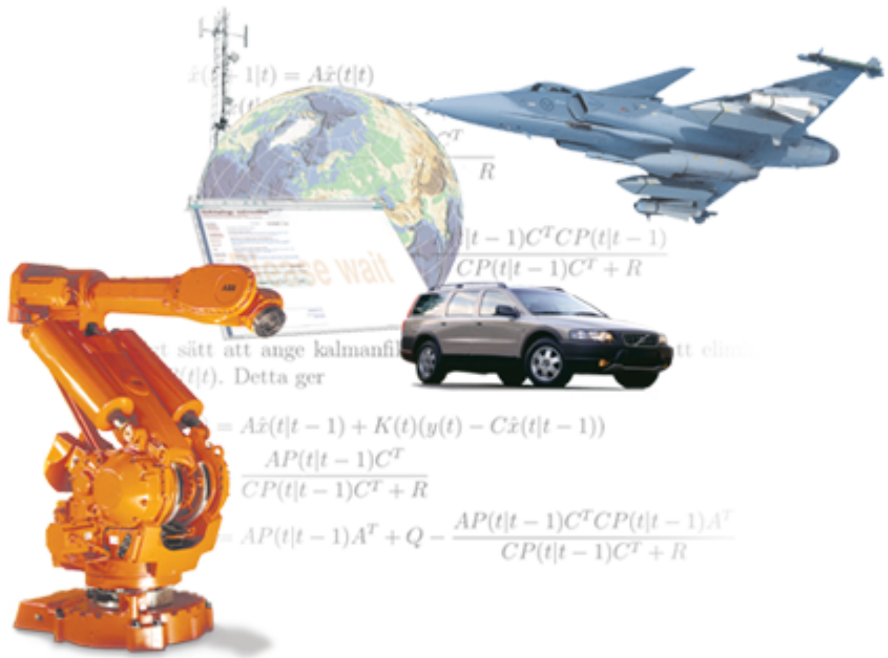
Sensor Fusion using Proprioceptive and Exteroceptive Sensors



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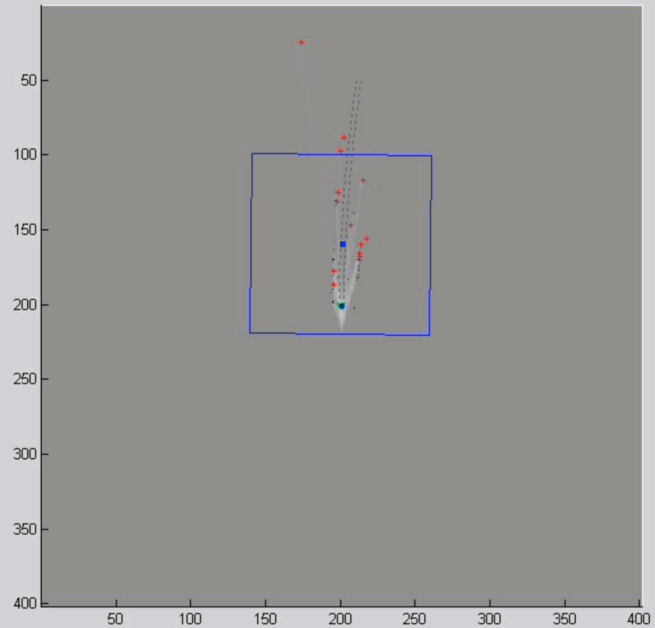
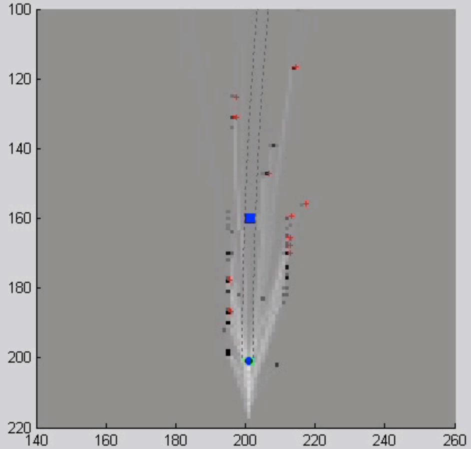
A first example - automotive sensor fusion





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 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. Road surface estimation
3. Autonomous helicopter landing
4. Helicopter pose estimation using a map
5. Indoor positioning using a map
6. Indoor human motion estimation

We are dealing with **dynamical** systems!

Probabilistic model

State

Known input

$$
\begin{aligned}
x_{t+1} &= f(x_t, u_t, \theta) + w_t \\
y_t &= h(x_t, u_t, \theta) + e_t
\end{aligned}
$$

Measurements

Parameters/ world model

Stochastic disturbances

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

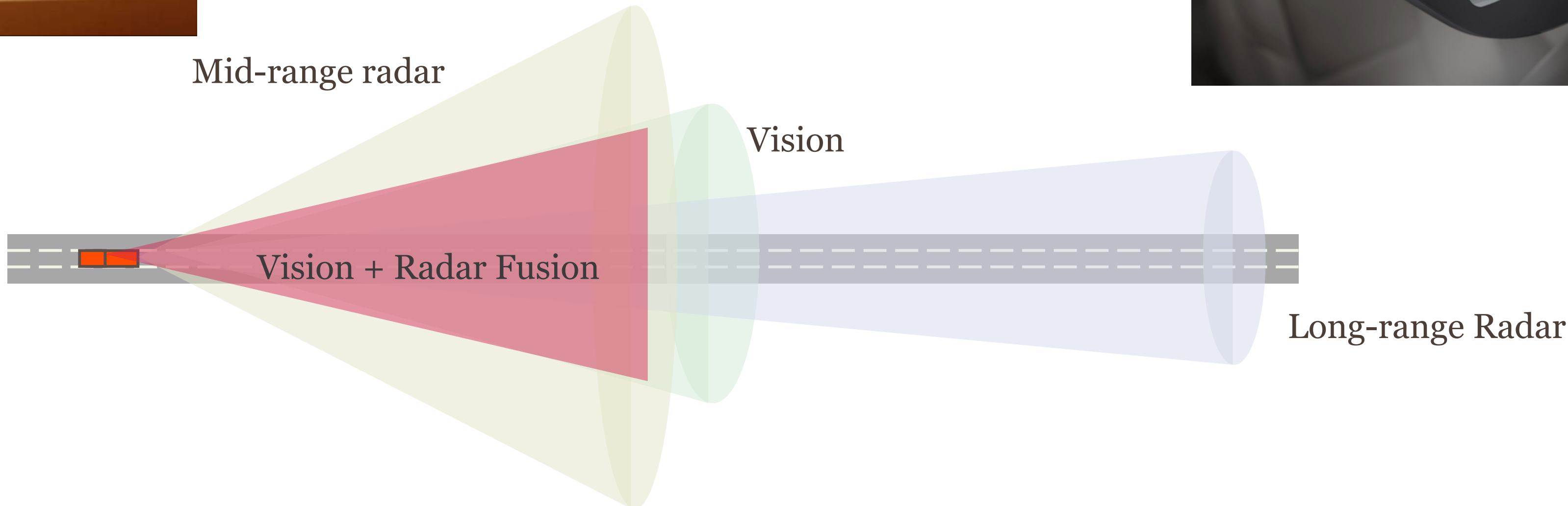
"The present state of a dynamical system depends on its history."

Application examples

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

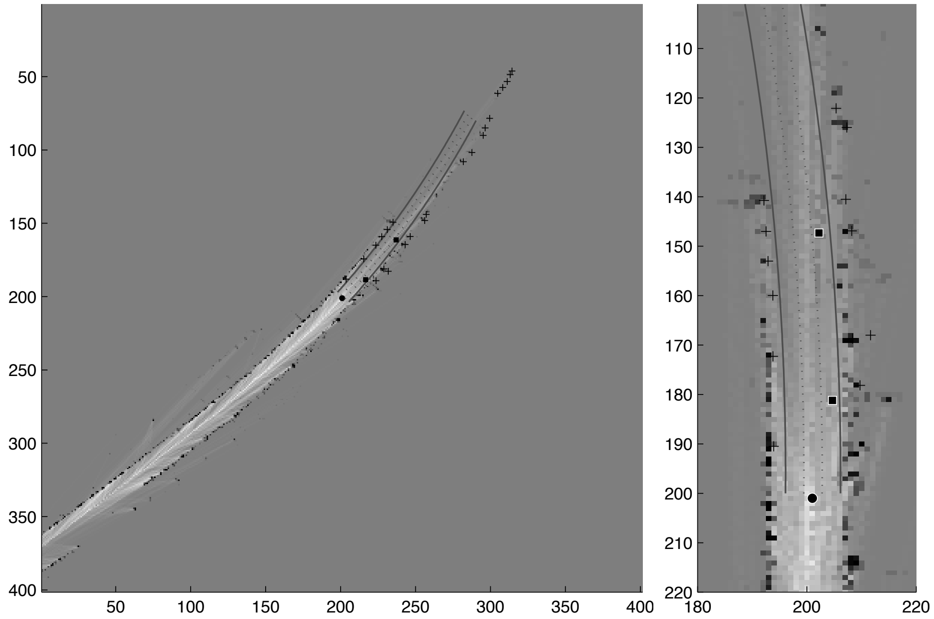
The dynamical systems exist in a context.

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...

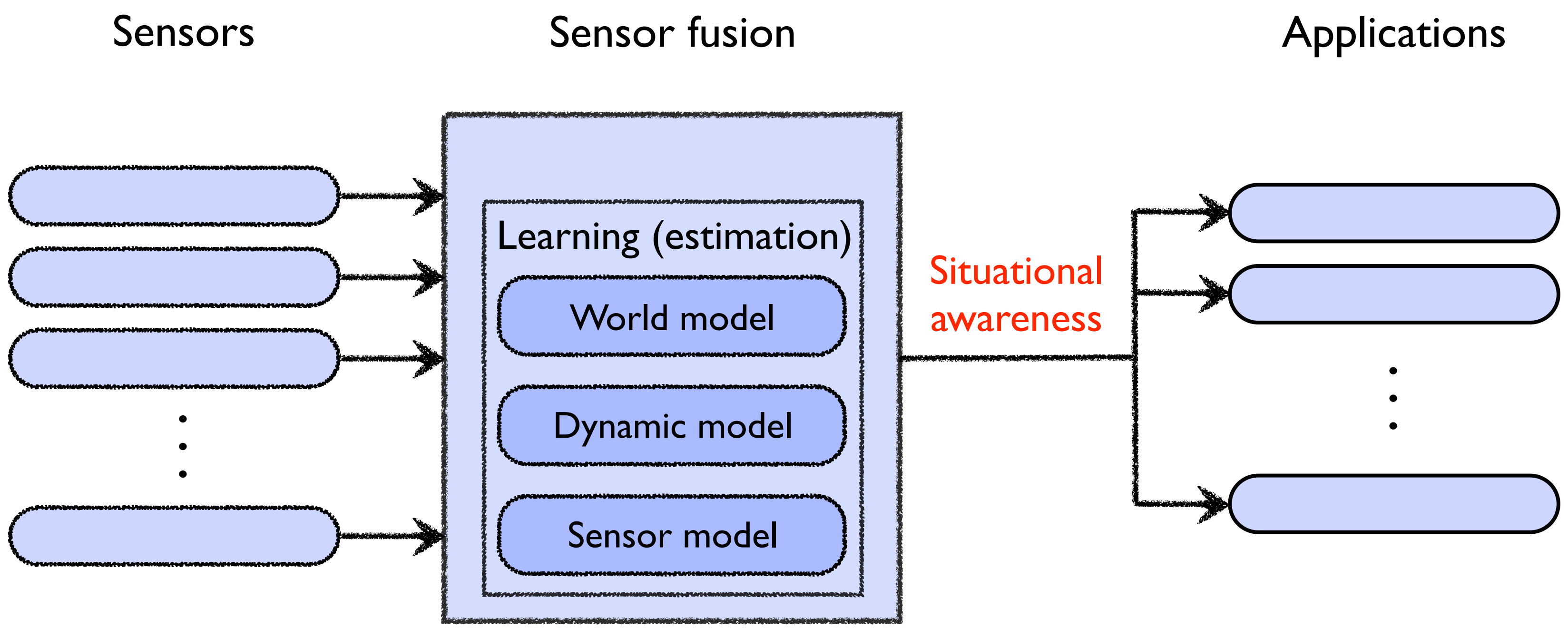
An example:

Relative pose calibration:

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

Definition (sensor fusion)

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



Learning/estimation

The task in the learning/estimation problem is to **combine** 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.

Estimation/learning - the filtering problem

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

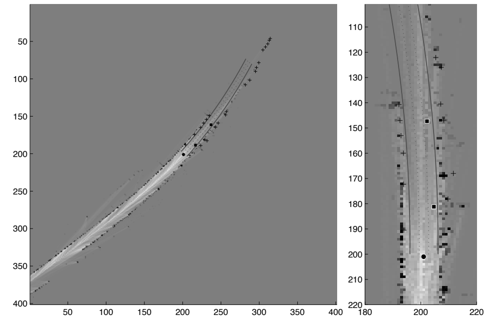
$$p(x_{t+1} \mid y_{1:t}) = \int \underbrace{p(x_{t+1} \mid x_t)}_{\text{dynamical model}} \underbrace{p(x_t \mid y_{1:t})}_{\text{filtering density}} dx_t$$

In the application examples this is handled 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**.

Outline

Sensor fusion

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

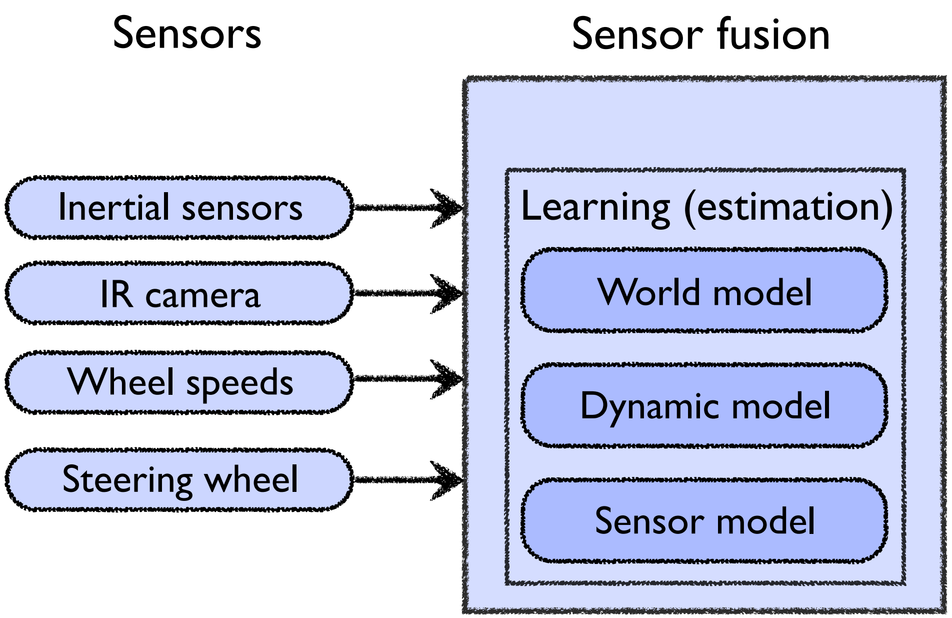
Application examples

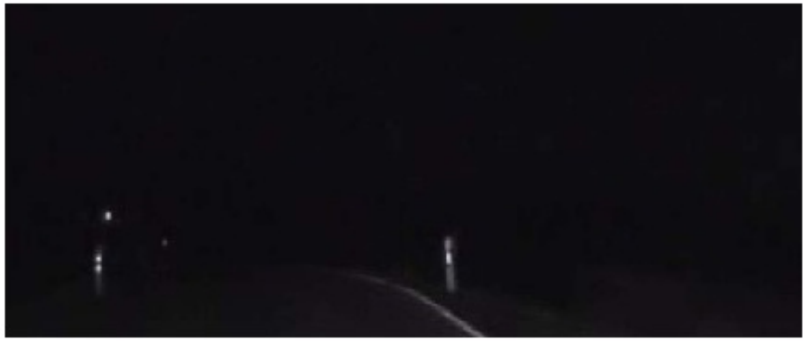
1. Vehicle motion estimation using night vision
2. Road surface estimation
3. Autonomous helicopter landing
4. Helicopter pose estimation using a map
5. Indoor positioning using a map
6. Indoor human motion estimation

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

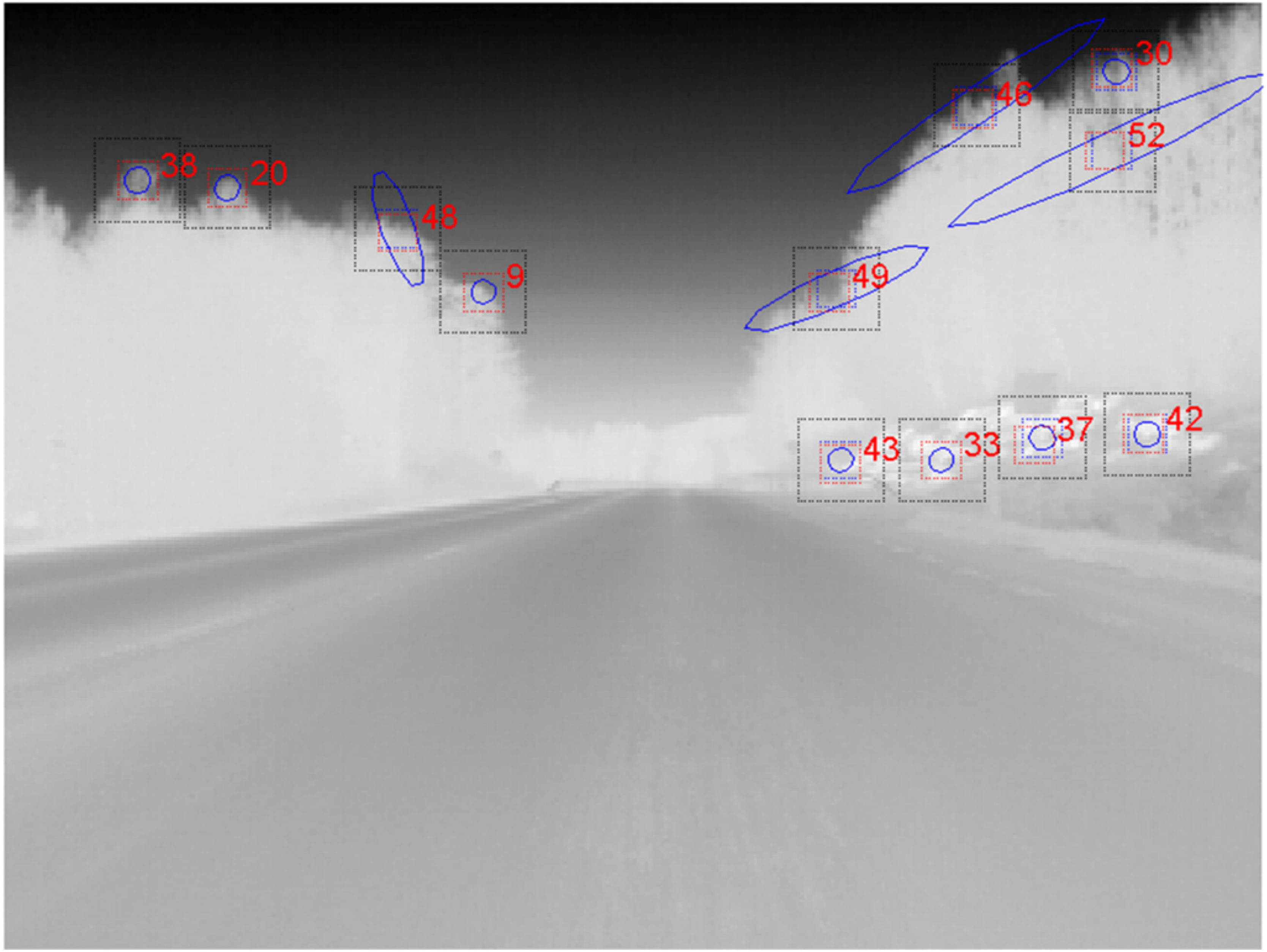




Road scene, as seen with a standard camera.

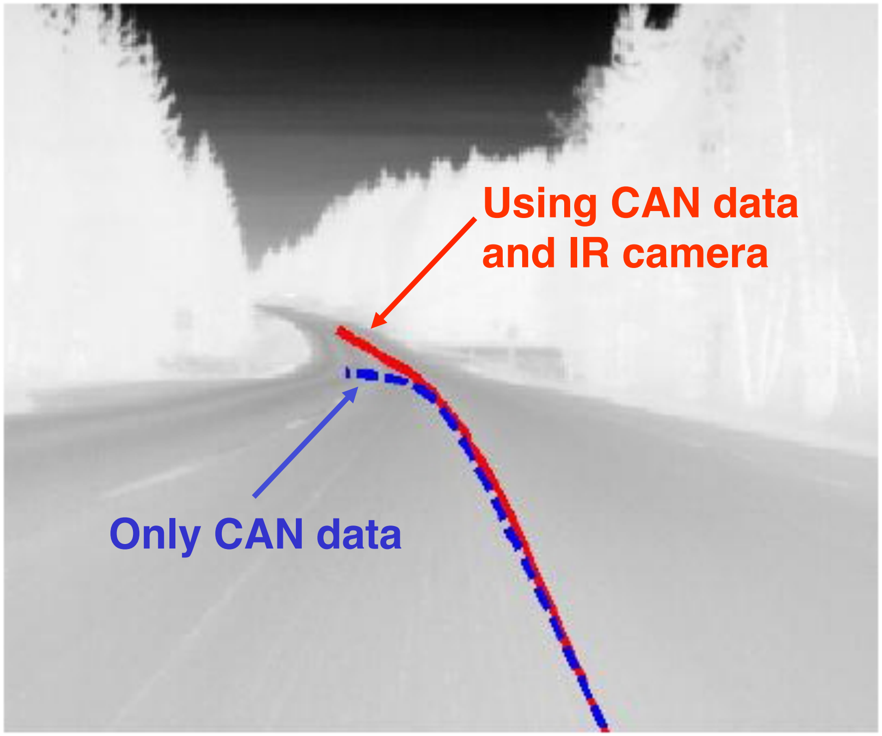
Same road scene as above, seen with the IR camera

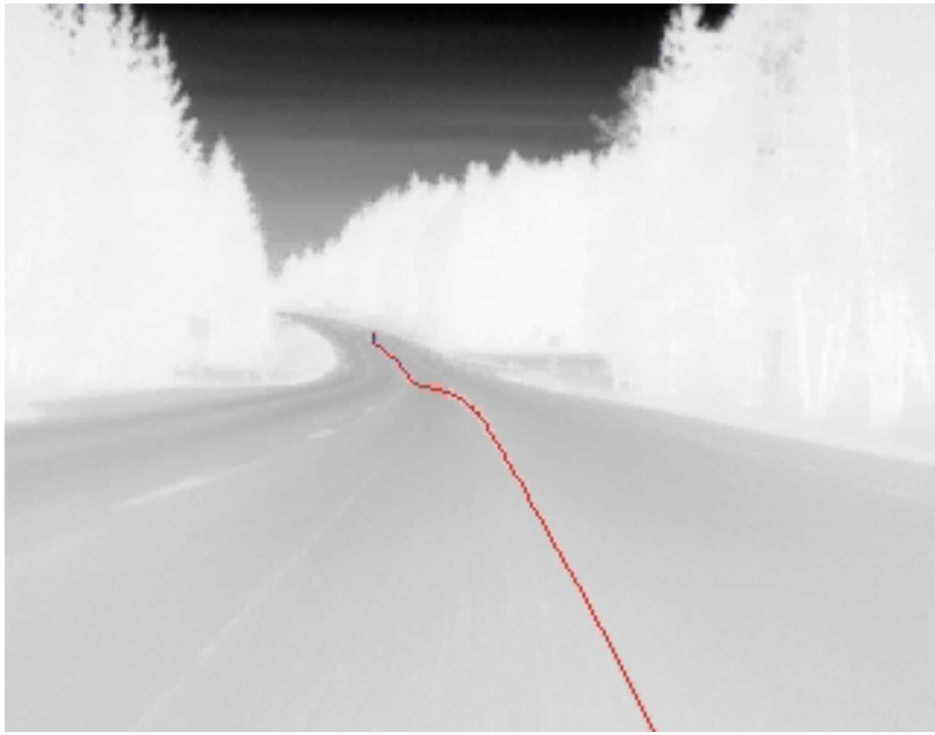
1. Vehicle motion estimation using night vision



1.Vehicle motion estimation using night vision - experiments

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



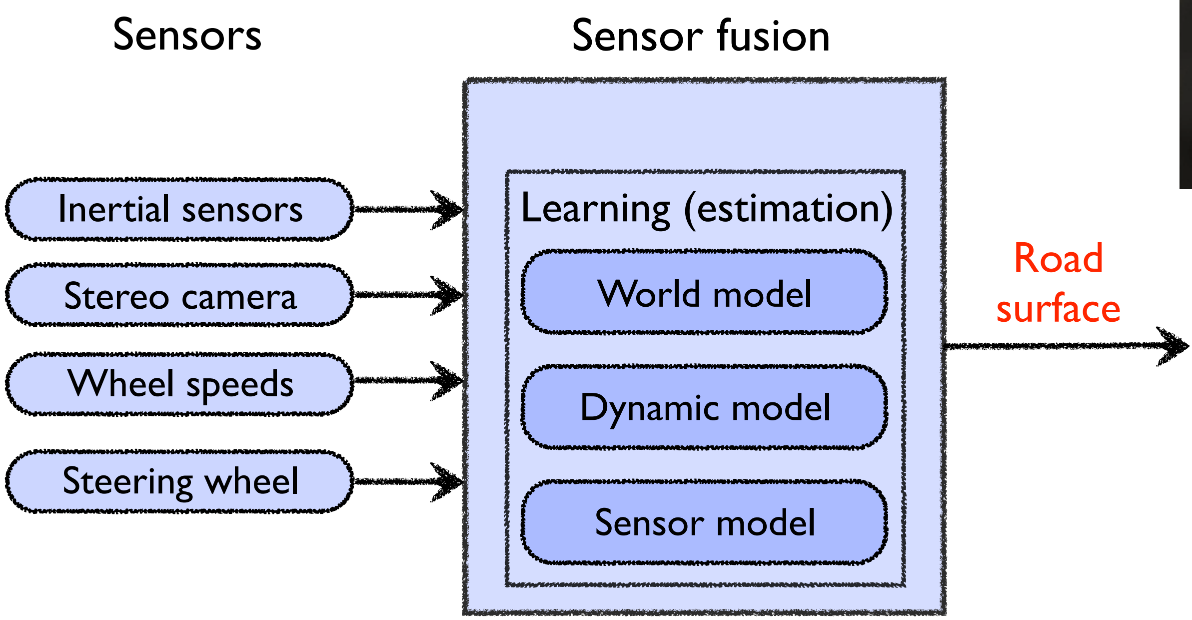


Showing the ego-motion estimates reprojected onto the images.

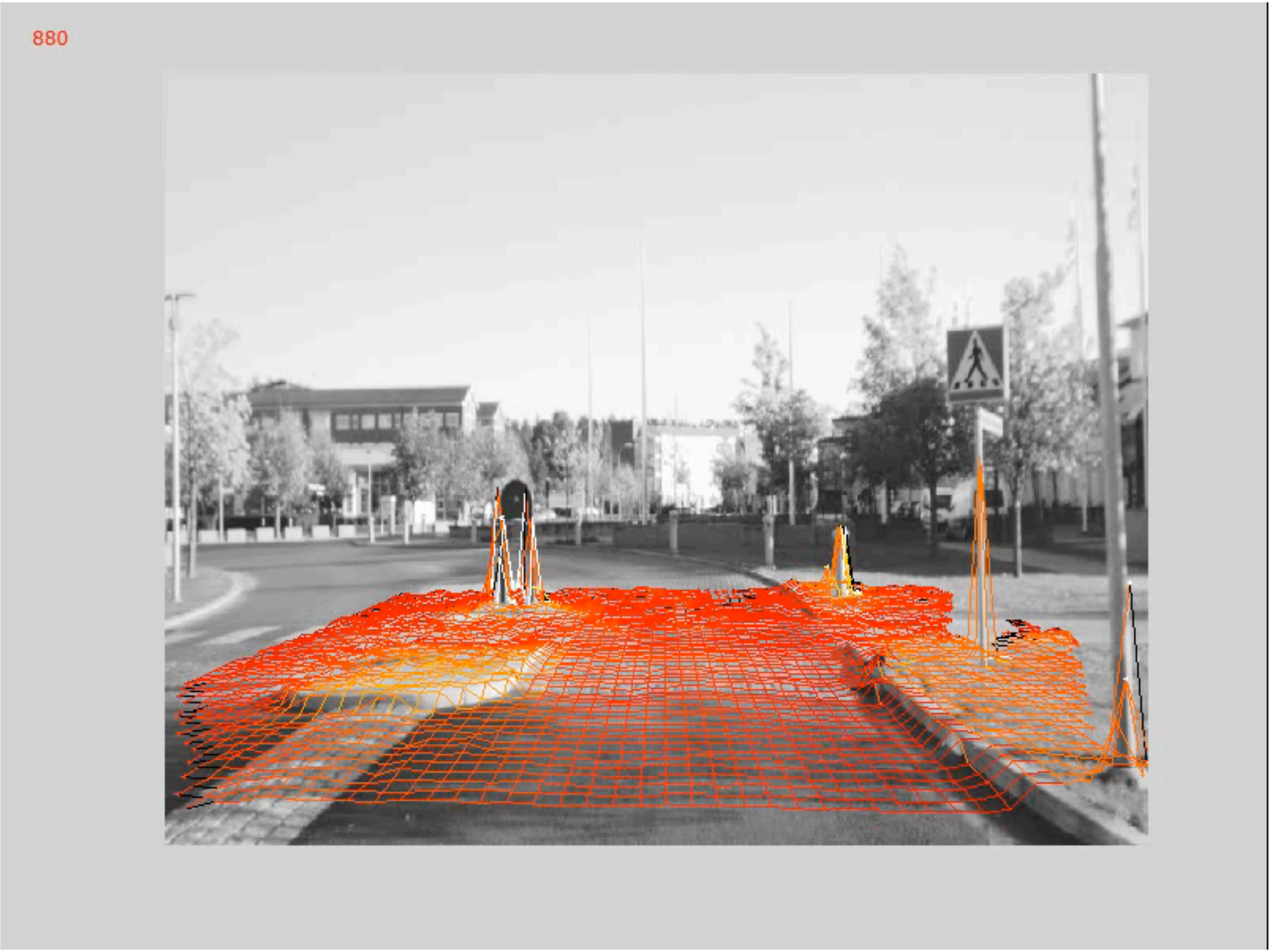
2. Road surface estimation

Aim: Compute an estimate of the road surface in front of the vehicle.

Industrial partner: Autoliv Electronics



2. Road surface estimation



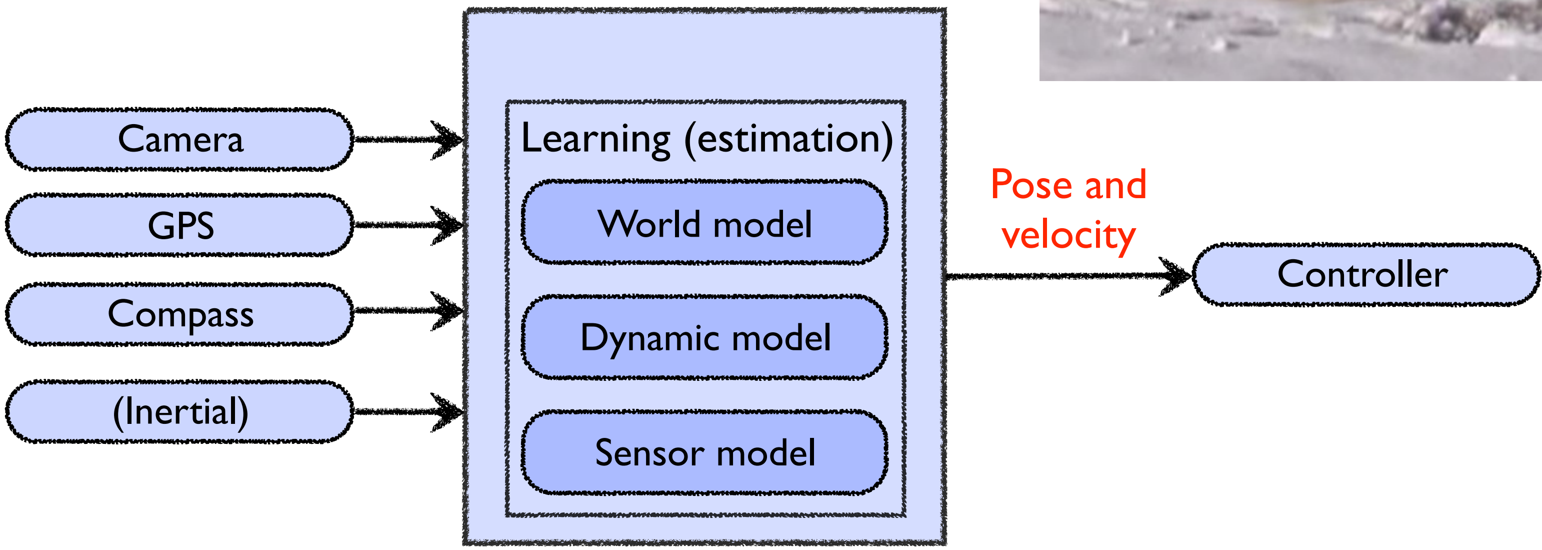
3. Autonomous helicopter landing

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

Industrial partner: Cybaero

Sensors

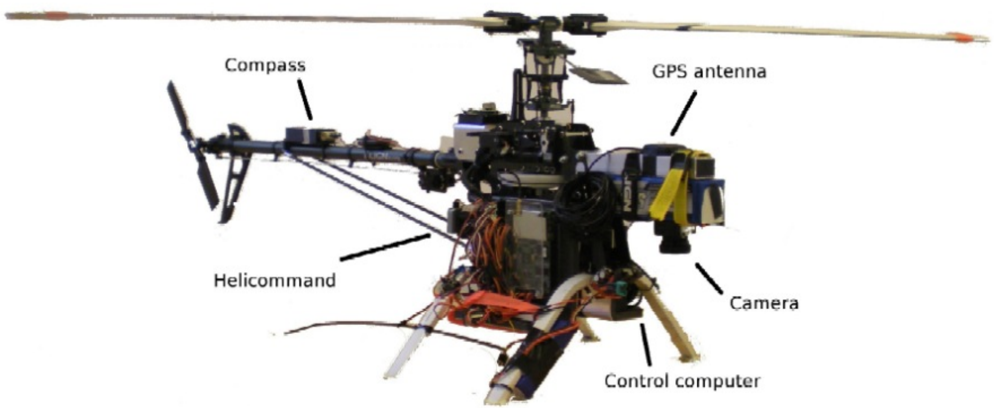
Sensor fusion



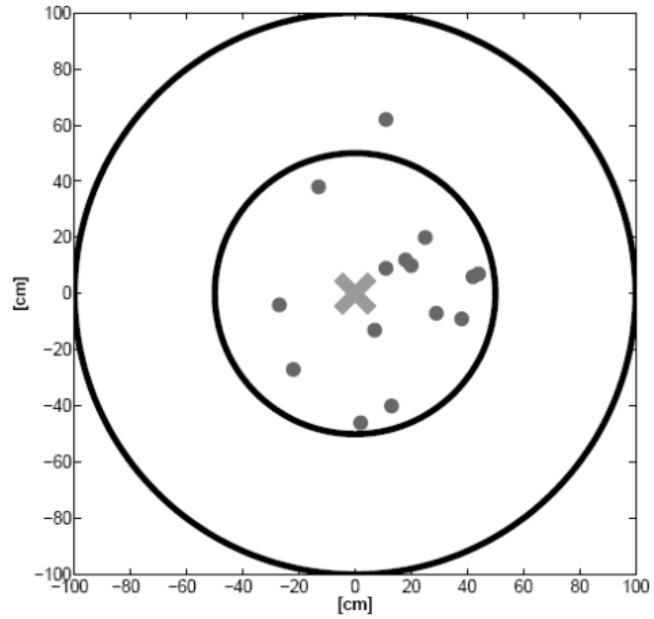
3. Autonomous helicopter landing

Experimental helicopter

- Weight: 5kg
- Electric motor



Results from 15 landings



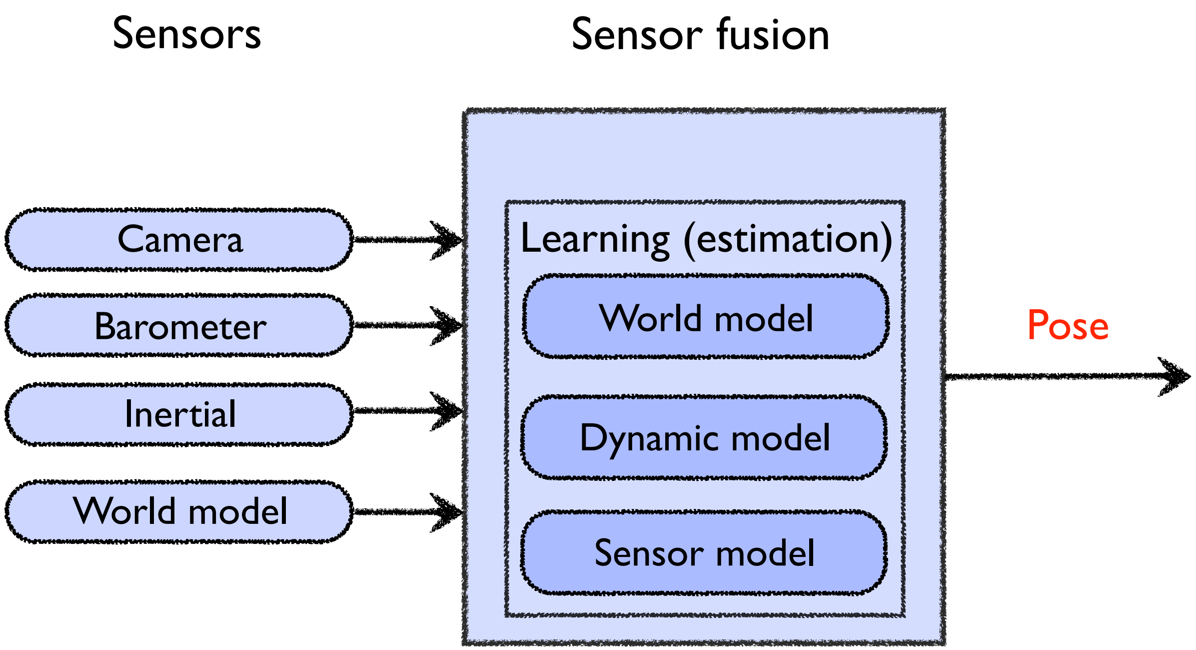
The two circles mark 0.5m and 1m landing error, respectively.

Dots = achieved landings
Cross = perfect landing

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.



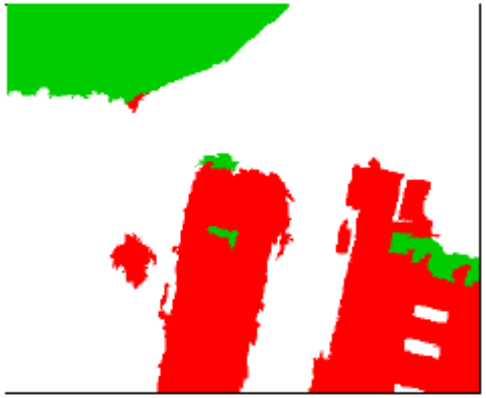
4. Helicopter pose estimation using a map

Map over the operational environment obtained from Google Earth.

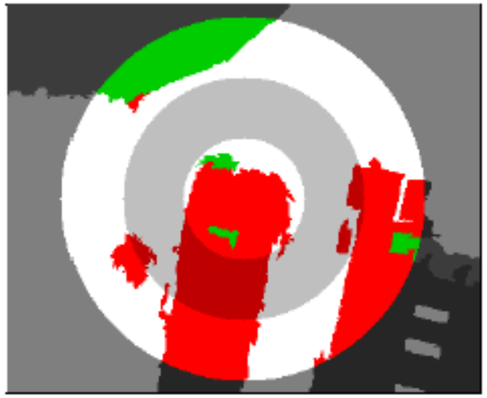
Manually classified map with grass, asphalt and houses as pre-specified classes.

Image from on-board camera

Extracted superpixels

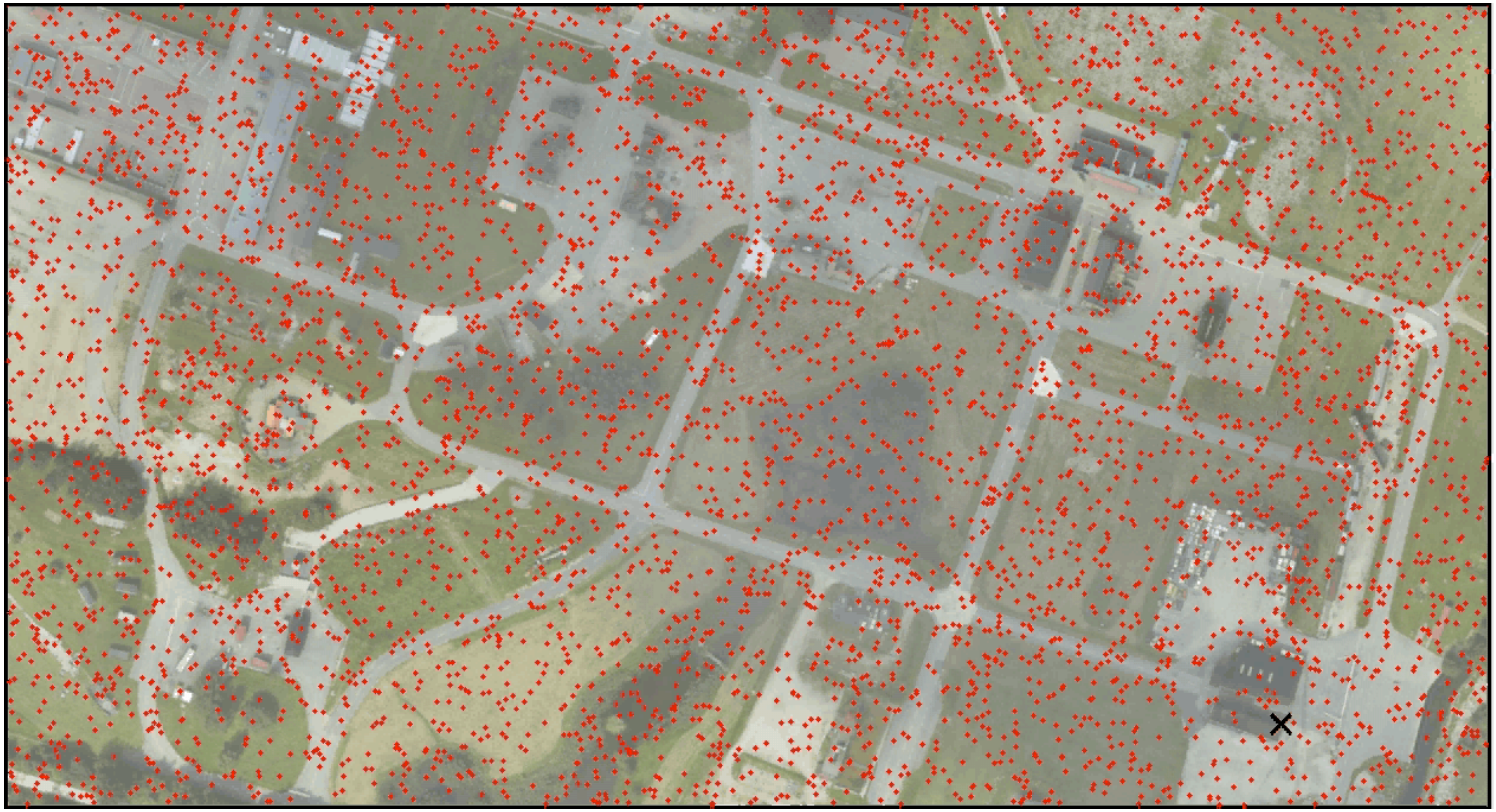


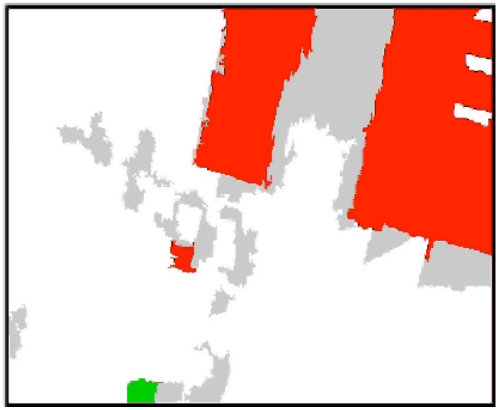
Superpixels classified as grass, asphalt or house



Three circular regions used for computing class histograms

4. Helicopter pose estimation using a map

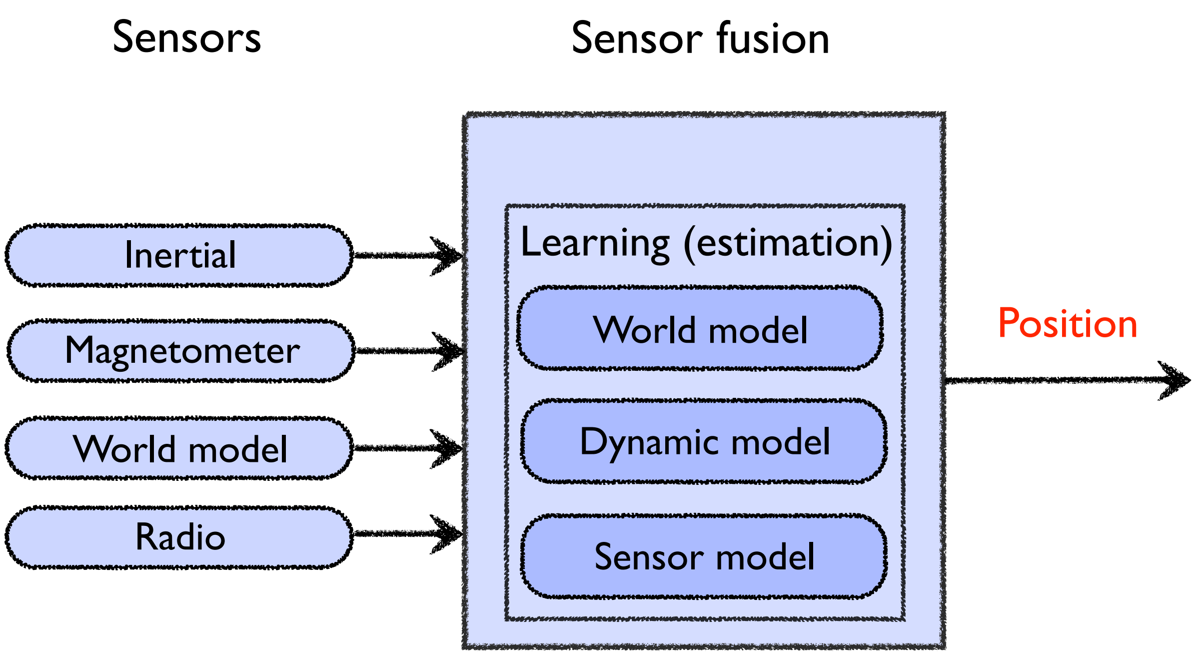




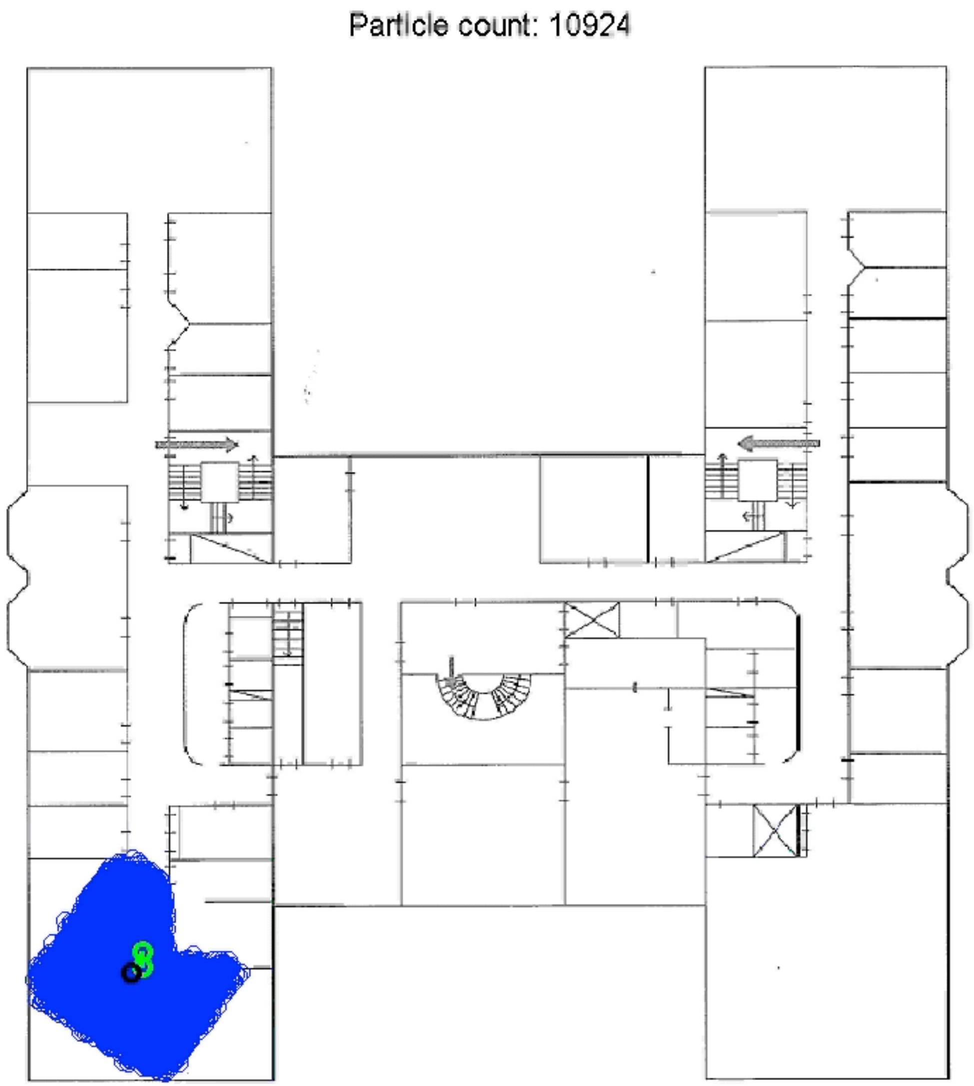
5. Indoor positioning using a map

Aim: Compute the position of a person moving around indoors using sensors located in an ID badge.

Industrial partner: Xdin



5. Indoor positioning using a map

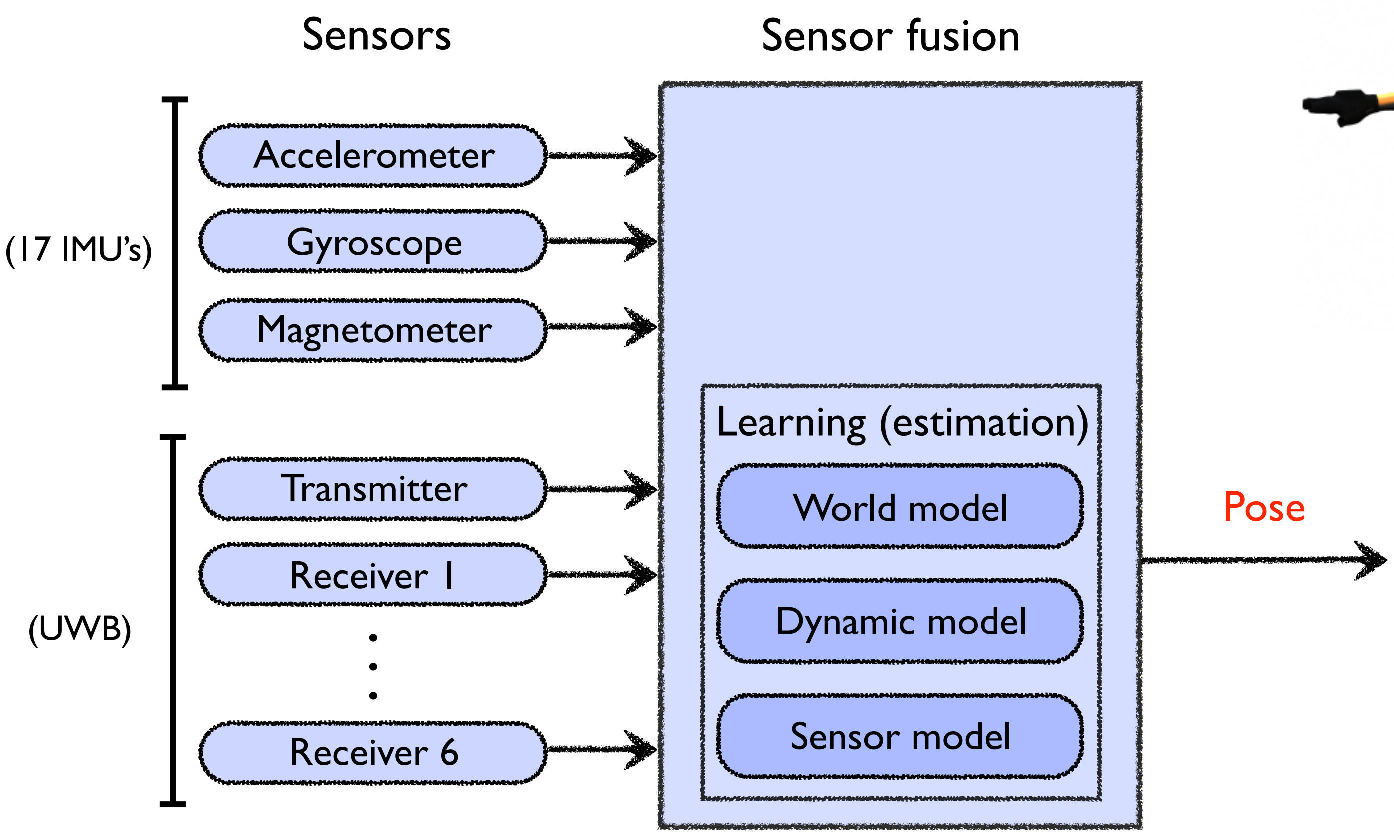


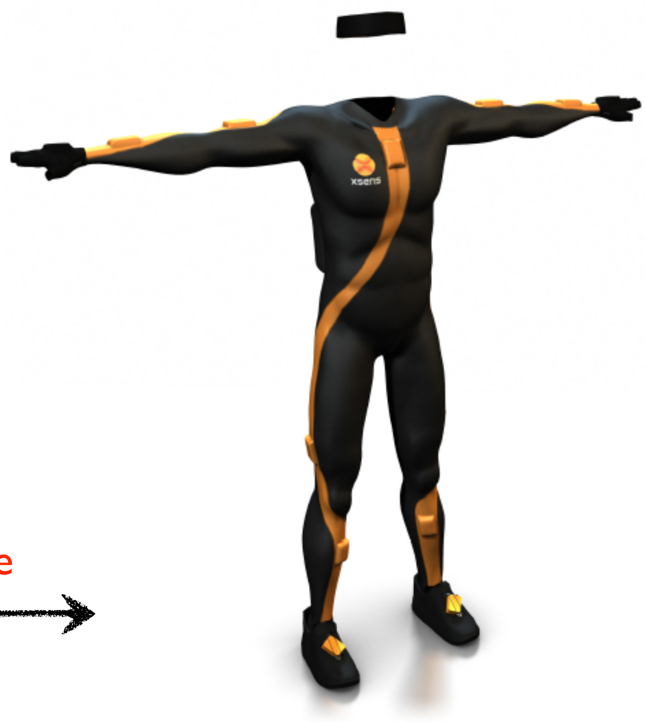
- Blue - particles
- Black - estimate
- Green - truth

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





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

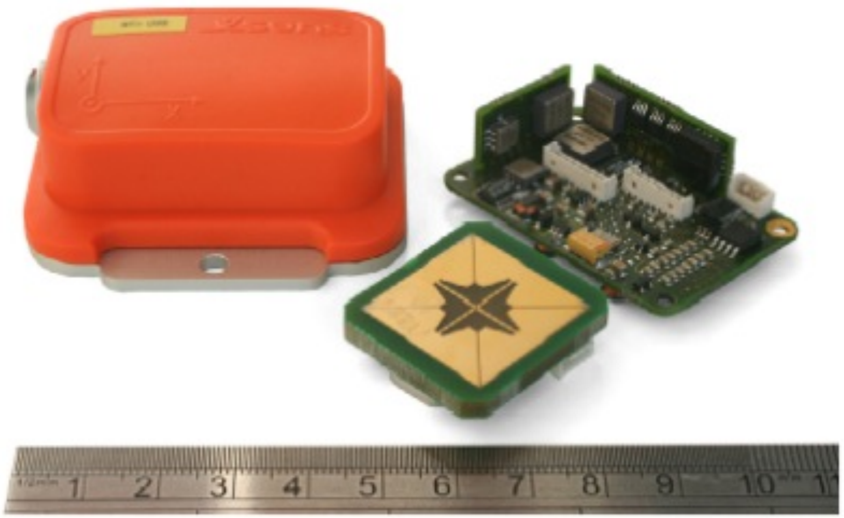
- Low energy over a wide frequency band
- High spatial resolution

Excellent for indoor positioning

Hardware

- Mobile transmitter and stationary, synchronized receivers
- Time-of-arrival (TOA) measurements

6. Indoor human motion estimation - IMU and UWB

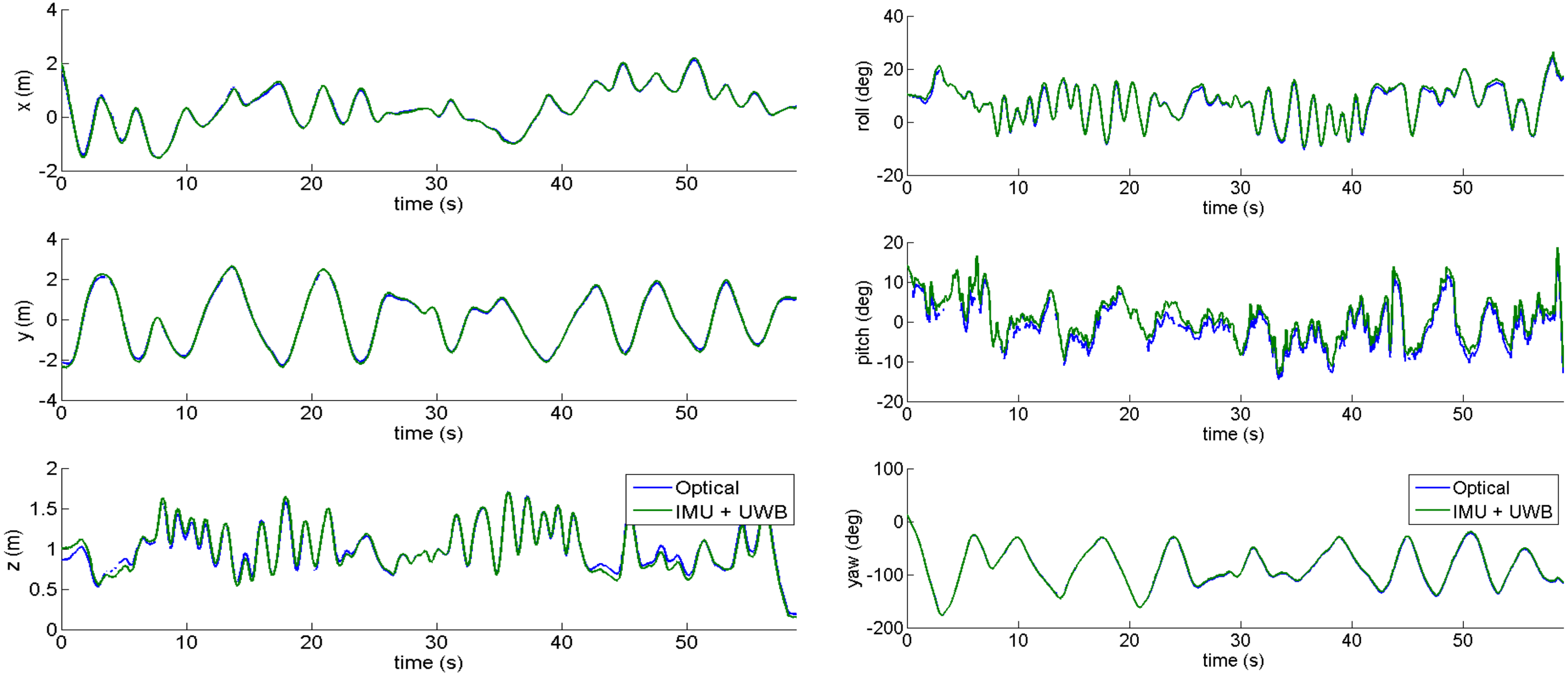


Sensor unit integrating an IMU and a UWB transmitter into a single housing.

- IMU @ 200 Hz
- UWB @ 50 Hz

- 6 UWB receivers at known positions
- Foot-mounted sensor unit

6. Indoor human motion estimation - experimental results



Performance evaluation using a VICON camera system providing a reference trajectory

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

6. Indoor human motion estimation - experiments

6. Indoor human motion estimation - experiments 2

Take home message

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

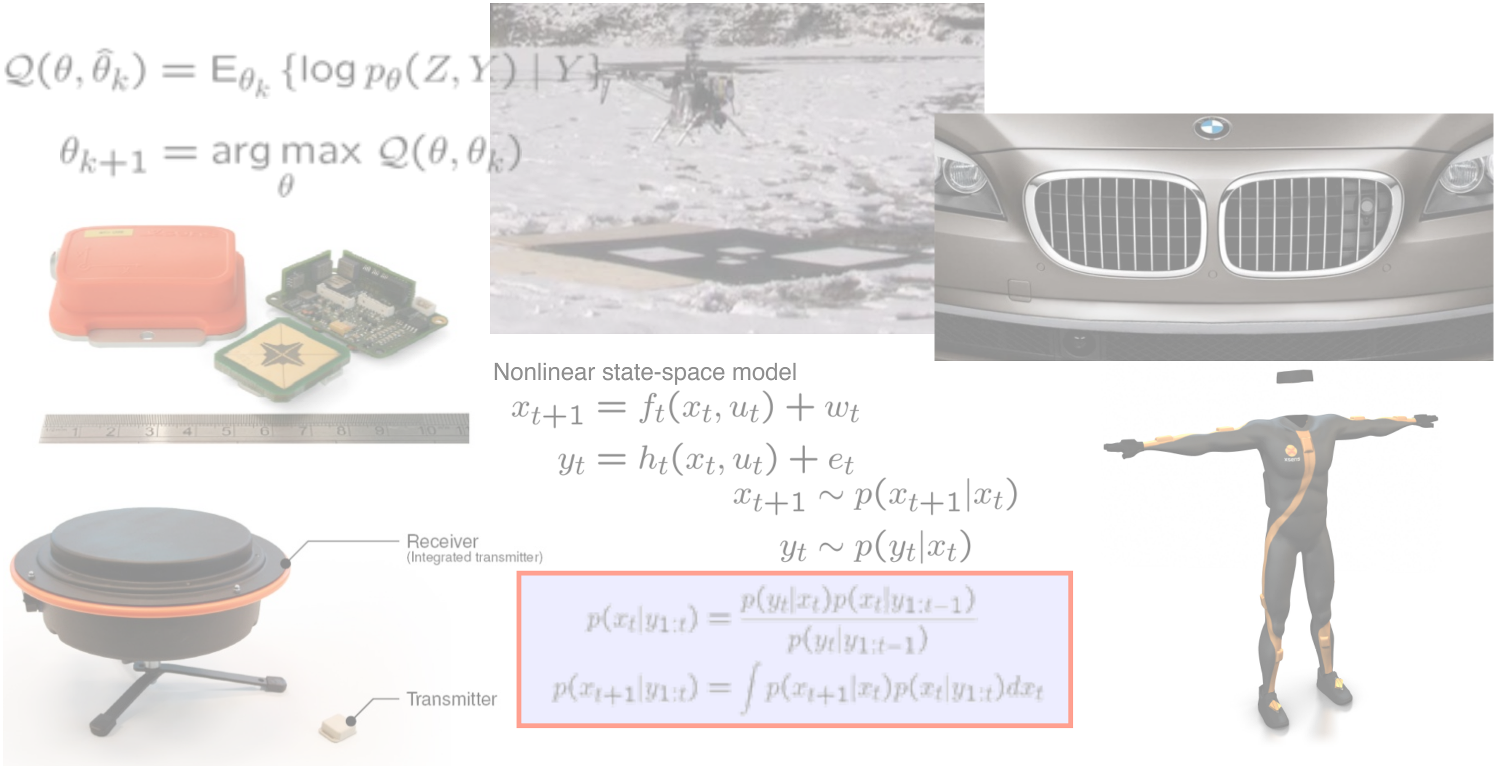
- **Model** the dynamics
- **Model** the sensors
- **Model** the world

- Solve the resulting **estimation** problem

and, do not underestimate the "surrounding infrastructure"!

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

Thank you for your attention!!



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