Classification Based Marker Selection for Watershed Transform of Hyperspectral Images

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Outline

1. Introduction
2. Marker-controlled watershed segmentation and classification
3. Conclusions and perspectives
Hyperspectral image

Every pixel contains a detailed spectrum (>100 spectral bands)

+ More information per pixel → increasing capability to distinguish objects
  − Dimensionality increases → image analysis becomes more complex

Efficient algorithms for automatic processing are required!
Classification problem

**Input AVIRIS image**

[145 × 145 × 200]

**Ground-truth data**

**Task**

Assign every pixel to one of the 16 classes:
- corn-no till
- corn-min till
- corn
- soybeans-no till
- soybeans-min till
- soybeans-clean till
- alfalfa
- grass/pasture
- grass/trees
- grass/pasture-mowed
- hay-windrowed
- oats
- wheat
- woods
- bldg-grass-tree-drives
- stone-steel towers
Classification approaches

Only spectral information

- Spectrum of each pixel is analyzed
- Directly accessible
- Kernel-based methods (e.g. SVM) → good classification results
Classification approaches

**Only spectral information**

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**Spectral + spatial information**

- Info about spatial structures included
- How to define structures?
  - closest neighborhood → not flexible enough
  - adaptive neighborhood (segmentation map) → currently investigated
**Our previous research (IGARSS’08)**

- **Segment** a hyperspectral image by watershed = find an exhaustive partitioning of the image into homogeneous regions
- **Spectral info + spatial info** → classify image (majority vote within each region)

![Segmentation map (3 spatial regions)](image)

![Spectral classification map (dark blue, white and light grey classes)](image)

![Combination of segmentation and spectral classification results (majority vote within 3 spatial regions)](image)

![Result of spectral-spatial classification (classification map after majority vote)](image)
Watershed segmentation

Region growing method:

- **Minimum** of a gradient = core of a homogeneous region
- **1 region** = set of pixels connected to 1 local minimum of the gradient
- **Watershed lines** = edges between adjacent regions
Watershed segmentation (IGARSS’08)

Original image

Robust Color Morpho Gradient

Watershed 1277 regions
Watershed segmentation (IGARSS’08)

Original image

Robust Color Morpho Gradient

Watershed 1277 regions

Severe oversegmentation!

Every local minimum of the gradient
↓
one region
Marker-controlled watershed segmentation

Determine markers for each region of interest
Marker-controlled watershed segmentation

Determine markers for each region of interest

Transform the gradient image

⇒ markers are the only local minima
Objective

- **Determine markers** automatically ← using results of a pixel-wise classification
- Marker-controlled watershed → **segment** and **classify** a hyperspectral image
- $B$-band hyperspectral image 

\[ \mathbf{X} = \{ \mathbf{x}_j \in \mathbb{R}^B, j = 1, 2, ..., n \} \]

- $B \sim 100$
Pixel-wise classification

- **SVM classifier** → well suited for hyperspectral images
- Output:
  - classification map
  - probability map

classification map

probability map

**Hyperspectral image**

\( (B \text{ bands}) \)

- Gradient
- Pixel-wise classification
- Selection of the most reliable classified pixels
- Marker-controlled watershed segmentation
- Segmentation map + classification map

probability estimate for each pixel to belong to the assigned class

Selection of the most reliable classified pixels

Analysis of classification and probability maps:

1. Perform connected components labeling of the classification map

2. Analyse each connected component:
   - If it is large (> 20 pixels) → use $P\%$ (5\%) of its pixels with the highest probabilities as a marker
   - If it is small → its pixels with probabilities $> T\%$ (90\%) are used as a marker
Selection of the most reliable classified pixels

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Sample image:

Must contain a marker!
Selection of the most reliable classified pixels

Analysis of classification and probability maps:

1. Perform connected components labeling of the classification map.

2. Analyse each connected component:
   - If it is large ($> 20$ pixels) → use $P\%$ (5\%) of its pixels with the highest probabilities as a marker.
   - If it is small → its pixels with probabilities $> T\%$ (90\%) are used as a marker.

**Diagram:**
- Hyperspectral image ($B$ bands)
- Pixel-wise classification
- Gradient
- Selection of the most reliable classified pixels
- Marker-controlled watershed segmentation
- Segmentation map + classification map

**Must contain a marker!**
**Selection of the most reliable classified pixels**

Analysis of classification and probability maps:

1. Perform connected components labeling of the classification map

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Has a marker only if it is very reliable
Selection of the most reliable classified pixels

Analysis of classification and probability maps:

- Each connected component $\rightarrow$ 1 or 0 marker (2250 regions $\rightarrow$ 107 markers)

- Marker is not necessarily a connected set of pixels

- Each marker has a class label

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Gradient

Original hyperspectral image

Robust Color Morphological Gradient*

Marker-controlled watershed segmentation

- Hyperspectral image ($B$ bands)
- Pixel-wise classification
  - Classification map
  - Probability map
- Selection of the most reliable classified pixels
- Gradient
  - Gradient image
- Marker-controlled watershed segmentation
- Segmentation map + classification map
Marker-controlled watershed segmentation and classification

Conclusions and perspectives

Marker-controlled watershed segmentation

1. Transform the gradient $f_g \rightarrow$ markers are the only minima

- Create a marker image:
  
  $$f_m(x) = \begin{cases} 
  0, & \text{if } x \text{ belongs to marker}, \\
  t_{\text{max}}, & \text{otherwise}
  \end{cases}$$

- Compute $(f_g + 1) \land f_m$

- Perform minima imposition: morphological reconstruction by erosion of $(f_g + 1) \land f_m$ from $f_m$:

  $$f_{gmi} = R^e_{(f_g + 1) \land f_m}(f_m)$$
Marker-controlled watershed segmentation

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Marker-controlled watershed segmentation

1. Transform the gradient $f_g \rightarrow$ markers are the only minima

2. Apply watershed on the filtered gradient image $f_{gmi}$ (Vincent and Soille, 1991)
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Marker-controlled watershed segmentation

1. Transform the gradient $f_g$ → markers are the only minima
2. Apply watershed on the filtered gradient image $f_{gmi}$ (Vincent and Soille, 1991)
3. Assign every watershed pixel to the spectrally most similar neighboring region
Marker-controlled watershed segmentation

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2. Apply watershed on the filtered gradient image $f_{gmi}$ (Vincent and Soille, 1991)

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\[ \rightarrow \text{Several minima in the filtered gradient} \rightarrow \text{Several regions in the segmentation map} \]
Marker-controlled watershed segmentation

1. Transform the gradient $f_g \rightarrow$ markers are the only minima

2. Apply watershed on the filtered gradient image $f_{gmi}$ (Vincent and Soille, 1991)

3. Assign every watershed pixel to the spectrally most similar neighboring region

4. Merge regions belonging to the same marker
Marker-controlled watershed segmentation

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3. Assign every watershed pixel to the spectrally most similar neighboring region

4. Merge regions belonging to the same marker

5. Class of each marker $\rightarrow$ class of the corresponding region
### Classification maps & classification accuracies (%)

<table>
<thead>
<tr>
<th></th>
<th>SVM</th>
<th>Proposed</th>
<th>Previous*</th>
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<tbody>
<tr>
<td>Overall Accuracy</td>
<td>78.17</td>
<td>85.99</td>
<td>86.63</td>
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<td>Average Accuracy</td>
<td>85.97</td>
<td>86.95</td>
<td>91.61</td>
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<td>Kappa Coefficient $\kappa$</td>
<td>75.33</td>
<td>83.98</td>
<td>84.83</td>
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<tr>
<td>Corn-no till</td>
<td>78.18</td>
<td>80.35</td>
<td>94.22</td>
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<td>Corn-min till</td>
<td>69.64</td>
<td>71.94</td>
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<td>Corn</td>
<td>91.85</td>
<td>73.37</td>
<td>88.59</td>
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<td>Soybeans-no till</td>
<td>82.03</td>
<td>98.91</td>
<td>96.30</td>
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<tr>
<td>Soybeans-min till</td>
<td>58.95</td>
<td>80.48</td>
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<td>Soybeans-clean till</td>
<td>87.94</td>
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<td>Alfalfa</td>
<td>74.36</td>
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<td>94.87</td>
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<td>95.08</td>
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<td>91.68</td>
<td>92.97</td>
<td>97.99</td>
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<td>Grass/pasture-mowed</td>
<td>100</td>
<td>100</td>
<td>100</td>
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<td>Hay-windrowed</td>
<td>97.72</td>
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<td>Oats</td>
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<td>100</td>
<td>100</td>
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<tr>
<td>Wheat</td>
<td>98.77</td>
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<td>Woods</td>
<td>93.01</td>
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<td>61.52</td>
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<td>69.39</td>
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<tr>
<td>Stone-steel towers</td>
<td>97.78</td>
<td>64.44</td>
<td>95.56</td>
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</table>

*IGARSS’08

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Conclusions and perspectives

Conclusions

1. Method for automatic selection of markers for watershed transform is proposed
2. Scheme for segmentation and classification of hyperspectral images is developed
3. The proposed method:
   - significantly decreases oversegmentation
   - improves classification accuracies
   - provides classification maps with homogeneous regions

Perspectives

- Use marker selection + other image segmentation methods

⇓

attend WHISPERS’09, France, August 2009!
Thank you for your attention!