Classification Based Marker Selection for Watershed Transform of Hyperspectral Images

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Outline

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

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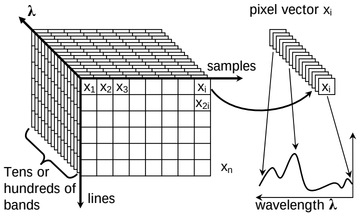
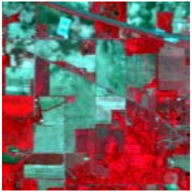
Efficient algorithms for automatic processing are required!



Classification problem

Input AVIRIS image $[145 \times 145 \times 200]$



Ground-truth data

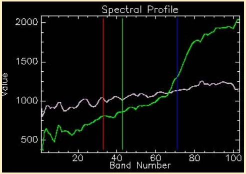
Task

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)
  $\rightarrow$ good classification results



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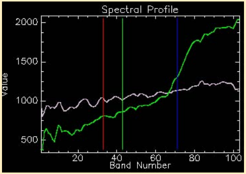
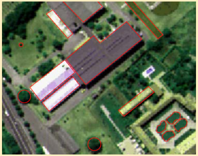


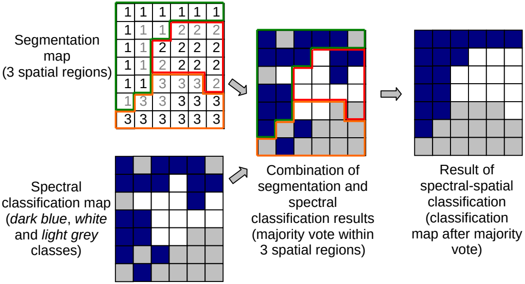
Spectral + spatial information

- Info about spatial structures included
- How to define structures?
  - closest neighborhood → not flexible enough
  - adaptive neighborhood (segmentation map)
    → currently investigated



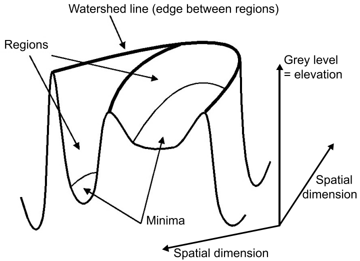
Our previous research (IGARSS'08)

- 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)



Watershed segmentation

gradient
$\Rightarrow$

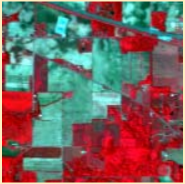


Region growing method:

- **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



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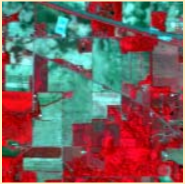
Robust Color Morpho Gradient

⇒

Watershed 1277 regions

Watershed segmentation (IGARSS'08)

Original image



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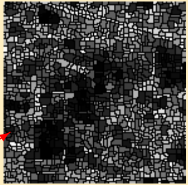
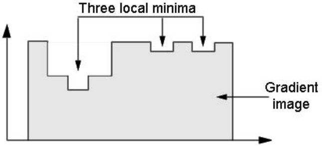


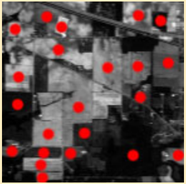
Severe oversegmentation!



Every local minimum of the gradient
↓
one region

Marker-controlled watershed segmentation

Determine markers for each region of interest



Marker-controlled watershed segmentation

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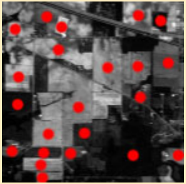

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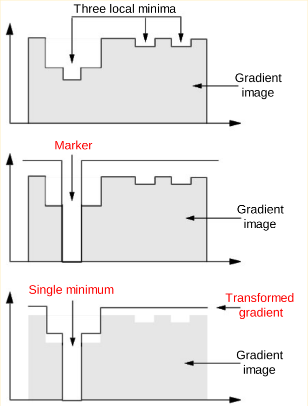
Transform the gradient image

⇓

markers are the only local minima

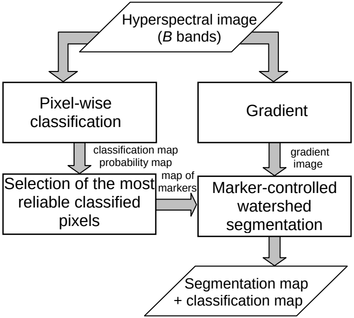


Objective

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

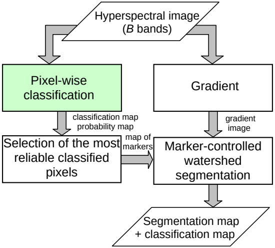
Input

- B-band hyperspectral image $\mathbf{X} = \{\mathbf{x}_j \in \mathbb{R}^B, j = 1, 2, ..., n\}$
- $B \sim 100$

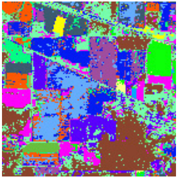


Pixel-wise classification

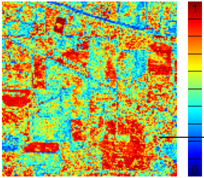
- SVM classifier* → well suited for hyperspectral images
- Output:



classification map



probability map



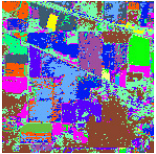
probability estimate for each pixel to belong to the assigned class

**C. Chang and C. Lin, "LIBSVM: A library for Support Vector Machines," Software available at http://www.csie.ntu.edu.tw/∼cjlin/libsvm, 2001.*

Selection of the most reliable classified pixels

Analysis of classification and probability maps:

classification map



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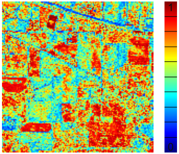

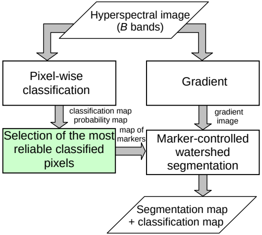

1. Perform connected components labeling of the classification map
2. Analyse each connected component:
   - If it is large (> 20 pixels) $\rightarrow$ use $P\%$ (5%) of its pixels with the highest probabilities as a marker
   - If it is small $\rightarrow$ its pixels with probabilities $> T\%$ (90%)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

Selection of the most reliable classified pixels

Analysis of classification and probability maps:

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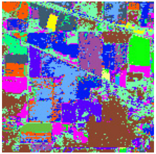

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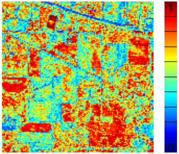

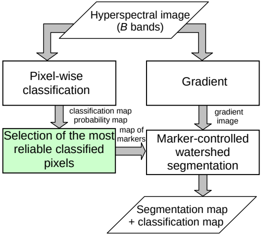

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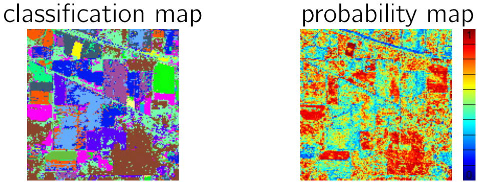

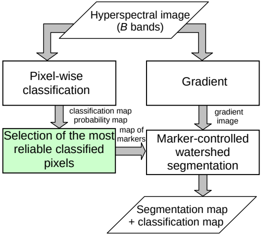

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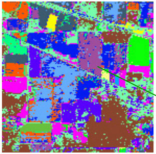
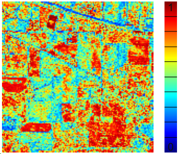
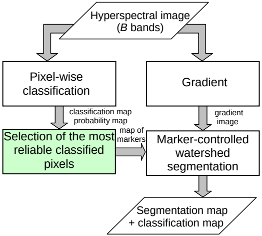


probability map





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Must contain a marker!

Selection of the most reliable classified pixels

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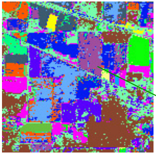

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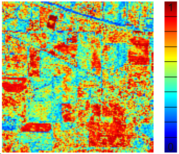

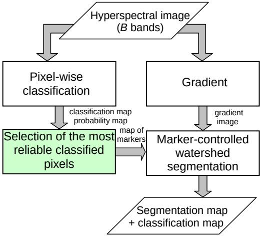

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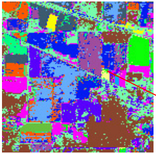
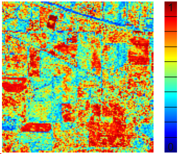
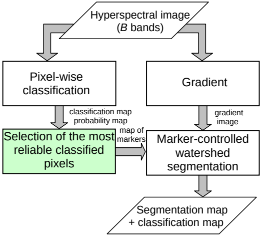


probability map





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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:

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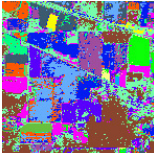

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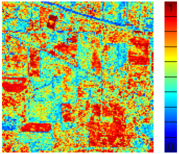
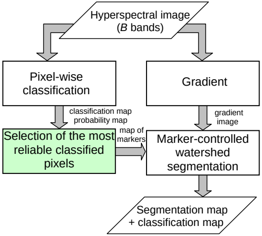
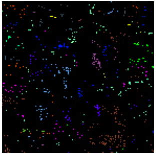




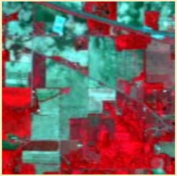
- Each connected component → 1 or 0 marker (2250 regions → 107 markers)
- Marker is not necessarily a connected set of pixels
- Each marker has a class label

map of 107 markers



Gradient

Original hyperspectral image



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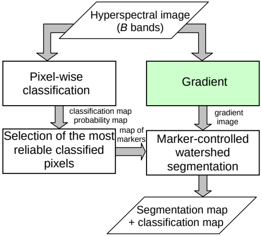
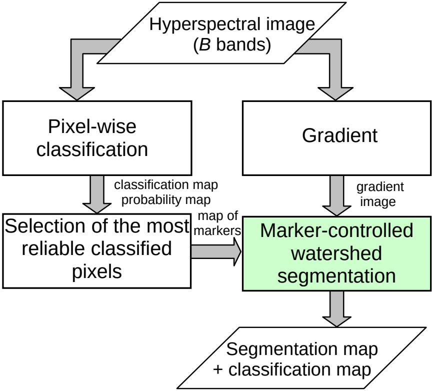
Robust Color Morphological Gradient*



**Y. Tarabalka et al., "Segmentation and classification of hyperspectral data using watershed," in Proc. of IGARSS'08, Boston, USA, 2008.*

Marker-controlled watershed segmentation



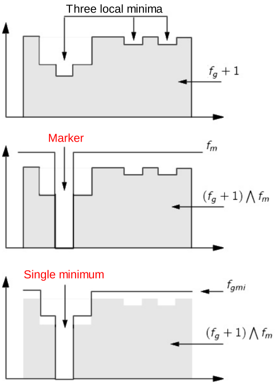
Marker-controlled watershed segmentation

1. Transform the gradient f_g $\rightarrow$ markers are the only minima
   - Create a marker image:

$$f_m(\mathbf{x}) = \begin{cases} 0, & \text{if } \mathbf{x} \text{ belongs to marker,} \\ t_{max}, & \text{otherwise} \end{cases}$$

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

$$f_{gmi} = R^{\varepsilon}_{(f_g+1) \bigwedge f_m}(f_m)$$



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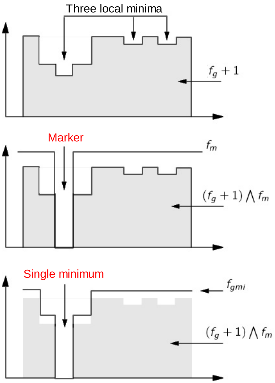

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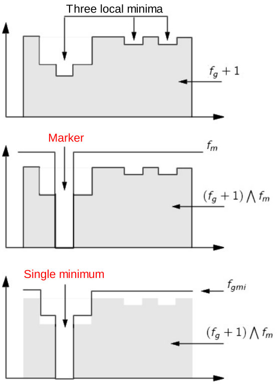

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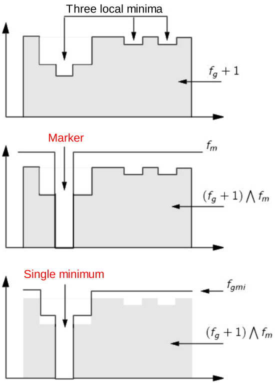
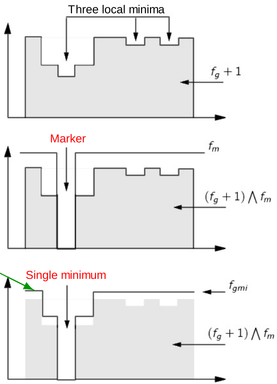


Marker-controlled watershed segmentation

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)



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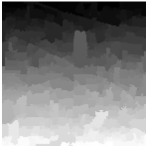
1. Transform the gradient f_g $\rightarrow$ markers are the only minima
2. Apply watershed on the filtered gradient image f_{gmi} (Vincent and Soille, 1991)
3. Assign every watershed pixel to the spectrally most similar neighboring region

$\Downarrow$



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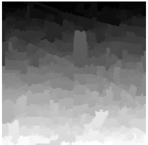

 $\rightarrow$ Several minima in the filtered gradient $\rightarrow$ Several regions in the segmentation map

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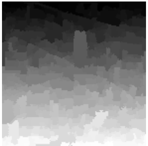
3. Assign every watershed pixel to the spectrally most similar neighboring region
4. Merge regions belonging to the same marker

$\Downarrow$



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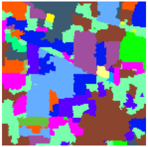

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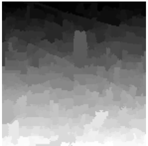
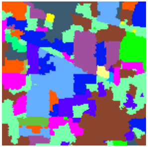
3. Assign every watershed pixel to the spectrally most similar neighboring region
4. Merge regions belonging to the same marker
5. Class of each marker $\rightarrow$ class of the corresponding region

$\Downarrow$

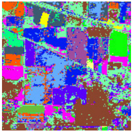


$\Downarrow$

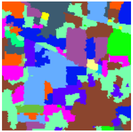


Classification maps & classification accuracies (%)

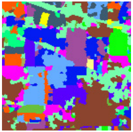
SVM



Proposed(107reg.)



Previous*(1277reg.)



**IGARSS'08*

	SVM	**Proposed**	Previous*
Overall Accuracy	78.17	85.99	**86.63**
Average Accuracy	85.97	86.95	**91.61**
Kappa Coefficient κ	75.33	83.98	**84.83**
Corn-no till	78.18	80.35	**94.22**
Corn-min till	69.64	71.94	**78.06**
Corn	**91.85**	73.37	88.59
Soybeans-no till	82.03	**98.91**	96.30
Soybeans-min till	58.95	**80.48**	68.82
Soybeans-clean till	87.94	84.75	**90.78**
Alfalfa	74.36	**94.87**	**94.87**
Grass/pasture	92.17	**95.30**	95.08
Grass/trees	91.68	92.97	**97.99**
Grass/pasture-mowed	**100**	**100**	**100**
Hay-windrowed	97.72	**99.54**	**99.54**
Oats	**100**	**100**	**100**
Wheat	98.77	**99.38**	**99.38**
Woods	93.01	**99.36**	97.11
Bldg-Grass-Tree-Drives	61.52	55.45	**69.39**
Stone-steel towers	**97.78**	64.44	95.56

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

$\Downarrow$

attend WHISPERS'09, France, August 2009!

Thank you for your attention!