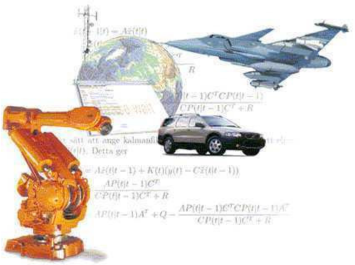
Licentiate seminar

Probabilistic modeling for positioning applications using inertial sensors



Manon Kok

Automatic Control, Linköping University, Sweden

Positioning applications

Outdoor positioning ...
to find your way to Linköping.

Positioning applications

Outdoor positioning ...
to find your way to Linköping.

Outdoor positioning ...
to find your way to Linköping.

Indoor positioning ...
to find your way to this presentation.

Outdoor positioning ...
to find your way to Linköping.

Indoor positioning ...
to find your way to this presentation.

Positioning: position yourself or an object with respect to the earth / a building / another object / person

Show movie

Courtesy of Xsens Technologies

Show movie

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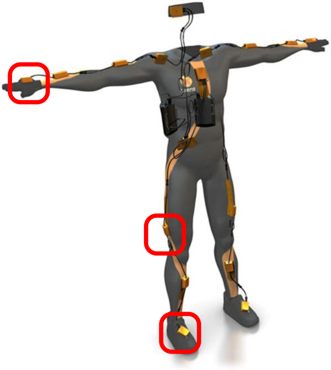

17 sensors placed on the body

Outline of the presentation

1. Background
   - Positioning applications
   - Inertial sensors
   - Probabilistic modeling
2. Contributions
   - Magnetometer calibration using inertial sensors
   - An optimization-based approach to human body inertial motion capture
   - Sensor fusion of inertial sensors and ultra-wideband
   - Pose estimation using inertial sensors and magnetometers in a known magnetic field
3. Conclusions and future work

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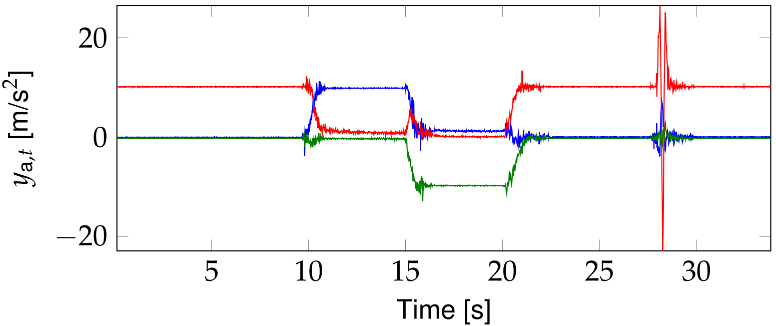
- Accelerometers
- Gyroscopes

} Inertial sensors

Inertial sensors

- Accelerometers
- Gyroscopes

} Inertial sensors



20
0
−20
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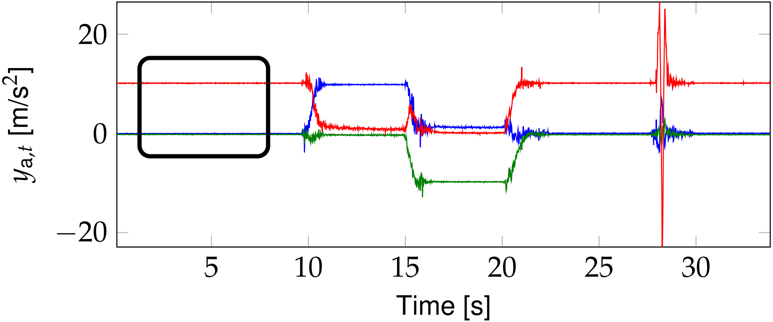
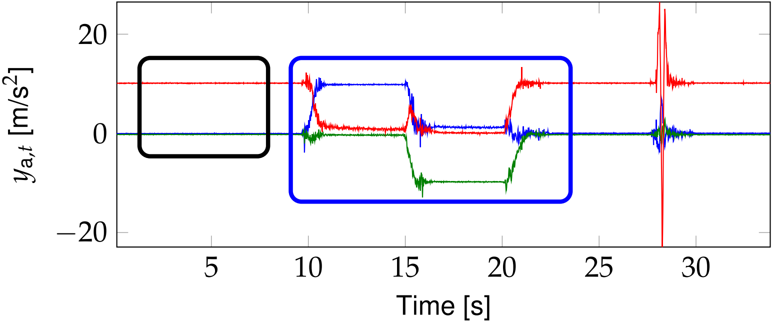
15
20
25
30
Time [s]
$y_{a,t}$ [m/s^2]



Stationary data ⇒ Earth gravity

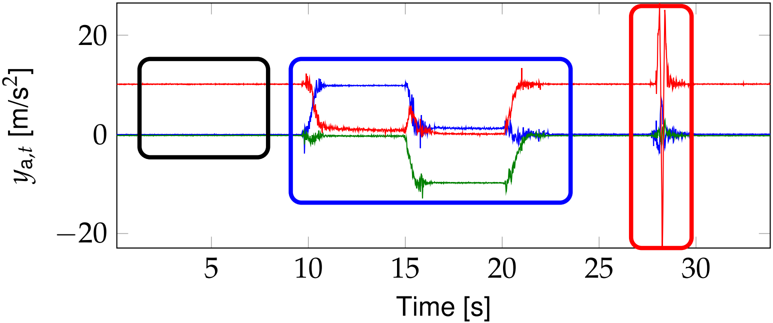
Accelerometer measurements



Stationary data ⇒ Earth gravity

Rotating sensor ⇒ Earth gravity

Accelerometer measurements



Stationary data ⇒ Earth gravity

Rotating sensor ⇒ Earth gravity

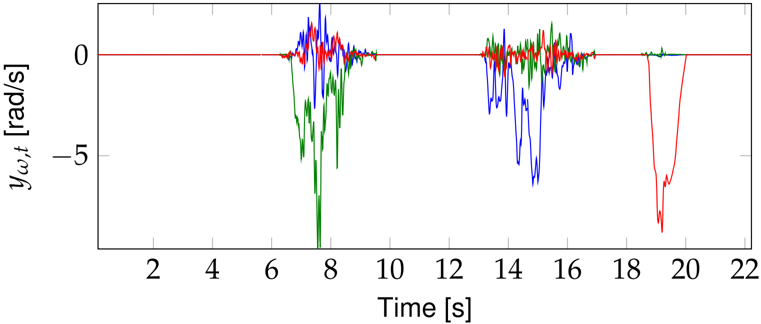
Quickly moving sensor ⇒ Earth gravity + sensor's acceleration

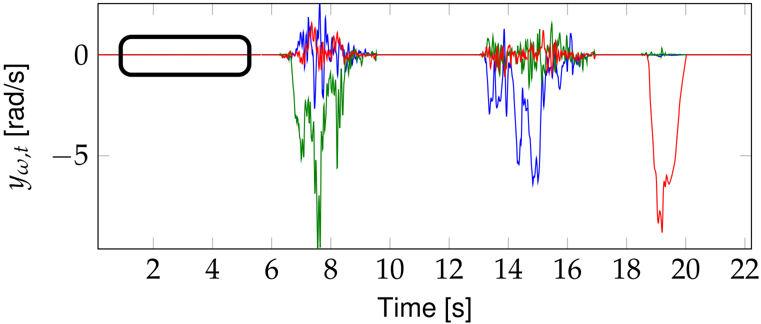
Inertial sensors

- Accelerometers
- Gyroscopes

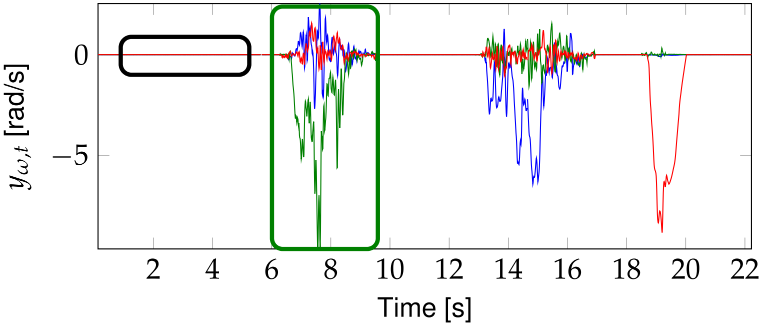
} Inertial sensors

Gyroscope measurements



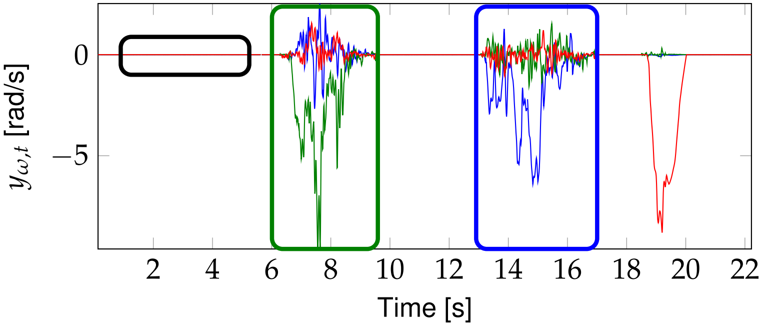


Stationary data ⇒ Zero angular velocity



Stationary data $\Rightarrow$ Zero angular velocity

Rotating the sensor around the y-axis

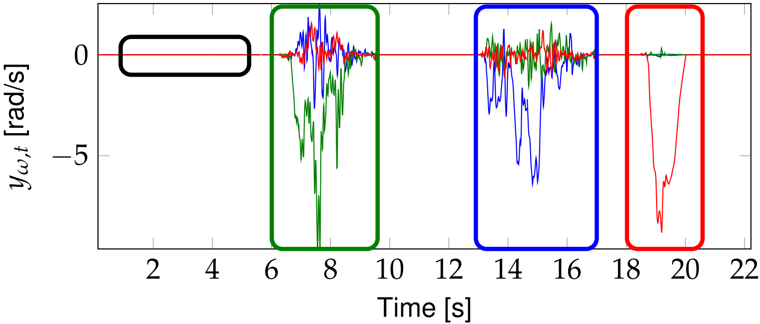


Stationary data ⇒ Zero angular velocity

Rotating the sensor around the y-axis

Rotating the sensor around the x-axis

Gyroscope measurements



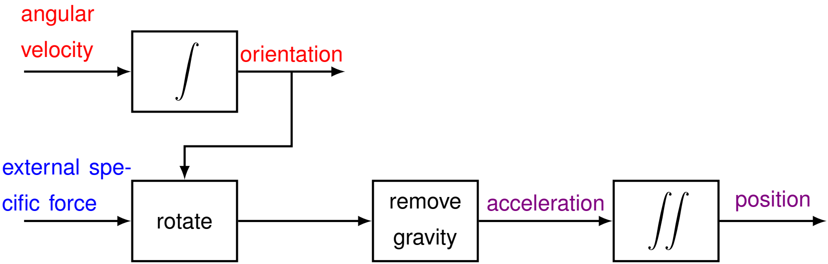
Stationary data ⇒ Zero angular velocity

Rotating the sensor around the y-axis

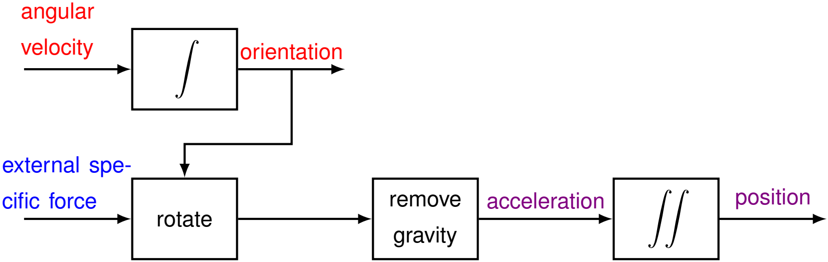
Rotating the sensor around the x-axis

Rotating the sensor around the z-axis

Inertial sensors for pose estimation



Inertial sensors for pose estimation

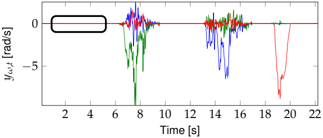


Accelerometers and gyroscopes (inertial sensors) can be used for position and orientation (pose) estimation but suffer from integration drift ⇒ Use additional sensors

Use inertial sensors in combination with other sensors to determine position and orientation.

Use inertial sensors in combination with other sensors to determine position and orientation.

- All sensors have measurement noise



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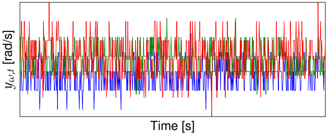

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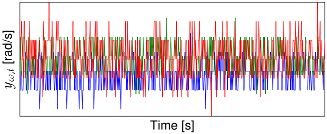

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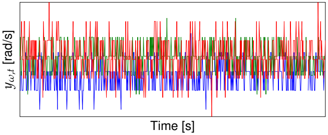
- All models are approximations
- The models might have unknown parameters (the sensors need to be calibrated)



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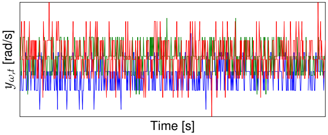

$\Rightarrow$ **Use probabilistic modeling to combine information from the different sensors and the different models both for position/orientation estimation and for sensor calibration**

State-space models

$$
\begin{aligned}
x_{t+1} &= f_t(x_t, \theta, u_t, v_t) \\
y_t &= h_t(x_t, \theta, e_t)
\end{aligned}
$$

Unknown state x at time t and $t+1$

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Inputs u at time t

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Nonlinear dynamic and measurement equations

The *maximum a posteriori* estimate of the state $x_{1:N} = \{x_1, \ldots, x_N\}$ is defined as

$$\hat{x}_{1:N}^{\text{MAP}} = \arg\max_{x_{1:N}} p(x_{1:N} \mid y_{1:N})$$

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Example: orientation estimation

$$\begin{aligned} R_{t+1}^{\text{nb}} &= f_t(R_t^{\text{nb}}, y_{\omega,t}, e_{\omega,t}) \\ y_{\text{a},t} &= R_t^{\text{bn}}\left(a^{\text{n}} - g^{\text{n}}\right) + e_{\text{a},t} \approx -R_t^{\text{bn}} g^{\text{n}} + e_{\text{a},t} \\ y_{\text{m},t} &= R_t^{\text{bn}} m^{\text{n}} + e_{\text{m},t} \end{aligned}$$

State estimation: MAP estimation

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Sensor calibration: ML estimation

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Example: magnetometer calibration

$$\begin{aligned} R^{\text{nb}}_{t+1} &= f_t(x_t, y_{\omega,t}, e_{\omega,t}) \\ y_{\text{a},t} &= R^{\text{bn}}_t (a^{\text{n}} - g^{\text{n}}) + e_{\text{a},t} \approx -R^{\text{bn}}_t g^{\text{n}} + e_{\text{a},t} \\ y_{\text{m},t} &= D R^{\text{bn}}_t m^{\text{n}} + o + e_{\text{m},t} \end{aligned}$$

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Use inertial sensors in combination with other sensors to estimate position and orientation

- The information of all models and sensors needs to be combined (sensor fusion)

  $\Rightarrow$ Determine *MAP* estimate of the state $x_{1:N}$

- The sensors need to be calibrated

  $\Rightarrow$ Determine *ML* estimate of the parameter vector θ

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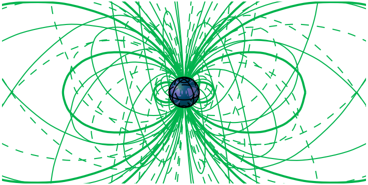
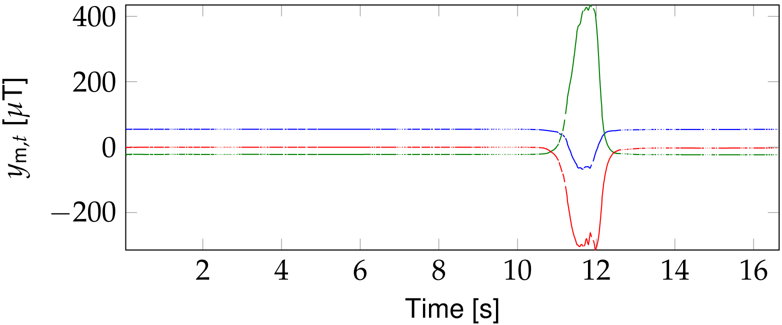
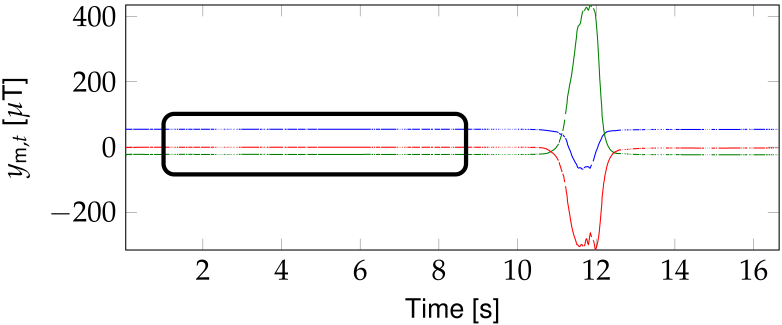
Magnetometers measure the local (earth) magnetic field



They can be used in combination with inertial sensors to determine the sensor’s orientation

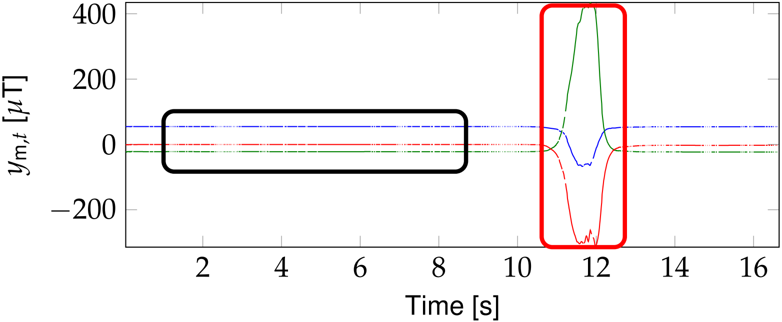
Magnetometer measurements





Stationary magnetometer data ⇒ Local (earth) magnetic field

Magnetometer measurements



Stationary magnetometer data ⇒ Local (earth) magnetic field

Magnetic disturbance close to sensor ⇒ Local (earth) magnetic field + magnetic disturbance

Magnetometers can be used in combination with inertial sensors to estimate the sensor's orientation ...

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Main contribution

Magnetometer calibration algorithm developed to correct for

1. magnetometer sensor errors,
2. presence of magnetic disturbances rigidly attached to the sensor,
3. misalignment between magnetometer and inertial sensor axes,

by solving a maximum likelihood problem.

Magnetometer calibration using inertial sensors

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Magnetometer calibration algorithm developed to correct for

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After magnetometer calibration, accurate orientation estimates can be obtained.

Magnetometer calibration algorithm

1. Rigidly mount the magnetometer and the inertial sensors on the platform to be used.
2. Rotate the assembly in all possible rotations to collect inertial and magnetometer measurements
   - $\Rightarrow$ Uncalibrated magnetometer measurements
   - $\Rightarrow$ Wrong orientation estimates
3. Estimate the calibration parameters
   1. Obtain an initial estimate of the parameters.
   2. Obtain a maximum likelihood estimate of the parameters.
4. Apply the estimated calibration parameters to the magnetometer measurements.
   - $\Rightarrow$ Calibrated magnetometer measurements
   - $\Rightarrow$ Correct orientation estimates

State-space model with unknown parameters

$$
\begin{aligned}
R^{\text{nb}}_{t+1} &= f_t(R^{\text{nb}}_t, y_{\omega,t}, e_{\omega,t}) \\
y_{\text{a},t} &= R^{\text{bn}}_t (a^{\text{n}} - g^{\text{n}}) + e_{\text{a},t} \approx -R^{\text{bn}}_t g^{\text{n}} + e_{\text{a},t} \\
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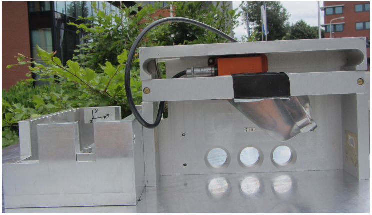
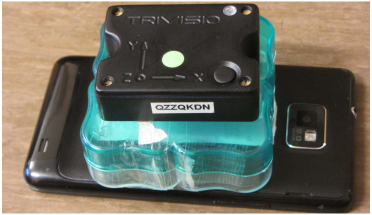
\end{aligned}
$$

where

$$
\begin{aligned}
y_{\omega,t} &= \omega_t + b_\omega + e_{\omega,t} \\
e_{\omega,t} &\sim \mathcal{N}(0, \Sigma_\omega) \\
e_{\text{a},t} &\sim \mathcal{N}(0, \Sigma_a) \\
e_{\text{m},t} &\sim \mathcal{N}(0, \Sigma_m)
\end{aligned}
$$





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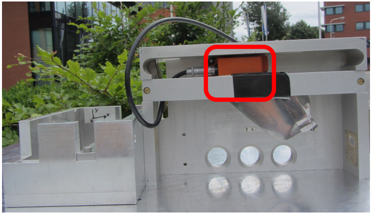
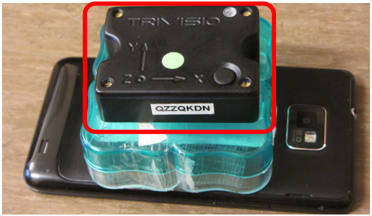
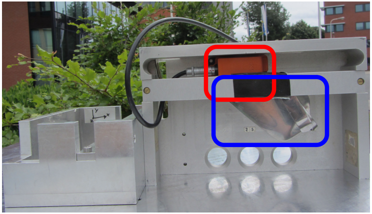
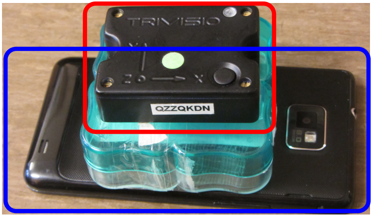




Inertial measurement unit (inertial sensors + magnetometer)

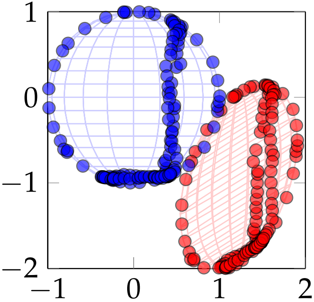
Experiments

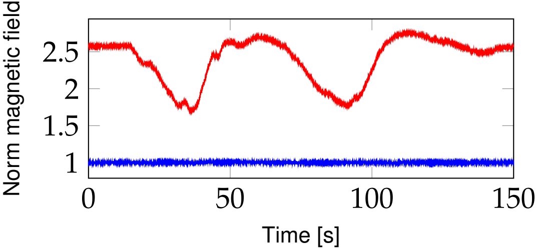




Inertial measurement unit (inertial sensors + magnetometer)

Magnetic disturbance

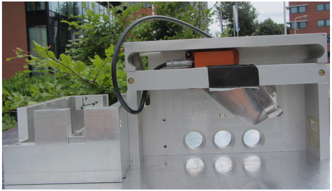


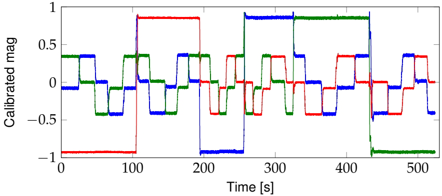


$$y_{\text{m},t} = DR_t^{\text{bn}} m^{\text{n}} + o + e_{\text{m},t}$$

$$\widehat{D} = \begin{pmatrix} 0.74 & -0.13 & 0.01 \\ -0.12 & 0.68 & 0.01 \\ -0.03 & 0.43 & 1.00 \end{pmatrix}, \quad \widehat{o} = \begin{pmatrix} 1.36 \\ 1.22 \\ -0.94 \end{pmatrix}$$

Resulting orientation (heading) error





z up	z down	x up	x down	y down
0.11	0.69	0.22	0.86	0.18
0.22	2.48	0.07	1.57	0.29
0.46	1.53	0.97	0.61	0.20
0.30	1.92	0.29	1.78	0.50

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3. Conclusions and future work

Show movie

Courtesy of Xsens Technologies

We solve the motion capture problem by solving a *maximum a posteriori* (MAP) problem

$$\min_{z=\{x_{1:N},\theta\}} \underbrace{-\log p(x_1 \mid y_1) - \log p(\theta)}_{\text{initialization}}$$

$$\underbrace{-\sum_{t=2}^{N} \log p(x_t \mid x_{t-1}, \theta)}_{\text{dynamic model}} \underbrace{-\sum_{t=1}^{N} \log p(y_t \mid x_t, \theta)}_{\text{biomechanical/sensor model}}$$

$$\text{s.t. } c_{\text{bio}}(z) = 0$$

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$x_{1:N}$: the sensors' positions, velocities and orientations, the body segments' positions and orientations.

θ: constant model parameters such as sensor biases

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$$\text{s.t. } c_{\text{bio}}(z) = 0$$

$x_{1:N}$: the sensors' positions, velocities and orientations, the body segments' positions and orientations.

θ: constant model parameters such as sensor biases

$c_{\text{bio}}(z)$: constraints based on the biomechanical model

Biomechanical model

The body segments are connected at the joints

The position and orientation of the sensors on the body is approximately constant

Some joints are restricted in their rotational freedom

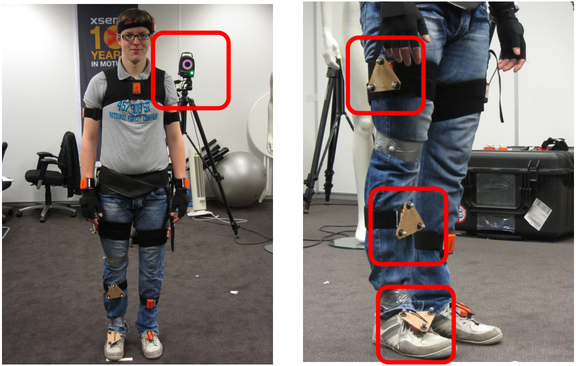
The body segments are connected at the joints
⇒ constraint

The position and orientation of the sensors on the body is approximately constant
⇒ objective

Some joints are restricted in their rotational freedom
⇒ objective

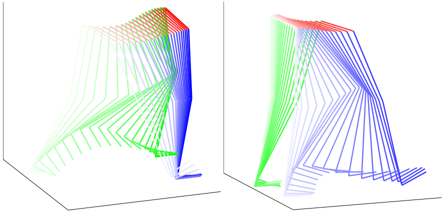

YEAR
IN MOTI
NATIONAL FOREST COMPANY

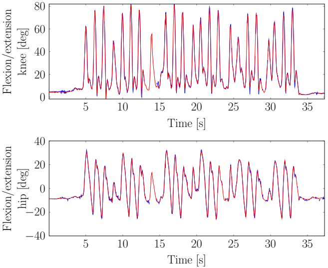
Experiments



Markers for an optical reference system

Show movie




Flexion/extension knee [deg]
0
20
40
60
80
5
10
15
20
25
30
35
Time [s]
Flexion/extension hip [deg]
−40
−20
0
20
40
5
10
15
20
25
30
35
Time [s]

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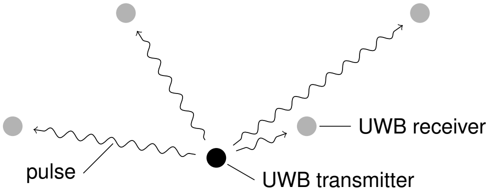
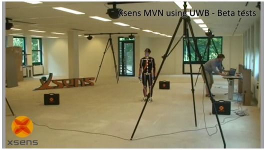
Ultra-wideband





Courtesy of Xsens Technologies

Use time of arrival measurements to determine the sensor position

Sensor fusion of inertial sensors and UWB

- Calibrate the ultra-wideband (UWB) system

  ⇒ Parameter estimation: Determine receiver positions and clock offsets

- Determine the sensor position and orientation using inertial and ultra-wideband measurements

  ⇒ State estimation

$$y_{\mathsf{u},mlk} = \tau_{lk} + \|r_m^{\mathsf{n}} - t_{lk}^{\mathsf{n}}\|_2 + \Delta\tau_m + e_{\mathsf{u},mlk}$$

$$y_{\mathrm{u},mlk} = \tau_{lk} + \|r_m^{\mathrm{n}} - t_{lk}^{\mathrm{n}}\|_2 + \Delta\tau_m + e_{\mathrm{u},mlk}$$

$y_{\mathrm{u},mlk}$: TOA measurements

t^{n}_{lk}: Transmitter position

τ_{lk}: Time of transmission of the pulse

$$y_{\mathrm{u},mlk} = \tau_{lk} + \|r^{\mathrm{n}}_m - t^{\mathrm{n}}_{lk}\|_2 + \Delta\tau_m + e_{\mathrm{u},mlk}$$

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r^{n}_{m}: Receiver position

$\Delta\tau_m$: Receiver clock offset

$y_{\mathrm{u},mlk}$: TOA measurements

$e_{\mathrm{u},mlk}$: measurement noise

t^{n}_{lk}: Transmitter position

τ_{lk}: Time of transmission of the pulse

$$y_{\mathrm{u},mlk} = \tau_{lk} + \|r^{\mathrm{n}}_{m} - t^{\mathrm{n}}_{lk}\|_2 + \Delta\tau_m + e_{\mathrm{u},mlk}$$

r^{n}_{m}: Receiver position

$\Delta\tau_m$: Receiver clock offset

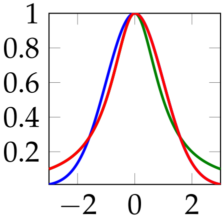
$y_{\mathrm{u},mlk}$: TOA measurements

$e_{\mathrm{u},mlk}$: measurement noise

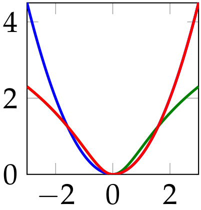
Ultra-wideband measurements suffer from non-line-of-sight and multipath

$$e_{\mathrm{u},mlk} \sim \begin{cases} \mathrm{Cauchy}(0, \gamma) & e_{\mathrm{u},mlk} \leq 0 \\ \mathcal{N}(0, \sigma^2) & e_{\mathrm{u},mlk} > 0 \end{cases}$$

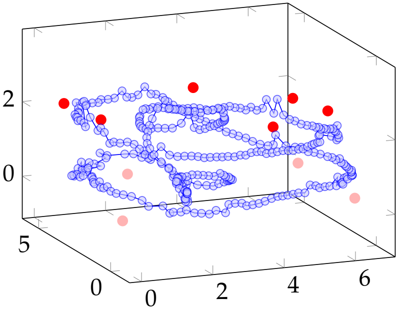
Probability density function

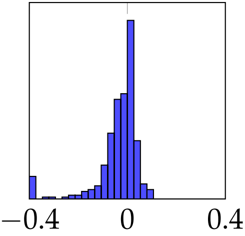


Cost function



Gaussian distribution
Cauchy distribution
The asymmetric distribution





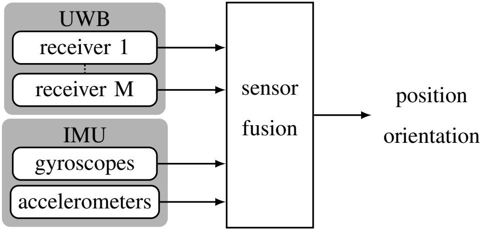
Calibration results:

- receiver positions
- (transmitter positions)

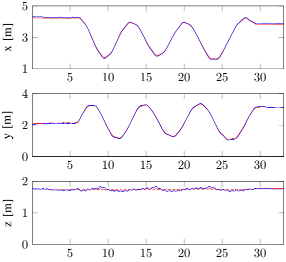
Residuals from one of the receivers

Estimate the pose of the sensor on the subject's head using inertial and UWB measurements

Estimate the pose of the sensor on the subject's head using inertial and UWB measurements



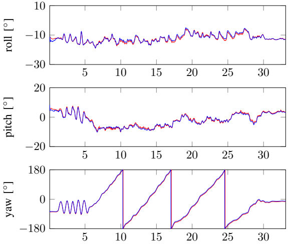
Use tightly-coupled EKF algorithm with outlier rejection

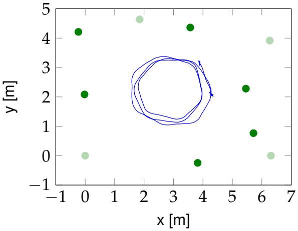


Blue: Our estimates

Red: Reference

Green: Receiver positions





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Pose estimation using magnetometers

Recap from before:

Inertial sensors can be used for position and orientation estimation but suffer from integration drift.

$\Rightarrow$ Use inertial sensors in combination with magnetometers for orientation estimation.

$\Rightarrow$ Use inertial sensors in combination with ultra-wideband for position and orientation (pose) estimation.

Pose estimation using magnetometers

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Inertial sensors can be used for position and orientation estimation but suffer from integration drift.

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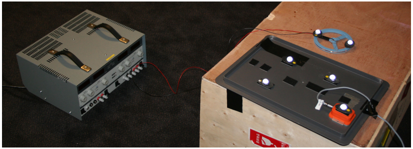
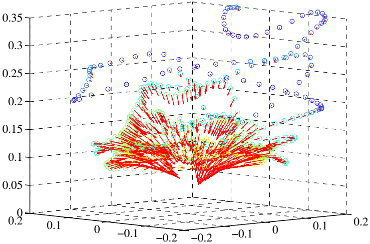
Alternative approach

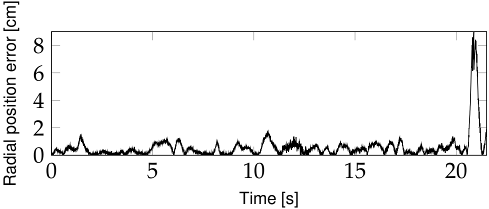
Use magnetometer data as a source of position information by using a map of the magnetic field.



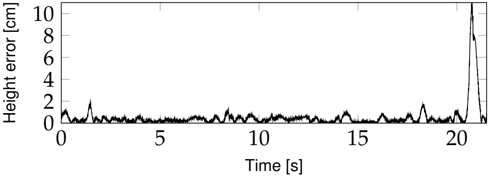


+ A magnetic coil generates an analytically known magnetic field that we can use to navigate in.

— The sensor position is not completely observable.

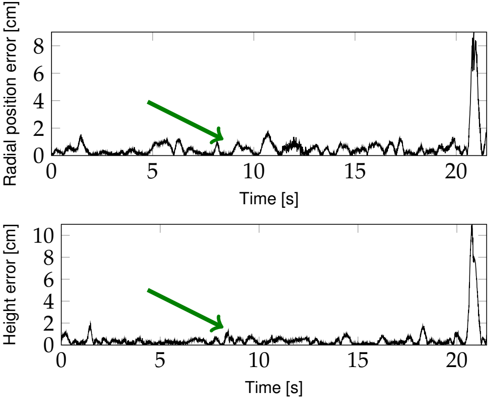


Radial position error [cm]
8
6
4
2
0
0
5
10
15
20
Time [s]



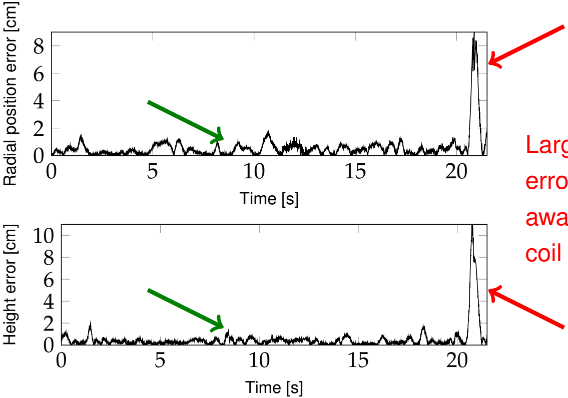
Height error [cm]
10
8
6
4
2
0
0
5
10
15
20
Time [s]

Small position error close to the coil



Experimental results

Small position error close to the coil



Larger position error further away from the coil

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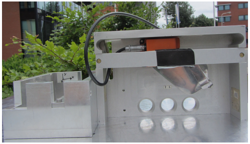
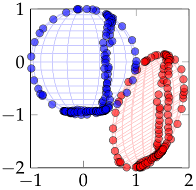
Sensor calibration:

- Developed a magnetometer calibration algorithm which calibrates a magnetometer in combination with inertial sensors to obtain better orientation estimates.

  Future work: Apply the algorithm to data from a smartphone.





Sensor calibration and sensor fusion:

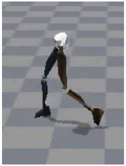
- Developed an ultra-wideband calibration algorithm.
- Developed a sensor fusion algorithm to combine inertial and UWB measurements.

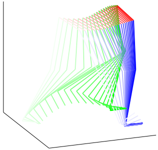
  Future work: Solve the sensor fusion problem as an optimization problem in which we take the asymmetric UWB noise distribution into account.

Sensor fusion:

- Developed an optimization-based approach to inertial human body motion capture.

  Future work: Extend the approach to more segments and for instance simultaneously estimate calibration parameters.

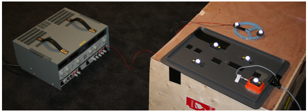


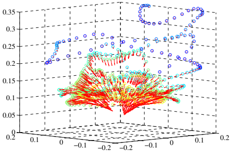


Sensor fusion:

- Developed an algorithm for pose estimation using the magnetic field as a source of position information.

  Future work: Extend the approach to also estimate the magnetic field map, i.e. extend to a *simultaneous localization and mapping* (SLAM) approach





Thank you for your attention

Questions?