Morphological and Attribute Profiles for Classification of Hyperspectral Remote Sensing Imagery

Prof. Jón Atli Benediktsson
University of Iceland

benedikt@hi.is
www.hi.is/~benedikt
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
Introduction

1. Very High Resolution Remote Sensing
2. Hyperspectral Imagery

Morphological Profiles and Attribute Filters

2. Morphological and Attribute Profiles for Single Data Channels
3. Extended Morphological and Attribute Profiles

Optimized Feature Selection for Attribute Filters

4. HML Algorithm
5. APs and Spectral Information: Automatic vs. Manual

Conclusions
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**
  - 1 band
  - 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
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
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

Spectral classification $\rightarrow$ Random permutation $\rightarrow$ Spectral classification

Need to incorporate information from the spatial domain
Spectral vs spatial analysis

Examples of maps obtained by classifying different 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.
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
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

Mathematical Morphology - 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 & 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

Examples of conventional Morphological operators and Connected Filters
Morphological & Attribute Profiles

Operators by Reconstruction

Opening

\[ \gamma_R^{(n)}(f) = R^0_k[\epsilon^{(n)}(f)] \]

Reconstruction by dilation

Original Image

Closing

\[ \phi_R^{(n)}(f) = R^e_k[\delta^{(n)}(f)] \]

Reconstruction by erosion

Two step procedure:
1. Erosion/Dilation
2. Reconstruction by dilation/erosion
Morphological Opening
\[ \gamma_B(f) = \delta_B[\varepsilon_B(f)] \]

Opening by reconstruction
\[ \gamma_R^{(n)}(f) = R_f^{\delta}[\varepsilon_B(f)], \text{ with } n \text{ size of } B \]

Geodesic Reconstruction
\[ R_f^{\delta}(\cdot) = \delta_f^{(i)} = \delta_f^{(1)} \cdot \delta_f^{(1)} \ldots \delta_f^{(1)}(\cdot) \]

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)

Morphological & Attribute Profiles

Introduction
MP and AF
Feature Selection
Conclusions

Image

$X$

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

Closing Profile

$\phi_{R}^{(n)}$

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

Opening Profile

$\gamma_{R}^{(n)}$

Morphological Profile

$MP$

$\geq 0$
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.

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

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

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

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.

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 $\lambda$.

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., $A > \lambda$).
**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.**

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

- **Non-increasing criteria.**
  - Perimeter
  - Shape index
  - Moment of inertia
  - Range of the pixels intensities
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**.

---

**Grayscale Image**

**Conn. Comp.**

**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

**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
## Morphological & Attribute Profiles

<table>
<thead>
<tr>
<th>Feature Type</th>
<th>Sizes/λ/Criterion</th>
<th>Derivative of Thickening Profile</th>
<th>Derivative of Thinning Profile</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Square SE (DMP)</strong></td>
<td>Sizes: 7, 13, 19</td>
<td><img src="image1.png" alt="Image" /></td>
<td><img src="image2.png" alt="Image" /></td>
</tr>
<tr>
<td><strong>Area Attribute</strong></td>
<td>λ: 45, 169, 361, Criterion: Area &gt; λ</td>
<td><img src="image3.png" alt="Image" /></td>
<td><img src="image4.png" alt="Image" /></td>
</tr>
<tr>
<td><strong>Moment of Inertia Attribute</strong></td>
<td>λ: 0.2, 0.1, 0.3, Criterion: Inertia &gt; λ</td>
<td><img src="image5.png" alt="Image" /></td>
<td><img src="image6.png" alt="Image" /></td>
</tr>
<tr>
<td><strong>STD Attribute</strong></td>
<td>λ: 10, 20, 30, Criterion: STD &gt; λ</td>
<td><img src="image7.png" alt="Image" /></td>
<td><img src="image8.png" alt="Image" /></td>
</tr>
</tbody>
</table>
Morphological & Attribute Profiles

The analysis on the APs built with different attributes can discriminate among the different thematic classes.
Morphological & Attribute Profiles

VHR PAN Image

Attribute Filter
Attribute 1
\( \Lambda_1 = \{ \lambda_{11}, ..., \lambda_{k1} \} \)

\( \gamma^{T_1}(X) \)

Attribute Filter
Attribute 2
\( \Lambda_2 = \{ \lambda_{12}, ..., \lambda_{k2} \} \)

\( \gamma^{T_2}(X) \)

Classification

Attribute Filter
Attribute \( n \)
\( \Lambda_n = \{ \lambda_{1n}, ..., \lambda_{kn} \} \)

\( \gamma^{T_n}(X) \)

Classification Map

Attribute profile 1

Attribute profile \( n \)
**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.

![Diagram](image)

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.

![Diagram](image)

Extended Morphological Profile (EMP)
Morphological & Attribute Profiles

Hyperspectral Image

Principal Component Analysis

$X$

$PC_1$

$PC_2$

$PC_n$

MP

Morphological profile $i$

$MP_1$

$MP_2$

$MP_n$

EMP

Extended Morphological Profile

Morphological profile $n$
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.

\[ \phi^i_r(PC_1), \phi^j_r(PC_1), PC_1, \gamma^i_r(PC_1), \gamma^j_r(PC_1), \phi^i_r(PC_2), \phi^j_r(PC_2), PC_2, \gamma^i_r(PC_2), \gamma^j_r(PC_2) \]

with \( i \leq j \)


Morphological & Attribute Profiles

Extended Attribute Profile (EAP)
Analogous definition to EMP: APs computed on n first PCs are concatenated together for obtaining the EAP.

$EAP_{area}$

$EAP_{diag}$

$EAP_{inertia}$

$EAP_{std}$

$AP_1$  $AP_2$

Morphological & Attribute Profiles

Hyperspectral Image → Principal Component Analysis → $PC_1$ → $AP$ → $AP_1$ → Classification

$PC_2$ → $AP$ → $AP_2$ → $AP_n$ → Classification

Attribute profile 1

Attribute profile $n$
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]

Number of samples per class

<table>
<thead>
<tr>
<th>Class</th>
<th>Training</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.
Morphological & Attribute Profiles

- **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)
## Morphological & Attribute Profiles

### 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><strong>OA (%)</strong></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><strong>89.89</strong></td>
</tr>
<tr>
<td><strong>AA (%)</strong></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><strong>90.25</strong></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><strong>0.87</strong></td>
</tr>
</tbody>
</table>
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

![Maps with classification results](image)

- **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.

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

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].

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 ($\lambda = 100, 500, 1000, 5000$)
  - 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).
# Morphological & Attribute Profiles

## Overall Accuracy [%]

<table>
<thead>
<tr>
<th>FE Technique</th>
<th>Classifier</th>
<th>EAPa</th>
<th>EAPd</th>
<th>EAPi</th>
<th>EAPs</th>
<th>EAPall</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.
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

AP (one level)

AF

MORPHOLOGICAL OPERATORS
Attribute: Area

AP (n-level)

AF

MORPHOLOGICAL OPERATORS

EAP
MORPHOLOGICAL OPERATORS

Attribute: Area

Lambda Area 1

Lambda Area 2

AP (n-level)

AF

Attribute: Standard Deviation

Lambda ST DV 1

Lambda ST DV 2

AP (n-level)

AF

EAP

EMAP
Problem Statement

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

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

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

Input Hypersp. Image → Feature Reduction → EEMAP → HML feature extraction → Classif.

Training Information
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

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 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 $\rightarrow$ HIGH importance.
  - LOW difference $\rightarrow$ 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.

```
H-1  H-2  H-3  H-4  .........  H-n
```

Final vector of features

First Generation

Second Generation

Until all the features are processed
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]
Optimal Selection: Experimental Results

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

<table>
<thead>
<tr>
<th>Class</th>
<th>User Accuracy (%)</th>
<th>Producer Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Trees</td>
<td>85.8919</td>
<td>96.9648</td>
</tr>
<tr>
<td>Asphalt</td>
<td>99.4850</td>
<td>99.0499</td>
</tr>
<tr>
<td>Bitumen</td>
<td>100.0000</td>
<td>100.0000</td>
</tr>
<tr>
<td>Gravel</td>
<td>98.6742</td>
<td>99.2654</td>
</tr>
<tr>
<td>Metal sheets</td>
<td>100.0000</td>
<td>99.5257</td>
</tr>
<tr>
<td>Shadow</td>
<td>99.8896</td>
<td>95.5649</td>
</tr>
<tr>
<td>Self-Block Bricks</td>
<td>98.5103</td>
<td>98.7778</td>
</tr>
<tr>
<td>Meadows</td>
<td>99.3713</td>
<td>97.4690</td>
</tr>
<tr>
<td>Bare Soil</td>
<td>99.8015</td>
<td>100.0000</td>
</tr>
</tbody>
</table>

Average Accuracy: 98.5597
Overall Accuracy: 98.2911
Kappa Accuracy: 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

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
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
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 attribute 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.
For more information see: [www.hi.is/~benedikt](http://www.hi.is/~benedikt)

Recent Papers related to this presentation:


For more information see: [www.hi.is/~benedikt](http://www.hi.is/~benedikt)

Acknowledgment to my collaborators, including:

- Mauro Dalla Mura
- Shutao Li
- Jun Li
- Jose Bioucas-Dias
- Mattia Perdegnana
- Jocelyn Chanussot
- Lorenzo Bruzzone
- Nicola Falco
- Yuliya Tarabalka
- Jón Ævar Pálsson
- Benquin Song
- Peijun Li
- Pedram Ghamisi
- Xudong Kang
- Antonio Plaza
- Prashanth Marpu
- Martino Pesaresi
- Mathieu Fauvel
- Silvia Valero
- Alberto Villa
- Gabriele Cavallaro
- Jóhannes R. Sveinsson
- Xin Huang
- Leyunan Fang
- ...