The Derivation of Current Fields from Multi-Sensor Satellite Data

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

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Outline

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

• Introduction
  – The task
  – Constraints, challenges and problems
  – Motivation

• Solving the correspondence problem
• Application to satellite images
• Conclusions and future work
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
Table of Contents

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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: \( \frac{\partial I}{\partial x} \frac{dx}{dt} + \frac{\partial I}{\partial y} \frac{dy}{dt} + \frac{\partial I}{\partial t} = 0 \)
  - 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:
    \[
    \left( \frac{\partial u}{\partial x} \right)^2 + \left( \frac{\partial u}{\partial y} \right)^2 \quad \text{and} \quad \left( \frac{\partial v}{\partial x} \right)^2 + \left( \frac{\partial v}{\partial y} \right)^2
    \]

- Local constraints
  - Assume local equality of the motion
  - Example: Lucas Kanade method:
    \[
    \begin{bmatrix}
    \sum_\sigma (I_x)^2 & \sum_\sigma I_x I_y \\
    \sum_\sigma I_y I_x & \sum_\sigma (I_y)^2
    \end{bmatrix}
    \begin{bmatrix} u \\ v \end{bmatrix} =
    \begin{bmatrix}
    \sum_\sigma I_x \\
    \sum_\sigma I_y
    \end{bmatrix} \cdot I_t
    \]

- Hybrid approaches
  - Combining local and global constraints
  - Example: Bruhn et. al
**Detail of Analysed Algorithms**

**Motion detection algorithms**

- Feature based
  - Monotony op.
  - Canny
  - Image features
  - Edge features
  - Fast CC matching
  - Fast NCC matching
  - Max likelihood
  - Smoothness
  - Relaxation

- Gradient based
  - Local constraints
    - Lucas Kanade
    - Structure Tensor
    - Constant Contrast
    - Farnebäck
  - Global constraints
    - Horn & Schunck
    - Horn & Schunk ex.
    - Nagel & Enkelmann
  - Hybrid algorithms
    - Combined Local Global
    - Combined Local Global non-linear
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:

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

- 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
- 08:57 UTC

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

Region of interest
**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

Region of interest
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 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 ↔ 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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