Morphological and Attribute Profiles for Classification of Hyperspectral Remote Sensing Imagery

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Outline

1. Introduction
   - Very High Resolution Remote Sensing
   - Hyperspectral Imagery

2. Morphological Profiles and Attribute Filters
   - Morphological and Attribute Profiles for Single Data Channels
   - Extended Morphological and Attribute Profiles

3. Optimized Feature Selection for Attribute Filters
   - HML Algorithm
   - APs and Spectral Information: Automatic vs. Manual

4. Conclusions

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Introduction: VHR Remote Sensing

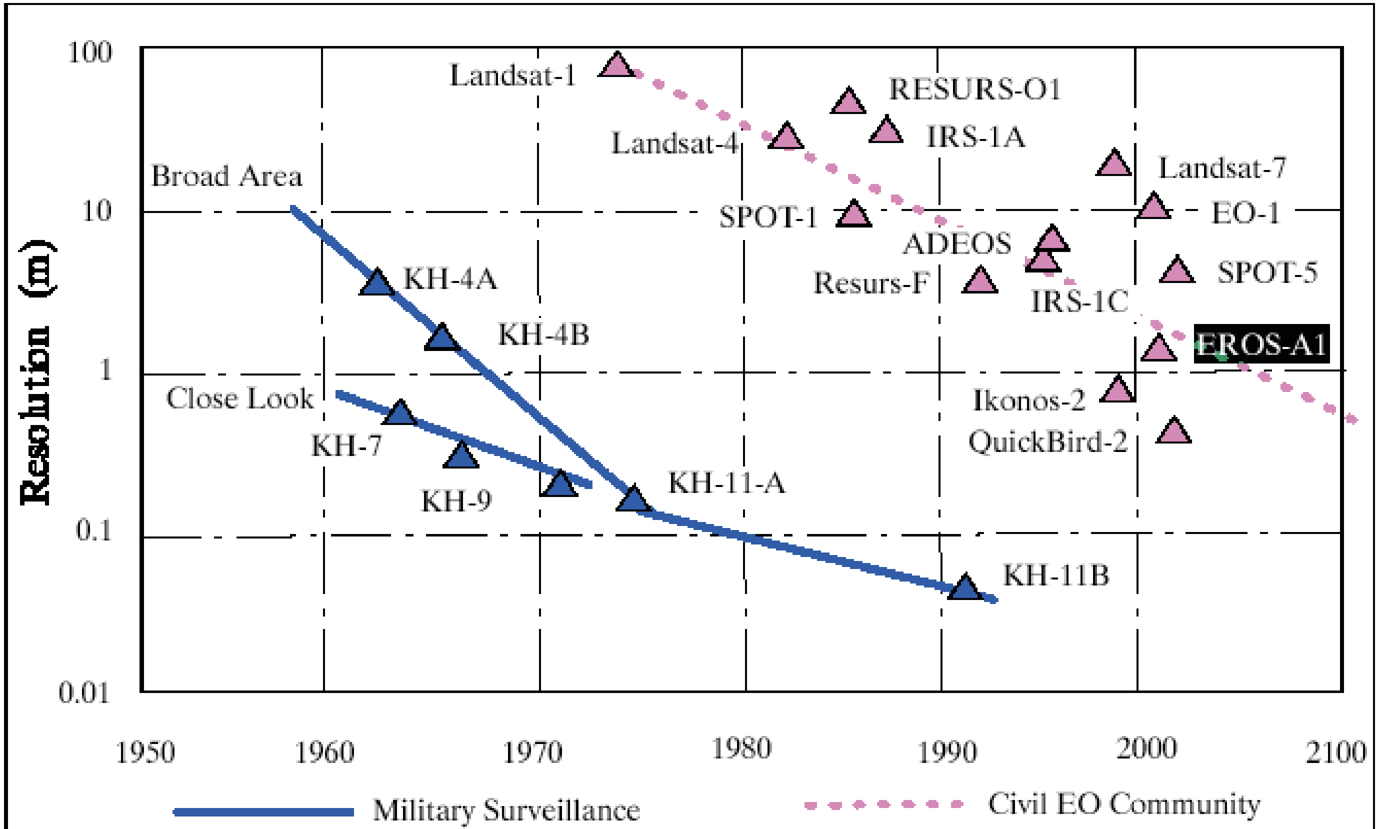
Remote sensing :
Observation of the Earth and the environment using airborne or satellite based sensors

Passive remote sensing : Optical sensors using the natural illumination from the sun

Active remote sensing : Radar systems

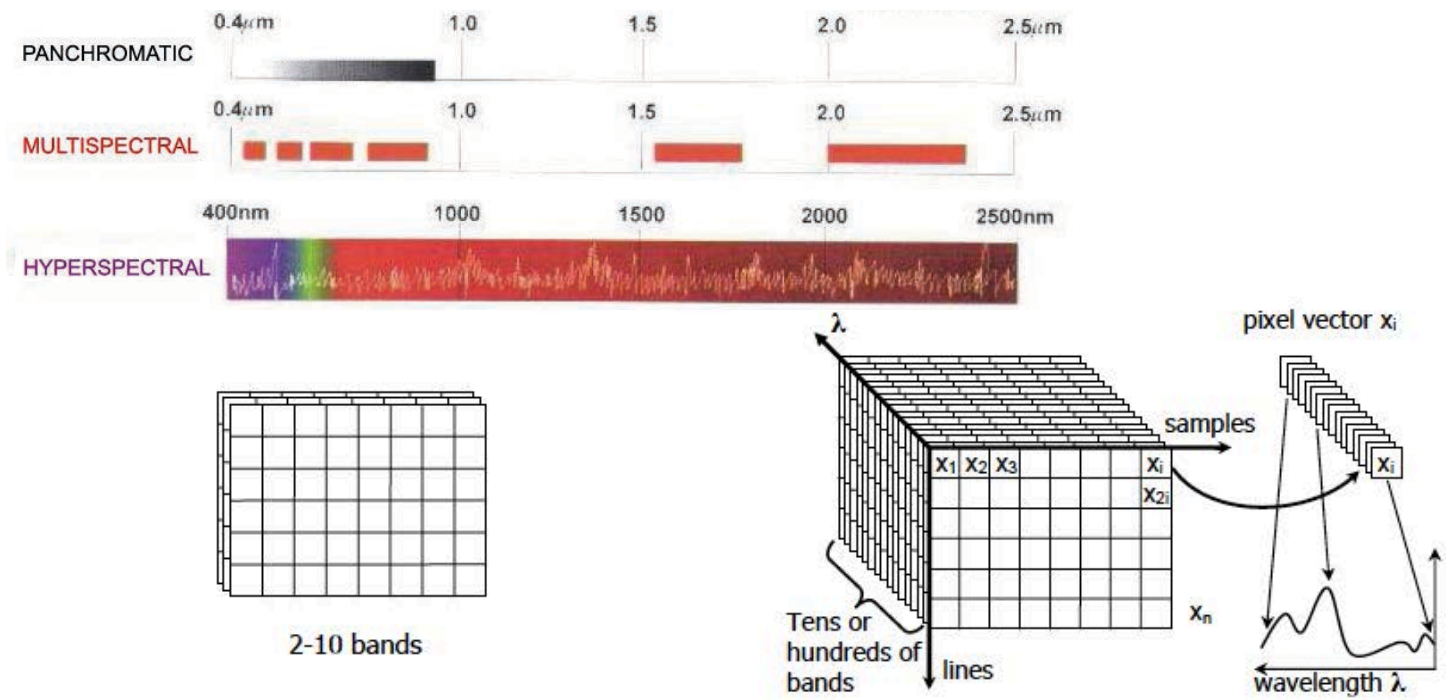
Very High Resolution (VHR) :
. Spatial resolution
. Spectral resolution
. Temporal resolution

Introduction: VHR Remote Sensing



Note: KH=Keyhole [designates several DoD reconnaissance satellite series, such as CORONA, ARGON, LANYARD, and LACROSSE - as well as the principal camera system of the S/C]

Introduction: VHR Remote Sensing



Panchromatic
. one grey level value per pixel

Multispectral
. 2-10 bands
. limited spectral info

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

Introduction: VHR Remote Sensing

Schönefeld airport
Landsat

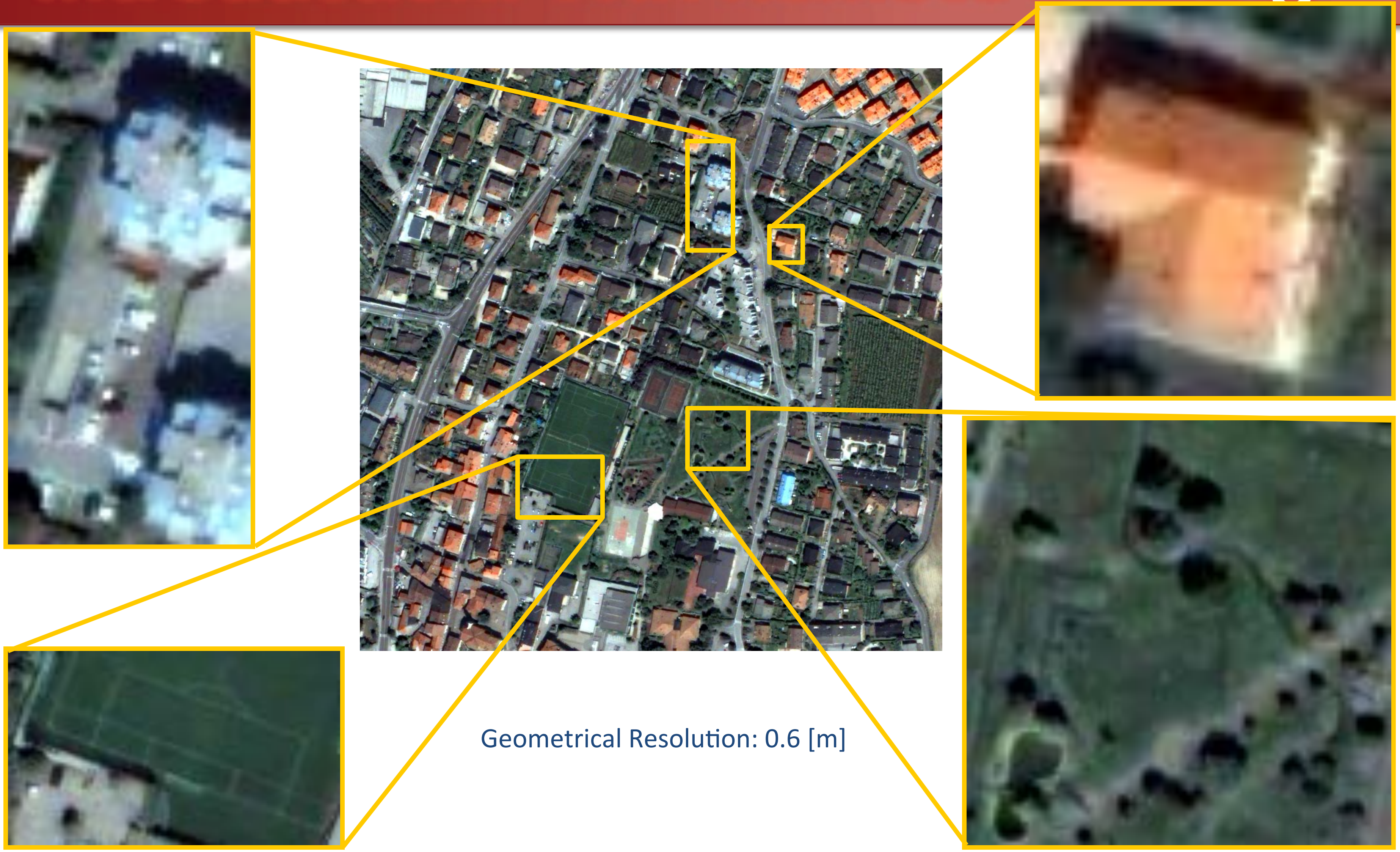
Introduction: VHR Remote Sensing

Reykjavik
Ikonos

Introduction: VHR Remote Sensing

Sunnyvale airport
Quickbird
Multispectral diversity

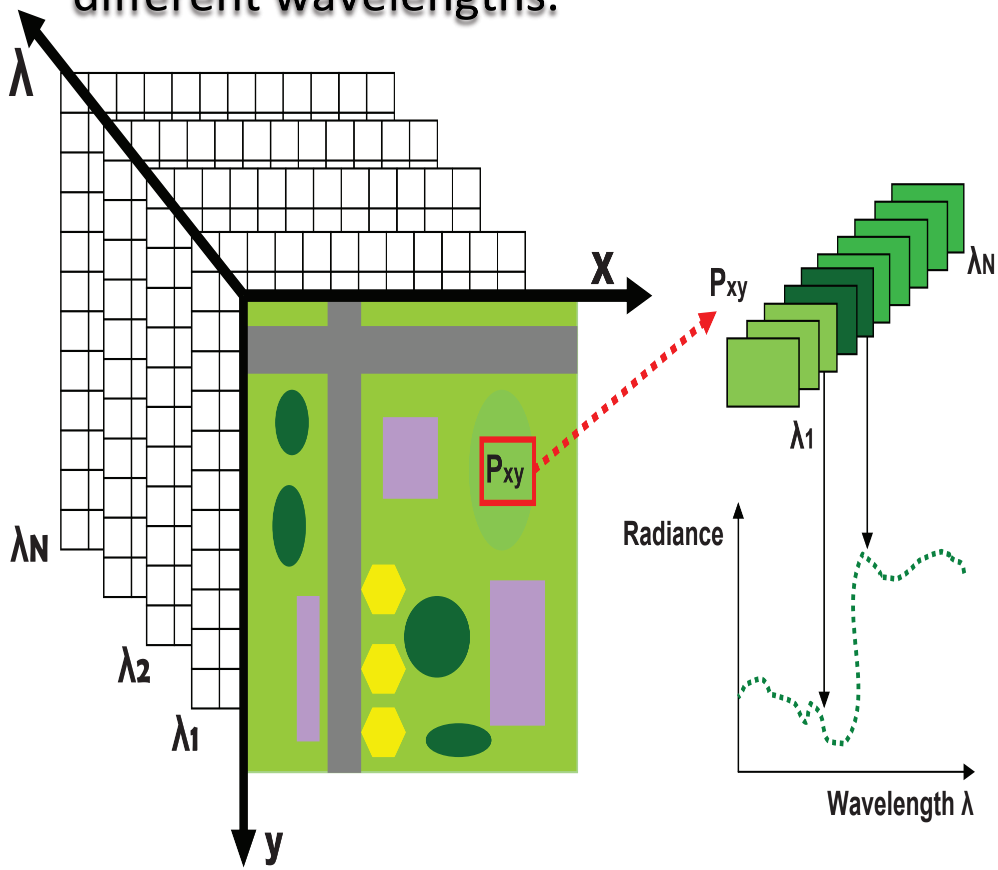
Introduction: VHR Remote Sensing



Geometrical Resolution: 0.6 [m]

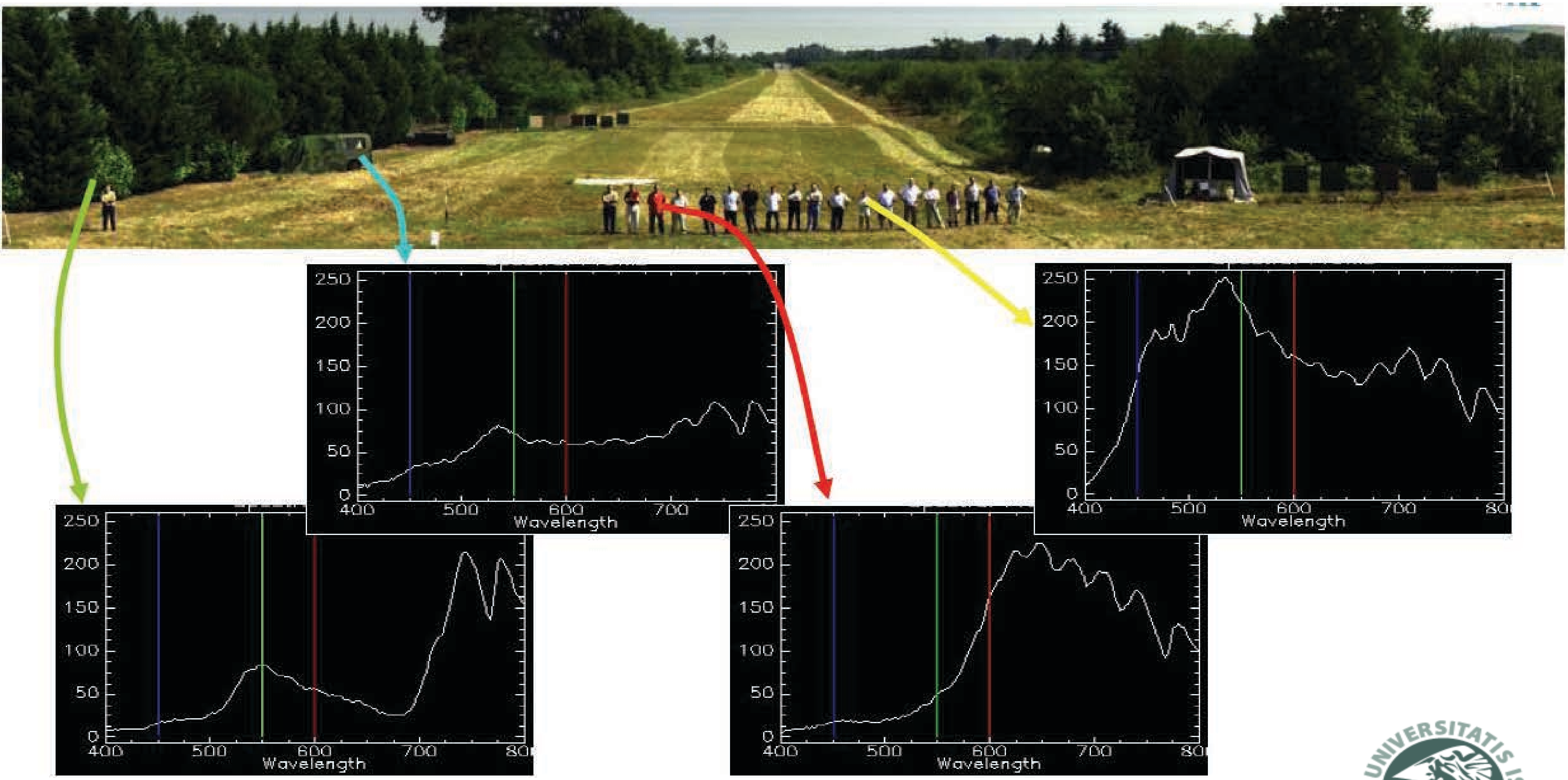
Hyperspectral Imagery

- 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

Hyperspectral Imagery

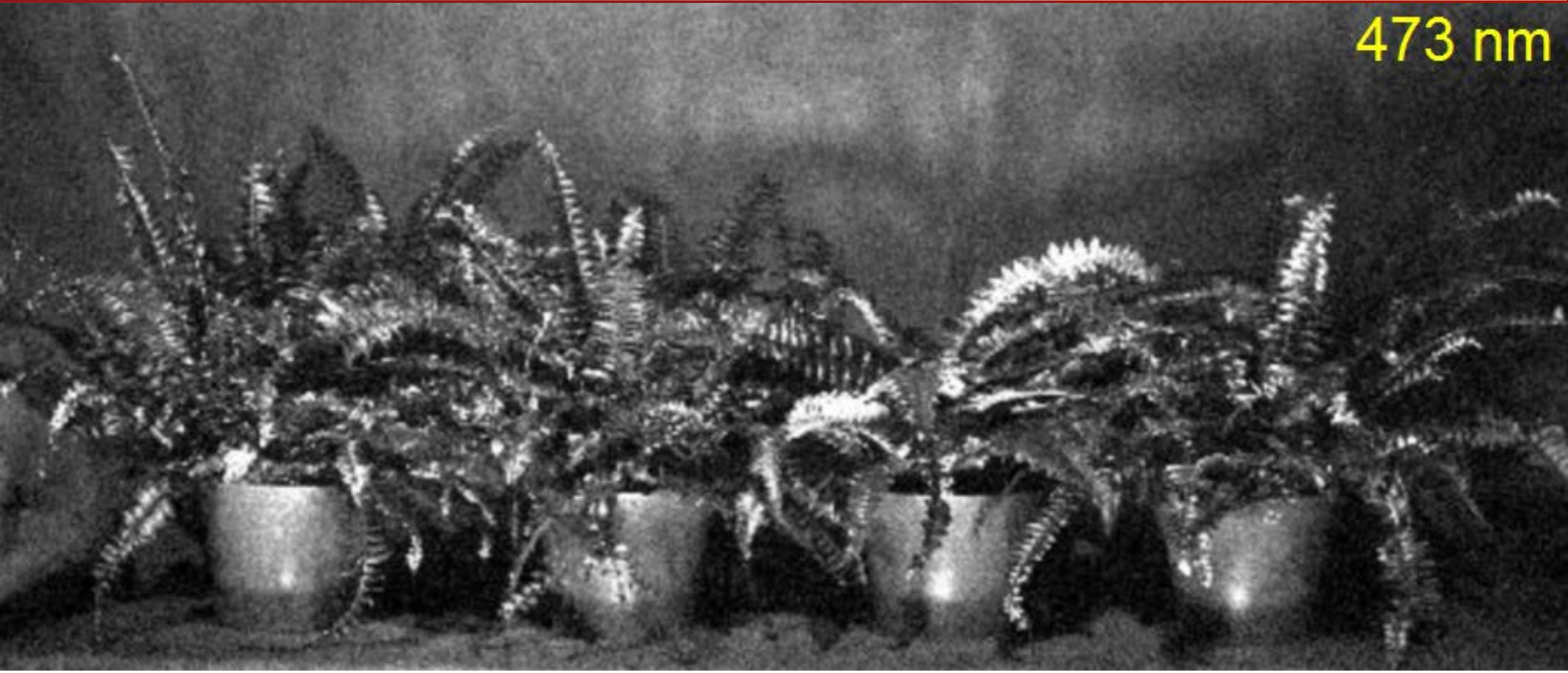


Improved spectral diversity : hyperspectral imagery

Hyperspectral Imagery

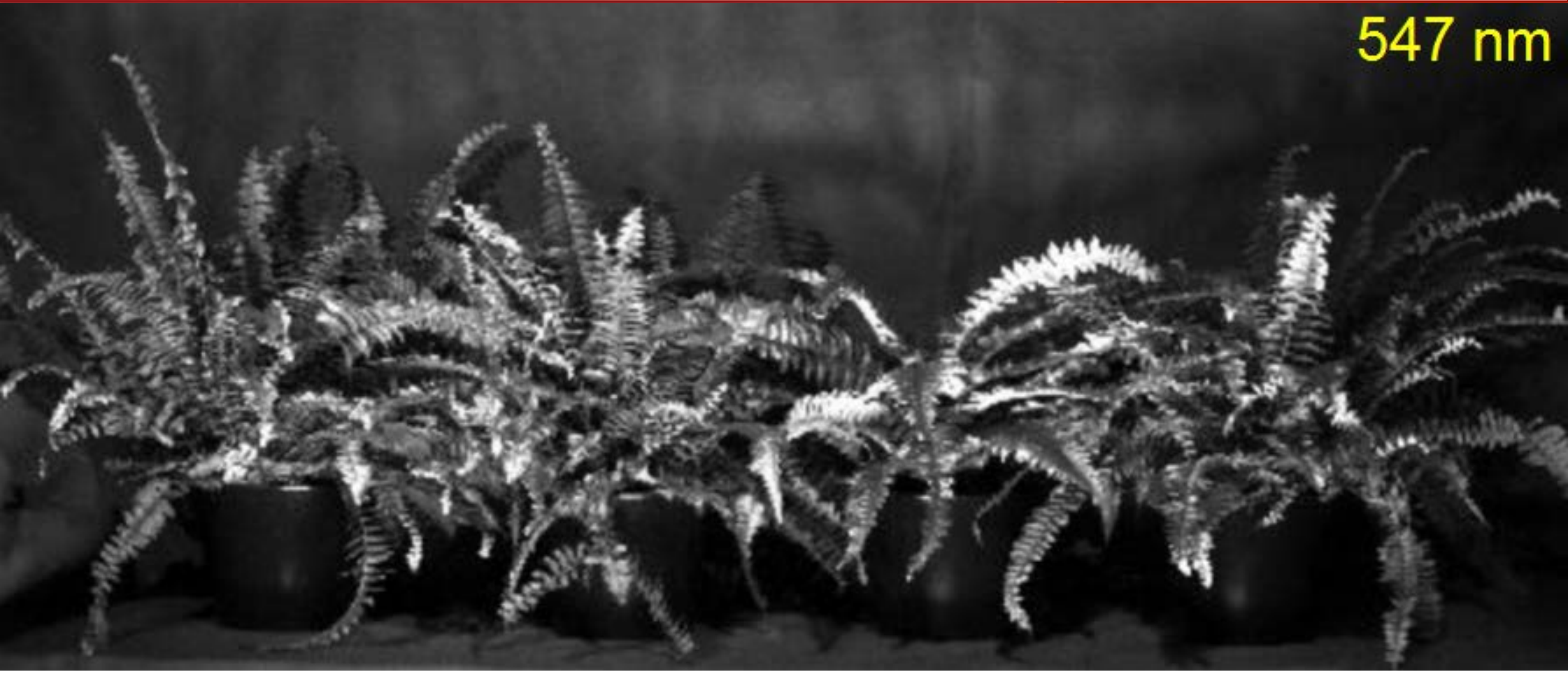
Anything wrong ?

Hyperspectral Imagery



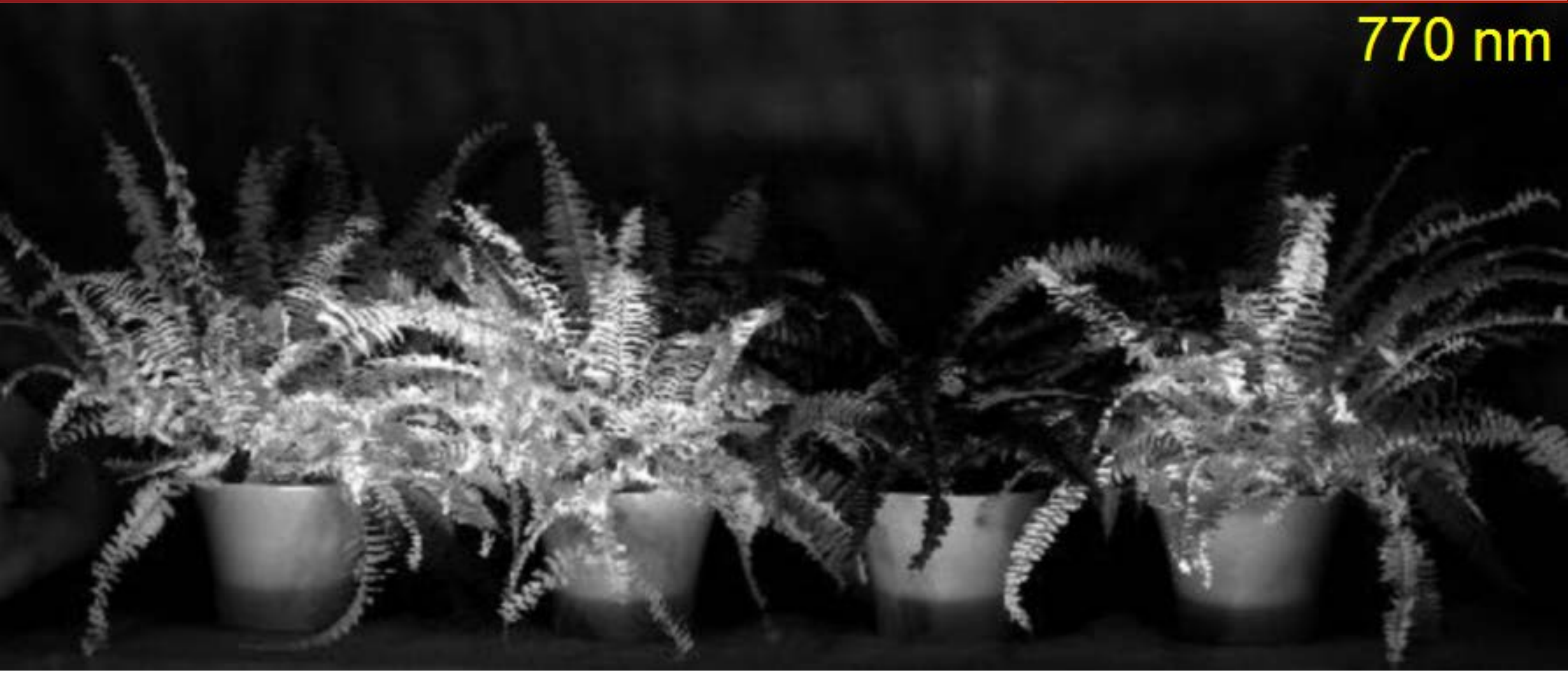
Anything wrong ?

Hyperspectral Imagery



Anything wrong ?

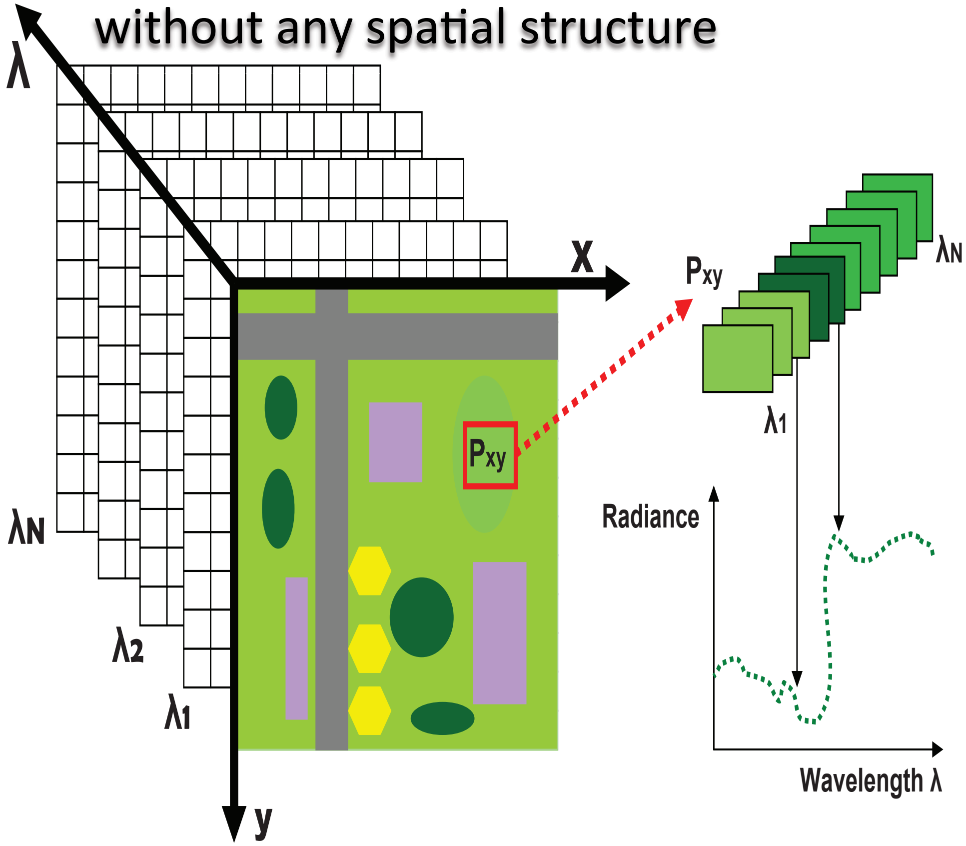
Hyperspectral Imagery



Spectral diversity provides a refined physical description of the material

Hyperspectral Imagery

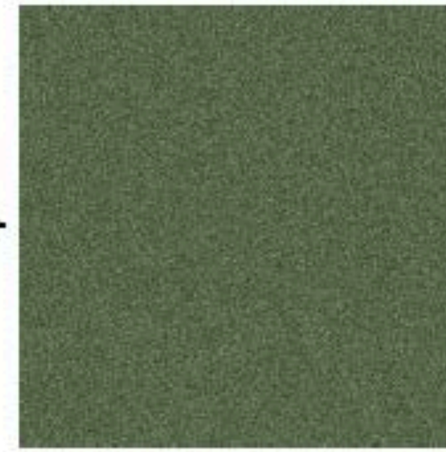
- Different analysis techniques have been proposed in the literature processing the pixels individually, as an array of spectral data without any spatial structure



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

Spectral *vs* Spatial Analysis

→ Random permutation →



Spectral classification → Same classification !! ← Spectral classification

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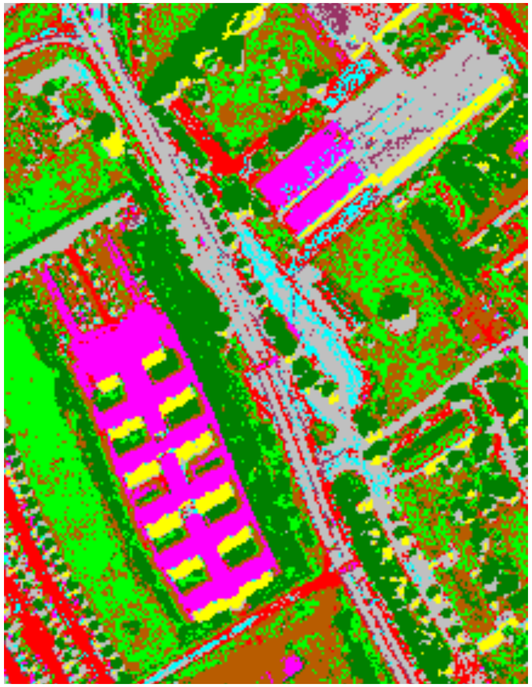
Need to incorporate information from the spatial domain

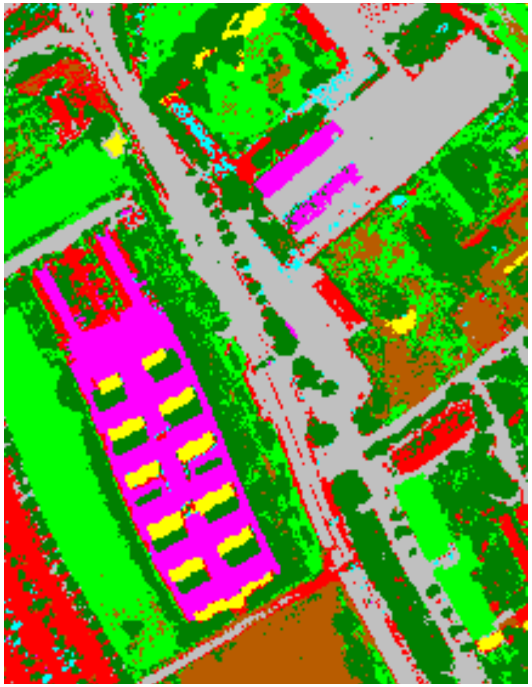
Spectral *vs* spatial analysis

Examples of maps obtained by classifying different features

True color image



Spectral features



Spectral + Spatial features

When dealing with images with high geometrical resolution, the use of spatial features increases the discrimination of the thematic classes leading to more accurate results.

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 **Morphological Filters**, before performing the pixelwise classification.

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Morphological & Attribute Profiles

High complexity of the scene (e.g., heterogeneous objects, huge amount of details)

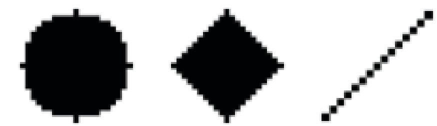
Extract the informative components (e.g., by reducing the image complexity)

Geometrical features and spatial details are perceptually significant and they have to be preserved

The spatial information has to be properly modeled in the analysis

Morphological & Attribute Profiles

f



Examples of
Structuring Elements (SEs).

Mathematical Morphology - Basic Operators

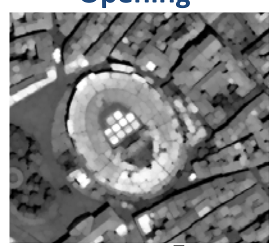
Erosion

ε_B

Dilation

δ_B

Opening

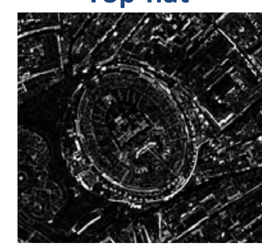


$\gamma_B(f) = \delta_{\breve{B}}\left[\varepsilon_B(f)\right]$

Closing

$\phi_B(f) = \varepsilon_{\breve{B}}\left[\delta_B(f)\right]$

Top-hat



$WTH = f - \gamma(f)$

Morphological & Attribute Profiles

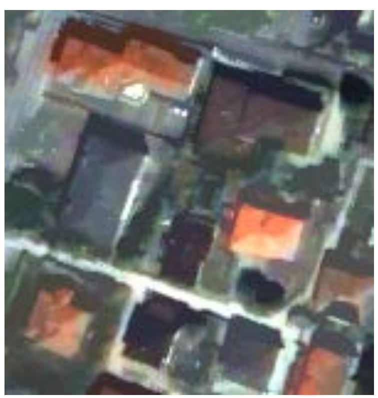
Morphological Connected Filters

They either completely remove or entirely preserve a structure in the image

They do not distort shape of structures nor introduce new edges

SUITABLE FOR THE ANALYSIS OF VERY HIGH RESOLUTION (VHR) IMAGES


Morphological closing


Closing with a connected filter


Original VHR image

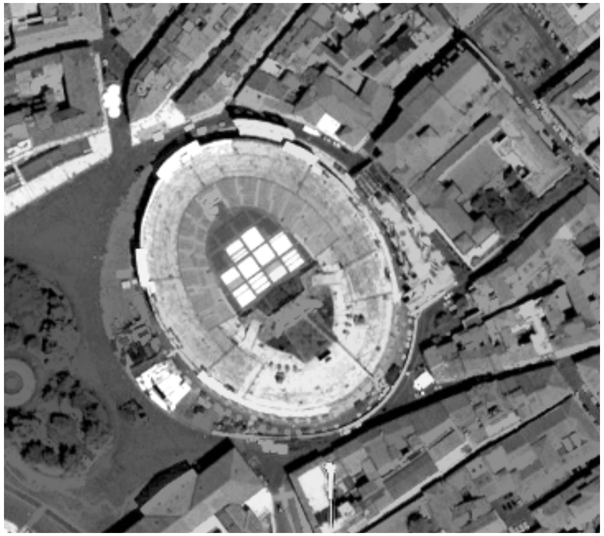

Opening with a connected filter


Morphological opening

Examples of conventional Morphological operators and Connected Filters

Morphological & Attribute Profiles

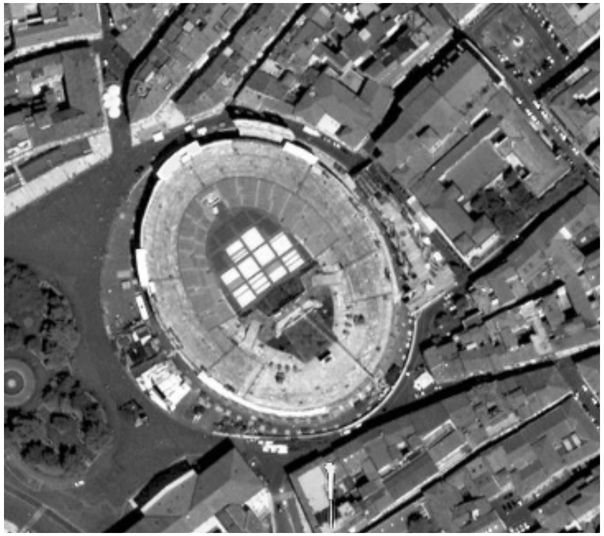
Operators by Reconstruction



Opening

$$\gamma_R^{(n)}(f) = R_f^{\delta}[\varepsilon^{(n)}(f)]$$

Reconstruction by dilation



Original Image

Closing

$$\phi_R^{(n)}(f) = R_f^{\varepsilon}[\delta^{(n)}(f)]$$

Reconstruction by erosion

Two step procedure:

1. Erosion/Dilation
2. Reconstruction by dilation/erosion

Morphological Opening

$$\gamma_B(f) = \delta_{\breve{B}}[\varepsilon_B(f)]$$

Opening by reconstruction

$$\gamma_R^{(n)}(f) = R_f^{\delta}[\varepsilon_B(f)]$$, with *n* size of B

Geodesic Reconstruction

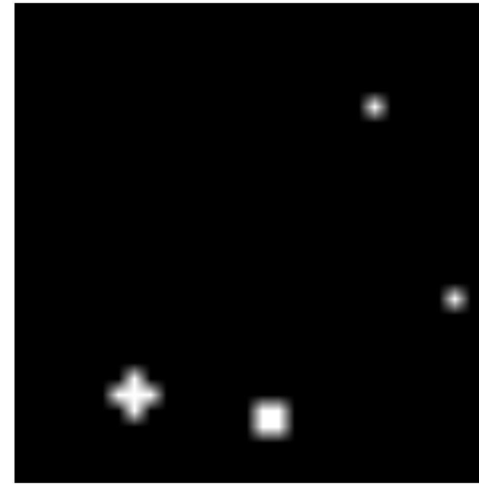
$$R_f^{\delta}(\cdot) = \delta_f^{(i)} = \underbrace{\delta_f^{(1)} \cdot \delta_f^{(1)} \dots \delta_f^{(1)}}_{i\ times}(\cdot)$$

Iterative Process

Idempotence property

$$\delta_f^{(i)}(\cdot) = \delta_f^{(i-1)}(\cdot)$$

f (30x30 binary image)



$\varepsilon_B(f)$

i = 27

i = 1, 2, 10, 20

SE: Disk diameter 5

Morphological & Attribute Profiles

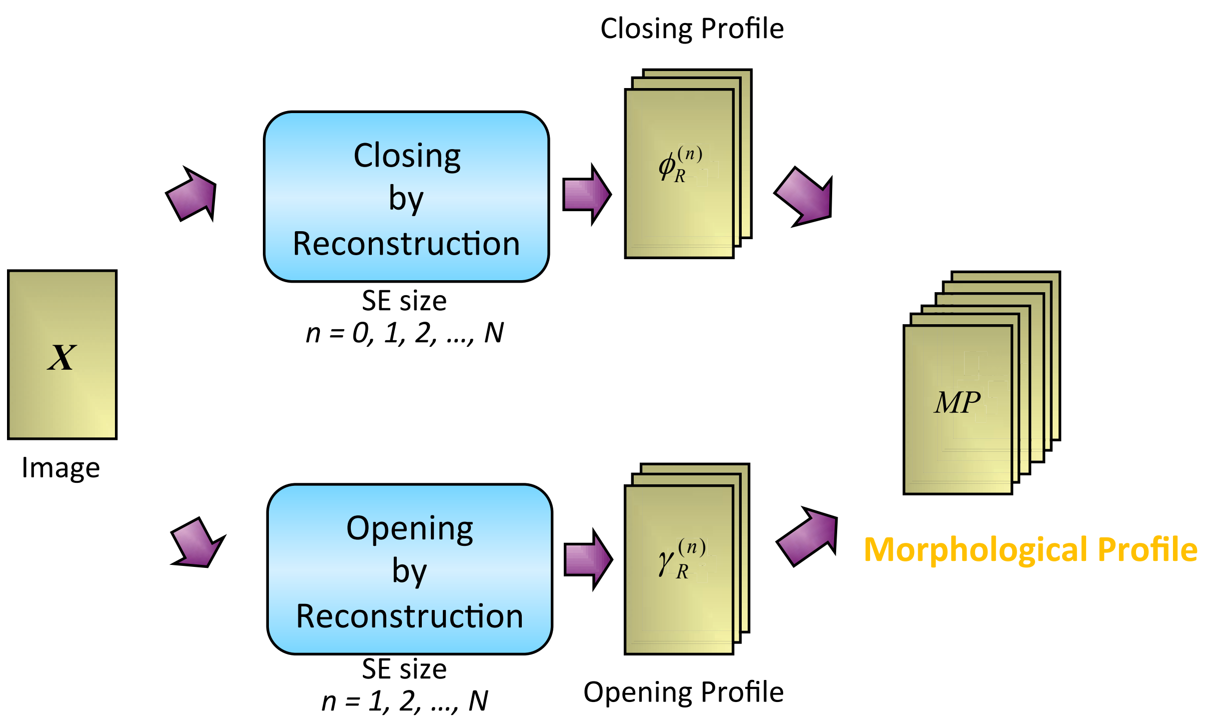
When dealing with real images it is difficult to identify a single filter parameter suitable to handle all the objects in the image

Perform a multilevel analysis by using several values for the filter parameters. Build a stack of images with different degrees of filtering

Morphological Profile (MP)

M. Pesaresi and J. A. Benediktsson, "A new approach for the morphological segmentation of high-resolution satellite imagery," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 39, no. 2, pp. 309-320, 2001.

Morphological & Attribute Profiles



Morphological & Attribute Profiles

Morphological Profiles (MPs) composed by a sequence of opening and closing with SE of increasing size.

Differential Morphological Profiles (DMPs) compute the residuals between adjacent levels of the MPs.

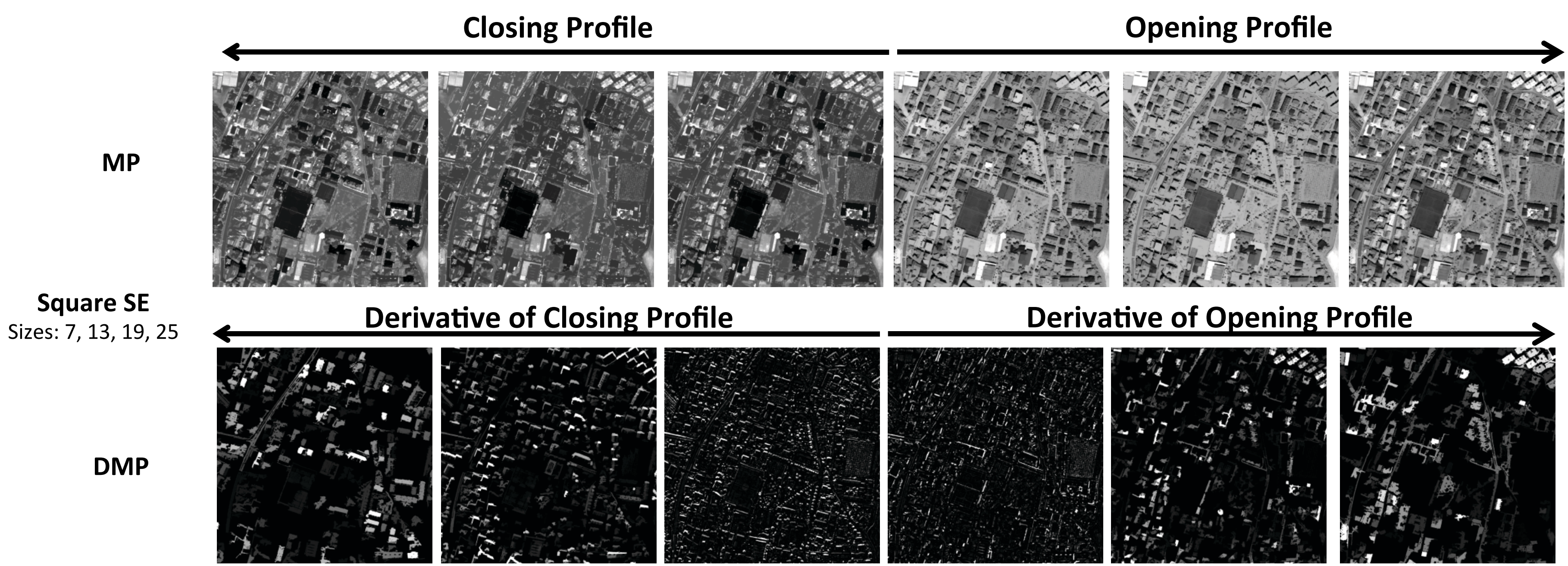
MP:

$$\Pi_\gamma = \left\{ \Pi_\gamma(i) : \Pi_\gamma(i) = \gamma_R^{(S_i)}(f) \right\} \quad i = 0,1,\ldots k$$

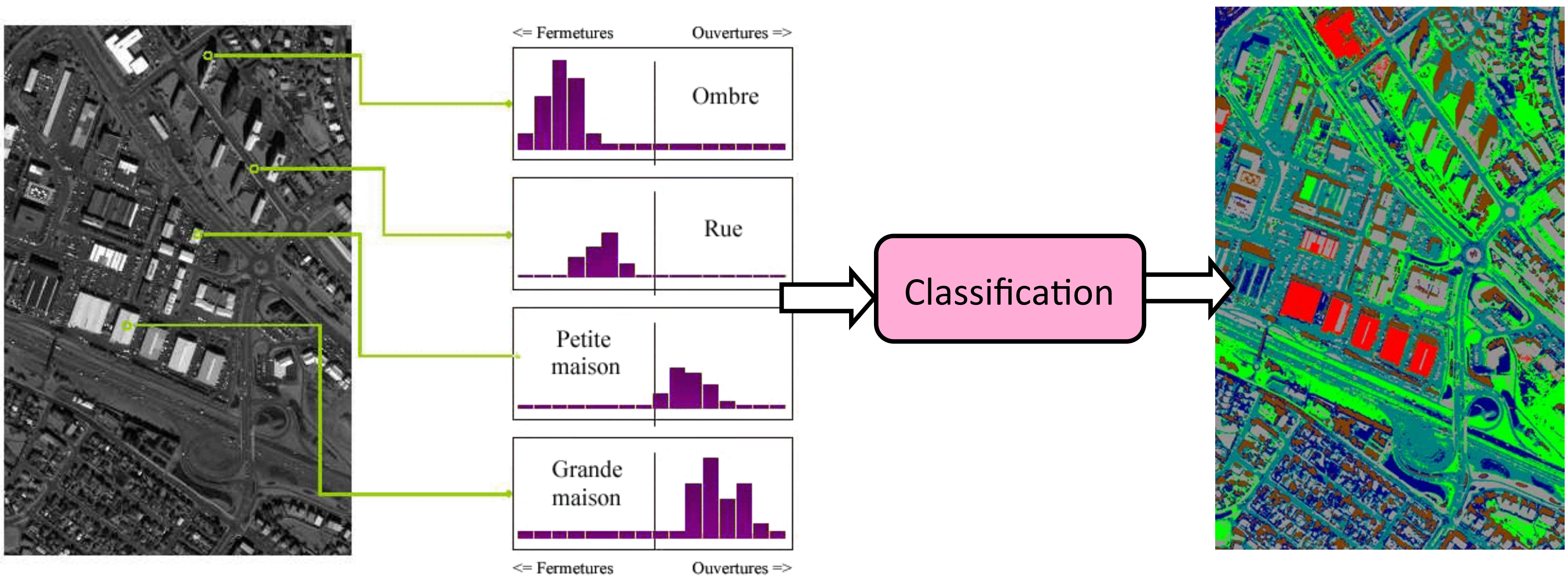
DMP:

$$\Delta_\gamma = \left\{ \Delta_\gamma(i) : \Delta_\gamma(i) = \left| \Pi_\gamma(i) - \Pi_\gamma(i-1) \right| \right\} \quad i = 1,\ldots k$$

$$\Delta_\phi = \left\{ \Delta_\phi(i) : \Delta_\phi(i) = \left| \Pi_\phi(i) - \Pi_\phi(i-1) \right| \right\} \quad i = 1,\ldots k$$



Morphological & Attribute Profiles



Morphological profiles (granulometries) with connected operators (standard openings and closings by reconstruction) have been extensively used for the analysis of remote sensing data.

Morphological & Attribute Profiles

Attribute Profiles are an extension of Morphological Profiles

- ✓ Drawbacks of MP:
  - ✓ Computational complexity - the standard implementation is $O(N^2)$ with N the number of pixels in the image.
  - ✓ Processing limited to the analysis of the scale.
  - ✓ Limitation in the characterization of the features to be modeled due to the usage of structuring elements.

- ✓ Morphological Attribute Filters have the following advantages:
  - ✓ Perform the processing with a reduced computational load, especially for multilevel analysis.
  - ✓ Model different types of features not necessarily related to the scale of the regions (i.e., texture, contrast, etc.).
  - ✓ Great freedom in the definition of the attributes employed in the filtering.

M. Dalla Mura, J. A. Benediktsson, B. Waske, and L. Bruzzone, "Morphological attribute profiles for the analysis of very high resolution images," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 48, no. 10, pp. 3747 – 3762, Oct. 2010.

Morphological & Attribute Profiles

Attribute filters are similar to operators by reconstruction since they are connected component transformations.

They either completely remove or entirely preserve a structure in the image.

They do not distort structures' shape nor introduce new edges.

Attribute filters are more general than operators by reconstruction because they can transform the image according to other attributes rather than shape and size of the structuring element used.

E. J. Breen and R. Jones, "Attribute openings, thinnings and granulometries," *Comput. Vis. Image Understand., vol. 64, no. 3, pp. 377–389,* 1996.

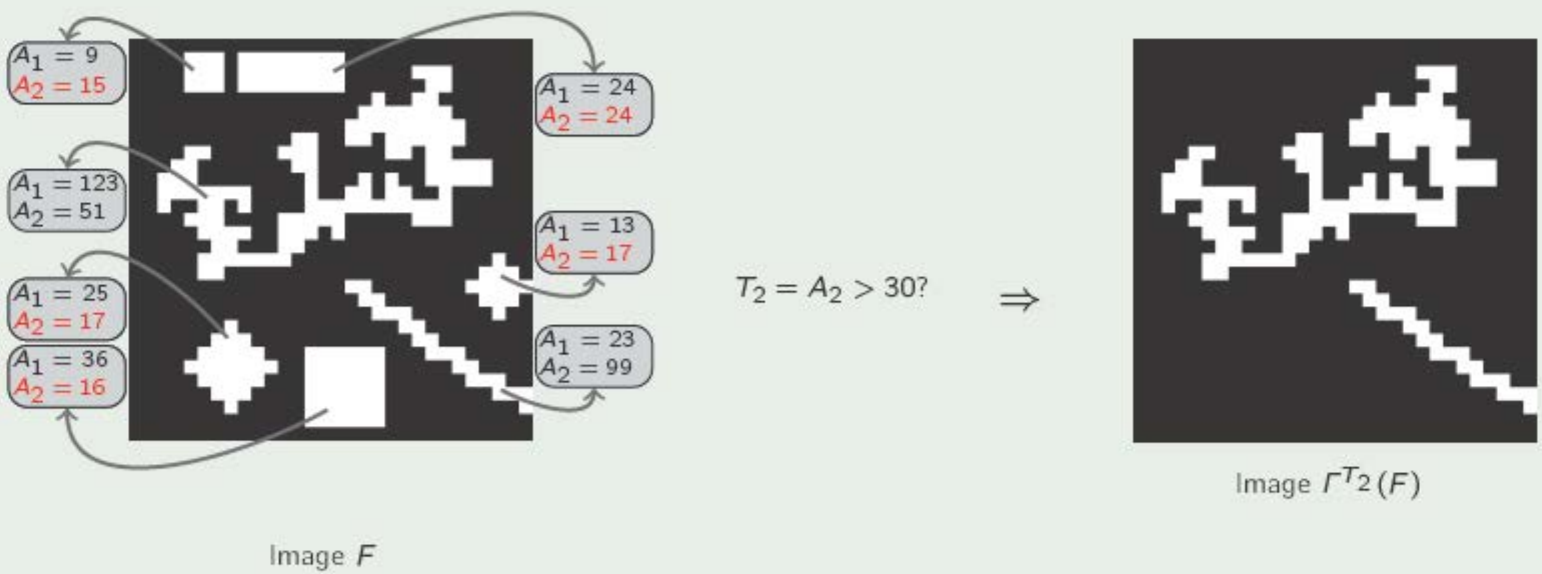
Morphological & Attribute Profiles

Attribute filters operate only on the connected components (regions of connected iso-level pixels) according to a criterion T which evaluates an attribute A against a threshold λ.

Attribute filters are based on the following operations:

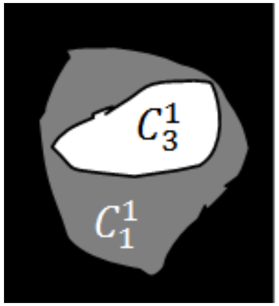
- ✓ Compute attribute for each connected component in the image;
- ✓ Keep the components that satisfy the criterion (e.g., $A > \lambda$).

Example



Morphological & Attribute Profiles

Increasing property. A criterion is satisfied for a connected region *R* it will also be satisfied for all those regions that include *R.*



✓If the criterion is increasing we have an attribute opening/thickening.
✓If the criterion is non-increasing we have an attribute closing/thinning.

Examples of criteria.

- ✓ Area
- ✓ Volume
- ✓ Lenght of the diagonal of the bounding box
- ✓ Area of the largest enclosed square.

Increasing criteria.

- ✓ Perimeter
- ✓ Shape index
- ✓ Moment of inertia
- ✓ Range of the pixels intensities

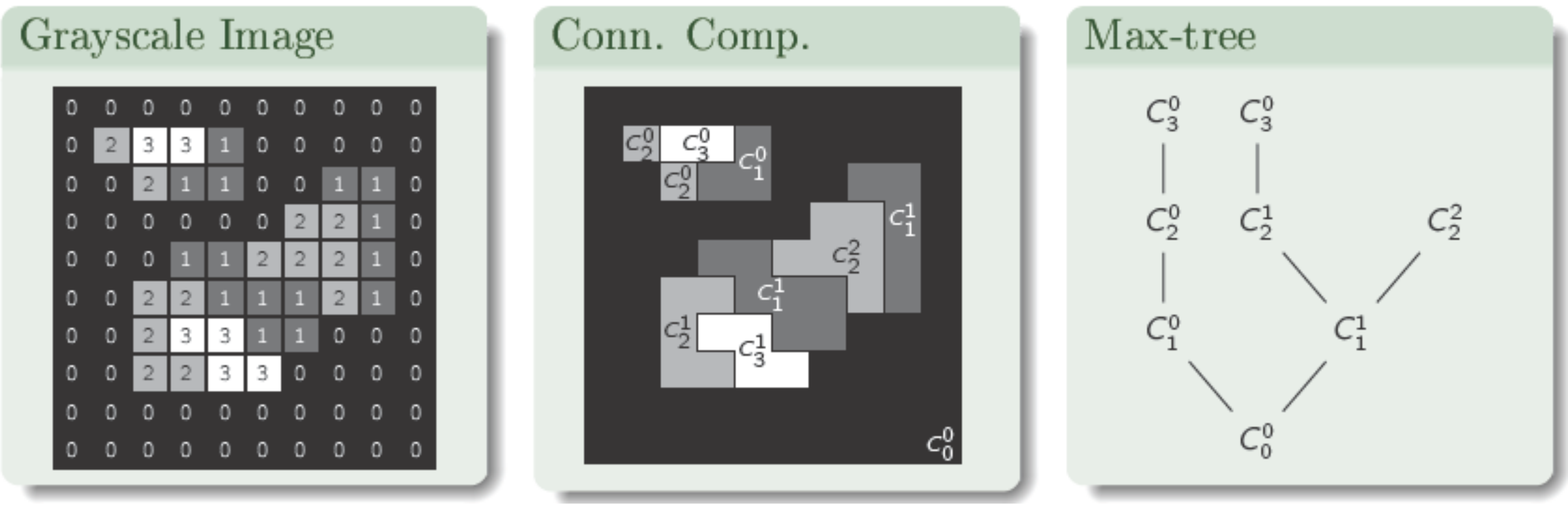
Non-increasing criteria.

Max-Tree

The Max-tree is an efficient image representation that associates all the regions in the image to nodes of a tree.

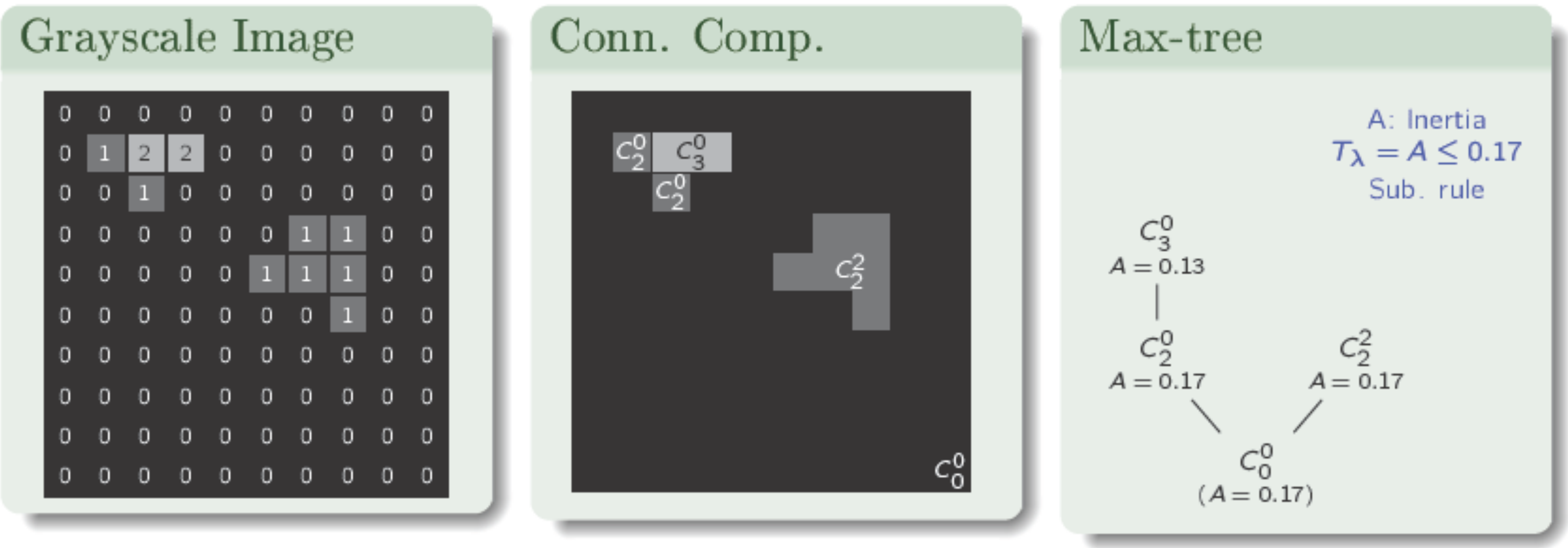
The depth of the tree refers to the gray-scale value.

The filtering stage is done by pruning the tree.



P. Salembier, A. Oliveras, and L. Garrido, "Anti-extensive connected operators for image and sequence processing," *IEEE Trans. Image Process., vol. 7, no. 4, pp. 555–570, Apr. 1998.*

Attribute Filters – Max-Tree



Filtering procedure:

1. Create the max-tree of the image
2. Compute the attribute A on each connected component (node in the tree) of the image
3. Evaluate the criterion T on all the nodes of the tree
4. Prune the tree by removing the nodes that do not fulfill the criterion
5. Transform the filtered tree back to an image

Morphological & Attribute Profiles

- ✓ In the filtering process, the Max-Tree creation takes ~99% of the total processing time.
- ✓ The time needed for filtering (i.e., pruning) and restituting the filtered image are negligible.

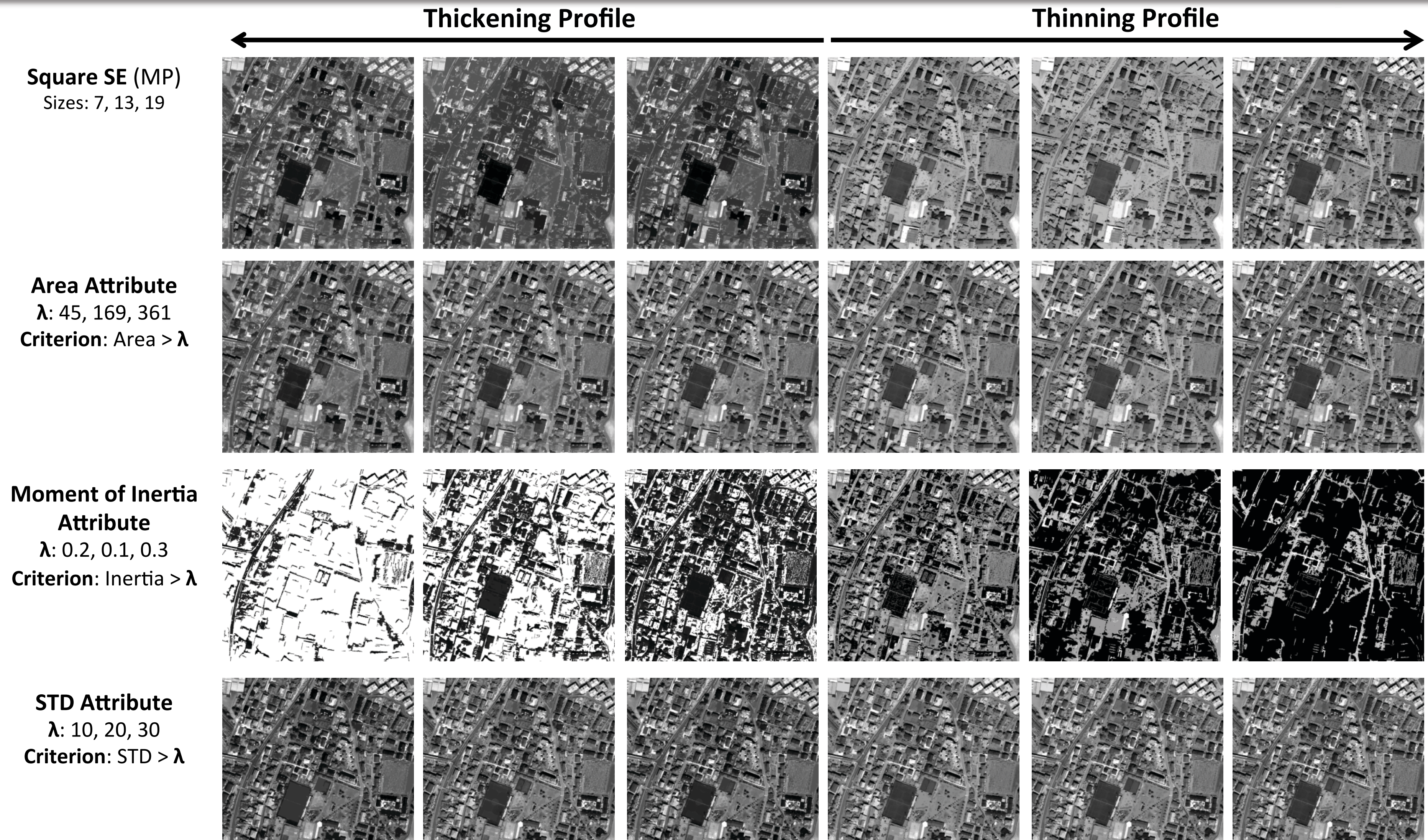
- ✓ Once the Max-Tree of an image is created and the attributes are computed for each node, it can be filtered multiple times according to different thresholds of the criterion without a significant increase in the processing time.

Efficient computation of granulometries (e.g., MPs).

- ✓ When using operators based on structuring elements, each threshold used by the criterion (e.g., size of the SE) needs to entirely process the image.

SLOW!

Morphological & Attribute Profiles



Morphological & Attribute Profiles

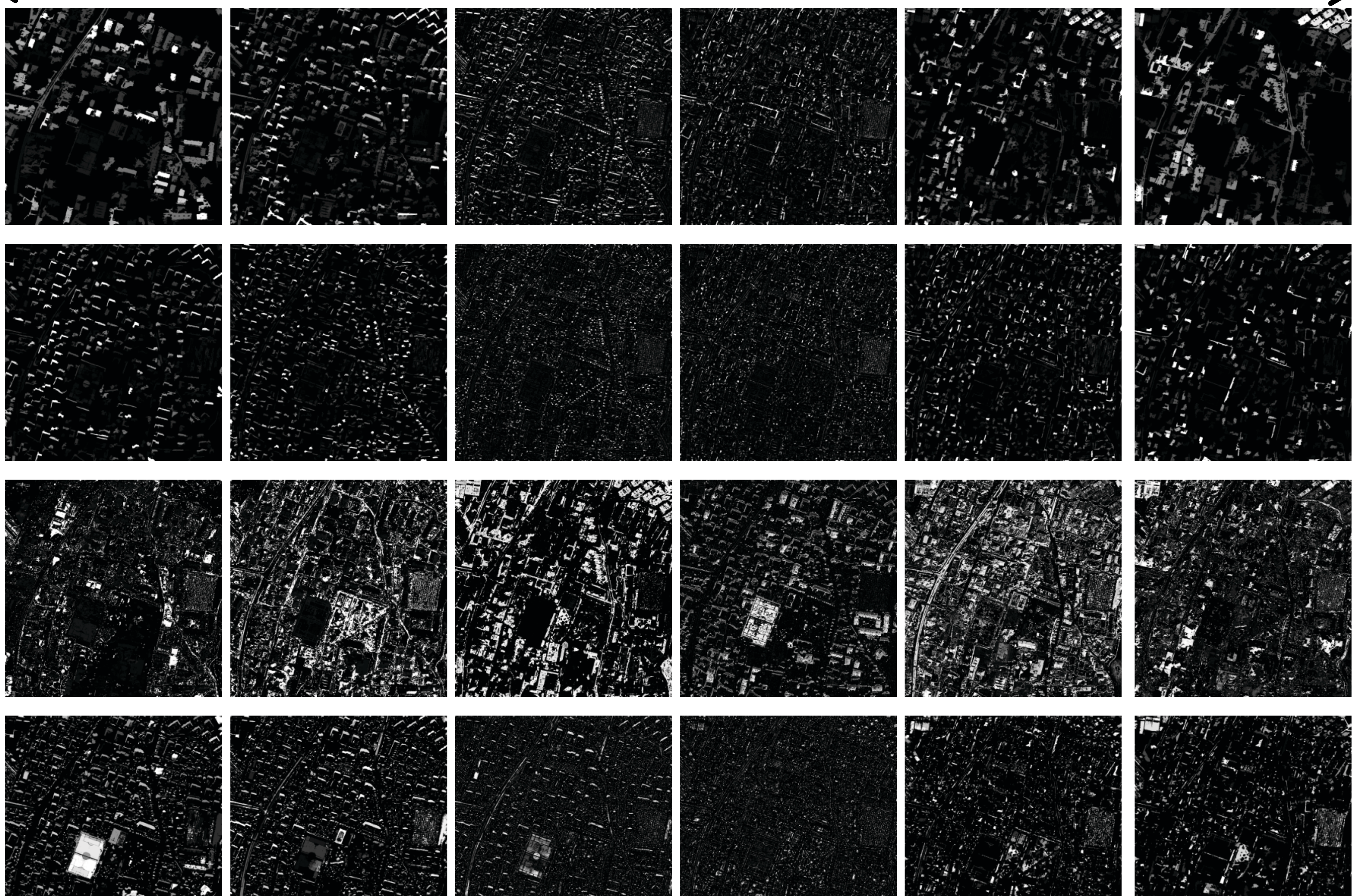
Derivative of Thickening Profile | **Derivative of Thinning Profile**

Square SE (DMP)
Sizes: 7, 13, 19

Area Attribute
λ: 45, 169, 361
Criterion: Area > **λ**

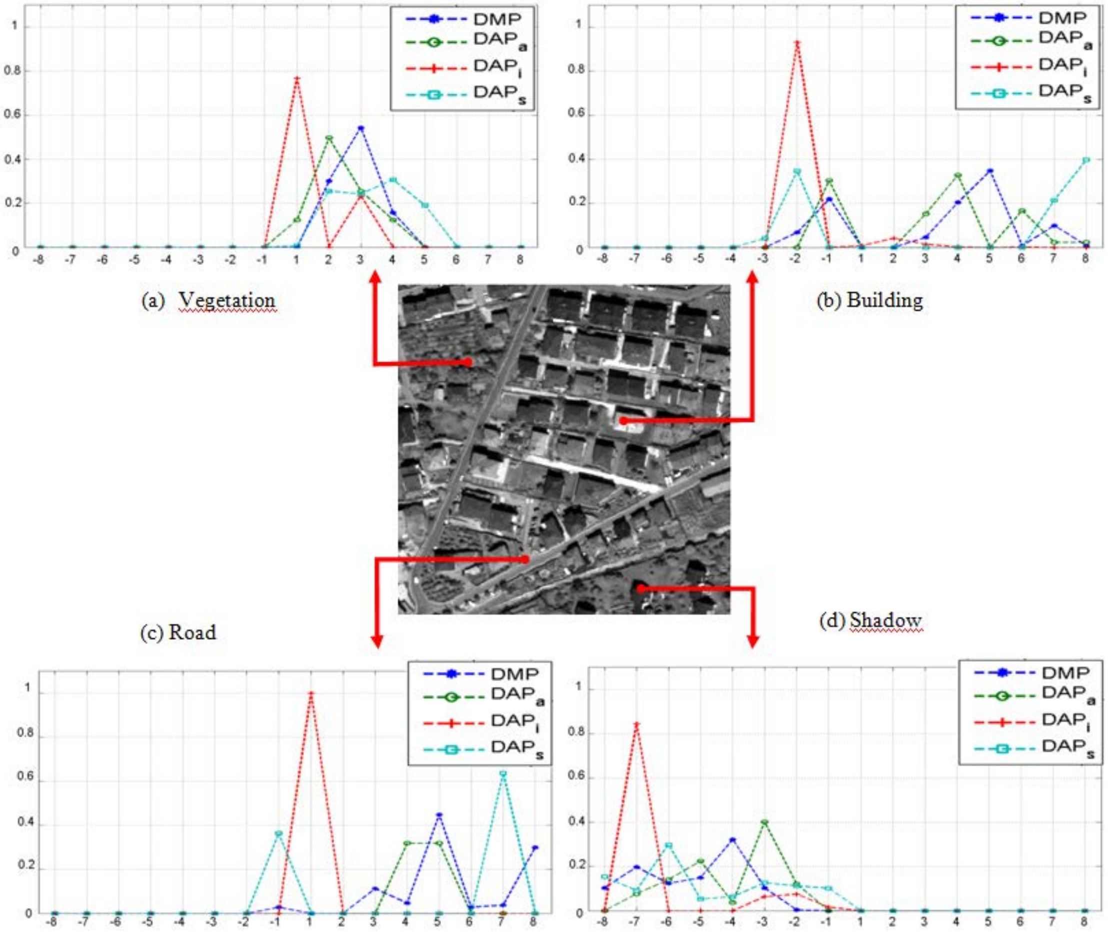
Moment of Inertia Attribute
λ: 0.2, 0.1, 0.3
Criterion: Inertia > **λ**

STD Attribute
λ: 10, 20, 30
Criterion: STD > **λ**

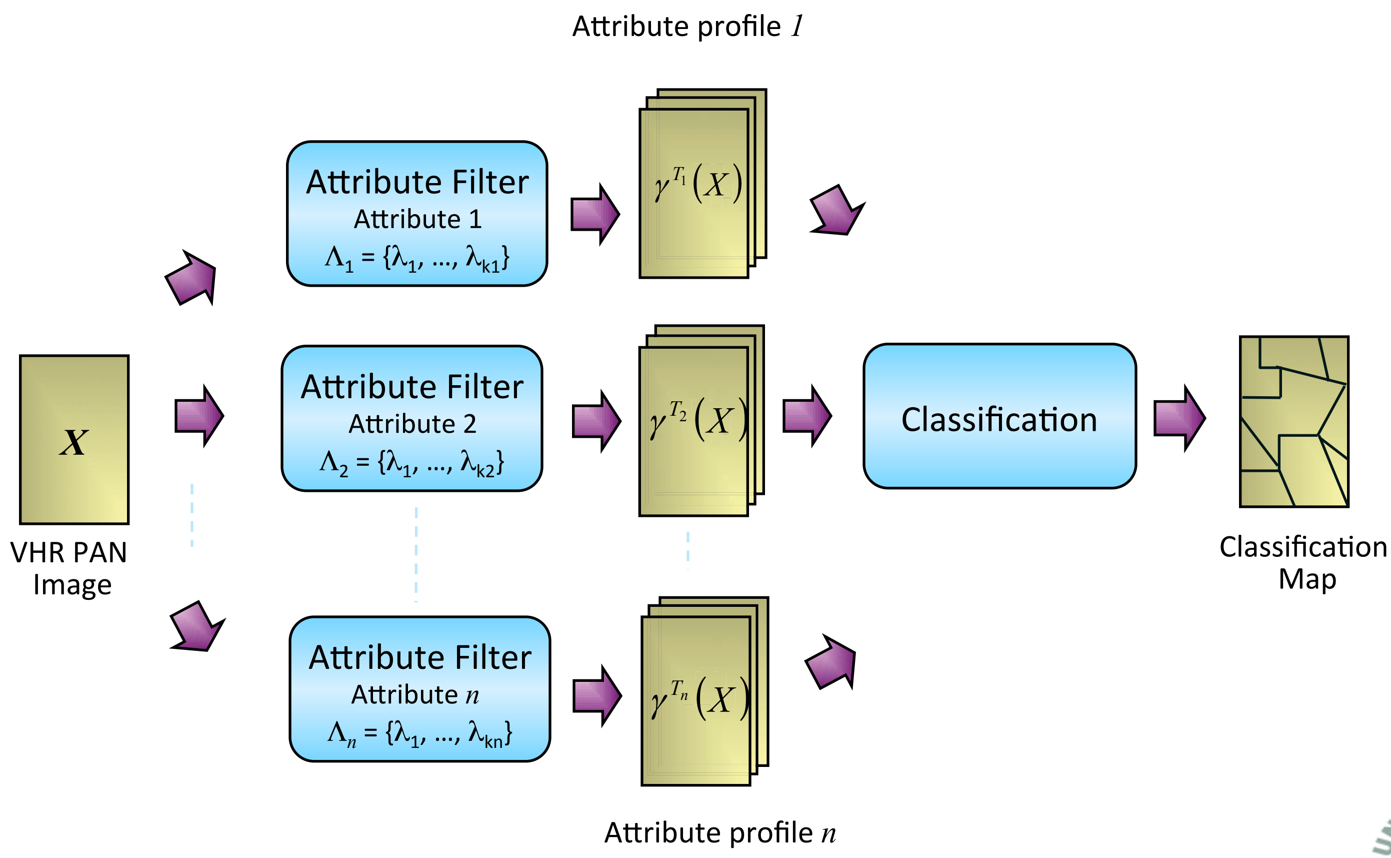


Morphological & Attribute Profiles

The analysis on the APs built with different attributes can discriminate among the different thematic classes.



Morphological & Attribute Profiles



Morphological & Attribute Profiles

Problem: Mathematical morphology operators defined for the analysis of single band images have no direct extension to multivariate data[1] (e.g., hyperspectral images).

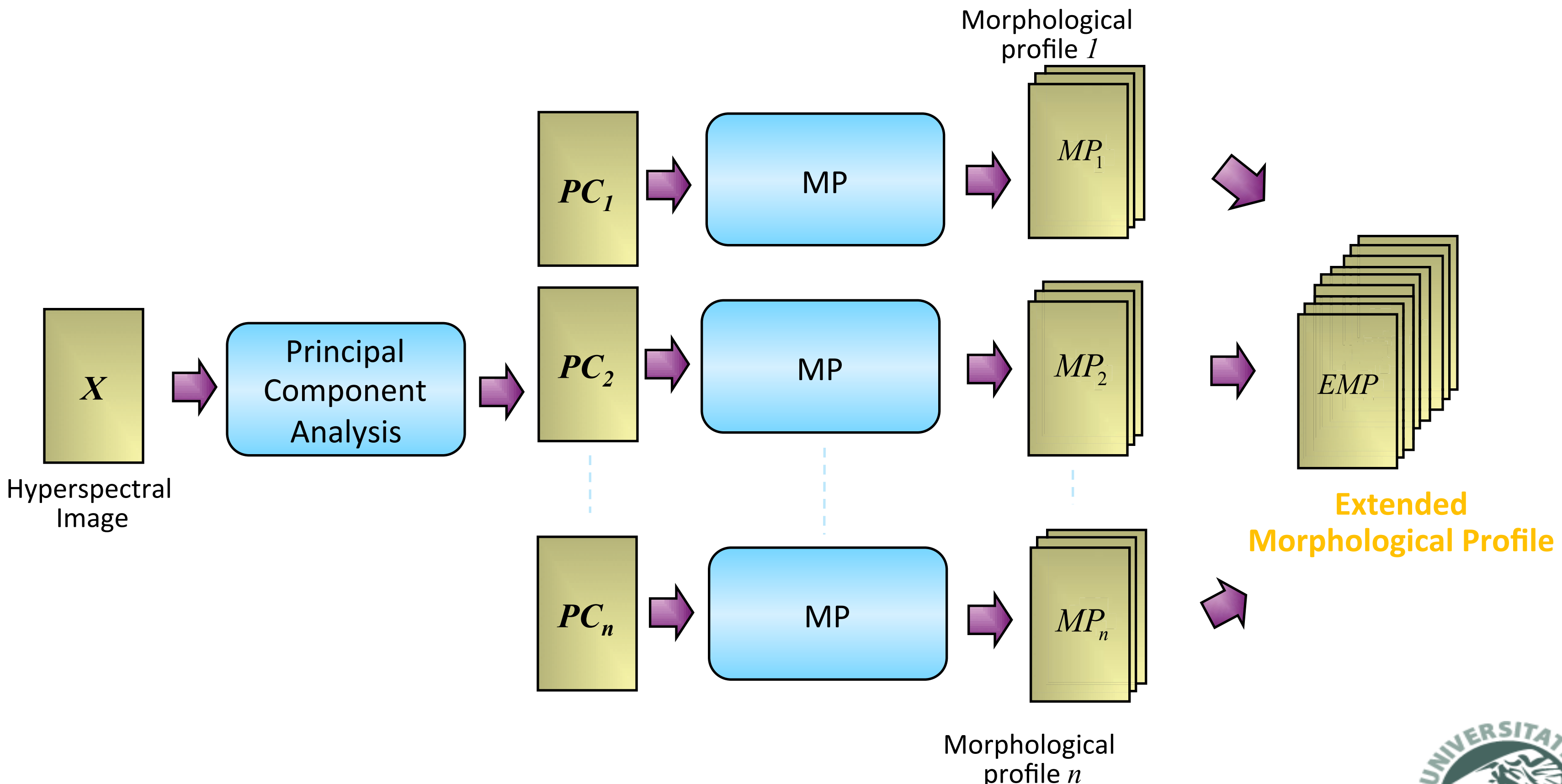
Trivial solution: Compute the operators on each single band of the data.

Computationally unfeasible for hyperspectral data.

A possible solution: Reduce the dimensionality of the data to few significant bands and apply the operators on each of them.

Extended Morphological Profile (EMP)

Morphological & Attribute Profiles

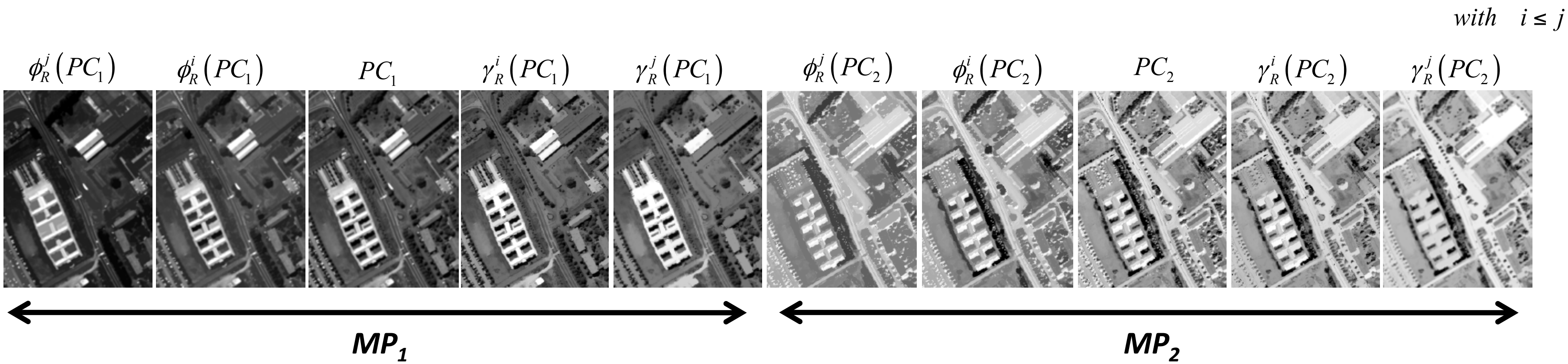


Morphological & Attribute Profiles

Extended Morphological Profile

On each of the first *n* principal component (*PC*) extracted from the hyperspectral image, a MP is computed.

The MPs are then concatenated for obtaining the EMP.



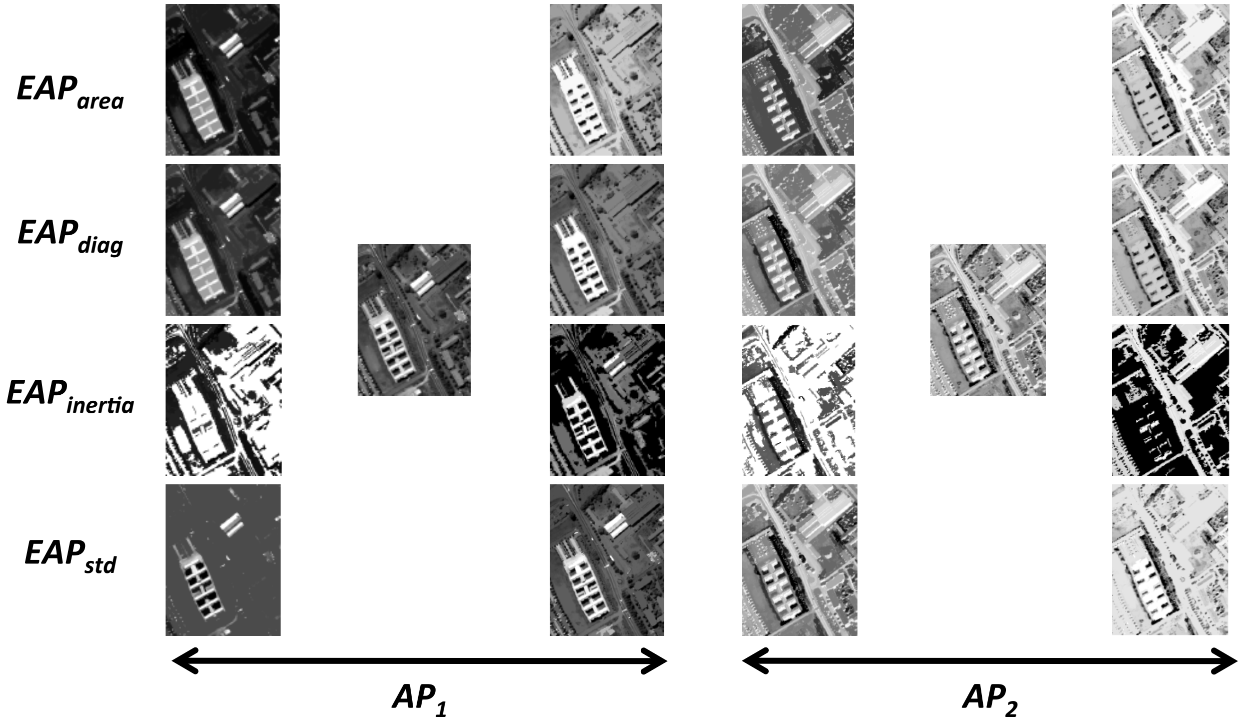
J. A. Benediktsson, M. Pesaresi, and K. Amason, "Classification and feature extraction for remote sensing images from urban areas based on morphological transformations," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 41, no. 9, pp. 1940-1949, 2003.

J. A. Benediktsson, J. A. Palmason, and J. R. Sveinsson, "Classification of hyperspectral data from urban areas based on extended morphological profiles," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 43, no. 3, pp. 480-491, 2005.

Morphological & Attribute Profiles

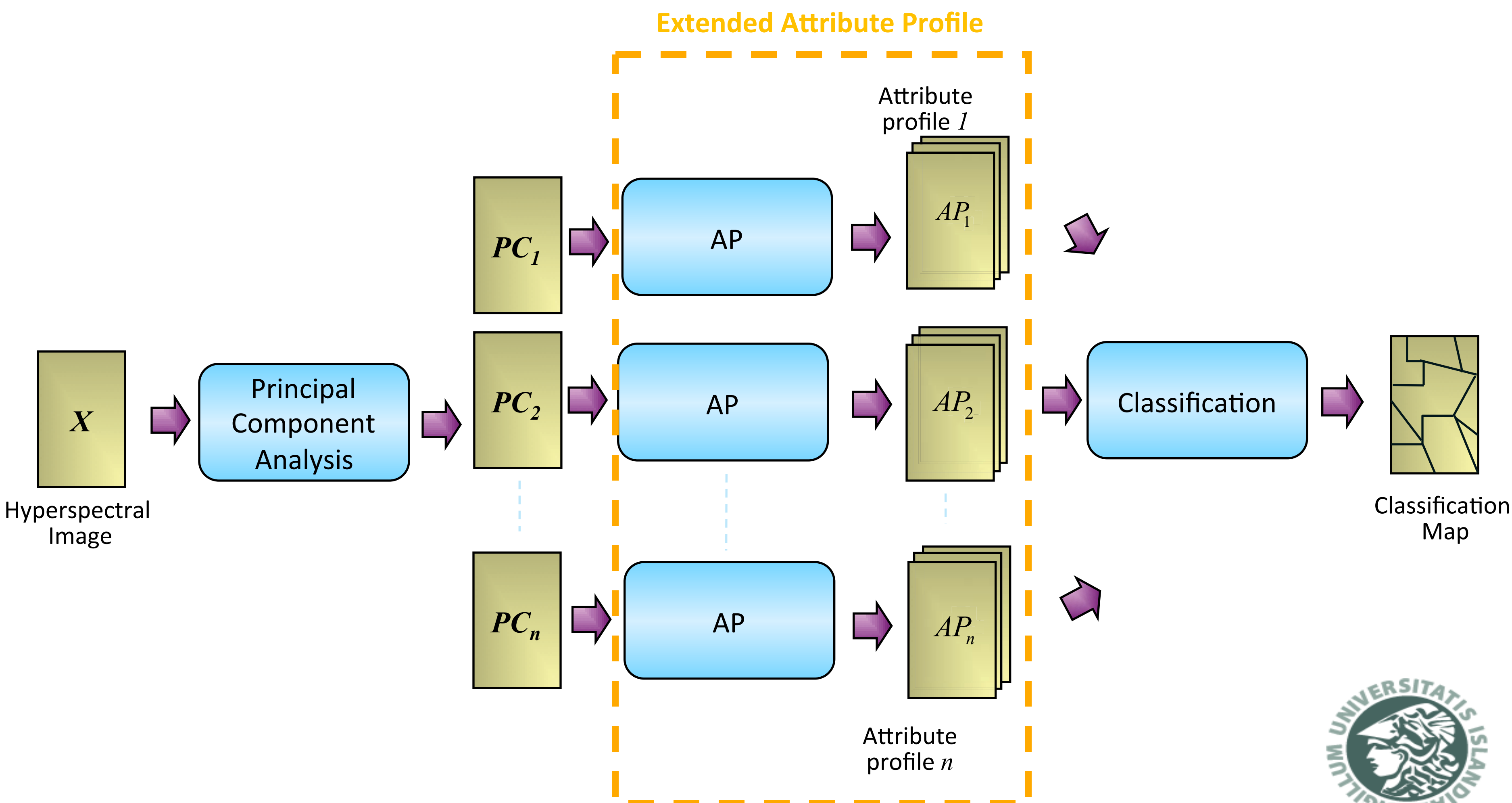
Extended Attribute Profile (EAP)

Analogous definition to EMP: APs computed on n first PCs are concatenated together for obtaining the EAP.



M. Dalla Mura, J. A. Benediktsson, B. Waske, and L. Bruzzone, "Extended profiles with morphological attribute filters for the analysis of hyperspectral data," *International Journal of Remote Sensing*, vol. 31, no. 22, pp. 5975–5991, Nov. 2010.

Morphological & Attribute Profiles



Morphological & Attribute Profiles

Hyperspectral image (610x340 pixels) of the city of Pavia acquired by ROSIS-03
103 spectral bands, geometrical resolution of 1.3 [m]

True color Image

Test set

Number of samples per class

Class	Training	Test
Trees	524	3064
Meadow	540	18649
Metal	265	1324
Gravel	392	2099
Bricks	514	3682
Bare Soil	532	5029
Asphalt	548	6631
Bitumen	375	1330
Shadow	231	947
Total	**3921**	**42776**

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

Morphological & Attribute Profiles

- ✓ Attribute Profiles built by four attributes on the first 4 PCs.
  - Area (λ = 100, 500, 1000, 5000)
  - Length diagonal of the bounding box (λ = 10, 25, 50, 100)
  - Moment of inertia (λ = 0.2, 0.3, 0.4, 0.5)
  - Standard deviation (λ = 20, 30, 40, 50)
- ✓ Comparison with EMP (disk shaped structuring element (SE) of sizes increased with a step 2)
- ✓ Classifier: Random Forest (100 trees)
- ✓ Protocol for accuracy assessment:
  - Overall Accuracy (computed on the test set)

Morphological & Attribute Profiles

Overall Accuracy [%]

	PCs	EMP	EAP area	EAP diagonal	EAP inertia	EAP std	EAP all
Features	4	36	36	36	36	36	144
OA (%)	70.42	80.71	**92.32**	86.84	76.26	78.68	89.89
AA (%)	79.25	86.64	**92.00**	88.00	84.68	86.27	90.25
Kappa	0.63	0.75	**0.90**	0.82	0.70	0.73	0.87

Morphological & Attribute Profiles

Classification maps obtained by considering only the spectral channels.

Maximum Likelihood
OA: **70.47**%

Random Forest
OA: **71.66**%

SVM
OA: **81.01**%

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

Morphological & Attribute Profiles

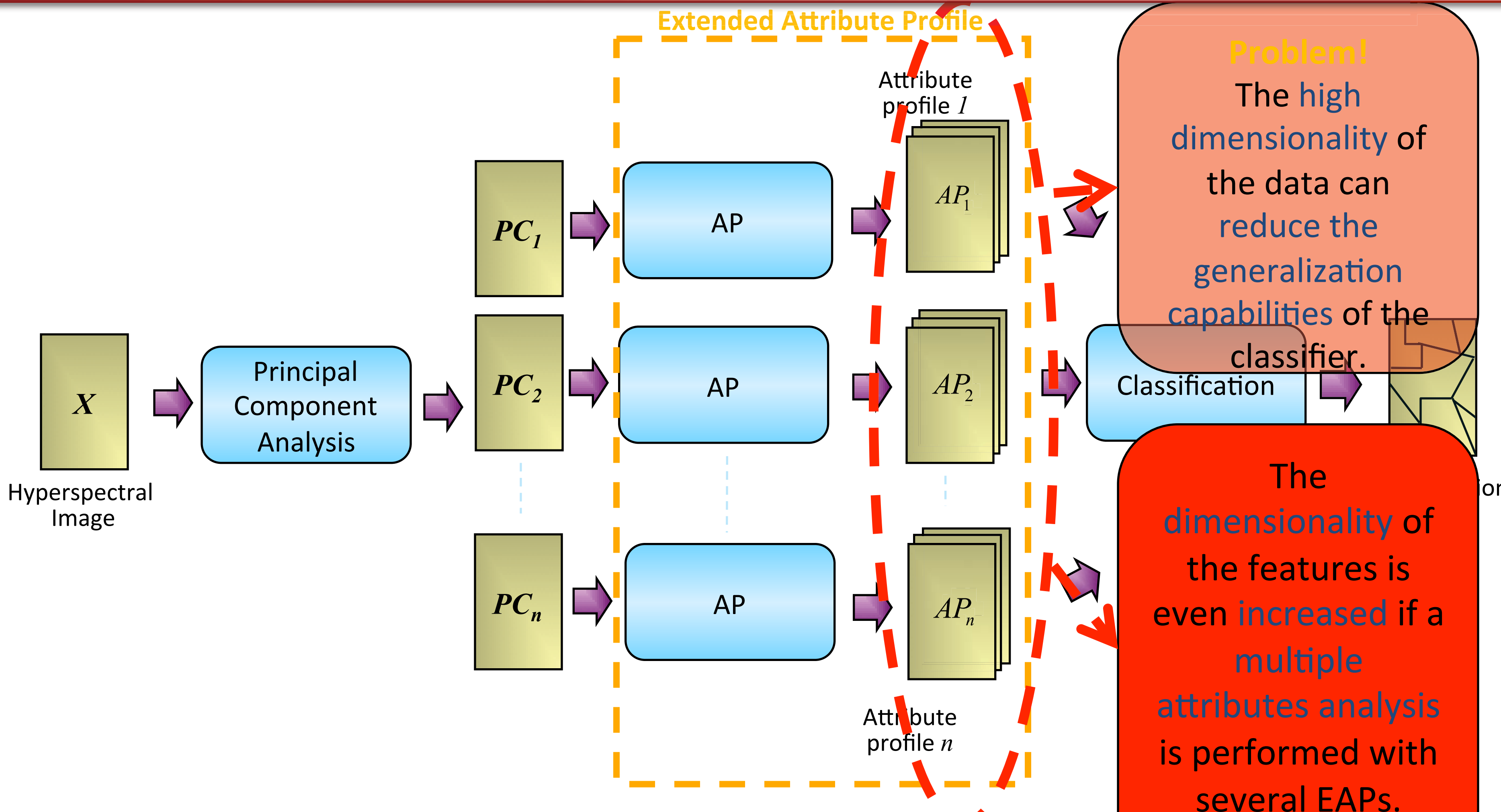
Spectral only (4 PCs)
OA: **70.42**%

EMP
OA: **80.71**%

EAPall
OA: **89.89**%

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

Morphological & Attribute Profiles



Problem! The high dimensionality of the data can reduce the generalization capabilities of the classifier.

The dimensionality of the features is even increased if a multiple attributes analysis is performed with several EAPs.

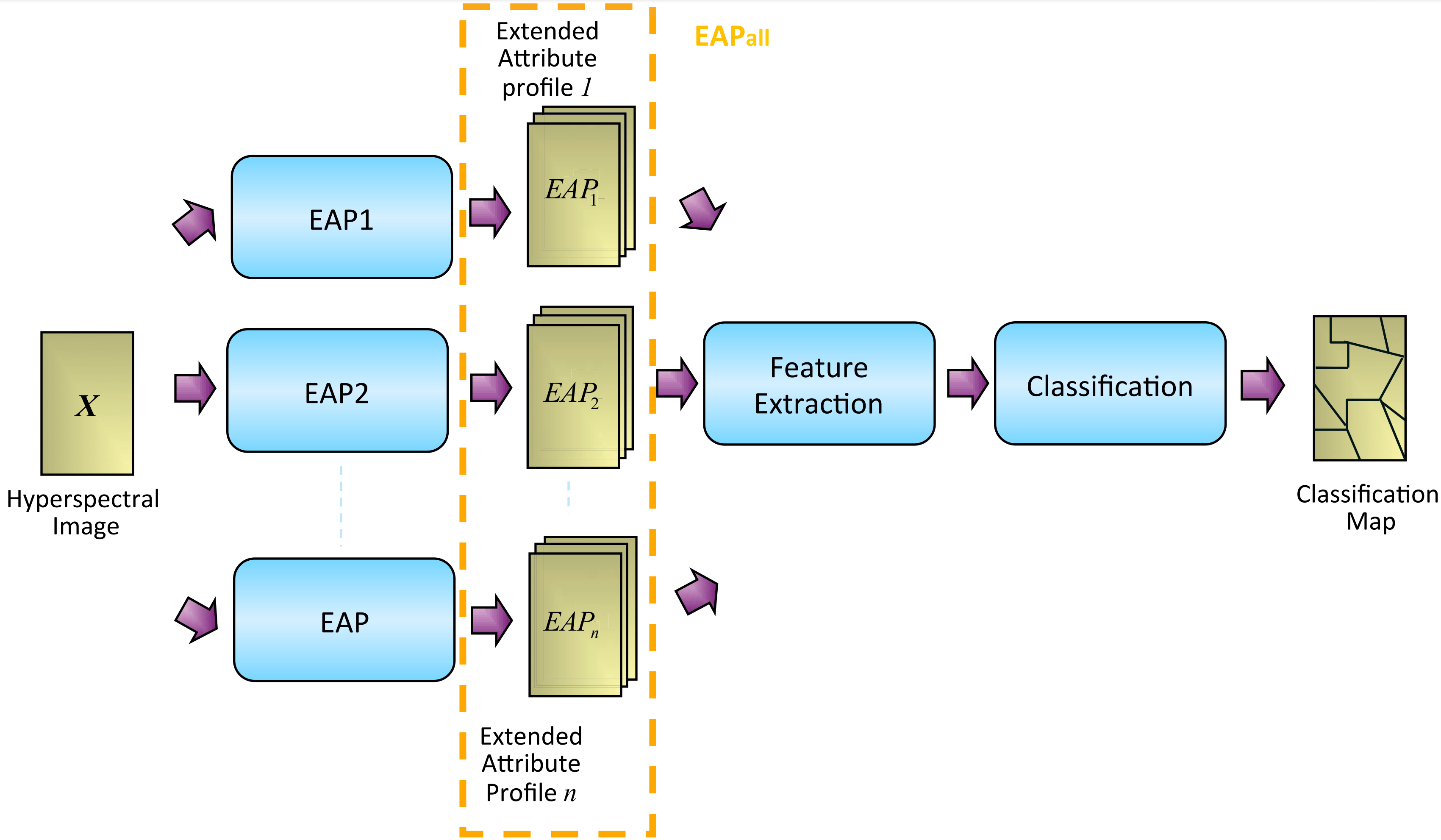
M. Dalla Mura, J. A. Benediktsson, B. Waske, and L. Bruzzone, "Extended profiles with morphological a hyperspectral data," *International Journal of Remote Sensing*, vol. 31, no. 22, pp. 5975–5991, Nov. 2010.

Morphological & Attribute Profiles

The reduction of the dimensionality of the data can be performed by a Feature Extraction (FE) technique.

- ✓ **Discriminant Analysis Feature Extraction (DAFE)**
  - ✓ Parametric technique.
  - ✓ Extract the features that maximize a criterion based on the within and between scatter matrices that estimates the separability of the classes distributions.
  - ✓ Classes assumed to be Gaussian.
- ✓ **Decision Boundary Feature Extraction (DBFE)**
  - ✓ Non parametric technique.
  - ✓ Features computed as direction orthogonal to the decision boundary.
  - ✓ Requires a significant number of training samples for a proper estimation of the decision boundary.
- ✓ **Non-Weighted Feature Extraction (NWFE)**
  - ✓ Combination of DAFE and DBFE.
  - ✓ The separability criterion is computed on non-parametric within and between scatter matrices.
  - ✓ Based on the concept of weighted means (samples weighted according to their distance to the decision boundary).

Morphological & Attribute Profiles

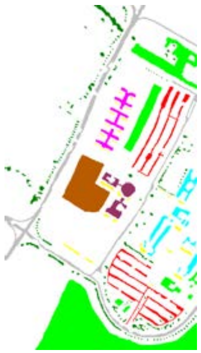


M. Dalla Mura, J. A. Benediktsson and L. Bruzzone, "Classification of Hyperspectral Images with Extended Attribute Profiles and Feature Extraction Techniques," *Proc. IEEE IGARSS 2010*, 2010, pp. 76 –79.

Morphological & Attribute Profiles

Data set Description:

True color Image



Test set

Hyperspectral image (610x340 pixels) of the city of Pavia acquired by ROSIS-03
103 spectral bands, geometrical resolution of 1.3 [m].

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

Experimental Set up:

✓ Attribute Profiles built by four attributes on the first 4 PCs.
  - Area (λ = 100, 500, 1000, 5000)
  - Length Diagonal of the bounding box (λ = 10, 25, 50, 100)
  - Moment of inertia (λ = 0.2, 0.3, 0.4, 0.5)
  - Standard deviation (λ = 20, 30, 40, 50)

✓ Feature Extraction Techniques: DAFE, DBFE, NWFE.

✓ Classifier: Random Forest (100 trees), Maximum Likelihood.

✓ Protocol for accuracy assessment: Overall Accuracy (computed on the test set).

Morphological & Attribute Profiles

Overall Accuracy [%]

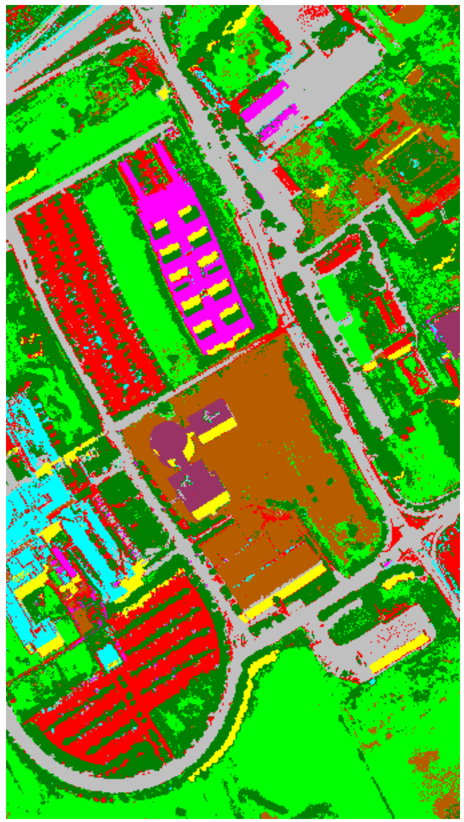
FE Technique	Classifier	EAPa	EAPd	EAPi	EAPs	EAPall
EAP with NO FE	ML	72.21	65.05	73.08	54.34	64.19
	RF	90.99	86.66	82.94	81.64	89.71
EAP with DAFE	ML	89.97 (7)	84.68 (8)	84.56 (10)	85.41 (8)	91.48 (11)
	RF	92.68 (20)	90.13 (25)	90.84 (35)	86.52 (14)	96.01 (121)
EAP with DBFE	ML	88.69 (6)	82.33 (8)	81.47 (7)	85.18 (5)	83.80 (11)
	RF	88.69 (30)	85.07 (36)	82.20 (36)	87.55 (20)	94.50 (81)
EAP with NWFE	ML	89.93 (14)	83.03 (4)	87.54 (10)	88.55 (12)	91.18 (11)
	RF	92.99 (24)	87.25 (30)	93.47 (27)	79.83 (5)	91.89 (41)

The number of features giving the highest accuracies is reported in brackets.

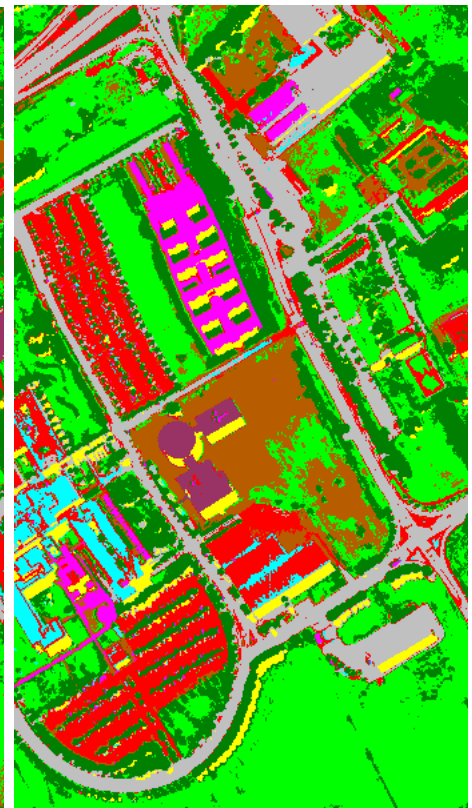
Morphological & Attribute Profiles

Classification Maps obtained with a Random Forest Classifier.

Spectral channels
OA: **71.66**%



EAPall with DAFE
OA: **96.01**%



EAPall with DBFE
OA: **94.50**%

EAPall with NWFE
OA: **91.89**%

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

Outline

1. Introduction
   - Very High Resolution Remote Sensing
   - Hyperspectral Imagery
2. Morphological Profiles and Attribute Filters
   - Morphological and Attribute Profiles for Single Data Channels
   - Extended Morphological and Attribute Profiles
3. **Optimized Feature Selection for Attribute Filters**
   - **HML Algorithm**
   - **APs and Spectral Information: Automatic vs. Manual**
4. Conclusions

Attribute: Area

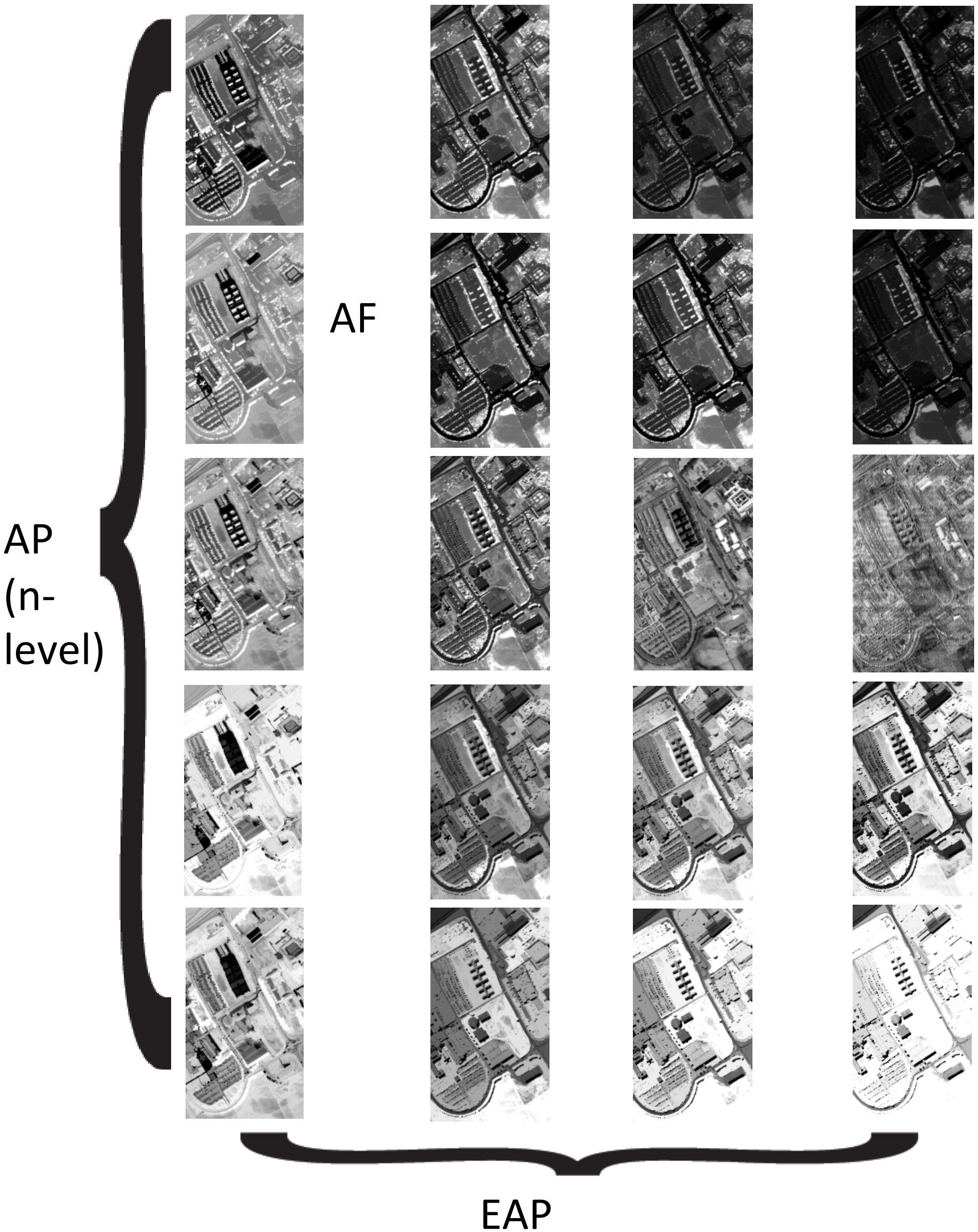
MORPHOLOGICAL
OPERATORS

AP
(one
level)

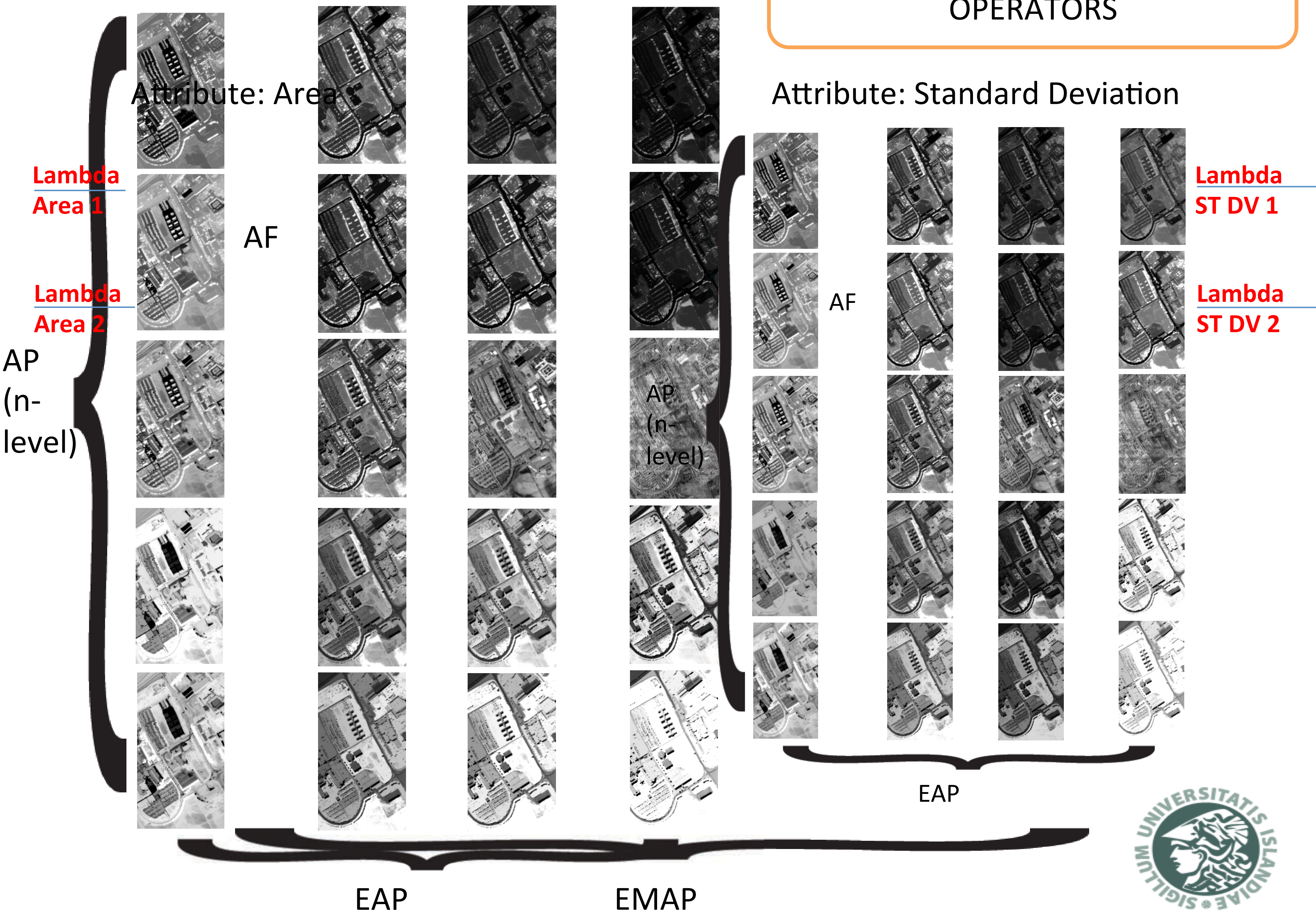
AF

MORPHOLOGICAL OPERATORS

Attribute: Area



MORPHOLOGICAL OPERATORS



Problem Statement

Lambda Area 1

Lambda Area 2

How could we compute automatically the values of these thresholds in order to construct the attribute profiles?

Lambda ST DV 1

Lambda ST DV 2

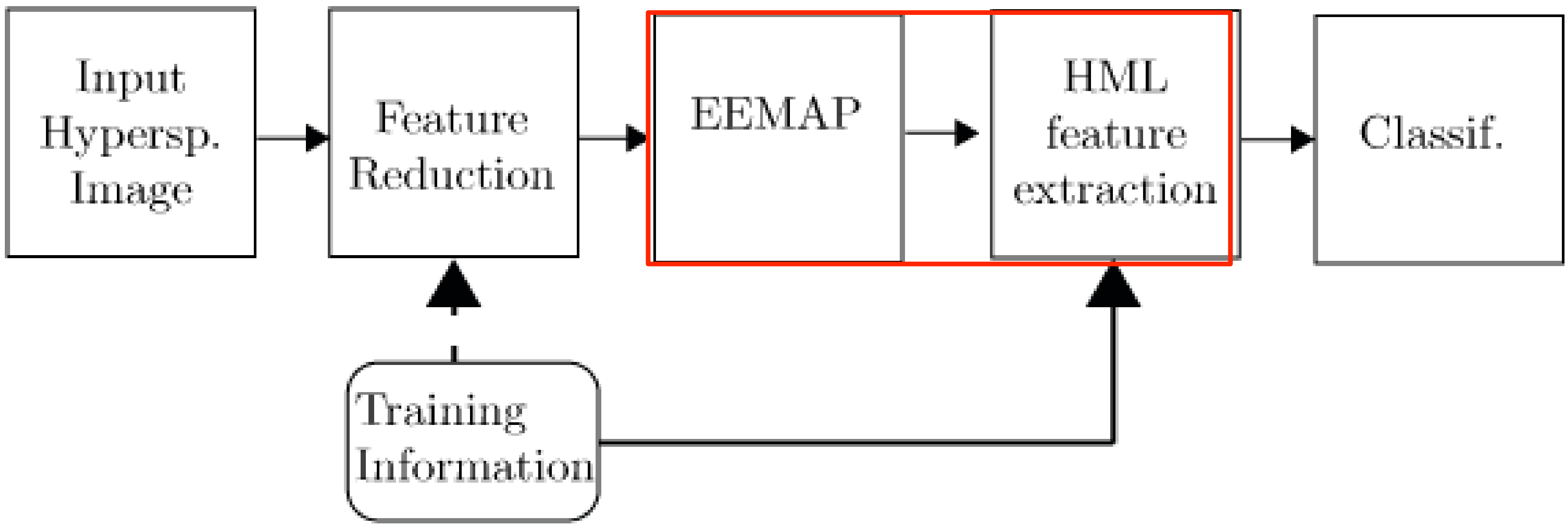
λ?

$$\Gamma_{\lambda}(f) = \left\{ x \in f : attr(\Gamma_{x}(f) \geq \lambda \right\}$$

The aim is to answer this question

- Approach based on the selection of attributes
- Approach based on the rank of the features (HML)

Block Diagram of the Proposed Approach



Optimal Selection of Features – HML Method

- **First step:** build an **EEMAP (Entire EMAP)**
- Standard deviation from 2.5% to 27.5% with 2.5% step.
- Area from 50 to 2100 square meters with step of 150.
- ……

- **Second Step:** feature selection
- New approach based on Genetic Algorithms (GAs) and the importance of the features.

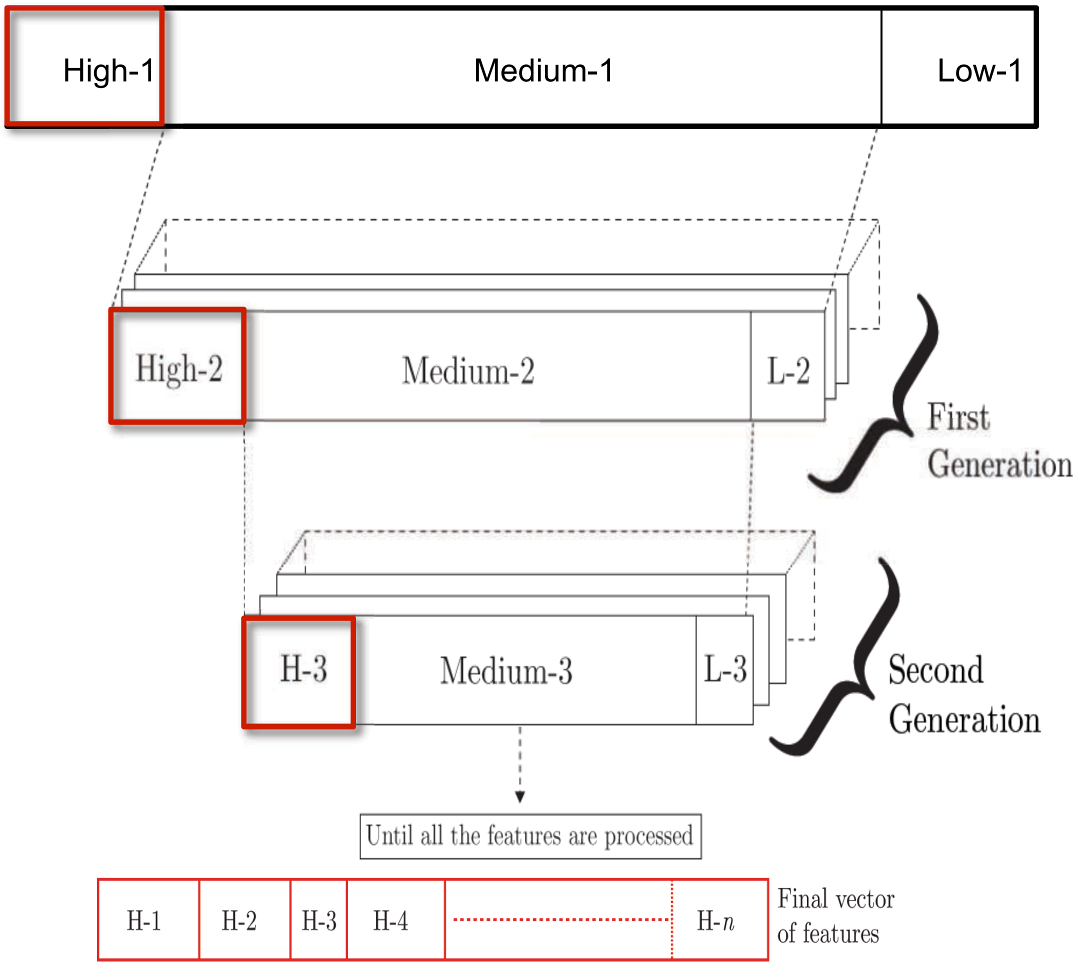
CLASSIFICATION

M. Pedergnana, P.R. Marpu, M. Dalla Mura, J.A. Benediktsson and L. Bruzzone, "A Novel technique for Optimal Feature Selection in Attribute Profiles Based on Genetic Algorithms," *IEEE Trans. on Geoscience and Remote Sensing*, vol. 51, pp. 3514- 3528.

Importance of the Features

- ✓ Is given by the random forest (RF) model.
- ✓ RF applies a permutation of the features in order to set a rank.
- ✓ RF checks if the there are differences between the classification accuracies if a feature is used or not.
  - ✓ *Variable importance*
- ✓ The rank of the features is related to the difference between the classification accuracies if the feature is used or not
- ✓ GREAT difference → HIGH importance.
- ✓ LOW difference → LOW importance.

Optimal Selection of Features – HML Method

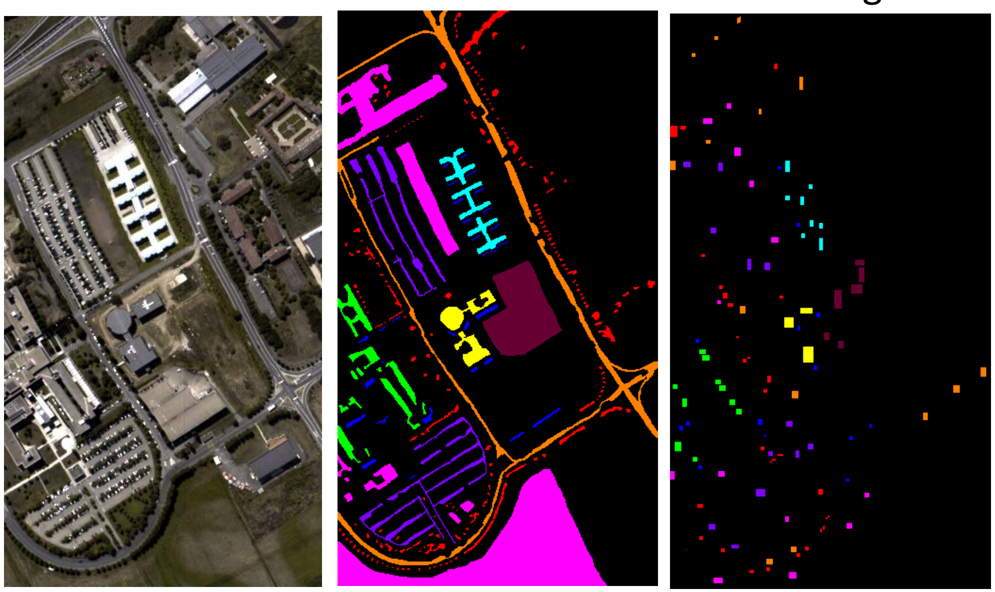


- The features are classified as high, medium and low priority features at every stage and genetic algorithms are employed to select the best features among the medium priority features.
- The final set of selected features is the combination of all the high priority features.

Optimal Selection: Experimental Results

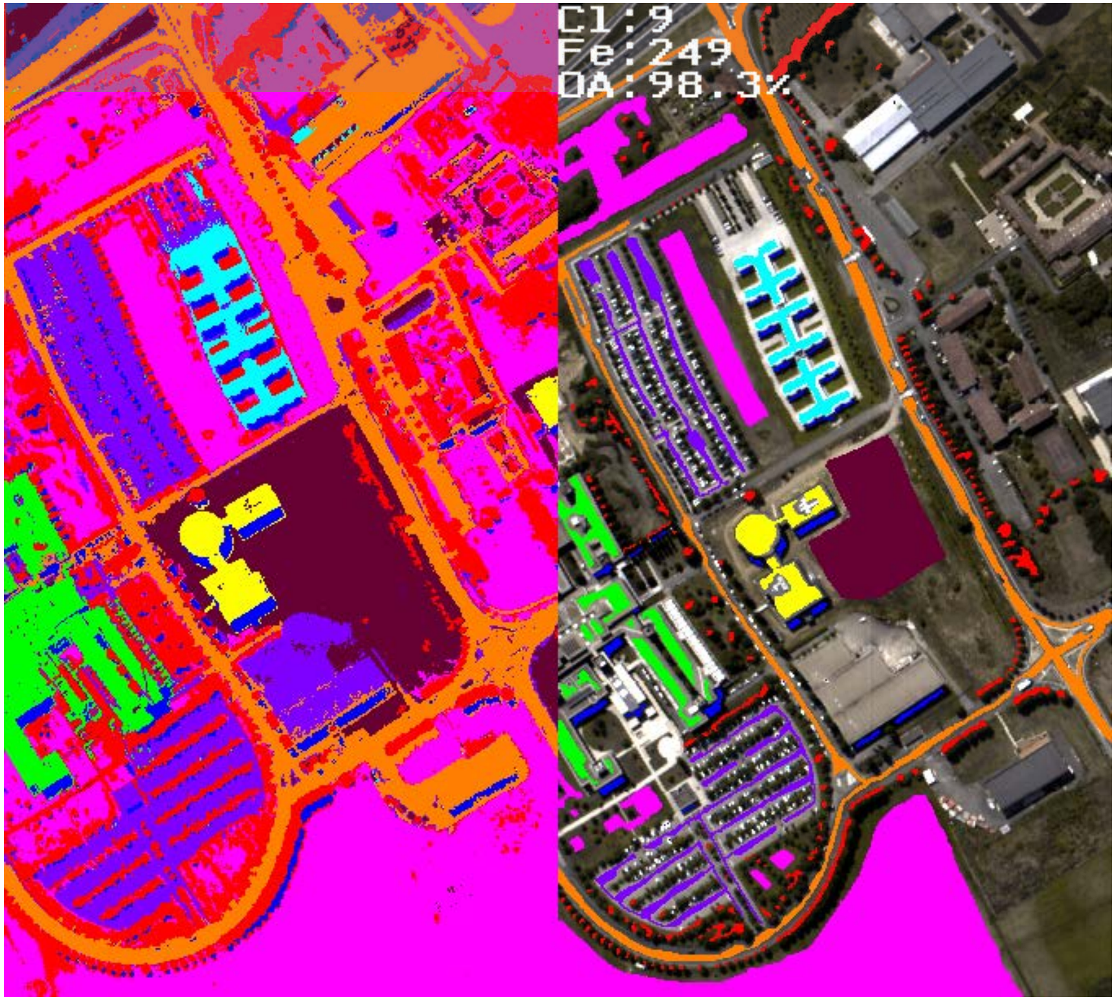
Hyperspectral image (610x340 pixels) of the University of Pavia acquired by ROSIS-03 . 103 spectral bands, geometrical resolution of 1.3 [m]

RGB Test-SET Training-SET



Optimal Selection: Experimental Results

- Pavia Dataset – HML Approach – Decision Boundary Feature Extraction (DBFE) + Random Forest (RF) classifier.



	User Accuracy (%)	Producer Accuracy (%)
Trees	85.8919	96.9648
Asphalt	99.4850	99.0499
Bitumen	100.0000	100.0000
Gravel	98.6742	99.2854
metal sheets	100.0000	99.9257
Shadow	99.8896	95.5649
Self-Block Bricks	98.5103	98.7778
Meadows	99.3713	97.4690
Bare Soil	99.8015	100.0000

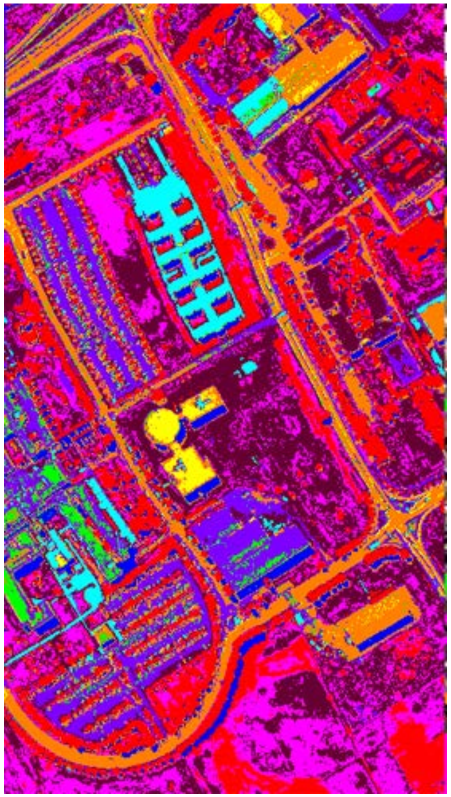
	Average Accuracy	Overall Accuracy	Kappa Accuracy
%	98.5597	98.2911	0.9774

Overall Accuracy: 98.3%

Average Accuracy: 98.6%

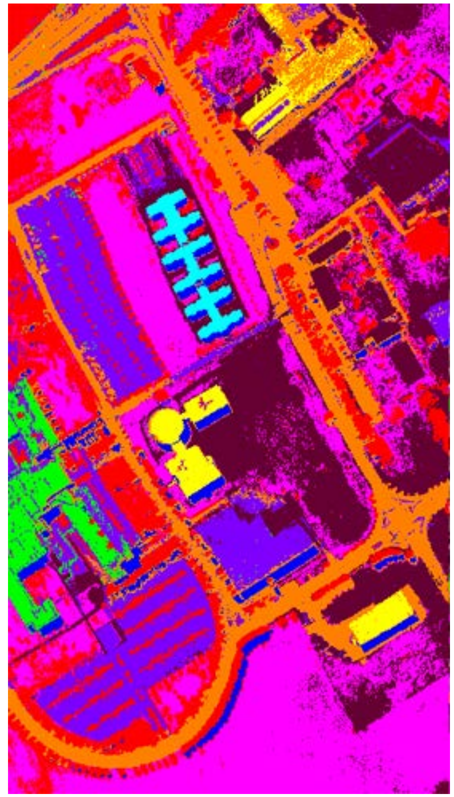
Experimental Results

Spectral



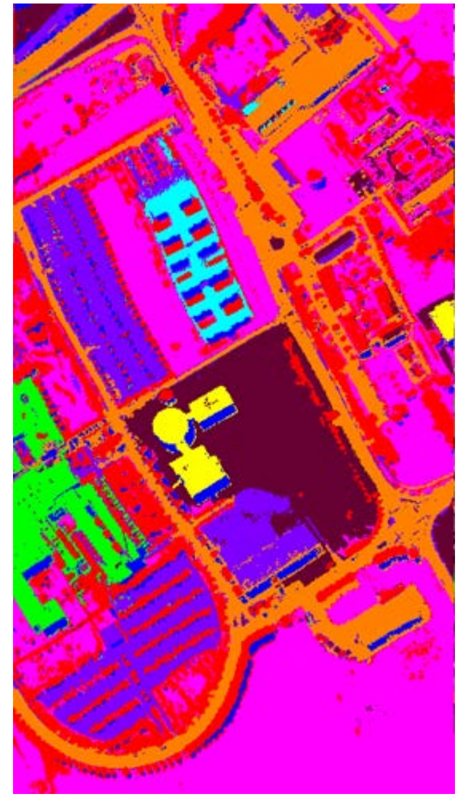
OA: 71.39%

EAP (Area 500, 1000, 2000)



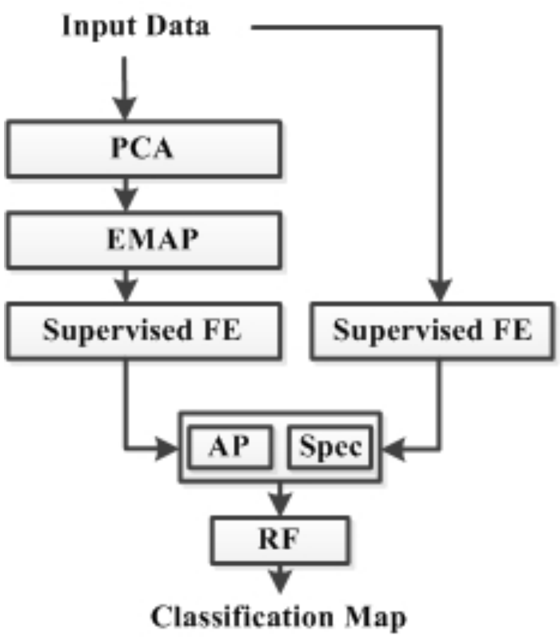
OA: 93.90%

HML approach

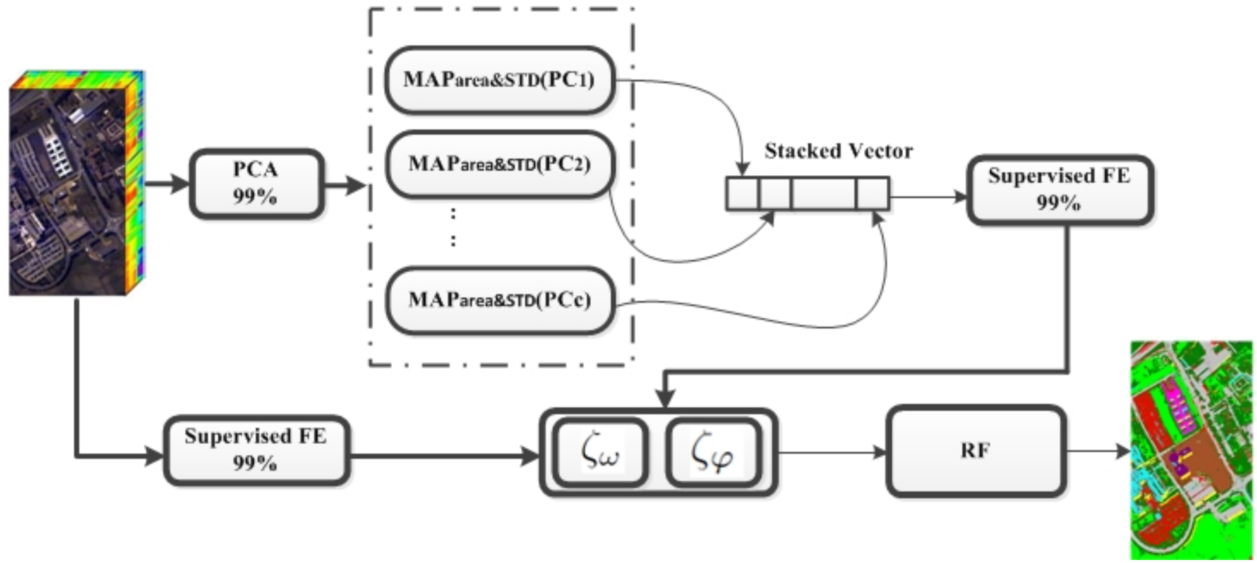


OA: 98.3%

APs and Spectral Information: Automatic vs. Manual



Manual



Automatic

P. Ghamisi, J.A. Benediktsson and J.R. Sveinsson, "Automatic Spectral-Spatial Framework Based on Attribute Profiles and Supervised Feature Extraction," *IEEE Trans. on Geoscience and Remote Sensing*.

APs and Spectral Information: Automatic vs. Manual

- ✓ Results for both schemes (Manual by using 4 attributes and Automatic by using only 2 attributes) were very close in terms of classification accuracies (97.0% and 96.3% with DAFE)
- ✓ The CPU processing time for the both schemes was almost the same
- ✓ For the automatic scheme there is no need to adjust the initial parameters for the attribute profiles

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   - HML Algorithm
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4. **Conclusions**

Conclusions

- Importance of incorporating spatial and spectral information
- Mathematical morphology used to handle the complexity of the data
- High spectral + high spatial resolutions → need for advanced algorithms

Conclusions

- ✓ Attribute filters are flexible tools: The attributes can be defined in any way. For instance, they can be purely geometrical (e.g., area, moment of inertia) or related to the gray-scale distributions of the pixels in the regions (e.g., std., entropy, uniformity, contrast)

- ✓ The union of attribute filters and Max-Tree image representation leads to an efficient and fast filtering procedure particularly effective for the computation of the profiles

- ✓ The results obtained by the profiles built with attribute filters outperformed in terms of overall accuracy those generated by considering conventional morphological operators

- ✓ The use of a FE technique led to a further increase in terms of accuracies when compared to the use of the data with full dimensionality

Conclusions

- ✓ The originally proposed morphological attibute profiles work only in a manual way by setting the thresholds experimentally

- ✓ Architectures capable to automatically find the best attributes and thresholds were defined
  - ✓ Using Genetic Algorithms
  - ✓ Using “stacked” MAP and spectral information with feature extraction

- ✓ Higher overall accuracies of classification obtained by using the proposed automatic methods when compared to the manual counterparts

Conclusions – Future Developments

- ✓ Definition of an architecture capable of automatically finding the best attributes and thresholds (e.g., with GAs) for different attributes.
- ✓ Application to specific tasks such as object detection (e.g., building detection, road networks extraction) and multitemporal image analysis (e.g., including the modeling of the spatial information provided by APs in the change detection analysis).
- ✓ Parallel implementation of the max-tree representation to be able to work on large images.

END

For more information see: www.hi.is/~benedikt

Recent Papers related to this presentation:

G. Camps-Valls, D. Tuia, L. Bruzzone, J.A. Benediktsson, „Advances in Hyperspectral Image Classification,“ *IEEE Signal Processing Magazine*, Vol. 31, pp. 45-54, 2014.

M. Fauvel, Y. Tarabalka, J.A. Benediktsson, J. Chanussot and J.C. Tilton, „Advances in Spectral-Spatial Classifciation of Hyperspectral Images, *Proceedings of the IEEE*, Vol. 101, no.3, pp. 652 – 675, 2013,

P. Ghamisi, M. Dalla Mura, J.A. Benediktsson "A Survey on Spectral-Spatial Techniques Based on Atribute Profiles," to appear *IEEE Trans. on Geoscience and Remote Sensing*, 2015.

J. Li, X. Huang, P. Gamba, J. Bioucas-Dias, L. Zhang, J.A. Benediktsson and A. Plaza, "Multiple Feature Learning for Hyperspectral Image Classification," *IEEE Trans. on Geoscience and Remote Sensing*, vol. 53, 1592 – 1606, 2015.

END

X. Huang, X. Guan, J.A. Benediktsson, L. Zhang, J. Li, A. Plaza, and M. Dalla Mura, "Multiple Morphological Profiles from Multicomponent Base Images for Hyperspectral Image Classification," to appear *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 2015.

Z. Lyu, P.L. Zhang, J.A. Benediktsson and W.Z. Shi, " Morphological Profiles Based on Differently Shaped Structuring Elements for Classification of Images With Very High Spatial Resolution," to appear *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 2015.

L. Fang, S. Li, X. Kang and J.A. Benediktsson, " Spectral–Spatial Hyperspectral Image Classification via Multiscale Adaptive Sparse Representation," *IEEE Trans. on Geoscience and Remote Sensing*, Vol. 52, pp. 7738-7749, 2014.

P. Ghamisi, J.A. Benediktsson, G. Cavallaro and A.J. Plaza, "Automatic Framework for Spectral–Spatial Classification Based on Supervised Feature Extraction and Morphological Attribute Profiles, " *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, Vol. 7, pp. 2147-2160, 2014.

END

P. Ghamisi, J.A. Benediktsson and J.R. Sveinsson, "Automatic Spectral-Spatial Classification Framework Based on Attribute Profiles and Supervised Feature Extraction," *IEEE Trans. on Geoscience and Remote Sensing*, Vol. 52, pp. 5771 – 5782, 2014.

B. Song, J. Li, M. Dalla Mura, A. Plaza, J. M. Bioucas Dias, J.A. Benediktsson, and J. Chanussot, "Remotely Sensed Image Classification Using Sparse Representations of Morphological Attribute Profiles," *IEEE Trans. on Geoscience and Remote Sensing*, 5122-5136, 2014.

J. Li, P.R. Marpu, A. Plaza, J. Bioucas-Dias and. J.A. Benediktsson, „Generalized Composite Kernel Framework for Hyperspectral Image Classification," IEEE Trans. on Geoscience and Remote Sensing, vol. 51, no. 9, pp. 4816-4829, 2013.

END

For more information see: www.hi.is/~benedikt

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Lorenzo Bruzzone	Silvia Valero
Nicola Falco	Alberto Villa
Yuliya Tarabalka	Gabriele Cavallaro
Jón Ævar Pálmason	Jóhannes R. Sveinsson
Benquin Song	Xin Huang
Peijun Li	Leyunan Fang
…	