Advanced Image Processing for NASA Applications

Abstract:
The future of space exploration will involve cooperating fleets of spacecraft or sensor webs geared towards coordinated and optimal observation of Earth Science phenomena. The main advantage of such systems is to utilize multiple viewing angles as well as multiple spatial and spectral resolutions of sensors carried on multiple spacecraft but acting collaboratively as a single system. Within this framework, our research focuses on all areas related to sensing in collaborative environments, which means systems utilizing intra-communicating spatially distributed sensor pods or crafts being deployed to monitor or explore different environments. Examples of such collaborative environments are found:

- in Earth Science with such concepts as spacecraft constellations or sensor webs of satellite, aircraft and in-situ simultaneous measurements,
- in Space Science with fleets of nano-satellites or deployable mirrors/telescopes, and
- in Exploration, for which the coordination between one or several orbiters and multiple planetary explorers, including humans and robots, will be essential.

This talk will describe the general concept of sensing in collaborative environments, will give a brief overview of several technologies developed at NASA Goddard Space Flight Center in this area, and then will concentrate on specific image processing research related to that domain, specifically image registration and image fusion.
Dr. Jacqueline Le Moigne is Head of the Advanced Architectures and Automation Branch of the NASA Goddard Space Flight Center, as well as a NASA Goddard Senior Fellow. She received a B.S and a M.S. in Mathematics and a Ph.D. in Computer Science (specialty: Computer Vision) from the University Pierre and Marie Curie, Paris. As an Assistant Research Scientist at the Computer Vision Laboratory of the University of Maryland, Dr. Le Moigne designed new algorithms and supervised the development of a visual navigation system for the Autonomous Land Vehicle (ALV) project. Jacqueline Le Moigne came to Goddard in 1990 as a National Research Council Senior Research Associate. She then became a Senior Scientist at the Center of Excellence in Space Data and Information Sciences (CESDIS), and then a Senior Computer Scientist in the Applied Information Sciences Branch of the Earth and Space Data and Computing Division. During that time, she focused her research interests on applying Computer Vision to Earth and Space Science problems such as robotics, land use/land cover assessment, and intelligent data management, and on utilizing high performance parallel computers. Some of her most recent research focuses on Parallel Registration of Multi-Sensor/Multi-Scale Satellite Image Data, for which she has been studying wavelets and their implementation on high performance computers. Current work includes the development of a web-based image registration toolbox, the registration of Landsat and EOS Core Sites imagery, the implementation of image processing techniques on reconfigurable computers for application to on-board processing, web sensors and formation flying systems, as well as to in-situ processing for planetary robotic vision systems. Dr. Le Moigne has published over 100 papers. She was appointed NASA Goddard Senior Fellow in 2005, elected IEEE Senior member in 1996 and was Associate Editor of the IEEE Transactions on Geoscience and Remote Sensing from 2001 to 2005. She was also an Associate Editor for Pattern Recognition from 2001 to 2003.

Speaker: Dr. Jacqueline Lemoigne

Organization: Advanced Architectures and Automation Branch, NASA Goddard Space Flight Center

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Advanced Image Processing for NASA Applications

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Sensor Webs, Constellation and Exploration
Sensing in Collaborative Environments for Science and Exploration At NASA
Challenges and Needs in Processing and Analyzing Earth Science Data

- Challenges:
  - Multiple Platforms/Sensors Missions for Earth System Science
  - Continuity of Data to Build Long-Term Datasets
  - Extrapolation among Several Scales, Temporal, Spatial and Spectral

- Project Goals:
  - Dimension Reduction, Image Registration and Fusion
    - Easier to Manipulate
  - On-The-Ground Fast High-Performance Implementations
  - On-Board Processing for Formation Flying Systems

What is Image Registration?

- Navigation or Model-Based Systematic Correction
  - Orbital, Attitude, Platform/Sensor Geometric Relationship, Sensor Characteristics, Earth Model, ...

- Image Registration or Feature-Based Precision Correction
  - Navigation within a Few Pixels Accuracy
  - Image Registration Using Selected Features (or Control Points) to Refine Geo-Location Accuracy

- 2 Approaches
  (1) Image Registration as a Post-Processing (Taken here)
  (2) Navigation and Image Registration in a Closed Loop
What is Image Registration? (cont.)

- $I_1(x,y)$ and $I_2(x,y)$: images or image/map
  - find the mapping $(f,g)$ which transforms $I_1$ into $I_2$:
    $I_2(x,y) = g(I_1(f_x(x,y), f_y(x,y)))$
    - $f$: spatial mapping
    - $g$: radiometric mapping

- Spatial Transformations
  - Translation, Rigid, Affine, Projective, Perspective, Polynomial, ...

- Radiometric Transformations (Resampling)
  - Nearest Neighbor, Bilinear, Cubic Convolution, Spline ...

Technical Approach to Automatic Image Registration

- Survey Registration Methods Applicable to Earth and Space Data Applications

- Provide a Quantitative Intercomparison of Selected Methods

- Build an Operational Image Registration Toolbox
Image Registration Challenges

- Multi-Resolution / Mono- or Multi-Instrument
  - Multi-temporal data
  - Various spatial resolutions
  - Various spectral resolutions

- Sub-Pixel Accuracy
  - 1 pixel misregistration => 50% error in NDVI computation

- Accuracy Assessment
  - Synthetic data
  - "Ground Truth" (manual registration?)
  - Use down-sampled high-resolution data
  - Consistency ("circular" registrations) studies

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Technical Approach

Automatic Image Registration (2)

- Image Registration Components:
  0 Pre-Processing: Cloud detection, Region of interest masking, ...
  1 Feature Extraction ("Control Points"):
    Edges, Regions, Contours, Wavelet Coefficients, ...
  2 Feature Matching
    - Spatial Transformation (a-priori knowledge)
    - Search Strategy (Global vs Local, Multi-Resolution, ...)
    - Choice of Similarity Metrics (Correlation, Optimization Method, Hausdorff Distance, ...)
  3 Resampling, Indexing or Fusion
Wavelet Studies: Rotation and Translation Invariance Issues

- With orthogonal wavelets, signal changes within or across subbands with subsampling

- Study for Shift Sensitivity [Stone et al.]:
  - low-pass subband relatively insensitive to translation, if features are twice the size of wavelet filters (Nyquist criterion, sample signal at least twice frequency of highest frequency component)
  - high-pass subband more sensitive than low-pass subband but can still be used.

Translation Invariance Experiment

Correlate Wavelets of Two Pulses.
Translation Sensitivity
Low-Pass Level 3

Correlation Minima vs Pulse width

Correlation Averages vs Pulse width

Translation Sensitivity
High-Pass Level 3

Correlation Minima vs Pulse width

Correlation Averages vs Pulse width

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Image Registration Components

Features

Similarity Measure

Strategy

A Framework for the Analysis of Various Image Registration Components

Features

Similarity Measure

Strategy

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Transformation of Starting Scene by:
- Scales in [0.8,1.2] (step = 0.05)
- Translations in [0,20] pixels (step = 0.5)
- Rotations in [0,20] degrees (step = 0.5)
- Gaussian noise in [0,20] (step = 1)
- Radiometric Transformation (PSF constructed from black 512x512 image with 5x5 white center)
Results TRU - Various Features - No Noise - No PSF

Sensitivity of TRU Algorithms to Initial Guess

Results TRU - Various Features - Varying Noise - No PSF

Sensitivity of TRU Algorithms to Noise
Results TRU - Various Features - Varying Noise - with or w/o PSF

Warping + Noise

Warping + PSF

Warping + PSF + Noise

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Results TRU - Two Different Metrics (L2 & MI) - With PSF

Sensitivity of TRU Algorithms to Initial Guess (with PSF)

Sensitivity of TRU/MI to Initial Guess
Findings from Experiments

(1) FEATURE SELECTION

a. Correlation Based
   i. **Gray Levels, Edges or Daubechies Coefficients**
      - Wavelet-Based Faster but Edge-Based More Accurate
   ii. **Daubechies and Simoncelli, i.e. Wavelets vs Wavelet-Like Features**
      - Simoncelli's More Accurate and Less Sensitive to Noise than Daubechies' Filters
b. Optimization-Based
   i. **Simoncelli (Low-Pass and Band-Pass) and Splines**
      - Simoncelli-LP = Best radius of convergence
      - Simoncelli-BP = Best for accuracy and consistency
      - When CV, Spline features have better accuracy

(2) SIMILARITY MEASURE SELECTION

a. Correlation vs Mutual Information (MI)
   - Sharper Peak for MI => enables better accuracy
   - MI less sensitive to noise
b. MI with Stochastic Gradient
   - Spall's Simultaneous Perturbation Stochastic Approximation (SPSA): based on gradient approximation computed from objective function (200 iterations)
   - Results: On synthetic test data, 0.01 pixel accuracy; 0.64 pixel on multi-temporal (cloudy) data, and 0.34 pixel accuracy on multi-sensor data.

Goals of a Modular Image Registration Framework

- Testing Framework to:
  - **Assess Various Combinations of Components**
  - **Assess a New Registration Component**

- Basis for Future Web-Based Registration Tool - User
  Could "Schedule" Combination of Components function of:
  - Application
  - Available Computational Resources
  - Required Registration Accuracy

- Prototype Web-Based Registration Toolbox:
  - 3 Different Methods Based on Simoncelli-Decomposition
  - Java Implementation: JNI-Wrapped Functions
Registration Test - Landsat Multi-Temporal Registration

- Landsat-5 and -7 Multi-Temporal Data:
  - Chips and Corresponding Windows

### One chip and 4 Corresponding Windows Extracted from 4 Multi-Temporal Landsat Imagery

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### Registration Test - Results

<table>
<thead>
<tr>
<th>Chip #</th>
<th>84240</th>
<th>87136</th>
<th>96193</th>
<th>97275</th>
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<td>0</td>
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<td>0</td>
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<td>21</td>
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<tr>
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<td>-29</td>
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<td>1.00</td>
<td>1.80</td>
<td>0.00</td>
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<tr>
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<td>0</td>
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<tr>
<td>TX</td>
<td>8</td>
<td>11</td>
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<td>22</td>
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<tr>
<td>TY</td>
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<td>-41</td>
<td>4</td>
<td>-30</td>
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<td>0.00</td>
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<tr>
<td>#3 - Rot</td>
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<td>-0.5</td>
<td>-63</td>
<td>0</td>
</tr>
<tr>
<td>TX</td>
<td>8</td>
<td>11</td>
<td>10.84</td>
<td>21</td>
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<tr>
<td>TY</td>
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<td>0</td>
<td>0</td>
</tr>
<tr>
<td>TX</td>
<td>9</td>
<td>12</td>
<td>12</td>
<td>22</td>
</tr>
<tr>
<td>TY</td>
<td>-40</td>
<td>-38</td>
<td>-94</td>
<td>-29</td>
</tr>
<tr>
<td>Distance</td>
<td>0.56</td>
<td>0.50</td>
<td>0.00</td>
<td>0.00</td>
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</tbody>
</table>

### Global Registration for 4 Scenes

<table>
<thead>
<tr>
<th>Transf.</th>
<th>84240</th>
<th>87136</th>
<th>96193</th>
<th>97275</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rotation</td>
<td>0.013</td>
<td>0.003</td>
<td>-0.042</td>
<td>-0.143</td>
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<tr>
<td>Transl-x</td>
<td>7.18</td>
<td>11.43</td>
<td>12.61</td>
<td>21.20</td>
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<tr>
<td>Transl-y</td>
<td>-41.12</td>
<td>-40.49</td>
<td>-95.38</td>
<td>-28.85</td>
</tr>
</tbody>
</table>

### Manual Registration for 4 Scenes

- This Chesapeake Bay Example:
  - Global Accuracy Error ≈ 0.82 pixel
- Other Virginia Scenes:
  - Global Accuracy Error ≈ 0.31 pixel

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Registration Test -
EOS Validation Core Sites

- Landsat-7/IKONOS/MODIS/SeaWiFS
  - Red and NIR for each sensor
  - 4 Spatial Resolutions:
    - IKONOS: 4 m; ETM+: 30 m; MODIS: 500 m; SeaWiFS: 1000 m

- 4 different sites:
  - Coastal Area: VA, Coast Reserve Area, October 2001
  - Agriculture Area: Konza Prairie in State of Kansas, July to August 2001
  - Mountainous Area: Cascades Site, September 2000
  - Urban Area: USDA Site, Greenbelt, MD, May 2001
## EOS Validation Core Sites - Results

### Multi-Sensor Image Registration

<table>
<thead>
<tr>
<th>Pair to Register</th>
<th>Method 1 (GC)</th>
<th>Method 2 (GGD)</th>
<th>Method 3 (WCE)</th>
<th>Method 4 (WMIE)</th>
<th>Method 5 (WHR)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1) etm_red_31.25.power / etm_red_31.25.extract</td>
<td>Rotation = 0, Translation = (0,0) computed by all methods using seven sub-windows pairs</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>(2) iko_nir_3.9l.power / etm_red_31.25.extract</td>
<td>(2,1)</td>
<td>(1.9671,0.0564)</td>
<td>0</td>
<td>(2,0)</td>
<td>(0,0)</td>
</tr>
<tr>
<td>(3) iko_red_3.9l.power / etm_red_31.25.extract</td>
<td>(3,1)</td>
<td>(1.7233,0.2761)</td>
<td>0</td>
<td>(2,0)</td>
<td>(0,0)</td>
</tr>
<tr>
<td>(4) etm_nir_31.25.power / modis_day249_cc_nir.extract</td>
<td>(4,-4)</td>
<td>(1.7793,3.9230)</td>
<td>0</td>
<td>(2,-4)</td>
<td>(0,-2.5)</td>
</tr>
<tr>
<td>(5) etm_red_31.25.power / modis_day249_cc_red.extract</td>
<td>(5,-4)</td>
<td>(1.5665,3.9938)</td>
<td>0</td>
<td>(2,-4)</td>
<td>(0,-2.5)</td>
</tr>
<tr>
<td>(6) modis_day249_cc_nir.power / seawifs_day256_to249_nir.extract</td>
<td>(6,-9)</td>
<td>(8.1700,2.2551)</td>
<td>0</td>
<td>(9,0)</td>
<td>0.5</td>
</tr>
<tr>
<td>(7) modis_day249_cc_red.power / seawifs_day256_to249_red.extract</td>
<td>(7,-9)</td>
<td>(7.6099,0.9721)</td>
<td>0</td>
<td>(9,0)</td>
<td>0.25</td>
</tr>
</tbody>
</table>

- GC: Gray Levels + Fast Fourier Correlation
- GGD: Gray Levels + Gradient Descent
- WCE: Wavelets + Correlation
- WMIE: Wavelets + Mutual Information
- WHR: Wavelets + Hausdorff + Robust Feature Matching

### Table 3 - Self-Consistency Study of the Normalized Correlation Results

<table>
<thead>
<tr>
<th>Image Name</th>
<th>Computed X</th>
<th>Computed Y</th>
<th>Comes from Registered Pair</th>
</tr>
</thead>
<tbody>
<tr>
<td>IKONOS red</td>
<td>0</td>
<td>0</td>
<td>(Starting Point)</td>
</tr>
<tr>
<td>IKONOS nir</td>
<td>0.2500</td>
<td>0.2500</td>
<td>IKO red to ETM red and ETM red to IKO nir</td>
</tr>
<tr>
<td>IKONOS nir</td>
<td>0.2500</td>
<td>-0.3125</td>
<td>IKO red to ETM nir and ETM nir to IKO nir</td>
</tr>
</tbody>
</table>

### Table 4 - Self-Consistency Study of the Mutual Information Results

<table>
<thead>
<tr>
<th>Image Name</th>
<th>Computed X</th>
<th>Computed Y</th>
<th>Comes from Registered Pair</th>
</tr>
</thead>
<tbody>
<tr>
<td>IKONOS red</td>
<td>0</td>
<td>0</td>
<td>(Starting Point)</td>
</tr>
<tr>
<td>IKONOS nir</td>
<td>0.2500</td>
<td>0.0000</td>
<td>IKO red to ETM red and ETM.red to IKO nir</td>
</tr>
<tr>
<td>IKONOS nir</td>
<td>0.1250</td>
<td>-0.1250</td>
<td>IKO red to ETM nir and ETM nir to IKO nir</td>
</tr>
</tbody>
</table>
Registration Test: Application to EO-1
ALI and Hyperion Registration

- Test Data Acquired
  - July 5, 2004
  - from Debeque near Grand Junction, Colorado, U.S.A
  - 256 columns x 3352 lines

- EO-1 (Earth Observing 1)
  - Hyperion
    - High spectral resolution (242 bands)
    - Spectral coverage: 356 nm to 2577 nm (~10nm / band)
    - Spatial resolution: 30 meter / pixel
  - ALI (Advanced Land Imager)
    - 9 Multispectral Bands
      - Same spectral coverage as Hyperion (much lower spectral resolution)
      - Same spatial resolution

ALI and Hyperion Registration

ALI
Band 4: Reference

Hyperion
Band 47: Input

Hyperion
Band 47 Registered to ALI
Band 4

Registered Subset
ALI

Hyperion

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IMAGE FUSION

Data and Image Fusion

- Data Fusion
  - Use multi-source data of different natures to increase quality of information contained in data (Pohl and Genderen, 1998)
  - A process dealing with association, correlation, and combination of data and information from single and multiple sources to achieve refined position and identity estimates, and complete and timely assessments of situations and threats, and their significance (Hall and Llinas, 2001).
Data and Image Fusion (2)

- Image Fusion
  - Data are images
  - General Objectives:
    - Image sharpening
    - Improving registration/classification accuracy
    - Temporal change detection
    - Feature enhancement
  - Application
    - Invasive Species Forecasting System
  - Objective
    - Improvement of classification accuracy
      - Tamarisk, Leafy Spurge, Cheat grass, Russian olive, etc.
    - Feature enhancement

Image Fusion Methods

- Principal Component Analysis, PCA
  - Input
    - Multivariate data set of inter-correlated variables
  - Output
    - Data set of new uncorrelated linear combinations of the original variable

- Wavelet-based Fusion
  - Use of Different Subbands in Reconstruction

- Cokriging
Wavelet-Based Image Fusion

High Spatial Resolution Data

Low Spatial Resolution Data

Decomposition

FUSED DATA

Improved Resolutions

Reconstruction

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Cokriging

- Interpolation Method
  - Geo-statistics, mining, and petroleum engineering applications
  - Pioneered by Danie Krige, 1951.
- Generalized version of kriging (B.L.U.E):
  - Best: aims to minimize variance of the errors
  - Linear: estimates are weighted linear combination of the available data
  - Unbiased: tries to have mean residual, or error, equal to zero.
  - Estimator.

Evaluation

- Past Quality Metrics
  - Piella, etc.
  - Gray level only
  - No support for multi-spectral image
- Objective:
  - Improved Classification
    - Performed k-means with k=7, max iterations 15 (for PCA and wavelets)
    - Needs ground truth
- Similarities
  - Spectral quality: correlation
- Differences
  - Added Texture
  - Co-occurrence matrix for statistical texture properties (Haralick)
  - Variance images
  - Entropy
Experiments: PCA

- Three experiments
- Input
  - 9 bands of ALI
  - 140 bands of Hyperion (calibrated and not corrupted bands)
  - Stack of both ALI and Hyperion bands above
- Output
  - Same number of PCs as input bands
  - Select PCs containing 99% of information

Results: PCA

<table>
<thead>
<tr>
<th></th>
<th>ALI V</th>
<th>Hyp V</th>
<th>Fused V</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>143.98</td>
<td>137.64</td>
<td>180.10</td>
</tr>
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</table>

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Experiments: Wavelets

- Fuse each multispectral band of ALI with one band of Hyperion
  - For each of 9 ALI bands
  - Select a Hyperion band within the wavelength range of corresponding ALI band which is
    - closest to the center of ALI’s wavelength range (experiment 1)
    - least correlated to the corresponding ALI band (experiment 2)

Results: Wavelets

Fused bands are highly correlated with their corresponding MS Hyperion band

<table>
<thead>
<tr>
<th>ALI MS band</th>
<th>Spectral range (nm)</th>
<th>CWL (nm)</th>
<th>Matching Hyperion bands (nm)</th>
<th>CWL (nm)</th>
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</thead>
<tbody>
<tr>
<td>3 (MS-2)</td>
<td>525-605</td>
<td>567.2</td>
<td>18</td>
<td>528.57</td>
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<tr>
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<td>23</td>
<td>579.45</td>
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<td></td>
<td>25</td>
<td>599.80</td>
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</table>

Exp1: Hyp-Fused pair | Corr | Exp2: Hyp-Fused pair | Corr
<table>
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<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>H9 : F1</td>
<td>0.929</td>
<td>H10 : F1</td>
<td>0.956</td>
</tr>
<tr>
<td>H16 : F2</td>
<td>0.949</td>
<td>H15 : F2</td>
<td>0.965</td>
</tr>
<tr>
<td>H23 : F3</td>
<td>0.955</td>
<td>H25 : F3</td>
<td>0.972</td>
</tr>
<tr>
<td>H28 : F4</td>
<td>0.952</td>
<td>H33 : F4</td>
<td>0.969</td>
</tr>
<tr>
<td>H43 : F5</td>
<td>0.913</td>
<td>H45 : F5</td>
<td>0.934</td>
</tr>
<tr>
<td>H50 : F6</td>
<td>0.890</td>
<td>H53 : F6</td>
<td>0.914</td>
</tr>
<tr>
<td>H106: F7</td>
<td>0.873</td>
<td>H113: F7</td>
<td>0.901</td>
</tr>
<tr>
<td>H160: F8</td>
<td>0.592</td>
<td>H160: F8</td>
<td>0.679</td>
</tr>
<tr>
<td>H195: F9</td>
<td>0.385</td>
<td>H198: F9</td>
<td>0.826</td>
</tr>
</tbody>
</table>

Jacqueline Le Moigne, 53
Results: Wavelets

- Clustering of fusion result of 9 bands of ALI with 9 bands of Hyperion
- Fusion: 4 Levels of Decomposition, Daubechies Filter of size 2

Mean of variance images of ALI, Hyperion, and Fused Bands

\( V = \text{Mean of Variance Image, Exp 1} \)

<table>
<thead>
<tr>
<th>ALI</th>
<th>V</th>
<th>Hyp</th>
<th>V</th>
<th>Fused</th>
<th>V</th>
</tr>
</thead>
<tbody>
<tr>
<td>A1</td>
<td>77.62</td>
<td>H9</td>
<td>85.63</td>
<td>F1</td>
<td>113.84</td>
</tr>
<tr>
<td>A2</td>
<td>99.49</td>
<td>H16</td>
<td>116.96</td>
<td>F2</td>
<td>138.72</td>
</tr>
<tr>
<td>A3</td>
<td>139.51</td>
<td>H23</td>
<td>158.87</td>
<td>F3</td>
<td>183.63</td>
</tr>
<tr>
<td>A4</td>
<td>193.03</td>
<td>H28</td>
<td>192.84</td>
<td>F4</td>
<td>212.16</td>
</tr>
<tr>
<td>A5</td>
<td>169.97</td>
<td>H43</td>
<td>176.24</td>
<td>F5</td>
<td>200.32</td>
</tr>
<tr>
<td>A6</td>
<td>168.54</td>
<td>H50</td>
<td>180.82</td>
<td>F6</td>
<td>208.95</td>
</tr>
<tr>
<td>A7</td>
<td>164.22</td>
<td>H106</td>
<td>157.81</td>
<td>F7</td>
<td>197.47</td>
</tr>
<tr>
<td>A8</td>
<td>344.53</td>
<td>H160</td>
<td>190.52</td>
<td>F8</td>
<td>261.85</td>
</tr>
<tr>
<td>A9</td>
<td>260.68</td>
<td>H195</td>
<td>179.91</td>
<td>F9</td>
<td>240.52</td>
</tr>
<tr>
<td>Overall V</td>
<td>179.73</td>
<td></td>
<td>159.96</td>
<td></td>
<td>195.27</td>
</tr>
</tbody>
</table>
**Results: Wavelets**

Mean of variance images of ALI, Hyperion, and Fused Bands
V= Mean of Variance Image, Exp2

<table>
<thead>
<tr>
<th>ALI</th>
<th>V</th>
<th>Hyp</th>
<th>V</th>
<th>Fused</th>
<th>V</th>
</tr>
</thead>
<tbody>
<tr>
<td>A1</td>
<td>77.62</td>
<td>H10</td>
<td>90.14</td>
<td>F1</td>
<td>101.65</td>
</tr>
<tr>
<td>A2</td>
<td>99.49</td>
<td>H15</td>
<td>111.12</td>
<td>F2</td>
<td>118.27</td>
</tr>
<tr>
<td>A3</td>
<td>139.51</td>
<td>H25</td>
<td>174.84</td>
<td>F3</td>
<td>176.30</td>
</tr>
<tr>
<td>A4</td>
<td>193.03</td>
<td>H33</td>
<td>217.32</td>
<td>F4</td>
<td>225.68</td>
</tr>
<tr>
<td>A5</td>
<td>169.97</td>
<td>H45</td>
<td>169.88</td>
<td>F5</td>
<td>182.35</td>
</tr>
<tr>
<td>A6</td>
<td>168.54</td>
<td>H53</td>
<td>166.87</td>
<td>F6</td>
<td>184.36</td>
</tr>
<tr>
<td>A7</td>
<td>164.22</td>
<td>H113</td>
<td>182.49</td>
<td>F7</td>
<td>197.00</td>
</tr>
<tr>
<td>A8</td>
<td>344.53</td>
<td>H160</td>
<td>190.52</td>
<td>F8</td>
<td>205.10</td>
</tr>
<tr>
<td>A9</td>
<td>260.68</td>
<td>H198</td>
<td>184.84</td>
<td>F9</td>
<td>173.18</td>
</tr>
<tr>
<td>Overall V</td>
<td>179.73</td>
<td></td>
<td>165.34</td>
<td></td>
<td>173.77</td>
</tr>
</tbody>
</table>

Jacqueline Le Moigne, 56

---

**Experiments: Cokriging Spectral Fusion**

- Spectral dimension
  - Increase spectral resolution of ALI where needed
- One pixel only
- Software used
  - UCL-FAO Agromet project
    - (http://www.aigeostats.org/software/Geostats_software/agromet.htm)
  - C++
  - Variogram modeling, coregionalization, cokriging

Jacqueline Le Moigne, 57
Fusion results on one pixel using cokriging by creating one band/value in center of each wavelength interval where ALI data is missing.
Spectral Fusion with Cokriging

Fusion results on one pixel using cokriging by estimating up to 3 values in each wavelength interval where ALI data is missing.

Jacqueline La Moigne, 60

Spectral Fusion with Cokriging

results on one pixel using cokriging by estimating values at all Hyperion centers in each wavelength interval where ALI data is missing.

Jacqueline La Moigne, 61
Spatial Fusion with Cokriging - Landsat TM

Multispectral Bands 2, 3, 4

Panchromatic

Spatial Fusion with Cokriging - Landsat TM

FUSION

Pan + MS-2 → fused_b2
Pan + MS-3 → fused_b3
Pan + MS-4 → fused_b4

Landsat-7 Pan-Sharpened MS Bands 2, 3 and 4

Through Cokriging with Pan Band 8

Spectral Resolution
1 pixel of an MS band

MS-Value1

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Pan</td>
<td></td>
</tr>
<tr>
<td>Value 1</td>
<td>Value 2</td>
</tr>
<tr>
<td>Pan</td>
<td></td>
</tr>
<tr>
<td>Value 3</td>
<td>Value 4</td>
</tr>
</tbody>
</table>

x1 y1 p1 ?
x2 y2 p2 ?
x3 y3 p3 msl
x4 y4 p4 ?
TABLE II
CORRELATION OF FUSED BANDS WITH MS INPUT BANDS

<table>
<thead>
<tr>
<th>Bands</th>
<th>Wavelet</th>
<th>PCA</th>
<th>Cokriging</th>
</tr>
</thead>
<tbody>
<tr>
<td>f2, b2</td>
<td>0.82</td>
<td>0.99</td>
<td>0.91</td>
</tr>
<tr>
<td>f3, b3</td>
<td>0.84</td>
<td>0.99</td>
<td>0.93</td>
</tr>
<tr>
<td>f4, b4</td>
<td>0.92</td>
<td>0.75</td>
<td>0.93</td>
</tr>
<tr>
<td>Average</td>
<td>0.86</td>
<td>0.91</td>
<td>0.92</td>
</tr>
</tbody>
</table>

TABLE III
ENTROPY OF MS AND FUSED BANDS

<table>
<thead>
<tr>
<th>Original Bands</th>
<th>Fused Bands</th>
<th>Wavelet</th>
<th>PCA</th>
<th>Cokriging</th>
</tr>
</thead>
<tbody>
<tr>
<td>b2</td>
<td>f2</td>
<td>3.12</td>
<td>2.69</td>
<td>3.23</td>
</tr>
<tr>
<td>b3</td>
<td>f3</td>
<td>3.28</td>
<td>3.72</td>
<td>3.64</td>
</tr>
<tr>
<td>b4</td>
<td>f4</td>
<td>3.93</td>
<td>5.21</td>
<td>4.90</td>
</tr>
<tr>
<td>Average</td>
<td></td>
<td>3.44</td>
<td>3.87</td>
<td>3.92</td>
</tr>
</tbody>
</table>
Spatial Fusion with Cokriging - Landsat TM

### Conclusions

- Registration and Fusion of Multiple Spatial and Spectral Resolutions Very Important for Future Remote Sensing Systems
- Study of Modular Framework for Image Registration, Mainly Based on Multi-Resolution Wavelet-Like Features and Matching by Optimization
- Comparison of Several Fusion Methods and Introduction of Cokriging for Fusion
- Experiments Using Landsat Multi-Temporal, EOS Validation Core Sites and EO-1 ALI/ Hyperion Data
- Work On-Going:
  - **Registration**
    - Conclude Components Evaluation
      - Sensitivity to noise, Radiometric transformations, Initial conditions and Computational and Memory Requirements
      - Integration of DEM Information
    - Complete Prototype Operational Registration Framework/Toolbox
  - **Fusion**
    - Application to:
      - Invasive Species: ALI and Hyperion, MODIS and Landsat
      - Precipitation Data Multiple Source

---

**TABLE IV**
MEAN ENTROPY OF ENTROPY IMAGES OBTAINED THROUGH CO-OCCURRENCE MATRICES

<table>
<thead>
<tr>
<th>Original Bands</th>
<th>Fused Bands</th>
<th>Wavelet</th>
<th>PCA</th>
<th>Cokriging</th>
</tr>
</thead>
<tbody>
<tr>
<td>b2</td>
<td>f2</td>
<td>1.37</td>
<td>1.37</td>
<td>1.44</td>
</tr>
<tr>
<td>b3</td>
<td>f3</td>
<td>1.45</td>
<td>1.49</td>
<td>1.45</td>
</tr>
<tr>
<td>b4</td>
<td>f4</td>
<td>1.78</td>
<td>2.02</td>
<td>1.96</td>
</tr>
<tr>
<td>Average</td>
<td></td>
<td>1.52</td>
<td>1.53</td>
<td>1.63</td>
</tr>
</tbody>
</table>

Jacqueline Le Moigne, 66
Thank you.

**Similarity Metrics**

- **Correlation**
  \[ C(A,B) = \frac{\sum_{i} (a_i - \text{MeanA}) \cdot (b_i - \text{MeanB})}{\sqrt{\sum_{i} (a_i - \text{MeanA})^2} \cdot \sqrt{\sum_{i} (b_i - \text{MeanB})^2}} \]

- **L2 Norm**
  \[ E(p) = \sum (f - Q_p(g))^2 \]

- **Mutual Information**:
  \[ I(A,B) = \sum_{a,b} h_{sw}(a,b) \cdot \log \frac{N \cdot h_{sw}(a,b)}{h(a) \cdot h(b)} \]

- **Partial Hausdorff Distance**:
  \[ H_k(A,B) = K^{th} \min_{a \in A} \min_{b \in B} \text{dist}(a,b) \]
  \( (1 \leq k \leq |A|; \ K^{th} \) is the \( k^{th} \) smallest element of set; \( \text{dist}(a,b) \): Euclidean distance)
Methods: Cokriging

\[ Var(R) = w' C_z w \]
\[ = \sum_{i=1}^{n} \sum_{j=1}^{n} a_i a_j \text{Cov}(U_i U_j) + \sum_{i=1}^{m} \sum_{j=1}^{m} b_i b_j \text{Cov}(V_i V_j) \]
\[ + 2 \sum_{i=1}^{n} \sum_{j=1}^{m} a_i b_j \text{Cov}(U_i V_j) - 2 \sum_{i=1}^{n} a_i \text{Cov}(U_i U_0) \]
\[ - 2 \sum_{j=1}^{m} b_j \text{Cov}(V_j U_0) + \text{Cov}(U_0 U_0). \]

\[ Var(R) = w' C_z w + 2 \mu_1 \left( \sum_{i=1}^{n} a_i - 1 \right) + 2 \mu_2 \left( \sum_{j=1}^{m} b_j \right). \]

Jacqueline Le Moigne, 72

\[ \sum_{i=1}^{n} a_i \text{Cov}(U_i U_j) + \sum_{i=1}^{m} b_i \text{Cov}(V_i U_j) + \mu_1 = \text{Cov}(U_0 U_j). \text{ for } (j = 1 \ldots n) \]

\[ \sum_{i=1}^{n} a_i \text{Cov}(U_i V_j) + \sum_{i=1}^{m} b_i \text{Cov}(V_i V_j) + \mu_2 = \text{Cov}(U_0 V_j). \text{ for } (j = 1 \ldots m) \]
\[ \sum_{i=1}^{n} a_i = 1 \]
\[ \sum_{j=1}^{m} b_j = 0 \]

Jacqueline Le Moigne, 73
Matching Strategies

- Exhaustive Search
- Fourier Transform
  - Translations
  - Very Fast Implementations
- Gradient Descent
  \[
  \begin{align*}
  \sum f_x^2 & \quad \sum f_x f_y \quad \sum R f_x \Delta x \\
  \sum f_x f_y & \quad \sum f_y^2 \quad \sum R f_y \Delta y \\
  \sum R f_x & \quad \sum R f_y \quad \sum R^2 \Delta \theta \\
  \end{align*}
  \]
- Robust Feature Matching
  - Hierarchical Subdivisions of Search Space
  - Pruning of Search Space

Methods: Cokriging

Interpolation using more than one type of variable to estimate an unknown value at a particular location.

\[
\hat{u}_0 = \sum_{i=1}^{n} a_i u_i + \sum_{j=1}^{m} b_j v_j
\]

Estimation error:

\[
R = \hat{U}_0 - U_0 = w'Z,
\]

\[
w' = (a_1, \ldots, a_n, b_1, \ldots, b_m, -1)
\]

\[
Z' = (U_1, \ldots, U_n, V_1, \ldots, V_m, U_0)
\]

Goal of cokriging is to minimize variance of error subject to some constraints (to ensure unbiasedness of our estimate):

\[
Var(R) = w' C_w w
\]

\[
\sum_{i=1}^{n} a_i = 1, \quad \sum_{j=1}^{m} b_j = 0
\]