



Magnetic tracking and mapping

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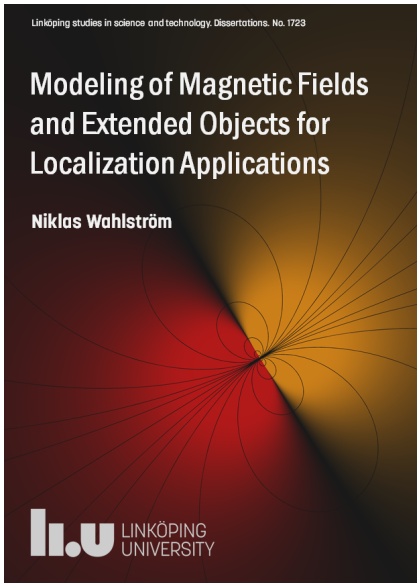
December 12, 2018



Short about me

- ▶ 2005 - 2010: Applied Physics and Electrical Engineering - International, Linköping University.
 - ▶ 2007-2008: Exchange student, ETH Zürich, Switzerland
- ▶ 2010-2015 : PhD student in Automatic Control, Linköping University
 - ▶ Spring 2014, Research visit, Imperial College, London, UK
- ▶ 2016- : *Postdoctoral researcher at Department of Information Technology, Uppsala University*

My thesis



Three areas:

- ▶ **Magnetic tracking and mapping**
- ▶ Extended target tracking
- ▶ Deep dynamical models for control

Papers about magnetic tracking/mapping

Paper A: N. Wahlström, F. Gustafsson, **Tracking Position of Magnetic Objects Using Magnetometer Networks** *in Modeling of Magnetic Fields and Extended Object for Localization Applications*. PhD Thesis.

Paper B: N. Wahlström, R. Hostettler, F. Gustafsson and W. Birk, **Classification of Driving Direction in Traffic Surveillance using Magnetometers**. *IEEE Transactions on Intelligent Transportation Systems*. 15(4), pp 1405-1418

Paper C: N. Wahlström, M. Kok, T.B. Schön, and F. Gustafsson. **Modeling Magnetic Fields using Gaussian Processes**. *The 38th International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, Vancouver, Canada, May, 2013.



Magnetometer measurement models

1. **Common use:** Magnetometer provides **orientation** heading information.

Assume that the magnetometer (almost) only measures the local (earth) magnetic field.



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Maxwell's equations

$$\nabla \cdot \mathbf{E} = \frac{\rho}{\epsilon_0}$$

$$\nabla \times \mathbf{E} + \frac{\partial \mathbf{B}}{\partial t} = \mathbf{0}$$

$$\nabla \cdot \mathbf{B} = 0$$

$$\nabla \times \mathbf{B} - \mu_0 \epsilon_0 \frac{\partial \mathbf{E}}{\partial t} = \mu_0 \mathbf{J}$$

Maxwell's equations

Electrostatics $\nabla \cdot \mathbf{E} = \frac{\rho}{\epsilon_0}$

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Magnetostatics

$$\nabla \times \mathbf{B} - \mu_0 \epsilon_0 \frac{\partial \mathbf{E}}{\partial t} = \mu_0 \mathbf{J}$$

E: Electric field

ρ : Charge density

B: Magnetic field

J: Current density

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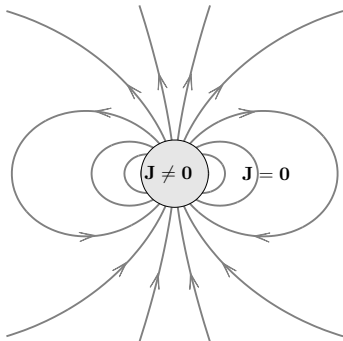
\mathbf{B} : Magnetic field

\mathbf{J} : Current density

The magnetostatic equations are difficult to solve...

Magnetic dipole

...however, if the current density is localized, an analytical solution exists!



Magnetic dipole field

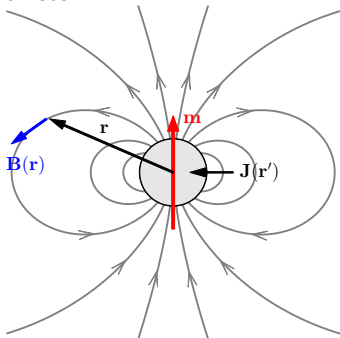
$$\mathbf{B}(\mathbf{r}) = \frac{\mu_0}{4\pi} \frac{3(\mathbf{r} \cdot \mathbf{m})\mathbf{r} - \|\mathbf{r}\|^2 \mathbf{m}}{\|\mathbf{r}\|^5}$$

Magnetic dipole moment

$$\mathbf{m} \triangleq \frac{1}{2} \int \mathbf{r}' \times \mathbf{J}(\mathbf{r}') d^3 r'$$

Magnetic dipole

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Sensor model - single dipole

The measurements can be described with a state-space model

$$\begin{aligned}\mathbf{x}_{k+1} &= F_k \mathbf{x}_k + G_k \mathbf{w}_k, & \mathbf{w}_k &\sim \mathcal{N}(\mathbf{0}, Q), \\ \mathbf{y}_{k,j} &= \mathbf{h}_j(\mathbf{x}_k) + \mathbf{e}_k, & \mathbf{e}_k &\sim \mathcal{N}(\mathbf{0}, R)\end{aligned}$$

Point target sensor model (one dipole)

$$\begin{aligned}\mathbf{h}_j(\mathbf{x}_k) &= C(\mathbf{r}_k - \boldsymbol{\theta}_j) \mathbf{m}_k, & \mathbf{x}_k &= [\mathbf{r}_k^\top \quad \mathbf{v}_k^\top \quad \mathbf{m}_k^\top \quad \boldsymbol{\omega}_k^\top]^\top \\ C(\mathbf{r}) &= \frac{\mu_0}{4\pi \|\mathbf{r}\|^5} (3\mathbf{r}\mathbf{r}^\top - \|\mathbf{r}\|^2 I_3),\end{aligned}$$

Measurement from a sensor network of magnetometers positioned at $\{\boldsymbol{\theta}_j\}_{j=1}^J$.

Degrees of freedom

- ▶ 3D position
- ▶ 2D orientation

Sensor model - multi-dipole

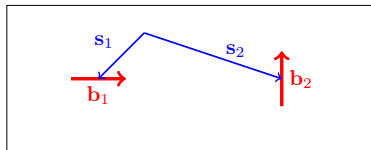
The measurements can be described with a state-space model

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Extended target sensor model (a structure of dipoles)

$$\mathbf{h}_j(\mathbf{x}_k) = \sum_{l=1}^L C(\mathbf{r}_k + R_k(\mathbf{q}_k) \mathbf{s}_l - \boldsymbol{\theta}_j) m_l R_k(\mathbf{q}_k) \mathbf{b}_l,$$

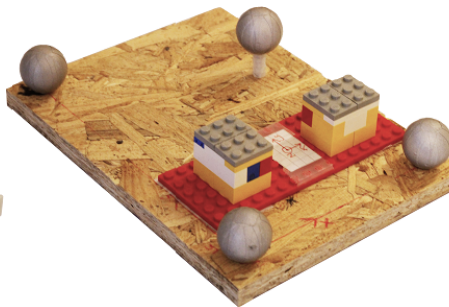
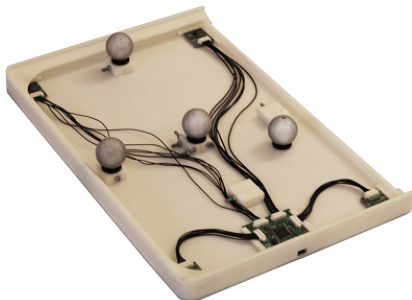
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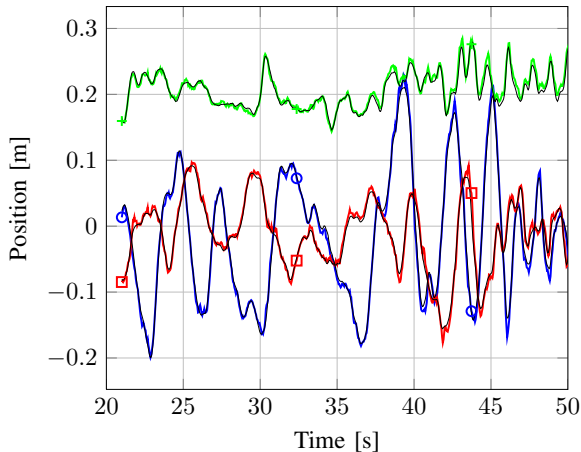
Degrees of freedom

- ▶ 3D position
- ▶ **3D** orientation

Experiment - setup

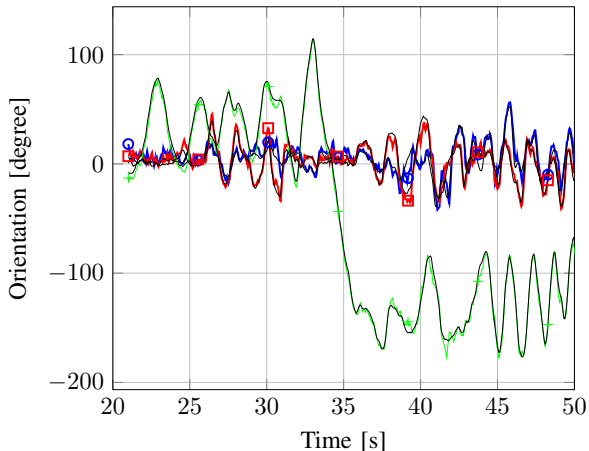


Experiment - results - position



Black: Ground truth position. Color: Estimated position

Experiment - results - orientation



Black: Ground truth orientation. Color: Estimated orientation

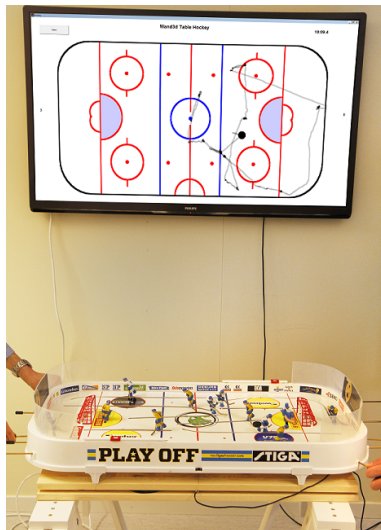
Application 1: Digital pathology



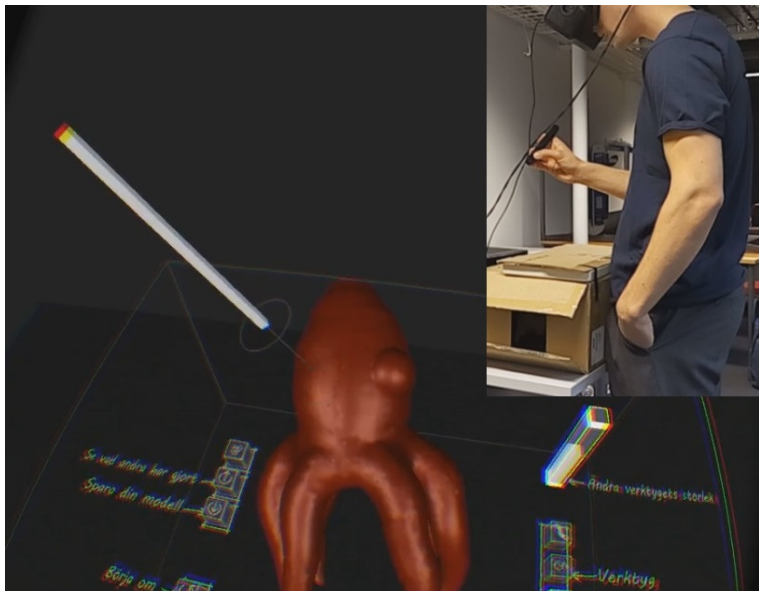
Application 2: Digital water colors



Application 3: Digital table hockey



Application 4: Interactive 3D modeling





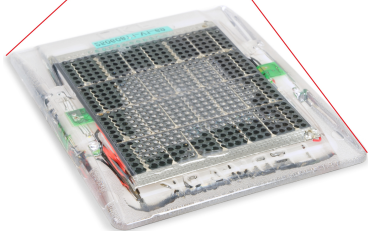
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Background



Traffic monitoring in wireless sensor network

- ▶ Sensor nodes equipped with a magnetometer.

Limitations:

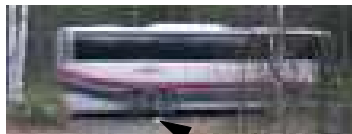
- ▶ Energy budget
- ▶ Computational resources.

Information you can extract

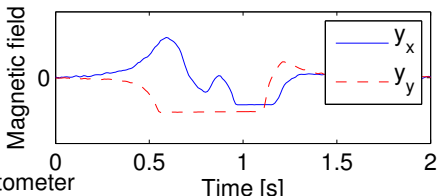
- ▶ Number of vehicles
- ▶ Type of vehicle
- ▶ *Heading direction*

Problem formulation

- ▶ 2-axis magnetometer has been deployed on the roadside



2-axis magnetometer



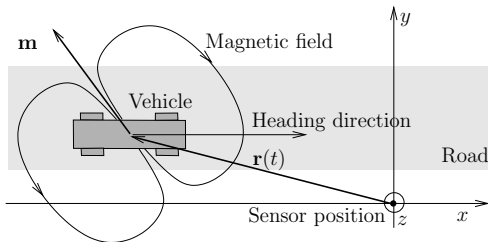
- ▶ Magnetometer measures a distortion of the magnetic field.

We want to classify the heading direction of the vehicle!

Magnetic dipole

The vehicle can be modeled as a magnetic dipole:

$$\mathbf{h}(t) = \frac{3(\mathbf{r}(t) \cdot \mathbf{m})\mathbf{r}(t) - \|\mathbf{r}(t)\|^2\mathbf{m}}{\|\mathbf{r}(t)\|^5}$$

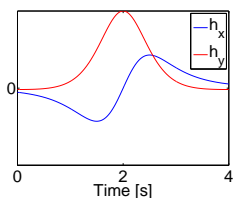
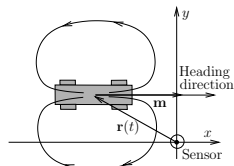
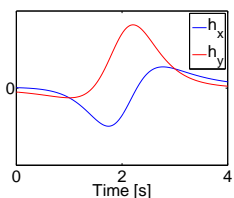
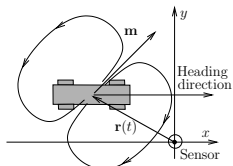
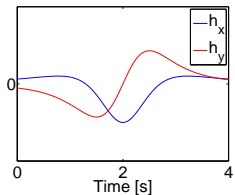
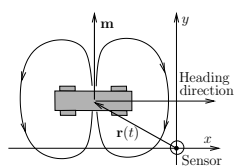


We measure two components of the magnetic field.

$$\mathbf{y}(kT) = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} \mathbf{h}(kT) + \mathbf{e}(kT), \quad k = 1, \dots, N$$

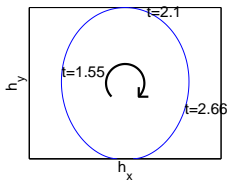
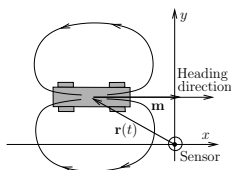
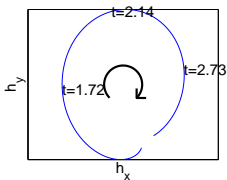
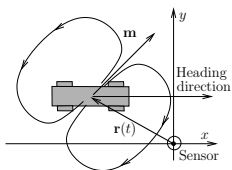
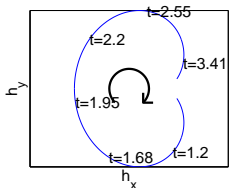
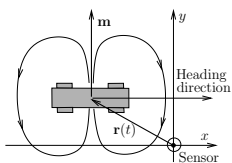
Simulated examples

Three different vehicle are heading in positive x -direction



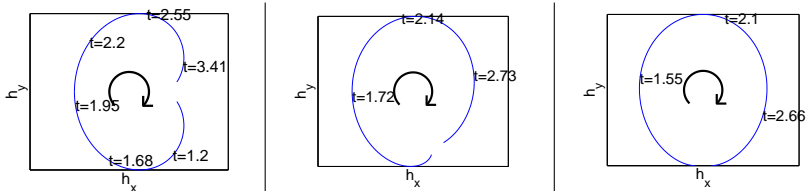
Simulated examples

Three different vehicle are heading in positive x -direction



- All measurement trajectories are turning clockwise!

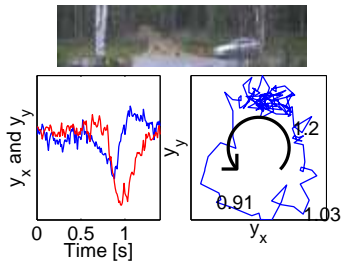
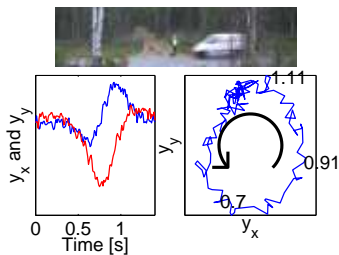
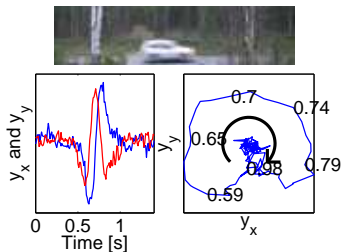
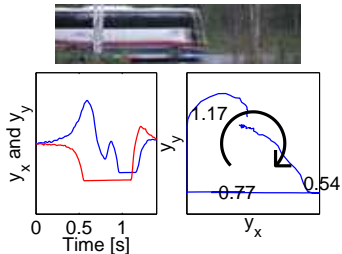
Key idea



Idea:

Classify heading direction by the turn of the measurement trajectory!

Real world data

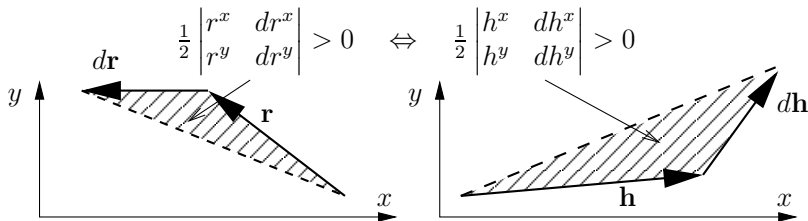


The theorem

Assume the magnetic dipole model

$$\mathbf{h} = \frac{3(\mathbf{r} \cdot \mathbf{m})\mathbf{r} - \|\mathbf{r}\|^2\mathbf{m}}{\|\mathbf{r}\|^5}$$

then



Observe: Independent of \mathbf{m} !

The classifier

Integrate over all infinitesimal area segments

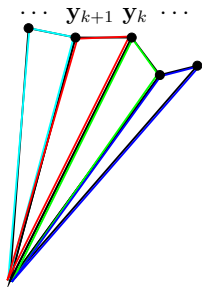
$$f = \int \begin{vmatrix} h^x & dh^x \\ h^y & dh^y \end{vmatrix} = \int \begin{vmatrix} h^x(t) & dh^x(t)/dt \\ h^y(t) & dh^y(t)/dt \end{vmatrix} dt.$$

The time discrete version will then be

$$\begin{aligned} f &= \sum_{k=1}^{N-1} \begin{vmatrix} h_k^x & (h_{k+1}^x - h_k^x)/T \\ h_k^y & (h_{k+1}^y - h_k^y)/T \end{vmatrix} T \\ &= \sum_{k=1}^{N-1} (h_k^x h_{k+1}^y - h_k^y h_{k+1}^x) \\ &= (\mathbf{h}_{1:(N-1)}^x)^T \mathbf{h}_{(1+1):N}^y - (\mathbf{h}_{1:(N-1)}^y)^T \mathbf{h}_{(1+1):N}^x \end{aligned}$$

The classifier

- ▶ Sum over all triangles
- ▶ The enclosed area can be computed as two inner products!



$$\hat{f} = (\mathbf{y}_{1:(N-1)}^x)^T \mathbf{y}_{(1+1):N}^y - (\mathbf{y}_{1:(N-1)}^y)^T \mathbf{y}_{(1+1):N}^x$$

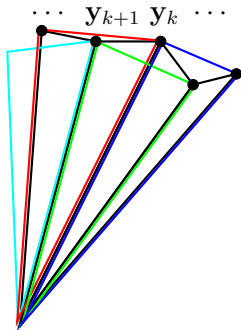
- ▶ The sign of \hat{f} determines the heading direction.

Note: \mathbf{h} has been replaced with the measurement \mathbf{y} which contains noise.

The improved classifier

The variance of \hat{f} can be reduced by trading for some bias.

- ▶ Idea: Average over larger triangles!

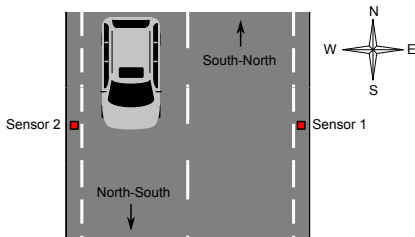


$$\hat{f}_p = (\mathbf{y}_{1:(N-p)}^x)^T \mathbf{y}_{(1+p):N}^y - (\mathbf{y}_{1:(N-p)}^y)^T \mathbf{y}_{(1+p):N}^x$$

Observe: The feature still only consists of two inner products!

Experimental results

- ▶ 2 sensor nodes
- ▶ 45 min
- ▶ 88 vehicles travelling south-north
- ▶ 99 vehicles travelling north-south



Correct classification by the two sensors

	South-North (Sensor 1)	North-South (Sensor 2)
Sensor 1	87/88	91/99
Sensor 2	82/88	99/99



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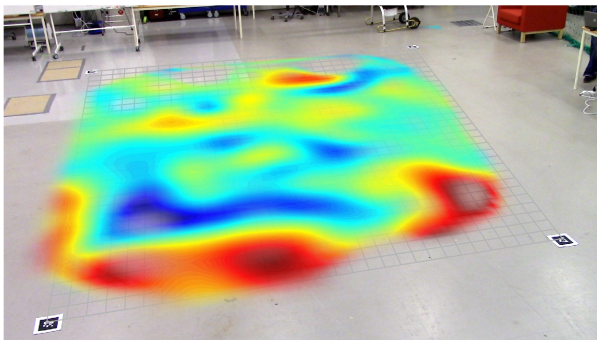
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Magnetic mapping

Build a map of the indoor magnetic field using Gaussian processes.

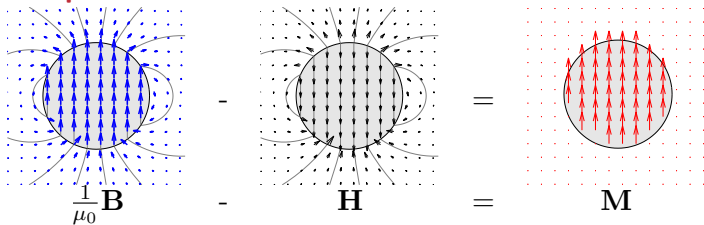


Magnetic fields

We use a slightly different version of the magnetostatic equations

$$\begin{aligned} \nabla \cdot \mathbf{B} &= 0, & \frac{1}{\mu_0} \mathbf{B} - \mathbf{H} &= \mathbf{M}, \\ \nabla \times \mathbf{H} &= \mathbf{0} \end{aligned}$$

Example



Gaussian processes

Gaussian processes can be seen as a distribution over functions

$$\mathbf{f}(\mathbf{u}) \sim \mathcal{GP}(\boldsymbol{\mu}(\mathbf{u}), K(\mathbf{u}, \mathbf{u}')),$$

Mean function \uparrow \uparrow Covariance function

It is a generalization of the multivariate Gaussian distribution

$$\begin{bmatrix} \mathbf{f}(\mathbf{u}_1) \\ \vdots \\ \mathbf{f}(\mathbf{u}_N) \end{bmatrix} \sim \mathcal{N}(\boldsymbol{\mu}, K), \quad \text{where} \quad \boldsymbol{\mu} = \begin{bmatrix} \boldsymbol{\mu}(\mathbf{u}_1) \\ \vdots \\ \boldsymbol{\mu}(\mathbf{u}_N) \end{bmatrix},$$

$$K = \begin{bmatrix} K(\mathbf{u}_1, \mathbf{u}_1) & \cdots & K(\mathbf{u}_1, \mathbf{u}_N) \\ \vdots & & \vdots \\ K(\mathbf{u}_N, \mathbf{u}_1) & \cdots & K(\mathbf{u}_N, \mathbf{u}_N) \end{bmatrix}.$$



Gaussian process regression

Objective: Estimate $f(u)$ from noisy observations $y_k = f(u_k) + e_k$



Gaussian process + magnetic fields

- ▶ The animation illustrated regression for one scalar function
 $f : \mathbb{R} \rightarrow \mathbb{R}$



Gaussian process + magnetic fields

- ▶ The animation illustrated regression for one scalar function $f : \mathbb{R} \rightarrow \mathbb{R}$
- ▶ We want to learn three different vector fields $\mathbf{f} : \mathbb{R}^3 \rightarrow \mathbb{R}^3$ In addition, these fields should obey



Gaussian process + magnetic fields

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- ▶ We want to learn three different vector fields $\mathbf{f} : \mathbb{R}^3 \rightarrow \mathbb{R}^3$ In addition, these fields should obey
 - ▶ $\nabla \cdot \mathbf{B} = 0$ (divergence free)
 - ▶ $\nabla \times \mathbf{H} = 0$ (curl free)

Gaussian process + magnetic fields

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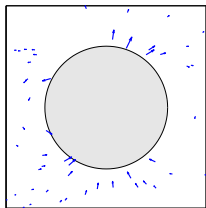
← There exist covariance functions for this!

Gaussian process + magnetic fields

- ▶ The animation illustrated regression for one scalar function $f : \mathbb{R} \rightarrow \mathbb{R}$
- ▶ We want to learn three different vector fields $\mathbf{f} : \mathbb{R}^3 \rightarrow \mathbb{R}^3$ In addition, these fields should obey
 - ▶ $\nabla \cdot \mathbf{B} = 0$ (divergence free) ← There exist covariance functions for this!
 - ▶ $\nabla \times \mathbf{H} = 0$ (curl free)
 - ▶ $\frac{1}{\mu_0} \mathbf{B} - \mathbf{H} = \mathbf{M}$

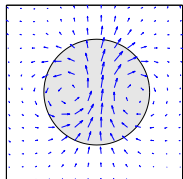
Simulation

Training data



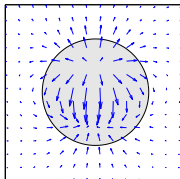
Predictions

Divergence free



$\frac{1}{\mu_0} \mathbf{B}$

Curl free



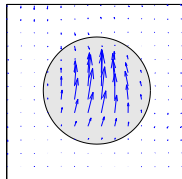
\mathbf{H}

-

=

-

=



\mathbf{M}

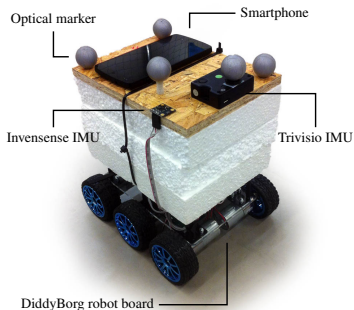


Building magnetic field maps (1)

Build a map of the indoor magnetic field using Gaussian processes.

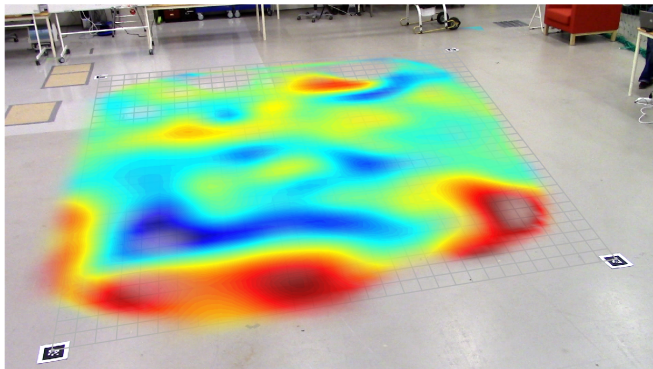
Building magnetic field maps (1)

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Building magnetic field maps (1)

Build a map of the indoor magnetic field using Gaussian processes.



Modeling the magnetic field

- ▶ The magnetic field \mathbf{H} is curl-free, i.e. $\nabla \times \mathbf{H} = \mathbf{0}$ [1]

$$\mathbf{y}_k = \mathbf{f}(\mathbf{x}_k) + \boldsymbol{\varepsilon}_k$$
$$\mathbf{f}(\mathbf{x}) \sim \mathcal{GP}(\mathbf{0}, \sigma_{\text{const.}}^2 I_3 + K_{\text{curl}}(\mathbf{x}, \mathbf{x}'))$$

[1] Niklas Wahlström, Manon Kok, Thomas B. Schön and Fredrik Gustafsson, **Modeling magnetic fields using Gaussian processes** *The 38th International Conference on Acoustics, Speech, and Signal Processing (ICASSP)*, Vancouver, Canada, May 2013.

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- ▶ If a vector-field is curl-free, a scalar potential φ exists
 $\mathbf{H} = -\nabla\varphi$ [2]

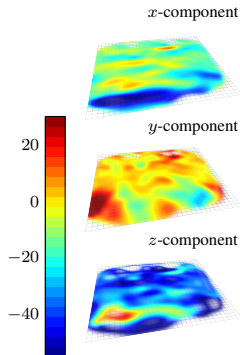
$$\mathbf{y}_k = -\nabla\varphi(\mathbf{x})\big|_{\mathbf{x}=\mathbf{x}_i} + \boldsymbol{\varepsilon}_k$$
$$\varphi(\mathbf{x}) \sim \mathcal{GP}(0, k_{\text{lin.}}(\mathbf{x}, \mathbf{x}') + k_{\text{SE}}(\mathbf{x}, \mathbf{x}'))$$

[1] Niklas Wahlström, Manon Kok, Thomas B. Schön and Fredrik Gustafsson, **Modeling magnetic fields using Gaussian processes** *The 38th International Conference on Acoustics, Speech, and Signal Processing (ICASSP)*, Vancouver, Canada, May 2013.

[2] Arno Solin, Manon Kok, Niklas Wahlström, Thomas B. Schön and Simo Särkkä, **Modeling and interpolation of the ambient magnetic field by Gaussian processes** *ArXiv e-prints*, September 2015. arXiv:1509.04634.

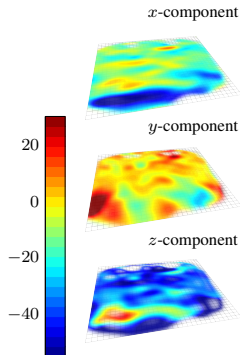
Building magnetic field maps (2)

- ▶ Encode physical knowledge in the kernel.



Building magnetic field maps (2)

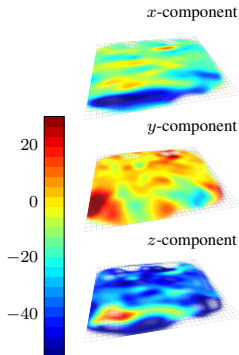
- ▶ Encode physical knowledge in the kernel.
- ▶ Use reduced-rank GP regression based on the method from [1].



[1] Hilbert Space Methods for Reduced-Rank Gaussian Process Regression – A. Solin, S. Särkkä.

Building magnetic field maps (2)

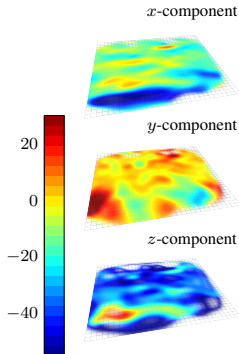
- ▶ Encode physical knowledge in the kernel.
- ▶ Use reduced-rank GP regression based on the method from [1].
- ▶ Use a Kalman filter formulation to allow for sequential updating.



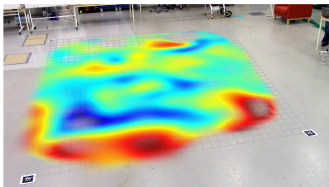
[1] Hilbert Space Methods for Reduced-Rank Gaussian Process Regression – A. Solin, S. Särkkä.

Building magnetic field maps (2)

- ▶ Encode physical knowledge in the kernel.
- ▶ Use reduced-rank GP regression based on the method from [1].
- ▶ Use a Kalman filter formulation to allow for sequential updating.
- ▶ Use a spatio-temporal model to allow for changes in the magnetic field.



[1] Hilbert Space Methods for Reduced-Rank Gaussian Process Regression – A. Solin, S. Särkkä.



Building the map:

Arno Solin, Manon Kok, Niklas Wahlström, Thomas B. Schön and Simo Särkkä, **Modeling and interpolation of the ambient magnetic field by Gaussian processes** *IEEE Transactions on Robotics*, 34(4):1112–1127, 2018

Localization in the map:

Arno Solin, Simo Särkkä, Juho Kannala, and Esa Rahtu. **Terrain navigation in the magnetic landscape: Particle filtering for indoor positioning** *In Proceedings of the European Navigation Conference*, Helsinki, Finland, May–June 2016.

SLAM:

Arno Solin, Manon Kok, **Scalable Magnetic Field SLAM in 3D Using Gaussian Process Maps** *ArXiv e-prints*, March 2018. arXiv:1804.01926.



Summary

- ▶ **Tracking** position and orientation of magnetic objects with magnetometer sensor network



Summary

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- ▶ **Vehicle heading direction classification** using a 2-axis magnetometer.



Summary

- ▶ **Tracking** position and orientation of magnetic objects with magnetometer sensor network
- ▶ **Vehicle heading direction classification** using a 2-axis magnetometer.
- ▶ **Mapping magnetic fields** using Gaussian processes.



Thank you!

Reduced-Rank GPR

Hilbert-space approximation of the covariance operator in terms of an eigenfunction expansion of the Laplace operator in a compact subset of \mathbb{R}^d .

- ▶ Assume that the measurements are confined to a certain domain.
- ▶ Approximate the covariance using the spectral density and a number of eigenvalues and eigenfunctions. For $d = 1$:

$$k(x, x') \approx \sum_{j=1}^m S(\lambda_j) \phi_j(x) \phi_j(x')$$

$$\phi_j(x) = \frac{1}{\sqrt{L}} \sin\left(\frac{\pi n_j (x+L)}{2L}\right), \quad \lambda_j = \frac{\pi j}{2L},$$

- ▶ Converges to the true GP when the number of basis functions and the size of the domain goes to infinity.



Reduced-Rank GPR

Consequences for our problem:

Original formulation:

50 or 100 Hz magnetometer data (in 3D)

⇒ Size of the matrix to invert grows very quickly with each additional second of data

⇒ Downsampling needed and large buildings become infeasible

Reduced-rank formulation:

Possible to use all data

⇒ Size of the problem does not grow for longer data sets

Sequential updating

Initialize $\mu_0 = 0$ and $\Sigma_0 = \Lambda_\theta$ (from the GP prior). For each new observation $i = 1, 2, \dots, n$ update the estimate according to

$$S_i = \nabla\Phi_i \Sigma_{i-1} [\nabla\Phi_i]^\top + \sigma_{\text{noise}}^2 \mathcal{I}_3,$$

$$K_i = \Sigma_{i-1} [\nabla\Phi_i]^\top S_i^{-1},$$

$$\mu_i = \mu_{i-1} + K_i (y_i - \nabla\Phi_i \mu_{i-1}),$$

$$\Sigma_i = \Sigma_{i-1} - K_i S_i K_i^\top.$$

Spatio-temporal modeling

Model the scalar potential magnetic field instead as

$$\varphi(x, t) \sim \mathcal{GP}(0, \kappa_{\text{lin.}}(x, x') + \kappa_{\text{SE}}(x, x')\kappa_{\text{exp}}(t, t')),$$

with

$$\kappa_{\text{exp}}(t, t') = \exp\left(-\frac{|t - t'|}{\ell_{\text{time}}}\right).$$

The scalar potential can then sequentially be estimated by adding a *time update* to the *measurement update* from before as

$$\tilde{\mu}_i = A_{i-1}\mu_{i-1},$$

$$\tilde{\Sigma}_i = A_{i-1}\Sigma_{i-1}A_{i-1}^{\text{T}} + Q_{i-1}.$$

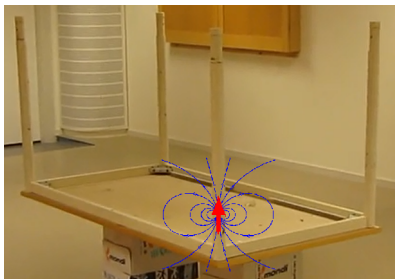
Problem formulation



How should the map be modeled?

We want to find
a magnetic map of
this object!

Problem formulation

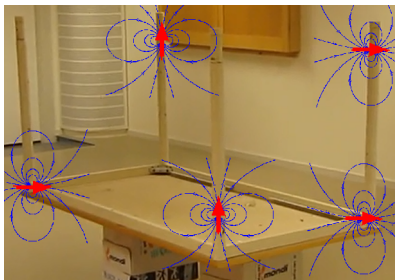


We want to find
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How should the map be modeled?

- ▶ Use the dipole model?

Problem formulation

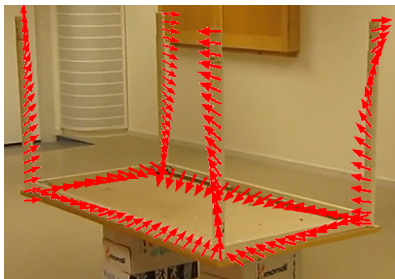


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- ▶ Use the dipole model?
- ▶ Use multiple dipoles?

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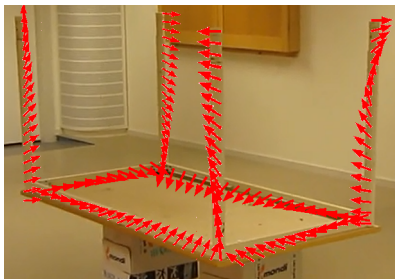


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- ▶ Use multiple dipoles?
- ▶ Use a **continuum of dipoles!**

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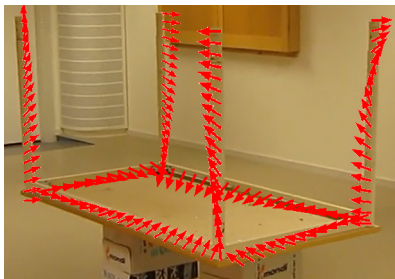


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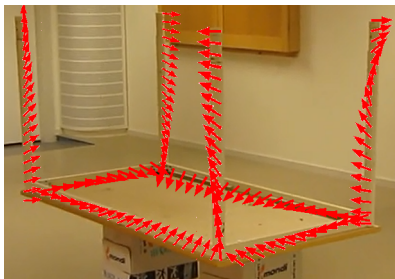


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- ▶ **Spatial correlation**

Problem formulation



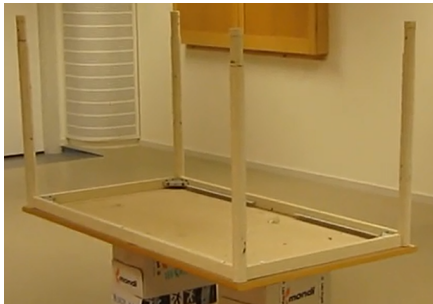
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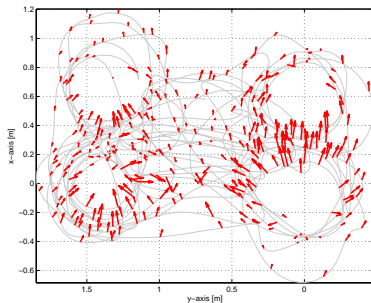
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- ▶ **Spatial correlation**

Real world experiment

- ▶ Measurements have been collected with a magnetometer
- ▶ An optical reference system (Vicon) has been used for determining the position and orientation of the sensor



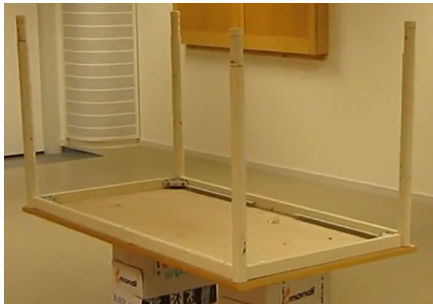
The magnetic environment



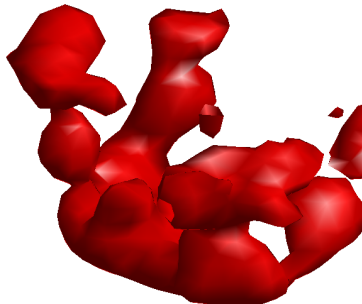
Training data

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The magnetic environment



Estimated magnetic content