensors and **sensor models**.

4. We must be able to transform the information from the sensors into knowledge about the dynamical systems and their surrounding world.

This requires **sensor fusion**.

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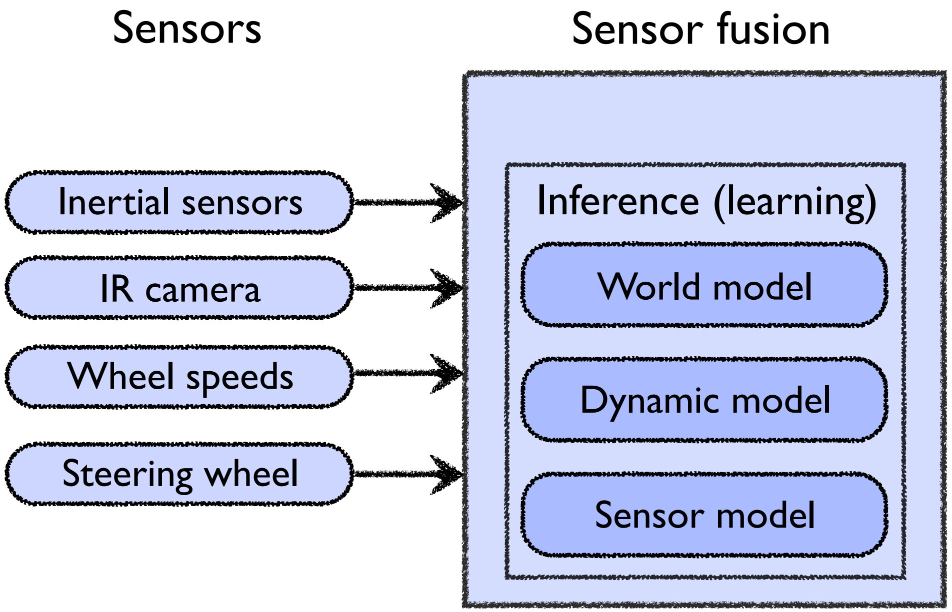
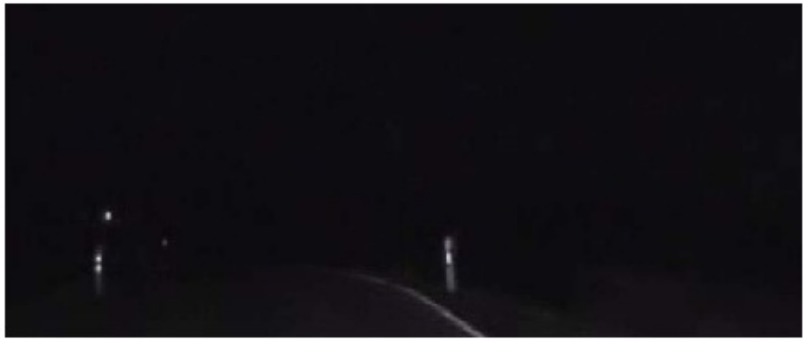
1.Vehicle motion estimation using night vision

Aim: Show how images from an infrared (IR) camera can be used to obtain better estimates of the ego-vehicle motion and the road geometry in 3D.

Industrial partner: Autoliv Electronics

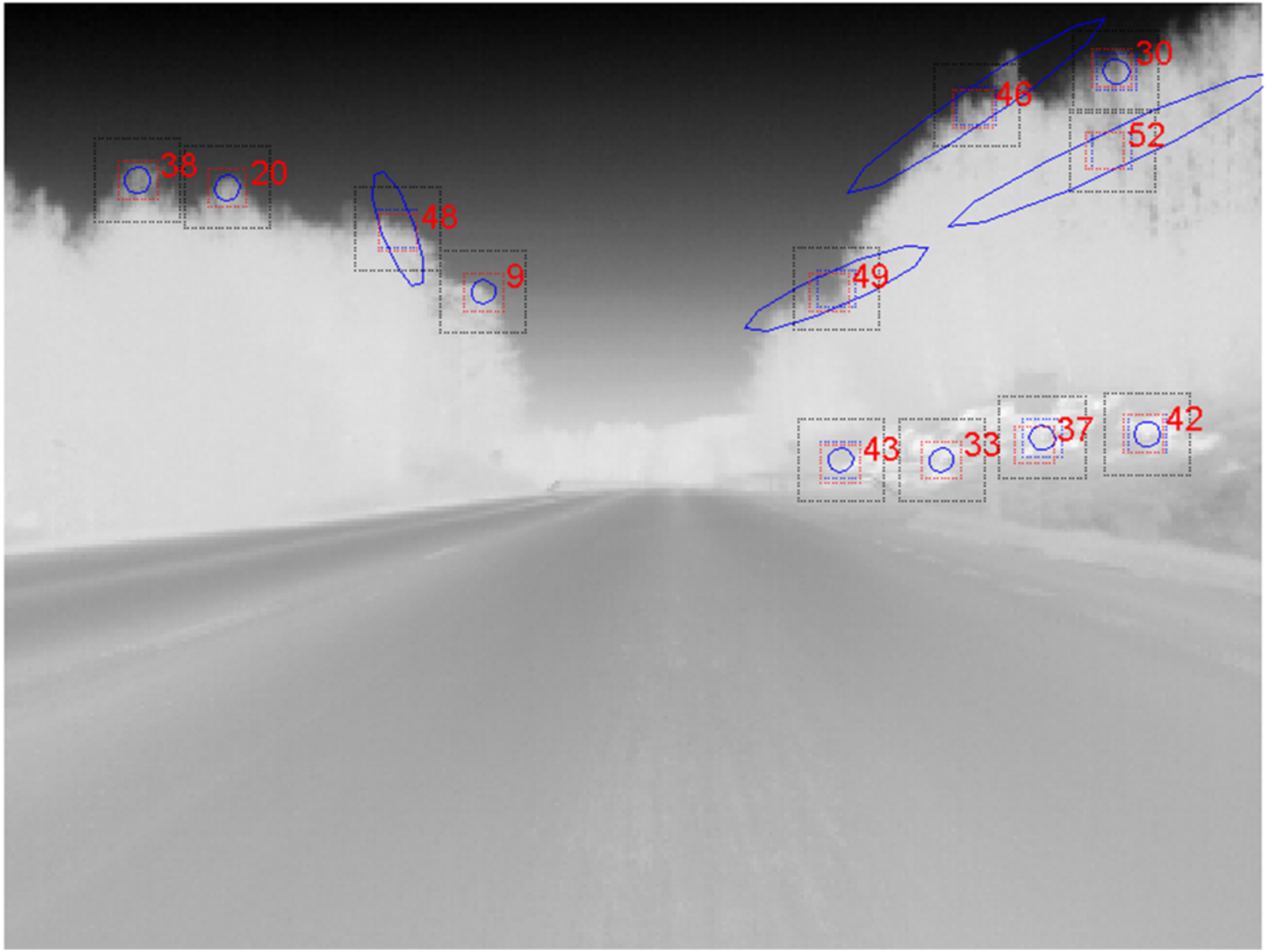




Road scene, as seen with a standard camera.

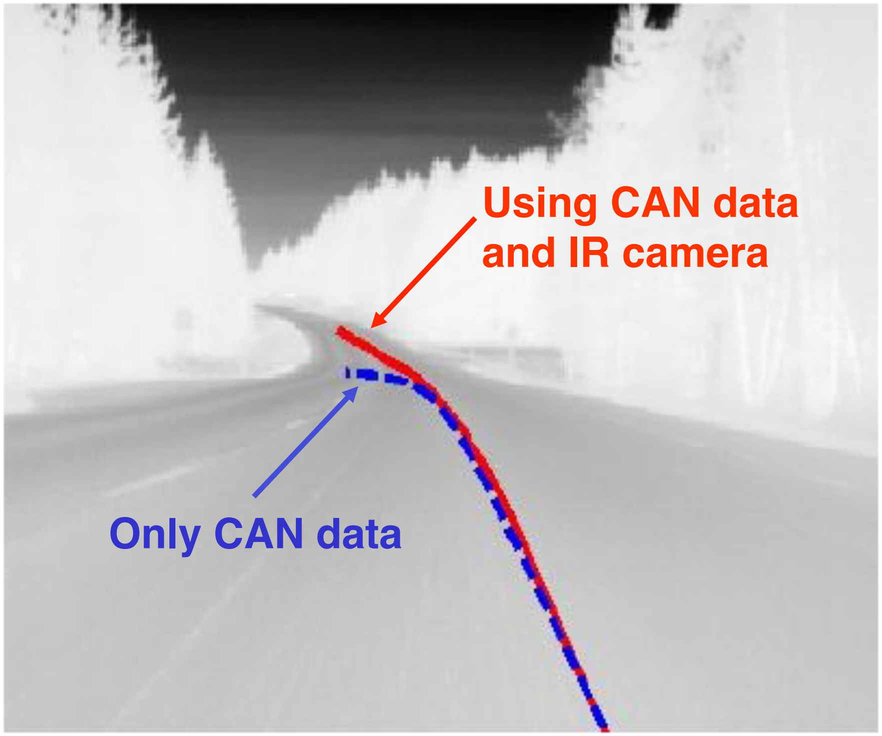
Same road scene as above, seen with the IR camera

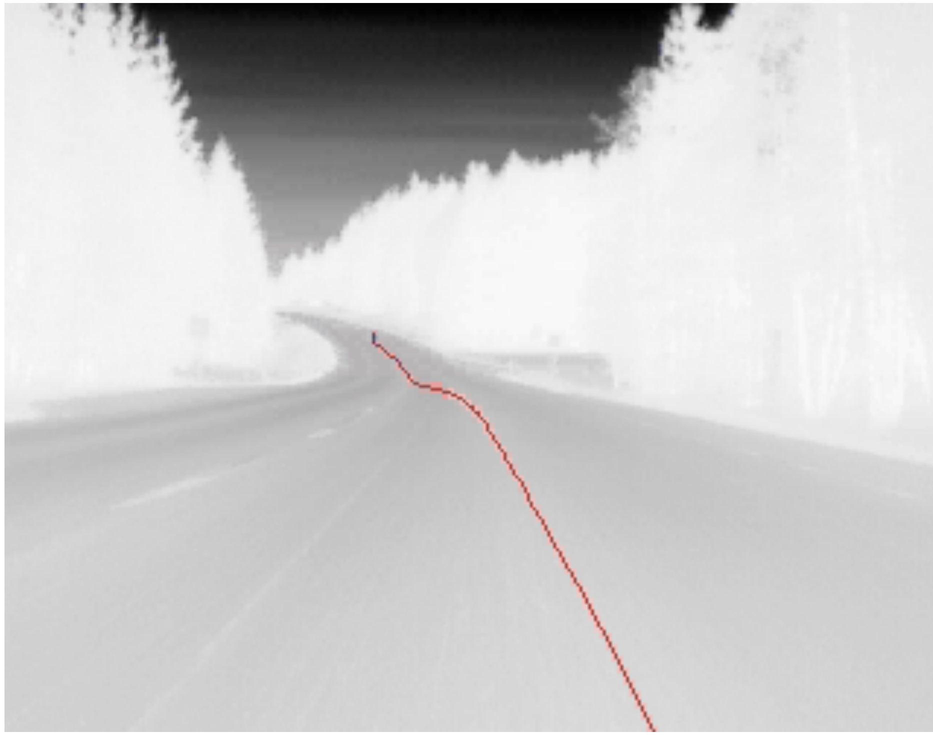
1. Vehicle motion estimation using night vision



1. Vehicle motion estimation using night vision - experiments

Results using measurements recorded during night time driving on rural roads in Sweden.





Showing the ego-motion estimates reprojected onto the images.

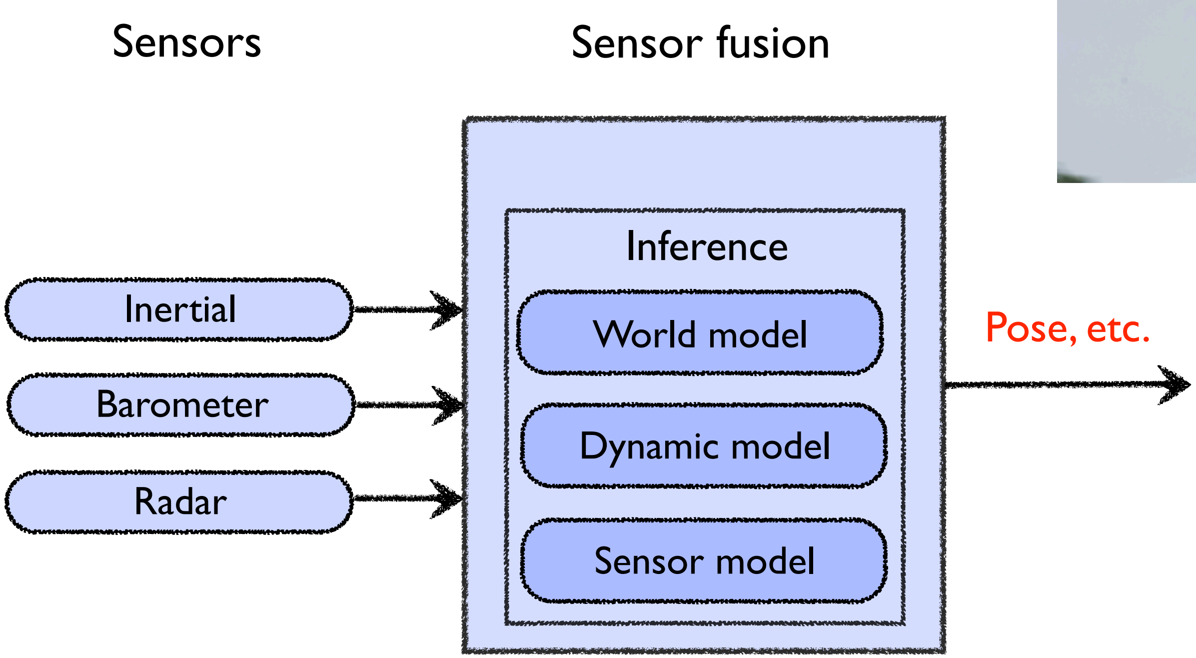
Emil Nilsson, Christian Lundquist, Thomas B. Schön, David Forslund and Jacob Roll, **Vehicle Motion Estimation Using an Infrared Camera**. *Proceedings of the 18th World Congress of the International Federation of Automatic Control (IFAC)*, Milan, Italy, August-September 2011.

Thomas B. Schön and Jacob Roll, **Ego-Motion and Indirect Road Geometry Estimation Using Night Vision**. *Proceedings of the IEEE Intelligent Vehicle Symposium (IV)*, Xi'an, Shaanxi, China, June 2009.

2. Fighter aircraft navigation

Aim: Find the position, velocity and orientation of a fighter aircraft.

Industrial partner: Saab



Particle filter - very brief introduction (I/II)

The particle filter provides an approximation of the filter PDF

$$p(x_t \mid y_{1:t})$$

when the state evolves according to an SSM

$$\begin{aligned} x_{t+1} \mid x_t &\sim f(x_{t+1} \mid x_t, u_t), \\ y_t \mid x_t &\sim h(y_t \mid x_t, u_t), \\ x_1 &\sim \mu(x_1). \end{aligned}$$

The particle filter maintains an empirical distribution made up N samples (particles) and corresponding weights

$$\widehat{p}(x_t \mid y_{1:t}) = \sum_{i=1}^{N} w_t^i \delta_{x_t^i}(x_t)$$

This approximation converge to the true filter PDF,

Xiao-Li Hu, Thomas B. Schön and Lennart Ljung. **A Basic Convergence Result for Particle Filtering**. *IEEE Transactions on Signal Processing*, 56(4):1337-1348, April 2008.

Particle filter - very brief introduction (II/II)

The weights and the particles in

$$\widehat{p}(x_t \mid y_{1:t}) = \sum_{i=1}^{N} w_t^i \delta_{x_t^i}(x_t)$$

are updated as new measurements becomes available. This approximation can for example be used to compute an estimate of the mean value,

$$\widehat{x}_{t|t} = \int x_t p(x_t \mid y_{1:t}) \mathrm{d}x_t \approx \int x_t \sum_{i=1}^{N} w_t^i \delta_{x_t^i}(x_t) \mathrm{d}x_t = \sum_{i=1}^{N} w_t^i x_t^i$$

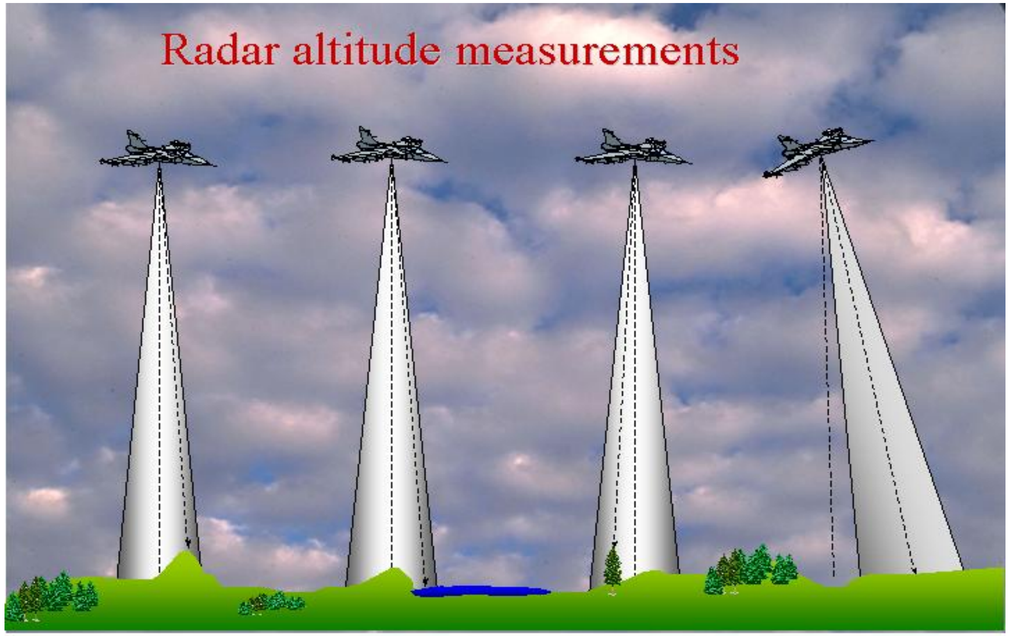
The theory underlying the particle filter has been developed over the past two decades and the theory and its applications are still being developed at a very high speed. For a timely tutorial, see

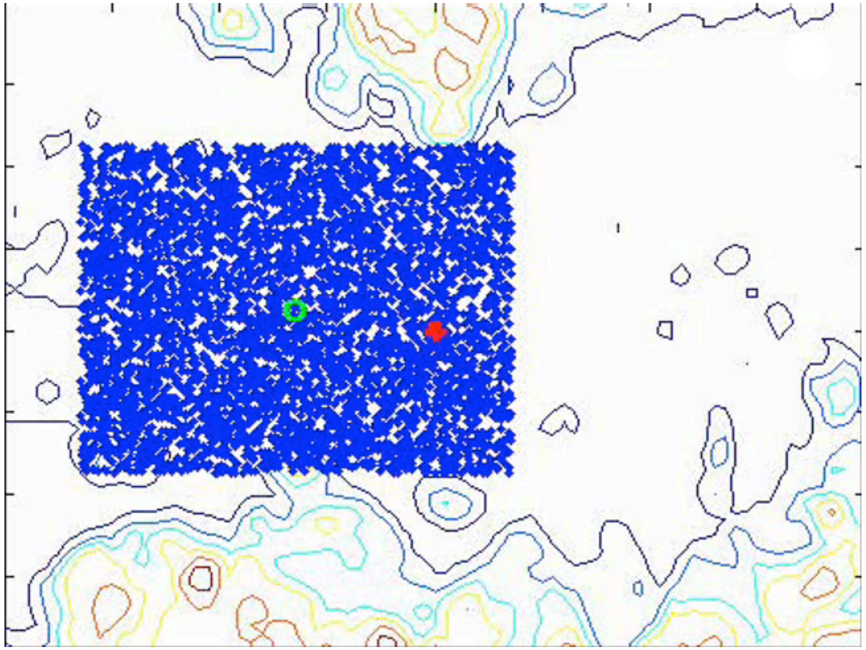
A. Doucet and A. M. Johansen. **A tutorial on particle filtering and smoothing: fifteen years later**. In *Oxford Handbook of Nonlinear Filtering*, 2011, D. Crisan and B. Rozovsky (eds.). Oxford University Press.

or my new PhD course on computational inference in dynamical systems

users.isy.liu.se/rt/schon/course_CIDS.html

2. Fighter aircraft navigation





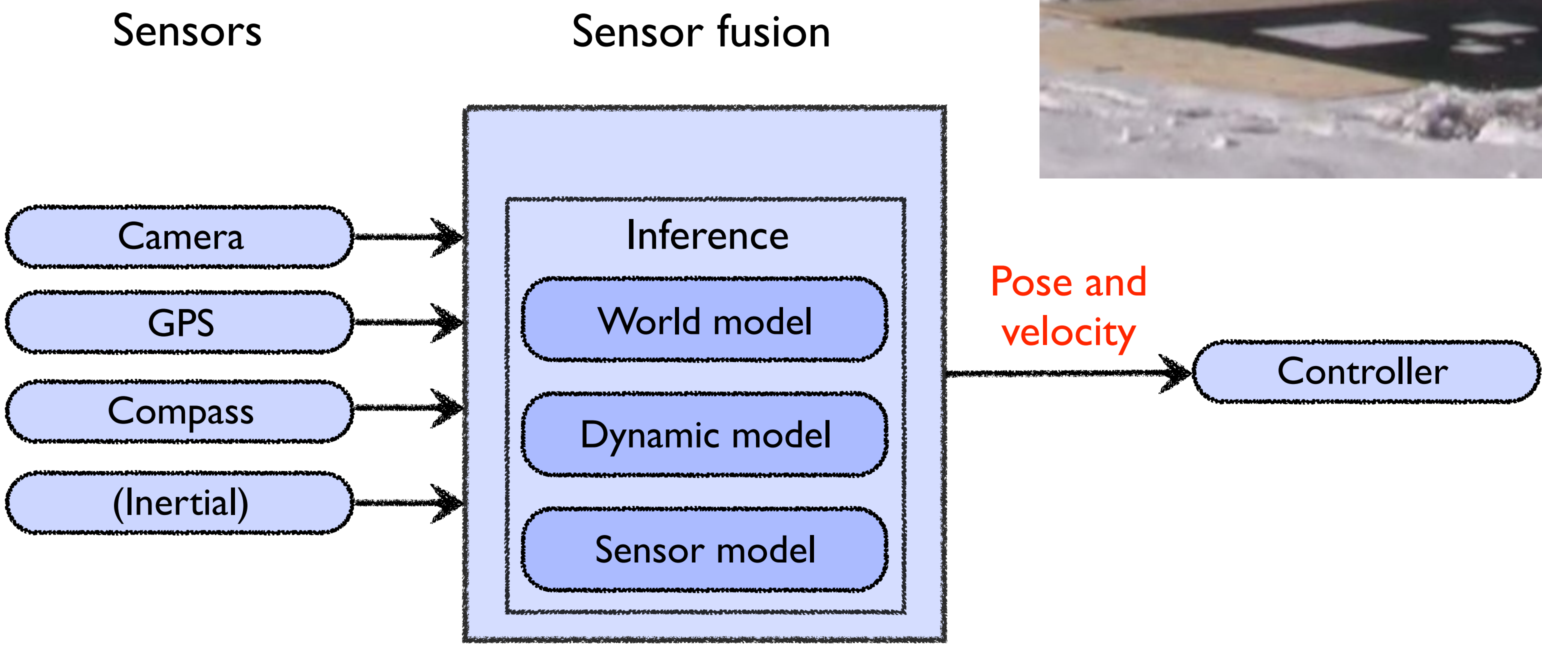
"Think of each particle as one simulation of the system state (in the movie, only the horizontal position is visualized). Only keep the good ones."

Thomas Schön, Fredrik Gustafsson, and Per-Johan Nordlund. **Marginalized Particle Filters for Mixed Linear/Nonlinear State-Space Models**. *IEEE Transactions on Signal Processing*, 53(7):2279-2289, July 2005.

3. Autonomous helicopter landing

Aim: Land a helicopter autonomously using information from a camera, GPS, compass and inertial sensors.

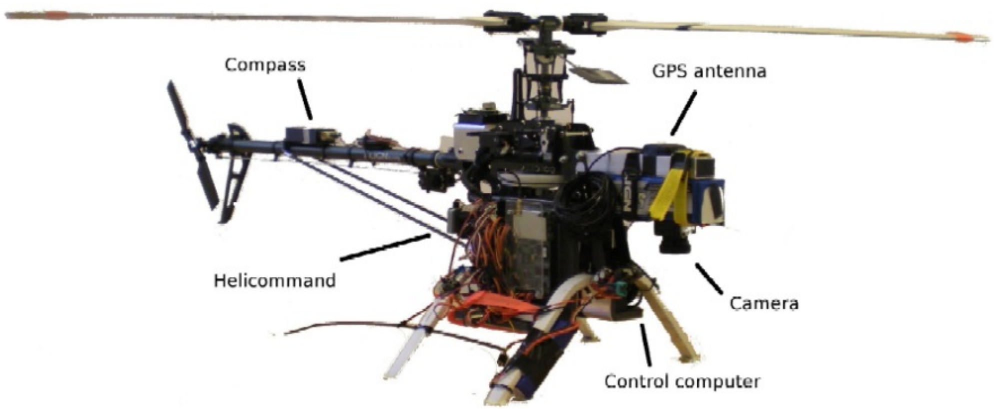
Industrial partner: Cybaero



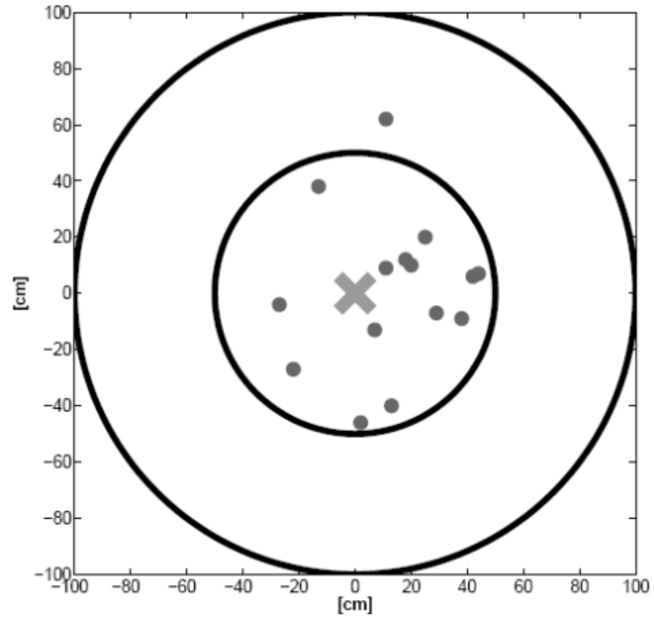
3. Autonomous helicopter landing

Experimental helicopter

- Weight: 5kg
- Electric motor



Results from 15 landings

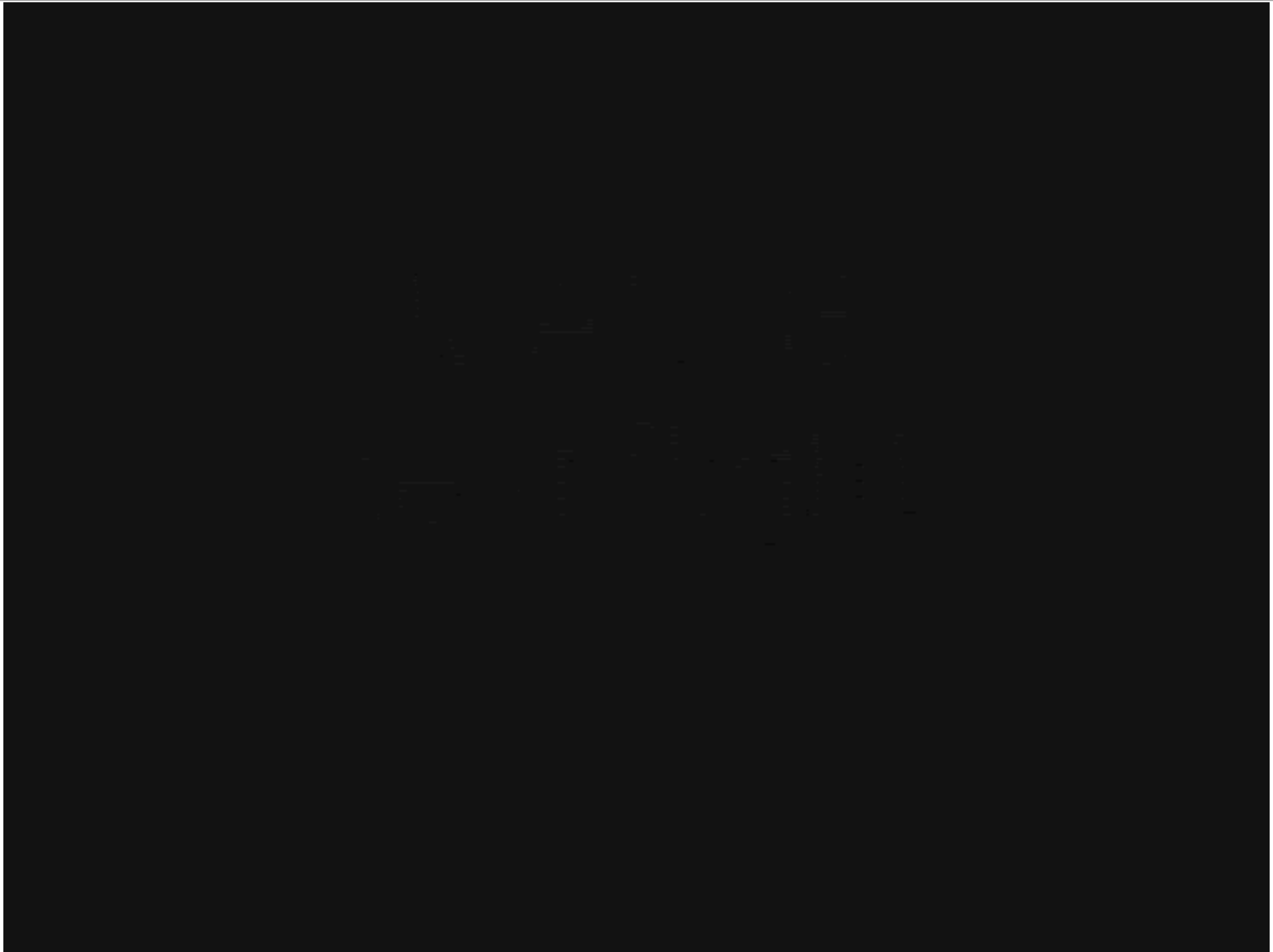


The two circles mark 0.5m and 1m landing error, respectively.

Dots = achieved landings
Cross = perfect landing

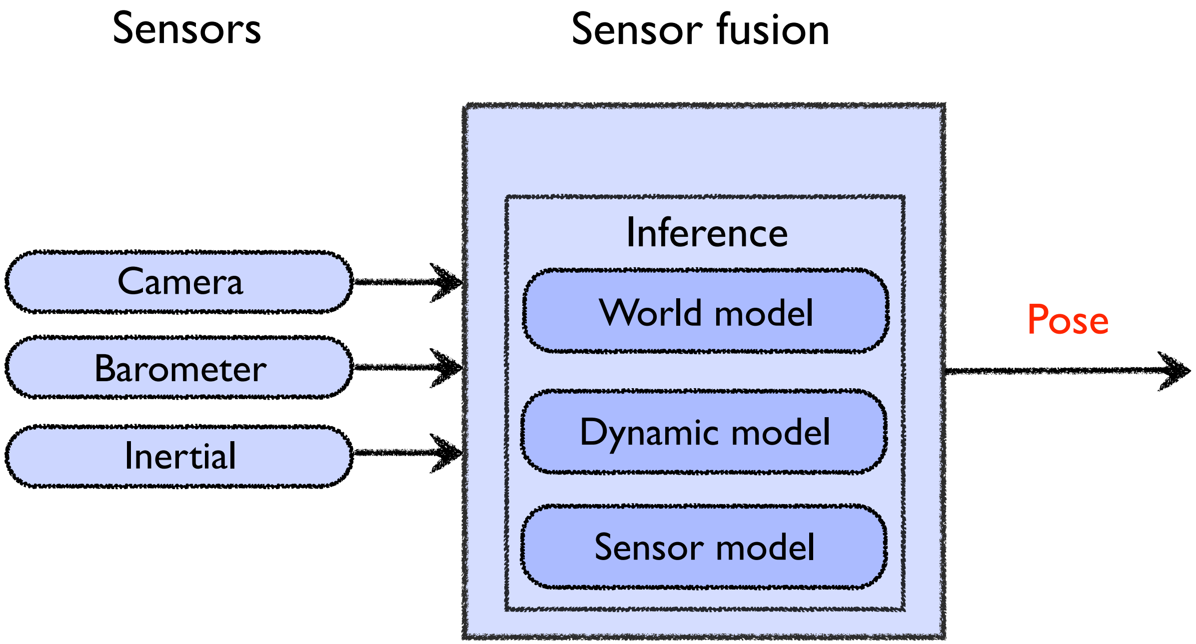
Joel Hermansson, Andreas Gising, Martin Skoglund and Thomas B. Schön. **Autonomous Landing of an Unmanned Aerial Vehicle**. *Reglermöte (Swedish Control Conference)*, Lund, Sweden, June 2010.

3. Autonomous helicopter landing



4. Helicopter pose estimation using a map

Aim: Compute the position and orientation of a helicopter by exploiting the information present in Google maps images of the operational area.



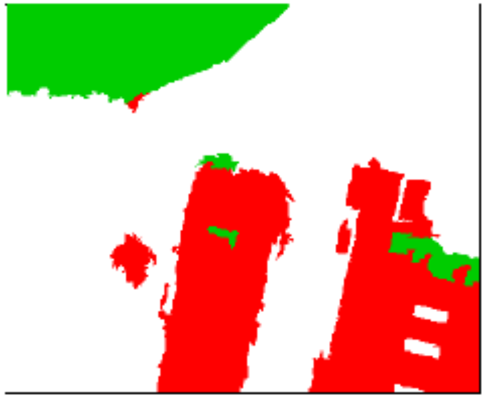
4. Helicopter pose estimation using a map

Map over the operational environment obtained from Google Earth.

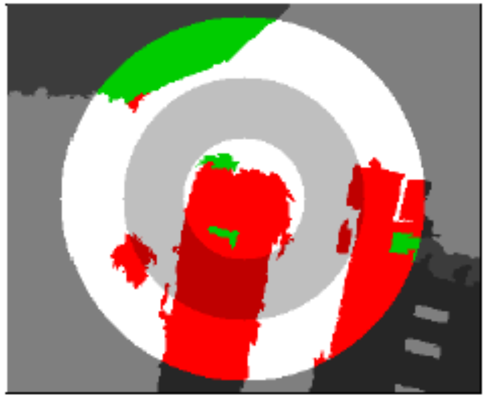
Manually classified map with grass, asphalt and houses as pre-specified classes.

Image from on-board camera

Extracted superpixels

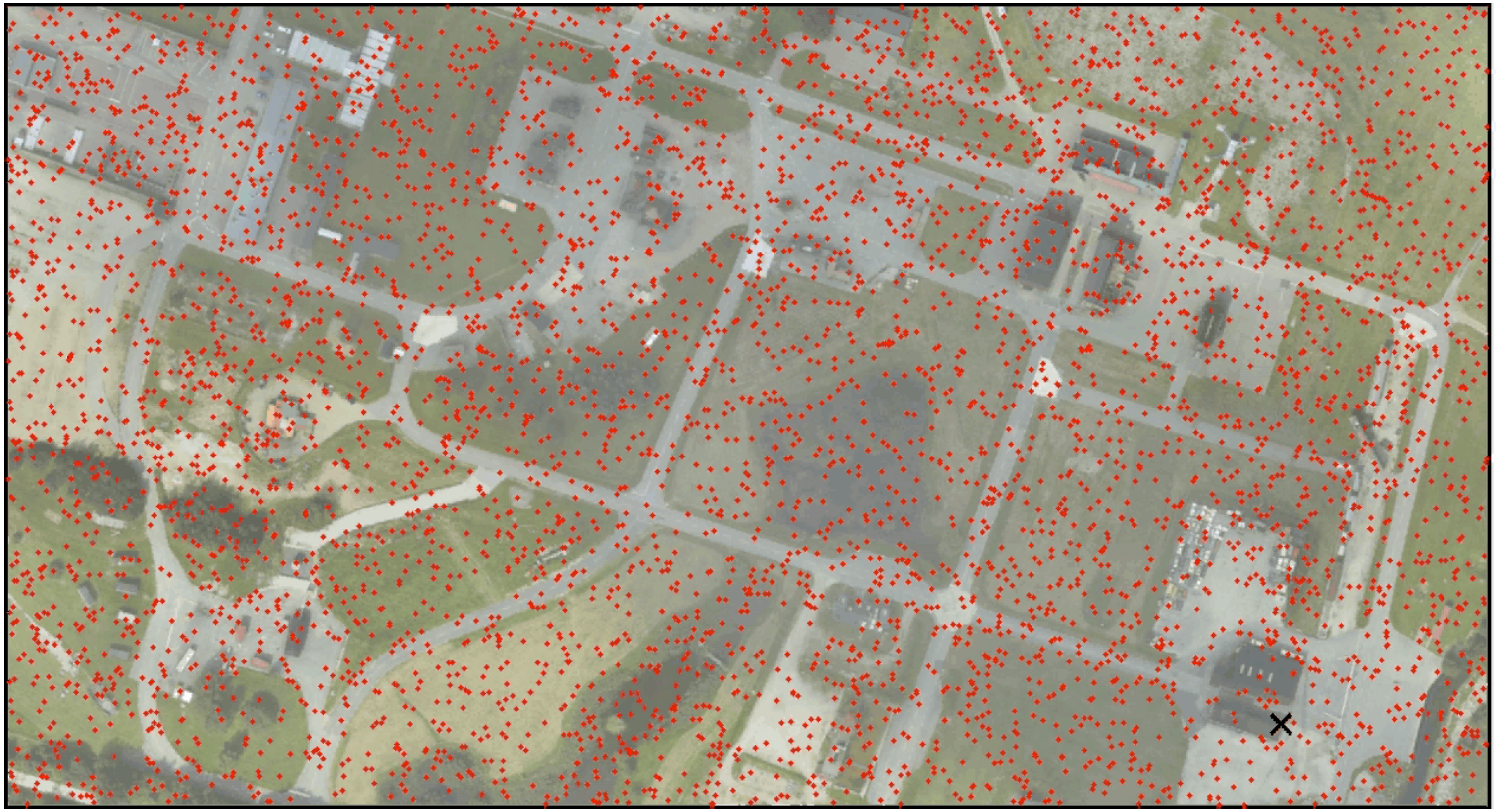


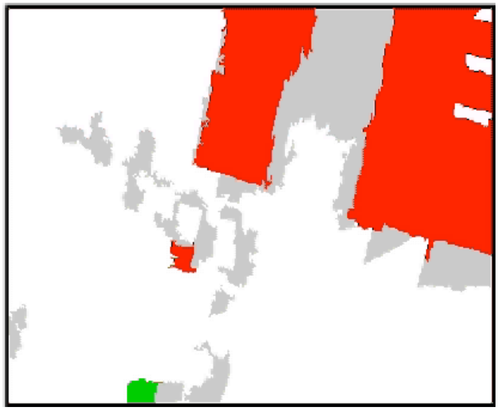
Superpixels classified as grass, asphalt or house



Three circular regions used for computing class histograms

4. Helicopter pose estimation using a map





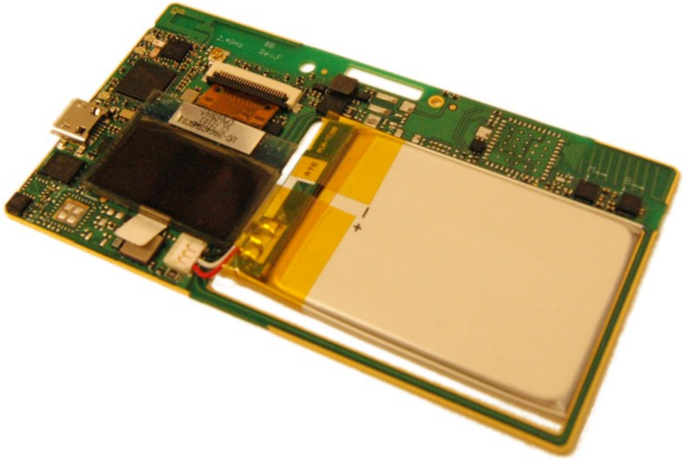
"Think of each particle as one simulation of the system state (in the movie, only the horizontal position is visualized). Only keep the good ones."

Fredrik Lindsten, Jonas Callmer, Henrik Ohlsson, David Törnqvist, Thomas B. Schön, Fredrik Gustafsson, **Geo-referencing for UAV Navigation using Environmental Classification**. *Proceedings of the International Conference on Robotics and Automation (ICRA)*, Anchorage, Alaska, USA, May 2010.

5. Indoor positioning using a map

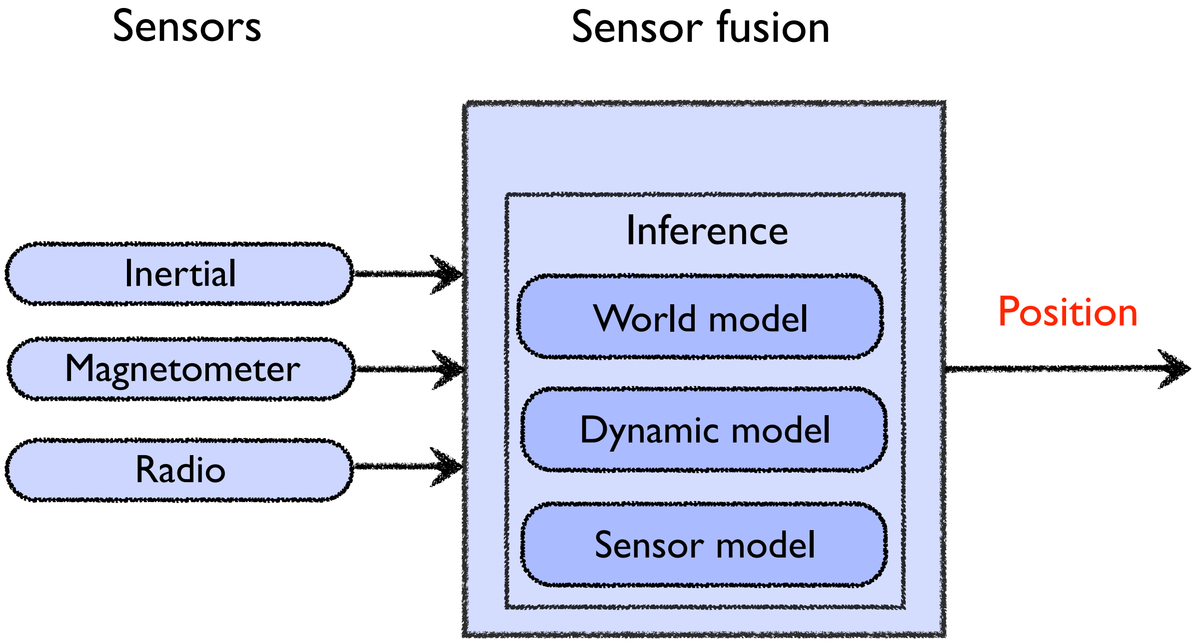
Aim: Compute the position of a person moving around indoors using sensors (inertial, magnetometer and radio) located in an ID badge and a map.

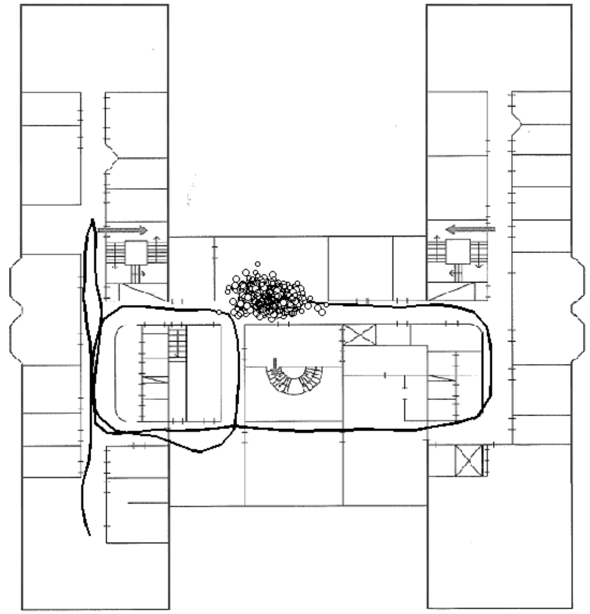
Industrial partner: Xdin

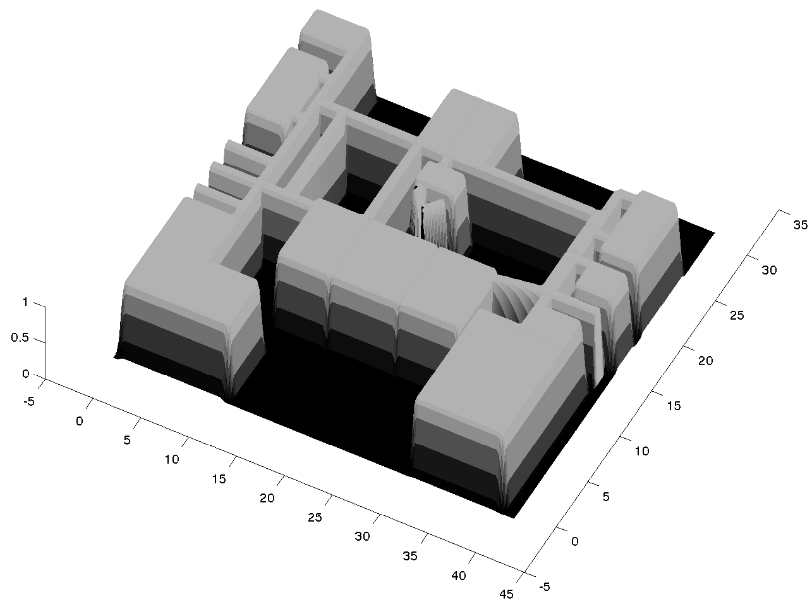


The inside of the ID badge.

5. Indoor positioning using a map



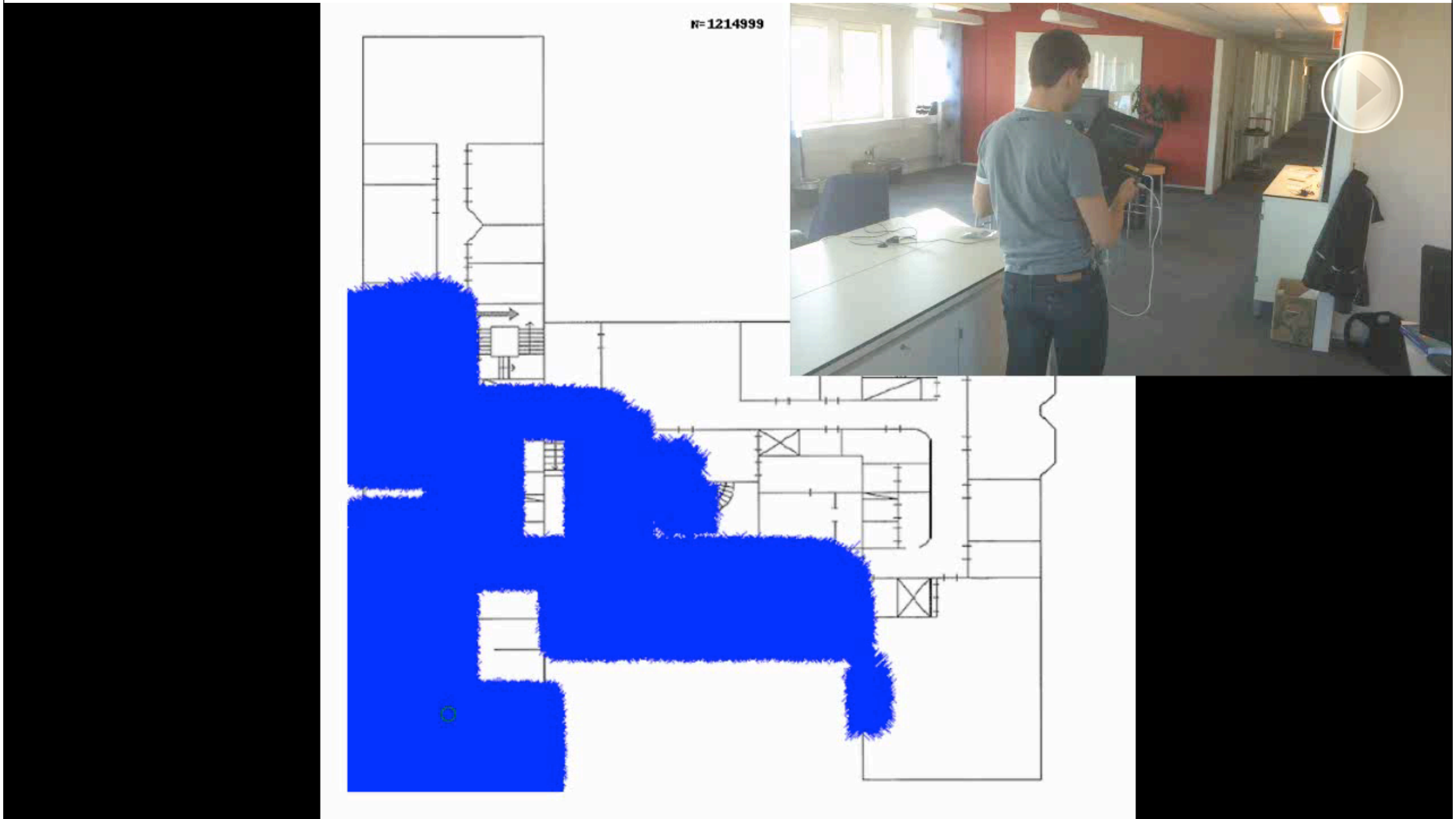




PDF of an office environment, the bright areas are rooms and corridors (i.e., walkable space).

J. Kihlberg and S. Tegelid. **Map aided indoor positioning**. Master's thesis LiTH-ISY-EX--12/4572--SE. Department of Electrical Engineering, Linköping University,

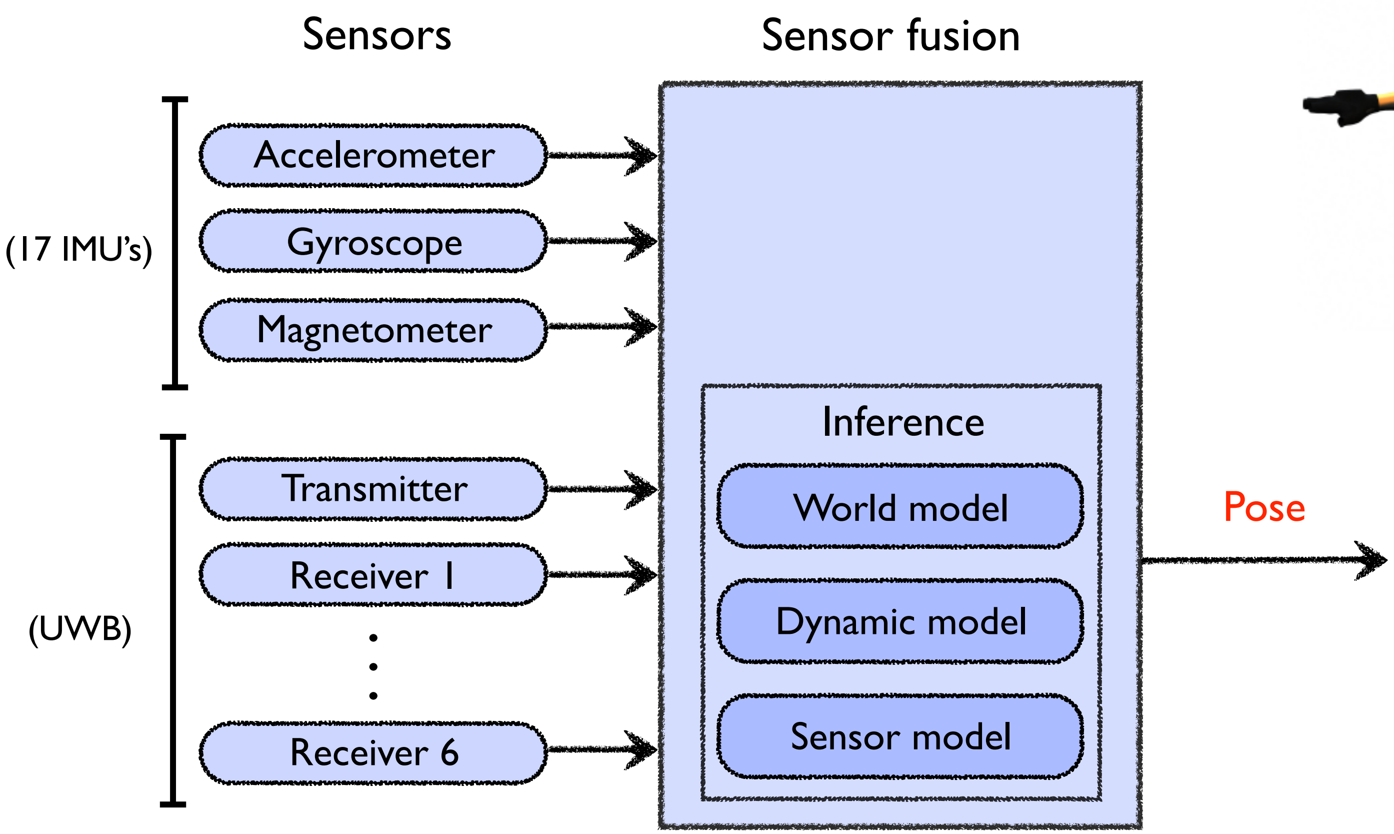
5. Indoor positioning using a map

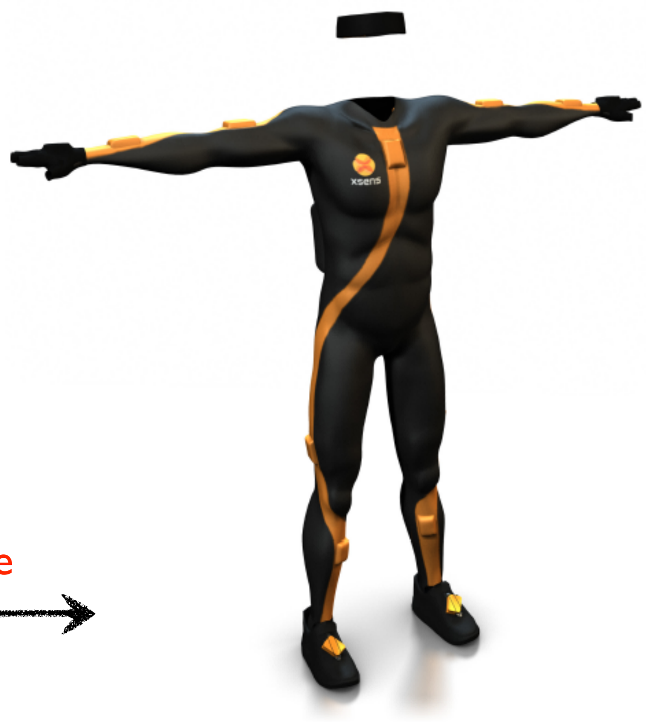


6. Indoor human motion estimation

Aim: Estimate the position and orientation of a human (i.e. human motion) using measurements from inertial sensors and ultra-wideband (UWB).

Industrial partner: Xsens Technologies





6. Indoor human motion estimation - sensors

Sensor unit integrating an IMU and a UWB transmitter into a single housing.

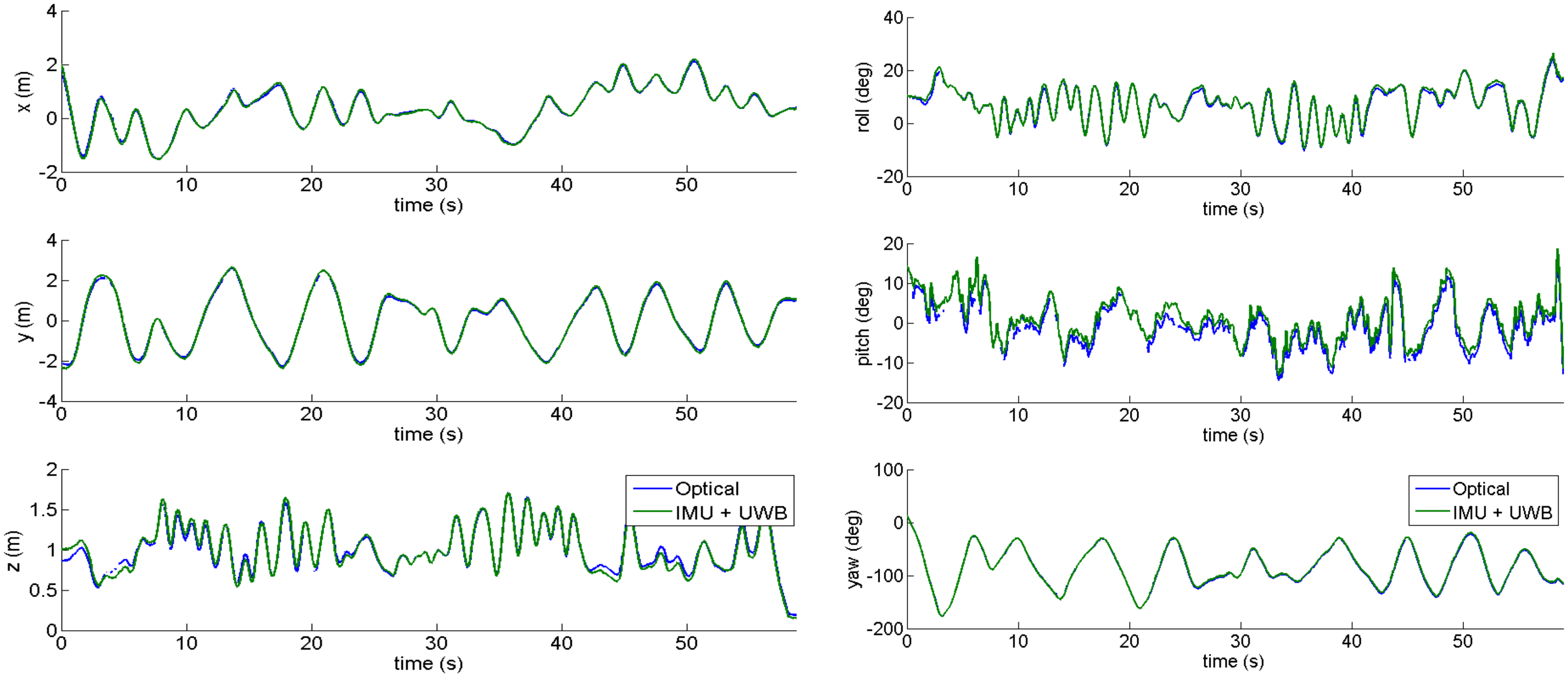
UWB - impulse radio using very short pulses (~ 1ns)

- Low energy over a wide frequency band
- High spatial resolution
- Time-of-arrival (TOA) measurements
- Mobile transmitter and 6 stationary, synchronized receivers at known positions.

Excellent for indoor positioning

- Inertial measurements @ 200 Hz
- UWB measurements @ 50 Hz

6. Indoor human motion estimation - experimental results



Performance evaluation using a camera-based reference system (Vicon).

RMSE: 0.6 deg. in orientation and 5 cm in position.

Jeroen Hol, Thomas B. Schön and Fredrik Gustafsson, **Ultra-Wideband Calibration for Indoor Positioning**. *Proceedings of the IEEE International Conference on Ultra-Wideband (ICUWB)*, Nanjing, China, September 2010.

Jeroen Hol, Fred Dijkstra, Henk Luinge and Thomas B. Schön, **Tightly Coupled UWB/IMU Pose Estimation**. *Proceedings of the IEEE International Conference on Ultra-Wideband (ICUWB)*, Vancouver, Canada, September 2009.

6. Indoor human motion estimation - experiment

6. Indoor human motion estimation - experiment

Sensor fusion - research challenges

- **Enable simple use of world models**
  - Representations, standards
  - Automatic reuse of already existing world models (includes everything from very simple to complex 3D photorealistic models)
  - Automatic building of world models
  - Collaborative (distributed) modeling of the world

Map over the operational

Manually classified map with grass, asphalt and

- **Surrounding infrastructure - "plug-and-playing"**
  - Calibration, synchronization, etc.

$$p(x_t \mid y_{1:t}) = \frac{h(y_t \mid x_t)p(x_t \mid y_{1:t-1})}{p(y_t \mid y_{1:t-1})}$$

$$p(x_{t+1} \mid y_{1:t}) = \int f(x_{t+1} \mid x_t)p(x_t \mid y_{1:t})\mathrm{d}x_t$$

- **New and better inference methods**

- **Cultural aspects**, sensor fusion is by definition a multi-disciplinary activity, collaboration and respect are important.

- **Computational power is steadily increasing**, enables us to work with richer models and better inference methods.

- **Scalability**, how can we leverage and use the fact that everyone is becoming a sensor?

Take home message

Quite a few different applications from different areas, all solved using the
same underlying sensor fusion strategy

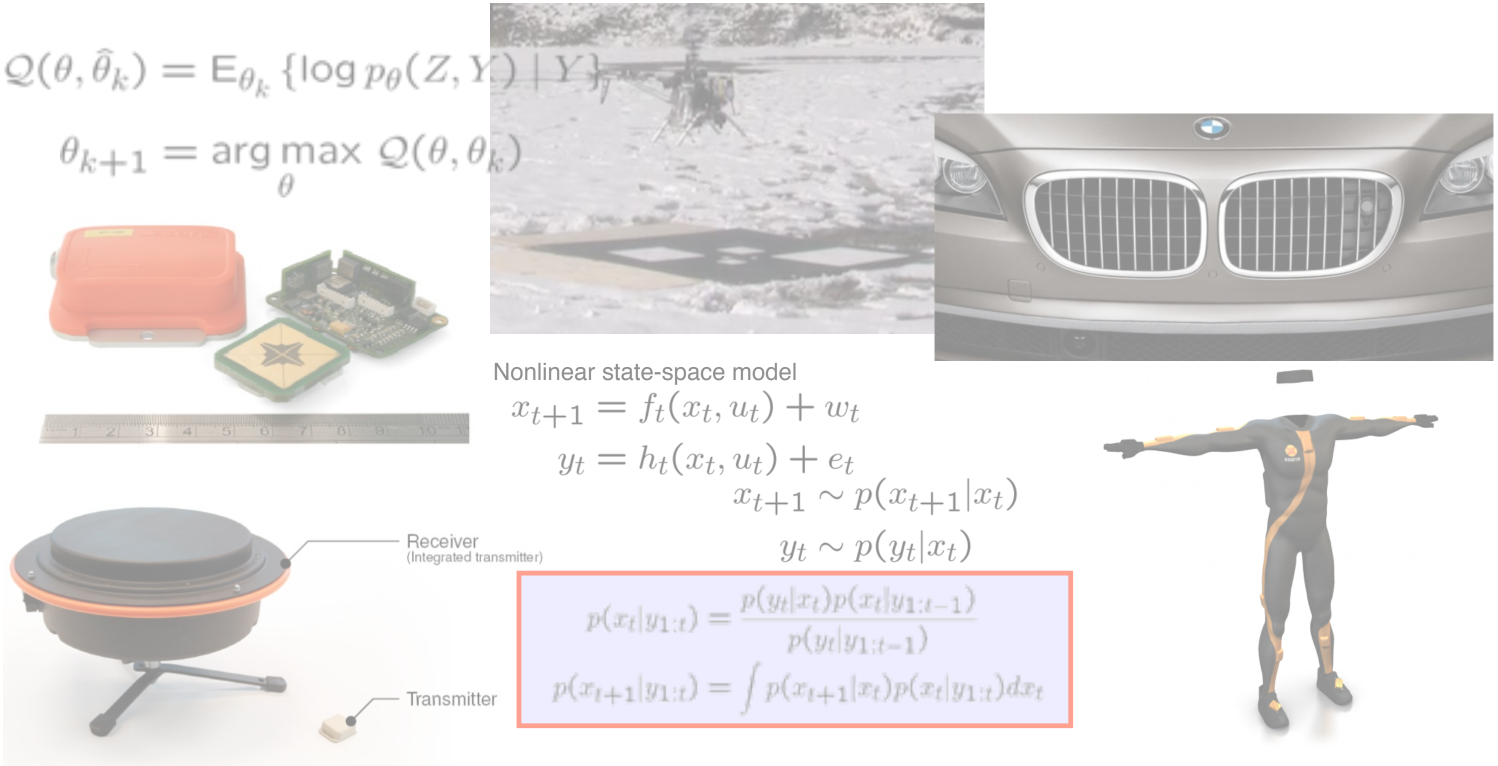
- **Model** the dynamics
- **Model** the sensors
- **Model** the world

- Solve the resulting **inference** problem

and, do not underestimate the "surrounding infrastructure"!

- There is a lot of **interesting research** that remains to be done!
- The number of available sensors is currently skyrocketing
- The **industrial utility** of this technology is **growing** as we speak!

Thank you for your attention!!



Joint work with (in alphabetical order): **Jonas Callmer** (*LiU*), **Andreas Eidehall** (*Volvo cars*), **David Forslund** (Autoliv), **Andreas Gising** (*Cybaero*), **Fredrik Gustafsson** (*LiU*), **Joel Hermansson** (*Cybaero*), **Jeroen Hol** (*Xsens*), **Johan Kihlberg** (*Xdin*), **Fredrik Lindsten** (*LiU*), **Henk Luinge** (*Xsens*), **Christian Lundquist** (*LiU*), **Johan Nordlund** (Saab), **Henrik Ohlsson** (*Berkeley*), **Jacob Roll** (*Autoliv*), **Simon Tegelid** (Xdin) and **David Törnqvist** (*LiU*).