Electrical and Computer Engineering Seminars

FEBRUARY 2007

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11	12	13	14	15	16	17
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MARCH 2007

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APRIL 2007

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SEMINAR

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.

Bio:

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

Location: EBII 1230

Start Date: March 23, 2007 1:00 PM

End Date: March 23, 2007 2:00 PM

Advanced Image Processing for NASA Applications

Jacqueline Le Moigne
NASA Goddard Space Flight Center
Advanced Architectures and Automation (AAA) Branch
Code 588
Information Systems Division

Collaborations

Including:

Arlene Cole-Rhodes	Morgan State University
Roger Eastman	Loyola College of Maryland
Tarek El-Ghazawi	The George Washington University
Peyush Jain	NASA GSFC - AAA Branch
Aimee Joshua	NASA GSFC - AAA Branch
Nargess Memarsadeghi	NASA GSFC - AAA Branch
Jeffrey Morisette	NASA GSFC - Lab. for Terrestrial Physics
David Mount	University of Maryland
Nathan Netanyahu	University of Maryland and Bar-Ilan University
Ezinne Uko-Ozoro	NASA GSFC - Adv. Data Mgt & Analysis Br.
Harold Stone	NEC Retiree
Ilya Zavorin	Former GEST -

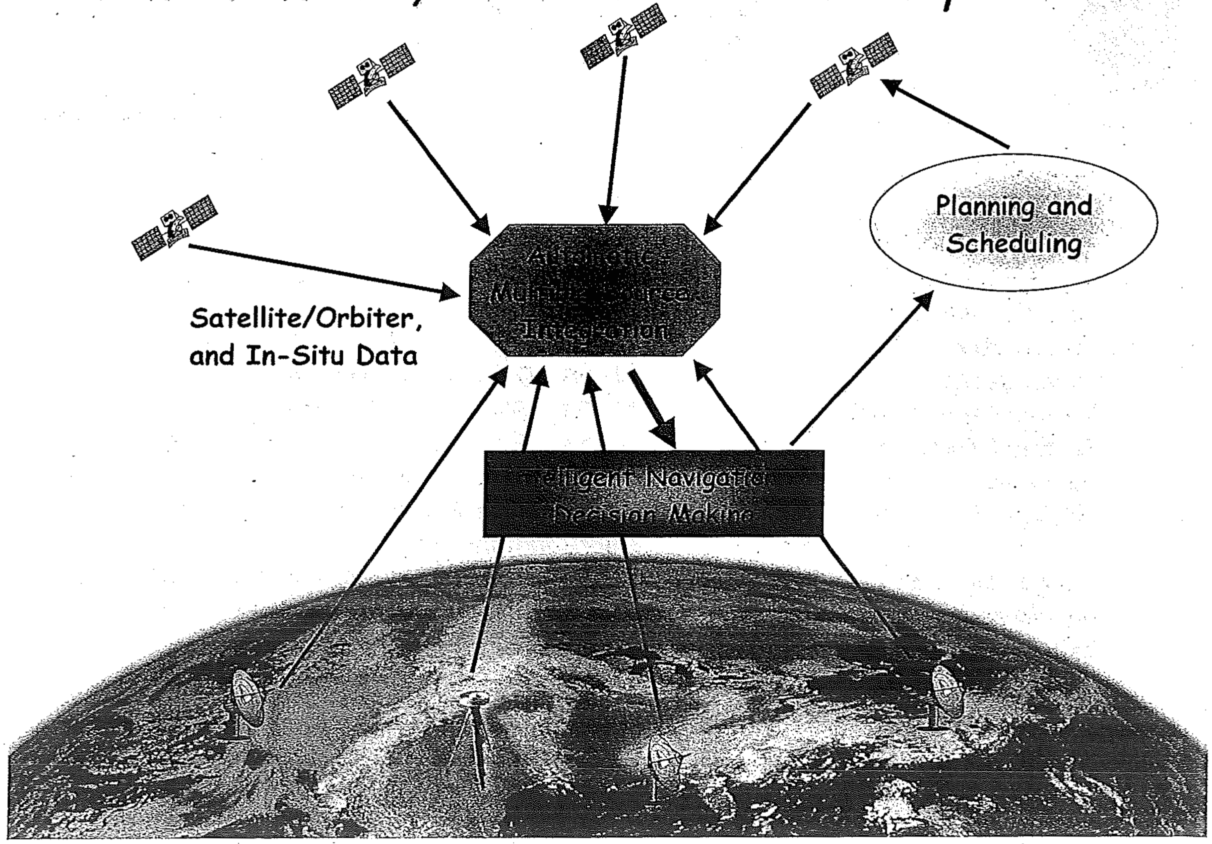
Code 588: The Advanced Architectures and Automation Branch

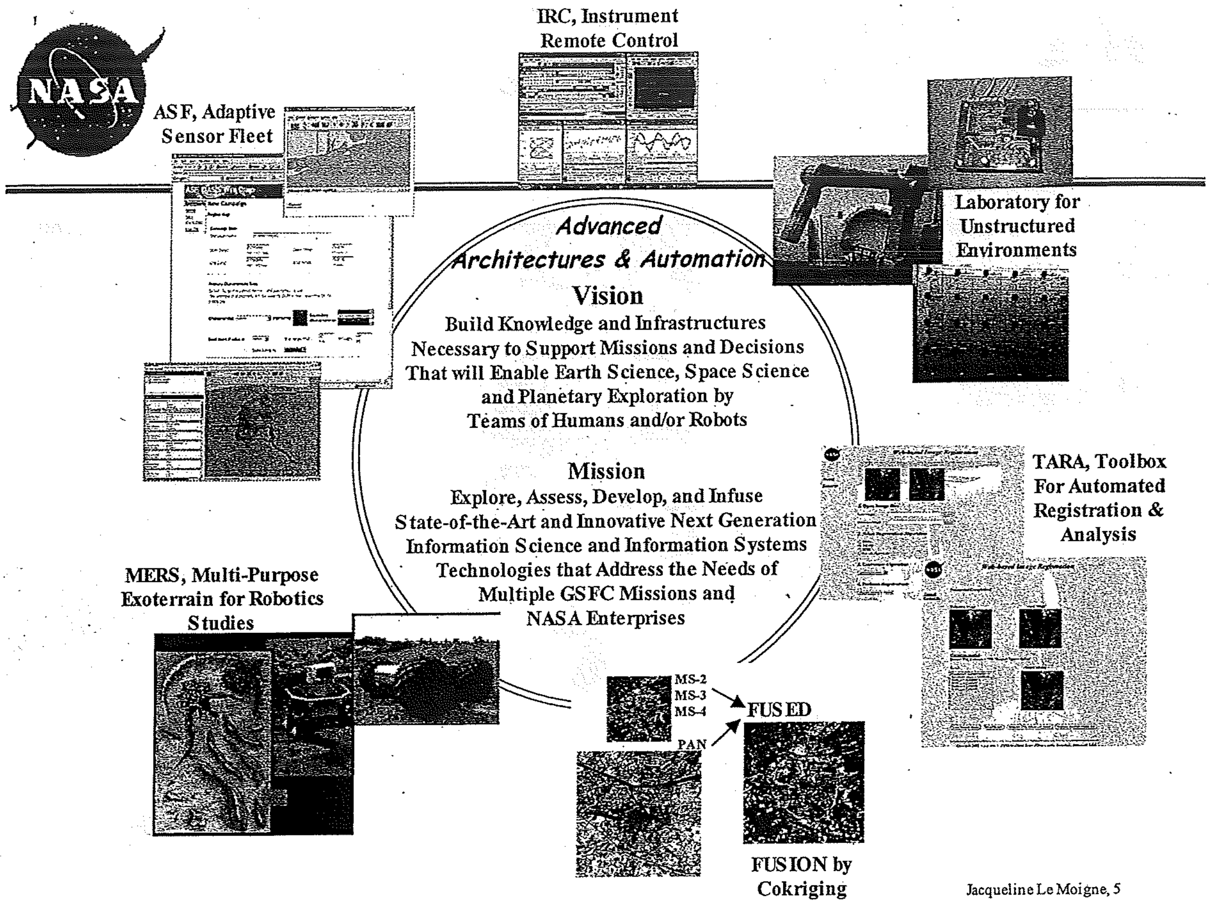
NASA

Goddard Space Flight Center

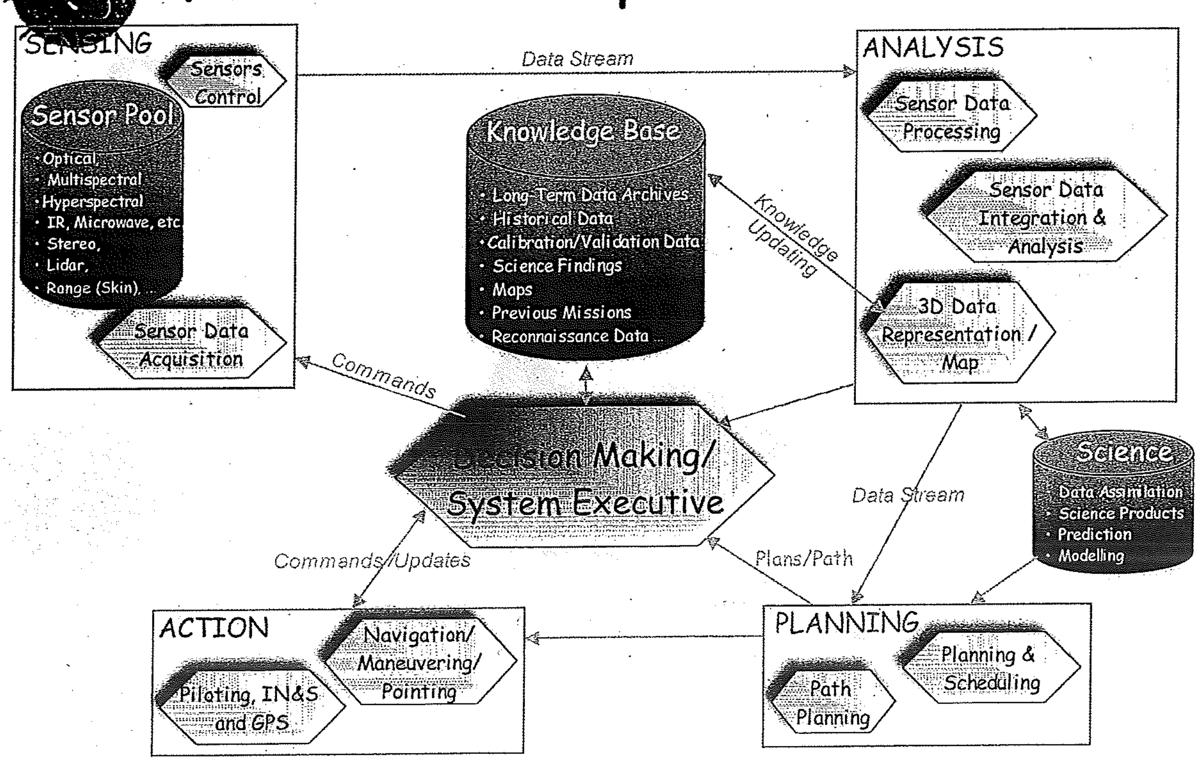
- Systems Safety & Mission Assurance
- Flight Projects
- Applied Engineering & Technology
  - Information Systems Division
    - Advanced Architectures & Automation
- Science & Exploration
- Information Technology & Communications
- Suborbital and Special Orbital Projects

Sensor Webs, Constellation and Exploration

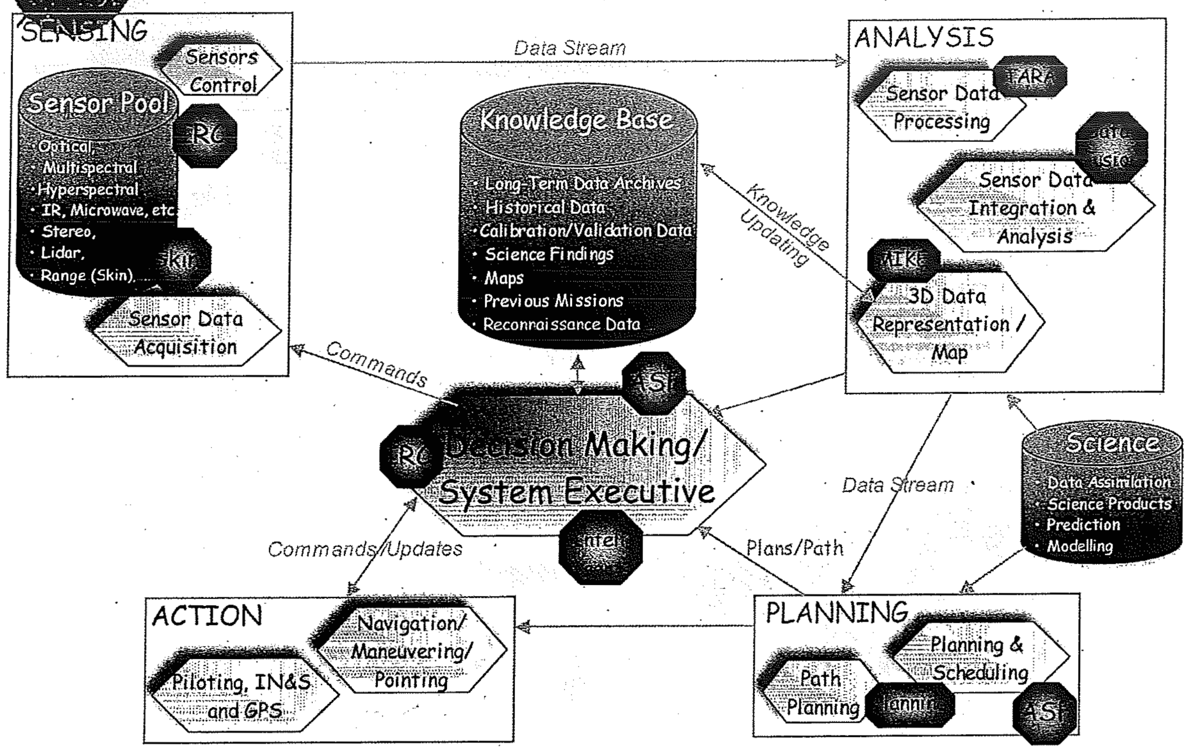




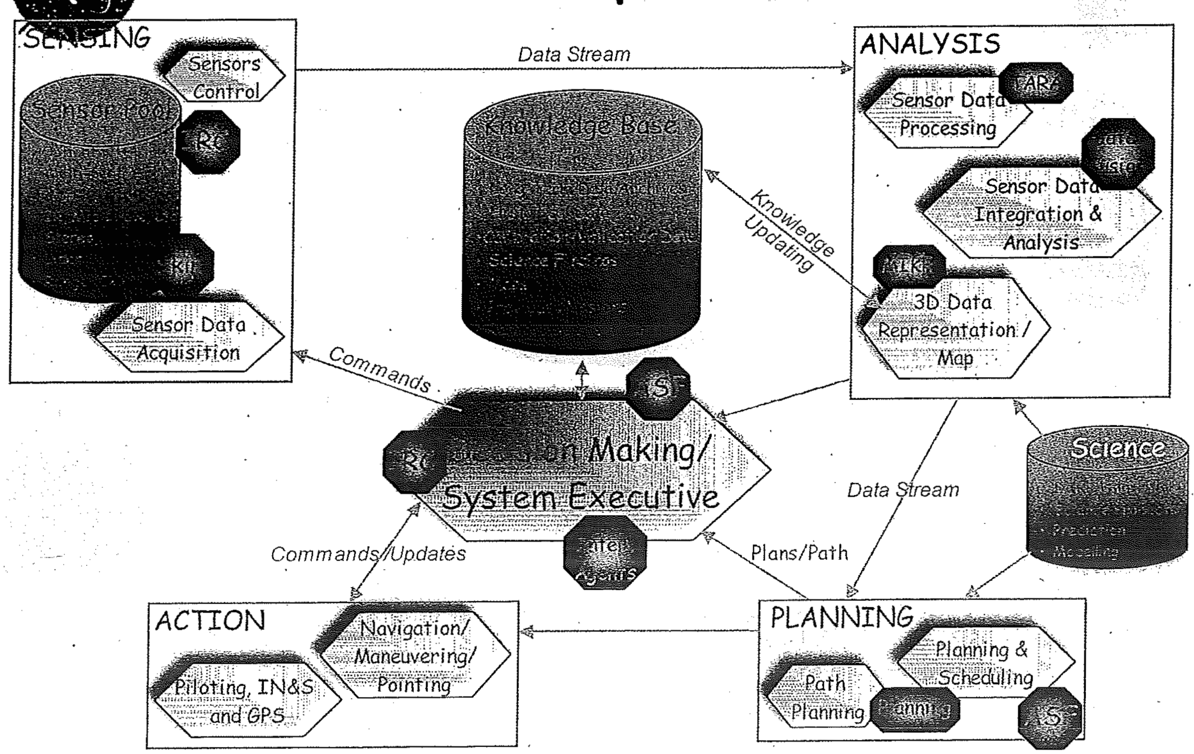
Sensing in Collaborative Environments for Science and Exploration At NASA



Sensing in Collaborative Environments for Science and Exploration At NASA

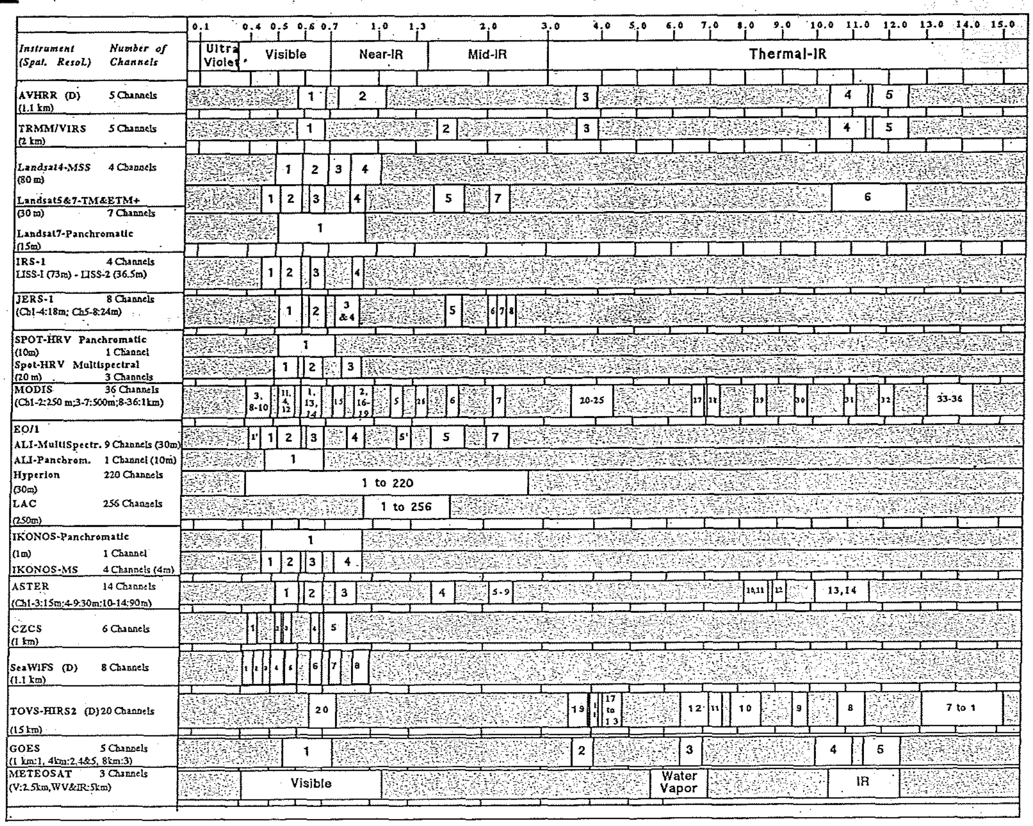


Sensing in Collaborative Environments for Science and Exploration At NASA



AUTOMATIC IMAGE REGISTRATION

Selected NASA Earth Science Missions (2004)



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.)

- $I1(x,y)$ and $I2(x,y)$: 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

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, ...

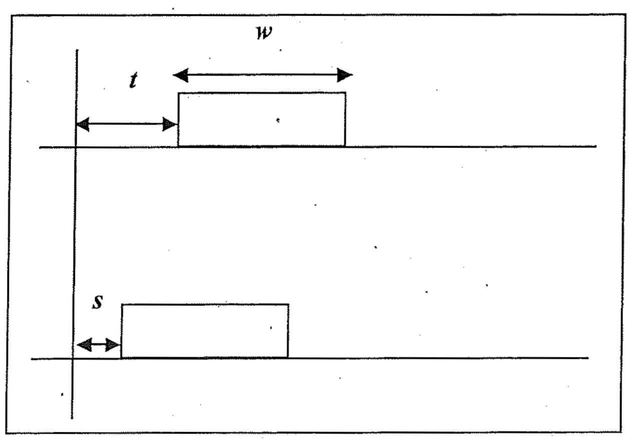
  2 Feature Matching
  - Spatial Transformation (a-priori knowledge)
  - Search Strategy (Global vs Local, Multi-Resolution, ...)
  - Choice of Similarity Metrics (Correlation, Optimization Method, Hausdorff Distance, ...)

  3 Resampling, Indexing or Fusion

Wavelet Studies: Rotation and Translation Invariance Issues

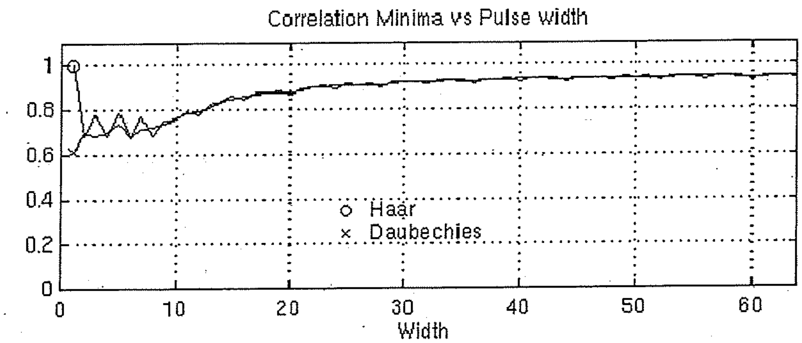
- With orthogonal wavelets, signal changes within or across subbands with subsampling
- Study for Shift Sensitivity [Stone et al]:
  - low-pass subband relatively insensitive to translation, if features are twice the size of wavelet filters (Nyquist criterion, sample signal at least twice frequency of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

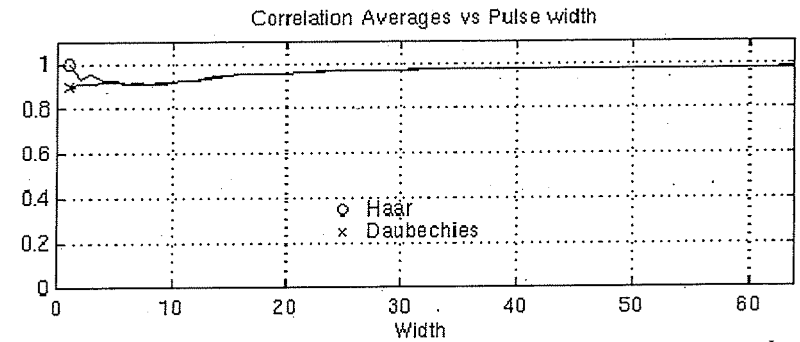
Translation Invariance Experiment



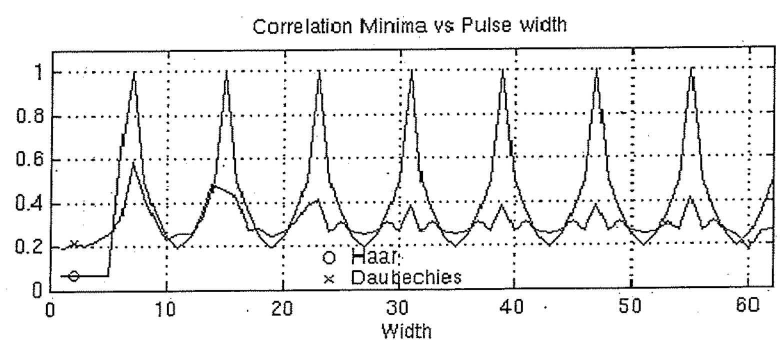
Correlate Wavelets of Two Pulses

Translation Sensitivity
Low-Pass Level 3





Translation Sensitivity
High-Pass Level 3



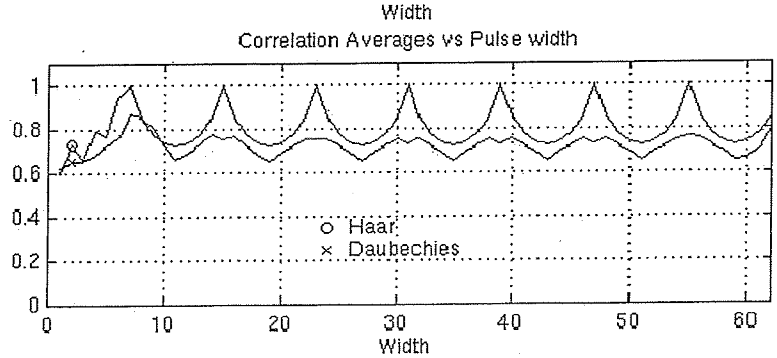


Image Registration Components

Features

Gray Levels | Edges | Wavelets or Wavelet-Like

Similarity Measure

Correlation | L2 Norm | Mutual Information | Hausdorff Distance

Strategy

Fast Fourier Transform | Gradient Descent | Thevenaz, Rutimann, Unser Optimization | Spall's Optimization | Robust Feature Matching

A Framework for the Analysis of Various Image Registration Components

Features

Gray Levels | Edges | Wavelets or Wavelet-Like

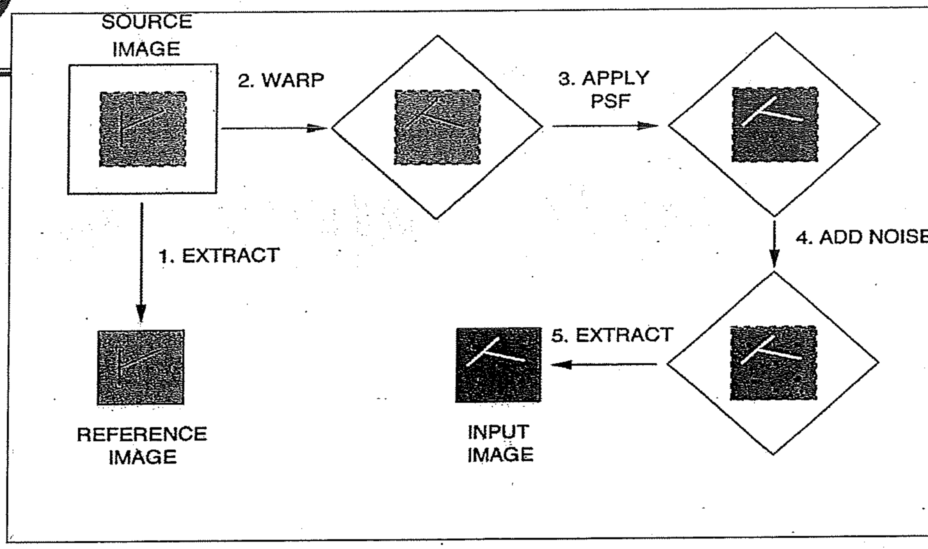
Similarity Measure

Correlation | L2 Norm | Mutual Information | Hausdorff Distance

Strategy

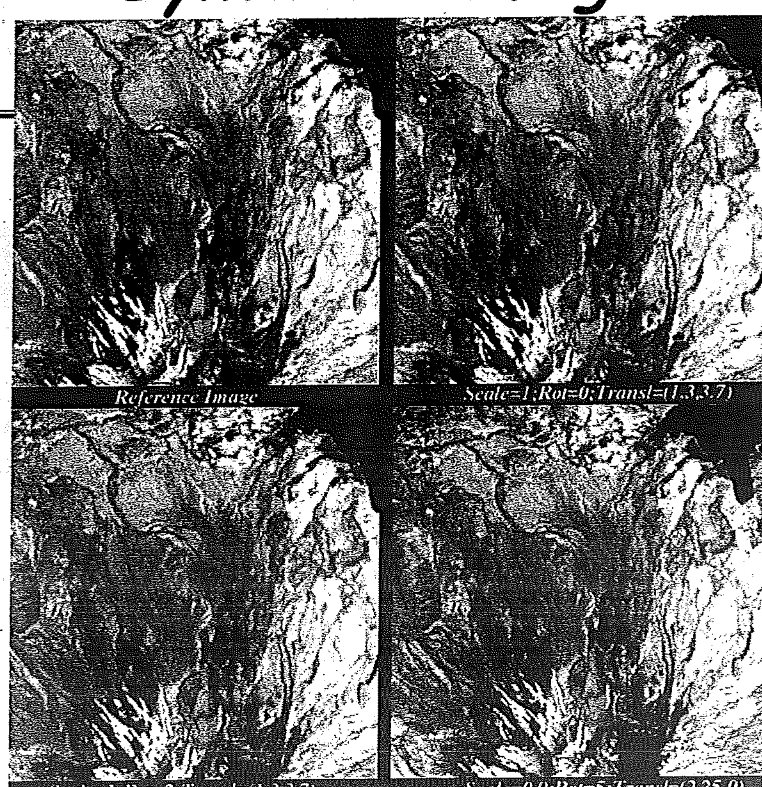
Fast Fourier Transform | Gradient Descent | Thevenaz, Rutimann, Unser Optimization | Spall's Optimization | Robust Feature Matching

Synthetic Data Experiments

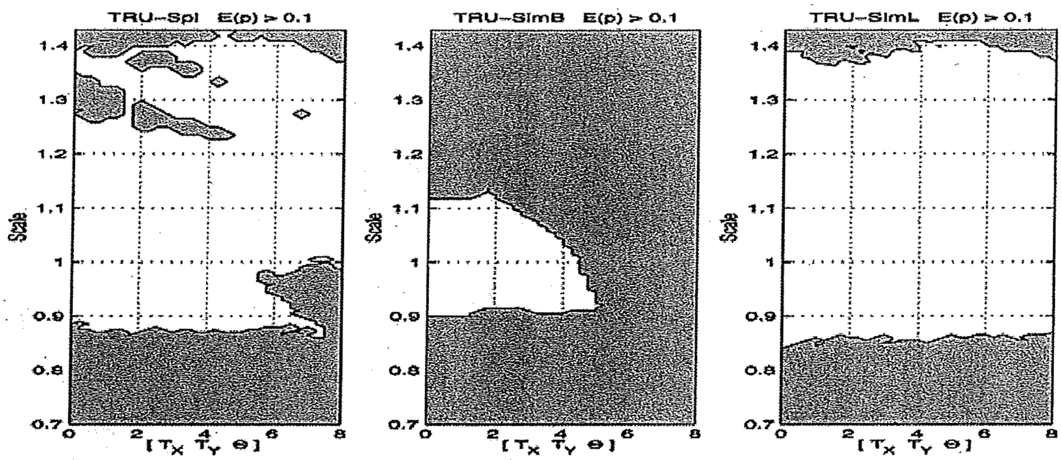


- **Transformation of Starting Scene by:**
  - Scales in [0.8,1.2] (step = 0.05)
  - Translations in [0,20] pixels (step = 0.5)
  - Rotations in in [0,20] degrees (step = 0.5)
  - Gaussian noise in [0,20] (step = 1)
  - Radiometric Transformation (PSF constructed from black 512x512 image with 5x5 white center)

Synthetic Images

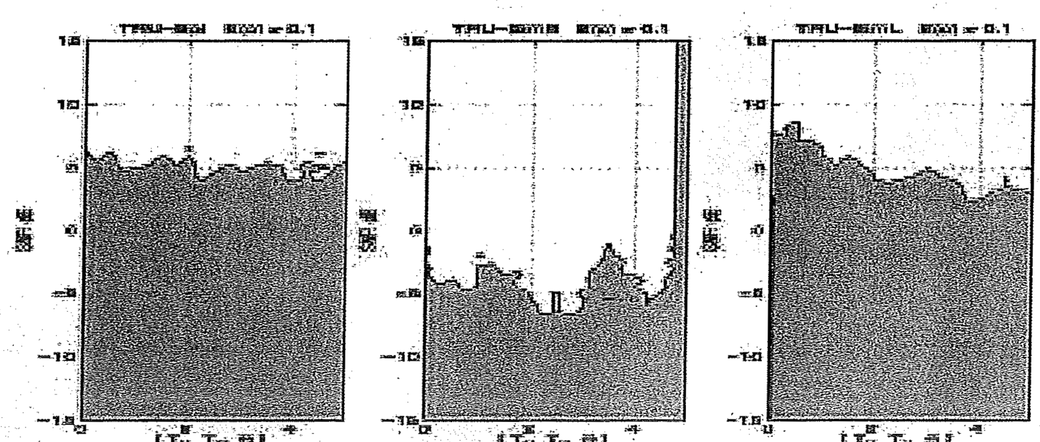


Results TRU - Various Features - No Noise - No PSF



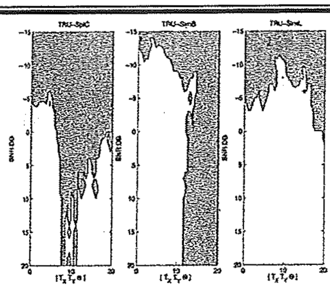
Sensitivity of TRU Algorithms to Initial Guess

Results TRU - Various Features - Varying Noise - No PSF

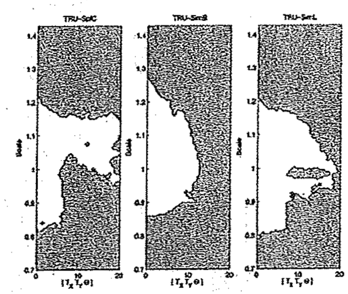


Sensitivity of TRU Algorithms to Noise

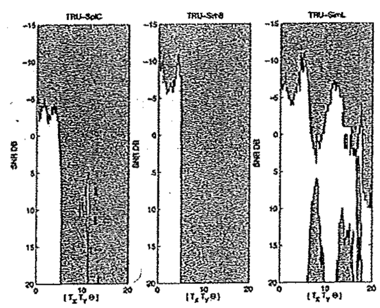
Results TRU - Various Features - Varying Noise - with or w/o PSF



Warping + Noise

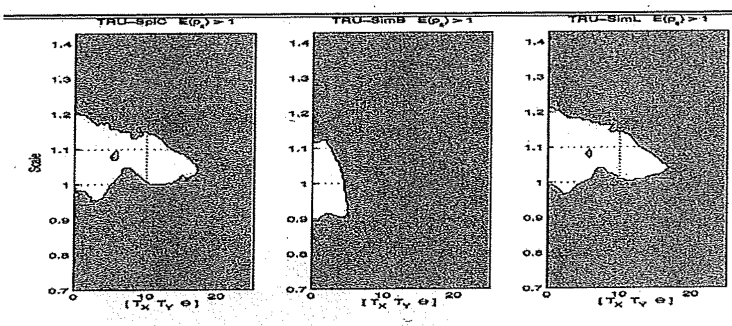


Warping + PSF

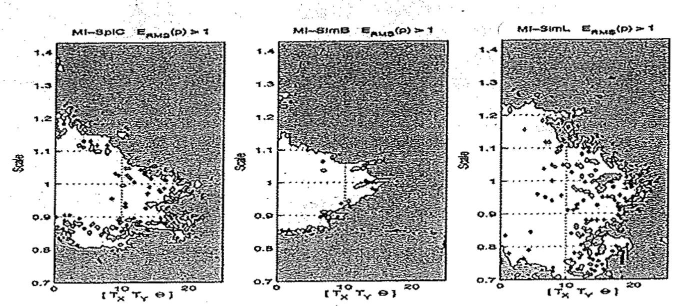


Warping + PSF + Noise

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 Stocchastic Gradient

- Spall's Simultaneous Perturbation Stocchastic 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.

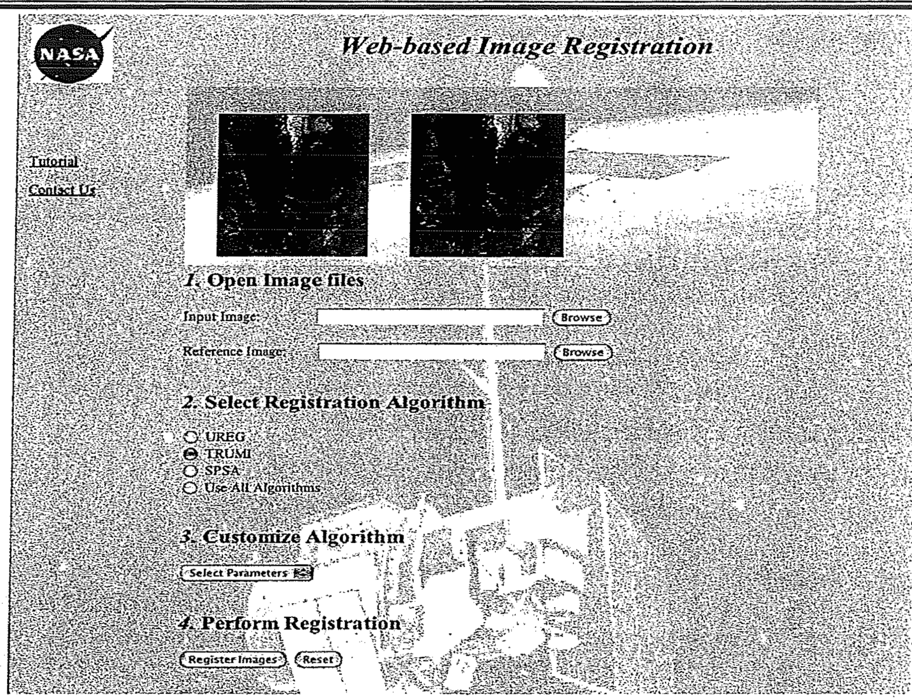
Goals of a Modular Image Registration Framework

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

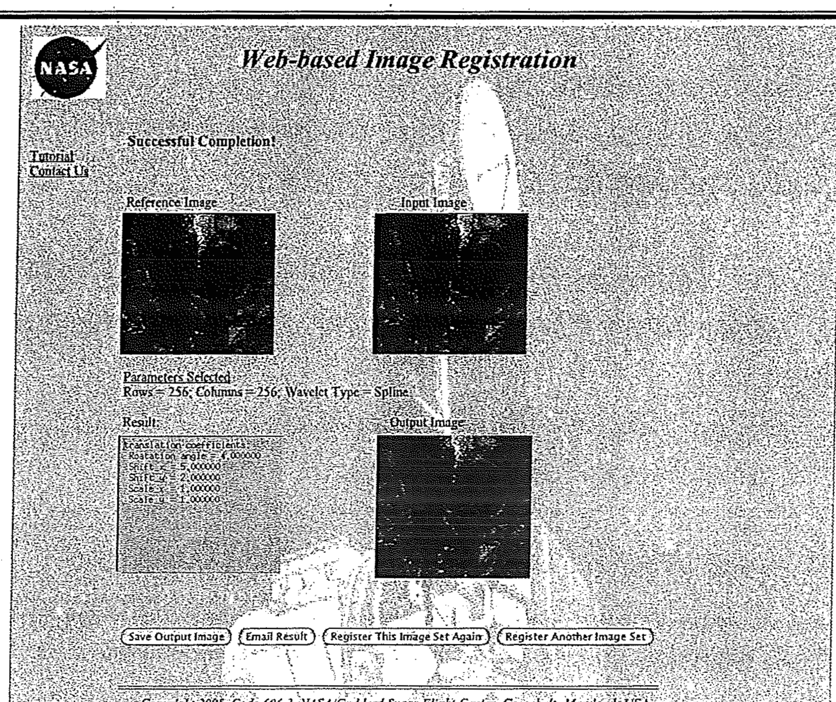
- Basis for Future Web-Based Registration Tool - User Could "Schedule" Combination of Components function of:
  - *Application*
  - *Available Computational Resources*
  - *Required Registration Accuracy*

- Prototype Web-Based Registration Toolbox:
  - *3 Different Methods Based on Simoncelli-Decomposition*
  - *Java Implementation; JNI-Wrapped Functions*

Web-Based Image Registration Toolbox: TARA ("Toolbox for Automated Registration & Analysis")

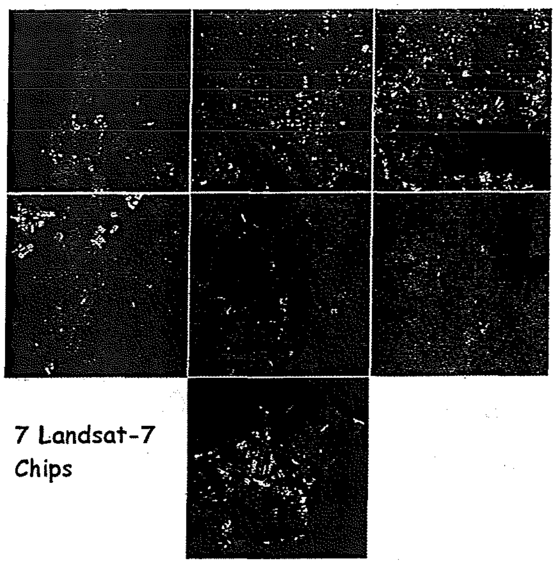


Web-Based Image Registration Toolbox: TARA ("Toolbox for Automated Registration & Analysis")

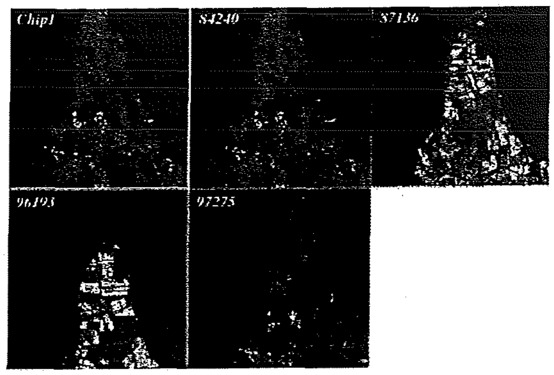


Registration Test - Landsat Multi-Temporal Registration

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



7 Landsat-7 Chips



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

Registration Test - Results Landsat Multi-Temporal Registration

Chip #	84240	87136	96193	97275
#1 - Rot:	0	0	1	0
TX	8	18	12	21
TY	-39	-25	-92	-28
Distance	0.00	1.00	1.80	0.00
#2 - Rot:	0	-0.5	1	0
TX	8	11	-66	22
TY	-41	-41	4	-30
Distance	0.00	0.62	1.93	0.00
#3 - Rot:	0	-0.5	-0.3	0
TX	8	11	10.84	21
TY	-40	-41	-96	-29
Distance	1.00	0.89	0.52	0.00
#4 - Rot:	0	0.8	0	0
TX	8	12.34	11	21
TY	-41	--38.12	-94	-28
Distance	1.00	0.96	0.00	0.00
#5 - Rot:	0.4	0.7	0	0
TX	7.8	10.4	-38	20
TY	-40.86	--40.34	52	-31
Distance	0.94	0.93	2.24	0.00
#6 - Rot:	0	-0.8	0.3	0
TX	6	10.61	11.5	22
TY	-41	-41.94	-99	-33
Distance	1.00	0.78	0.70	0.00
#7 - Rot:	0.5	0	0	0
TX	9	12	12	22
TY	-40	-38	-94	-29
Distance	0.56	0.00	0.00	0.00

Transf.	84240	87136	96193	97275
Rotation	0.013	0.003	-0.042	-0.143
Transl-x	7.18	11.43	12.61	21.20
Transl-y	-41.12	-40.49	-95.38	-28.85

Global Registration for 4 Scenes

Transf.	84240	87136	96193	97275
Rotation	0.00	0.00	0.00	0.00
Transl-x	7.18	10.55	9.48	20.97
Transl-y	-40.06	-39.16	-95.16	-28.97

Manual Registration for 4 Scenes

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

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: 500m; SeaWIFS: 1000m
- 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

Registration Test - EOS Validation Core Sites

ETM/IKONOS Mosaic of Coastal VA Data

ETM+

IKONOS

Registration Test - EOS Validation Core Sites

ETM/IKONOS Agricultural Konza Data

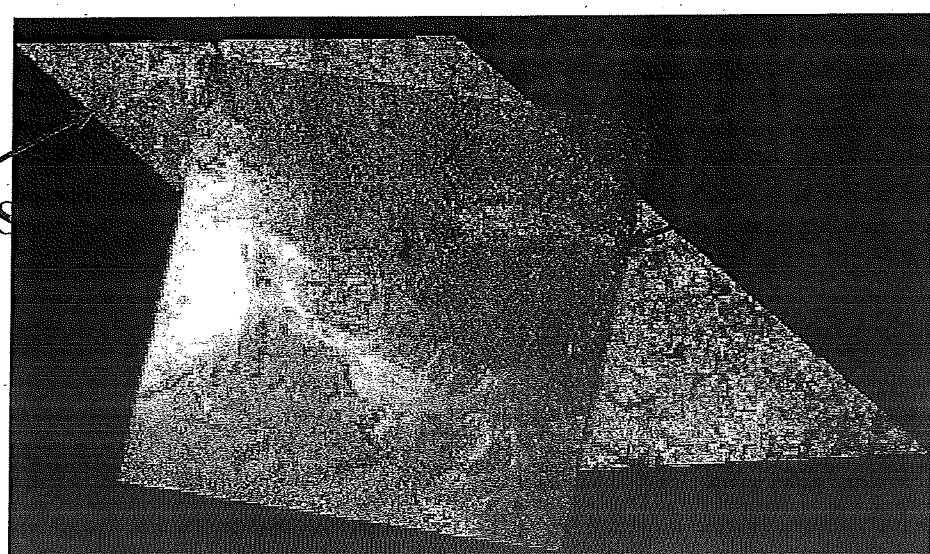
ETM+

Registration Test - EOS Validation Core Sites

ETM/MODIS of Agricultural Konza Data

ETM+

MODIS



EOS Validation Core Sites - Results
Multi-Sensor Image Registration

Pair to Register	Method 1 (GC)		Method 2 (GGD)		Method 3 (WCE)		Method 4 (WMIE)		Method 5 (WHR)	
	Rotation	Translation	Rotation	Translation	Rotation	Translation	Rotation	Translation	Rotation	Translation
(1) etm_nir_31.25.power / etm_red_31.25.extract	Rotation = 0 , Translation = (0,0) computed by all methods, using seven sub-windows pairs									
(2) iko_nir_3.91.power / etm_nir_31.25.extract	–	(2,1)	0.0001	(1.9871,-0.0564)	0	(2,0)	0	(2,0)	0	(0,0)
(3) iko_red_3.91.power / etm_red_31.25.extract	–	(2,1)	-0.0015	(1.7233,0.2761)	0	(2,0)	0	(2,0)	0	(0,0)
(4) etm_nir_31.25.power / modis_day249_cc_nir.extract	–	(-2,-4)	0.0033	(-1,7752,-3.9238)	0	(-2,-4)	0	(-2,-4)	0	(-3,-3.5)
(5) etm_red_31.25.power / modis_day249_cc_red.extract	–	(-2,-4)	0.0016	(-1.9665,-3.9038)	0	(-2,-4)	0	(-2,-4)	0	(-2,-3.5)
(6) modis_day249_cc_nir.power / seawifs_day256_to249_nir.extract	–	(-9,0)	0.0032	(-8.1700,0.2651)	0	(-8,0)	0	(-9,0)	0.5	(-6,2)
(7) modis_day249_cc_red.power / seawifs_day256_to249_red.extract	–	(-9,0)	0.0104	(-7.6099,0.5721)	0	(-8,0)	0	(-8,0)	0.25	(-7,1)

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

EOS Validation Core Sites - Results
Multi-Sensor Image Registration

Image Name	Computed X	Computed Y	Comes from Registered Pair
IKONOS red	0	0	(Starting Point)
IKONOS nir	-0.2500	-0.2500	IKO red to ETM red and ETM red to IKO nir
IKONOS nir	-0.2500	-0.3125	IKO red to ETN nir and ETM nir to IKO nir

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

Image Name	Computed X	Computed Y	Comes from Registered Pair
IKONOS red	0	0	(Starting Point)
IKONOS nir	0.2500	0.0000	IKO red to ETM red and ETM red to IKO nir
IKONOS nir	0.1250	-0.1250	IKO red to ETN nir and ETM nir to IKO nir

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

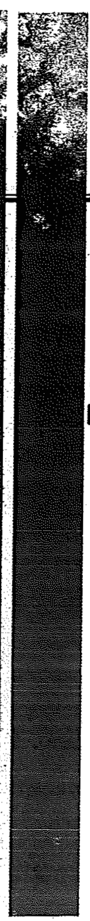
Registration Test: Application to EO-1 ALI and Hyperion Registration

- 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

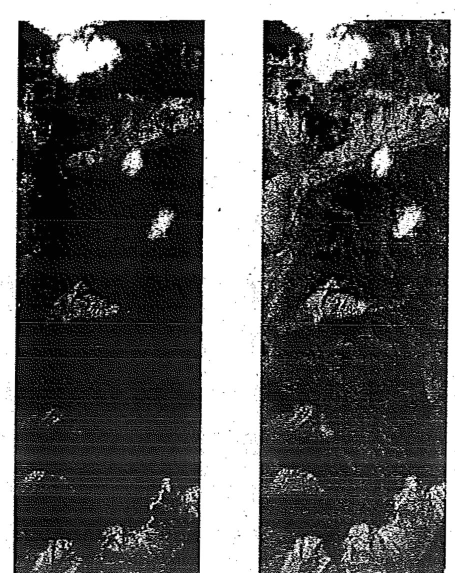
ALI and Hyperion Registration

ALI Band 4: Reference



Hyperion Band 47: Input

Hyperion Band 47 Registered to ALI Band 4



Registered Subset

ALI Hyperion

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).

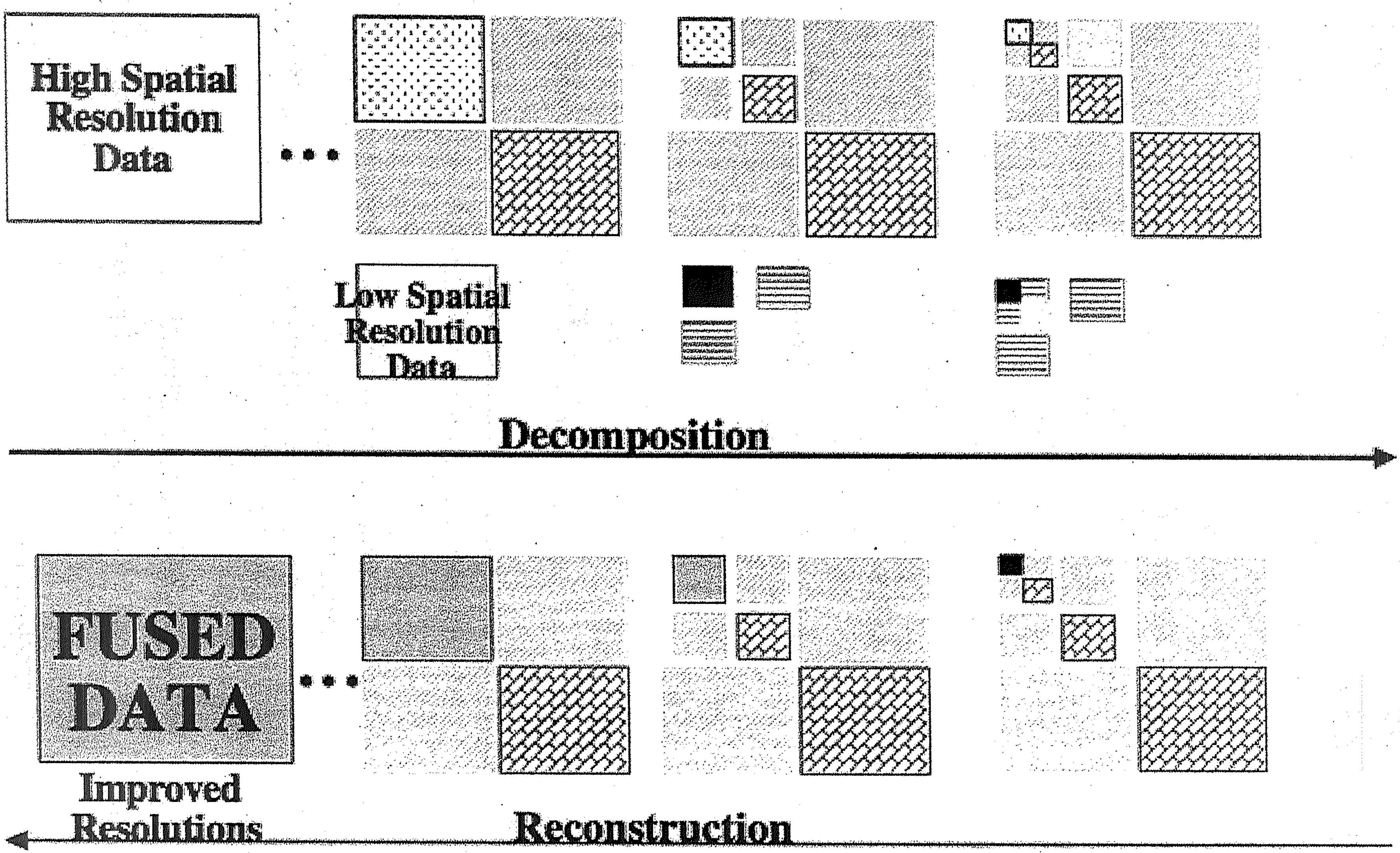
Data and Image Fusion (2)

- 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



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

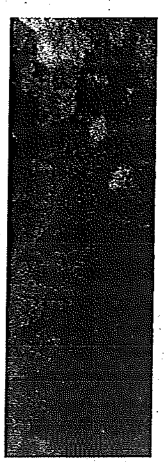
- Past Quality Metrics
  - Piella, etc.
  - Gray level only
  - No support for multi-spectral image
- Objective:
  - Improved Classification
    - Performed k-means with k=7, max iterations 15 (for PCA and wavelets)
  - Needs ground truth
- Similarities
  - Spectral quality: correlation
- Differences
  - 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

ALI V	Hyp V	Fused V
143.98	137.64	180.10



ALI PCs 1,2,3

ALI PCs 1,2,3 clustering

Hyperion First 7 PCs clustering

ALI-Hyp First 9 PCs clustering

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)

ALI MS band	Spectral range (nm)	CWL (nm)	Matching Hyperion bands (nm)	CWL (nm)
3 (MS-2)	525-605	567.2	18 .... 23 ... 25	528.57 ... 579.45 .... 599.80

Results: Wavelets

Fused bands are highly correlated with their corresponding MS Hyperion band

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

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

ALI

Hyperion1

Fused: First test

Fused: 2nd test

Results: Wavelets

Mean of variance images of ALI, Hyperion, and Fused Bands
V= Mean of Variance Image, Exp 1

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

Results: Wavelets

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

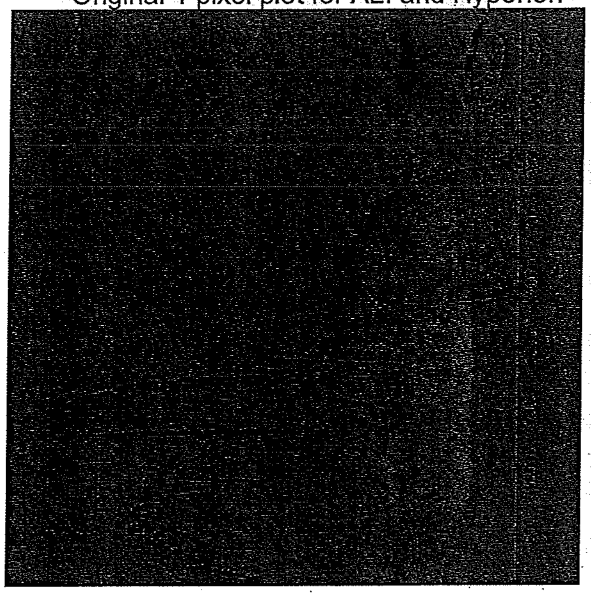
ALI	V	Hyp	V	Fused	V
A1	77.62	H10	90.14	F1	101.65
A2	99.49	H15	111.12	F2	118.27
A3	139.51	H25	174.84	F3	176.30
A4	193.03	H33	217.32	F4	225.68
A5	169.97	H45	169.88	F5	182.35
A6	168.54	H53	166.87	F6	184.36
A7	164.22	H113	182.49	F7	197.00
A8	344.53	H160	190.52	F8	205.10
A9	260.68	H198	184.84	F9	173.18
Overall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

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

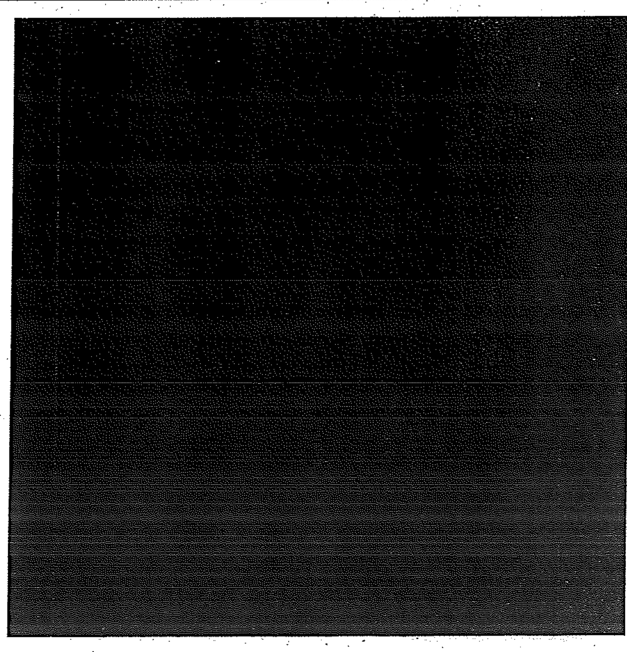
Spectral Fusion with Cokriging

Original 1 pixel plot for ALI and Hyperion



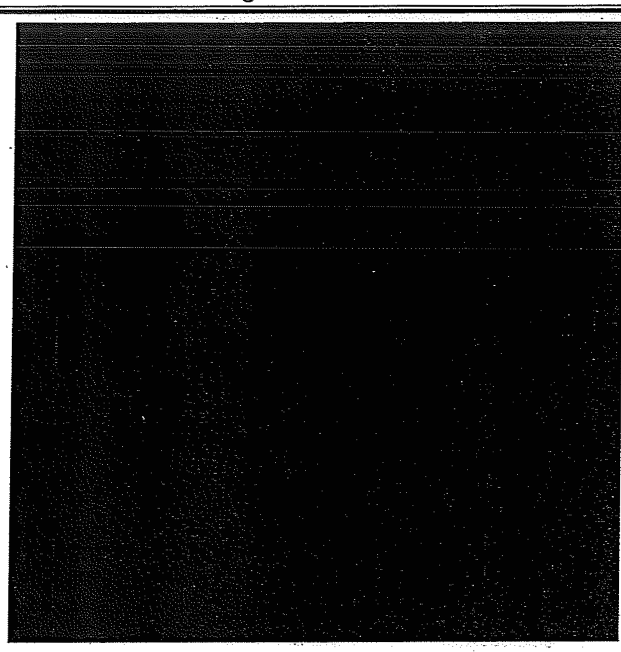
Spectral Fusion with Cokriging

Fusion results on one pixel using cokriging by creating one band/value in center of each wavelength interval where ALI data is missing.



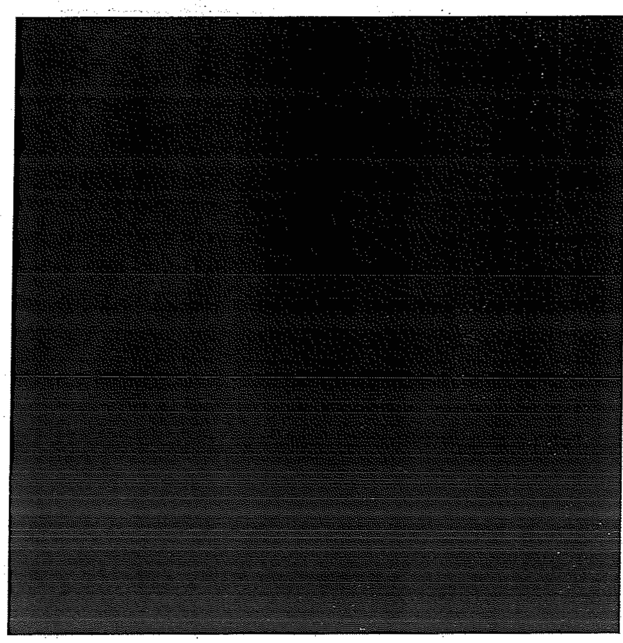
Spectral Fusion with Cokriging

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

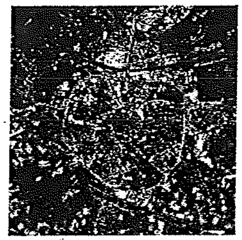


Spectral Fusion with Cokriging

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



Spatial Fusion with Cokriging - Landsat TM

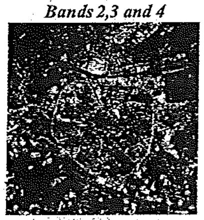


Multispectral Bands 2, 3, 4

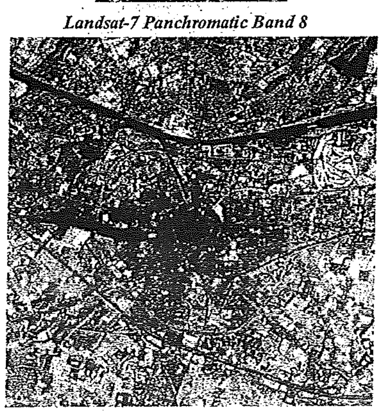
Panchromatic

Spatial Fusion with Cokriging - Landsat TM

Landsat-7 Multispectral Bands 2,3 and 4



Landsat-7 Panchromatic Band 8



FUSION

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

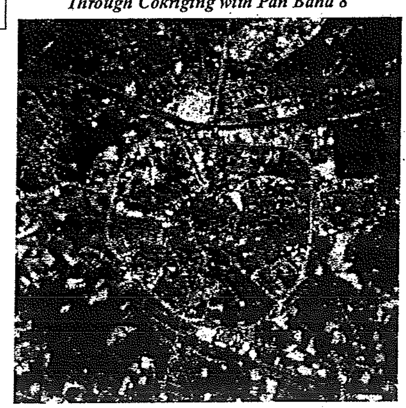
Spectral Resolution
1 pixel of an MS band

MS-Value1

Pan Value 1	Pan Value 2
Pan Value 3	Pan Value 4

x1	y1	p1	?
x2	y2	p2	?
x3	y3	p3	ms1
x4	y4	p4	?

Landsat-7 Pan-Sharpened MS Bands 2,3 and 4 Through Cokriging with Pan Band 8



Spatial Fusion with Cokriging - Landsat TM

TABLE II
CORRELATION OF FUSED BANDS WITH MS INPUT BANDS

Bands	Wavelet	PCA	Cokriging
f2, b2	0.82	0.99	0.91
f3, *b3*	0.84	0.99	0.93
f4, *b4*	0.92	0.75	0.93
Average	0.86	0.91	0.92

Spatial Fusion with Cokriging - Landsat TM

TABLE III
ENTROPY OF MS AND FUSED BANDS

Original Bands		Fused Bands	Wavelet	PCA	Cokriging
b2	2.68	*f2*	3.12	2.69	3.23
b3	3.01	*f3*	3.28	3.72	3.64
b4	3.44	*f4*	3.93	5.21	4.90
Average	3.04		3.44	3.87	3.92

Spatial Fusion with Cokriging - Landsat TM

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

Original Bands		Fused Bands	Wavelet	PCA	Cokriging
b2	1.37	*f2*	1.37	1.37	1.44
b3	1.42	*f3*	1.45	1.49	1.45
b4	1.77	*f4*	1.78	2.02	1.96
Average	1.52		1.53	1.63	1.62

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*

THANK YOU

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Similarity Metrics

- Correlation

$$C(A,B) = \frac{\sum_i (a_i - \mathrm{MeanA}) * (b_i - \mathrm{MeanB})}{\sqrt{\sum_i (a_i - \mathrm{MeanA})^2} * \sqrt{\sum_i (b_i - \mathrm{MeanB})^2}}$$

- L2 Norm

$$E(p) = \sum (f - Q_p(g))^2$$

- Mutual Information:

$$I(A,B) = \sum_{a,b} h_{AB}(a,b).\log \frac{N.h_{AB}(a,b)}{h_A(a).h_B(b)}$$

- Partial Hausdorff Distance:

$$H_k(A, B) = K^{th}{}_{a\ in\ A}\ \min_{b\ in\ B}\ \mathrm{dist}\ (a,b)$$

($1 \leq k \leq |A|$; K^{th} is the k^{th} smallest element of set; dist(a,b): Euclidean distance)

Methods: Cokriging

$$
\begin{aligned}
Var(R) &= w^t C_z w \\
&= \sum_i^n \sum_j^n a_i a_j Cov(U_i U_j) + \sum_i^m \sum_j^m b_i b_j Cov(V_i V_j) \\
&\quad + 2\sum_i^n \sum_j^m a_i b_j Cov(U_i V_j) - 2\sum_i^n a_i Cov(U_i U_0) \\
&\quad - 2\sum_j^m b_j Cov(V_j U_0) + Cov(U_0 U_0).
\end{aligned}
$$

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

Methods: Cokriging

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

$$\sum_{i=1}^n a_i Cov(U_i V_j) + \sum_{i=1}^m b_i Cov(V_i V_j) + \mu_2 = Cov(U_0 V_j).$$ for (j = 1…m)

$$\sum_{i=1}^n a_i = 1$$

$$\sum_{j=1}^m b_j = 0$$

Matching Strategies

- Exhaustive Search
- Fourier Transform
  - Translations
  - Very Fast Implementations
- Gradient Descent

$$\begin{bmatrix} \sum f_x^2 & \sum f_x f_y & \sum Rf_x \\ \sum f_x f_y & \sum f_x^2 & \sum Rf_y \\ \sum Rf_x & \sum Rf_y & \sum R^2 \end{bmatrix} \begin{bmatrix} \Delta x \\ \Delta y \\ \Delta \theta \end{bmatrix} = \begin{bmatrix} \sum (f-g) f_x \\ \sum (f-g) f_y \\ \sum (f-g) R \end{bmatrix}$$

- Robust Feature Matching
  - Hierarchical Subdivisions of Search Space
  - Pruning of Search Space

Methods: Cokriging

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

$$\widehat{u}_0 = \sum_{i=1}^{n} a_i u_i + \sum_{j=1}^{m} b_j v_j$$

Estimation error:

$$R = \widehat{U}_0 - U_0 = w^t Z,$$
$$w^t = (a_1, \ldots, a_n, b_1, \ldots, b_m, -1)$$
$$Z^t = (U_1, \ldots, U_n, V_1, \ldots, V_m, U_0)$$

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

$$Var(R) = w^t C_z w$$
$$\sum_{i=1}^{n} a_i = 1, \sum_{j=1}^{m} b_j = 0$$