Morphological Profiles for Classification of Panchromatic and Hyperspectral Images

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Outline

1. Introduction
2. Preliminaries on Mathematical Morphology
3. Morphological Profiles and Attribute Profiles
4. Extended Morphological Profiles and Extended Attribute Profiles
5. Reduction of the dimensionality with Feature Extraction Techniques
5. Conclusions and Future Developments
Geometrical Resolution: 0.6 [m]
Very-High Resolution (VHR) Images – Main Features

- Contextual relations are highly 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.
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 misalignment between the two images.
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.
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

Basic Operators

- Erosion: $\varepsilon_B$
- Dilation: $\delta_B$
- Opening: $\gamma_B(f) = \delta_B[\varepsilon_B(f)]$
- Closing: $\phi_B(f) = \varepsilon_B[\delta_B(f)]$
- Top-hat: $WTH = f - \gamma(f)$

Examples of Structuring Elements (SEs).
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

Examples of conventional Morphological operators and Connected Filters

Morphological closing  Closing with a connected filter  Original VHR image  Opening with a connected filter  Morphological opening
Morphological Operators by Reconstruction

Operators by Reconstruction

Two step procedure:
1. Erosion/Dilation
2. Reconstruction by dilation/erosion

Opening

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

Reconstruction by dilation

Original Image

Closing

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

Reconstruction by erosion

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Reconstruction Process

Morphological Opening
$$\gamma_B(f) = \delta_B[\varepsilon_B(f)]$$

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

Geodesic Reconstruction
$$R_f^{\delta}(\cdot) = \delta_f^{(i)}(\cdot) = \delta_f^{(1)} \cdot \delta_f^{(1)} \cdots \delta_f^{(1)}(\cdot) \quad \text{(i times)}$$

Iterative Process

Idempotence property
$$\delta_s^{(n)}(\cdot) = \delta_s^{(n-1)}(\cdot)$$

$$f \quad (30 \times 30 \text{ binary image})$$
$$\varepsilon^{(n)}(f)$$

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

$$i = 1, 2, 10, 20$$

SE: Disk diameter 5

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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.

Attribute filters operate only on the connected components (regions of connected iso-level pixels) according to a criterion $T$ which evaluates an attribute $\text{attr}$ against a threshold $\lambda$.

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., $\text{attr} > \lambda$).

e.g., Area opening.

\[
\Gamma_\lambda(f) = \{x \in f : \text{Area}(\Gamma_x(f)) \geq \lambda\}
\]

The filtered image contains all those regions that have an area of $\lambda$ or more.
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.

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

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

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!
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)

MP Architecture

Image

Closing by Reconstruction
SE size
\( n = 0, 1, 2, \ldots, N \)

Opening by Reconstruction
SE size
\( n = 1, 2, \ldots, N \)

Closing Profile
\( \phi_R^{(n)} \)

Opening Profile
\( \gamma_R^{(n)} \)

Morphological Profile

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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.

\[ \Pi_\gamma = \left\{ \Pi_\gamma (i) : \Pi_\gamma (i) = \gamma^{(S_i)}_R (f) \right\} i = 0,1,...k \]
\[ \Pi_\phi = \left\{ \Pi_\phi (i) : \Pi_\phi (i) = \phi^{(S_i)}_R (f) \right\} i = 0,1,...k \]

\[ \Delta_\gamma = \left\{ \Delta_\gamma (i) : \Delta_\gamma (i) = |\Pi_\gamma (i) - \Pi_\gamma (i-1)| \right\} i = 1,...k \]
\[ \Delta_\phi = \left\{ \Delta_\phi (i) : \Delta_\phi (i) = |\Pi_\phi (i) - \Pi_\phi (i-1)| \right\} i = 1,...k \]
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.

## Attribute Profiles

<table>
<thead>
<tr>
<th>Thickening Profile</th>
<th>Thinning Profile</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Square SE (MP)</strong></td>
<td></td>
</tr>
<tr>
<td>Sizes: 7, 13, 19</td>
<td></td>
</tr>
<tr>
<td><strong>Area Attribute</strong></td>
<td></td>
</tr>
<tr>
<td>$\lambda$: 45, 169, 361</td>
<td></td>
</tr>
<tr>
<td><strong>Criterion</strong>: Area $&gt;$ $\lambda$</td>
<td></td>
</tr>
<tr>
<td><strong>Moment of Inertia Attribute</strong></td>
<td></td>
</tr>
<tr>
<td>$\lambda$: 0.2, 0.1, 0.3</td>
<td></td>
</tr>
<tr>
<td><strong>Criterion</strong>: Inertia $&gt;$ $\lambda$</td>
<td></td>
</tr>
<tr>
<td><strong>STD Attribute</strong></td>
<td></td>
</tr>
<tr>
<td>$\lambda$: 10, 20, 30</td>
<td></td>
</tr>
<tr>
<td><strong>Criterion</strong>: STD $&gt;$ $\lambda$</td>
<td></td>
</tr>
</tbody>
</table>

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### Attribute Profiles

<table>
<thead>
<tr>
<th>Square SE (DMP)</th>
<th>Sizes: 7, 13, 19</th>
</tr>
</thead>
<tbody>
<tr>
<td>Area Attribute</td>
<td>$\lambda$: 45, 169, 361</td>
</tr>
<tr>
<td>Criterion: Area &gt; $\lambda$</td>
<td></td>
</tr>
<tr>
<td>Moment of Inertia Attribute</td>
<td>$\lambda$: 0.2, 0.1, 0.3</td>
</tr>
<tr>
<td>Criterion: Inertia &gt; $\lambda$</td>
<td></td>
</tr>
<tr>
<td>STD Attribute</td>
<td>$\lambda$: 10, 20, 30</td>
</tr>
<tr>
<td>Criterion: STD &gt; $\lambda$</td>
<td></td>
</tr>
</tbody>
</table>
The analysis on the APs built with different attributes can discriminate among the different thematic classes.
Classification with APs

VHR PAN Image

Attribute Filter
Attribute 1
\( \Lambda_1 = \{\lambda_1, \ldots, \lambda_{k_1}\} \)

Attribute Filter
Attribute 2
\( \Lambda_2 = \{\lambda_1, \ldots, \lambda_{k_2}\} \)

Attribute Filter
Attribute \( n \)
\( \Lambda_n = \{\lambda_1, \ldots, \lambda_{k_n}\} \)

\( \gamma_T^1(X) \)

\( \gamma_T^2(X) \)

\( \gamma_T^n(X) \)

Classification

Classification Map

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Data Set Description

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

<table>
<thead>
<tr>
<th>Data</th>
<th>Road</th>
<th>Building</th>
<th>Shadow</th>
<th>Vegetation</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training</td>
<td>58</td>
<td>178</td>
<td>43</td>
<td>88</td>
<td>367</td>
</tr>
<tr>
<td>Test</td>
<td>110</td>
<td>337</td>
<td>86</td>
<td>140</td>
<td>673</td>
</tr>
</tbody>
</table>

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Four multilevel attribute filters computed on the panchromatic image:

- Area ($\lambda = 50, 200, 500, 1000$)
- Diagonal of the bounding box ($\lambda = 50, 125, 200, 400$)
- Moment of inertia ($\lambda = 0.3, 0.5, 0.7, 0.9$)
- Standard deviation ($\lambda = 10, 30, 50, 70$)

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).

# Results: Classification Errors

<table>
<thead>
<tr>
<th>Attribute Filters</th>
<th>Thematic Error</th>
<th>Geometric Errors</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1-Kappa</td>
<td>OS(*)</td>
</tr>
<tr>
<td>Only PAN</td>
<td>0.512</td>
<td>0.488</td>
</tr>
<tr>
<td>MP (Square SE)</td>
<td>0.366</td>
<td>0.211</td>
</tr>
<tr>
<td>AP (Area)</td>
<td>0.448</td>
<td>0.241</td>
</tr>
<tr>
<td>AP (Diag)</td>
<td>0.351</td>
<td>0.204</td>
</tr>
<tr>
<td>AP (Inertia)</td>
<td>0.451</td>
<td>0.213</td>
</tr>
<tr>
<td>AP (Std Dev)</td>
<td>0.326</td>
<td>0.206</td>
</tr>
<tr>
<td>AP (All)</td>
<td>0.306</td>
<td>0.246</td>
</tr>
</tbody>
</table>

**Geometric Indexes (*)**
- ✓ OS: Over segmentation
- ✓ US: Under Segmentation
- ✓ ED: Edge Error
- ✓ FG: Fragmentations Error
- ✓ SH: Shape Error

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Results: Classification Maps

PAN

MP (square)

AP (area)

AP (moment of inertia)

AP (standard deviation)

AP (all)

Panchromatic Image

Legend:
- Road
- Building
- Shadow
- Vegetation
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)
Hyperspectral Image

Principal Component Analysis

$PC_1 \rightarrow MP \rightarrow MP_1$

$PC_2 \rightarrow MP \rightarrow MP_2$

$PC_n \rightarrow MP \rightarrow MP_n$

Morphological profile $i$

Morphological profile $n$

Extended Morphological Profile

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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 \( i \leq j \)


**Extended Attribute Profile (EAP)**

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

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

Classification with EAP

Hyperspectral Image $X$ is subjected to Principal Component Analysis (PCA) to obtain $PC_1$, $PC_2$, ..., $PC_n$. The Extended Attribute Profile (EAP) for each principal component is constructed. Attribute profiles $AP_1$, $AP_2$, ..., $AP_n$ are derived from these EAPs. The attribute profiles are then used for classification, resulting in a Classification Map.

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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]

<table>
<thead>
<tr>
<th>Class</th>
<th>Train</th>
<th>Test</th>
</tr>
</thead>
<tbody>
<tr>
<td>Trees</td>
<td>524</td>
<td>3064</td>
</tr>
<tr>
<td>Meadow</td>
<td>540</td>
<td>18649</td>
</tr>
<tr>
<td>Metal</td>
<td>265</td>
<td>1324</td>
</tr>
<tr>
<td>Gravel</td>
<td>392</td>
<td>2099</td>
</tr>
<tr>
<td>Bricks</td>
<td>514</td>
<td>3682</td>
</tr>
<tr>
<td>Bare Soil</td>
<td>532</td>
<td>5029</td>
</tr>
<tr>
<td>Asphalt</td>
<td>548</td>
<td>6631</td>
</tr>
<tr>
<td>Bitumen</td>
<td>375</td>
<td>1330</td>
</tr>
<tr>
<td>Shadow</td>
<td>231</td>
<td>947</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>3921</strong></td>
<td><strong>42776</strong></td>
</tr>
</tbody>
</table>

Thematic classes: *Trees, Meadow, Metal, Gravel, Bricks, Bare Soil, Asphalt, Bitumen, Shadow.*
Attribute Profiles built by four attributes on the first 4 PCs.
  • Area ($\lambda = 100, 500, 1000, 5000$)
  • Length Diagonal of the bounding box ($\lambda = 10, 25, 50, 100$)
  • Moment of inertia ($\lambda = 0.2, 0.3, 0.4, 0.5$)
  • Standard deviation ($\lambda = 20, 30, 40, 50$)

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).
## Overall Accuracy [%]

<table>
<thead>
<tr>
<th>Features</th>
<th>PCs</th>
<th>EMP</th>
<th>EAP area</th>
<th>EAP diagonal</th>
<th>EAP inertia</th>
<th>EAP std</th>
<th>EAP all</th>
</tr>
</thead>
<tbody>
<tr>
<td>Features</td>
<td>4</td>
<td>36</td>
<td>36</td>
<td>36</td>
<td>36</td>
<td>36</td>
<td>144</td>
</tr>
<tr>
<td>OA (%)</td>
<td>70.42</td>
<td>80.71</td>
<td><strong>92.32</strong></td>
<td>86.84</td>
<td>76.26</td>
<td>78.68</td>
<td>89.89</td>
</tr>
<tr>
<td>AA (%)</td>
<td>79.25</td>
<td>86.64</td>
<td><strong>92.00</strong></td>
<td>88.00</td>
<td>84.68</td>
<td>86.27</td>
<td>90.25</td>
</tr>
<tr>
<td>Kappa</td>
<td>0.63</td>
<td>0.75</td>
<td><strong>0.90</strong></td>
<td>0.82</td>
<td>0.70</td>
<td>0.73</td>
<td>0.87</td>
</tr>
</tbody>
</table>
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%
Thematic classes: Trees, Meadow, Metal, Gravel, Bricks, Bare Soil, Asphalt, Bitumen, Shadow.

EMP
OA: 80.71%

EAPall
OA: 89.89%
Considerations for Classification with EAP


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.
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

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.

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

**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

<table>
<thead>
<tr>
<th>FE Technique</th>
<th>Classifier</th>
<th>EAPₐ</th>
<th>EAPₖ</th>
<th>EAPᵢ</th>
<th>EAPₛ</th>
<th>EAPₐₐ𝑙₁</th>
</tr>
</thead>
<tbody>
<tr>
<td>EAP with NO FE</td>
<td>ML</td>
<td>72.21</td>
<td>65.05</td>
<td>73.08</td>
<td>54.34</td>
<td>64.19</td>
</tr>
<tr>
<td></td>
<td>RF</td>
<td>90.99</td>
<td>86.66</td>
<td>82.94</td>
<td>81.64</td>
<td>89.71</td>
</tr>
<tr>
<td>EAP with DAFE</td>
<td>ML</td>
<td>89.97 (7)</td>
<td>84.68 (8)</td>
<td>84.56 (10)</td>
<td>85.41 (8)</td>
<td>91.48 (11)</td>
</tr>
<tr>
<td></td>
<td>RF</td>
<td>92.68 (20)</td>
<td>90.13 (25)</td>
<td>90.84 (35)</td>
<td>86.52 (14)</td>
<td>96.01 (121)</td>
</tr>
<tr>
<td>EAP with DBFE</td>
<td>ML</td>
<td>88.69 (6)</td>
<td>82.33 (8)</td>
<td>81.47 (7)</td>
<td>85.18 (5)</td>
<td>83.80 (11)</td>
</tr>
<tr>
<td></td>
<td>RF</td>
<td>88.69 (30)</td>
<td>85.07 (36)</td>
<td>82.20 (36)</td>
<td>87.55 (20)</td>
<td>94.50 (81)</td>
</tr>
<tr>
<td>EAP with NWFE</td>
<td>ML</td>
<td>89.93 (14)</td>
<td>83.03 (4)</td>
<td>87.54 (10)</td>
<td>88.55 (12)</td>
<td>91.18 (11)</td>
</tr>
<tr>
<td></td>
<td>RF</td>
<td>92.99 (24)</td>
<td>87.25 (30)</td>
<td>93.47 (27)</td>
<td>79.83 (5)</td>
<td>91.89 (41)</td>
</tr>
</tbody>
</table>

The number of features giving the highest accuracies is reported in brackets.
Results: Classification Maps

Classification Maps obtained with a Random Forest Classifier.

<table>
<thead>
<tr>
<th>Method</th>
<th>OA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spectral channels</td>
<td>71.66%</td>
</tr>
<tr>
<td>EAP\textsubscript{all} with DAFE</td>
<td>96.01%</td>
</tr>
<tr>
<td>EAP\textsubscript{all} with DBFE</td>
<td>94.50%</td>
</tr>
<tr>
<td>EAP\textsubscript{all} with NWFE</td>
<td>91.89%</td>
</tr>
</tbody>
</table>

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

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