

The Derivation of Current Fields from Multi-Sensor Satellite Data

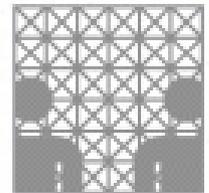
Challenges, approaches and validations for
the current derivation from multi-sensor
imagery

Joint Workshop in Tarusa 02/2012
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DER FORSCHUNG | DER LEHRE | DER BILDUNG



Outline

- Introduction
- Solving the correspondence problem
- Application to satellite images
- Conclusions and future work

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- Introduction
 - The task
 - Constraints, challenges and problems
 - Motivation
- Solving the correspondence problem
- Application to satellite images
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The Task

- Brief description

Derive / compute the sea surface currents from at least two satellite images

- Basic Assumption

There are some „scene objects“ in the images, whose motion is caused only by the local sea surface current, e.g.:

- Algae- or other surface films
- Ice floe

Image Constraints

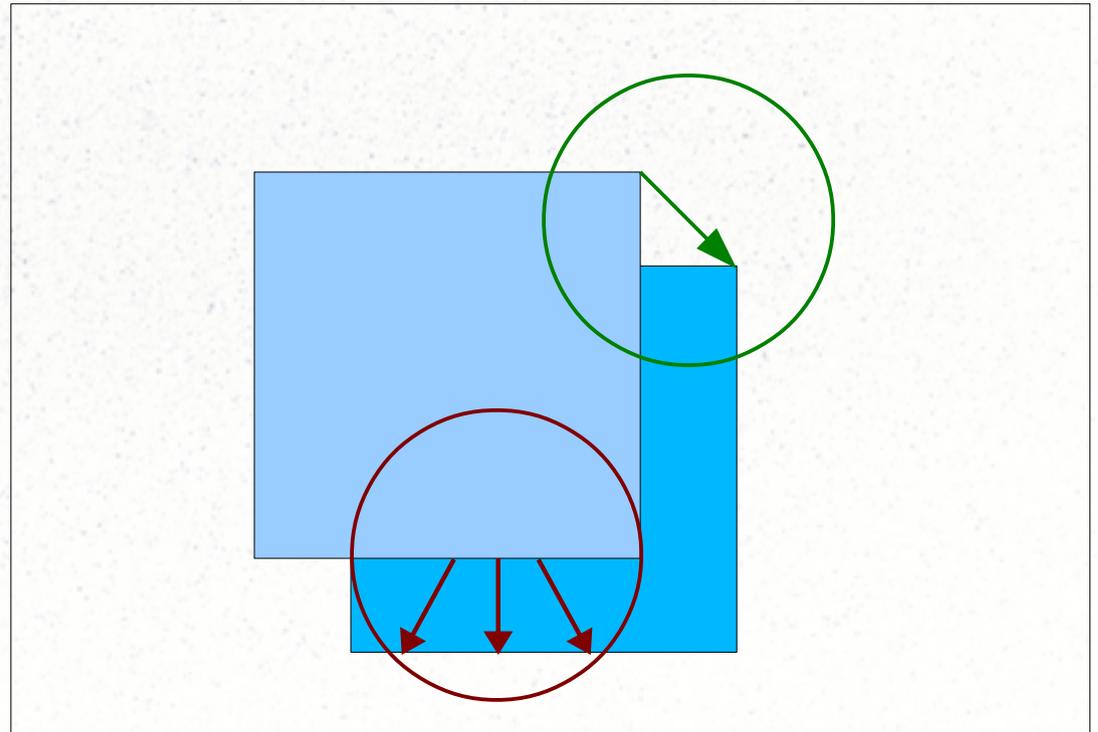
- The spectral domains of the images can be quite different, e.g.:
 - infrared
 - multispectral or even hyperspectral
 - microwave (active / passive)
- Additionally, the spatial domain of the images is never equal
- Hard to find images with big spatial overlap and small temporal distance

Some Challenges

- Different types of sensors:
 - Specific noise
 - Different properties are imaged
- Atmospheric interference and distortion
- Low sampled time axis:
 - Mainly just two images
 - Big temporal distances
- The aperture problem

The Aperture Problem

- Even if an object was sampled “optimally” at both images, it may be impossible to calculate a displacement vector only based on local information.



Optical Flow vs. “Real Motion”

Show movies...

Motivation

- Currently, there is research interest for high-resolution surface current **measurements**, e.g.:
 - Validate or refine climate or oceanographic *models*
 - Improve accuracy of the measurement of ice drift or biological development e.g. of algae blooms
 - ➔ General enhancement of predictions
- Further advantages:
 - Satellite images are relatively cheap compared to other methods
 - Allow the highest resolution current fields
 - Greatest possible amount of **measurements** overall

Other Methods of Current Derivation

- Buoys or other in-situ measurements
- Climate or oceanographic models
- SAR-Techniques
 - Along-Track Interferometry
 - Doppler-Centroid Analysis
- HF-Radar arrays

HF-Radar

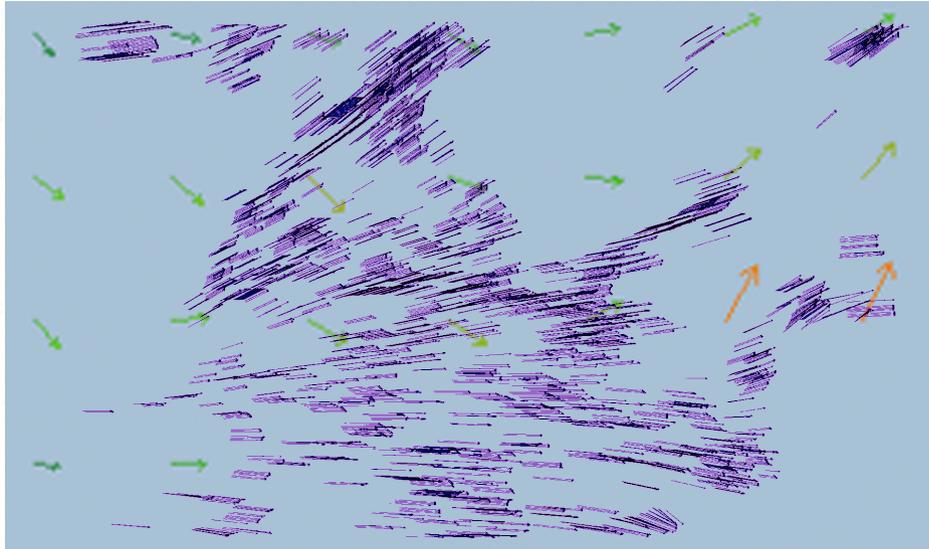
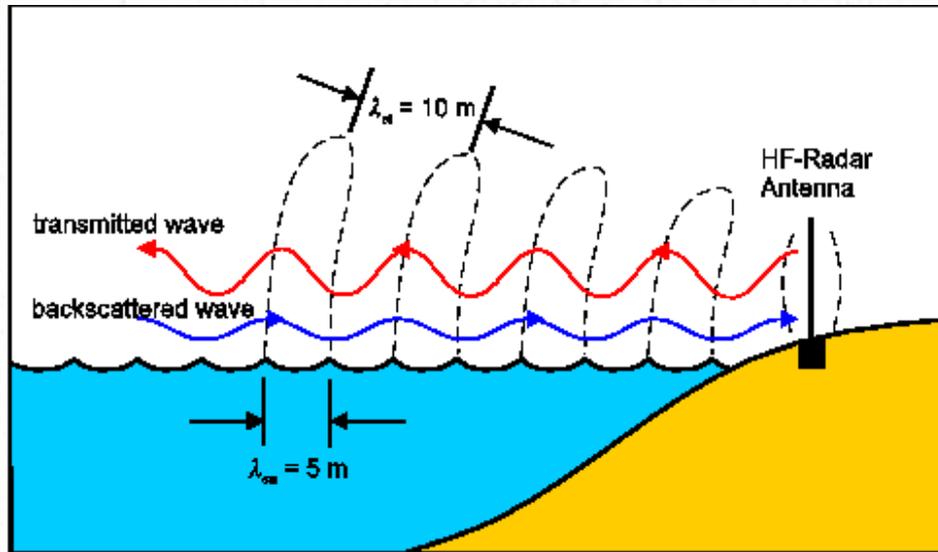


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- Solving the correspondence problem
 - Feature based approaches
 - Gradient based approaches
 - Problems and improvements
- Application to satellite images
- Conclusions and future work

The Feature Based Approach

1. Step: Find the features

- There are many possible operators like e.g. the Monotony and Moravec operator [MORAVEC 1977]
- Wavelet based approaches [LIU ZHAO HSU 2006]
- Model based approaches like Snakes [OETJENS 1997], [WENDKER 1997]

2. Step: Calculate the similarity between the features

- General pattern matching problem, Solution via (normalised) cross-correlation, shape context algorithm or other metrics

3. Step: Determination of correspondences

- Maximum likelihood decider
- Smooth vector-field decider
- ➔ Relaxation [KITCHEN ROSENFELD 1979], [BARNARD THOMPSON 1981]

The Gradient Based Approach

- Basic assumption [HORN SCHUNK 1981]:
 - Flat surfaces (Intensity of objects does not change at movement)
- Let $I(x,y,t)$ be the intensity of a pixel (x,y) at time t
 - $\frac{dI}{dt}=0$, and using the chain rule: $\frac{\partial I}{\partial x} \cdot \frac{dx}{dt} + \frac{\partial I}{\partial y} \cdot \frac{dy}{dt} + \frac{\partial I}{\partial t} = 0$
 - Substitution of $u = \frac{dx}{dt}$, $v = \frac{dy}{dt}$ results in a linear system of equations:
$$I_x \cdot u + I_y \cdot v + I_t = 0$$
where I_x , I_y and I_t are the partial derivatives of the intensity function.
 - Problem: One equation for two unknowns u and v !

Constraints for Gradient Based Methods

- Global constraints

- Example: Horn & Schunk: Smoothness of movement
- Minimization of the quadratic gradient magnitude of the flow velocity:

$$\left(\frac{\partial u}{\partial x}\right)^2 + \left(\frac{\partial u}{\partial y}\right)^2 \text{ and } \left(\frac{\partial v}{\partial x}\right)^2 + \left(\frac{\partial v}{\partial y}\right)^2$$

- Local constraints

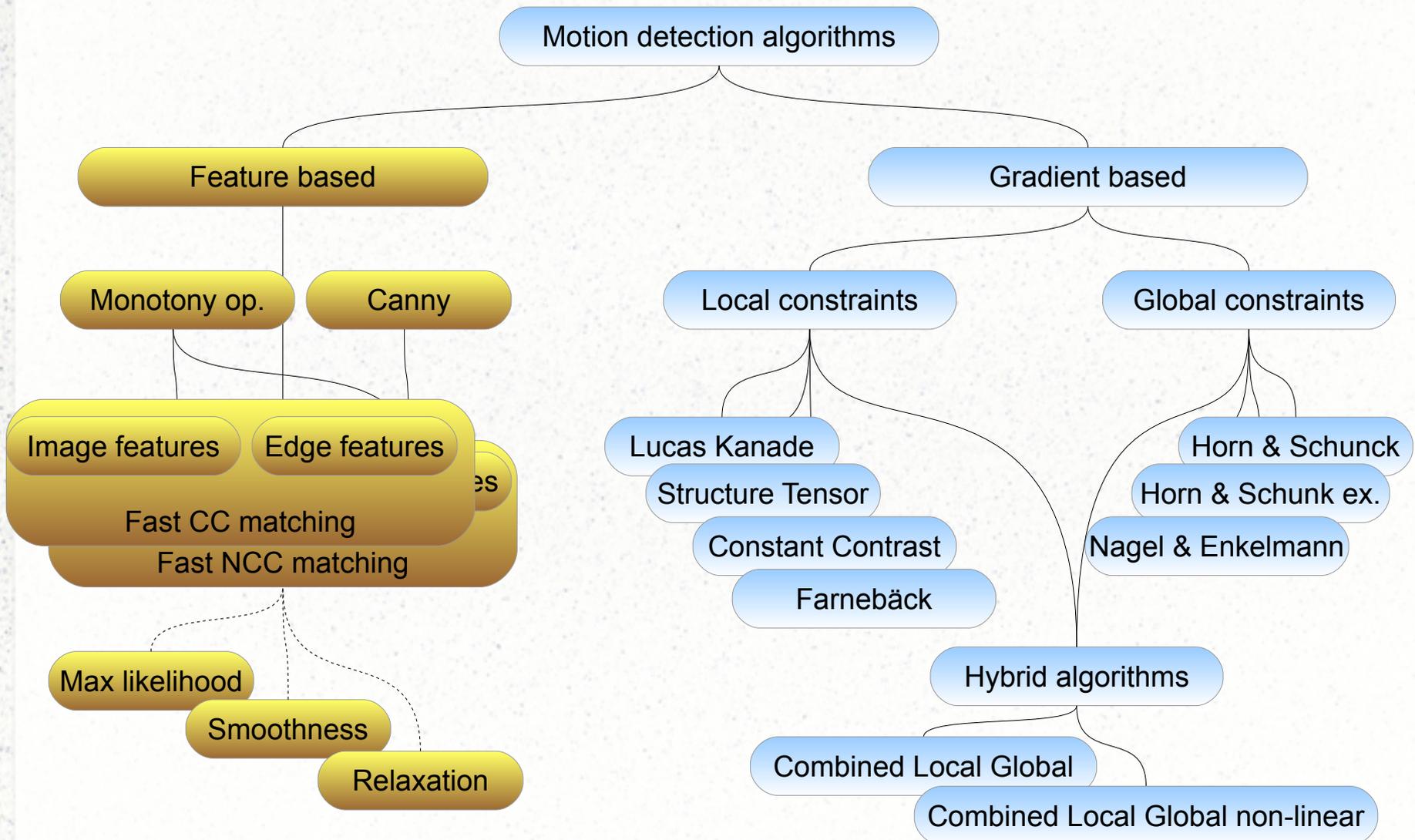
- Assume local equality of the motion

- Example: Lucas Kanade method:
$$\begin{bmatrix} \sum_{\sigma} (I_x)^2 & \sum_{\sigma} I_x \cdot I_y \\ \sum_{\sigma} I_y \cdot I_x & \sum_{\sigma} (I_y)^2 \end{bmatrix} \cdot \begin{bmatrix} u \\ v \end{bmatrix} = - \begin{bmatrix} \sum_{\sigma} I_x \\ \sum_{\sigma} I_y \end{bmatrix} \cdot I_t$$

- Hybrid approaches

- Combining local and global constraints
- Example: Bruhn et. al

Detail of Analysed Algorithms



Problems of Each Approach

- Gradient based
 - Calculation for the whole image
 - No explicit quality index for the vectors
 - Poor quality if constraints are violated, e.g. flexible objects, change of illumination or at big spatio-temporal distances
 - Do not have to select and adjust special feature detectors
 - No final determination of correspondences needed
- Feature based
 - Calculation only for the features of interest
 - The quality of each vector is explicitly given
 - Less problems at changes in illumination, big spatio-temporal distances and a time axis containing just two images
 - Difficult selection of feature detectors depending on task
 - Difficult final determination of correspondences

Improvements

- Accuracy of gradient based approaches
 - Extended original Horn & Schunck algorithm
 - Moved from Lucas Kanade algorithm to Structure Tensor approach
 - Embedded state-of-the art algorithms
 - Hybrid Models / non-linear approaches
- Speed of the feature matching
- Split motion detection
 - A global motion / non-global motion part
 - Hierarchically

The Fast Normalized Cross-Correlation [LEWIS 1995]

- Given the mask-image t and the image to correlate with f , the normalized cross-correlation can be described by:

$$g(u, v) = \frac{\sum_{x,y} (f(x, y) - \bar{f}_{u,v})(t(x-u, y-v) - \bar{t})}{\sqrt{\sum_{x,y} (f(x, y) - \bar{f}_{u,v})^2 \cdot \sum_{x,y} (t(x-u, y-v) - \bar{t})^2}}$$

- Improve speed by using the Fast Fourier Transform (FFT)

$$FT^{-1}(FT(f') \cdot \text{conj}(FT(t')))$$

- Re-use the constant right part of the nominator

$$\sqrt{\sum_{x,y} (t(x-u, y-v) - \bar{t})^2}$$

- Improve speed by calculating sum-tables for the non-constant right part of the nominator

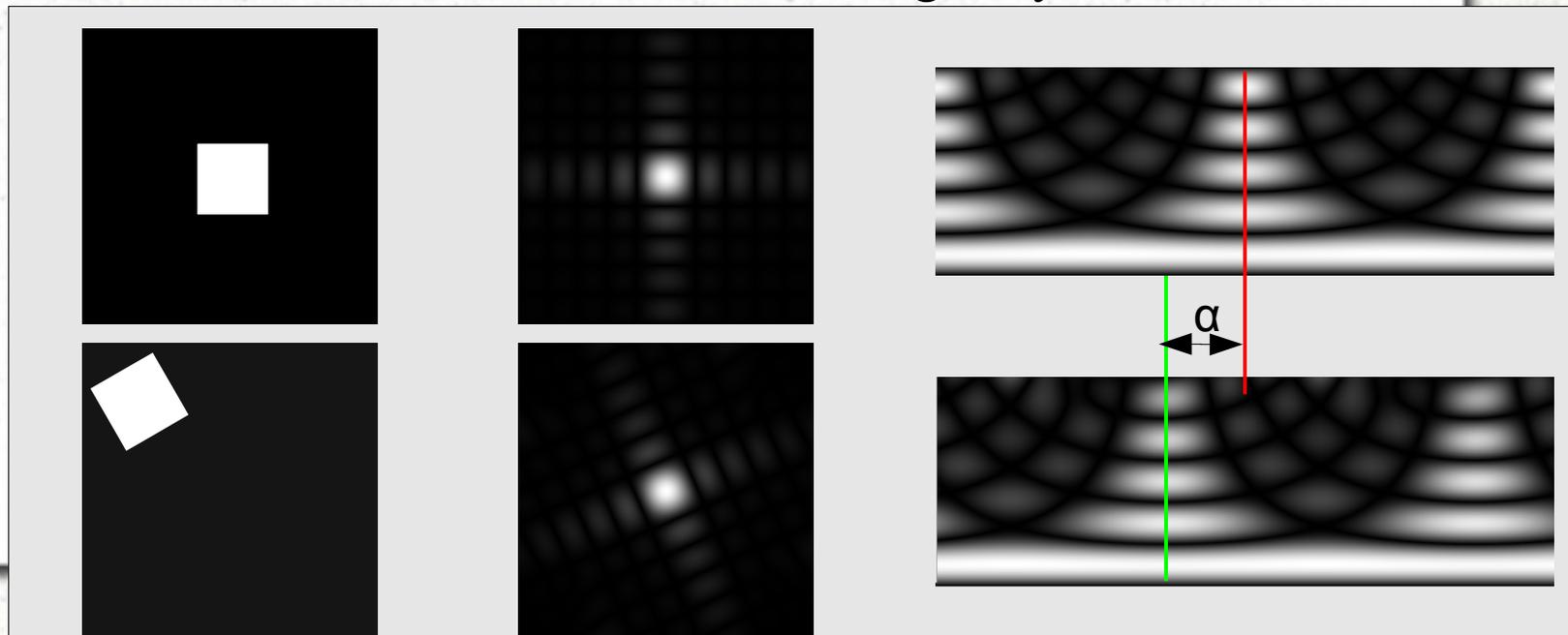
$$\sqrt{n \cdot \sum_{x,y} f(x, y)^2 - \left(\sum_{x,y} f(x, y)\right)^2}$$

Sum of squares

Squared sum

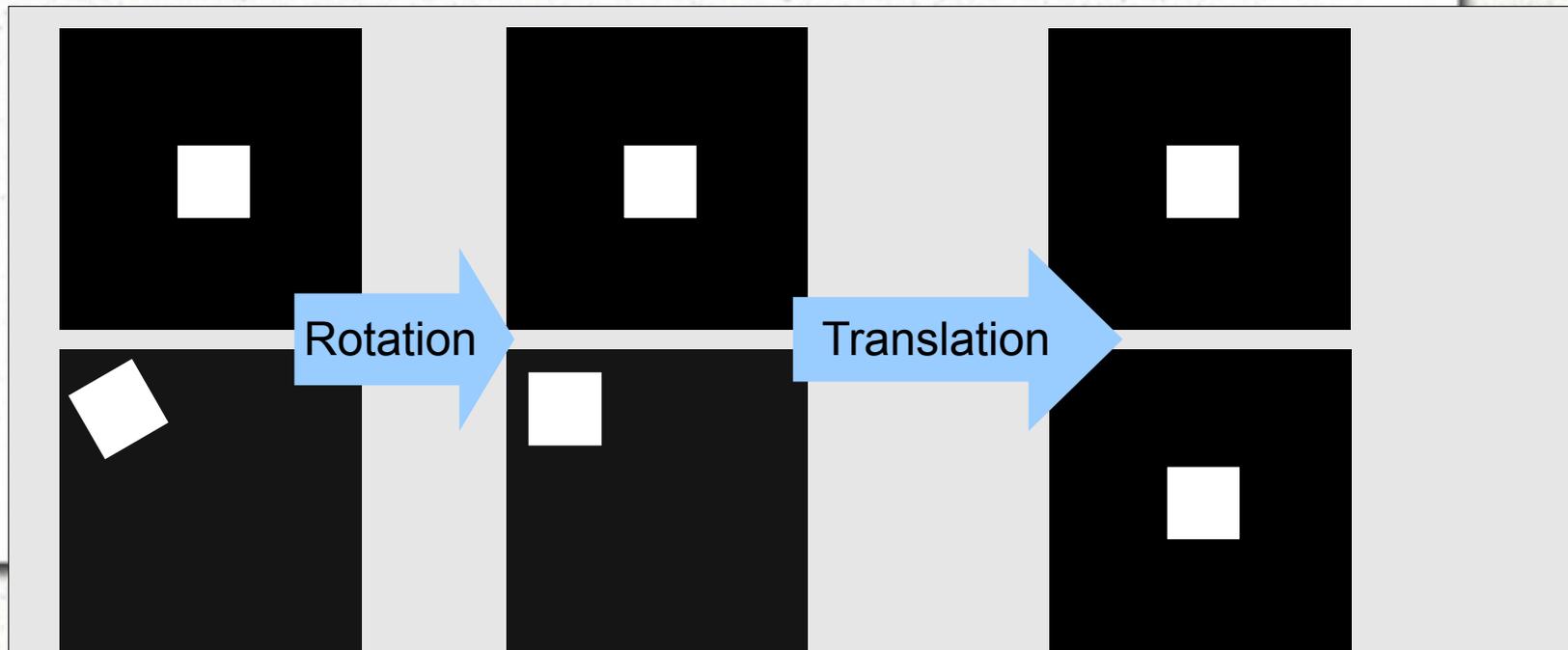
Global Motion Estimation: Rotation

- Assumption: The motion can be split into two parts:
 - A global rotation and translation and
 - A non-global part, that describes the individual motion
- Calculation
 - Determine the rotation between the images by means of FFT



Global Motion Estimation: Translation

- Calculation
 - Determine the rotation between the images at the Fourier Space (in polar coordinates)
 - Correct the rotation of the second image
 - Perform a (unnormalized) cross correlation using FFT



Outline

- Introduction
- Solving the correspondence problem
- **Application to satellite images**
 - Multi-Sensor application (Landsat TM & SAR)
 - Single-Sensor application
 - SeaWiFS images
 - SAR images
- Conclusions and future work

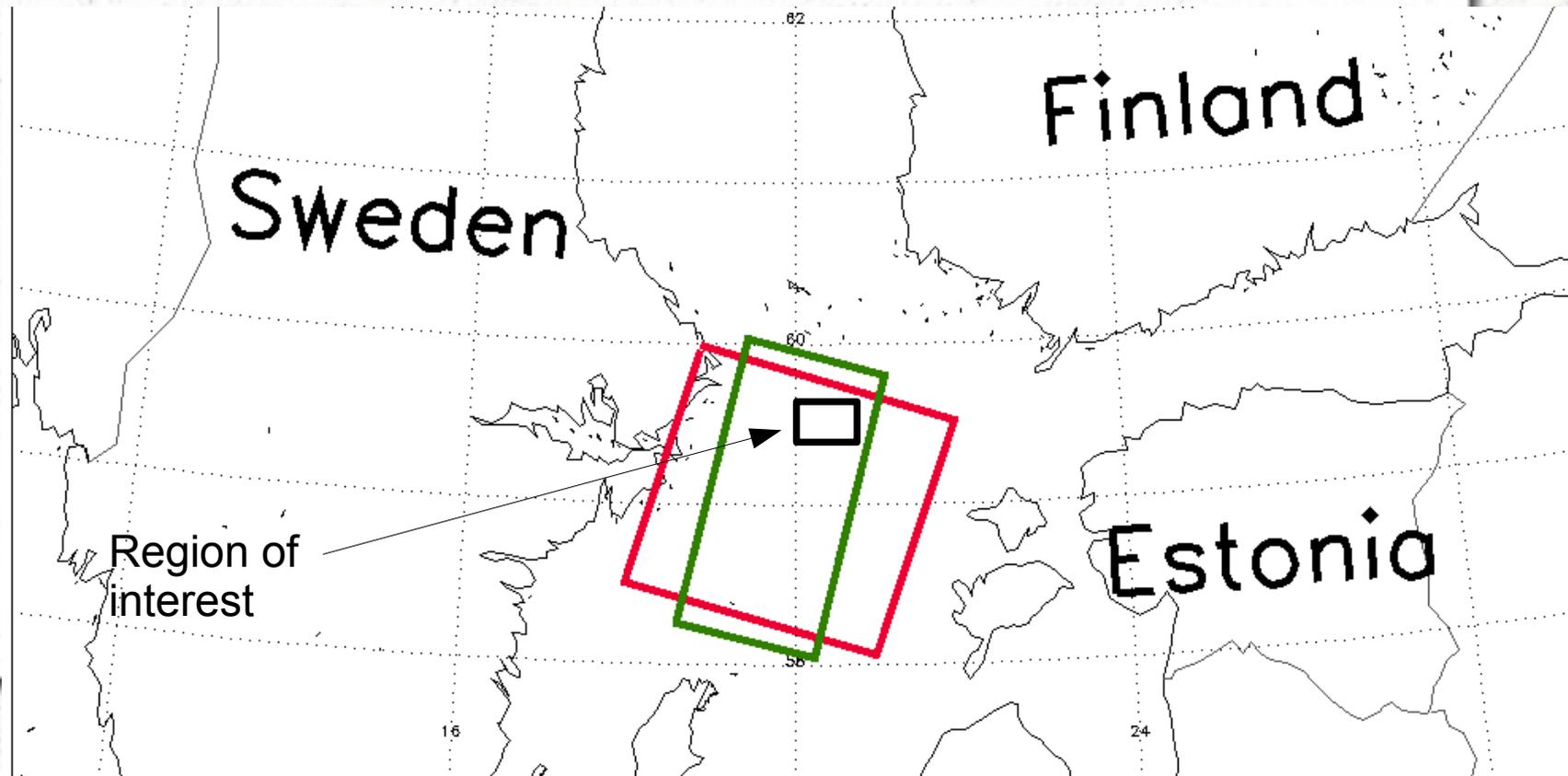
Multi-Sensor Data: Overview

- Image 1

- Landsat TM
- 15.07.1997
- 08:57 UTC

- Image 2

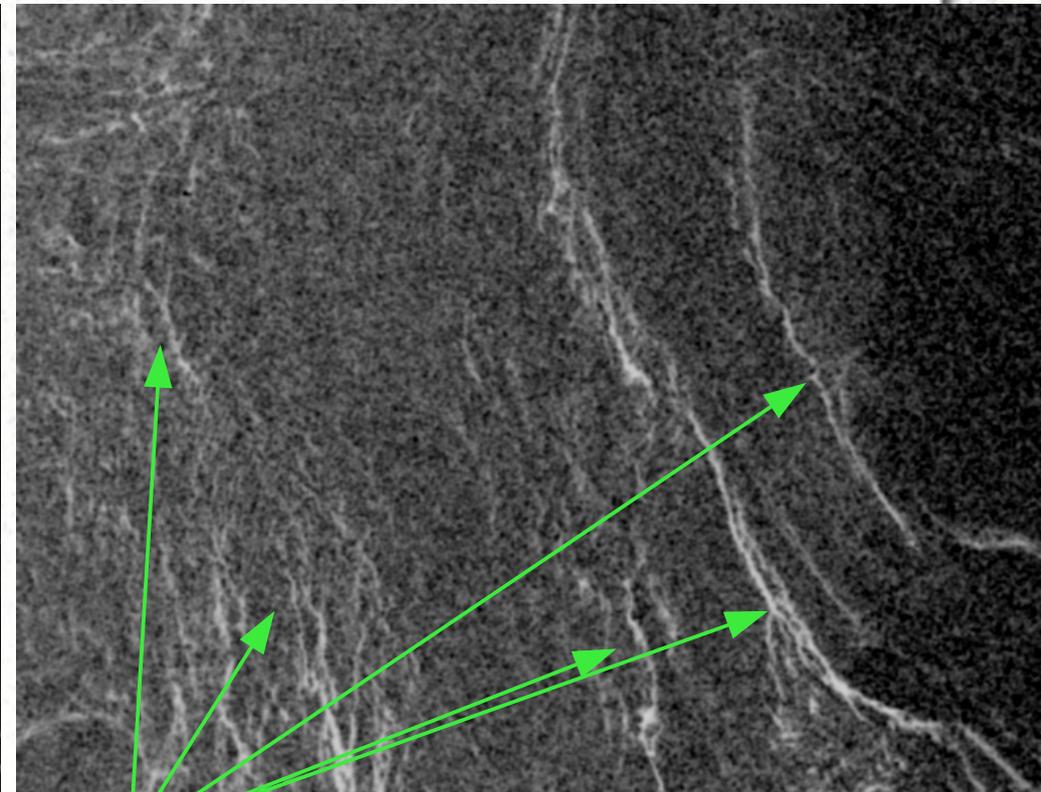
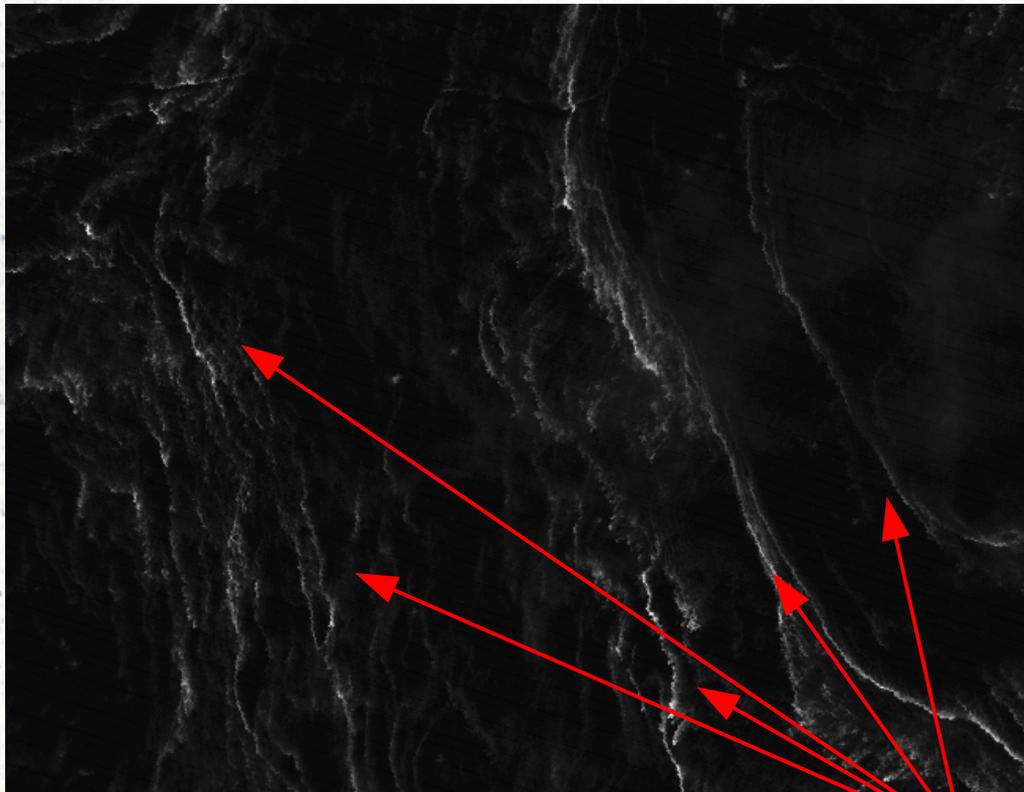
- ERS-2 SAR
- 15.07.1997
- 09:47 UTC



Multi-Sensor Data: The Images

- ROI of Landsat TM
 - 15.07.1998
 - 08:57 UTC

- Inverted ROI of ERS-2 SAR
 - 15.07.1998
 - 09:47 UTC



Surface films

Multi-Sensor Data: Motion Derivation

Entering interactive demonstration...

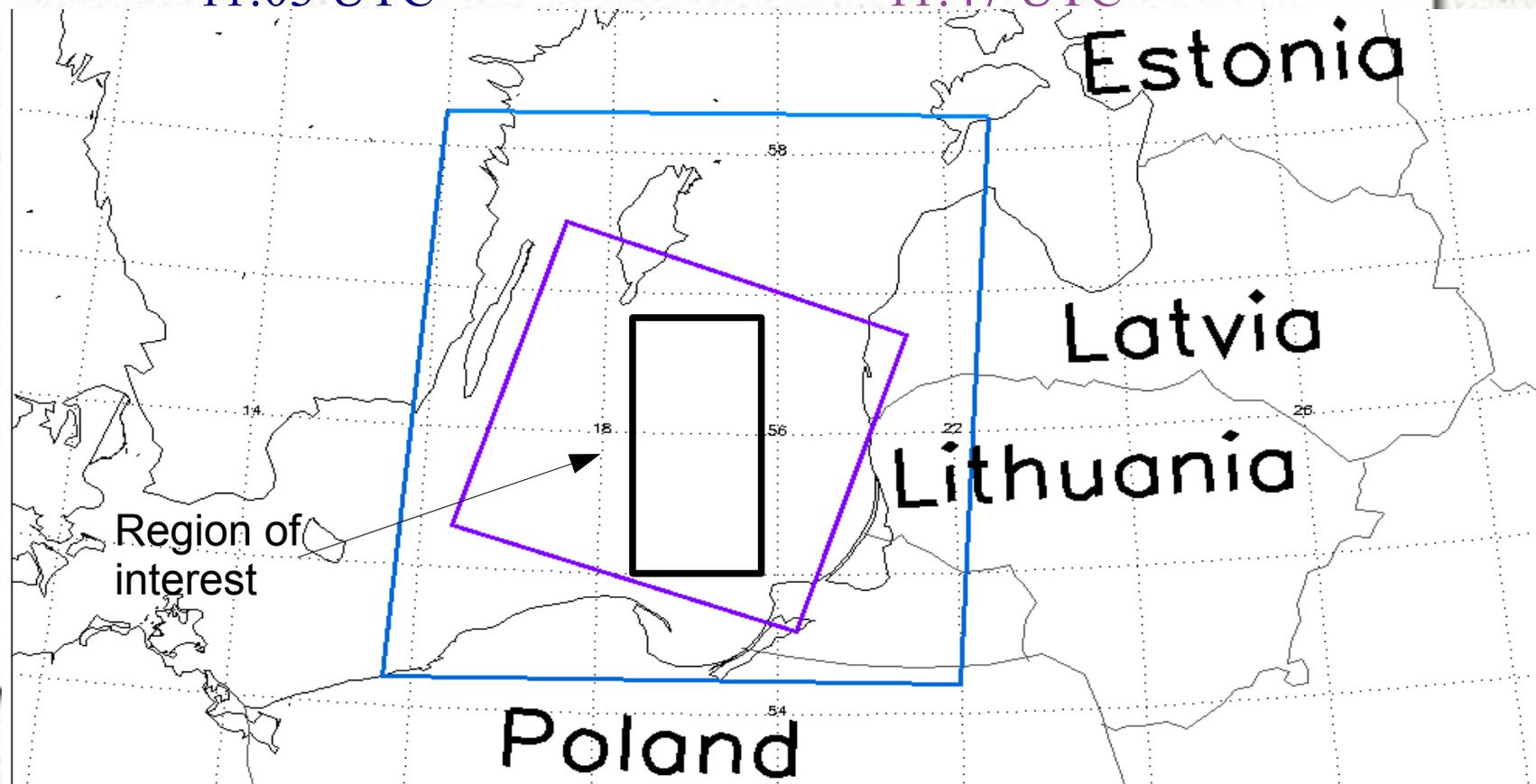
Single-Sensor WiFS: Overview

- Image 1

- SeaStar SeaWiFS
- 1.08.1999
- 11:03 UTC

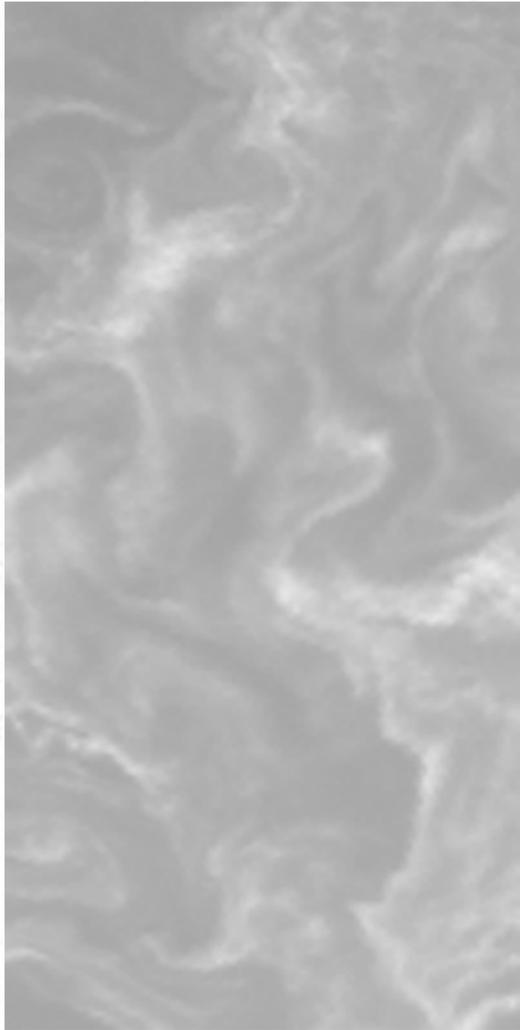
- Image 2

- SeaStar SeaWiFS
- 2.08.1999
- 11:47 UTC

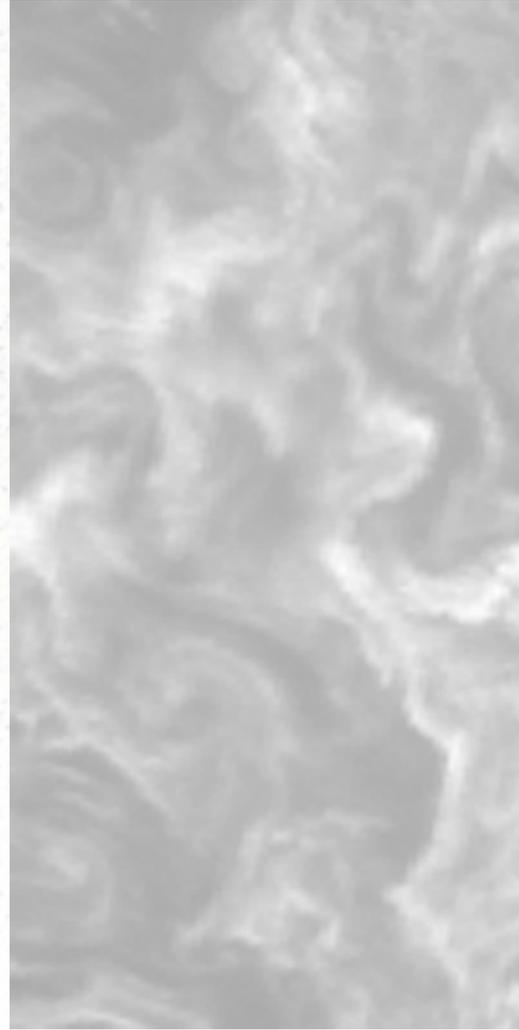


Single-Sensor WiFS: The Images

- ROI of image 1
01.08.1999 / 11:03 UTC



- ROI of image 2
02.08.1999 / 11:47 UTC

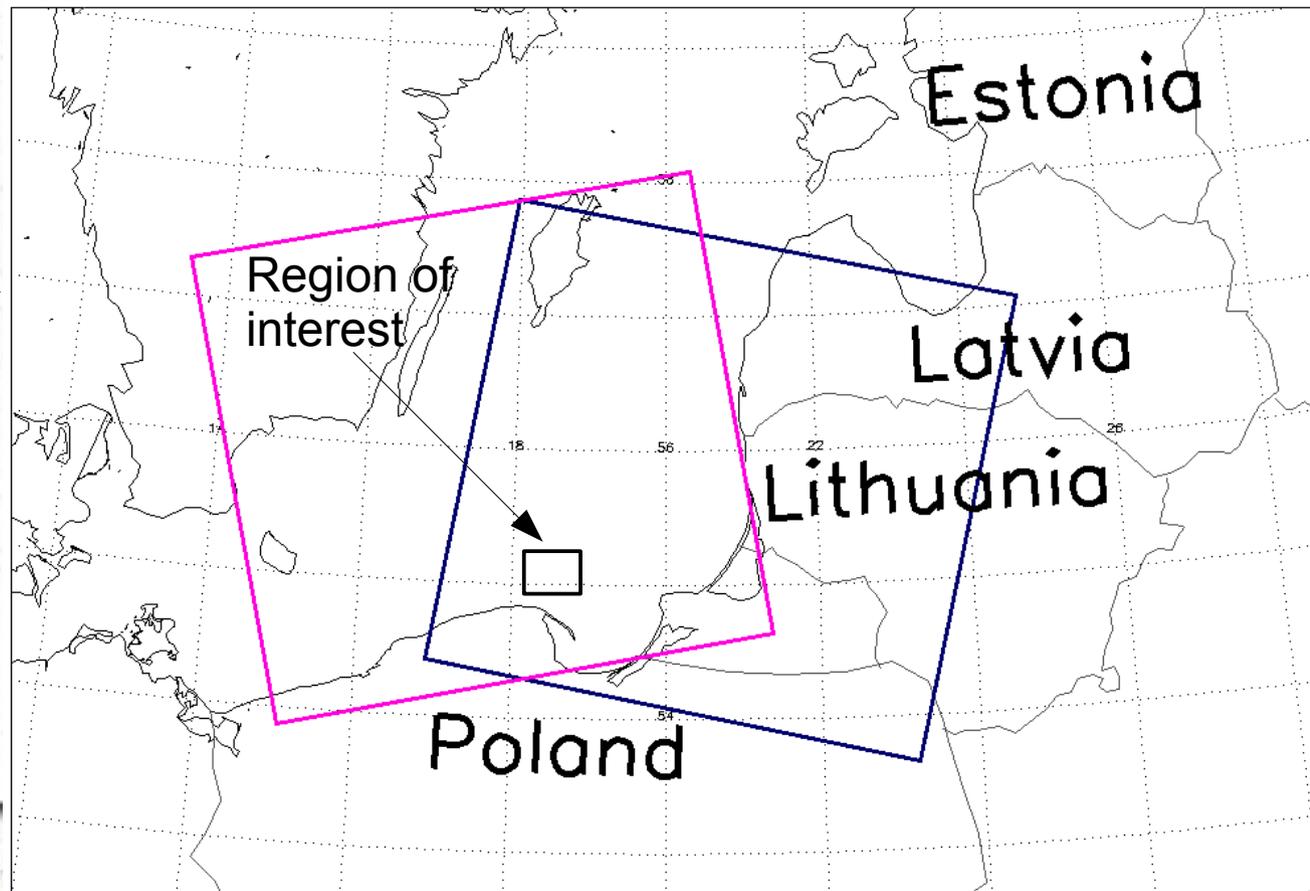


Single-Sensor WiFS: Motion Derivation

Entering interactive demonstration...

Single-Sensor SAR: Overview

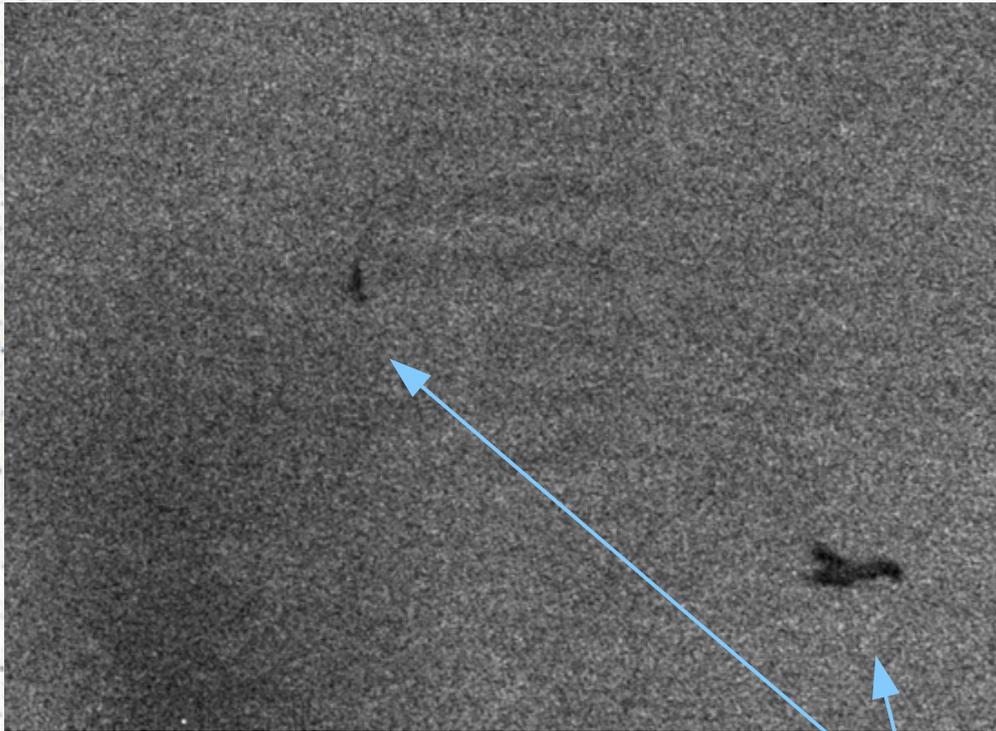
- Image 1
 - ENVISAT ASAR
 - 15.05.2005
 - 09:00 UTC
- Image 2
 - ENVISAT ASAR
 - 15.05.2005
 - 20:25 UTC



Single-Sensor SAR: The Images

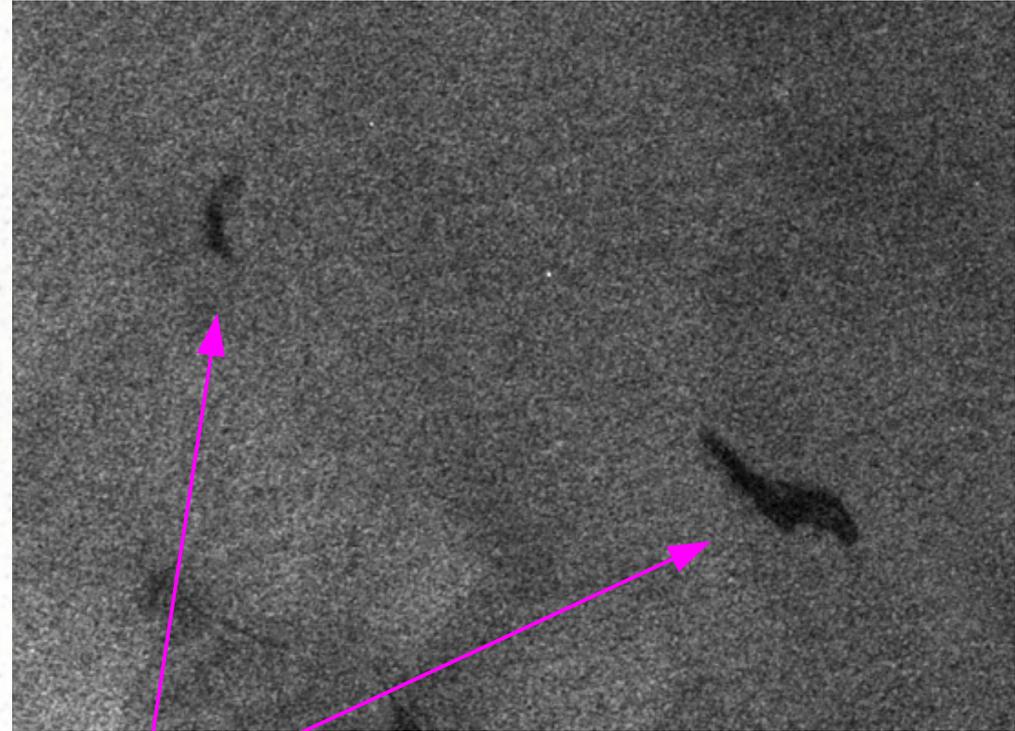
- ROI of Image 1

- 15.05.2005 / 09:00 UTC



- ROI of Image 2

- 15.05.2005 / 20:25 UTC



Oil spills

Single-Sensor SAR: Motion Derivation

Entering interactive demonstration...

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- **Conclusions and future work**

Conclusions I

- In many cases, we get promising results!
- Different sensors
 - Spectral sensors
 - SAR
- Different kinds of tracked objects
 - Algae films
 - Oil spills
- The results refine the model currents on a mesoscale

Conclusions II

- Algorithmic improvements lead to speed or accuracy improvements (or both)
- If applicable, gradient based approaches result in high resolution current fields
- However, in some cases we currently have to “fall back” to fast normalized cross-correlation
- Hard to get satellite images that:
 - show “objects of interest” and
 - have a spatiotemporal overlap.
- Ground-truth or gold-standard?

Future work I

- Improve current low-level image processing
 - Make algorithms more robust
 - Self detection of failures
 - Implement and test other algorithms
- Use the spectral information of multi-spectral images
 - Move from single band image \leftrightarrow single band image processing to multi-band processing
 - Use multi-spectral information for feature detection
 - Multi-sensor multi-sensor fusion
- Further development of GRAIPE

Future work II

- Use more high-level knowledge
 - Improve the results (e.g. filtering unreliable currents)
 - Perform reasoning on images and currents
 - Explicit representation of different domains
- Where could high-level knowledge support us?
 - Automatic learning of feature detectors
 - Designing optimized gradient based algorithms for sea surface currents
 - Interpretation of the calculated currents
- Extend to different areas

End of presentation

Thank you for your attention!

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