Remote Sensing Laboratory
Dept. of Information Engineering and Computer Science
University of Trento
Via Sommarive, 14, I-38123 Povo, Trento, Italy

Jon Atli Benediktsson
Professor of Electrical & Computer Engineering
University of Iceland
benedikt@hi.is

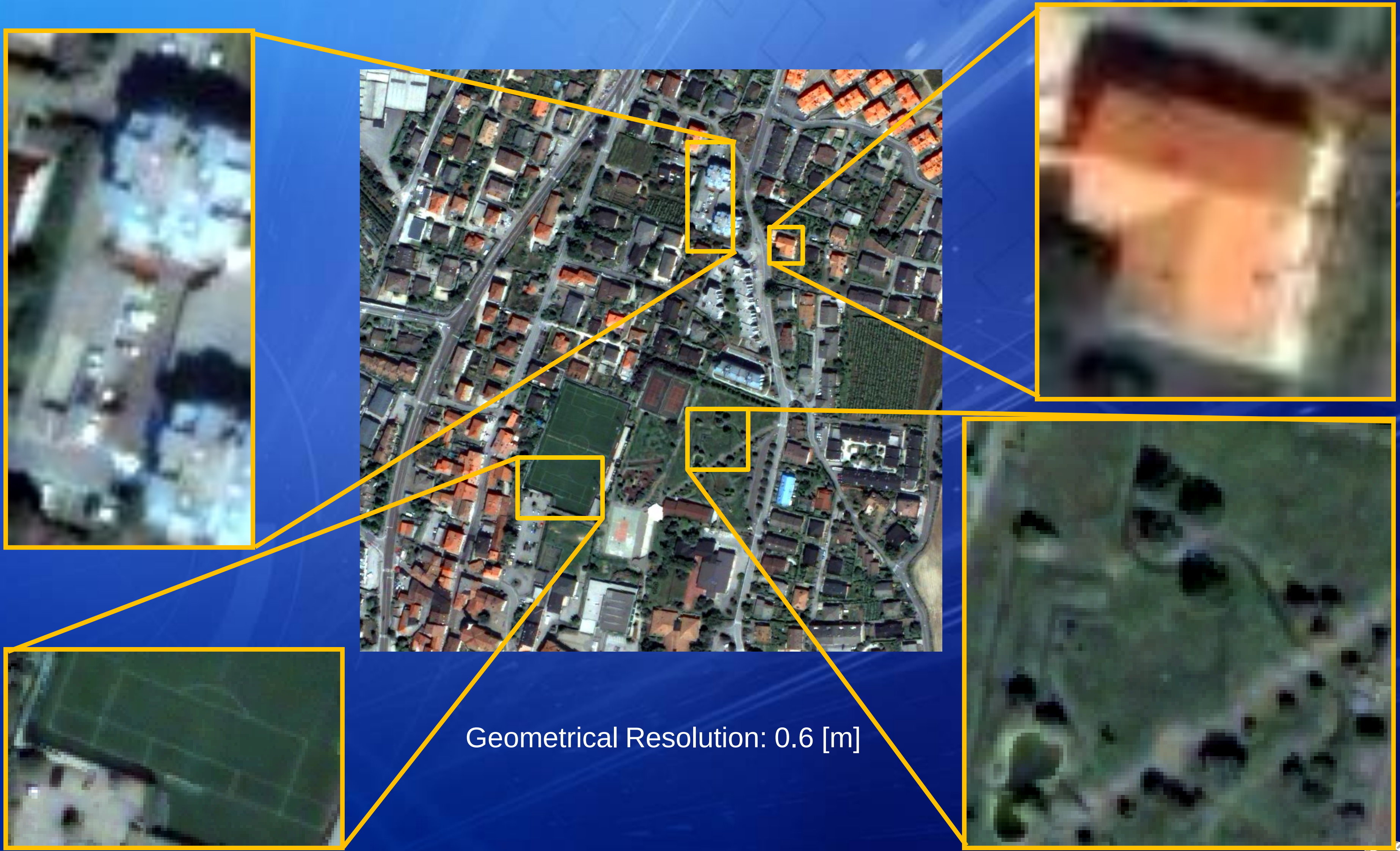
Morphological Profiles for Classification of Panchromatic and Hyperspectral Images

Mauro Dalla Mura
Jon Atli Benediktsson
Lorenzo Bruzzone

E-mail: dallamura@disi.unitn.it
benedikt@hi.is
bruzzone@ing.unitn.it
Web page: http://rslab.disi.unitn.it

Outline

Introduction



Geometrical Resolution: 0.6 [m]

Introduction

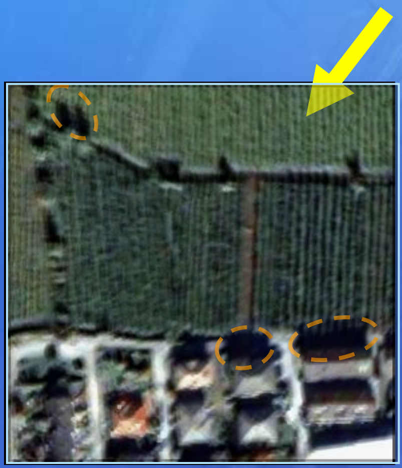
Very-High Resolution (VHR) Images – Main Features

- ✓ Contextual relations are higly informative.
- ✓ Fine representation of details in the scene (spatial resolution up to 0.60 [m] for imagery acquired by Quickbird satellite).
- ✓ High complexity of the scene (especially in dense urban areas).

⇓

Objects of heterogeneous sizes, shapes, orientation, morphology, etc.

Introduction



October 2005

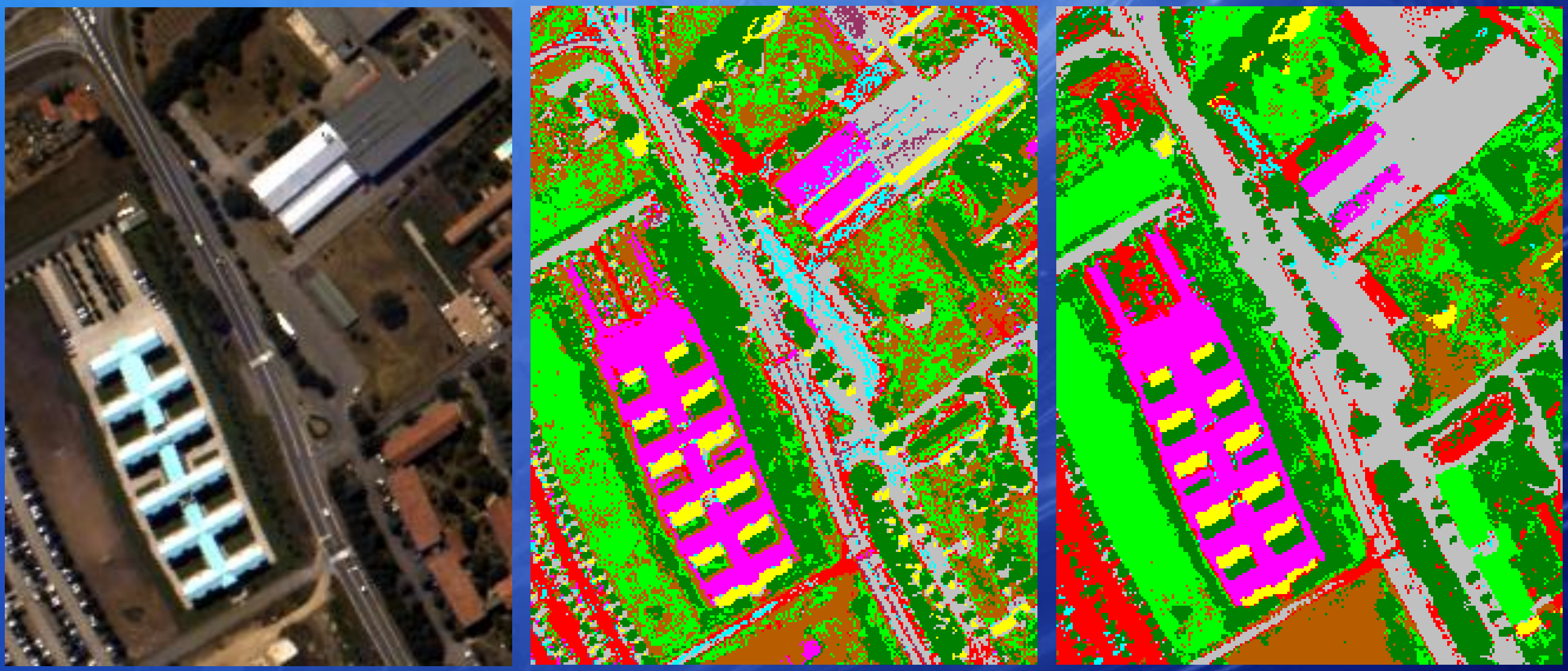
July 2006

Issues in analyzing VHR multitemporal images:

- ✓ Different atmospheric conditions and angles of view during subsequent acquisitions can yield:
  - ✓ Differences of illumination;
  - ✓ Presence of shadows.
- ✓ Structures in the scene with different spatial scales.
- ✓ Misregistration noise, due to a residual misaligment between the two images.

Introduction

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.

General Requirements

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.

Modeling of Spatial Information

Open Issues

- ✓ Approaches based on conventional filtering techniques are inadequate to preserve the geometrical information.
- ✓ The images are in general analyzed by describing the objects in the scene with simple geometrical features (mainly the size).
- ✓ The modeling of the spatial information performed in the analysis can significantly increase the computational load, the complexity of the architecture and the volume of the data to handle.

Introduction on Morphological Operators

f

Basic Operators

Examples of
Structuring Elements (SEs).

Erosion

ε_B

Dilation

δ_B

Opening

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

Closing

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

Top-hat

$WTH = f-\gamma(f)$

Morphological Connected Filters

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.

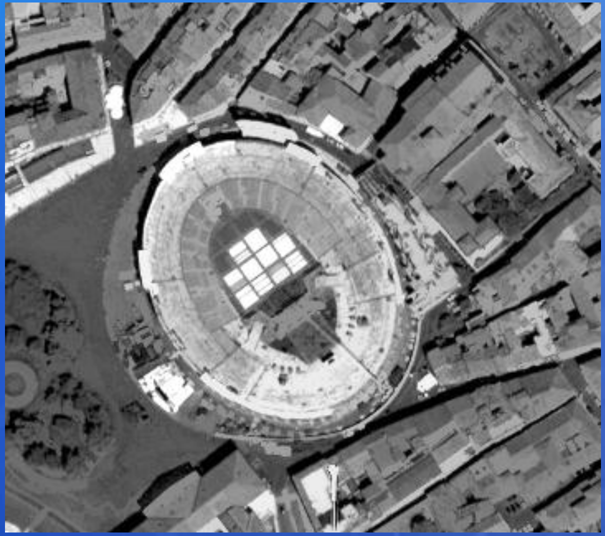
SUITABLE FOR THE ANALYSIS OF VERY HIGH RESOLUTION (VHR) IMAGES

Morphological closing | Closing with a connected filter | Original VHR image | Opening with a connected filter | Morphological opening

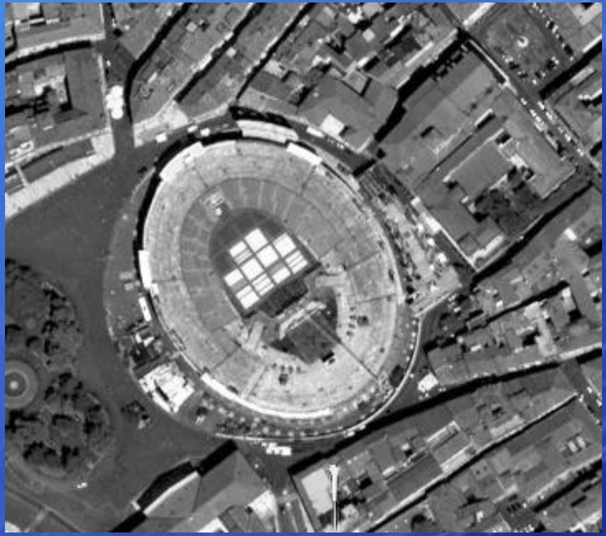
Examples of conventional Morphological operators and Connected Filters

Morphological Operators by Reconstruction

Operators by Reconstruction



Opening



Original Image

Closing

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

Reconstruction by dilation

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

Reconstruction by erosion

Two step procedure:

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

Reconstruction Process

Morphological Opening

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

Opening by reconstruction

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

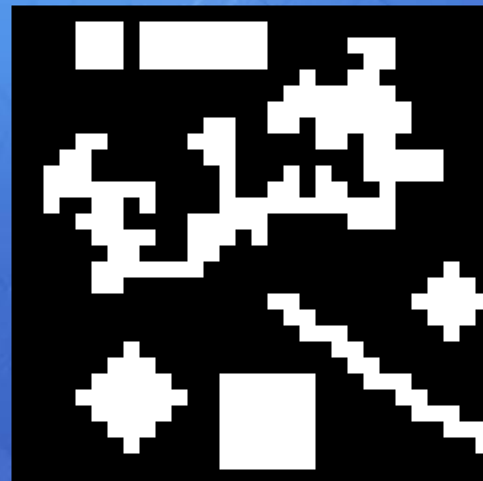
Geodesic Reconstruction

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

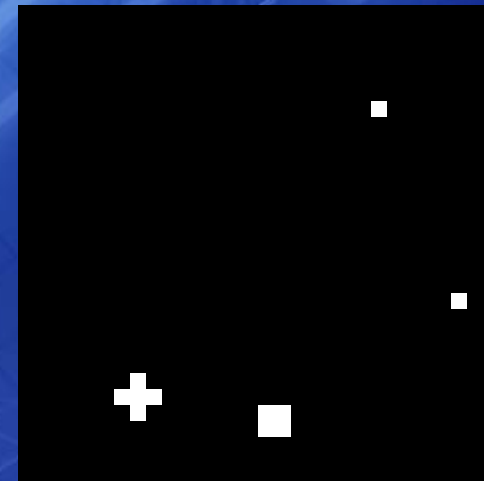
Iterative Process

Idempotence property

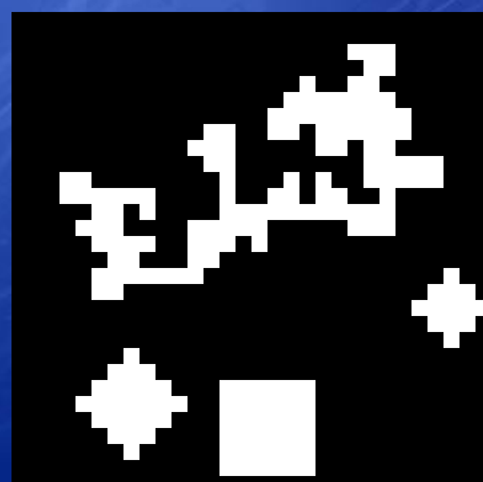
$$\delta_g^{(n)}(\cdot) = \delta_g^{(n-1)}(\cdot)$$



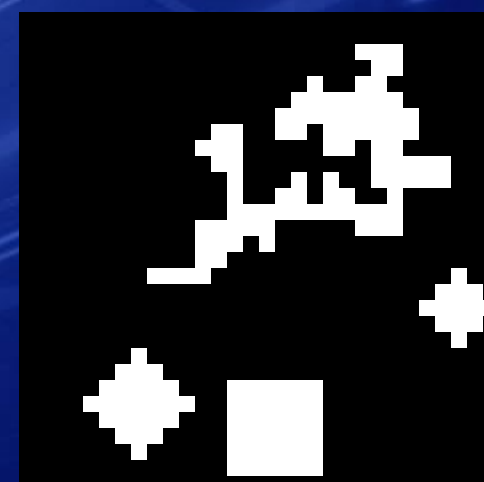
f (30x30 binary image)



$\varepsilon^{(n)}(f)$



$\gamma_R^{(n)}(f)$ *i = 27*



i = 1, 2, 10, 20

SE: Disk diameter 5

Attribute Filters

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.

Attribute Filters - Operators

Attribute filters operate only on the connected components (regions of connected iso-level pixels) according to a **criterion** *T* which evaluates an attribute *attr* 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., *attr > λ).*

e.g., **Area opening.**

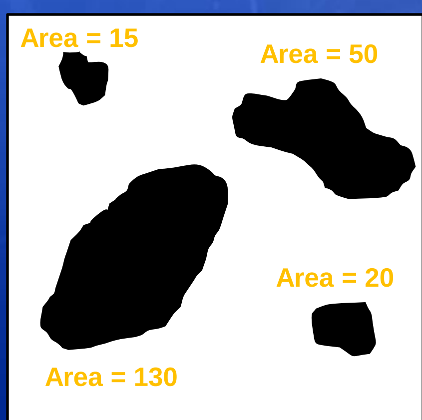
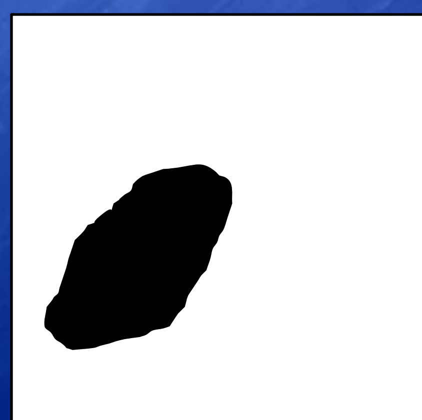


Image *f*



$\Gamma_\lambda(f)$ *with λ=100*

$$\Gamma_\lambda(f) = \{x \in f : Area(\Gamma_x(f) \geq \lambda\}$$

The filtered image contains all those regions that have an area of *λ* or more.

Attribute Filters - Operators

Increasing property. A criterion is satisfied for a connected region *R* it will be also 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.

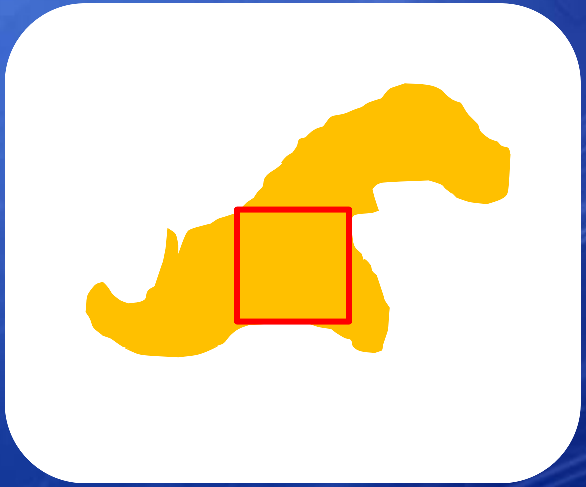
Examples of criteria.

Increasing criteria.	Non-increasing criteria.
✓ Area	✓ Perimeter
✓ Volume	✓ Shape index
✓ Lenght of the diagonal of the bounding box	✓ Moment of inertia
✓ Area of the largest enclosed square.	✓ Range of the pixels intensities

Attribute Filters - Operators

Opening by reconstructions is an attribute opening. The attribute is the largest SE that can be contained by the region.

E.g., If the criterion is “the largest square that can fit into the region” we obtain the same results as for an opening by reconstruction with a square SE.



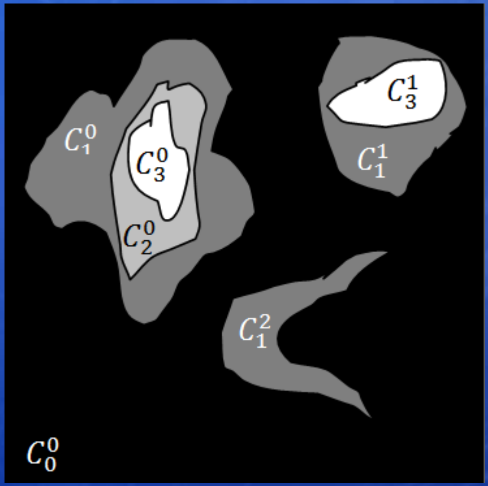
Operators by reconstruction are a subset of attribute filters.

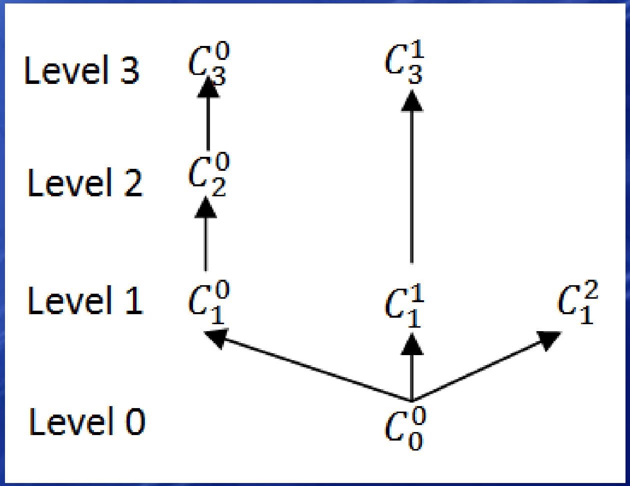
Attribute Filters – Max Tree

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:

- ✓ For each connected component (i.e., a node in the tree) the attribute is computed.
- ✓ The attribute is associated to the correspondent node.
- ✓ The tree is pruned by removing all nodes whose attribute does not satisfy the criterion.
- ✓ The filtered image is retrieved by the pruned tree.

Attribute Filters – Max Tree

- ✓ 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 Profiles

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

⇓

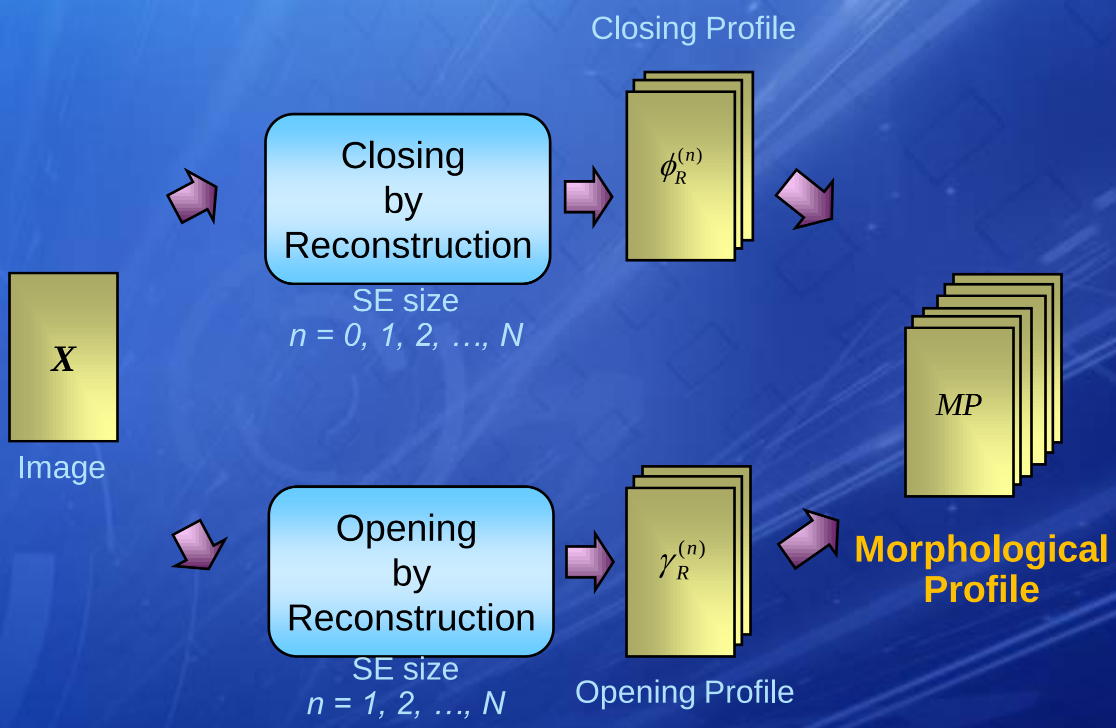
Perform a multilevel analysis by using several values for the filter parameters. Build a stack of images with different degrees of filtering.

⇓

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.

MP Architecture



Morphological 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:

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

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

DMP:

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

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

Attribute Profiles

Attribute Profiles as 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.

- ✓ We propose to use Morphological Attribute Filters which permit to:
  - ✓ Perform the processing with a reduced computational load, especially for multilevel analysis.
  - ✓ Model different types of features non 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*, in press.

Attribute Profiles

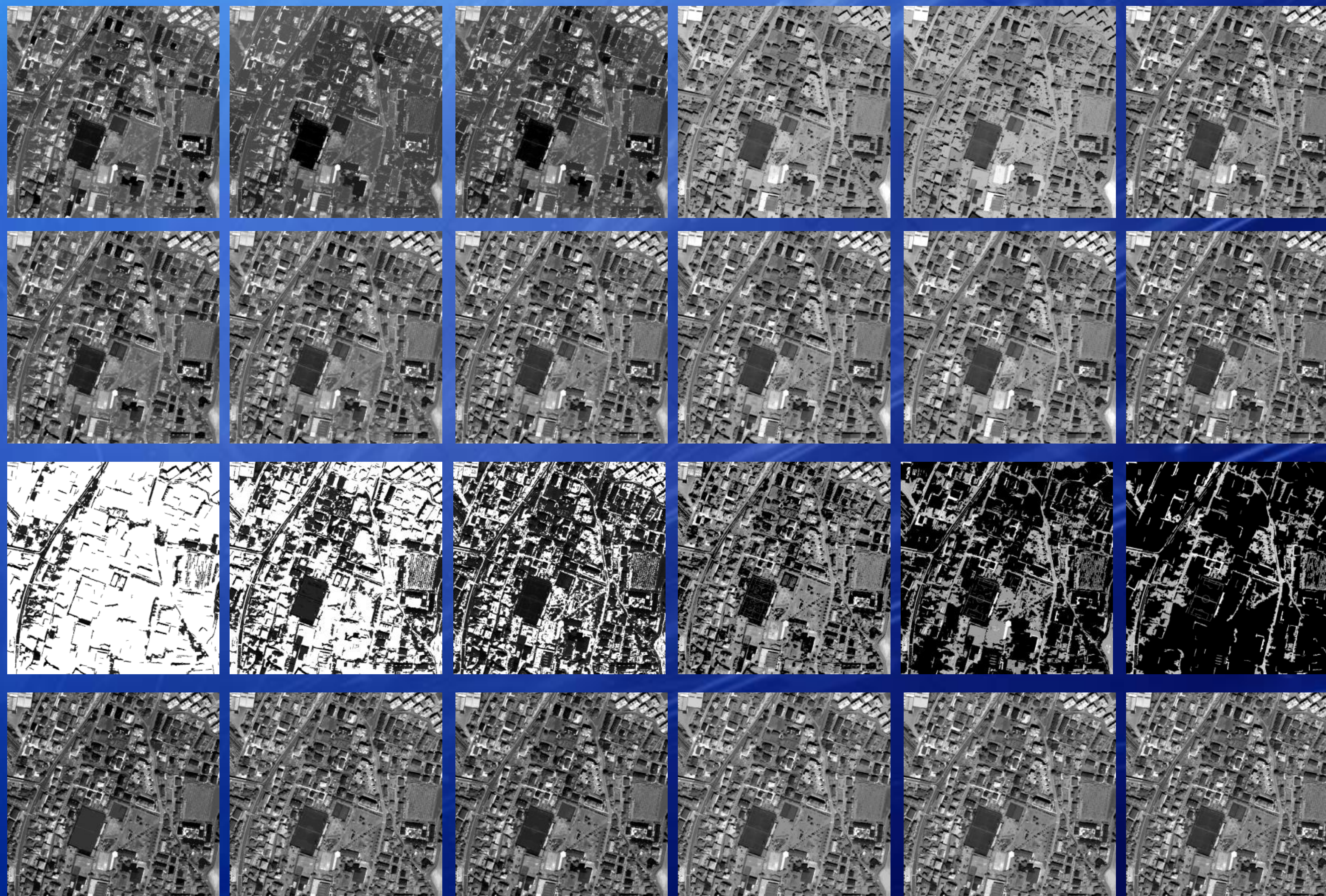
Thickening Profile ← | → **Thinning Profile**

Square SE (MP)
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**



Attribute Profiles

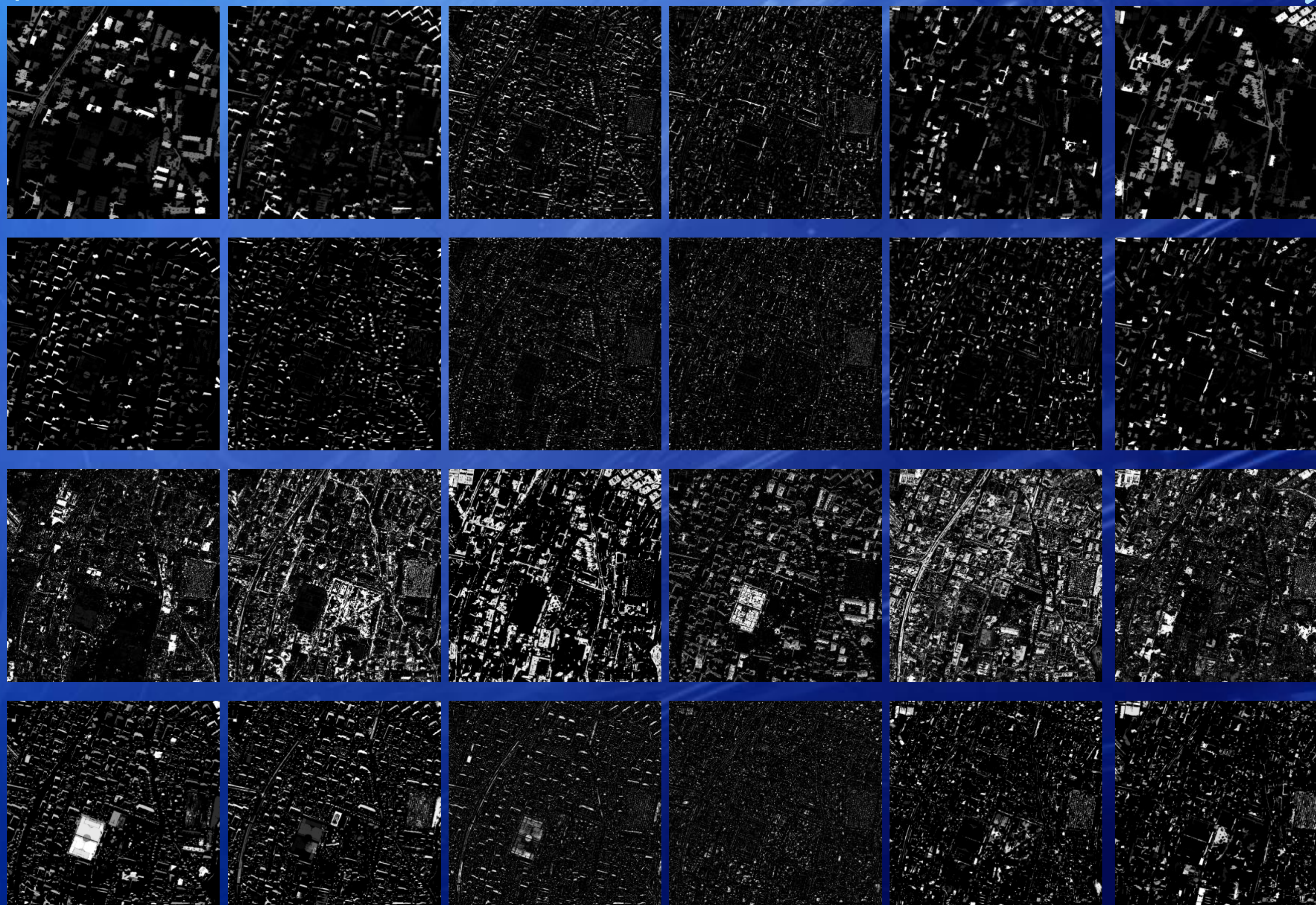
Derivative of Thickening Profile ← → **Derivative of Thinning Profile**

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

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

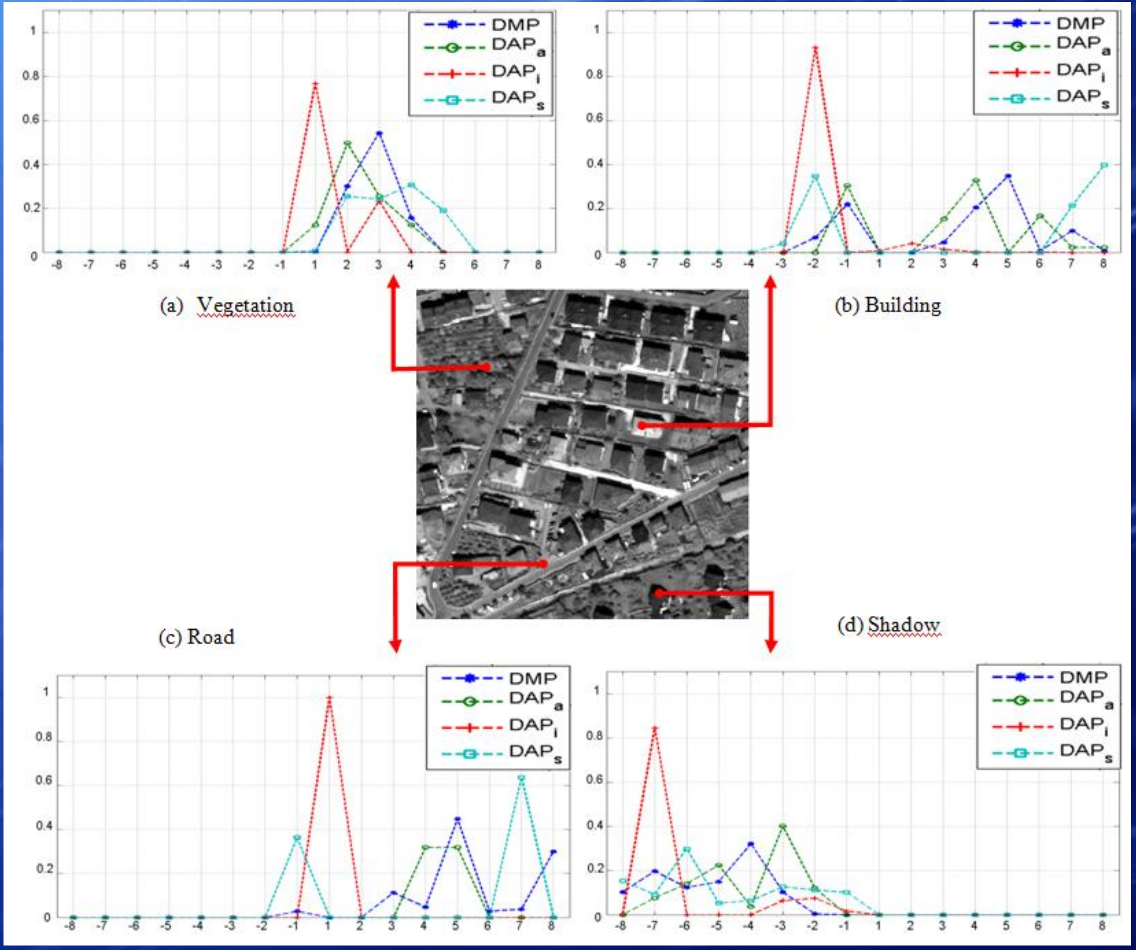
Moment of Inertia Attribute
λ: 0.2, 0.1, 0.3
Criterion: Inertia > **λ**

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

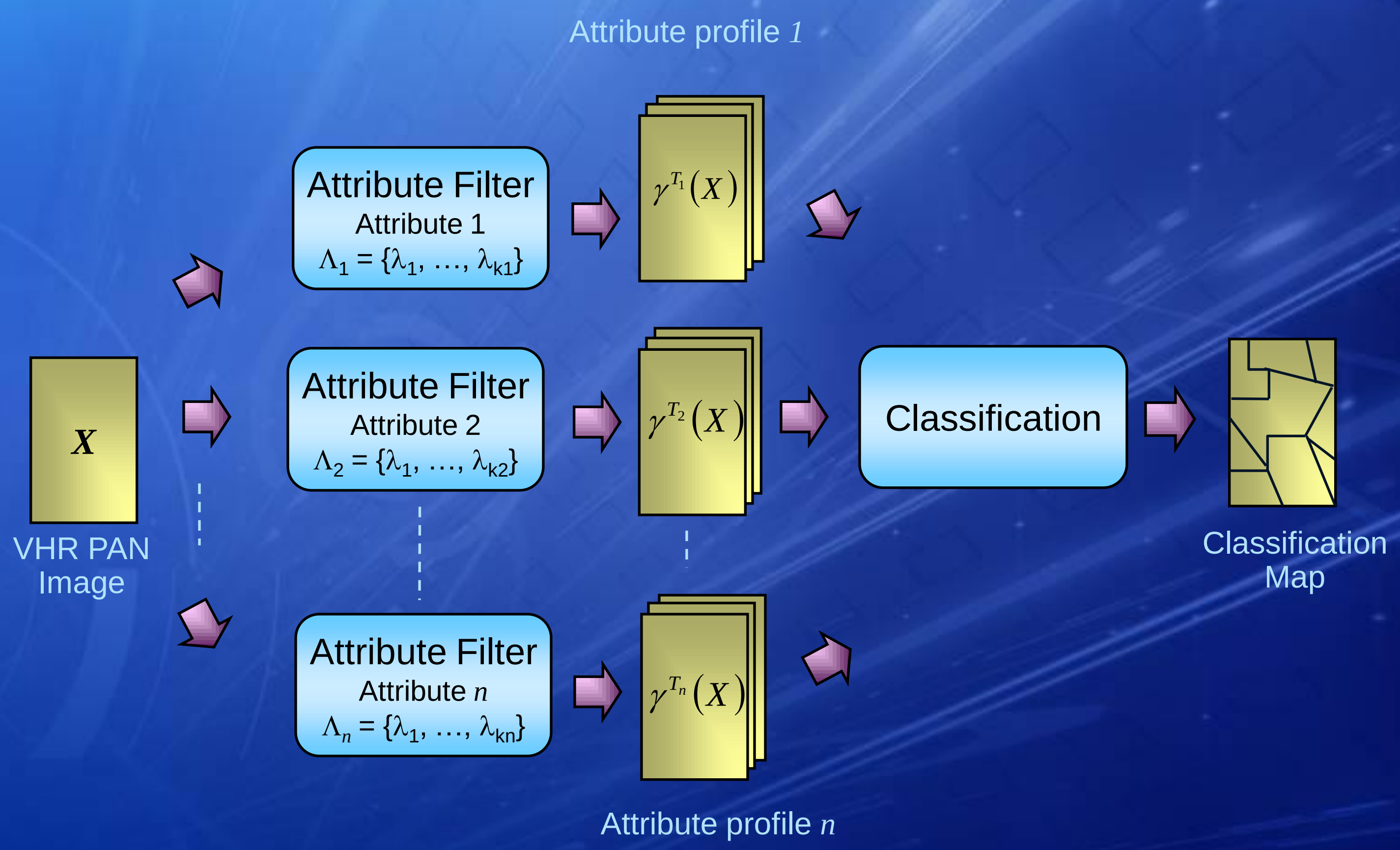


Attribute Profiles

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



Classification with APs



Data Set Description

Panchromatic image (500x500 pixels) of the city of Trento acquired by Quickbird (geometrical resolution of 0.6 [m])

Pansharpened Image

Panchromatic Image

Number of samples for each thematic class

Data	Road	Building	Shadow	Vegetation	Total
Training	58	178	43	88	367
Test	110	337	86	140	673

Design of Experiments

- ✓ Four multilevel attribute filters computed on the panchromatic image:
  - Area (λ = 50, 200, 500, 1000)
  - Diagonal of the bounding box (λ = 50, 125, 200, 400)
  - Moment of inertia (λ = 0.3, 0.5, 0.7, 0.9)
  - Standard deviation (λ = 10, 30, 50, 70)
- ✓ Comparison with MP computed on the panchromatic image (square structuring element (SE) of sizes 11, 23, 35, and 47).
- ✓ Classifier: Random Forest (200 trees).
- ✓ Protocol for accuracy assessment [1]:
  - Thematic error (computed on the test set).
  - Geometrical errors (computation of five geometrical error index on 11 reference objects).

[1] C. Persello and L. Bruzzone, "A Novel Protocol for Accuracy Assessment in Classification of Very High Resolution Images," *IEEE Transactions on Geoscience and Remote Sensing,* vol.48, no.3, pp.1232-1244, March 2010.

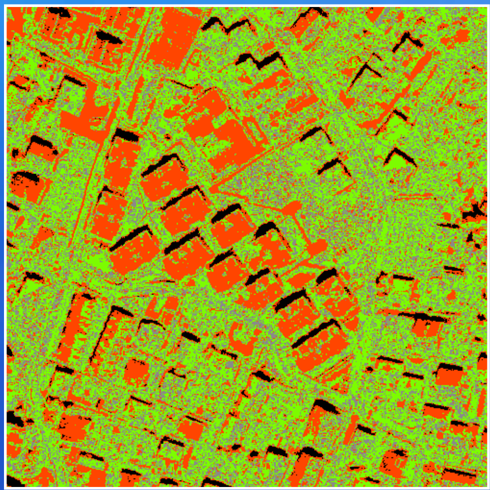
Results: Classification Errors

Attribute Filters	Thematic Error	Geometric Errors				
	1-Kappa	OS(*)	US(*)	ED(*)	FG(*)	SH(*)
Only PAN	0.512	0.488	0.375	0.714	0.159	0.161
MP (Square SE)	0.366	0.211	0.842	0.930	0.074	0.269
AP(Area)	0.448	0.241	0.658	0.864	0.123	0.237
AP (Diag)	0.351	0.204	0.829	0.924	0.115	0.223
AP (Inertia)	0.451	0.213	0.594	0.814	0.106	0.218
AP (Std Dev)	0.326	0.206	0.660	0.855	0.166	0.233
AP (All)	0.306	0.246	0.638	0.842	0.115	0.234

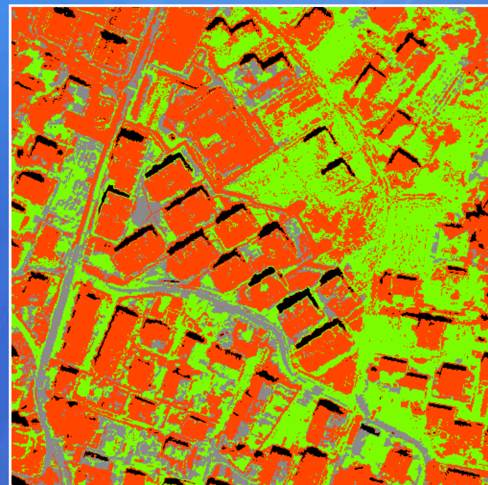
Geometric Indexes (*)

- ✓ OS: Over segmentation
- ✓ US: Under Segmentation
- ✓ ED: Edge Error
- ✓ FG: Fragmentations Error
- ✓ SH: Shape Error

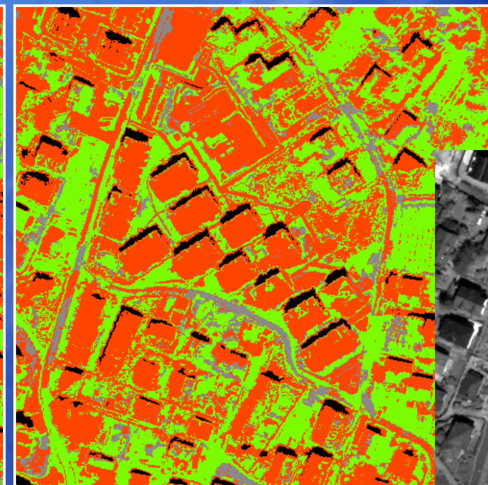
Results: Classification Maps



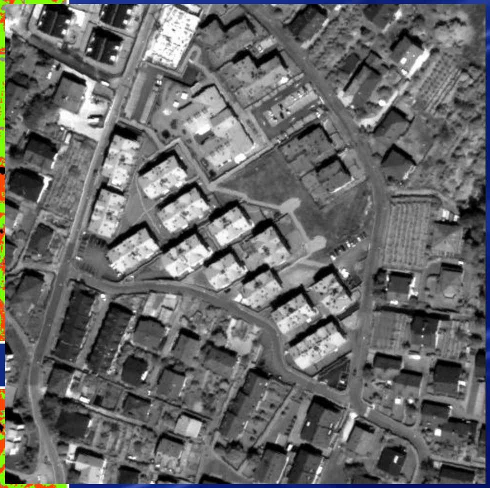
PAN



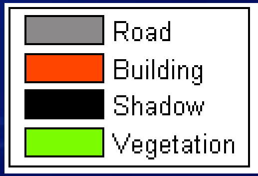
MP (square)

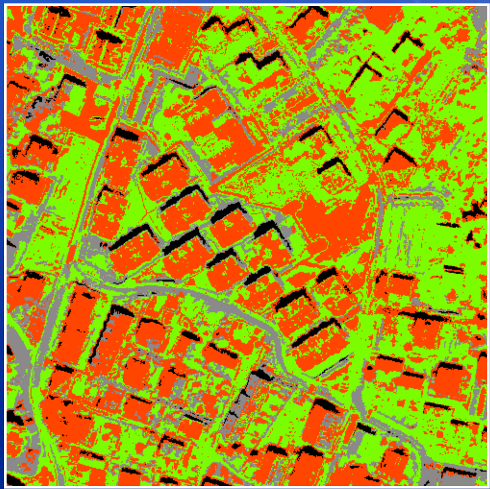


AP (area)

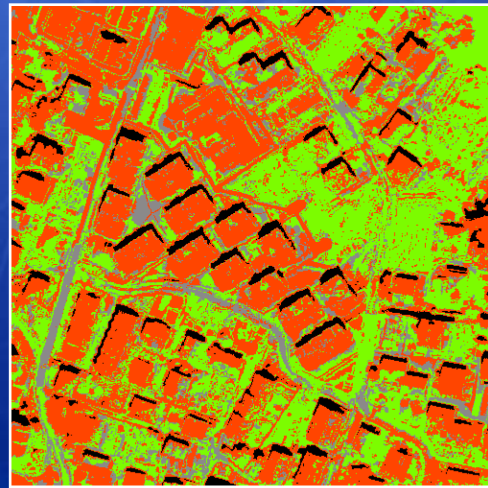


Panchromatic Image

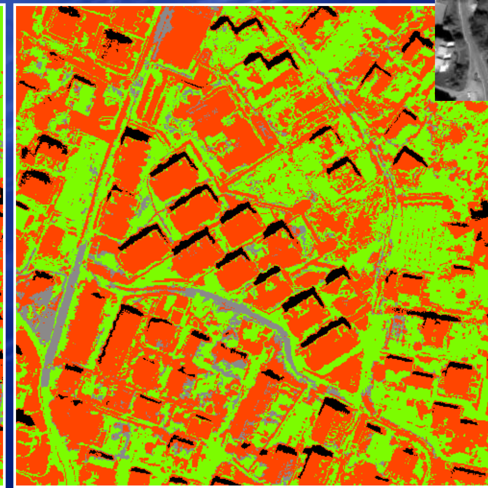




AP (moment of inertia)



AP (standard deviation)



AP(all)

Extended Profile

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

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

⇓

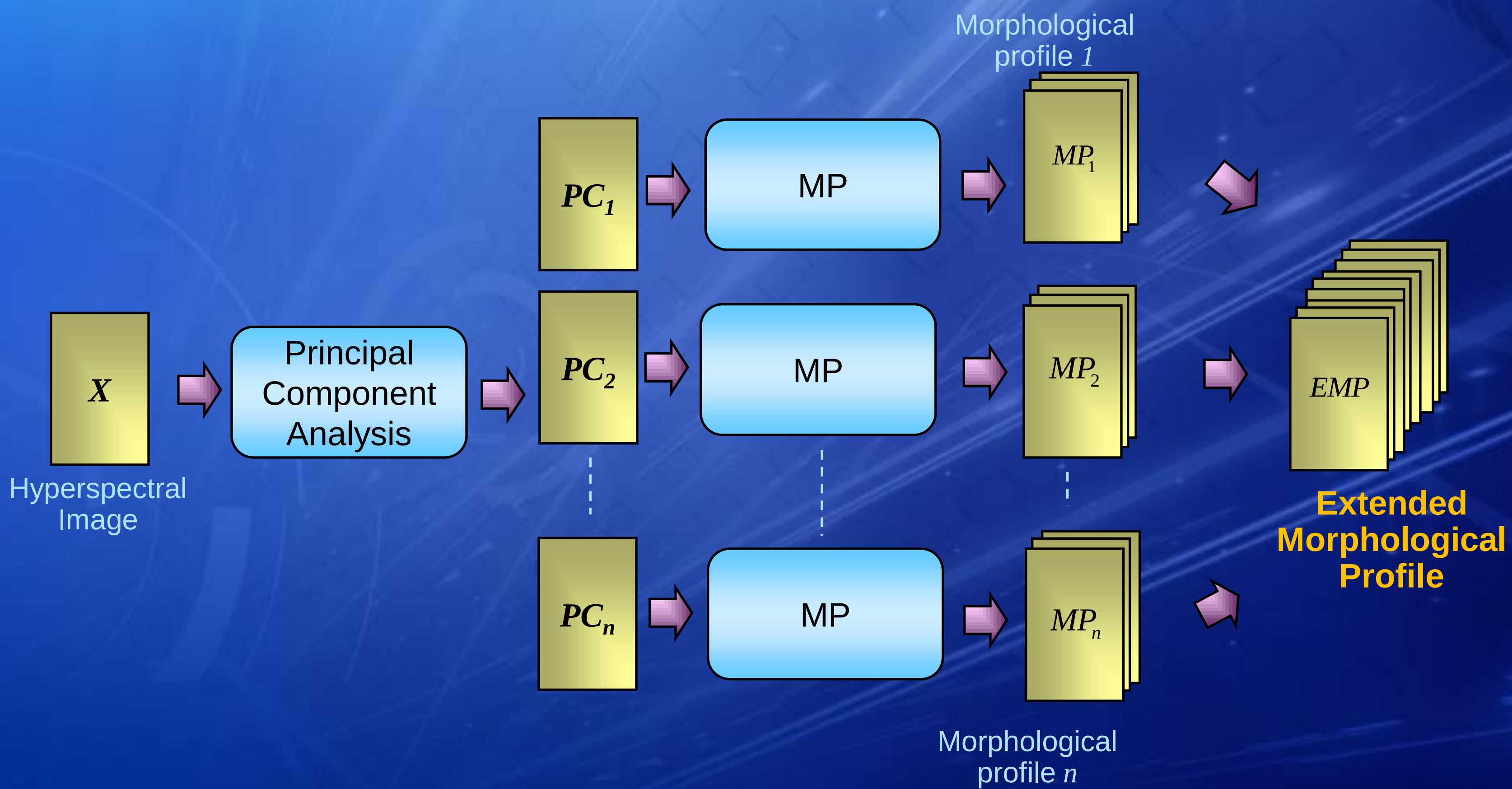
Computationally unfeasible for hyperspectral data.

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)

EMP Architecture



Extended Morphological Profile

On each first *n* principal component (*PC*) extracted from the hyperspectral image, a MP is computed.
The MPs are then concatenated for obtaining the EMP.

$$EMP = \{MP(PC_1), MP(PC_2), \ldots, MP(PC_n)\}$$

with $i \leq j$

$\phi_R^j(PC_1)$ $\phi_R^i(PC_1)$ PC_1 $\gamma_R^i(PC_1)$ $\gamma_R^j(PC_1)$ $\phi_R^j(PC_2)$ $\phi_R^i(PC_2)$ PC_2 $\gamma_R^i(PC_2)$ $\gamma_R^j(PC_2)$

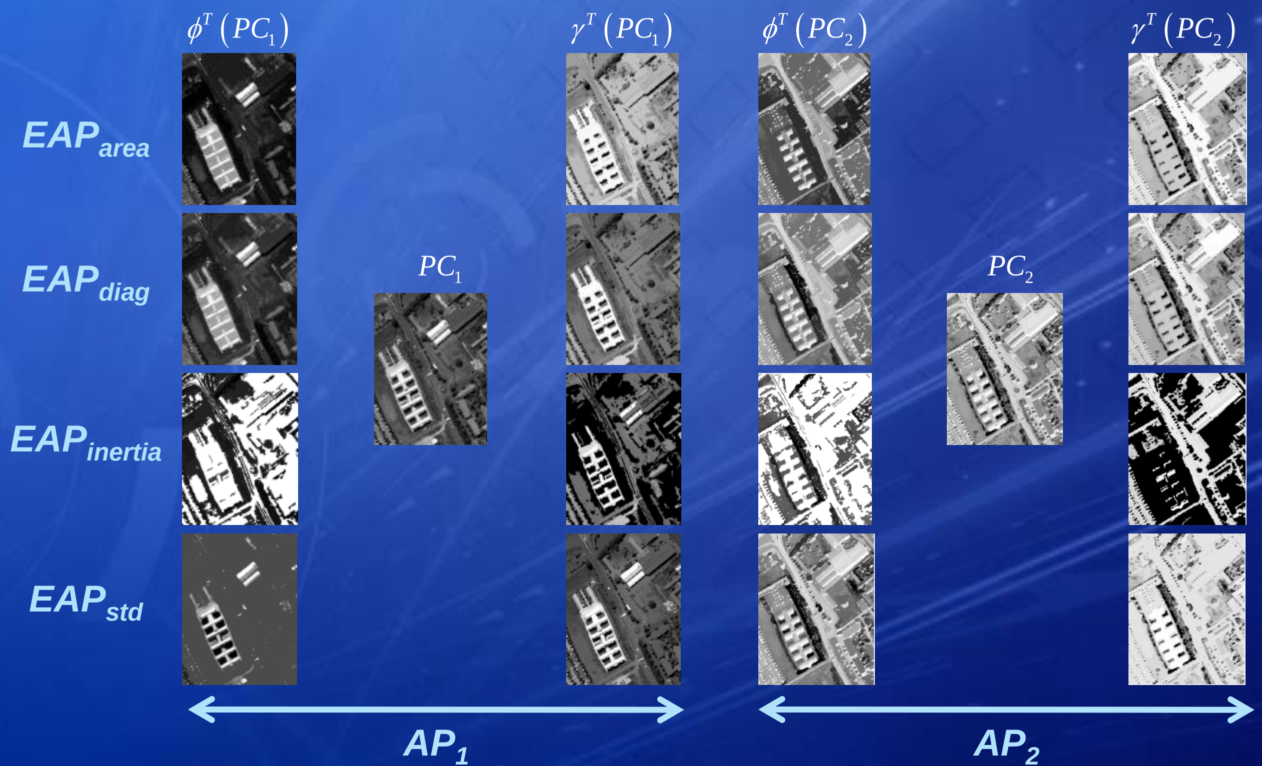
MP_1 MP_2

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.

Extended Attribute Profile (EAP)

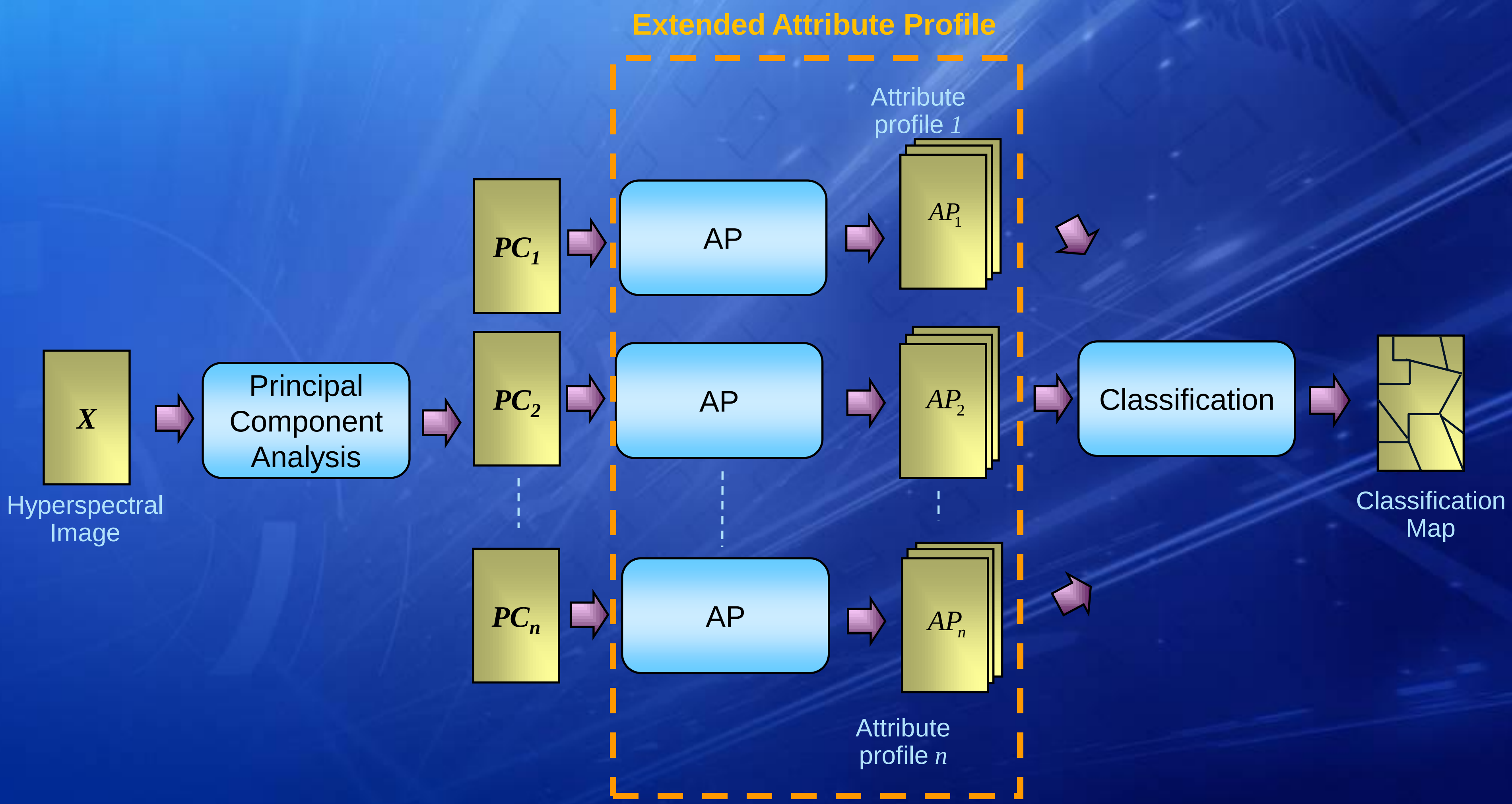
Analogous definition to EMP: APs computed on n first PCs are concatenated together for obtaining the EAP.

$$EAP = \{AP(PC_1), AP(PC_2), \ldots, AP(PC_n)\}$$



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*, in press.

Classification with EAP



Data Set Description

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	Train	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**.

Design of Experiments

- ✓ 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).

Results: Classification Accuracies

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

Results: Classification Maps

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**.

Attribute Filters – Hyperspectral dataset

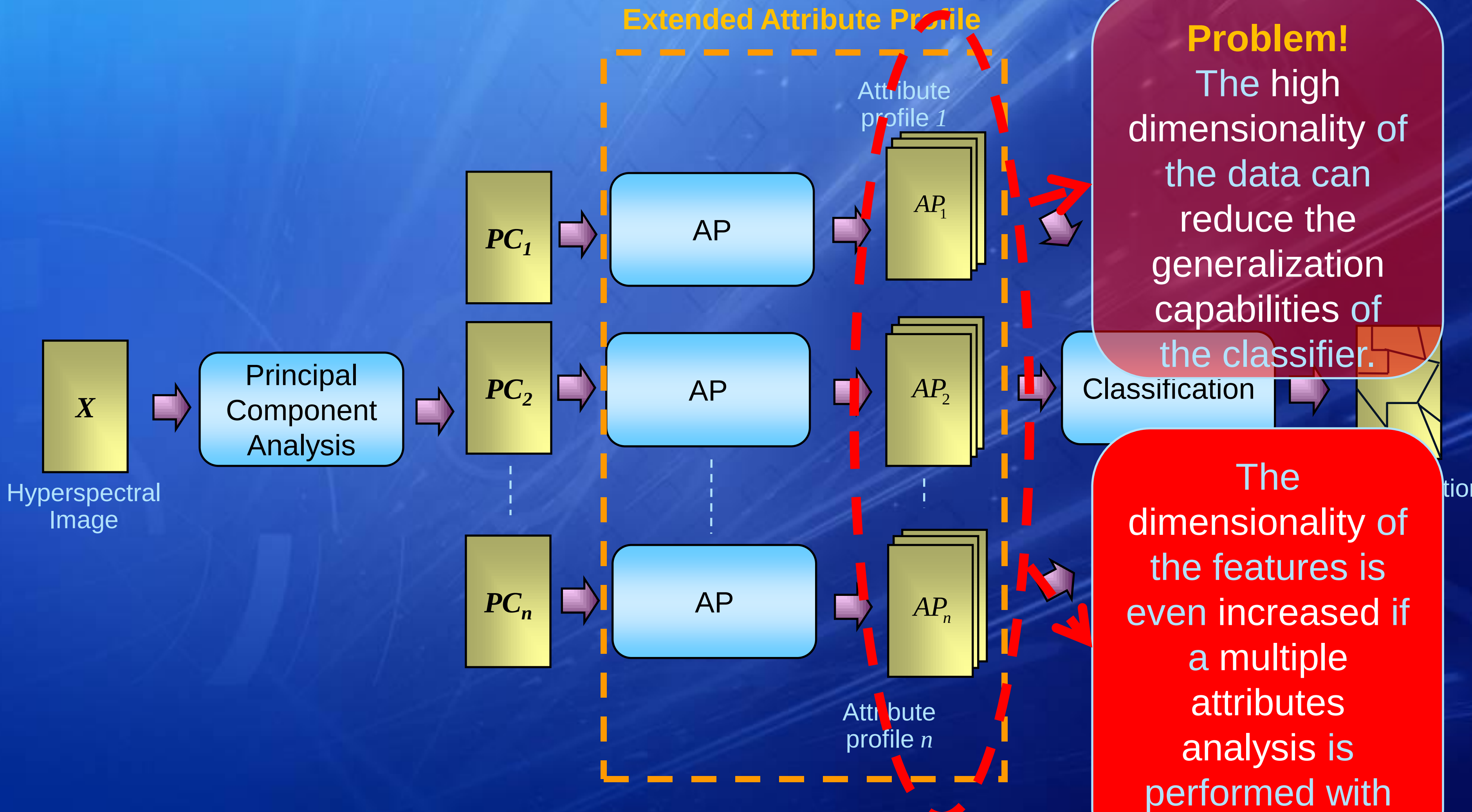
Spectral only (4 PCs)
OA: **70.42**%

EMP
OA: **80.71**%

EAPall
OA: **89.89**%

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

Considerations for Classification with EAP



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.

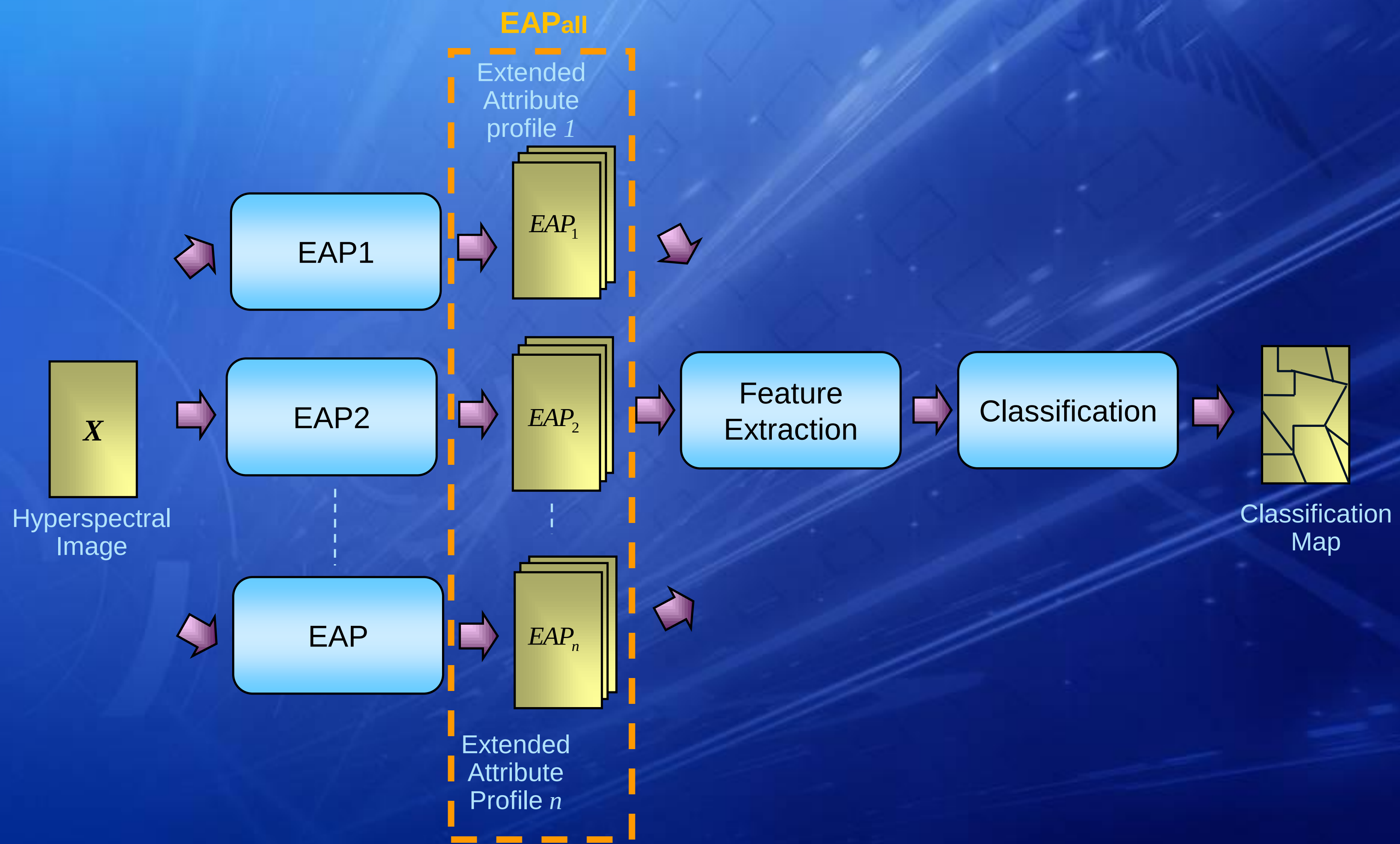
M. Dalla Mura, J. A. Benediktsson, B. Waske, and L. Bruzzone, "Extended profiles with morph… analysis of hyperspectral data," *International Journal of Remote Sensing*, in press.

Feature Extraction Techniques

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 Gaussians.
- ✓ **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).

Architecture with FE



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*, in press.

Design of Experiments

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).

Results: Classification Accuracies

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.

Results: Classification Maps

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**.

Conclusions

- ✓ Classification of panchromatic and hyperspectral high geometrical resolution remote sensing image was investigated.
- ✓ Attribute filters proved to be really 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 benefit of including spatial information modelled by the APs/EAPs was confirmed by the obtained accuracies in comparison to the only use of the spectral channels.
- ✓ The results obtained by the profiles built with attribute filters outperformed in terms of overall accuracy those generated by considering the conventional morphological operators.
- ✓ The use of a FE technique led to a further increase in terms of accuracies with respect to consider the data with full dimensionality.

Future Developments

- ✓ Consider **Feature Selection techniques** for reducing the dimensionality of the profiles.

- ✓ **Definition of an architecture** capable to automatically find the **best attributes** and **thresholds** (e.g., with GAs).

- ✓ 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).