

Licentiate seminar

Localization using Magnetometers and Light Sensors



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Automatic control is about making a system to behave in the way you want.



Example: Unmanned Aerial Vehicle (UAV)



Automatic control is about making a system to behave in the way you want.



Example: Unmanned Aerial Vehicle (UAV)

- The system has to sense its surrounding (for example in order to determine its **position**)



Automatic control is about making a system to behave in the way you want.



Example: Unmanned Aerial Vehicle (UAV)

- The system has to sense its surrounding (for example in order to determine its position)
- The control has to be accomplished automatically



Localization can be defined as

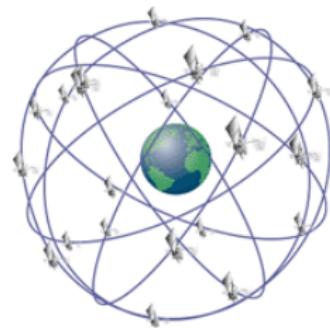
The process of **automatically** determining a **position** of an object

In this thesis we will investigate two different localization techniques

- *Magnetic localization*
- Localization with *light levels*



- Satellite navigation



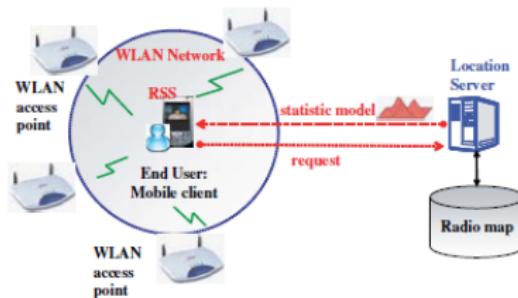
Source: NASA



Standard Localization Techniques

4(31)

- Satellite navigation
- Radio navigation



Ivanov, S., Nett, E., Schemmer, S. **Automatic WLAN localization for industrial automation** *IEEE International Symposium on Intelligent Signal Processing*, 2009.



Standard Localization Techniques

4(31)

- Satellite navigation
- Radio navigation
- Radar



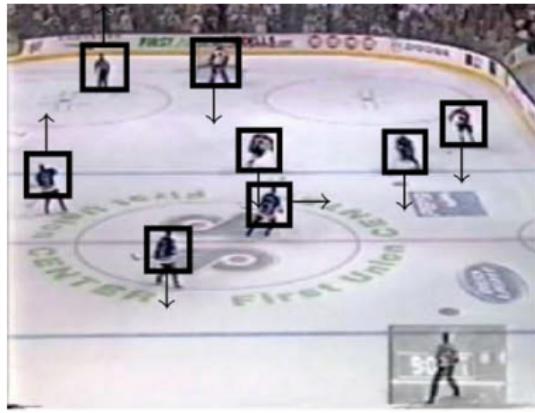
Photo: US army



Standard Localization Techniques

4(31)

- Satellite navigation
- Radio navigation
- Radar
- Computer vision



Lu, W.-L., Okuma, K. and Little, J. J. **Tracking and Recognizing Actions of Multiple Hockey Players using the Boosted Particle Filter**. *Image and Vision Computing*, 27(1–2):189–205, 2009.



Standard Localization Techniques

4(31)

- Satellite navigation
- Radio navigation
- Radar
- Computer vision
- Inertial navigation



Source: wikipedia

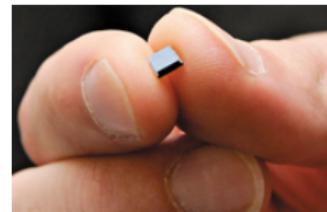


Photo: <http://theenergycollective.com/>



Alternative Localization Techniques

5(31)

In this thesis, two alternative localization techniques are investigated.

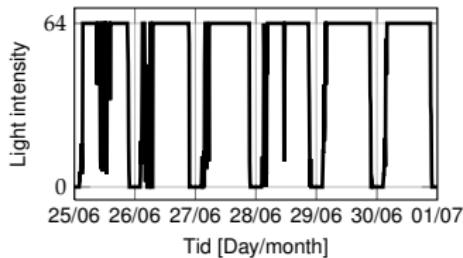
Magnetic localization



Light levels



Source: Forskning & Framsteg 5/6 - 2012.



Courtesy of Geveko ITS



The two localization techniques have very different properties

	Magnetic localization	Light levels
Coverage	Vicinity of the sensor	The whole earth
Accuracy	> 5 mm	>150 km
Update frequency	100 Hz (sensor dependent)	Twice a day



The two localization techniques have very different properties

	Magnetic localization	Light levels
Coverage	1×10^1 m	1×10^7 m
Accuracy	1×10^{-1} m	1×10^5 m
Update frequency	1×10^2 Hz	1×10^{-6} Hz



The two localization techniques have very different properties

	Magnetic localization	Light levels
Coverage	1×10^1 m	1×10^7 m
Accuracy	1×10^{-1} m	1×10^5 m
Update frequency	1×10^2 Hz	1×10^{-6} Hz

They also have common advantages

- Cheap
- Small
- Low energy consumption



- Traffic surveillance

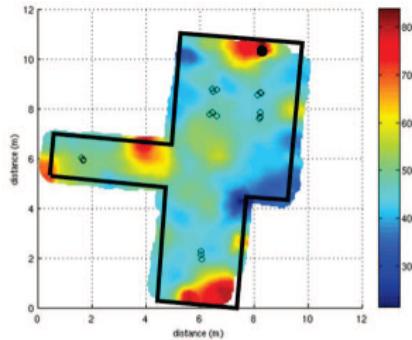


In Paper A and Paper B

Applications

7(31)

- Traffic surveillance
- Indoor navigation



I. Vallivaara, J. Haverinen, A. Kemppainen, and J. Roning
Simultaneous localization and mapping using ambient magnetic field. In *Proc. of the IEEE Conference on Multisensor Fusion and Integration for Intelligent Systems (MFI)*, 2010

Models for magnetic maps are investigated in **Paper C**



- Traffic surveillance
- Indoor navigation
- Localization in public environments



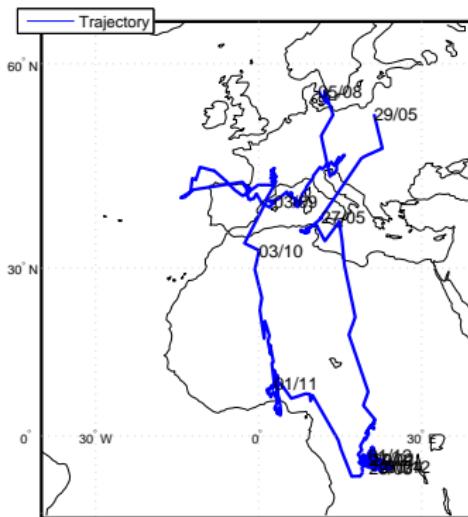
Visit *Visualiseringscenter C* in Norrköping!

This application is not further analyzed in this thesis.

Applications

7(31)

- Traffic surveillance
- Indoor navigation
- Localization in public environments
- Bird localization



Presented in Paper D



Introduction

Electromagnetic theory

Localizing moving magnetic objects

Mapping magnetic environments

Geolocation using Light levels

Concluding remarks



Maxwell's equations

9(31)

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

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

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

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

E: Electric field

ρ : Charge density

B: Magnetic field

J: Current density



Maxwell's equations

Electrostatics

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Magnetostatics

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Maxwell's equations

9(31)

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Maxwell's equations

9(31)

Electrostatics

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Magnetostatics

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

E: Electric field

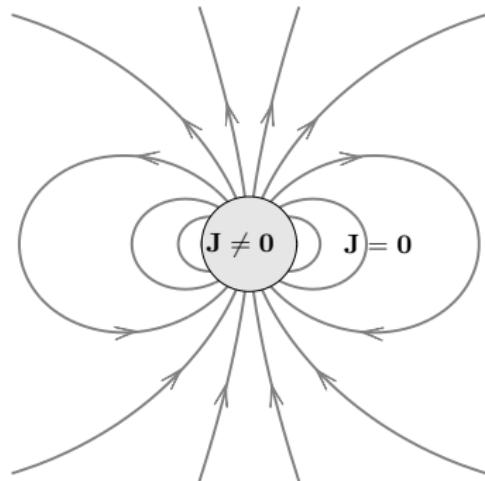
ρ : Charge density The magnetostatic equations are difficult to solve...

B: Magnetic field

J: Current density



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



Magnetic dipole field

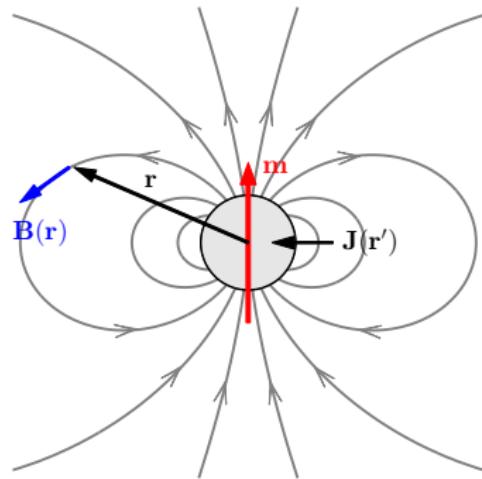
$$\mathbf{B}(\mathbf{r}) = \frac{\mu_0}{4\pi} \frac{3(\mathbf{r} \cdot \mathbf{m})\mathbf{r} - \|\mathbf{r}\|^2 \mathbf{m}}{\|\mathbf{r}\|^5}$$

Magnetic dipole moment

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



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



Magnetic dipole field

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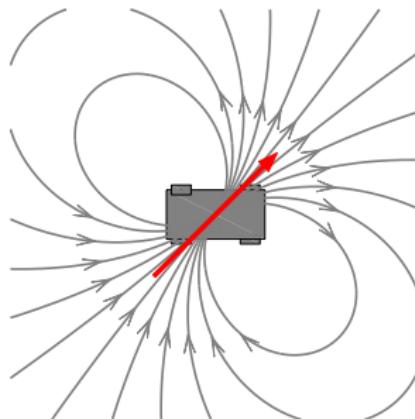
Magnetic dipole moment

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

Application: Traffic surveillance

Contributions:

- Multiple sensors (**Paper A**)
 - Point target model

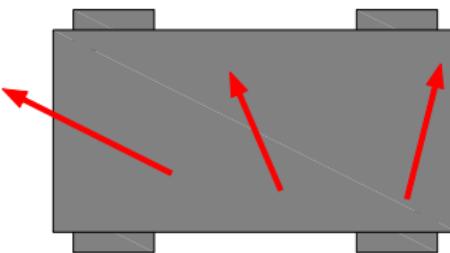


Idea: Model the **vehicle** as a
magnetic dipole

Application: Traffic surveillance

Contributions:

- Multiple sensors (**Paper A**)
 - Point target model
 - Extended target model



Idea: Use **multiple magnetic dipoles** to describe target extent

Application: Traffic surveillance

Contributions:

- Multiple sensors (**Paper A**)

- Point target model
- Extended target model
- Target orientation dependent model

Idea: Decompose **dipole moment** into **hard iron** and **soft iron** components.



Application: Traffic surveillance

Contributions:

- Multiple sensors ([Paper A](#))
 - Point target model
 - Extended target model
 - Target orientation dependent model
 - Observability analysis



Application: Traffic surveillance

Contributions:

- Multiple sensors (**Paper A**)

- Point target model
- Extended target model
- Target orientation dependent model
- Observability analysis

- One 2-axis sensor (**Paper B**)

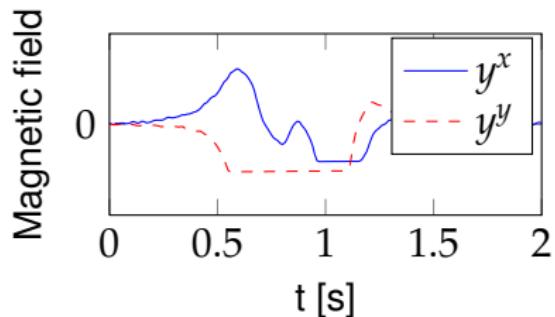
- Determine driving direction



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



Magnetometer

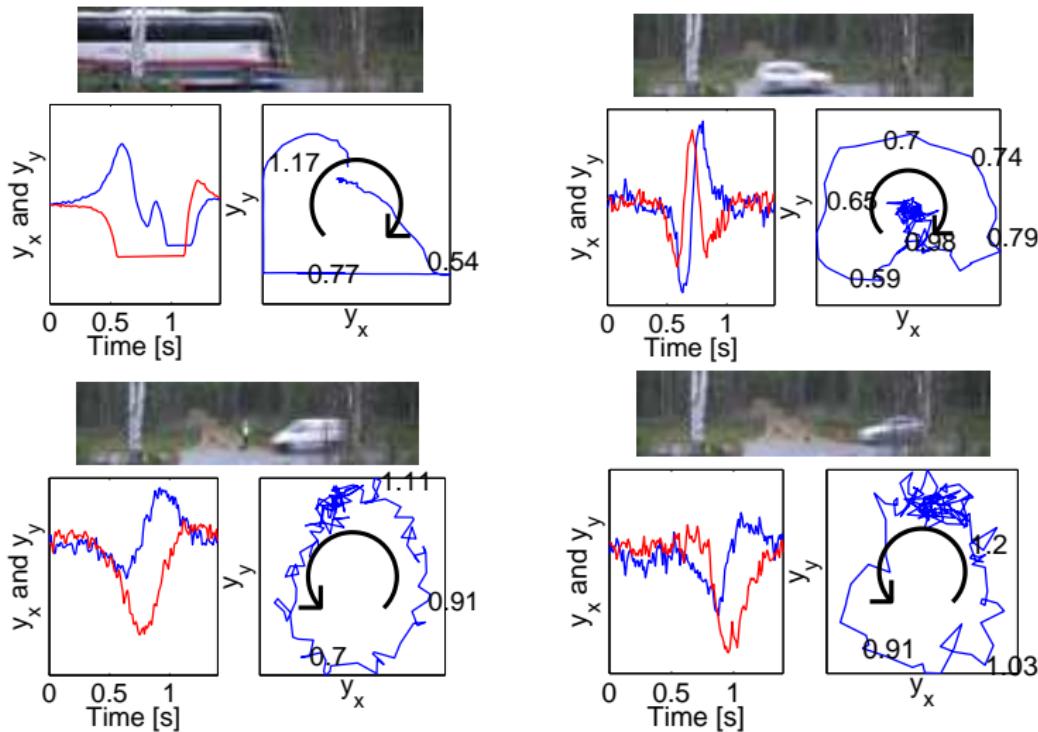


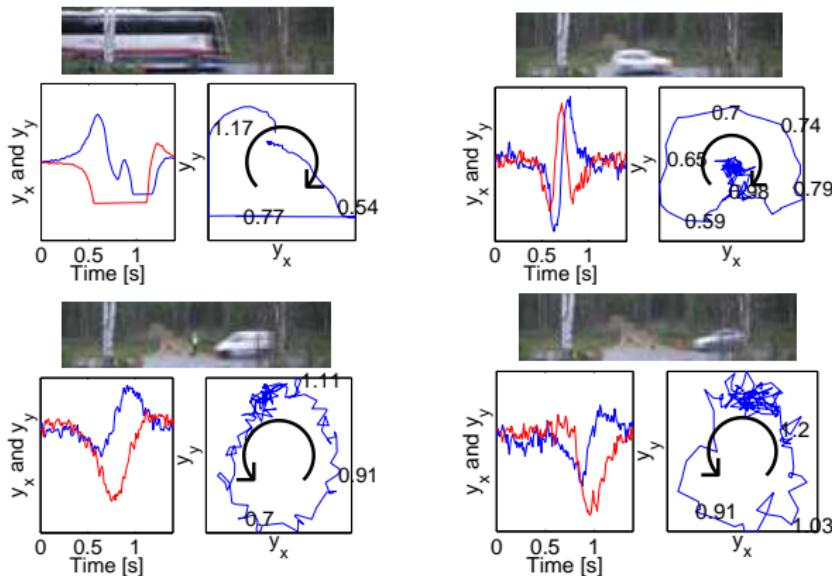
- The magnetometer measures a distortion of the magnetic field.

We want to classify the driving direction of the vehicle!

Real world data

13(31)

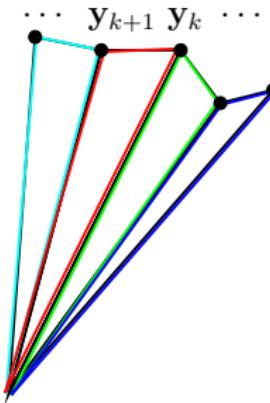




Classify driving direction by the turn of the measurement trajectory!

The area of one triangle is

$$\frac{1}{2} \begin{vmatrix} y_k^x & y_{k+1}^x \\ y_k^y & y_{k+1}^y \end{vmatrix} = \frac{1}{2} (y_k^x y_{k+1}^y - y_k^y y_{k+1}^x)$$



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

$$\hat{f} = \frac{1}{2} ((\mathbf{y}_{1:N}^x)^T \mathbf{y}_{2:(N+1)}^y - (\mathbf{y}_{1:N}^y)^T \mathbf{y}_{2:(N+1)}^x)$$

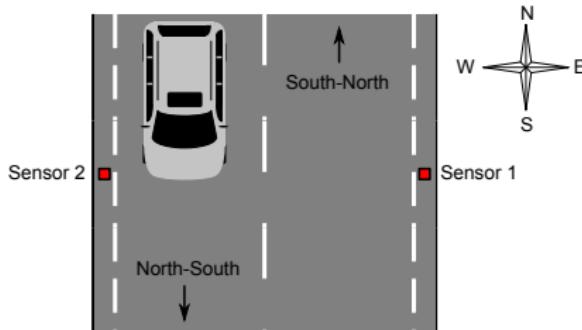
- The sign of \hat{f} determines the driving direction.



Experimental results

16(31)

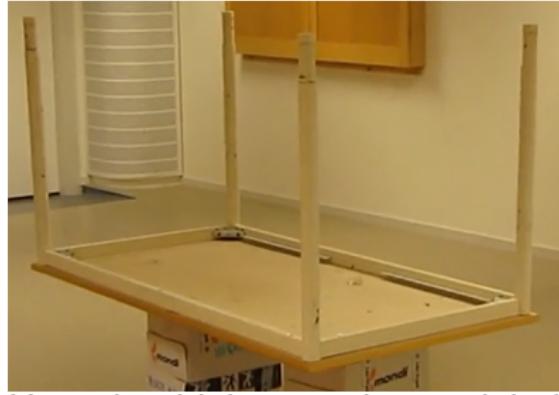
- 2 sensor nodes
- 158 min
- 291 vehicles travelling south-north
- 220 vehicles travelling north-south



Correct classification by the two sensors

	South-North (Sensor 1)	North-South (Sensor 2)
Sensor 1	290/291	189/220
Sensor 2	265/291	220/220

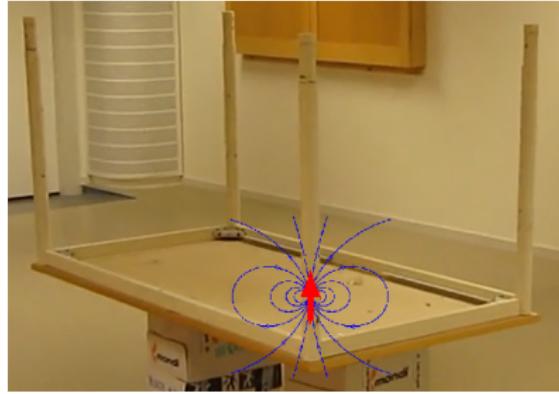




How should the map be modeled?

We want to find a magnetic map of this object!



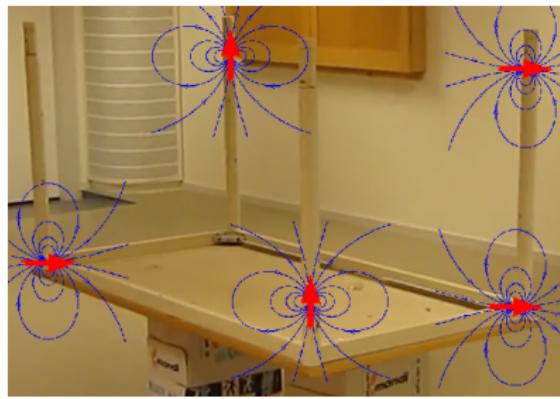


How should the map be modeled?

- Use the dipole model?

We want to find a magnetic map of this object!





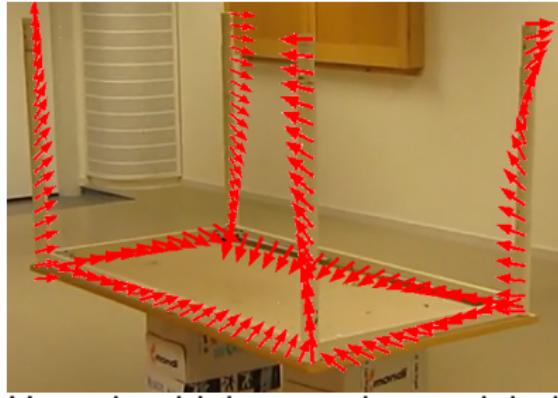
How should the map be modeled?

- Use the dipole model?
- Use multiple dipoles?

We want to find a magnetic map of this object!

← Parametric models





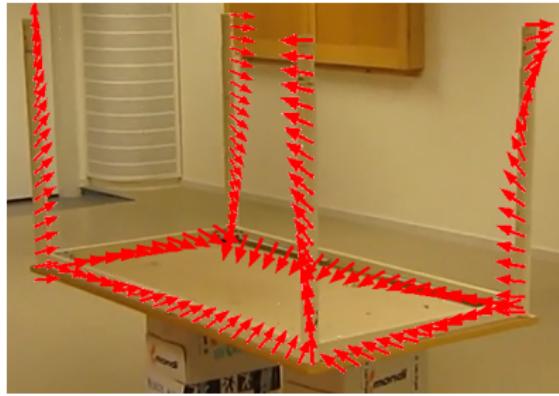
How should the map be modeled?

- Use the ~~dipole model~~?
- Use ~~multiple dipoles~~?
- Use a **continuum of dipoles!**

We want to find a magnetic map of this object!

← Parametric models





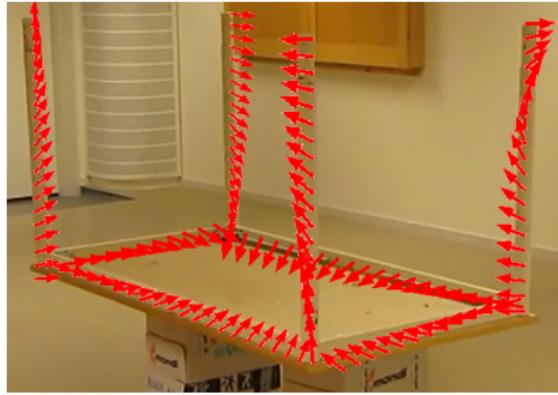
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We want to find a magnetic map of this object!

← Parametric models

← Nonparametric models!



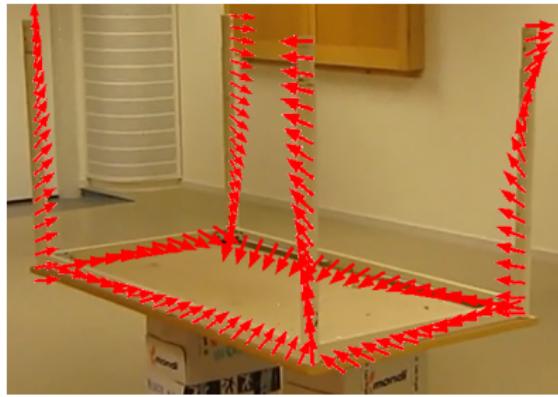
How should the map be modeled?

- Use the ~~dipole model~~?
- Use ~~multiple dipoles~~?
- Use a ~~continuum of dipoles!~~
- Spatial correlation

We want to find a magnetic map of this object!

← Parametric models

← Nonparametric models!



How should the map be modeled?

- Use the ~~dipole model~~?
- Use ~~multiple dipoles~~?
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We want to find a magnetic map of this object!

← Parametric models

← Nonparametric models!

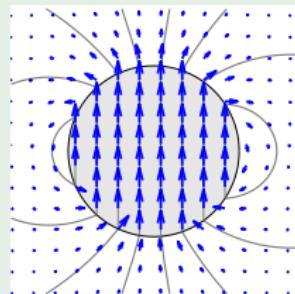
← Gaussian processes!

We use a slightly different version of the magnetostatic equations

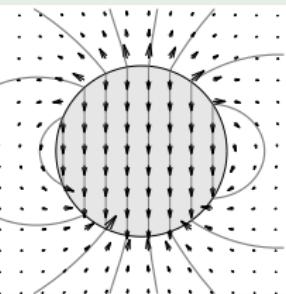
$$\nabla \cdot \mathbf{B} = 0, \quad \frac{1}{\mu_0} \mathbf{B} - \mathbf{H} = \mathbf{M},$$

$$\nabla \times \mathbf{H} = 0$$

Example



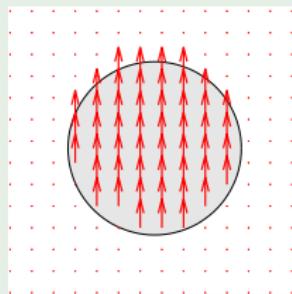
$$\frac{1}{\mu_0} \mathbf{B}$$



$$\mathbf{H}$$

$$=$$

$$=$$



$$\mathbf{M}$$



Gaussian processes can be seen as a distribution over functions

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

Mean function ↑ ↑ Covariance function

It is a generalization of the multivariate Gaussian distribution

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

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



Objective: Estimate $\mathbf{f}(\mathbf{u})$ from noisy observations $\mathbf{y}_k = \mathbf{f}(\mathbf{u}_k) + \mathbf{e}_k$

Lindsten F. A semiparametric Bayesian approach to Wiener system identification *Presentation at SYSID12*



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



- 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



- The animation illustrated regression for one scalar function
 $f : \mathbb{R} \rightarrow \mathbb{R}$
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 - $\nabla \cdot \mathbf{B}$ (divergence free)
 - $\nabla \times \mathbf{H}$ (curl free)



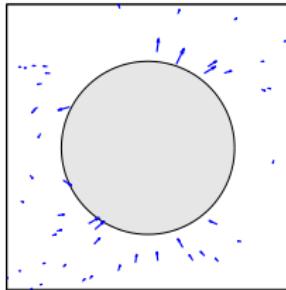
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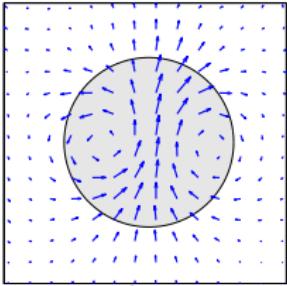
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 - $\frac{1}{\mu_0} \mathbf{B} - \mathbf{H} = \mathbf{M}$



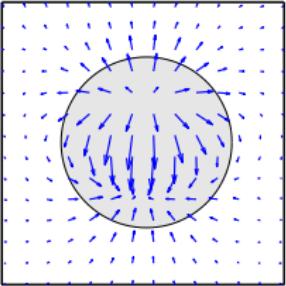
Training data



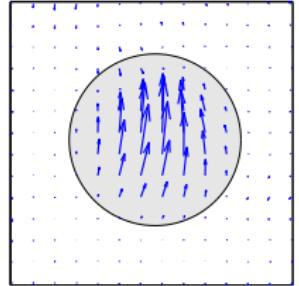
Estimated data



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



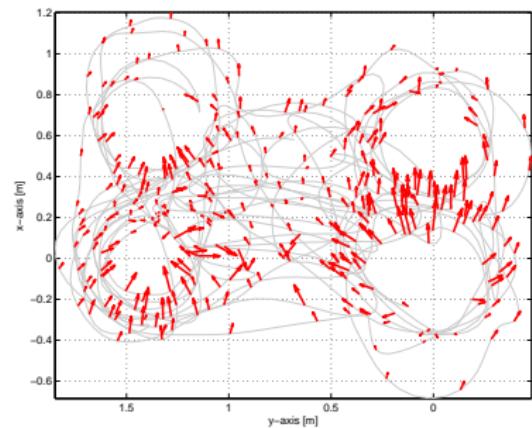
$$\mathbf{H}$$



- 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

- 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



Estimated magnetic content

Introduction

Electromagnetic theory

Localizing moving magnetic objects

Mapping magnetic environments

Geolocation using Light levels

Concluding remarks



- Common swift, *Apus apus*. Weight: 40 g
- Equipped with light logger (light sensor, battery, memory, clock).
Weight: 2g
- Released on Aug. 5, 2010, found 298 days later

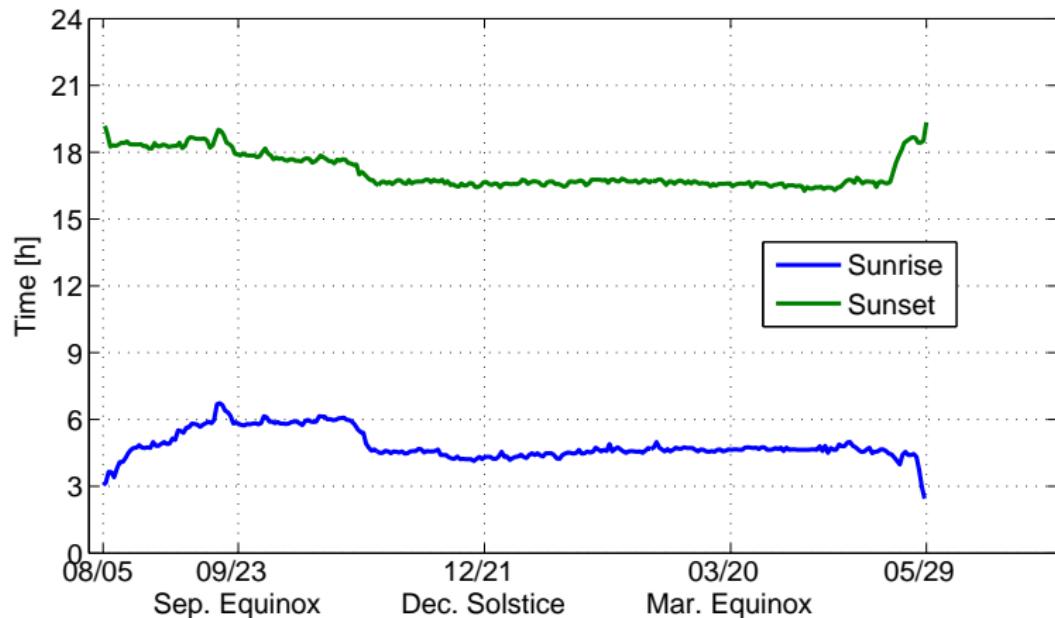


We want to localize Mr Swift!



Sunrise and sunset

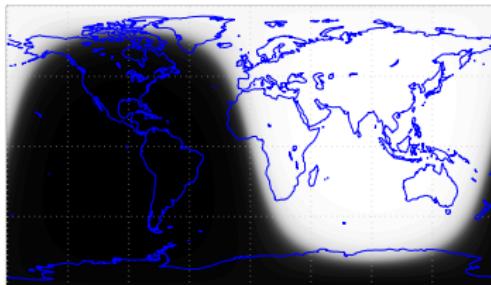
26(31)



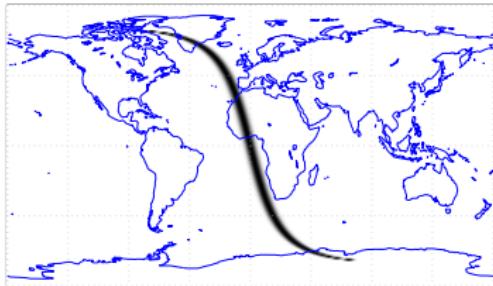
The likelihood - May 6

27(31)

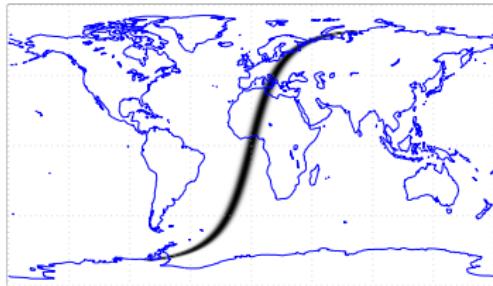
Daylight map, 06–May–2011 06:00:00



Likelihood, sunrise, 06–May–2011 06:00:00



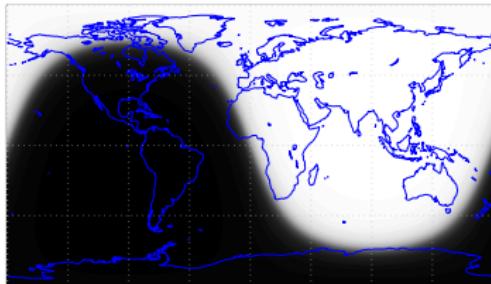
Likelihood, sunset, 06–May–2011 18:00:00



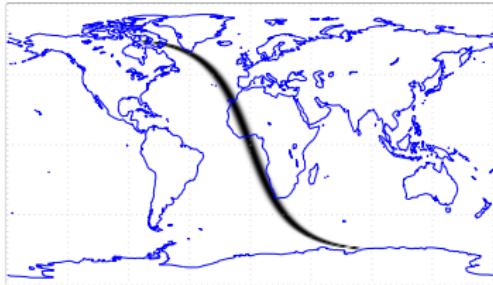
The likelihood - Summer solstice

27(31)

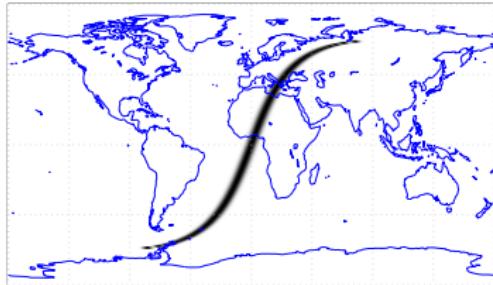
Daylight map, 21-Jun-2011 06:00:00



Likelihood, sunrise, 21-Jun-2011 06:00:00



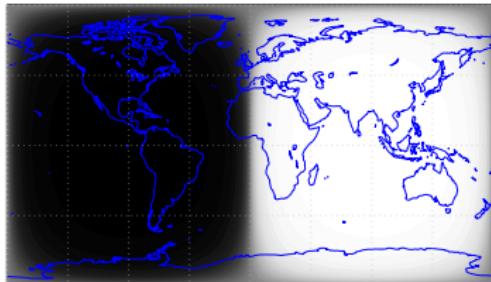
Likelihood, sunset, 21-Jun-2011 18:00:00



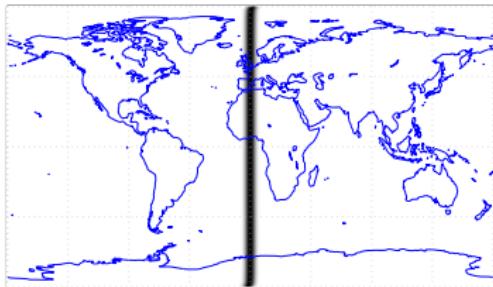
The likelihood - Autumn equinox

27(31)

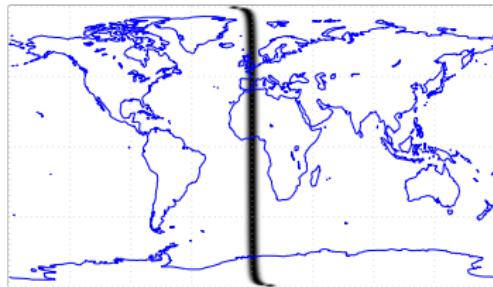
Daylight map, 21–Sep–2011 06:00:00

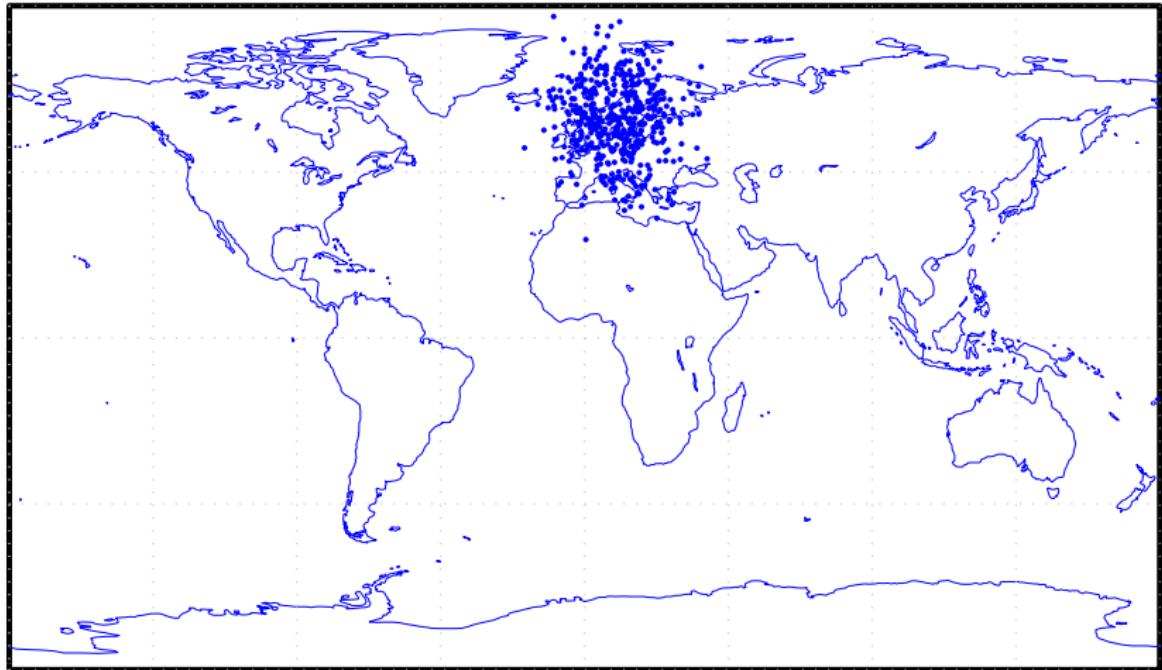


Likelihood, sunrise, 21–Sep–2011 06:00:00



Likelihood, sunset, 21–Sep–2011 18:00:00

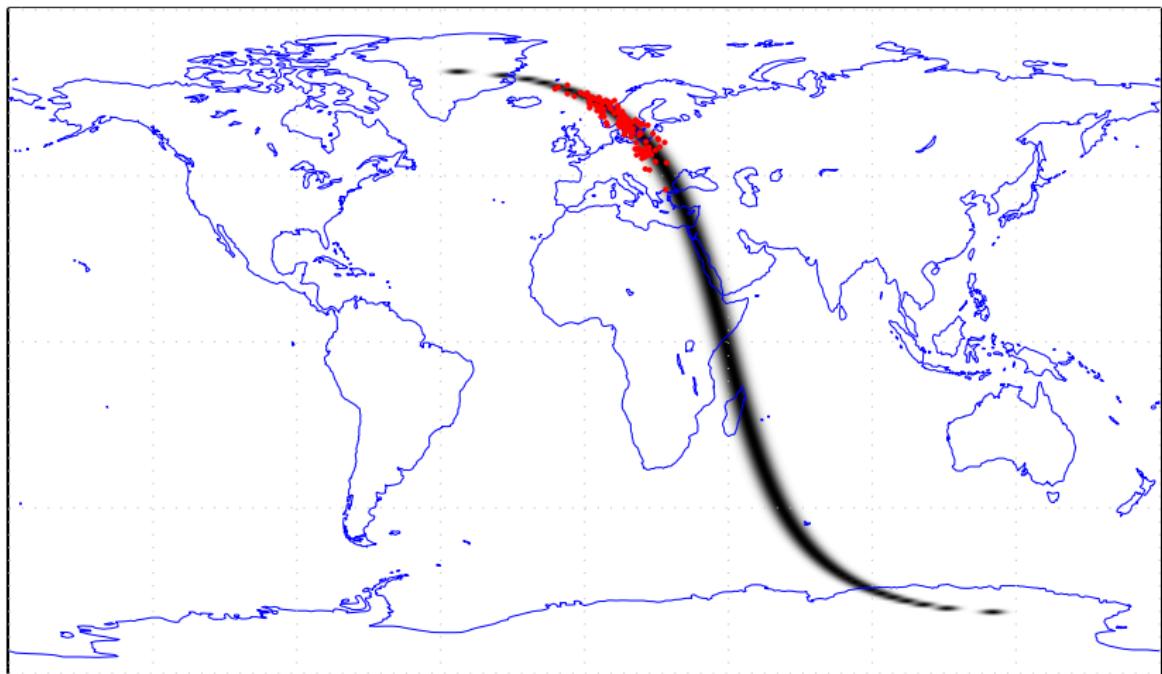




Measurement update - sunrise.

Time: 05-Aug-2010 03:04:00

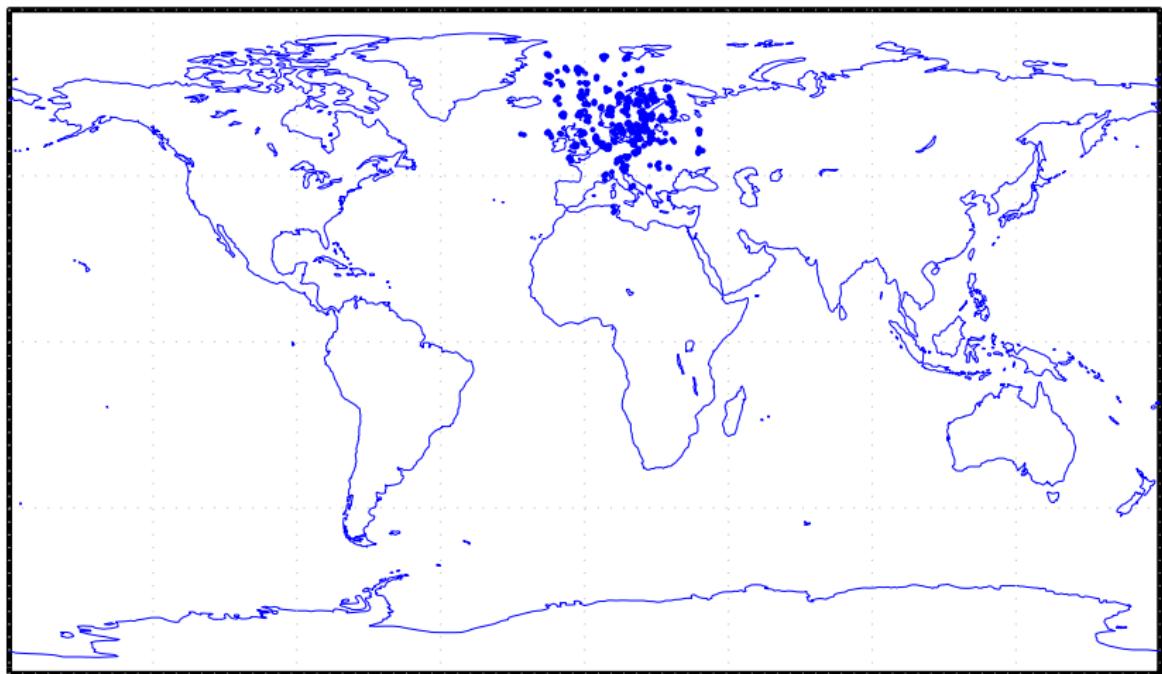
28(31)



Time update.

Time: 05-Aug-2010 19:10:59

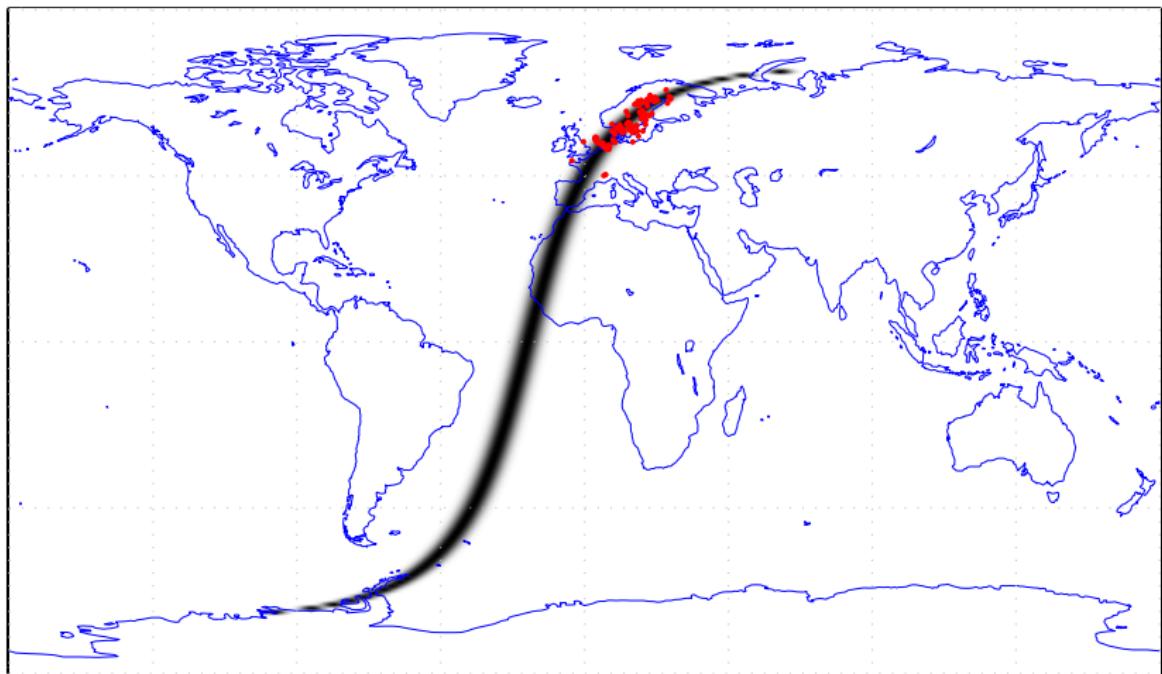
28(31)



Measurement update - sunset.

Time: 05-Aug-2010 19:11:00

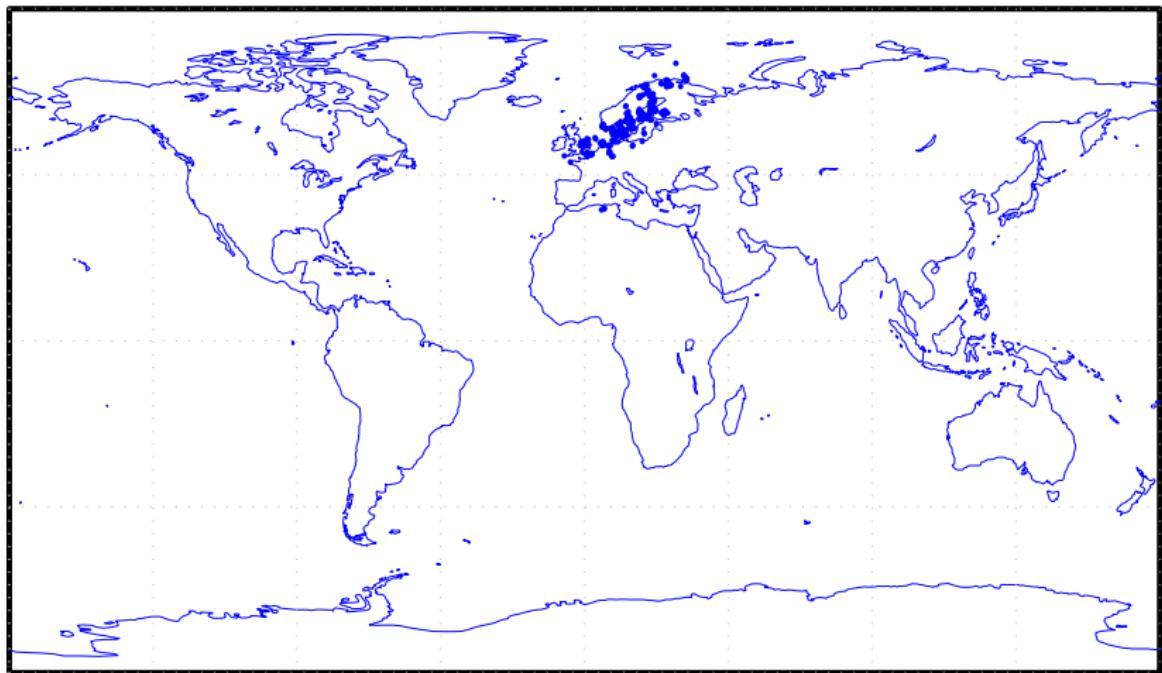
28(31)



Time update.

Time: 06-Aug-2010 03:08:59

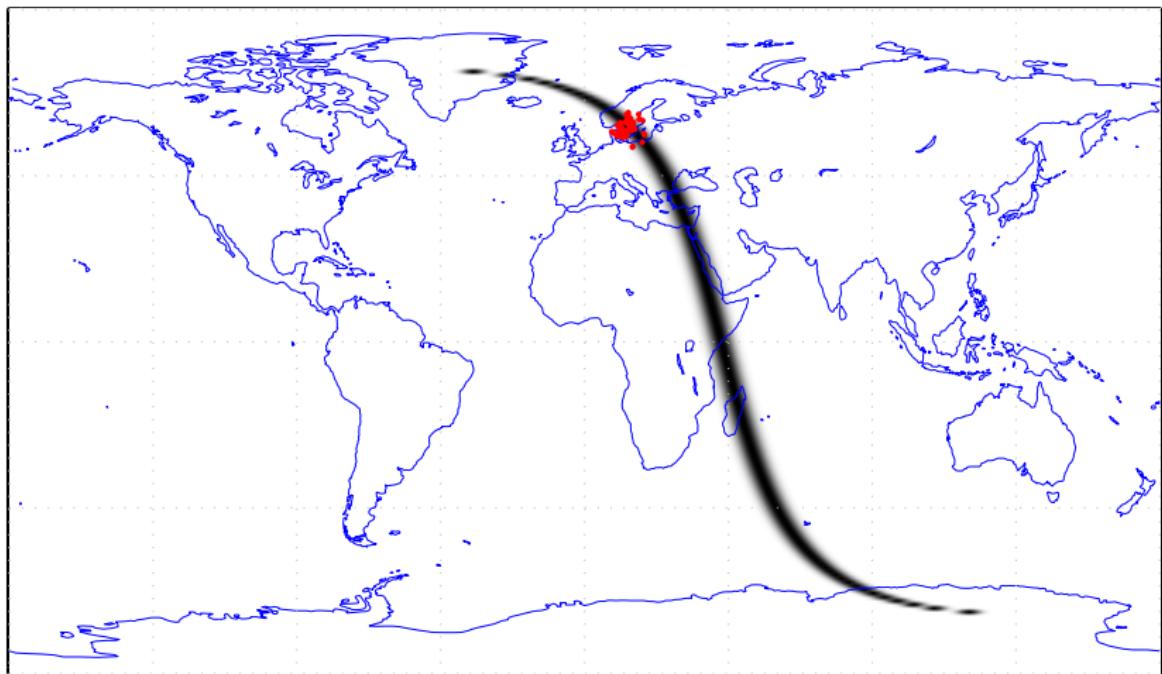
28(31)



Measurement update - sunrise.

Time: 06-Aug-2010 03:09:00

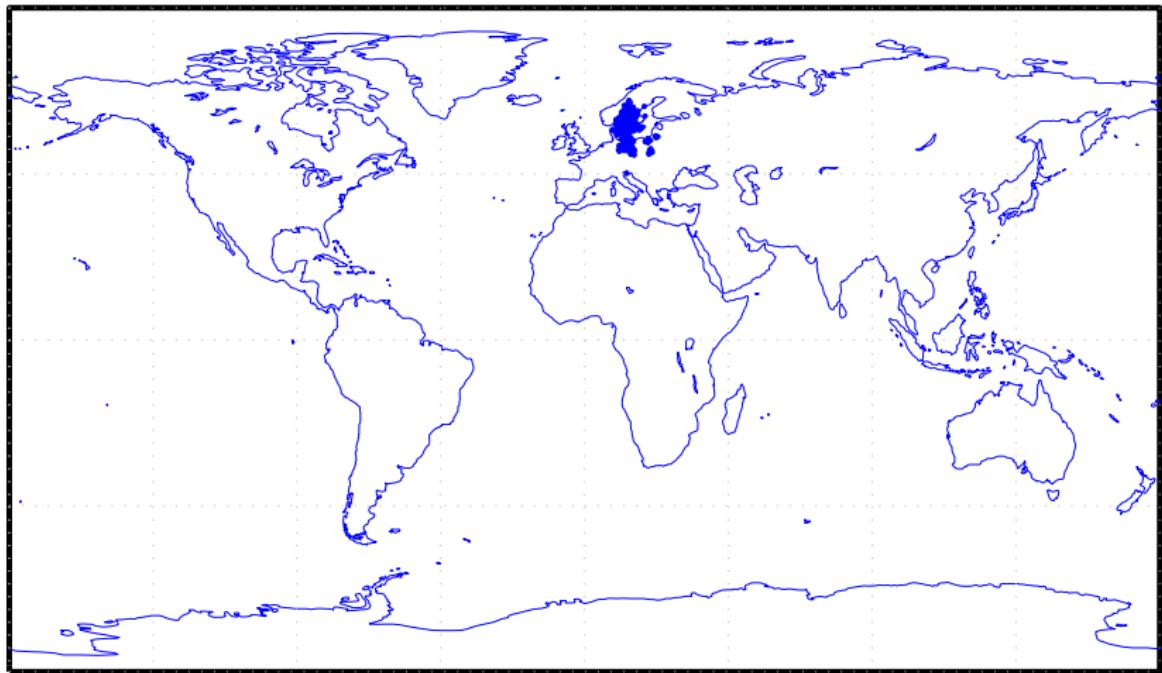
28(31)



Time update.

Time: 06-Aug-2010 18:46:59

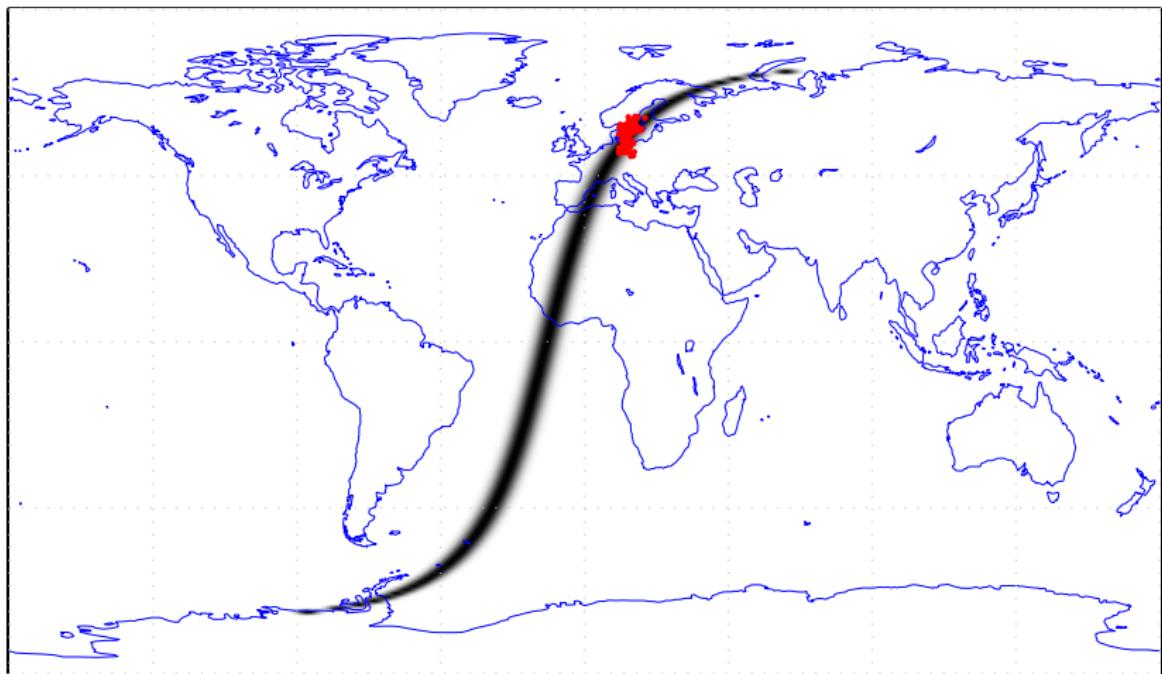
28(31)



Measurement update - sunset.

Time: 06-Aug-2010 18:47:00

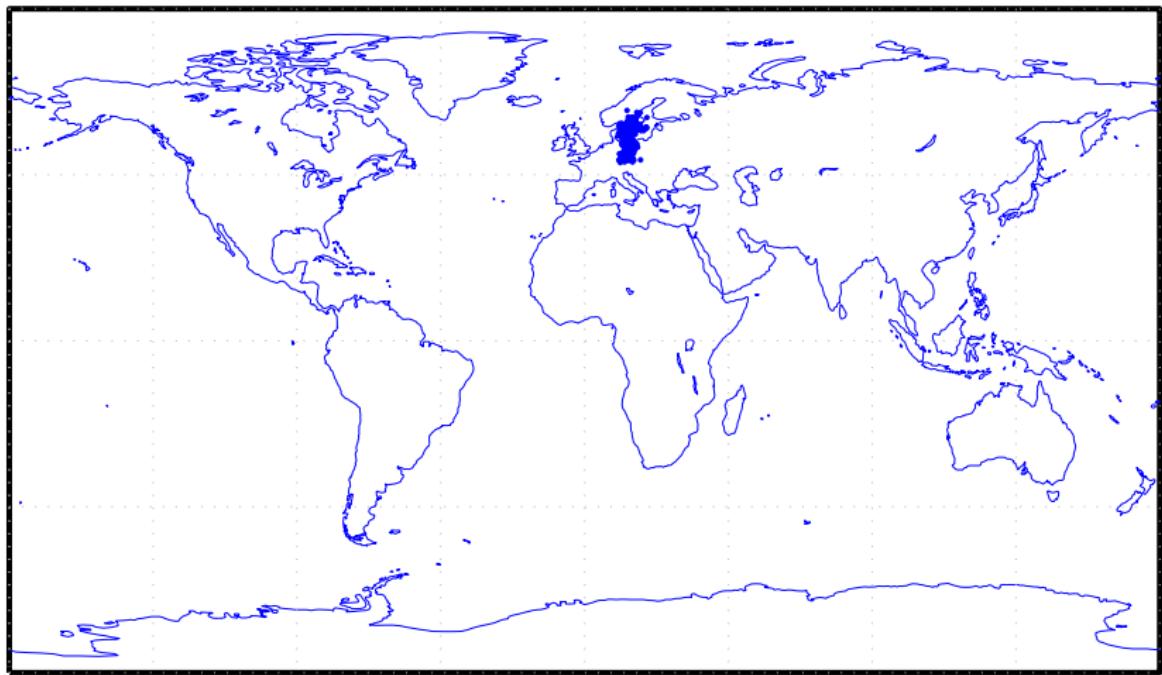
28(31)



Time update.

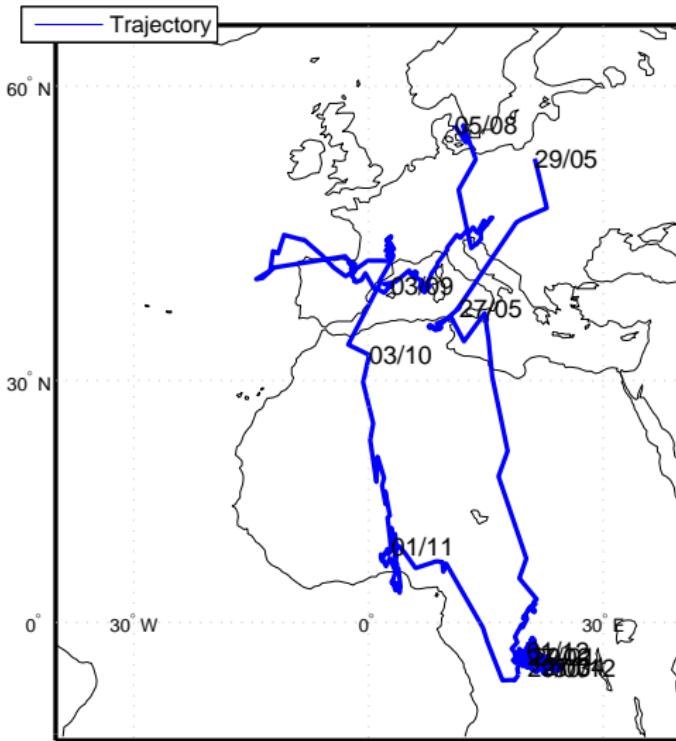
Time: 07-Aug-2010 03:38:59

28(31)



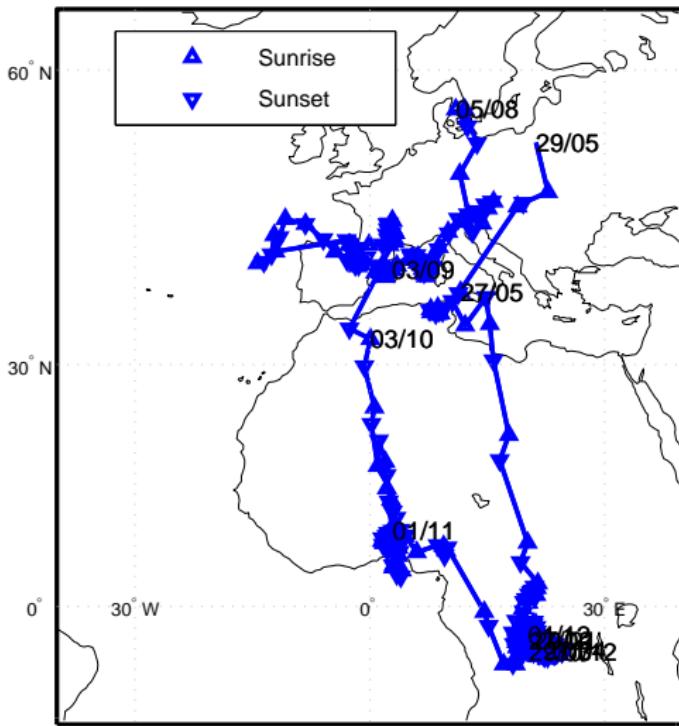
The Voyage

29(31)



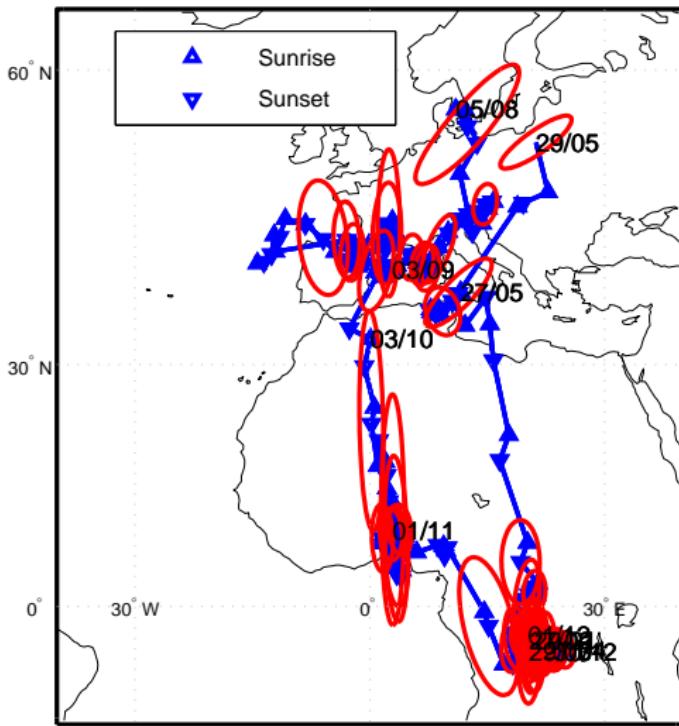
The Voyage

29(31)



The Voyage

29(31)



■ Localizing moving magnetic objects

- Various parametric models: point target model, extended target model, target orientation dependent model
- Classifying driving direction with only one 2-axis magnetometer



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 - Various parametric models: point target model, extended target model, target orientation dependent model
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- Geolocation using light levels
 - Filtering framework suitable for localizing migrating birds



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 - Full framework with detection integrated
 - Implementation in a real sensor network



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- Localizing moving magnetic objects
 - Full framework with detection integrated
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 - Final goal: Simultaneous Localization And Mapping
- Localizing migrating birds using light levels
 - Do smoothing
 - Process light intensity data directly

