Introduction to Remote Sensing
Image Registration

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Problem Description

• Earth Science studies such as:
  o Climate change over multiple time scales
  o Predicting crop production
  o Monitoring land resources
  o Understanding the impact of human activity on major Earth ecosystems

• Addressed by using global and repetitive measurements provided by a wide variety of satellite remote sensing systems
  o Multiple-time or simultaneous observations of the same Earth features by different sensors
  o Global measurements with remote sensing systems
  o Complemented by regional and local measurements using ground and airborne sensors
  o Addressed by using global and repetitive measurements provided by a wide variety of satellite remote sensing systems

• Need to correlate and integrate all these complementary data
NASA Earth Global Measurements
Example of International Measurements

GPM Constellation of Satellites

NPP (NASA/IPO)

GPM Core Observatory (NASA/JAXA)

MetOp B & C (EUMETSAT)

Megha-Tropiques (CNES/ISRO)

JPSS-1 (NASA/NOAA)

NOAA 19 (NOAA)

DMSP F19/F20 (DOD)

GCOM-W1 (JAXA)
Image Registration Challenges

- **Remote Sensing vs. Medical or Other Imagery**
  - Variety in the types of sensor data and the conditions of data acquisition
  - Size of the data
  - Lack of a known image model
  - Lack of well-distributed “fiducial points” resulting in lack of algorithms validation

- **Navigation Error**

- **Atmospheric and Cloud Interactions**

*Three Landsat images over Virginia acquired in August, October, and November 1999 (Courtesy: Jeffrey Masek, NASA Goddard Space Flight Center)*
Atmospheric and Cloud Interactions

* Baja Peninsula, California; 4 different times of the day (GOES-8)

(Reproduced from Le Moigne & Eastman, 2005)
Image Registration Challenges

*Multi-Temporal*

*Mississippi and Ohio Rivers before & after Flood of Spring 2002 (Terra/MODIS)*
What is Image Registration?

• Image Registration/Feature-Based Precision Correction vs. Navigation or Model-Based Systematic Correction
  1. Orbital, Attitude, Platform/Sensor Geometric Relationship, Sensor Characteristics, Earth Model, etc.
  2. Navigation within a Few Pixels Accuracy
  3. Image Registration Using Selected Features (or Control Points) to Refine Geo-Location Accuracy

• Mathematical Framework
  o \( I_1(x,y) \) and \( I_2(x,y) \): images or image/map
    ✓ find the mapping \((f,g)\) which transforms \( I_1 \) into \( I_2 \): \( I_2(x,y) = g(I_1(fx(x,y),fy(x,y))) \)
    a. \( f \): spatial mapping
    b. \( g \): radiometric mapping
  o Spatial Transformations “\( f \)”
    ✓ Translation, Rigid, Affine, Projective, Perspective, Polynomial, …
  o Radiometric Transformations “\( g \)” (Resampling)
    ✓ Nearest Neighbor, Bilinear, Cubic Convolution, …

• Algorithmic Framework (Brown, 1992)
  1. Search Space of potential transformations
  2. Feature Space of information extracted from the 2 datasets
  3. Similarity Metric used to match the 2 sets of features
  4. Search Strategy to find the optimal transformation
  5. Resampling Method to create the corrected image
  6. Validation Method to evaluate the accuracy of the registration
What is Image Registration?

• Image Registration/Feature-Based Precision Correction vs. Navigation or Model-Based Systematic Correction
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• Mathematical Framework
  - $I_1(x,y)$ and $I_2(x,y)$: images or image/map
    - find the mapping $(f,g)$ which transforms $I_1$ into $I_2$: $I_2(x,y) = g(I_1(f(x,y),f(y,x)))$
      - $f$: spatial mapping
      - $g$: radiometric mapping
  - Spatial Transformations “$f$”
    - Translation, Rigid, Affine, Projective, Perspective, Polynomial, …
  - Radiometric Transformations “$g$” (Resampling)
    - Nearest Neighbor, Bilinear, Cubic Convolution, …

• Algorithmic Framework (Brown, 1992)
  1. **Search Space** of potential transformations
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  5. **Resampling Method** to create the corrected image
  6. **Validation Method** to evaluate the accuracy of the registration
Operational Solutions

*The Landsat ETM+ Example*

- **Sensor Knowledge**
  - Sensor geometry
  - Sensor to platform
  - Orbit
  - Terrain data (DEM)
  - Radiometric model

- **Geodetic accuracy**
  - Database of GCPs derived from USGS data
  - Normalized correlation
  - Updates navigation models
  - Results: RMSE ~54m

- **Band-to-band registration**
  - Selected tie-points in high-freq. arid regions
  - Normalized correlation
  - Subpixel by second order fit to 3x3 neighborhood
  - Result: 0.1 to 0.2 subpixel
# Operational Solutions

**Normalized Cross-Correlation (NCC) Often Used**

<table>
<thead>
<tr>
<th>Instrument</th>
<th>Satellite</th>
<th>Resolution</th>
<th>Similarity</th>
<th>Subpixel</th>
</tr>
</thead>
<tbody>
<tr>
<td>ASTER</td>
<td>Terra</td>
<td>15m-90m</td>
<td>NCC w/ DEM</td>
<td>Fit to surface</td>
</tr>
<tr>
<td>GOES</td>
<td>GOES I-M</td>
<td>1km-8km</td>
<td>NCC w/ vector coastlines</td>
<td>Bi-section search</td>
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<tr>
<td>MISR</td>
<td>Terra</td>
<td>275m</td>
<td>NCC w/ DEM</td>
<td>Least squares</td>
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<tr>
<td>MODIS</td>
<td>Terra</td>
<td>250m-1km</td>
<td>NCC w/ DEM</td>
<td>Fixed grid</td>
</tr>
<tr>
<td>HRS</td>
<td>SPOT</td>
<td>2.5m</td>
<td>NCC w/ DEM</td>
<td>Not described</td>
</tr>
<tr>
<td>ETM+</td>
<td>Landsat-7</td>
<td>15m-60m</td>
<td>NCC to arid region CPs</td>
<td>Fit to surface</td>
</tr>
<tr>
<td>VEGETATION</td>
<td>SPOT</td>
<td>1km</td>
<td>NCC w/ DEM</td>
<td>Not described</td>
</tr>
</tbody>
</table>
Image Registration Algorithm
Classifications

• Area-Based vs. Feature-Based
  o Often Combination of Area- and Feature-Based

• Alternate Classification:
  o Manual Registration
  o Correlation-Based Methods
  o Fourier-Domain and Other Transform-Based Methods
  o Mutual Information and Distribution-Based Approaches
  o Feature-Point Methods
  o Contour- and Region-Based Approaches
Feature Extraction

- Features:
  - Gray levels
  - Salient points - *Matched point-to-point or globally*
    - Edge or edge-like, e.g., Sobel, Canny
    - Fourier coefficients
    - Gabor, Wavelets, Directional Gabor or Wavelets, Shearlets, etc.
    - Corners, e.g., Kearny, Harris and Stephens, Shi and Tomasi
  - Lines (Hough and Generalized), Contours (Govindu et al), Regions (Region Segmentation, e.g., Tilton)
    - Marked Point Processes (MPP): probabilistic framework with configuration space consisting of an unknown number of parametric objects
  - Scale invariant feature transform (SIFT-Lowe) and variants, e.g., Speeded Up Robust Features (SURF)
  - More recently, Neural Networks (NN) have been used for registration
Similarity Metrics

- **Cross-correlation**
  - Maximize cross-correlation over image overlap
  \[
  I_1(x, y) \circ I_2(x, y) = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} I_1(m, n) I_2(x + m, y + n)
  \]

- **Normalized cross-correlation (NCC)**
  - Maximize normalized cross-correlation
  \[
  NCC_{I_1, I_2}(x, y) = \frac{\sum_{m=0}^{M-1} \sum_{n=0}^{N-1} [I_1(m, n) - \bar{I}_1][I_2(x + m, y + n) - \bar{I}_2]}{\sqrt{\sum_{m=0}^{M-1} \sum_{n=0}^{N-1} [I_1(m, n) - \bar{I}_1]^2 \cdot \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} [I_2(x + m, y + n) - \bar{I}_2]^2}}
  \]

- **Mutual information (MI):**
  Maximizes the degree of statistical dependence between the images
  \[
  MI(I_1, I_2) = \sum_{g_1} \sum_{g_2} p_{I_1, I_2}(g_1, g_2) \cdot \log \left( \frac{p_{I_1, I_2}(g_1, g_2)}{p_{I_1}(g_1) \cdot p_{I_2}(g_2)} \right),
  \]
  or using histograms, maximizes
  \[
  MI(I_1, I_2) = \frac{1}{M} \sum_{g_1} \sum_{g_2} h_{I_1, I_2}(g_1, g_2) \cdot \log \left( \frac{Mh_{I_1, I_2}(g_1, g_2)}{h_{I_1}(g_1) \cdot h_{I_2}(g_2)} \right)
  \]
  where \( M \) is the sum of all histogram entries, i.e., number of pixels (in overlapping subimage)
Similarity Metrics (cont.)

MI vs. $L_2$-norm and NCC applied to Landsat-5 images
Other Similarity Metrics

- **Partial Hausdorff distance (PHD):**

\[
H_K(I_1, I_2) = K_{p_i \in I_1} \min_{p_j \in I_2} \text{dist}(p_1, p_2),
\]

where \(1 \leq K \leq |I_1|\) (Huttenlocher et al, Mount et al)

- **Discrete Gaussian mismatch (DGM):**

\[
\text{DGM}_\sigma(I_1, I_2) = 1 - \frac{\sum_{a \in I_1} w_\sigma(a)}{|I_1|}
\]

where \(w_\sigma(a)\) denotes the weight of point \(a\), and \(w_\sigma(a) = \exp\left(-\frac{\text{dist}(a, I_2)^2}{2\sigma^2}\right)\)
Image Matching Strategies

- Matching strategies matched with feature extraction techniques
- Some methods:
  - Exhaustive Search
  - FFT/Phase Correlation – Fourier Mellin Transform
  - Optimization:
    - Steepest Gradient Descent
    - Levenberg-Marquart
    - Stochastic Gradient
  - Robust Feature Matching (RFM)
  - Genetic algorithms (including binary shapes)
  - Neural Networks (esp. for quantum & cognitive computing)
- Global or local registration
- Various image representations, e.g., Multi-resolution and quadtrees
Some Recent Image Registration Results
Wavelet and Wavelet-Like Based Algorithms

Edge, Wavelet and Wavelet-Like Based Registration Framework

- Wavelets are fundamentally *isotropic*, i.e., no directional sensitivity
- Generalization of wavelets to be *anisotropic* $\Rightarrow$ *Shearlets*, which *refine the wavelet construction by including a directional component*

![Wavelet Features](image1.png)

![SAR image (1024x1024)](image2.png)

![Shearlet Features](image3.png)
Some Recent Image Registration Results
Landsat Warped and Noise Experiments

Geometrically warped synthetic input images. The full source image is 1024 x 1024 Landsat-5 TM image from the Mount Hood area. The extracted images are 256 x 256.

256 x 256 Landsat-7 ETM+ images of Washington, DC, (left) without and (right) with Gaussian noise added. The parameters for the noise are mean $\mu = 0$ and variance $\sigma^2 = 0.05$.
Shearlet-Based Registration Results
As a Function of Warp

Comparison of Registration Algorithms for Landsat-TM Geometrically Warped Synthetic Experiments

<table>
<thead>
<tr>
<th>Registration Technique</th>
<th>Number of Converged Experiments (out of 200)</th>
<th>Percentage of Converged Experiments</th>
<th>Mean RMSE</th>
<th>Standard Deviation RMSE</th>
<th>Relative Improvement</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spline Wavelets</td>
<td>108</td>
<td>54.00%</td>
<td>0.0019</td>
<td>0.0017</td>
<td>-</td>
</tr>
<tr>
<td>Simoncelli Band-Pass</td>
<td>21</td>
<td>10.50%</td>
<td>0.0045</td>
<td>0.0014</td>
<td>-</td>
</tr>
<tr>
<td>Simoncelli Low-Pass</td>
<td>113</td>
<td>55.50%</td>
<td>0.0040</td>
<td>0.0036</td>
<td>-</td>
</tr>
<tr>
<td>Shearlets</td>
<td>154</td>
<td>77.00%</td>
<td>3.9513</td>
<td>1.5506</td>
<td>-</td>
</tr>
<tr>
<td>Shearlet+ Spline Wavelets</td>
<td>154</td>
<td>77.00%</td>
<td>0.0058</td>
<td>0.0062</td>
<td>42.59%</td>
</tr>
<tr>
<td>Shearlet+ Simoncelli Band-Pass</td>
<td>154</td>
<td>77.00%</td>
<td>0.0080</td>
<td>0.0050</td>
<td>633.33%</td>
</tr>
<tr>
<td>Shearlet + Simoncelli Low-Pass</td>
<td>154</td>
<td>77.00%</td>
<td>0.0081</td>
<td>0.0081</td>
<td>36.28%</td>
</tr>
</tbody>
</table>
Shearlet-Based Registration Results
As a Function of Noise

Comparison of Registration Algorithms for Noisy Landsat-ETM+ Synthetic Experiments (Variance = 0.05)

<table>
<thead>
<tr>
<th>Registration Technique</th>
<th>Number of Converged Experiments (out of 201)</th>
<th>Percentage of Converged Experiments</th>
<th>Mean RMSE</th>
<th>Standard Deviation RMSE</th>
<th>Relative Improvement</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spline Wavelets</td>
<td>31</td>
<td>15.42%</td>
<td>0.0579</td>
<td>0.0001</td>
<td>-</td>
</tr>
<tr>
<td>Simoncelli Band-Pass</td>
<td>42</td>
<td>20.90%</td>
<td>0.0805</td>
<td>~ 0</td>
<td>-</td>
</tr>
<tr>
<td>Simoncelli Low-Pass</td>
<td>67</td>
<td>33.33%</td>
<td>0.0560</td>
<td>~ 0</td>
<td>-</td>
</tr>
<tr>
<td>Shearlets</td>
<td>98</td>
<td>48.76%</td>
<td>1.8486</td>
<td>1.1933</td>
<td>-</td>
</tr>
<tr>
<td>Shearlet+Spline Wavelets</td>
<td>98</td>
<td>48.76%</td>
<td>0.0468</td>
<td>~ 0</td>
<td>216.13%</td>
</tr>
<tr>
<td>Shearlet+Simoncelli Band-Pass</td>
<td>98</td>
<td>48.76%</td>
<td>0.0805</td>
<td>~ 0</td>
<td>133.33%</td>
</tr>
<tr>
<td>Shearlet + Simoncelli Low-Pass</td>
<td>99</td>
<td>48.76%</td>
<td>0.0560</td>
<td>~ 0</td>
<td>46.27%</td>
</tr>
</tbody>
</table>
Shearlet-Based Registration Results
Multimodal Experiments

1024 x 1024 images of (left) ETM+ Infared/Red band and (right) Near-Infared/NIR band of the Konza Prairie

Pixels computed by SIFT in the LIDAR shaded-relief (left) and optical (right) images of Washington State, connected by line segments. Note the lack of correspondence; such points are unsuitable for a registration algorithm.
Shearlet-Based Registration Results for LIDAR Data

Comparison of Registration Algorithms for LIDAR Warped Synthetic Experiments

<table>
<thead>
<tr>
<th>Registration Technique</th>
<th>Number of Converged Experiments (out of 201)</th>
<th>Percentage of Converged Experiments</th>
<th>Mean RMSE</th>
<th>Standard Deviation RMSE</th>
<th>Relative Improvement</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spline Wavelets</td>
<td>74</td>
<td>36.82%</td>
<td>.3552</td>
<td>.0256</td>
<td>-</td>
</tr>
<tr>
<td>Simoncelli Band-Pass</td>
<td>42</td>
<td>20.90%</td>
<td>.0074</td>
<td>~ 0</td>
<td>-</td>
</tr>
<tr>
<td>Simoncelli Low-Pass</td>
<td>72</td>
<td>35.82%</td>
<td>.2412</td>
<td>.0166</td>
<td>-</td>
</tr>
<tr>
<td>Shearlets</td>
<td>108</td>
<td>53.73%</td>
<td>.0304</td>
<td>.0012</td>
<td>-</td>
</tr>
<tr>
<td>Shearlet+ Spline Wavelets</td>
<td>111</td>
<td>55.22%</td>
<td>.3222</td>
<td>.0143</td>
<td>50.00%</td>
</tr>
<tr>
<td>Shearlet+ Simoncelli Band-Pass</td>
<td>108</td>
<td>53.73%</td>
<td>.0075</td>
<td>~ 0</td>
<td>157.14%</td>
</tr>
<tr>
<td>Shearlet + Simoncelli Low-Pass</td>
<td>111</td>
<td>55.22%</td>
<td>.2432</td>
<td>~ 0</td>
<td>54.71%</td>
</tr>
</tbody>
</table>
# Shearlet-Based Registration Results

## Multimodal Experiments

Comparison of Registration Algorithms for ETM+ Infrared to NIR Multimodal Experiments

<table>
<thead>
<tr>
<th>Registration Technique</th>
<th>Number of Converged Experiments (out of 41)</th>
<th>Percentage of Converged Experiments</th>
<th>Mean RMSE</th>
<th>Standard Deviation RMSE</th>
<th>Relative Improvement</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spline Wavelets</td>
<td>25</td>
<td>60.98%</td>
<td>.2389</td>
<td>.0137</td>
<td>-</td>
</tr>
<tr>
<td>Simoncelli Band-Pass</td>
<td>18</td>
<td>43.90%</td>
<td>.2492</td>
<td>~ 0</td>
<td>-</td>
</tr>
<tr>
<td>Simoncelli Low-Pass</td>
<td>34</td>
<td>82.93%</td>
<td>.2100</td>
<td>~ 0</td>
<td>-</td>
</tr>
<tr>
<td>Shearlets</td>
<td>38</td>
<td>92.68%</td>
<td>.6678</td>
<td>.3917</td>
<td>-</td>
</tr>
<tr>
<td>Shearlet + Spline Wavelets</td>
<td>38</td>
<td>92.68%</td>
<td>.2465</td>
<td>.0336</td>
<td>52.00%</td>
</tr>
<tr>
<td>Shearlet + Simoncelli Band-Pass</td>
<td>38</td>
<td>92.68%</td>
<td>.2492</td>
<td>~ 0</td>
<td>111.11%</td>
</tr>
<tr>
<td>Shearlet + Simoncelli Low-Pass</td>
<td>38</td>
<td>92.68%</td>
<td>.2100</td>
<td>~ 0</td>
<td>11.76%</td>
</tr>
</tbody>
</table>
Comparison of Registration Algorithms for LIDAR to Optical Multimodal Experiments

<table>
<thead>
<tr>
<th>Registration Technique</th>
<th>Number of Converged Experiments (out of 101)</th>
<th>Percentage of Converged Experiments</th>
<th>Mean RMSE</th>
<th>Standard Deviation RMSE</th>
<th>Relative Improvement</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spline Wavelets</td>
<td>55</td>
<td>54.46%</td>
<td>3.4499</td>
<td>.0012</td>
<td>-</td>
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<tr>
<td>Simoncelli Band-Pass</td>
<td>61</td>
<td>60.40%</td>
<td>3.6542</td>
<td>.0174</td>
<td>-</td>
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<tr>
<td>Simoncelli Low-Pass</td>
<td>86</td>
<td>85.15%</td>
<td>3.5918</td>
<td>.0066</td>
<td>-</td>
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<tr>
<td>Shearlets</td>
<td>44</td>
<td>87.13%</td>
<td>15.6428</td>
<td>6.1668</td>
<td>-</td>
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<tr>
<td>Shearlet + Spline Wavelets</td>
<td>60</td>
<td>59.41%</td>
<td>3.4222</td>
<td>~ 0</td>
<td>9.09%</td>
</tr>
<tr>
<td>Shearlet + Simoncelli Band-Pass</td>
<td>65</td>
<td>64.36%</td>
<td>3.6518</td>
<td>.0174</td>
<td>6.56%</td>
</tr>
<tr>
<td>Shearlet + Simoncelli Low-Pass</td>
<td>83</td>
<td>87.13%</td>
<td>3.5912</td>
<td>.0083</td>
<td>2.33%</td>
</tr>
</tbody>
</table>
Preliminary Image Registration Results
Using Artificial Neural Networks

Feed-forward neural network (FF-NN) for subpixel accuracy

- Using Discrete Cosine Transform (DCT) coefficients as input provides subpixel accuracy
- **Input:** 100 DCT coefficients from reference image + 100 DCT coefficients from test image
- **Output:** Transformation Variables \((T_x, T_y, \Theta, s)\)
- **Score:** Subpixel registration accuracy if mean RMS error < 1.0 per pixel

- Subpixel accuracy on 50% of the test images in < 500 training epochs. Running for longer increases accuracy
- Training set must be large enough to capture the range of values for rotation/translation in the test set
  - Training set of 100 images randomly rotated/translated from a source image is enough to learn:
    - +/- 45º rotation coupled with +/- 10 pixels translation
  - Training set of 300 images is enough to learn:
    - +/- 120º rotation, no translation
    - +/- 80 pixels translation, no rotation
- Current experiments using Deep Belief Networks and Restricted Boltzman Machines
Conclusions

• Brief introduction to remote sensing image registration and its main components:
  o Feature Extraction
  o Similarity Metrics
  o Search Strategies

• Components combined appropriately and adapted to:
  o Type of data (e.g., edge- vs. texture-rich)
  o Size of data and computational resource needed
  o Required accuracy
  o Initial conditions

• Future Work:
  o Systematic assessment of various algorithms
  o Creating benchmark datasets