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/

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❖ 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
IEEE GRSS **W**orkshop on
Hyperspectral **I**mage and **S**ignal **P**rocessing:
Evolution in **R**emote **S**ensing

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/

Outline

1. Introduction: Hyperspectral Imagery
2. Within a pixel
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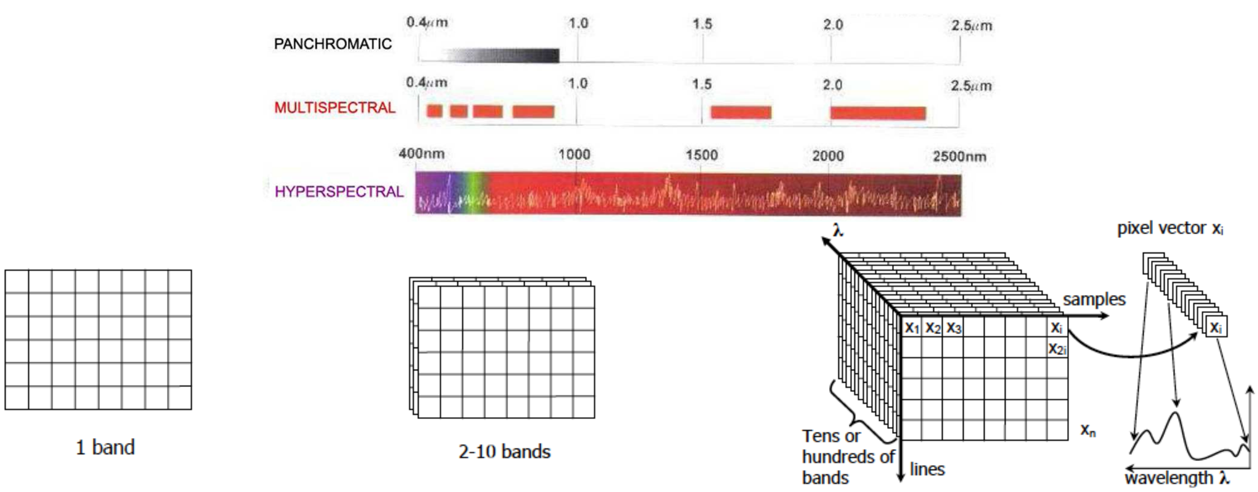
Hyperspectral imagery

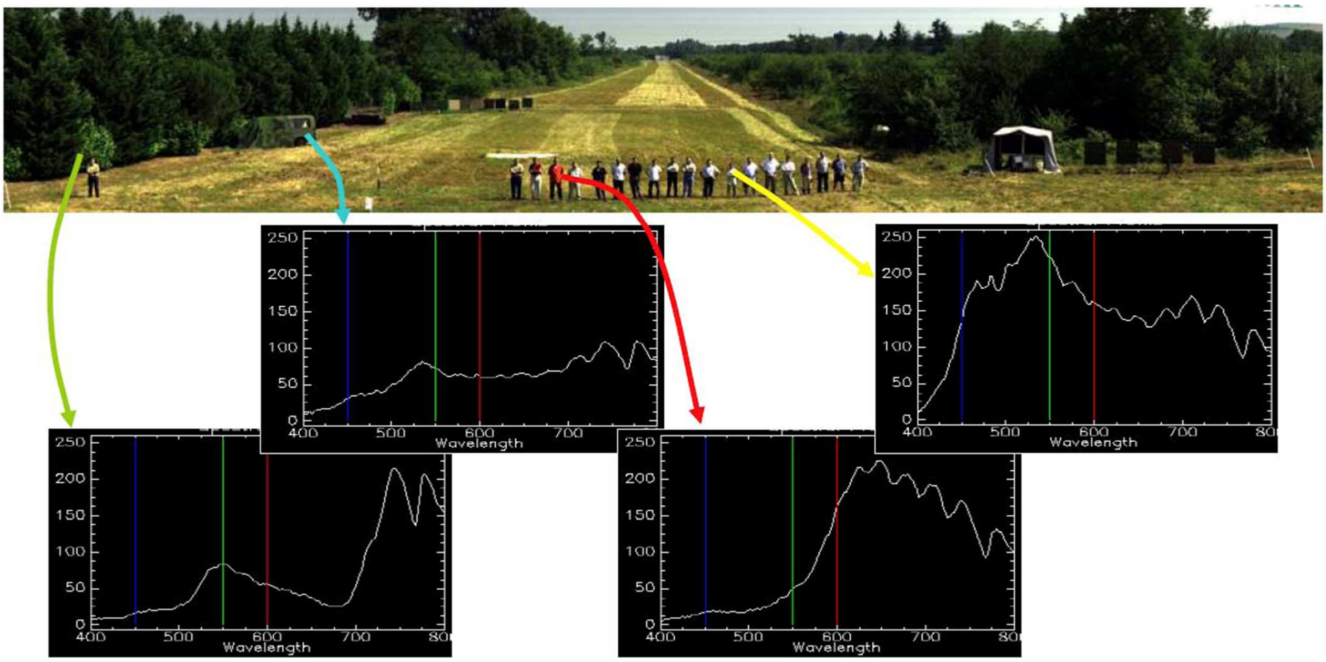


Panchromatic
. one grey level value per pixel

Multispectral
. 2-10 bands
. limited spectral info

Hyperspectral
. tens or hundreds of narrow bands
. detailed spectral info

Hyperspectral imagery

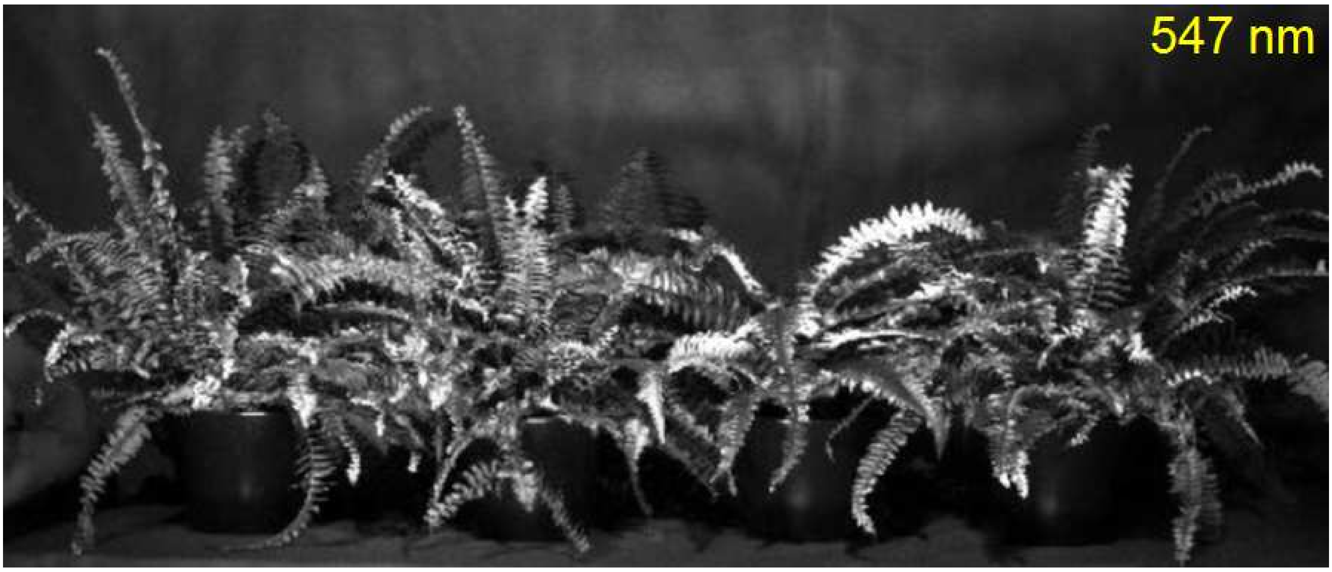


Improved spectral diversity : hyperspectral imagery

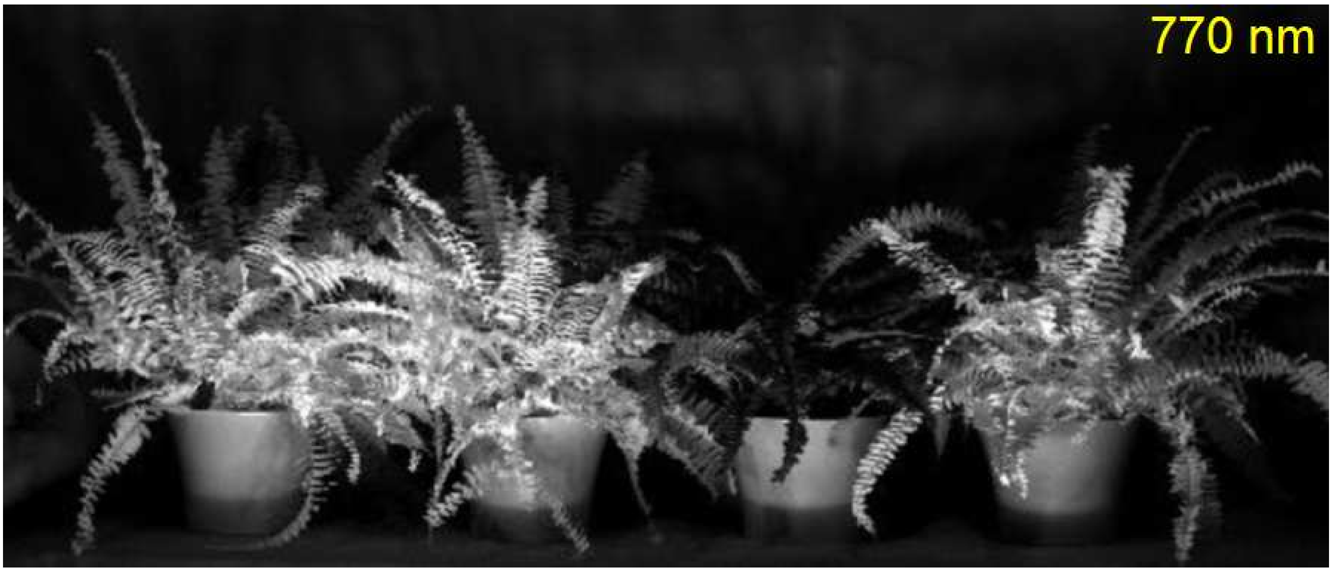
Hyperspectral imagery

Hyperspectral imagery

Hyperspectral imagery

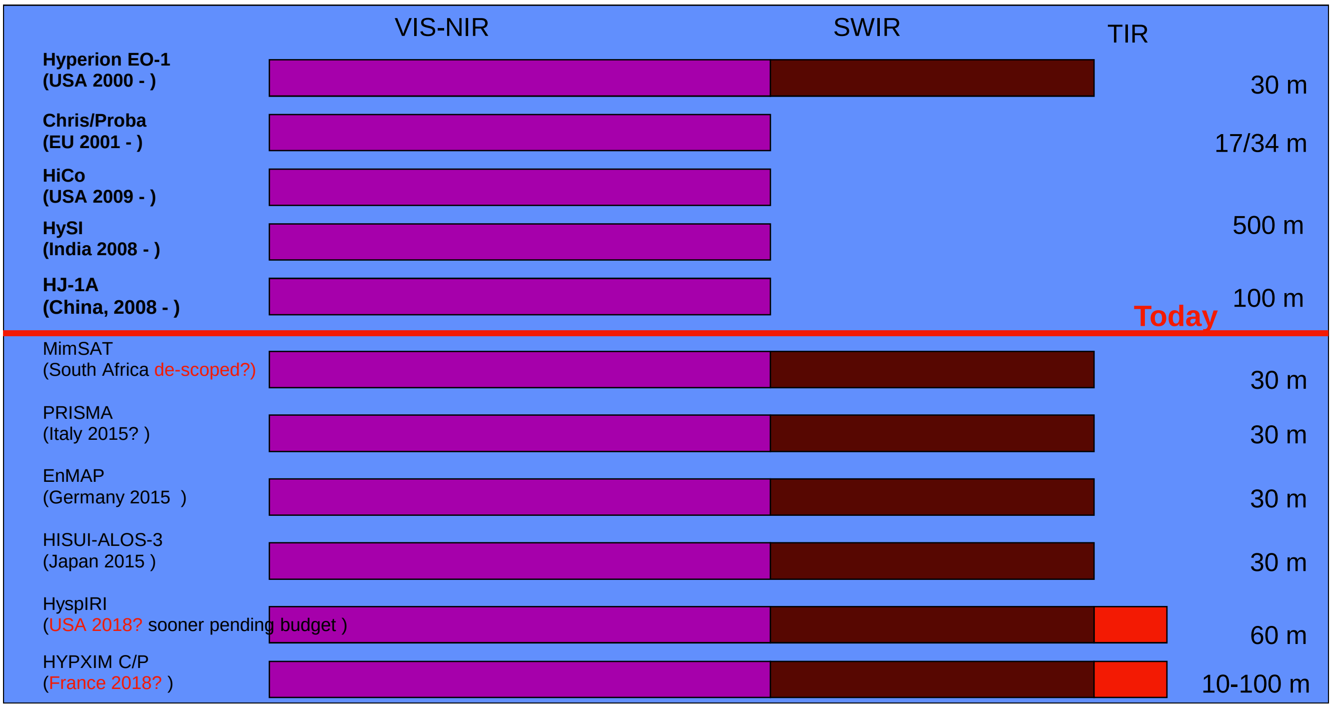


Hyperspectral imagery



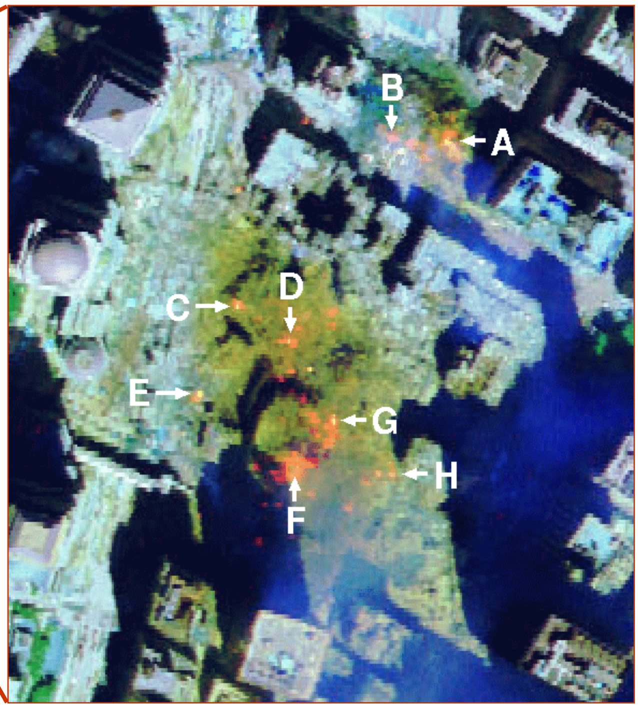
Spaceborne Imaging Spectrometers

Current and planned civilian hyperspectral satellite missions



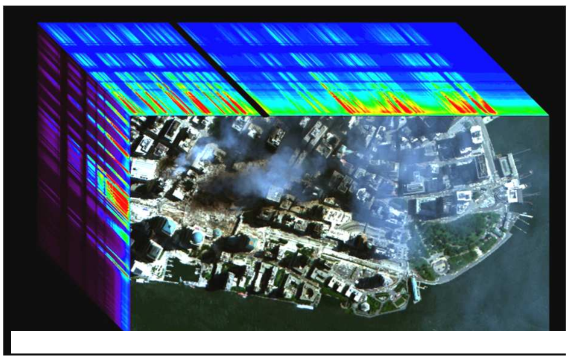
Example: anomaly detection

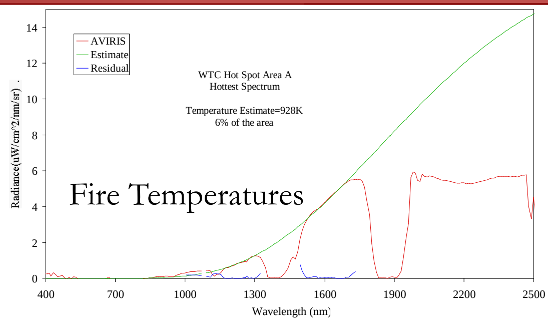
AVIRIS data over lower Manhattan (09/15/01)



Spatial location of thermal hot spots in WTC area

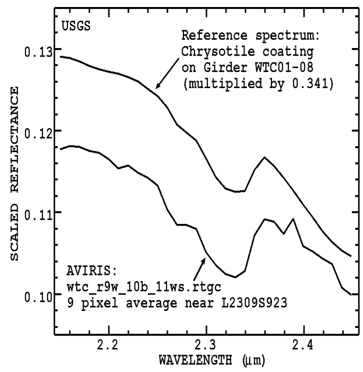
Example: anomaly detection





Debris Composition

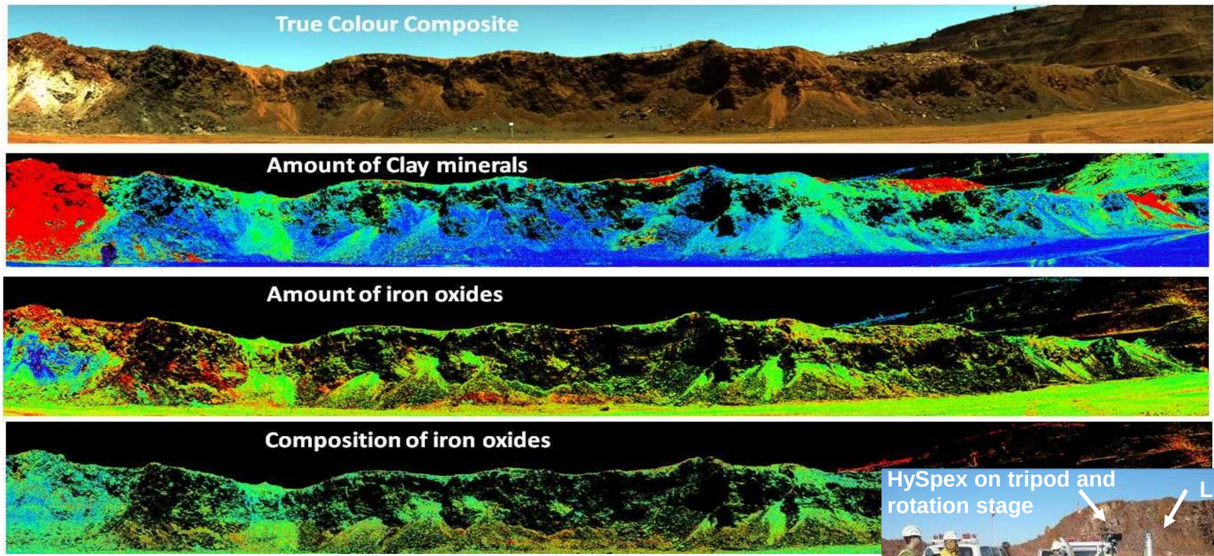
Asbestos



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

Field applications

Spectral Mine Imaging



Scanning time: a few minutes

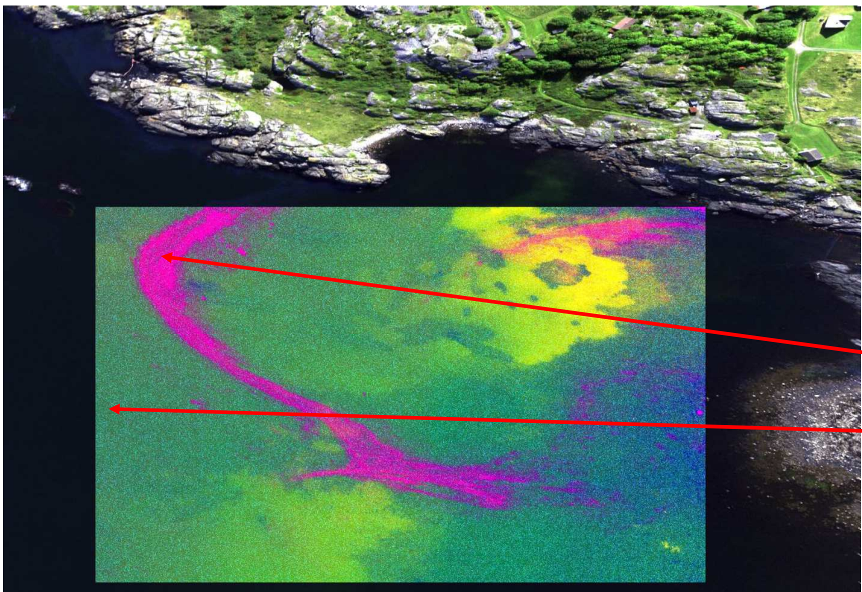
Courtesy of CSIRO

HySpex norsk elektro optikk

Airborne application

Oil spill detection - MV "Full City" Grounding

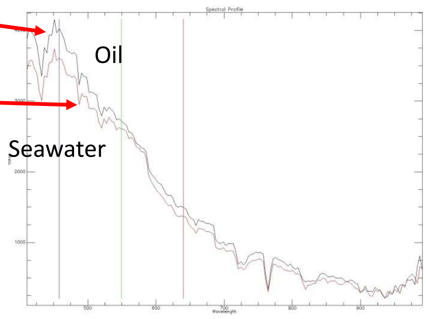
(~1000 tons of heavy bunker oil (IF 180) & ~120 tons of marine diesel oil on board)



PCA visualization of oil spill (Pink = oil on seawater, Yellow = sand on sea floor, Green = Seawater).

norsk elektro optikk

HySpex



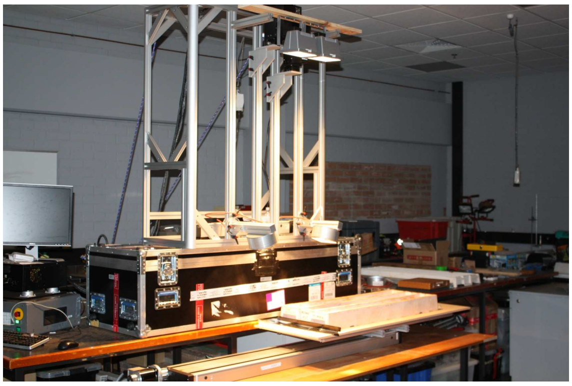
Laboratory/In-line applications

Drill Core Imaging

Scanning time: 1 min

Courtesy of CSIRO

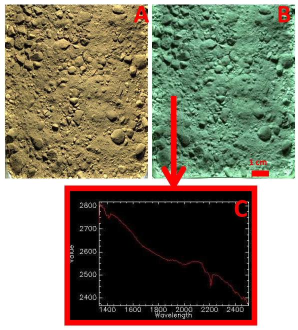
Mineral mapping



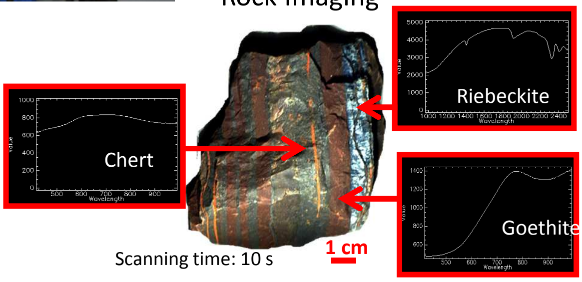
HySpex

norsk elektro optikk

Drill Chips Imaging



Rock Imaging



Scanning time: 10 s

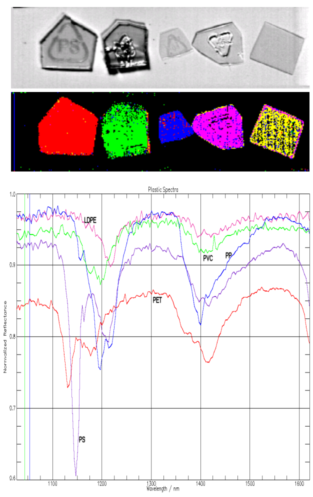
Quality control

Recycling - Sorting

NIR spectral imaging

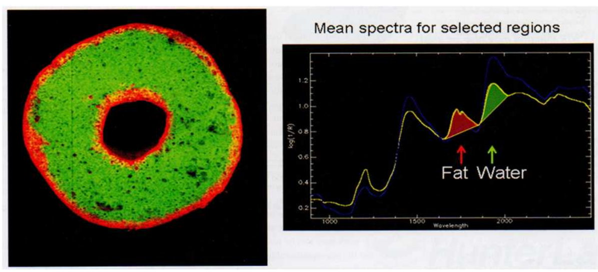
Plastics sorting

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

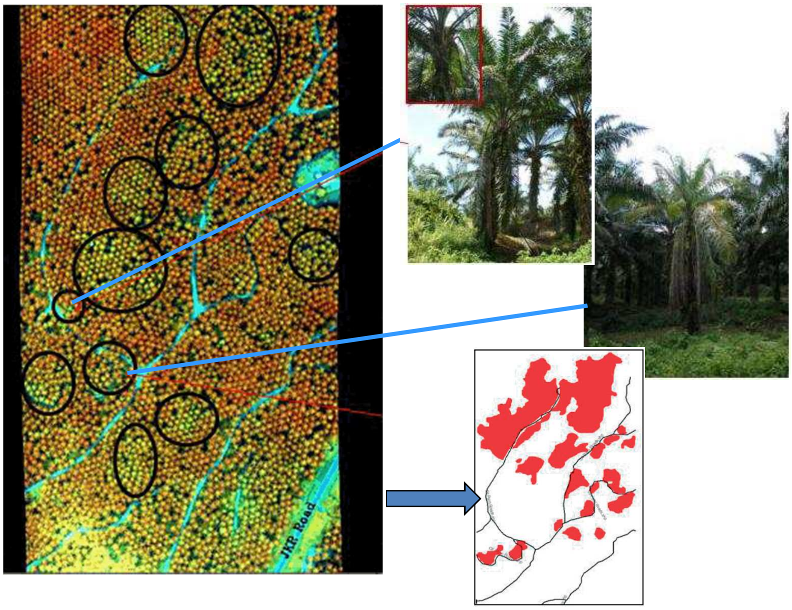
Specim

Natural Resources Mapping

Sarawak Forest Department
Malaysia - AisaEAGLE

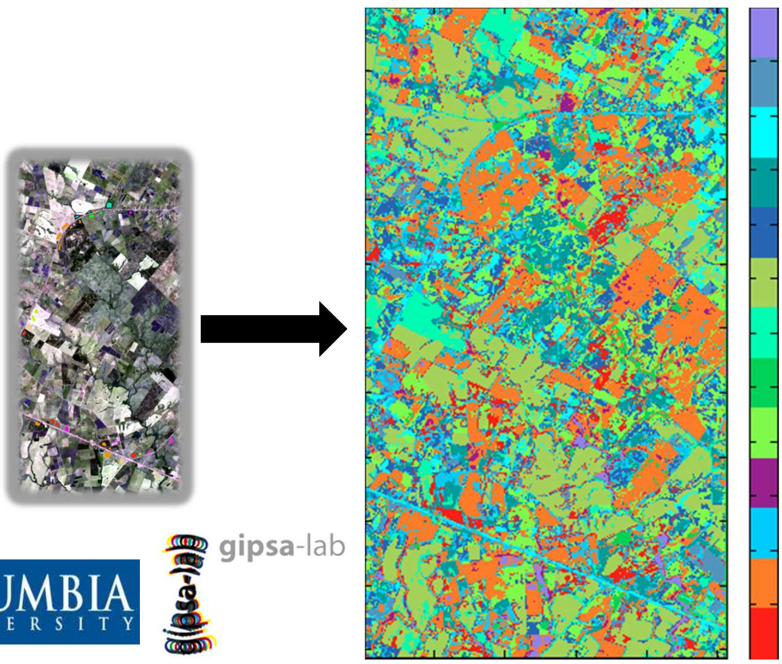
Airborne HSI in VNIR provides sensitive and high resolution detection and mapping of **fungus disease in oil palm trees**

>50 km^2/h
@0.5 m ground resolution
@50 m/s (100 knots)



Agricultural crop identification

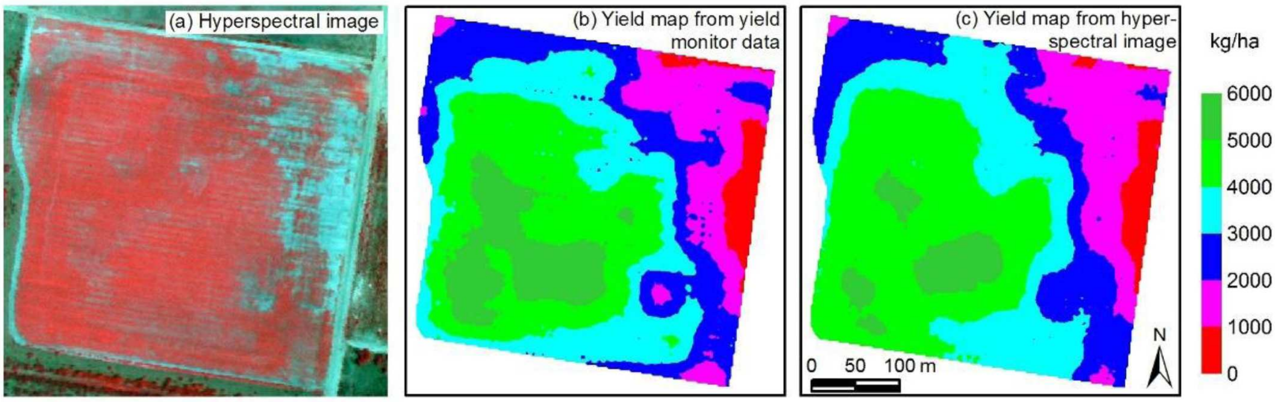
- Study in Uruguay



COLUMBIA UNIVERSITY
gipsa-lab

Agricultural crop identification

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



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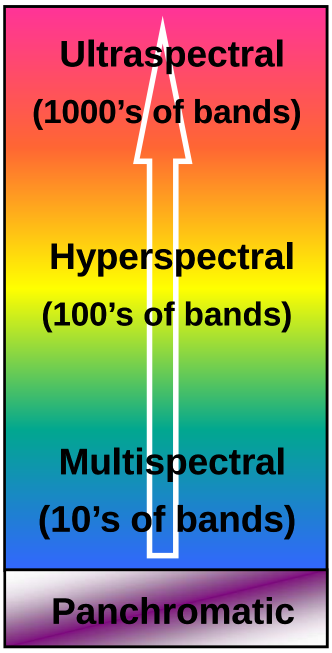
Opportunities



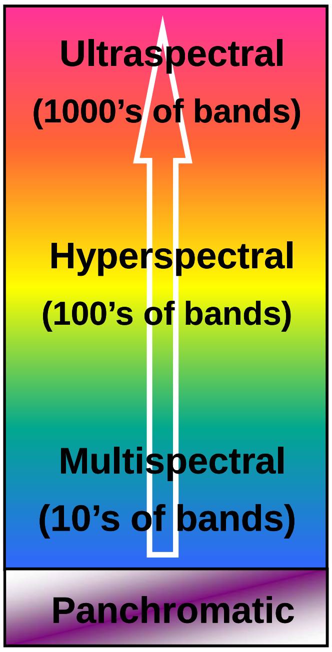
Spectral mixture analysis / source separation: Determines the abundance of materials

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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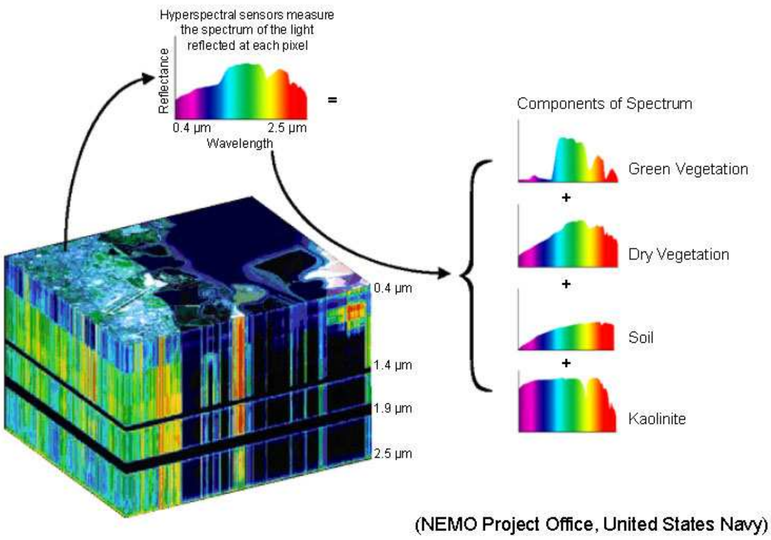
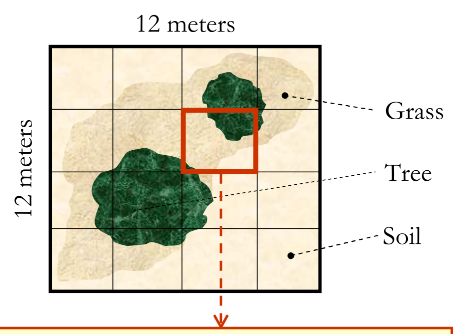
Spectral mixture



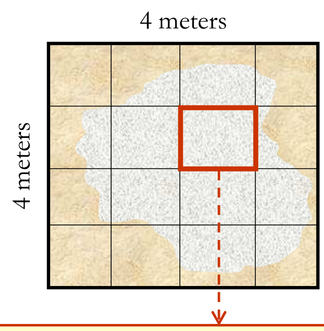
(NEMO Project Office, United States Navy)

Spectral mixture



Macroscopic mixture:

15% soil, **25%** tree, **60%** grass in a 3x3 meter-pixel

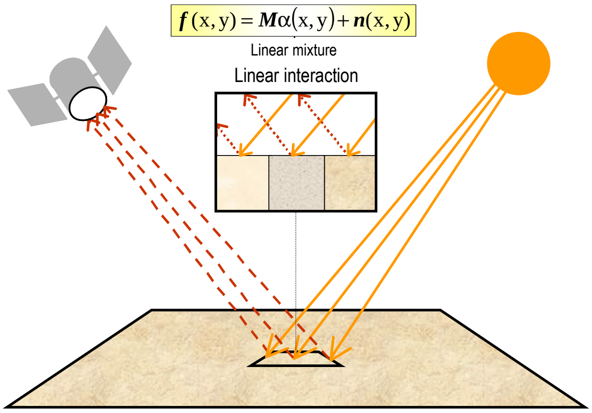


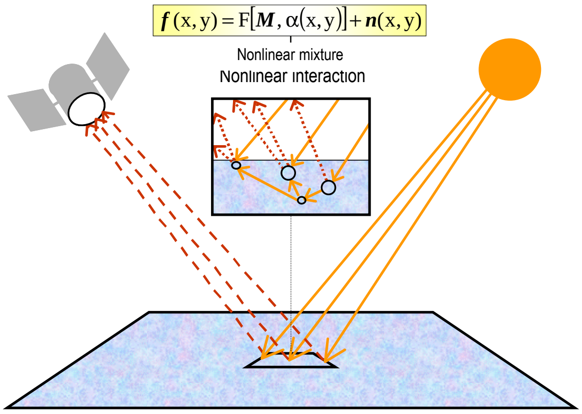
Intimate mixture:

Minerals intimately mixed in a 1-meter pixel

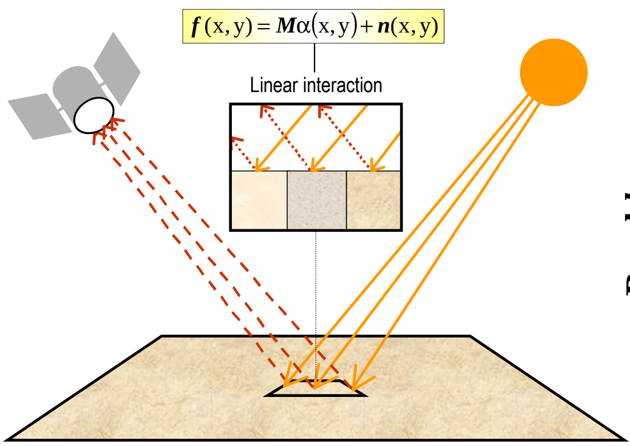
Spectral unmixing

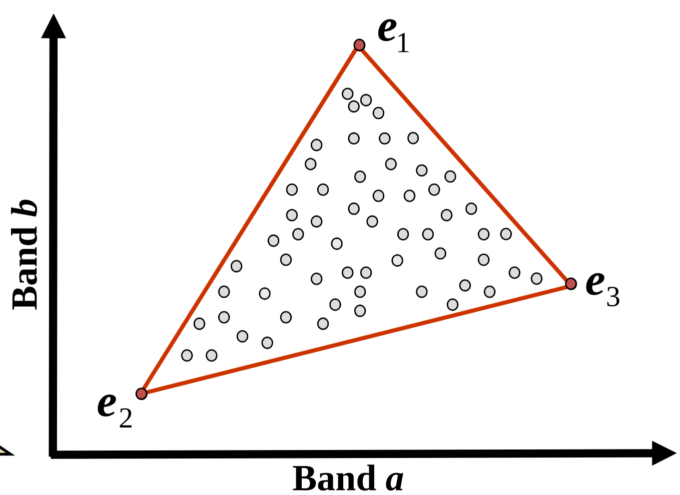
- Interpreted as a (blind) source separation problem.
- Linear vs nonlinear models



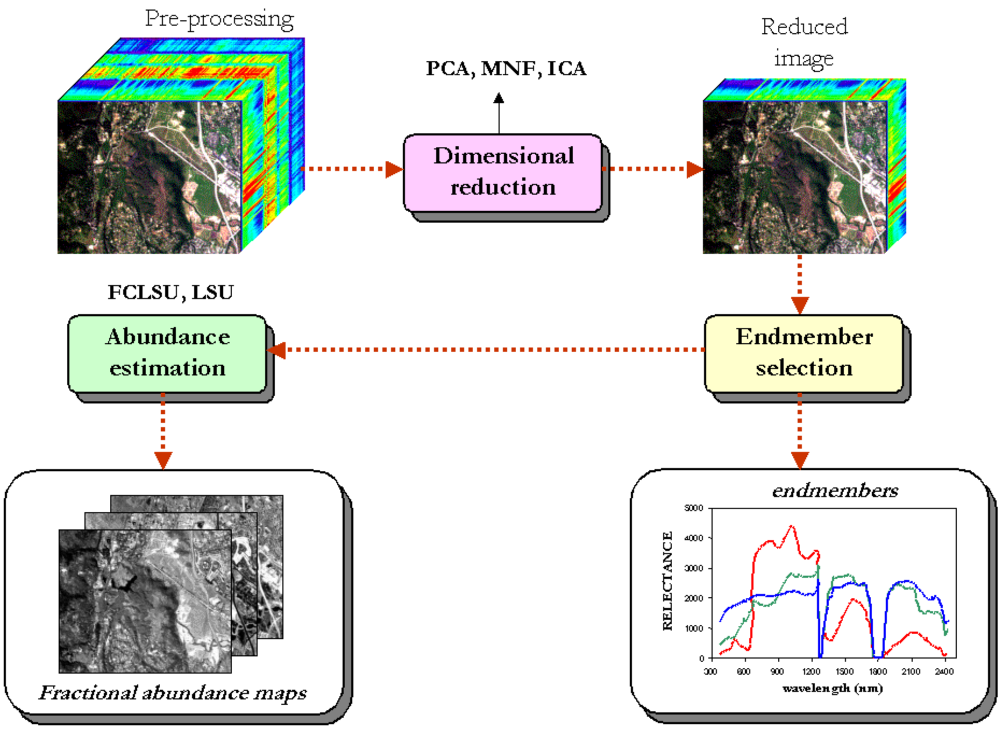


Spectral unmixing

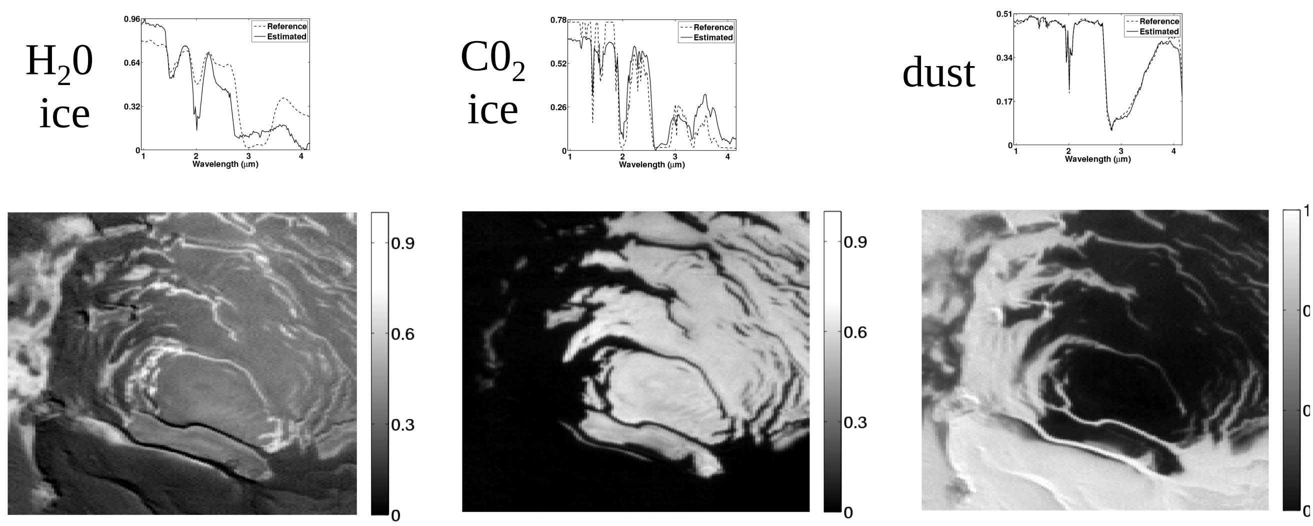




Spectral unmixing



Spectral unmixing

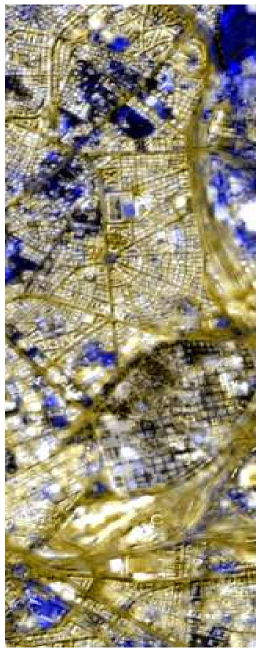


The physical meaning of independent components and artifact removal of hyperspectral data from Mars using ICA.
H. Hauksdottir, Ch. Jutten, F. Schmidt, J. Chanussot, J.A. Benediktsson & S. Douté
IEEE NORSIG'06 - 7th Nordic Signal Processing Symposium, june 2006, Reykjavik, Iceland
Best Student Paper Award

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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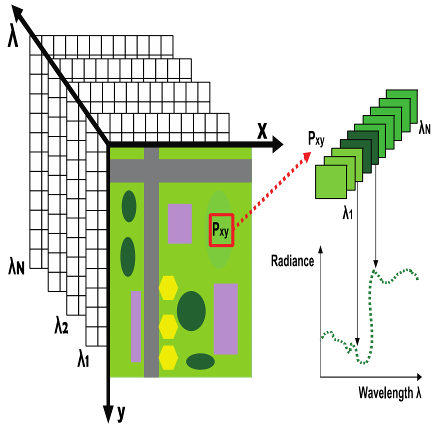
Hyperspectral Imagery

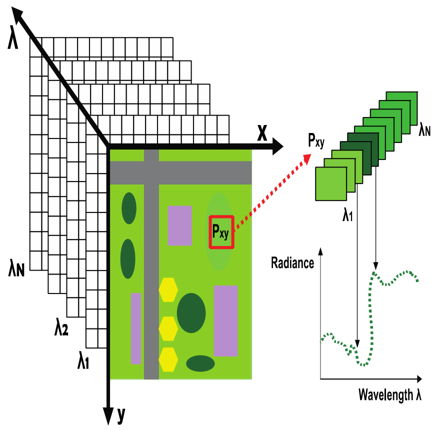
- Hyperspectral data cubes contain hundreds of images captured at different wavelengths Each pixel is a discrete spectrum containing the reflected solar radiance of the spatial region that it represents



- Each pixel is a discrete spectrum containing the reflected solar radiance of the spatial region that it represents

Hyperspectral Imagery

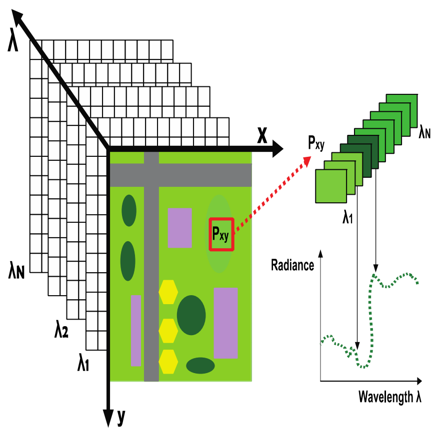
- This new source of information has led to use this images in a growing number of real-life applications



- Remote sensing, food safety, medical research or environmental applications

Hyperspectral Imagery

❖ Different analysis techniques have been proposed in the literature processing the pixels individually, as an array of spectral data without any spatial structure



Pixels are studied as **isolated** discrete **spectra**

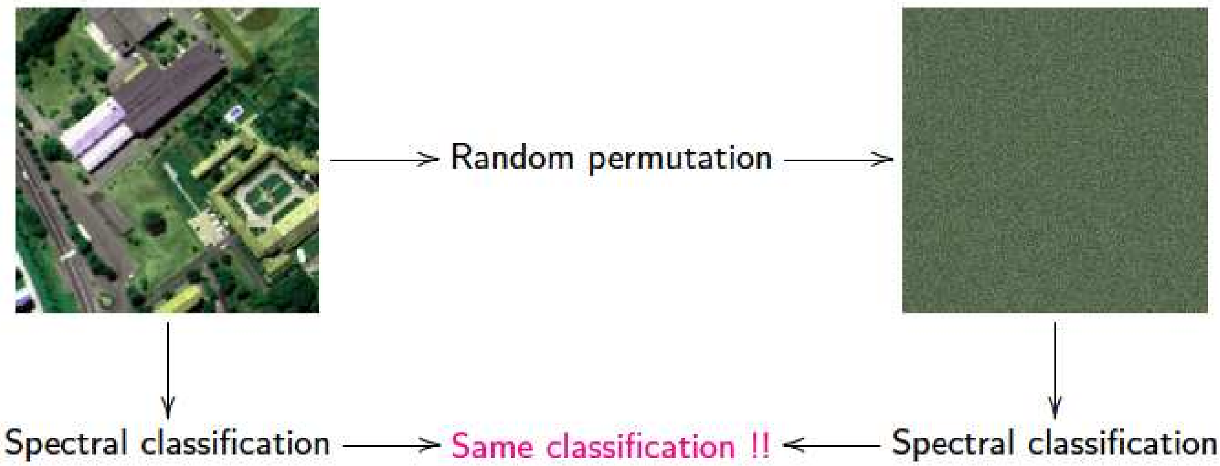
Hyperspectral Imagery

❖ 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.

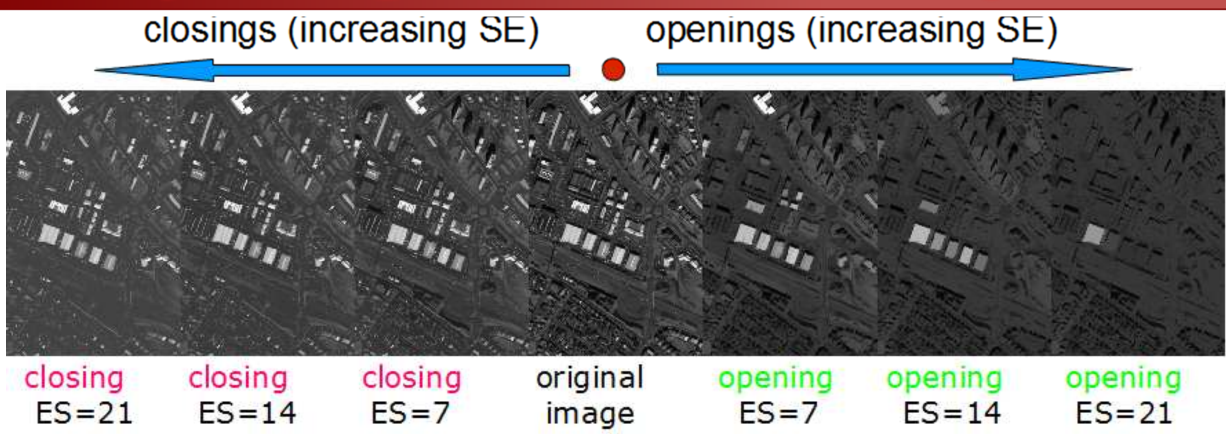
❖ Another strategy consists in using a region-based approach. One example of such representation is **Binary Partition Trees.** BPTs offer a powerful structured and hierarchical representation of the image

Spectral *vs* spatial analysis



Need to incorporate information from the spatial domain

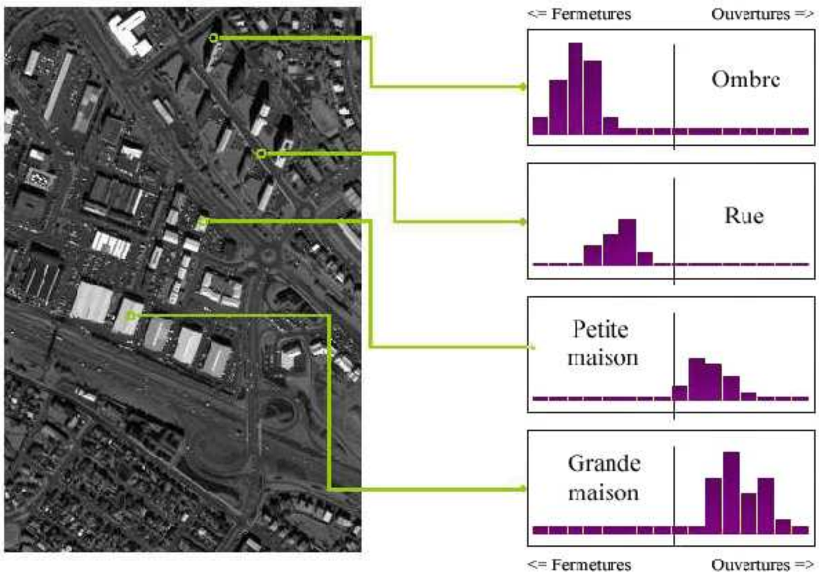
Morphological & attribute profiles



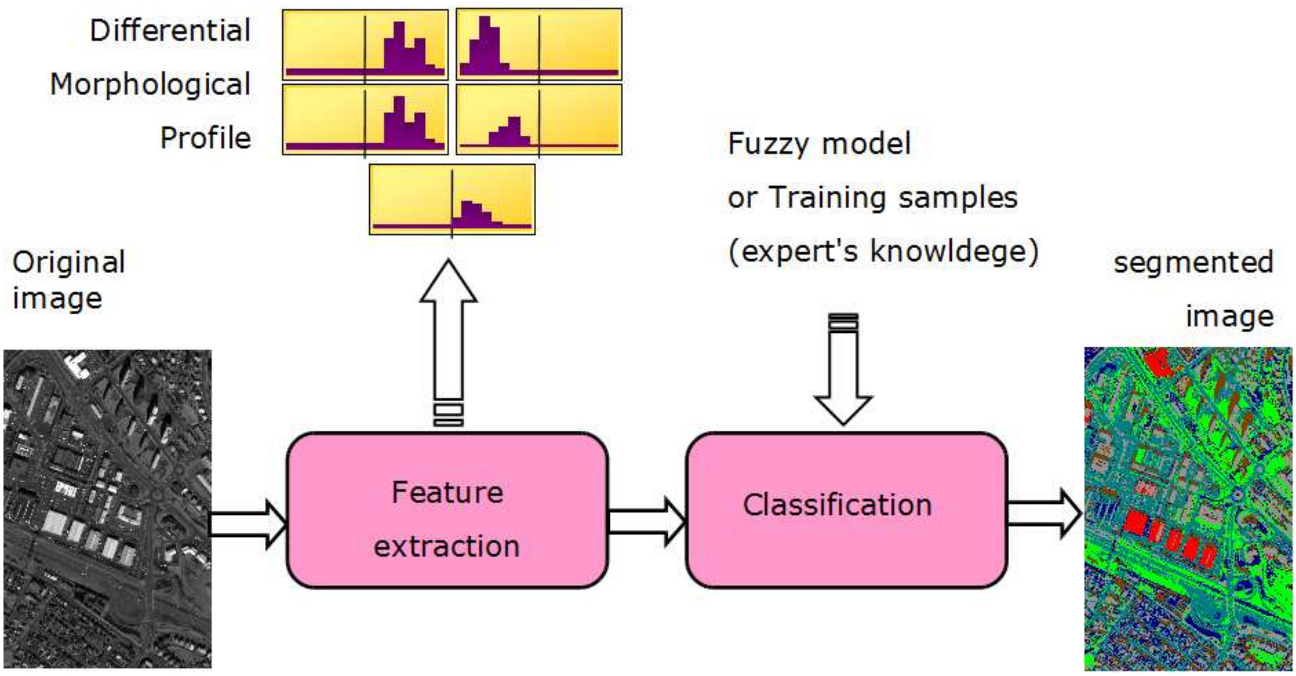
Differential morphological profile (DMP)

Morphological & attribute profiles

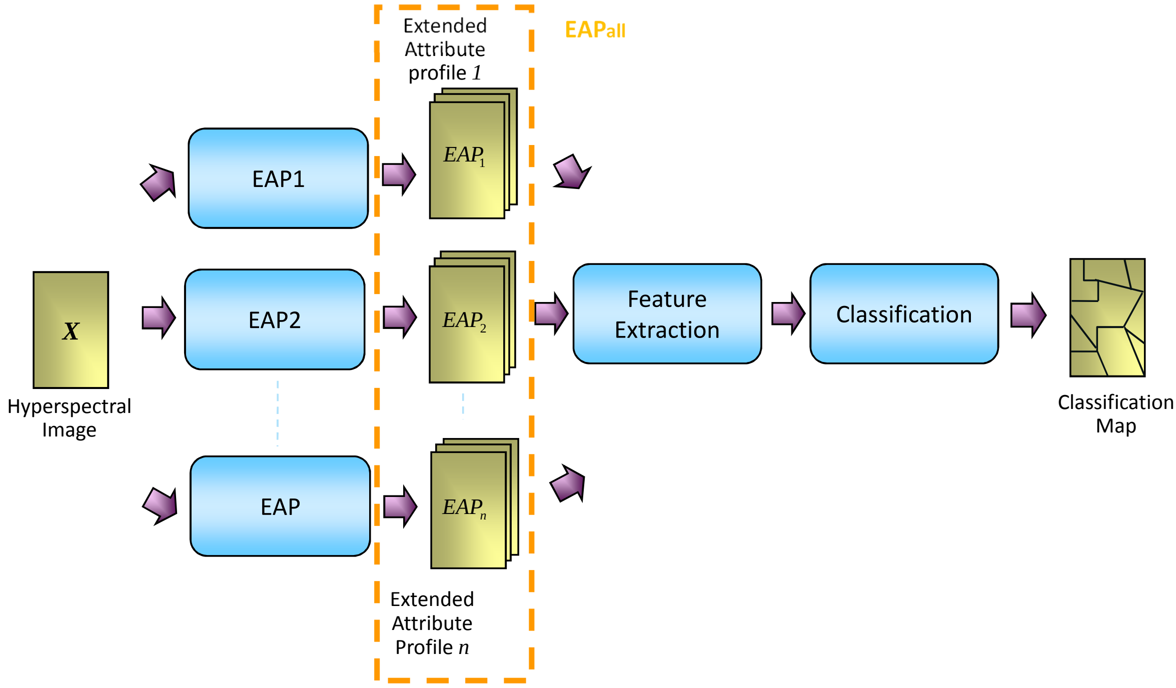
DMP = vector of attributes for each pixel



Morphological & attribute profiles



Morphological & attribute profiles

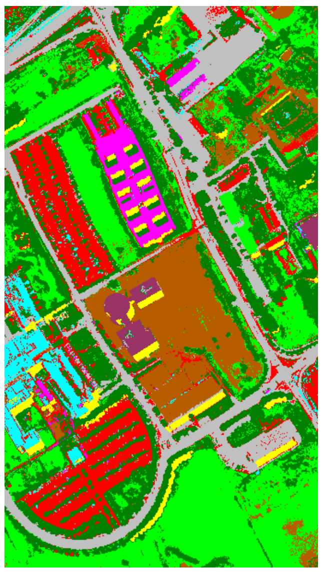


M. Dalla Mura, J. A. Benediktsson and L. Bruzzone, "Classification of Hyperspectral Images with Extended Attribute Profiles and Feature Extraction Techniques," *Proc. IEEE IGARSS 2010*, 2010, pp. 76 –79.

Morphological & attribute profiles

Classification Maps.

Spectral channels
OA: **71.66%**



EAPall with DAFE
OA: **96.01%**

Thematic classes: **Trees**, **Meadow**, **Metal**, **Gravel**, **Bricks**, **Bare Soil**, **Asphalt**, **Bitumen**, **Shadow**.

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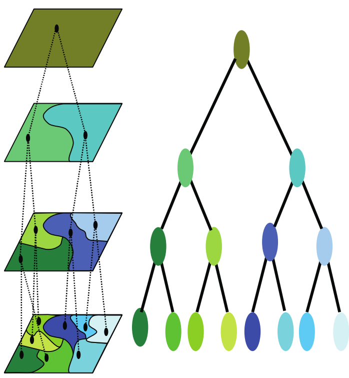
5 Conclusions

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



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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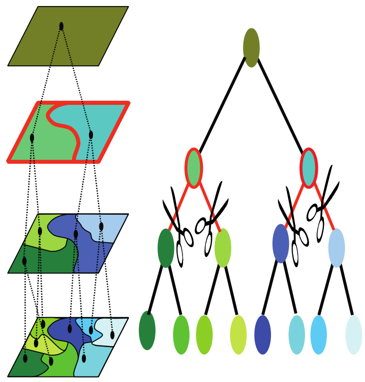

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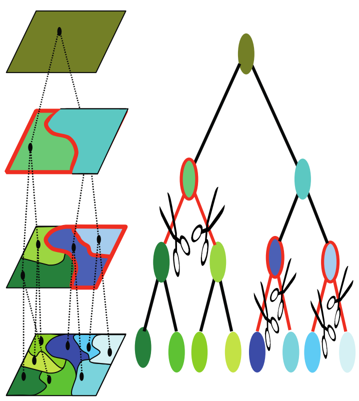

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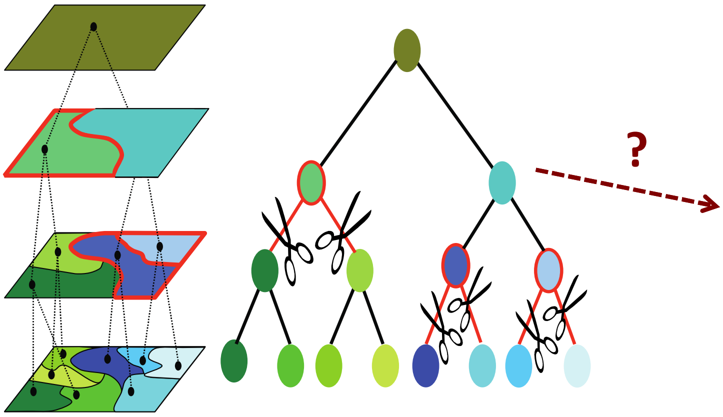
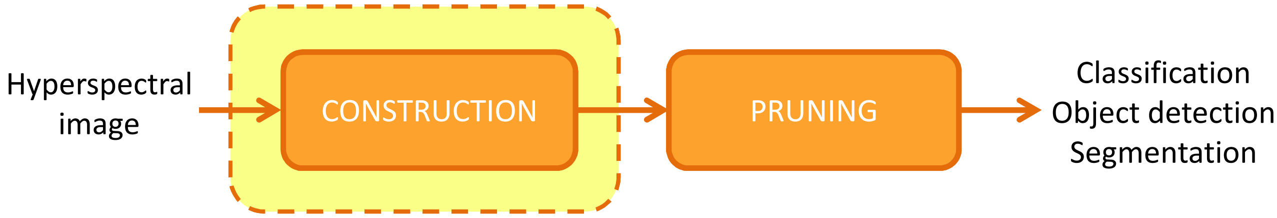


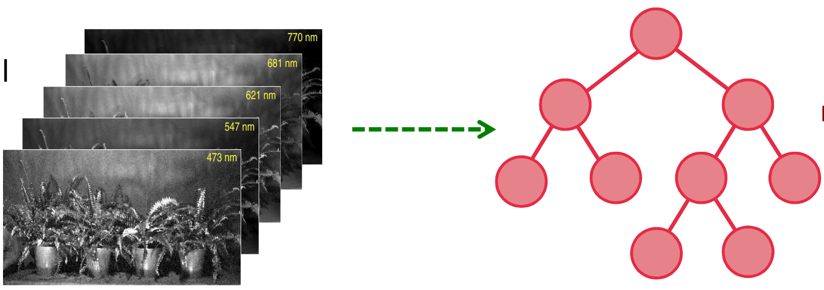
How can BPT be extended to the case of **hyperspectral data** ?

Binary Partition Trees



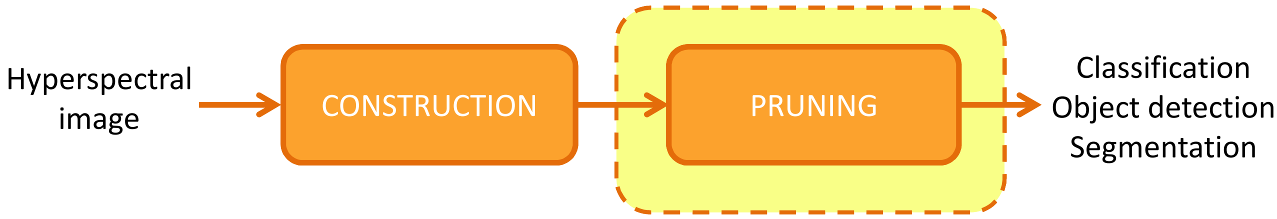
- We propose to construct a BPT in order to represent an HS image with a new region-based hierarchical representation

Hyperspectral image

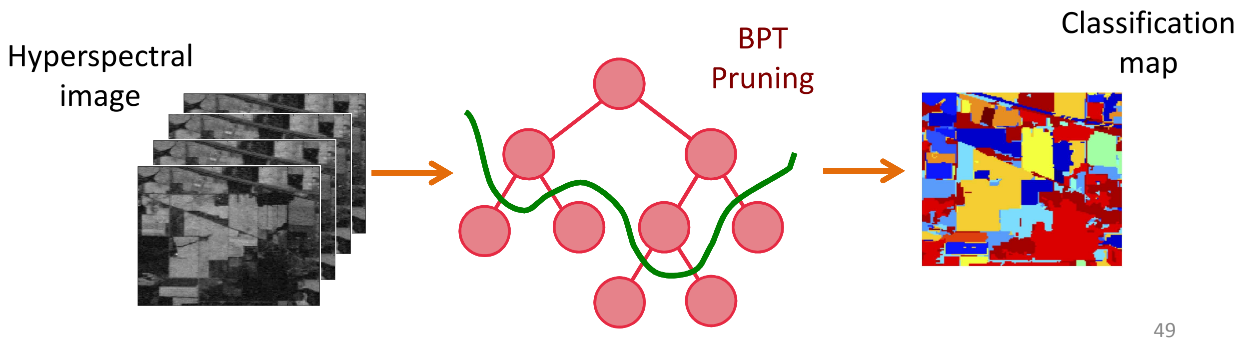


BPT representation

Binary Partition Trees



❖ Pruning strategy aiming at image classification is proposed



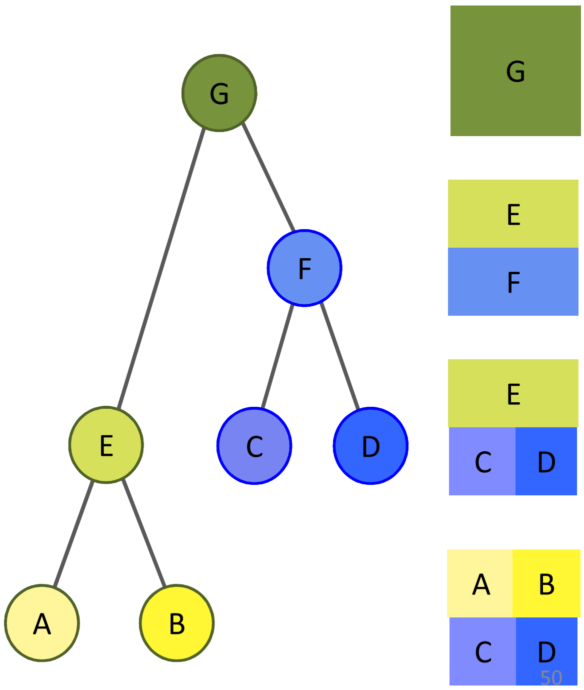
Binary Partition Trees

❖ The BPT is a hierarchical tree structure representing an image

❖ The tree leaves correspond to individual pixels, whereas the root represent 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

- ❖ The BPT is a hierarchical tree structure representing an image
- ❖ The tree leaves correspond to individual pixels, whereas the root represent the entire image
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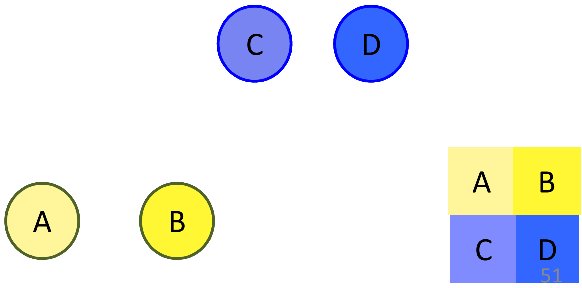

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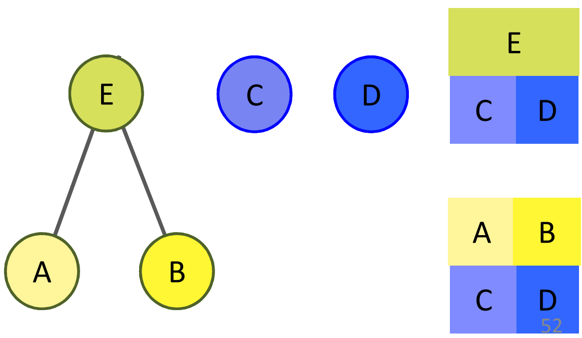

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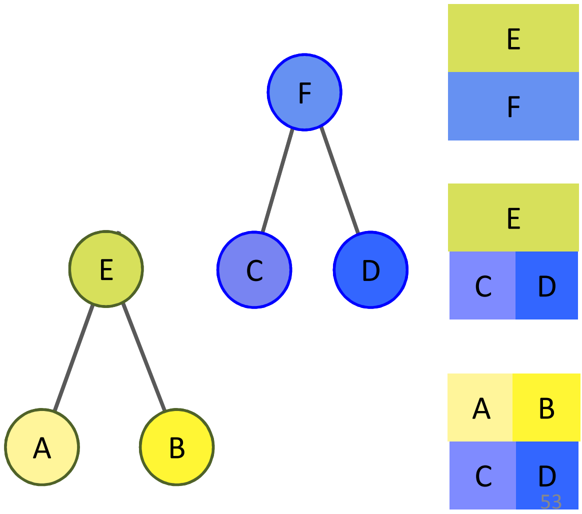

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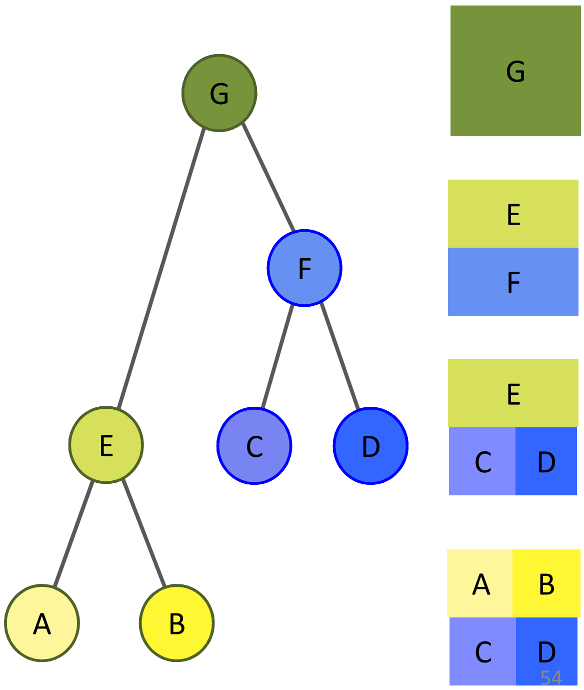
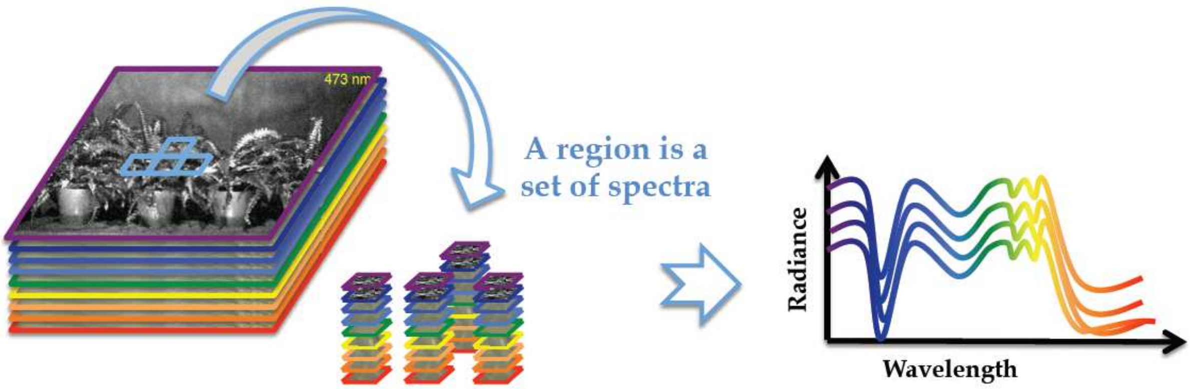


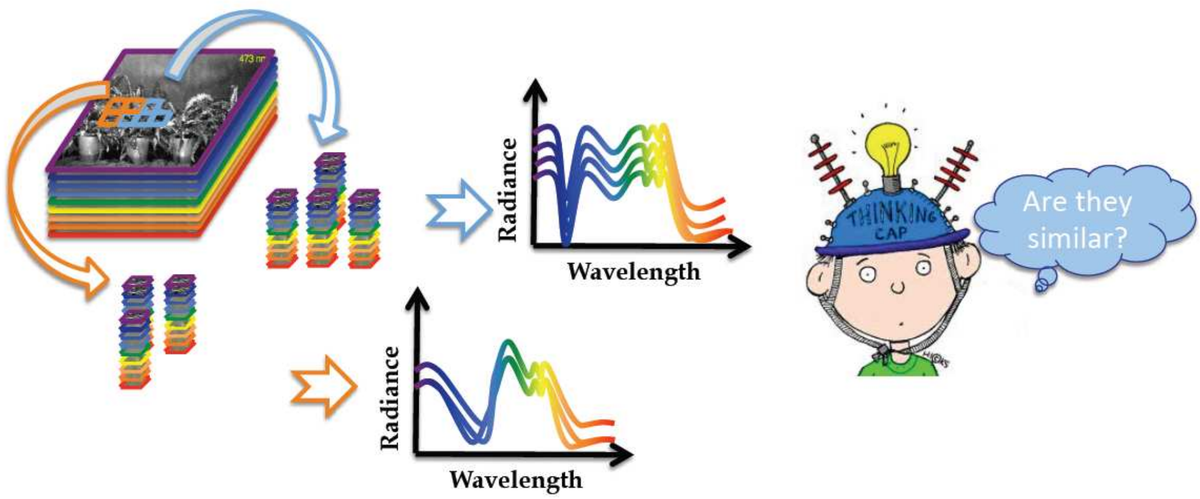
Binary Partition Trees

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



Binary Partition Trees

The merging criterion corresponds to the similarity measure between two neighboring regions

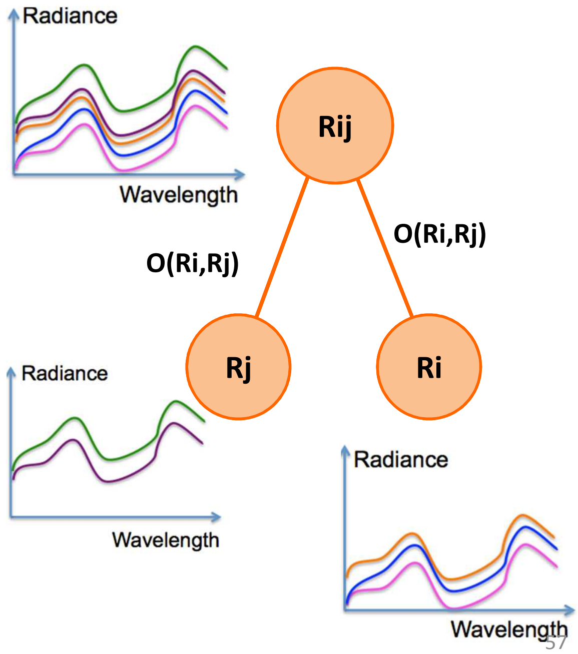


Aim: BPT for HS image analysis

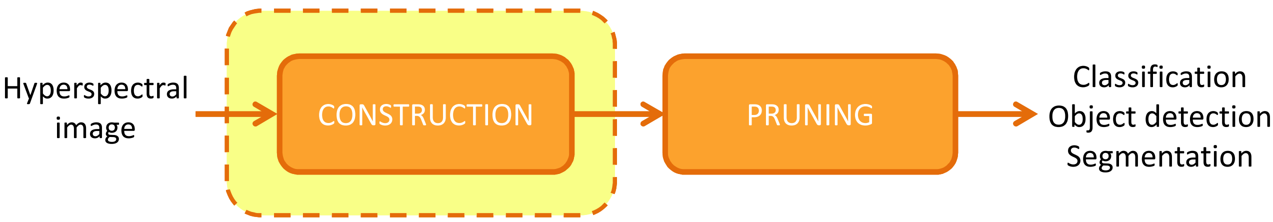
The creation of BPT implies two important notions

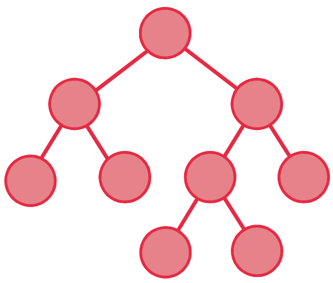
- ❖ **Region model MRi**
  It specifies how an hyperspectral region is represented and how to model the union of two regions.

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



Aim: BPT for HS image analysis





- ❖ **How to represent hyperspectral image regions?**

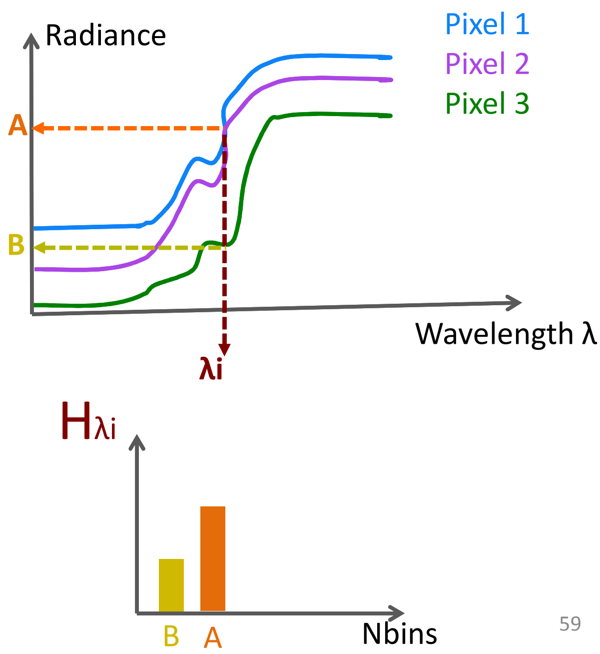
- ❖ Which similarity measures defines a good merging order?

Region Model

We propose a non-parametric statistical region model consisting in a set of N probability density functions

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

where each Pi represents the probabilitiy that the spectra data set has a specific radiance value in the wavelength λi



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

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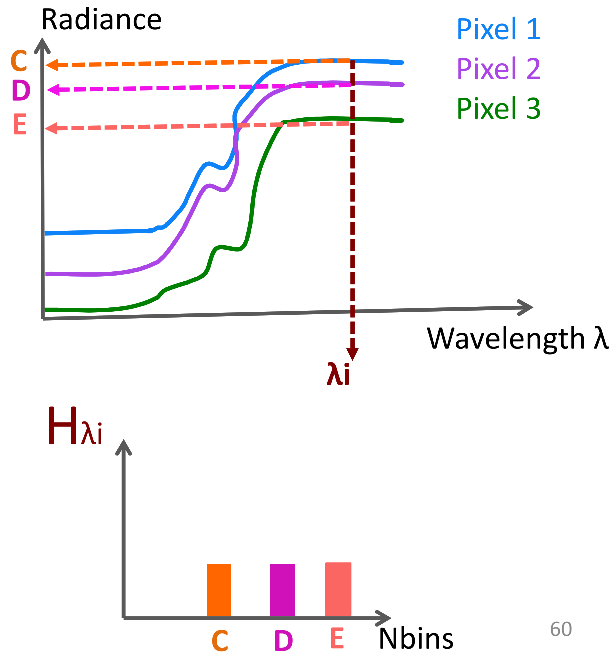

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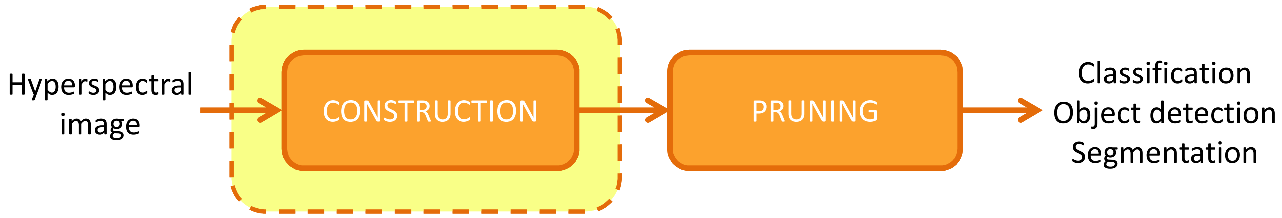
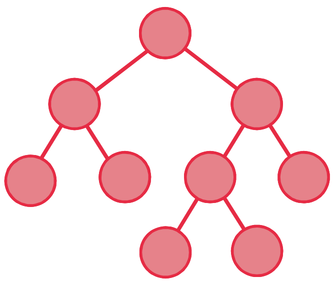
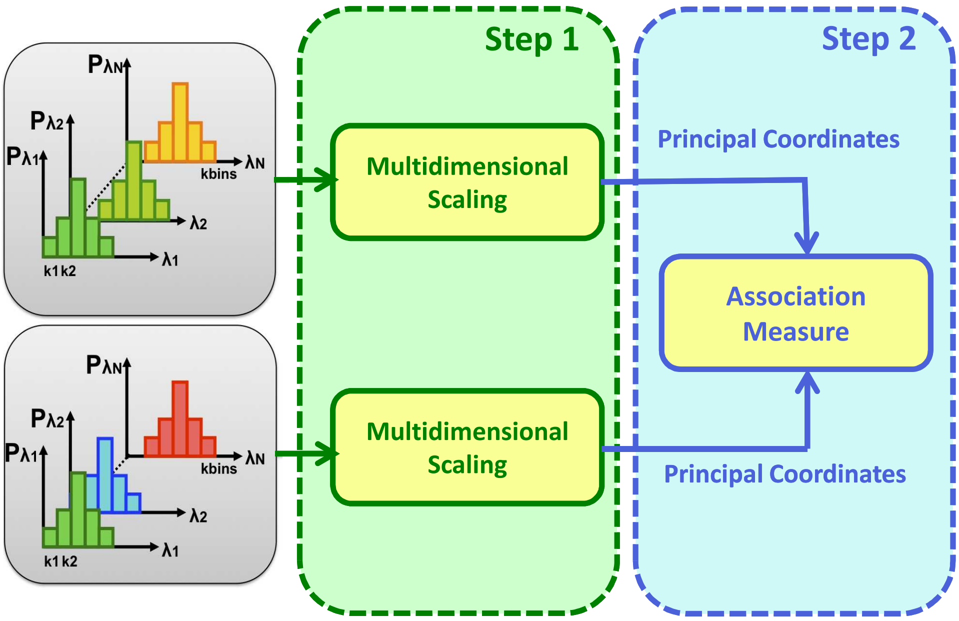


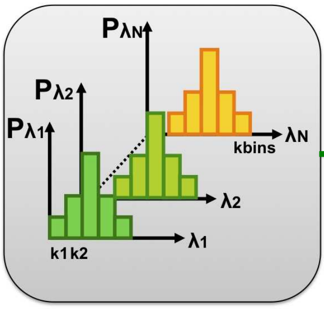


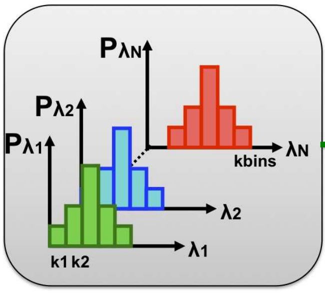
- How to represent hyperspectral image regions?
- **Which similarity measures defines a good merging order?**

Merging Criterion



Merging Criterion





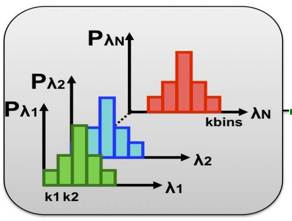
Step 1

Multidimensional Scaling → **Principal Coordinates**

To analyze the inter-waveband similarity relationships for each data via metric scaling to obtain the principal coordinates

Multidimensional Scaling → **Principal Coordinates**

Merging Criterion : Step 1



Step 1

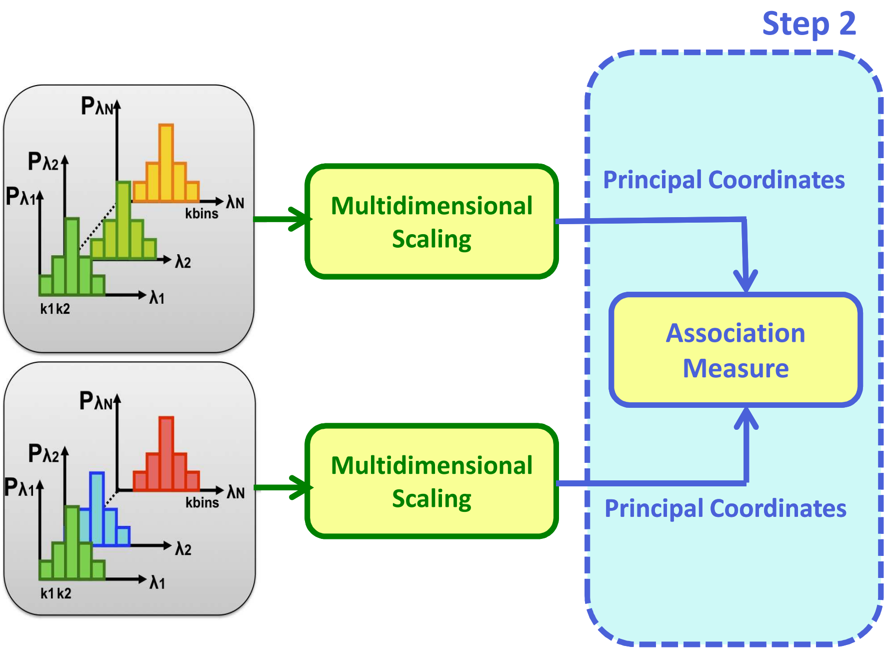
Multidimensional Scaling → **Principal Coordinates**

Having N probability distributions

N x N distance matrix → **Gram Matrix** → **Single Value Decomposition** →

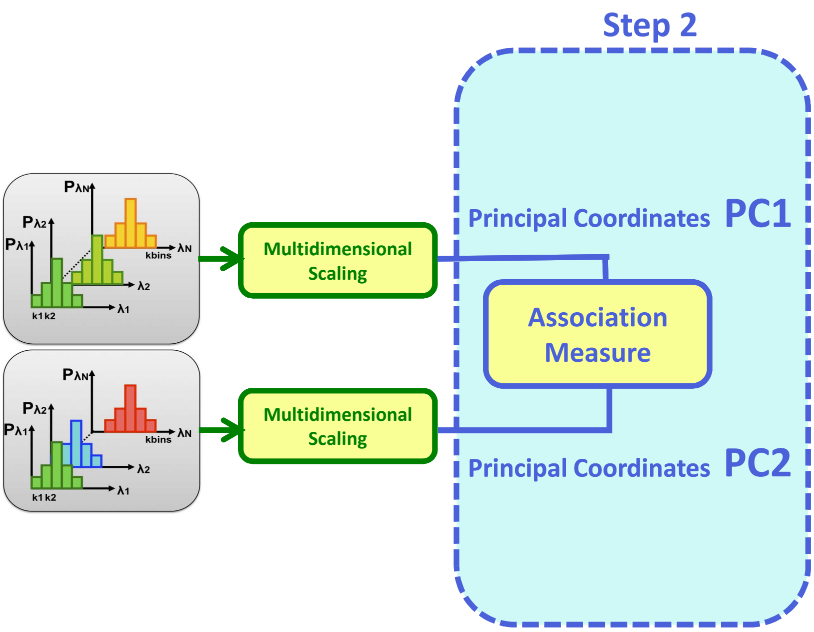
N x N distance matrix	**Gram Matrix**	**Single Value Decomposition**
This matrix contains the distances between all the bands	To substract the row and colum average of each entry and adds back the overall matrix average	The first eigenvectors and eigenvalues give the principal coordinates

Merging Criterion



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

$$PC1 = PC2\beta + e$$

Merging Criterion: Step 2

- A multivariate linear regression model

Error Matrix

$$Y = X\beta + \varepsilon$$

Regression Coefficients

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

$$W(R_i, R_j) = det(E)/det(E+H) = det(I - X'YY'X)$$

Merging Criterion: Step 2

- A multivariate linear regression model

Error Matrix

$$Y = X\beta + \varepsilon$$

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If Lambda Wilks test ≈1, the hypothesis β= 0 is true X and Y have no relationship
If Lambda Wilks test ≈0, the hypothesis β= 0 is false and X and Y are highly correlated

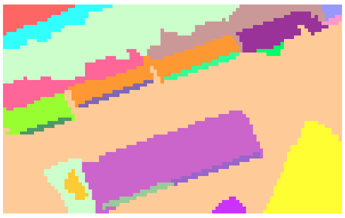
Rosis Hyperspectral data

Data Set : Rosis Pavia Center 103 bands

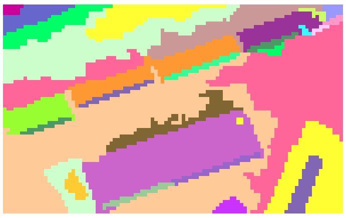
RGB Composition

103 bands

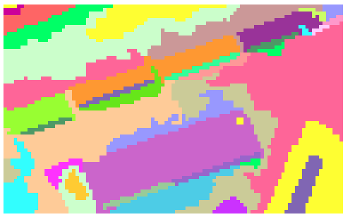
BPT is constructed by using the proposed merging order



$N_R=22$



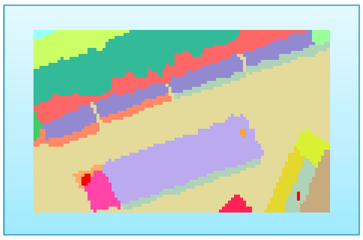
$N_R=32$



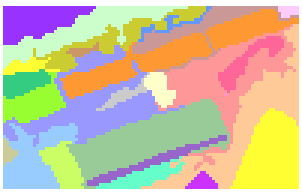
$N_R=42$

Rosis Hyperspectral data

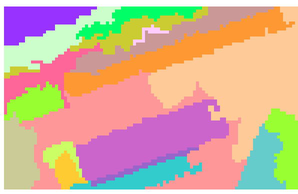
Ground truth manually created



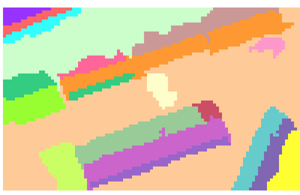
RHSEG software



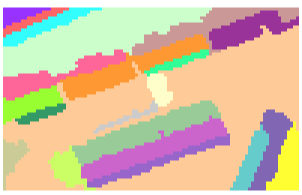
SID



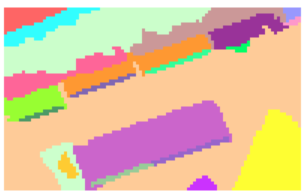
Battacharryya



Diffusion



MDS



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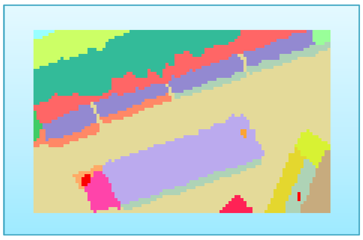
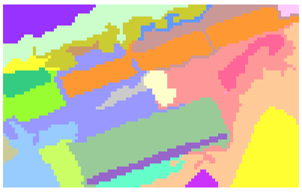


RHSEG software



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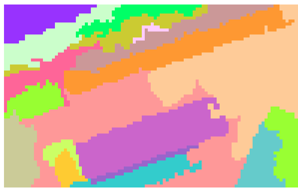
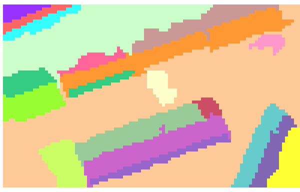


Battacharyya



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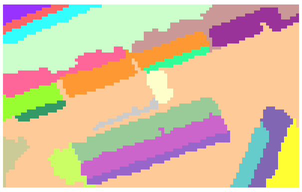
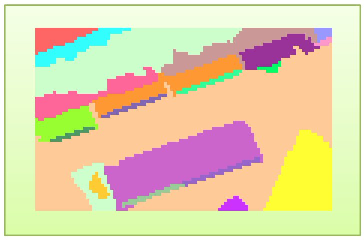
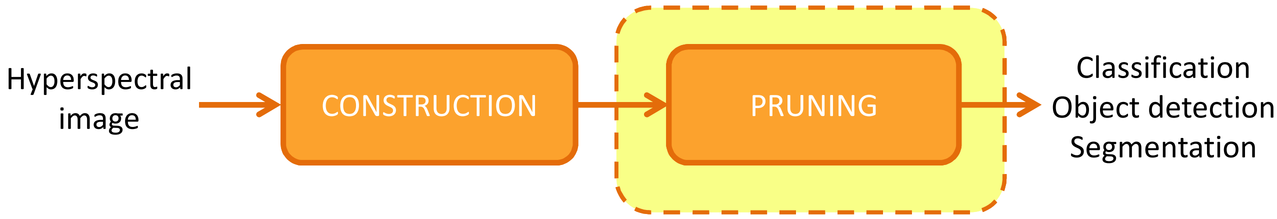


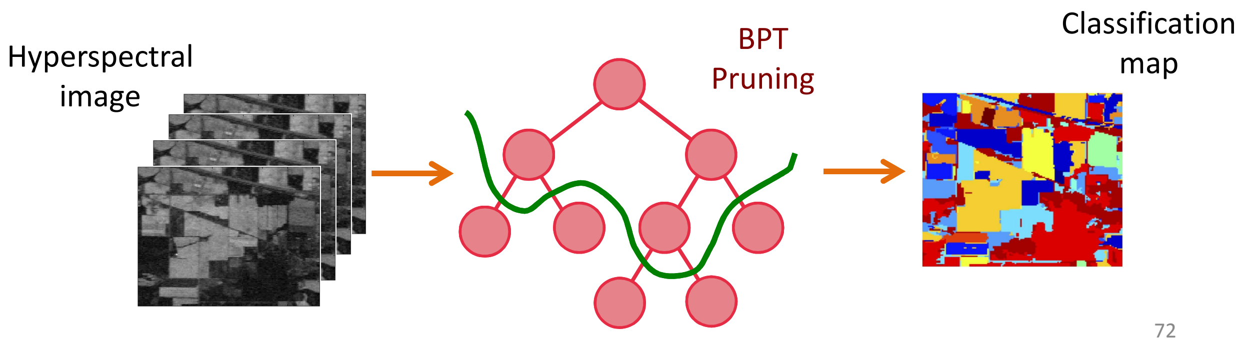
Our proposal



Aim: BPT for HS image analysis

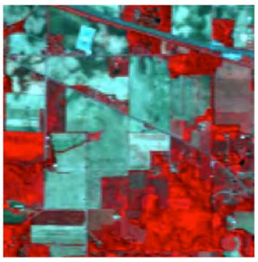


- Pruning strategy aiming at image classification is proposed

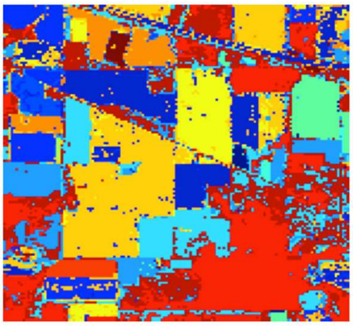


Aviris Indian Pines

Hyperspectral AVIRIS Indian Pines, 220 bands

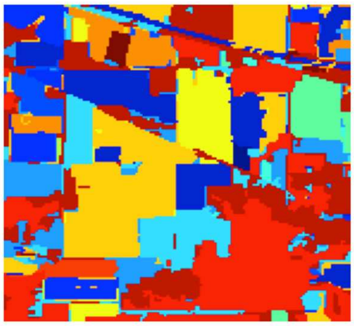


Pixel-wise classification using pixel-based representation



Total accuracy: 89.52%

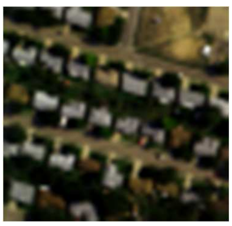
BPT classification pruning by selecting leaves of pruned BPT



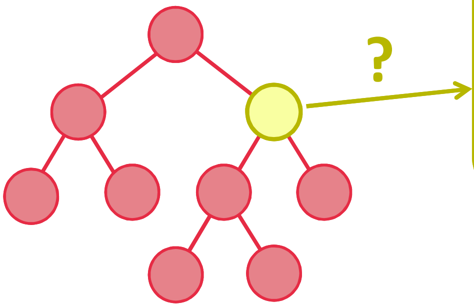
Total accuracy: 96%

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.



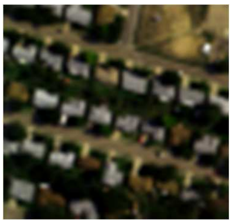
Hydice Hyperspectral image



Extraction of the roads as one node ?
→ Mixture of spectral characteristics and shape descriptors

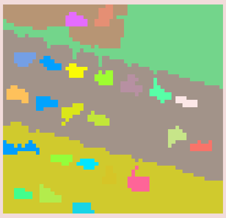
S. Valero, P. Salembier, J. Chanussot and C.M. Cuadras,
Improved Binary Partition Tree Construction for hyperspectral images: Application to object detection
IEEE - International Geoscience and Remote Sensing Symposium, 2011, Vancouver

Object Detection: Example of Roads

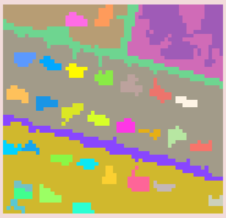


Hydice Hyperspectral image

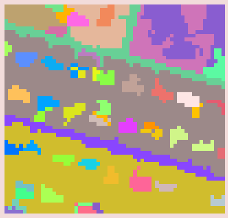
Partitions contained in BPT



27 regions



37 regions



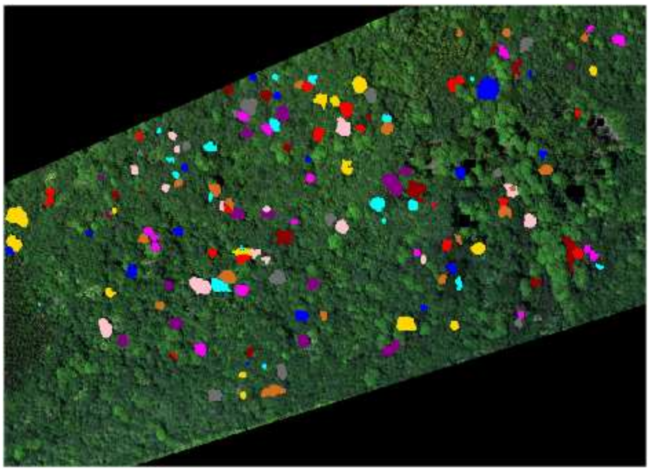
57 regions

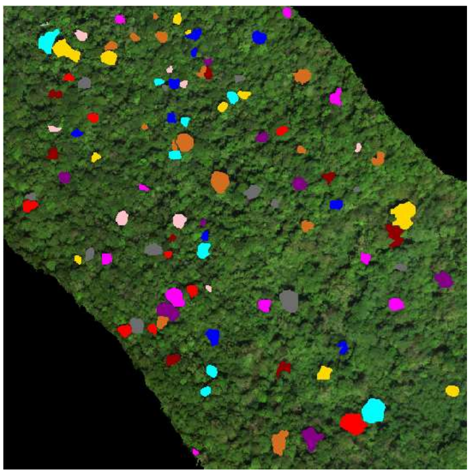
Road detection using pixel-wise asphalt detection

BPT pruning strategy oriented to object detection

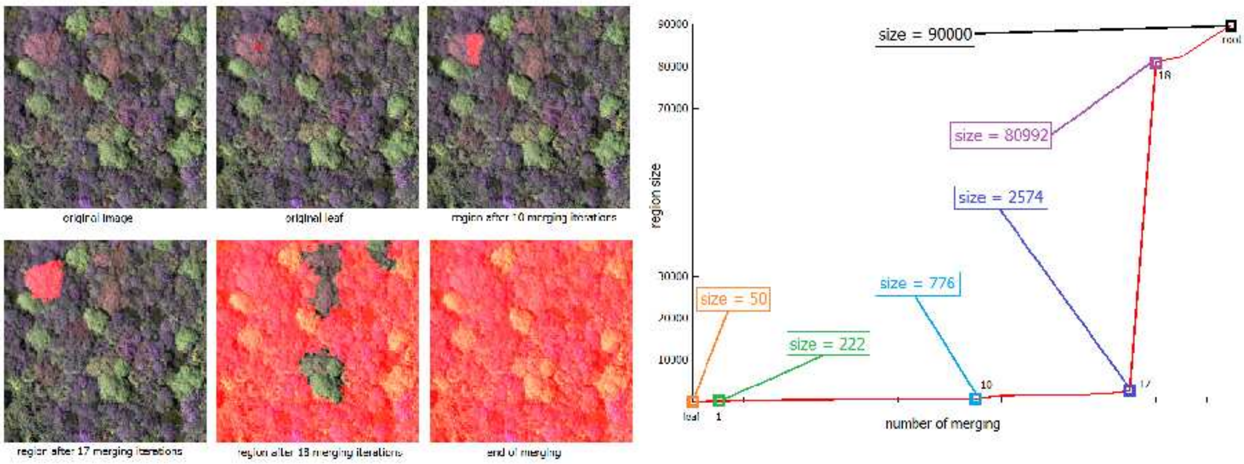
Application in rainforest

- 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



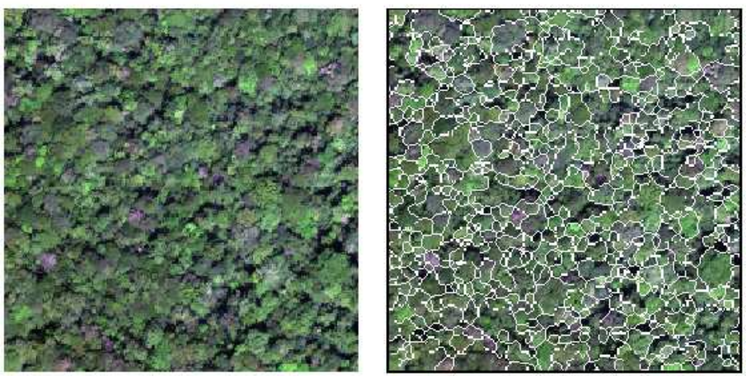
Application in rainforest

CARNEGIE INSTITUTION FOR SCIENCE

STANFORD UNIVERSITY

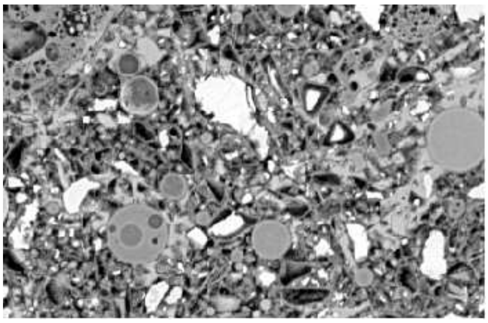
gipsa-lab

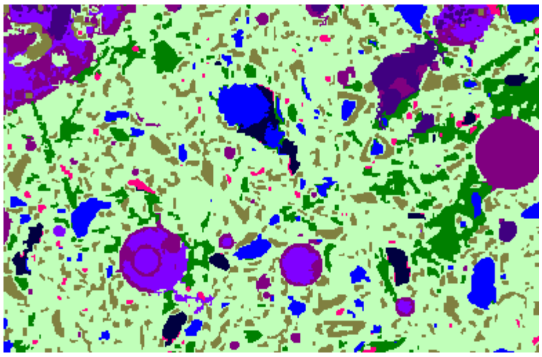
- ❖ Hawaii
- ❖ Panama



- ❖ Canopy species richness assessmennt 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

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
- Pruning of the BPT for Segmentation, Classification and Object Detection

5 **Conclusions**

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

- S.Valero, P.Salembier and J.Chanussot.
  Hyperspectral image representation and processing with Binary Partition Trees
  IEEE Transactions in Image Processing, 2013
- C.M. Cuadras, S. Valero, D. Cuadras, P. Salembier and J. Chanussot,
  Distance-based measure of association with applications in relating HS images,
  Communications in Statistics – Theory and Methods, 2012
- A. Alonso-Gonzalez, S. Valero, J. Chanussot, C. Lopez-Martinez, & Ph. Salembier
  Processing multidimensional SAR and hyperspectral images with BPT
  Proceedings of the IEEE, 2013
- 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

Community of communities

INRIA

ACTIMAR

FP7

CEA

GRETSI

SAGEM

ASTRIUM

ANR

DGA

TOTAL

GDR ISIS

THALES

CNES

SFTH / SFPT

OBS

ONERA

CNRS

IRSTEA

INRA

ASTRO/PLANETO/AGRO/BIOMED/MATERIALS/SECURITY/ENVIRONMEN