

Terrain Navigation Using the Ambient Magnetic Field as a Map

Arno Solin

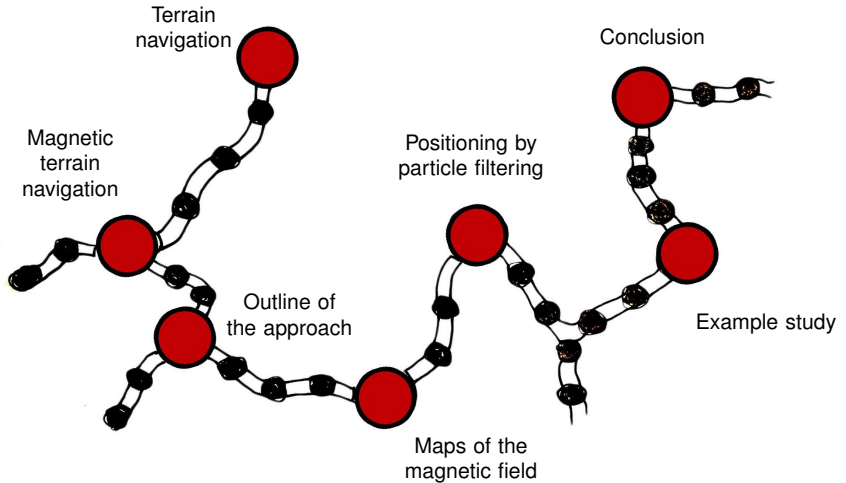
Aalto University

IndoorAtlas Ltd.

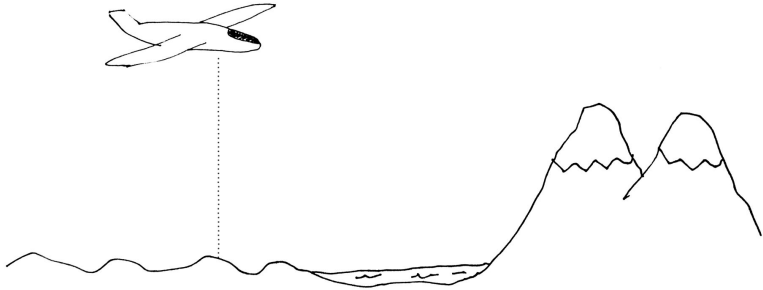
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In collaboration with
M. Kok, N. Wahlström, T. B. Schön, J. Kannala, E. Rahtu, and S. Särkkä

Presentation Outline



(Classical) Terrain Navigation



Terrain Matching in the Magnetic Landscape



Outline of the Approach

- ▶ **Magnetic terrain map:**

A Gaussian process model for the magnetic field estimate and its variance for any spatial location in the building.

- ▶ **Particle filtering:**

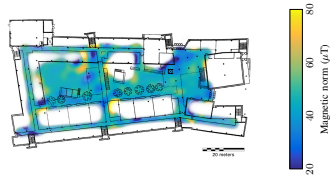
A sequential Monte Carlo approach for proposing different state histories and finding which one matches the data the best.

- ▶ **Pedestrian dead reckoning:**

A model for the movement of the person being tracked.

Maps of the Magnetic Field

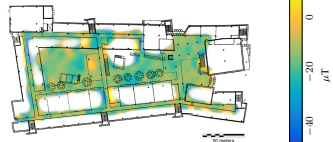
- ▶ A map of the magnetic field is required.
- ▶ The magnetic field is a **vector field**.
- ▶ A set of measurements of the magnetic field at known spatial points.
- ▶ Interpolation and extrapolation of the magnetic field done by a **Gaussian process** (GP) regression model [1].
- ▶ The model combines the **noisy measurements** with prior information from the **physical properties** of magnetic fields.
- ▶ The output is both the mean and marginal variance of the magnetic field at **any spatial input**.



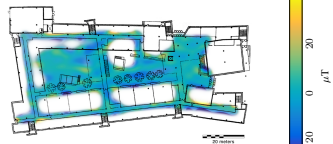
Magnitude of the magnetic field.

Maps of the Magnetic Field

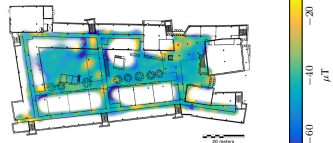
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(a) x-component



(b) y-component



(c) z-component

Positioning by Particle Filtering

- ▶ Probabilistic statistical inference on where the user is based on his/her history of magnetometer observations.
- ▶ Concerned with state space models of form

$$\begin{aligned}\mathbf{x}_{k+1} &\sim p(\mathbf{x}_{k+1} \mid \mathbf{x}_k), \\ \mathbf{y}_k &\sim p(\mathbf{y}_k \mid \mathbf{x}_k).\end{aligned}$$

- ▶ State variables: user position and heading angle.
- ▶ Combining assumptions of user movement (PDR) and ...
- ▶ ... how the assumed positions match the magnetic field.

Positioning by Particle Filtering

Initialization: Draw n samples from the prior $\mathbf{x}_0^{(i)} \sim p(\mathbf{x}_0)$, $i = 1, \dots, n$.

For each time step $k = 1, 2, \dots$

1. **Prediction:** Draw samples $\mathbf{x}_k^{(i)}$ from the importance distributions

$$\mathbf{x}_k^{(i)} \sim \pi(\mathbf{x}_k \mid \mathbf{x}_{k-1}^{(i)}, \mathbf{y}_{1:k}), \quad i = 1, 2, \dots, n.$$

This propagates the particles according to the PDR model.

2. **Map matching:** Calculate new weights according to

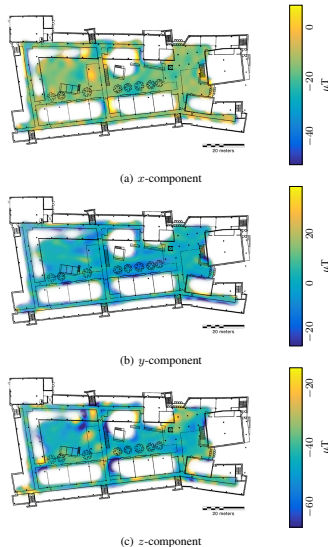
$$w_k^{(i)} \propto w_{k-1}^{(i)} \frac{p(\mathbf{y}_k \mid \mathbf{x}_k^{(i)}) p(\mathbf{x}_k^{(i)} \mid \mathbf{x}_{k-1}^{(i)})}{\pi(\mathbf{x}_k^{(i)} \mid \mathbf{x}_{k-1}^{(i)}, \mathbf{y}_{1:k})}$$

and normalize them to sum to unity.

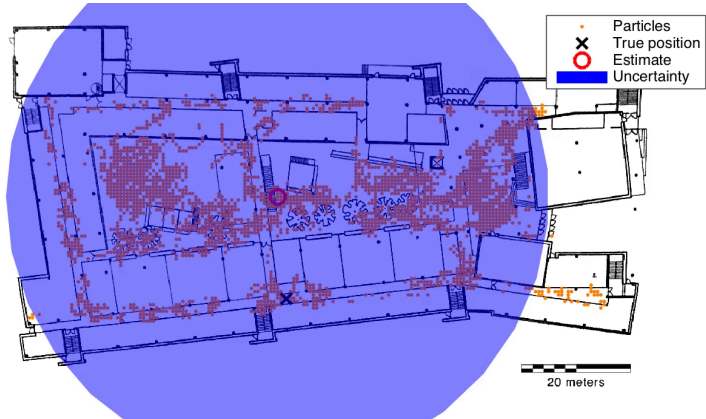
3. **Resampling**

Example Study

- ▶ **Case study:**
 - CS Building at Aalto University.
- ▶ **Mapping:**
 - Nexus 5 smartphone.
 - 867 m of mapping paths in 15 min.
 - Some 42 000 measurements.
- ▶ **Test paths:**
 - Collected two weeks later.
 - Sampling rate in the test paths is 5 Hz.
 - Each test case roughly 30 s long.
 - 100 test paths altogether.
- ▶ **Setup:**
 - Particles $n = 5000$.
 - Sensors calibrated off-line.



Example Study



The videos are available on YouTube:
<https://youtu.be/UuUo9Q00T1Q>

Conclusion

- ▶ Good performance even using magnetic only:
 - ▶ Time-to-convergence: 12 s.
 - ▶ Distance-to-convergence: 13 m.
 - ▶ Error after convergence: 5 m (best case 1–2 m.).
- ▶ What to do to take this further:
 - ▶ Sensor calibration.
 - ▶ Pedestrian dead-reckoning.
 - ▶ Further sensor fusion (satellite and radio).
 - ▶ SLAM.

Bibliography

- [1] Arno Solin, Manon Kok, Niklas Wahlström, Thomas B. Schön, and Simo Särkkä. *Modeling and interpolation of the ambient magnetic field by Gaussian processes*. Accepted for publication in IEEE Transactions on Robotics.
- [2] Arno Solin, Simo Särkkä, Juho Kannala, and Esa Rahtu (2016). *Terrain navigation in the magnetic landscape: Particle filtering for indoor positioning*. Proceedings of the European Navigation Conference.

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- The methods and results in this poster are from [1] and [2].
- Anomalies in the Earth magnetic field can be used as features in indoor positioning [3].
- To aircraft and vehicle positioning, classical *inertial navigation* considers matching movement to pre-existing contour map of the terrain [4].
- It is similar to positioning by matching pedestrian movement to a vector-valued map of the environment [5].
- The method has three parts:
 - 1) Magnetic map-making
 - 2) Pedestrian dead reckoning
 - 3) Map matching
- Here we focus on [1] and [2].
- The PGFM is a binary movement model described at [Amdo](#).
- All other methods are

- ▶ The magnetic field is a **vector** field
- ▶ A set of measurements of the magnetic field at known spatial points
- ▶ Interpolation and extrapolation done by a **Gaussian process** (GP regression model [1, 2])
- ▶ The model **assumes** the assumption of the fact being generated by a latent scalar potential function: $\mathbf{v}(\mathbf{x}) \leftarrow \nabla \Phi(\mathbf{x}; \boldsymbol{\mu}, \mathbf{K}, \mathbf{C}) + \boldsymbol{\eta}_0(\mathbf{x})$
- ▶ The hyperparameters of the covariance function are **learned** from data
- ▶ The **vector** dimensionality of the

where $\mathbf{x}_i \sim \text{N}(\mathbf{0}, \frac{1}{\lambda} \mathbf{I})$. Or add observations $\mathbf{z} = \mathbf{I}, \mathbf{I}, \dots, \mathbf{I}$.

- The additional prior information helps the model

- The output is both the mean and marginal variance of the magnet field at any spatial input.

• An example of a perturbed magnetic field is shown in Figure

- Probabilistic statistical inference where the user is, based on the history of magnetometer observations
- Concerned with state space models of form

$$\mathbf{x}_{k+1} \sim p(\mathbf{x}_{k+1} | \mathbf{x}_k),$$

$$\mathbf{y}_k \sim p(\mathbf{y}_k | \mathbf{x}_k)$$
- State variables: user position and heading angle
- Containing assumptions of user movement (JCR) and ...
- ... how the assumed position match the magnetic field

- Initialisation: Draw i -sampled $\mathbf{x}_i^{(0)} \sim p(\mathbf{x})$, $i = 1, \dots, N$

3 | **Prediction:** Draw samples \mathbf{y}_i^j from the importance distribution

$$w_{ij}^{(2)} = w_{ij}^{(1)} \frac{f(x_{ij})}{f(x_{ij}) + \frac{1}{n} \sum_{k=1}^n f(x_{ik}) + \frac{1}{n} \sum_{k=1}^n f(x_{kj})}$$

(2) Resampling

- Case study:
 - CD-Building at RMIT University
- Mapping:
 - 12 Flexus 3 smartphone
 - BET in mapping path is 18 mm
 - Some 42000 measurements
- Test paths:
 - Collected two weeks later
 - Sampling rate only 5 Hz
 - Each test case roughly 30 s long
 - 100 test paths altogether
- Setup:
 - Particles $n = 30000$
 - Sensors calibrated off line
- Good performance extracting movement only:
 - Distance-to-convergence: 12 s
 - Time-to-convergence: 13 min
 - Error after convergence: 5 cm
 - (best case 1-2 cm)
- Not extended respectively a universal Feature 3.

DISCUSSION

- Magnetic tensor mapping is a feasible approach to robust positioning.
- For convergence, movement over several meters is required.
- The method provides high accuracy, but with a risk of no convergence if the mapping is insufficient.
- The method can be improved with better PCB, movement detection, and additional information sources (GPS, Wi-Fi, barometer, ...).

5. A. Aoki, S. Nishio, S. Yamamoto, S. H. Lee, and S. Kuroki, Modeling and simulation of the air-breathing ramjet fuel by the neural network, accepted for publication in *IEEE Transactions on Systems, Man, and Cybernetics*.
6. A. Aoki, S. Yamamoto, S. Yamamoto, S. H. Lee, S. Kuroki, and S. Yamamoto, Air-breathing ramjet fuel by the neural network, accepted for publication in *IEEE Transactions on Systems, Man, and Cybernetics*.
7. A. Aoki and S. Yamamoto, Global model identification of the air-breathing ramjet fuel, *IEEE Transactions on Systems, Man, and Cybernetics*, 1999, vol. 29, no. 5, pp. 670-676.
8. J. Kurihara, J. Kurihara, S. Yamamoto, S. H. Lee, and S. Kuroki, Air-breathing ramjet fuel by the neural network, *IEEE Transactions on Systems, Man, and Cybernetics*, 1999, vol. 29, no. 5, pp. 677-683.
9. S. H. Lee, S. Yamamoto, and S. Kuroki, Global model identification of the air-breathing ramjet fuel, *IEEE Transactions on Systems, Man, and Cybernetics*, 1999, vol. 29, no. 5, pp. 670-676.

Figure 1-23 is a schematic diagram of a vehicle chassis, specifically focusing on the front suspension and steering components. It shows a side view of the front wheel assembly, including the steering knuckle, upper and lower control arms, and the wheel hub. The diagram is labeled with various components and their functions, such as 'Steering Knuckle', 'Upper Control Arm', 'Lower Control Arm', 'Wheel Hub', and 'Brake Disc'. The diagram is labeled with 'Figure 1-23' at the bottom.

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