Hierarchical analysis of hyperspectral images.

Jocelyn Chanussot

GIPSA-Lab, Signal & Image Dept, Grenoble-INP, Grenoble, France
http://www.gipsa-lab.grenoble-inp.fr/~jocelyn.chanussot/

Acknowledgments

Many THANKS to...

- My former PhD students: Mathieu Fauvel, Murtaza Kahn, Yuliya Tarabalka, Silvia Valero, Alberto Villa
- My colleagues and collaborators: Jon Atli Benediktsson, University of Iceland, Lorenzo Bruzzone, University of Trento, Italy, Paolo Gamba, University of Pavia, Italy, Antonio Plaza, University of Extremadura, Caceres, Spain, Philippe Salembier, UPC, Barcelona, Spain, Mauro Dalla Mura, Grenoble Institute of Technology
- and post-docs: Bin Luo, Giorgio Licciardi
Editor-in-Chief, IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing (JSTARS)

2011 Impact Factor: 1.5
average time between submission and 1st decision: 50 days

Regular Papers and special issues
2013 Vol 6 n 2 (60+ submissions)
Hyperspectral Remote Sensing: theory, methods and applications

Guest Editor, IEEE Signal Processing Magazine
Signal and Image Processing in Hyperspectral Remote Sensing
White paper due: December 9 2012

Traitement du Signal – projet de numéro spécial (A. Mansouri, S. Treuillet, L. Macaire)
suite action et journées GDR ISIS

Program Chair

WHISPERS

Full Paper submission - 4 pages IEEE format
3 days, 2 tracks
2.5 reviewers / paper
Proceedings available on site / Xplore
160-180 attendees

http://www.ieee-whispers.com/
Introduction: Hyperspectral Imagery

Within a pixel

Morphological Profiles and Attribute Filters

Binary Partition Trees (BPT)
- Construction of the BPT: A Hierarchical Representation
- Pruning of the BPT for Segmentation, Classification and Object Detection

Conclusions
Hyperspectral imagery

Improved spectral diversity: hyperspectral imagery

Hyperspectral imagery
Hyperspectral imagery

473 nm

547 nm
Hyperspectral imagery

770 nm

Spaceborne Imaging Spectrometers

Current and planned civilian hyperspectral satellite missions

<table>
<thead>
<tr>
<th>Mission</th>
<th>Spatial Resolution</th>
<th>VIS-NIR</th>
<th>SWIR</th>
<th>TIR</th>
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<td>Hyperion EO-1</td>
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<td>Chris/Proba</td>
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<td>HySI</td>
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<td>HJ-1A</td>
<td>100 m</td>
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<td>PRISMA</td>
<td>30 m</td>
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<td>EnMAP</td>
<td>30 m</td>
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<td>(Germany 2015 )</td>
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<td>HISUI-ALOS-3</td>
<td>30 m</td>
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<td>(Japan 2015 )</td>
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<td>HyspIRI</td>
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<td>(USA 2018? sooner pending budget)</td>
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<td>HYPXIM C/P</td>
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<td>(France 2018?)</td>
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Today
Example: anomaly detection

Data set provided by Robert O. Green at NASA/JPL

AVIRIS data over lower Manhattan (09/15/01)

Spatial location of thermal hot spots in WTC area

AVIRIS spectra were used to measure fire temperature, asbestos contamination, and debris spread.
**Field applications**

Spectral Mine Imaging

- True Colour Composite
- Amount of Clay minerals
- Amount of iron oxides
- Composition of iron oxides

Scanning time: a few minutes

Courtesy of Spectral Mine Imaging

**Airborne application**

Oil spill detection - MV “Full City” Grounding

(~1000 tons of heavy bunker oil (IF 180) & ~120 tons of marine diesel oil on board)

PCA visualization of oil spill (Pink = oil on seawater, Yellow = sand on sea floor, Green = Seawater).
Laboratory/In-line applications

Drill Core Imaging

Mineral mapping

Drill Chips Imaging

HySpex

Scanning time: 1 min

Courtesy of CSIRO

Rock Imaging

Scanning time: 10 s

Quality control

Recycling - Sorting

NIR spectral imaging
Plastics sorting
PS, PET, LDPE, PVC...

Mapping food composition

- VNIR and SWIR range
- Based on C-H, O-H and N-H bonds
- Fat, protein, carbohydrate and water content

Frying - Fat and Water content in a donut

Reference: CCFRA, Campden, UK
Airborne HSI in VNIR provides sensitive and high resolution detection and mapping of **fungus disease in oil palm trees**

>50 km²/h  
@0.5 m ground resolution  
@50 m/s (100 knots)

- Study in Uruguay
Agricultural crop identification

Crop yield estimation (With Chenghai Yang, USDA, Welasco, Texas)

Opportunities

Spectral mixture analysis / source separation: Determines the abundance of materials

Characterization: Determines variability of identified material (e.g., wet/dry sand, soil particle size effects).

Classification: Separates materials into spectrally similar groups (e.g., urban data classification).

Detection: Determines the presence of materials, objects, activities, or events.
Challenges – every rose has its thorns

- **Dimension of the data**: high performance computing required

- **Dimensionality of the data**: a curse... and a blessing... band selection, feature extraction

- **Understanding the physics**: of the studied object and of the acquisition (incl. calibration, corrections...)

- **And including it in the models**: linear, non linear

- **And including it in the processing**: signal, image

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Outline

1. Introduction: Hyperspectral Imagery
2. Within a pixel
3. Morphological Profiles and Attribute Filters
4. Binary Partition Trees (BPT)
   - Construction of the BPT: A Hierarchical Representation
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5. Conclusions
Spectral mixture

Macrosopic mixture:
15% soil, 25% tree, 60% grass in a 3x3 meter-pixel

Intimate mixture:
Minerals intimately mixed in a 1-meter pixel
Spectral unmixing

- Interpreted as a (blind) source separation problem.
- Linear vs nonlinear models
Spectral unmixing

The physical meaning of independent components and artifact removal of hyperspectral data from Mars using ICA.

IEEE NORSIG'06 - 7th Nordic Signal Processing Symposium, June 2006, Reykjavik, Iceland
Best Student Paper Award
Spectral pansharpening

**ALI PAN**
10 m spatial resolution
480 nm – 690 nm

**Hyperion**
220 (168) Bands
40 m Spatial resolution
400 nm – 2500 nm

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Hyperspectral Imagery

- Hyperspectral data cubes contain hundreds of images captured at different wavelengths. Each pixel is a discrete spectrum containing the reflected solar radiance of the spatial region that it represents.

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This new source of information has led to use this images in a growing number of real-life applications.

- Remote sensing, food safety, medical research or environmental applications.
Different analysis techniques have been proposed in the literature processing the pixels individually, as an array of spectral data without any spatial structure.

The initial pixel-based representation is a very low level and unstructured representation.

Instead of working with a purely spectral representation, a more advanced strategy consists in extracting context-based features, such as with Attribute Filters, before performing the pixelwise classification.

Another strategy consists in using a region-based approach. One example of such representation is Binary Partition Trees. BPTs offer a powerful structured and hierarchical representation of the image.
Spectral vs spatial analysis

Random permutation

Spectral classification

Same classification!!

Spectral classification

Need to incorporate information from the spatial domain

Morphological & attribute profiles

closings (increasing SE) openings (increasing SE)

closing ES=21 closing ES=14 closing ES=7 original image opening ES=7 opening ES=14 opening ES=21

Differential morphological profile (DMP)
Morphological & attribute profiles

DMP = vector of attributes for each pixel

Morphological & attribute profiles

Differential Morphological Profile

Original image

Fuzzy model or Training samples (expert's knowledge)

segmented image

Feature extraction

Classification
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**Binary Partition Trees**

- BPTs can be interpreted as a structured image representation containing a set of hierarchical regions stored in a tree structure
- Each node representing a region in the image, BPTs allow us to extract many different partitions at different levels of resolution

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S. Valero, Ph. Salembier and J. Chanussot,
New hyperspectral data representation using binary partition tree
IEEE - International Geoscience and Remote Sensing Symposium, 2010, USA
Symposium Prize paper Award
Binary Partition Trees

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Binary Partition Trees

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- Each node representing a region in the image, BPTs allow us to extract many different partitions at different levels of resolution.

How can BPT be extended to the case of hyperspectral data?

We propose to construct a BPT in order to represent an HS image with a new region-based hierarchical representation.
Binary Partition Trees

Pruning strategy aiming at image classification is proposed

The BPT is a hierarchical tree structure representing an image.

The tree leaves correspond to individual pixels, whereas the root represents the entire image.

The remaining nodes represent regions formed by the merging of two children.

The tree construction is performed by an iterative region merging algorithm.
Binary Partition Trees

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Binary Partition Trees

The region model defines how to represent an hyperspectral region and how to model the union of two regions.

The merging criterion corresponds to the similarity measure between two neighboring regions.
Aim: BPT for HS image analysis

The creation of BPT implies two important notions

- **Region model MRi**
  It specifies how an hyperspectral region is represented and how to model the union of two regions.

- **Merging criterion O(Ri,Rj)**
  The similarity between neighboring regions determining the merging order

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Aim: BPT for HS image analysis

Hyperspectral image

- CONSTRUCTION
- PRUNING

Classification
Object detection
Segmentation

- **How to represent hyperspectral image regions?**
- **Which similarity measures defines a good merging order?**
We propose a non-parametric statistical region model consisting in a set of $N$ probability density functions

$$M_R = \{ H^\lambda_R^{\lambda_1}, H^\lambda_R^{\lambda_2}, \ldots, H^\lambda_R^{\lambda_N} \}$$

where each $P_i$ represents the probability that the spectra data set has a specific radiance value in the wavelength $\lambda_i$. 

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Hyperspectral image representation and processing with Binary Partition Trees
S. Valero, Ph. Salembier and J. Chanussot
accepted for publication
IEEE Transactions on Image Processing.
Aim: BPT for HS image analysis

- How to represent hyperspectral image regions?
- Which similarity measures define a good merging order?

Merging Criterion

- Step 1: Multidimensional Scaling
- Step 2: Principal Coordinates
To analyze the inter-waveband similarity relationships for each data via metric scaling to obtain the principal coordinates.

**Step 1**

- **Multidimensional Scaling**
- **Principal Coordinates**

Having N probability distributions

- N x N distance matrix
- Gram Matrix
- Single Value Decomposition

This matrix contains the distances between all the bands.
To subtract the row and column average of each entry and adds back the overall matrix average.
The first eigenvectors and eigenvalues give the principal coordinates.
Merging Criterion

Step 2

Principal Coordinates
Multidimensional Scaling
Association Measure

Similarity measure correlating the principal axis of both data sets

Merging Criterion: Step 2

An association measure is defined by considering that PC1 and PC2 are the predictor and the response variable of a multivariate regression model

PC1=PC2β+e
A multivariate linear regression model

\[ Y = X\beta + \epsilon \]

- If there is no relationship between X and Y, the matrix \( \beta \) is equal to 0.
- The idea is to compute a Lambda Wilks test verifying if the hypothesis \( \beta = 0 \) is true or false between the principal components

\[
W(R_i, R_j) = \frac{det(E)}{det(E + H)} = det(I - X'YY'X)
\]

- If Lambda Wilks test \( \approx 1 \), the hypothesis \( \beta = 0 \) is true X and Y have no relationship
- If Lambda Wilks test \( \approx 0 \), the hypothesis \( \beta = 0 \) is false and X and Y are highly correlated
Data Set: Rosis Pavia Center 103 bands

BPT is constructed by using the proposed merging order

Ground truth manually created

BPT is constructed by using the proposed merging order

Rosis Hyperspectral data

BPT is constructed by using the proposed merging order

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Rosis Hyperspectral data

Ground truth manually created

Battacharyya
Diffusion
Our proposal

Aim: BPT for HS image analysis

Pruning strategy aiming at image classification is proposed
Object Detection Strategy

- BPT can also be used for object detection.
- Selecting one node in the tree structure enables the segmentation of one region, *i.e.* one object
- The criterion to select the relevant node is application dependent.

S. Valero, P. Salembier, J. Chanussot and C.M. Cuadras,
Improved Binary Partition Tree Construction for hyperspectral images: Application to object detection
Object Detection: Example of Roads

Partitions contained in BPT

Road detection using pixel-wise asphalt detection

BPT pruning strategy oriented to object detection

Application in rainforest

- Nanawale tropical rainforest, Hawaii.
  - 0.56 m/pix
  - 24 bands (390nm – 1044nm)
  - 1980x1420 pix – 160 labeled trees

- San Lorenzo tropical rainforest, Panama.
  - 2 m/pix
  - 214 bands (378nm – 2510nm)
  - 600x600 pix – 100 labeled trees
Application in rainforest

- Canopy species richness assessment in tropical rainforests using hyperspectral imagery, G. Tochon, J.B. Feret, J. Chanussot & G. Asner
  IEEE IGARSS'12
Application in material sciences

- MEB multivariate image analysis of cementitious materials
  18 spectral bands
  Collaboration Société Lafarge

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**Conclusions**

- Need for **structured representations**
- Binary Partition Tree offers a good solution for a variety of applications
- The pruning step requires more investigations
- Further integration of spectral and spatial dimensions

**References on Hyperspectral BPT**

Community of communities

CEA  FP7  INRIA  ACTIMAR
DGA  ANR  GRETSI  SAGEM  TOTAL
CNES  ASTRIMUM  THALES  SFTH / SFPT  OBS
ONERA  CNRS  TOTAL
IRSTEA  INRA

ASTRO/PLANETO/AGRO/BIOMED/MATERIALS/SECURITY/ENVIRONMENT

5th Workshop on Hyperspectral Image and Signal Processing: Evolution in Remote Sensing

25 - 28, June 2013
Gainesville, Florida, USA
submission deadline: February 15, 2013