Classification of Hyperspectral Data Using Spectral-Spatial Approaches

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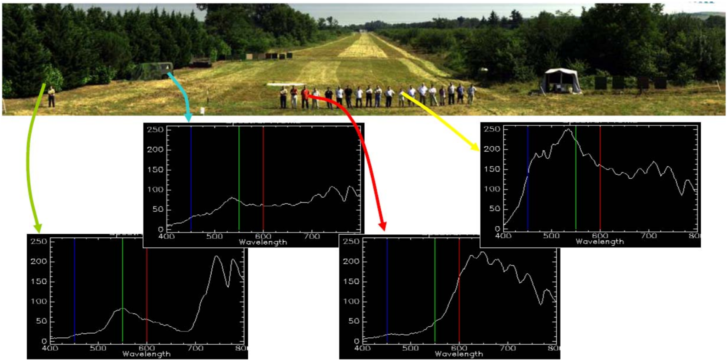
Department of Electrical and Computer Engineering, University of Iceland, Iceland

May 13, 2010

Hyperspectral image

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

$+$ More information per pixel $\rightarrow$ increasing capability to distinguish objects



Hyperspectral image

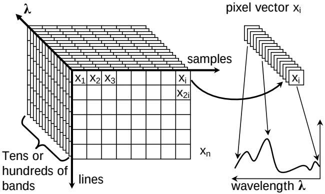
Every pixel contains a detailed spectrum (>100 spectral bands)

+ More information per pixel → increasing capability to distinguish objects

– Dimensionality increases → image analysis becomes more complex

⇓

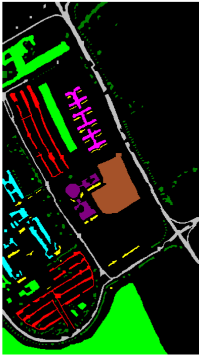
Efficient algorithms for automatic processing are required!



Classification problem

ROSIS image
Spatial resolution: 1.3m/pix
Spectral resolution: 103 bands

Ground-truth data



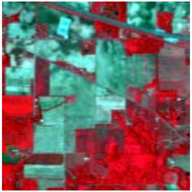
Task

Assign **every** pixel to **one** of the **nine** classes:

alphalt
meadows
gravel
trees
metal sheets
bare soil
bitumen
bricks
shadows

Classification problem

AVIRIS image
Spatial resolution: 20m/pix
Spectral resolution: 200 bands



Ground-truth data

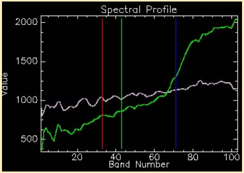
Task

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
- Variety of methods
  - Support Vector Machines (SVM) → good classification results [Camps-Valls05]



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Overall accuracy = 81.01%

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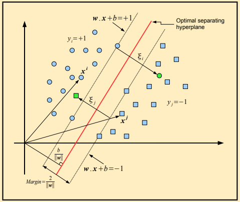

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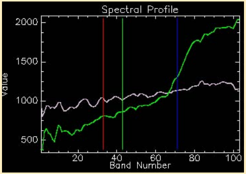
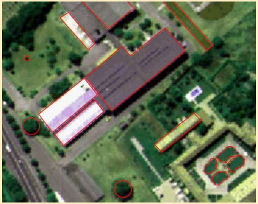


Spectral + spatial information

- Info about spatial structures is included
  - Since neighboring pixels are related
- How to define spatial structures?
- How to combine spectral and spatial information?

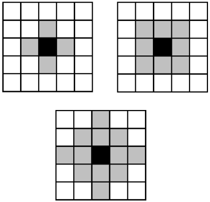


State of the art: Approaches for extracting spatial info

1. Closest fixed neighborhoods
   - Markov Random Field [Pony00, Jackson02, Farag05]
   - Contextual features [Camps-Valls06]

   \+ Simplicity

   − Imprecision at the border of regions



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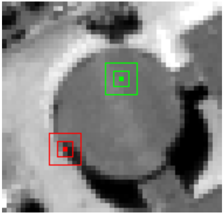

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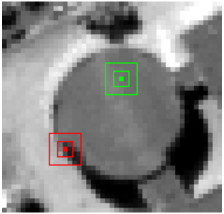

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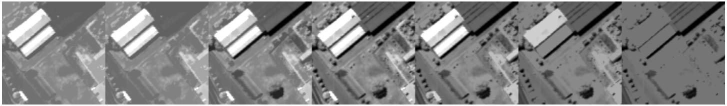
2. Morphological and area filtering
   - Morphological profiles [Dell'Acqua04, Benediktsson05, Fauvel07]
   - Area filtering [Fauvel07]

   \+ Neighborhoods are adapted to the structures

   – Neighborhoods are scale dependent ⇒ imprecision in the spatial info



Closing – Original – Opening

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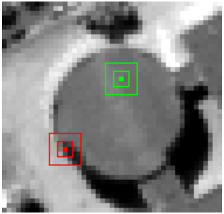

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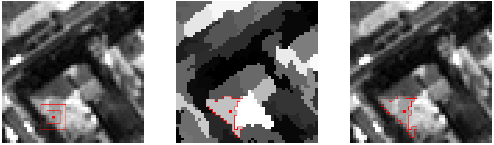


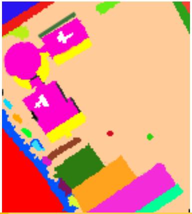
State of the art: Approaches for extracting spatial info

3. Segmentation map = exhaustive partitioning of the image into homogeneous regions

- Extraction and Classification of Homogeneous Objects [Kettig76]
  + Has become a standard spectral-spatial classification technique
  − Statistical approach ⇒ not well adapted for hyperspectral data

Recent works:

- Multiscale segmentation + SVM classification [Linden07, Huang09]
  − Computationally demanding
- Marker selection by morphological filtering + watershed [Noyel08]
  + Minimized dependence on the thresholds



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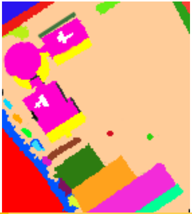

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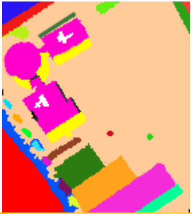
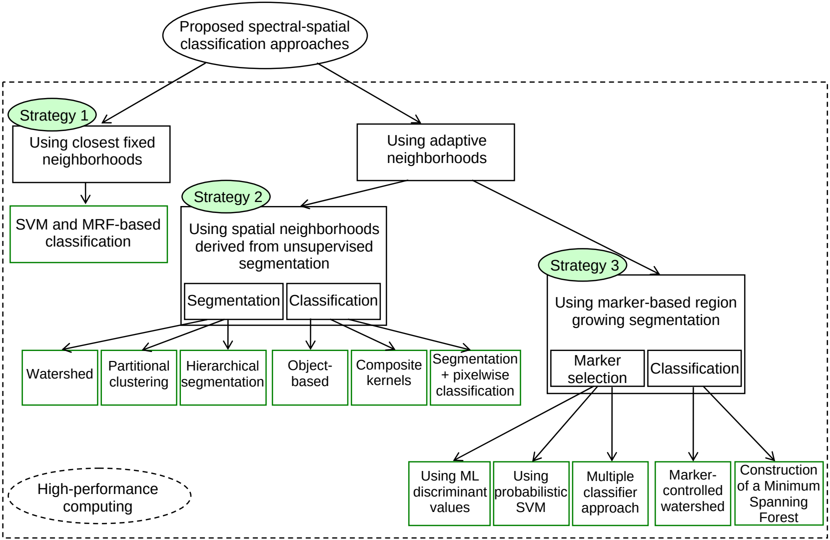


combine spectral and spatial info



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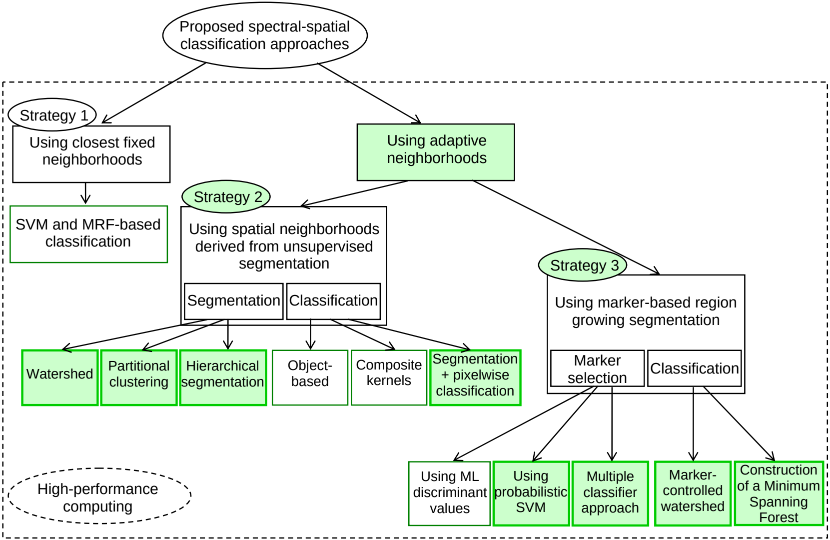
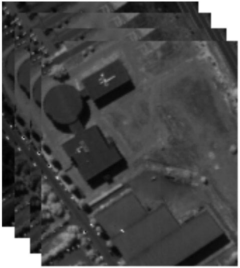


Outline

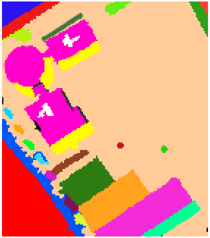
1. Introduction
2. Classification using segmentation-derived adaptive neighborhoods
   - Segmentation
   - Spectral-spatial classification
   - Concluding discussion
3. Segmentation and classification using automatically selected markers
   - Marker selection
   - Classification using marker-controlled region growing
   - Concluding discussion
4. Conclusions and perspectives

Objective

1. Automatically segment a hyperspectral image into homogeneous regions
2. Spectral info + spatial info → classify image



+



→ Classification map

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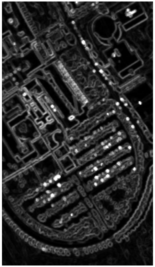
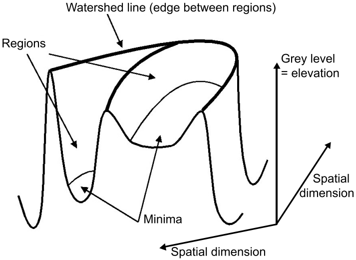
1. Watershed segmentation

gradient
⇒





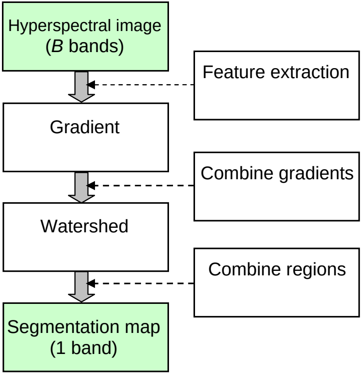
Region growing method:

- **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

1. Watershed segmentation for hyperspectral image

From B-band image $\rightarrow$
1-band segmentation map:

- Feature extraction (PCA, ICA,...)?
- Vectorial gradient?
- Combine B gradients?
- Combine B watershed regions?



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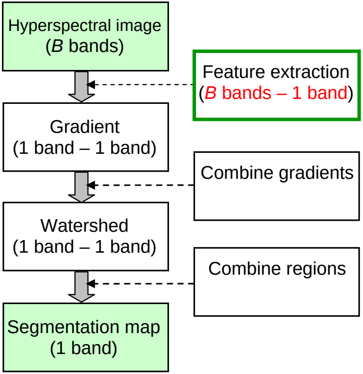

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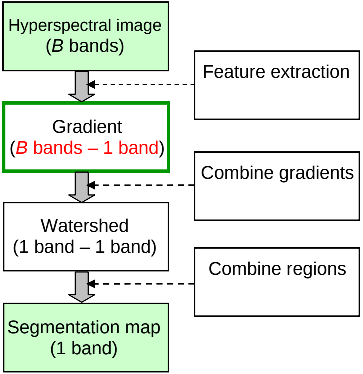

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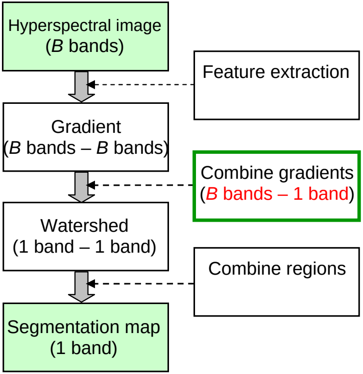

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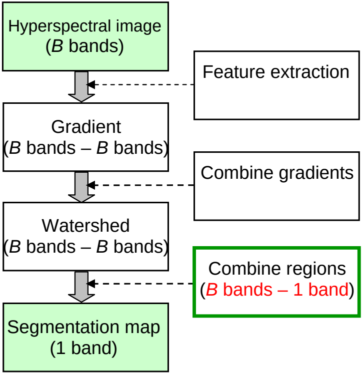

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Original image

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Original image

⇒

Robust Color Morpho Gradient

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Watershed 11802 regions

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Original image

⇒

Robust Color Morpho Gradient

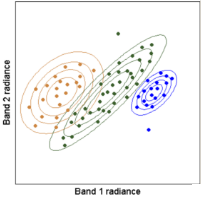
⇒

Watershed 11802 regions

⇒

Edges → to adjacent regions

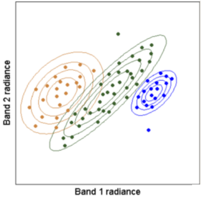
2. Partitional clustering (EM)



1. Clustering
   - pixels are grouped into C clusters
   - in each cluster $\rightarrow$ pixels drawn from a Gaussian distribution
   - distribution parameters $\rightarrow$ EM algorithm
2. Labeling of connected components

10 clusters
$\Rightarrow$

2. Partitional clustering (EM)



1. Clustering
   - pixels are grouped into C clusters
   - in each cluster → pixels drawn from a Gaussian distribution
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2. Labeling of connected components

10 clusters
⇒
21450
regions

same cluster, but different regions!

3. Hierarchical SEGmentation (HSEG,[Tilton98])

- Region growing + Spectral Clustering
- Dissimilarity criterion (DC):
  Spectral Angle Mapper (SAM)
  between the region mean vectors u_i and u_j

$$SAM(u_i, u_j) = \arccos\left(\frac{u_i \cdot u_j}{\|u_i\|_2 \|u_j\|_2}\right)$$

1. Each pixel - one region
2. Find DC_{min} between adjacent regions
3. Merge adjacent regions with $DC = DC_{min}$
4. Merge non-adjacent regions with $DC \leq DC_{min} \cdot SpectralClusterWeight$
5. If not converge, go to 2

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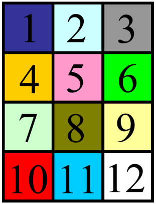

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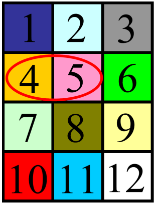

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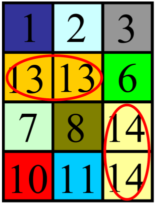

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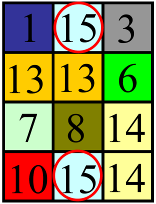

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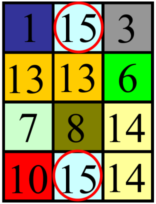

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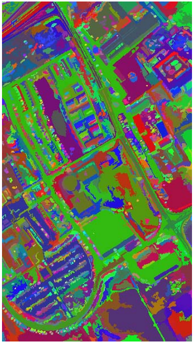

$SCW = 0.0$
7231 regions

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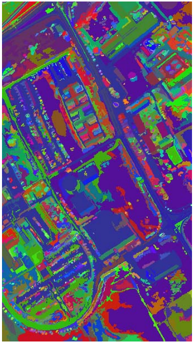
  Spectral Angle Mapper (SAM)
  between the region mean vectors u_i and u_j

$$SAM(u_i, u_j) = \arccos\left(\frac{u_i \cdot u_j}{\|u_i\|_2 \|u_j\|_2}\right)$$

1. Each pixel - one region
2. Find DC_{min} between adjacent regions
3. Merge adjacent regions with $DC = DC_{min}$
4. Merge non-adjacent regions with
   $DC \leq DC_{min} \cdot SpectralClusterWeight$
5. If not converge, go to 2



$SCW = 0.1$
7575 regions

Outline

1 Introduction

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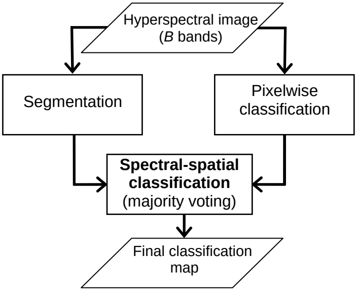
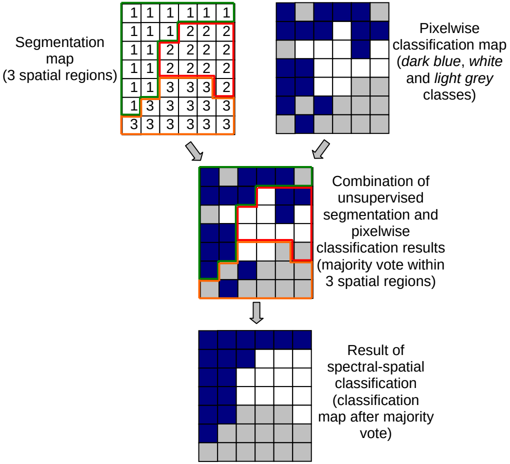
Spectral-spatial classification: majority vote





Spectral-spatial classification

Original image

Spectral-spatial classification

Original image

⇒

SVM classification

OA = 81.01%
AA = 88.25%

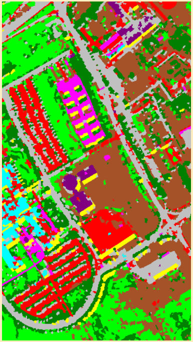
Spectral-spatial classification

SVM classification

OA = 81.01%
AA = 88.25%

⇒

SVM + Watershed

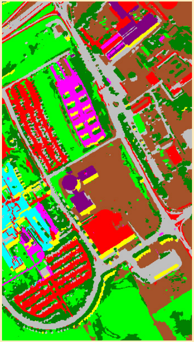


OA = 85.42%
AA = 91.31%

SVM + Partit.clustering

OA = 94.00%
AA = 93.13%

SVM + HSEG ($SCW = 0.1$)



OA = 93.85%
AA = 97.07%

Classification accuracies (%)

	SVM	+Watersh.	+Part.Cl.	+HSEG		EMP[1]	ECHO
SCW				0.0	0.1		
Overall Acc.	81.01	85.42	94.00	90.00	**93.85**	85.22	87.58
Average Acc.	88.25	91.31	93.13	94.15	**97.07**	90.76	92.16
Kappa Coef.κ	75.86	81.30	91.93	86.86	**91.89**	80.86	83.90
Asphalt	84.93	93.64	90.10	73.33	94.77	**95.36**	87.98
Meadows	70.79	75.09	**95.99**	88.73	89.32	80.33	81.64
Gravel	67.16	66.12	82.26	**97.47**	96.14	87.61	76.91
Trees	97.77	98.56	85.54	98.45	98.08	98.37	**99.31**
Metal sheets	99.46	99.91	**100**	99.10	99.82	99.48	99.91
Bare soil	92.83	97.35	96.72	98.43	**99.76**	63.72	93.96
Bitumen	90.42	96.23	91.85	95.92	**100**	98.87	92.97
Bricks	92.78	97.92	98.34	98.81	**99.29**	95.41	97.35
Shadows	98.11	96.98	97.36	97.11	96.48	97.68	**99.37**

[1] *A. Plaza et al., "Recent advances in techniques for hyperspectral image processing," Remote Sensing of Environment, vol. 113, Suppl. 1, 2009.*

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1. Spectral-spatial classification improves accuracies when compared to pixel-wise classification
2. Several segmentation techniques are investigated
3. The HSEG segmentation map leads to the best classification
4. Obtained classification accuracies > all previous results

However...

Unsupervised segmentation

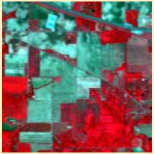
- Unsupervised segmentation = exhaustive partitioning into homogeneous regions
- How to define a measure of homogeneity?

Unsupervised segmentation

- Unsupervised segmentation = exhaustive partitioning into homogeneous regions
- How to define a measure of homogeneity?

Hierarchical SEGmentation (HSEG, [Tilton98])

Image



$\Rightarrow$

2381reg.	1389reg.	280reg.
pgflastimage	pgflastimage	pgflastimage

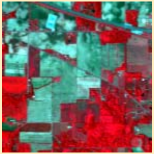
Oversegmentation! Undersegmentation?

Unsupervised segmentation

- Unsupervised segmentation = exhaustive partitioning into homogeneous regions
- How to define a measure of homogeneity?

Hierarchical SEGmentation (HSEG, [Tilton98])

Image



⇒

2381reg.	1389reg.	280reg.
pgflastimage	pgflastimage	pgflastimage

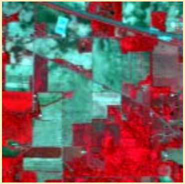
Oversegmentation Undersegmentation?

$\Downarrow$

Preferred in previous works $\rightarrow$ not to lose objects

Watershed segmentation

Original image



⇒

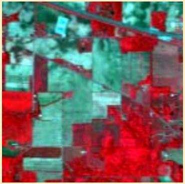
Robust Color Morpho Gradient

⇒

Watershed 1277 regions

Watershed segmentation

Original image



⇒

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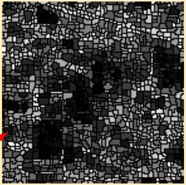
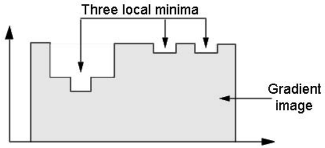
Watershed 1277 regions



Severe oversegmentation!



Every local minimum of the gradient

↓

one region

Marker-controlled segmentation

- Reduce oversegmentation $\Leftarrow$ incorporate an additional knowledge into segmentation
- We propose to use **markers**

Determine markers for each region of interest

$\Rightarrow$

Segment an image

One region
in a segmentation map
$\Uparrow$
One marker

Objective

- Determine markers automatically $\leftarrow$ using probabilistic classification results
- Marker-controlled region growing $\rightarrow$ segment and classify a hyperspectral image

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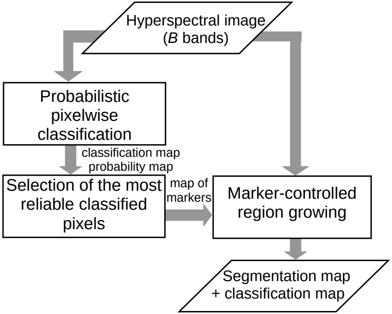
Using probabilistic SVM

Marker selection using probabilistic SVM

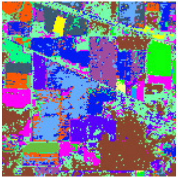
- B-band hyperspectral image $\mathbf{X} = \{\mathbf{x}_j \in \mathbb{R}^B, j = 1, 2, ..., n\}$
- $B \sim 100$



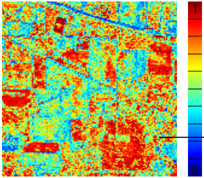
Marker selection using probabilistic SVM

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

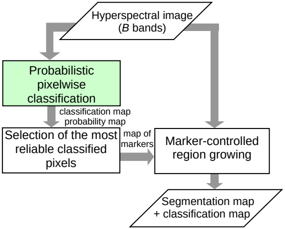
classification map



probability map



probability estimate for each pixel to belong to the assigned class

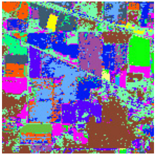


**C. Chang and C. Lin, "LIBSVM: A library for Support Vector Machines," Software available at http://www.csie.ntu.edu.tw/~cjlin/libsvm, 2001.*

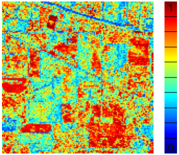
Marker selection using probabilistic SVM

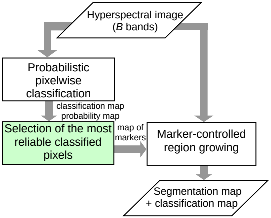
Analysis of classification and probability maps:

classification map



probability map



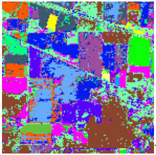


1. Perform connected components labeling of the classification map
2. Analyze each connected component:
   - If it is large ($>$ 20 pixels) $\rightarrow$ use $P\%$ (5%) of its pixels with the highest probabilities as a marker
   - If it is small $\rightarrow$ its pixels with probabilities $> T\%$ (90%)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

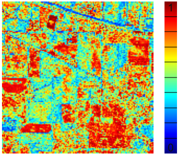
Marker selection using probabilistic SVM

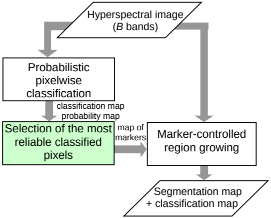
Analysis of classification and probability maps:

classification map



probability map





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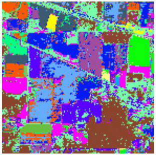

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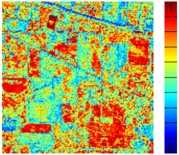

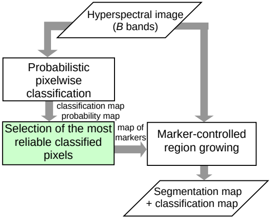

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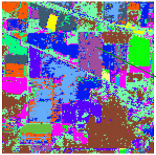
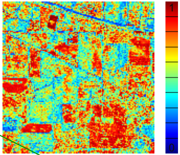
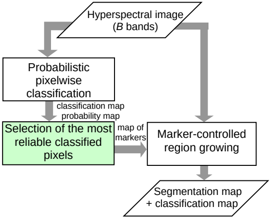


probability map





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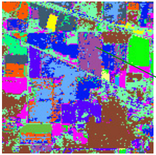
Must contain a marker!

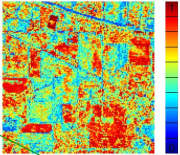
Marker selection using probabilistic SVM

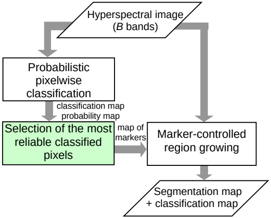
Analysis of classification and probability maps:

classification map



probability map





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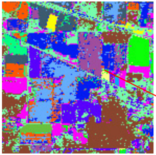
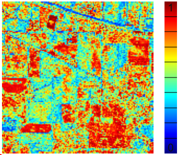
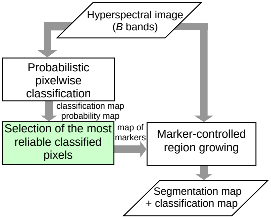


probability map





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Has a marker only if it is very reliable

Marker selection using probabilistic SVM

Analysis of classification and probability maps:

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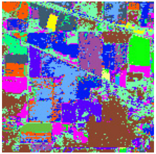
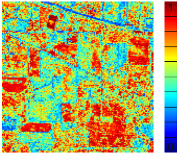
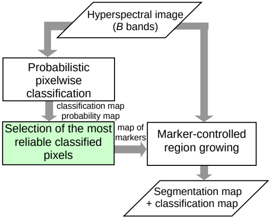


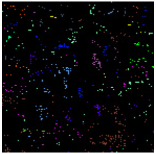
probability map





- 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

map of 107 markers



Multiple classifier approach

Multiple classifier approach for marker selection

- Previous method: strong dependence on the performances of the selected probabilistic classifier
- Objective: mitigate this dependence
  $\rightarrow$ using multiple classifiers

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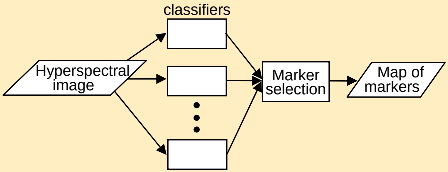
- Objective: mitigate this dependence
  $\rightarrow$ using multiple classifiers

Multiple classifier marker selection approach

1. Classify an image by several **independent** classifiers
2. Pixels assigned by **all** the classifiers to the same class

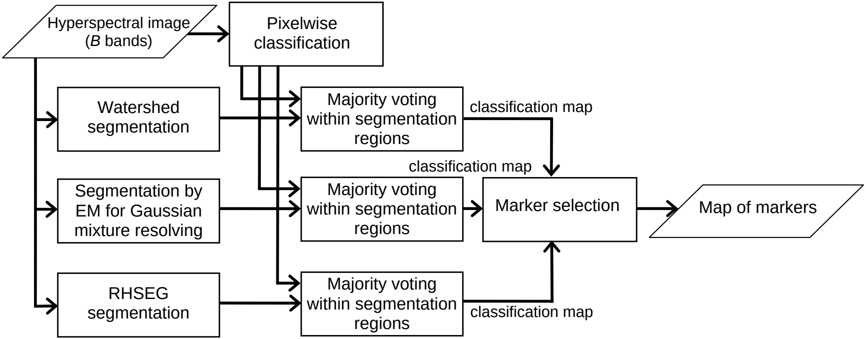
$\Downarrow$

Map of markers



Multiple spectral-spatial classifier marker selection

- Take into account spatial context



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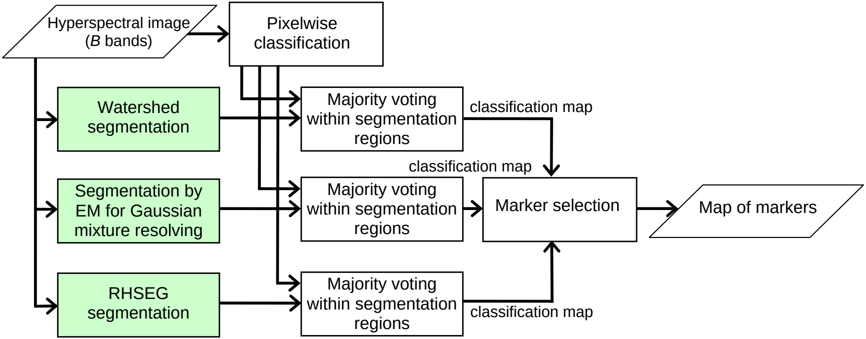

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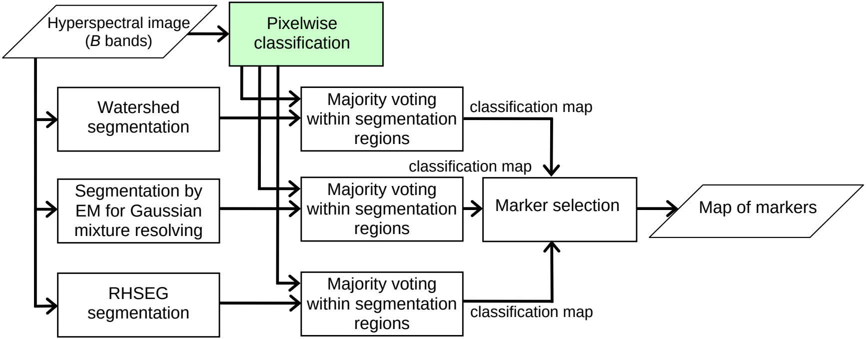

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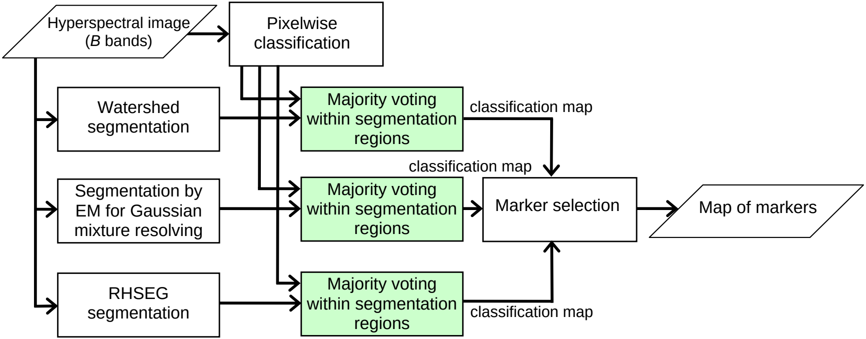

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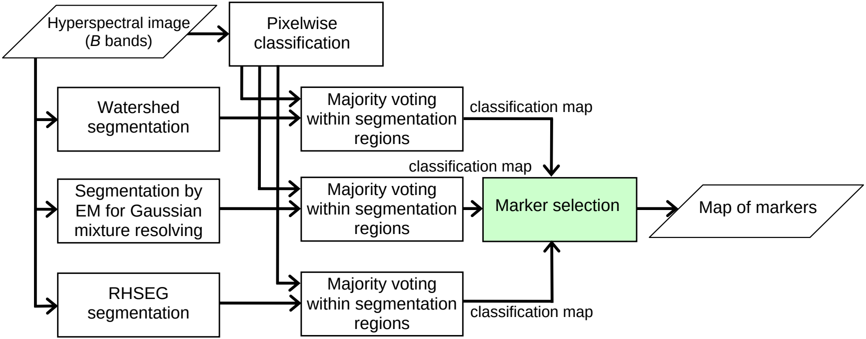

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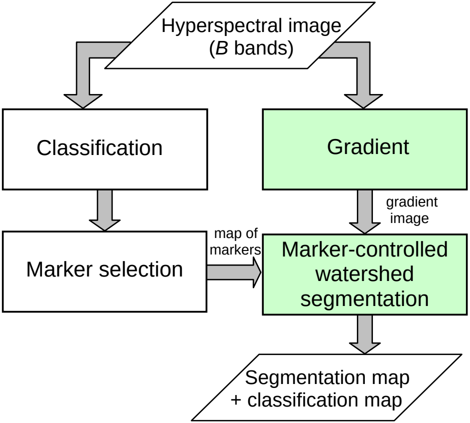
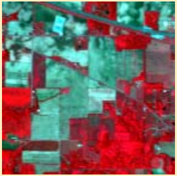
Marker-controlled watershed

1. Marker-controlled watershed



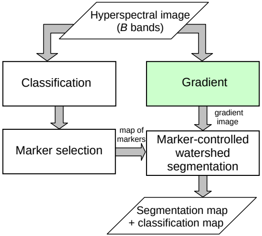
1. Marker-controlled watershed / Gradient

Original hyperspectral image



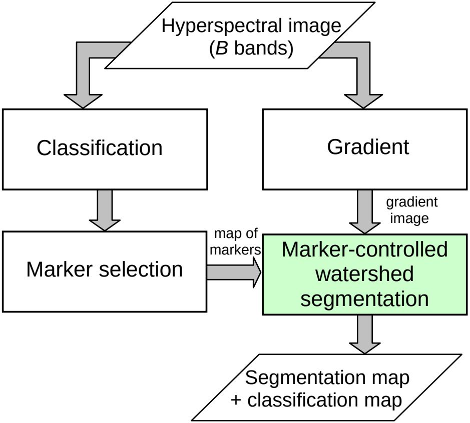
⇒

Robust Color Morphological Gradient*



**Y. Tarabalka, J. Chanussot, and J. A. Benediktsson, "Segmentation and classification of hyperspectral images using watershed transformation," Pattern Recognition, vol. 43, no. 7, pp. 2367-2379, July 2010.*

1. Marker-controlled watershed



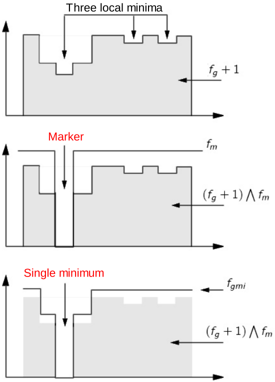
1. Marker-controlled watershed

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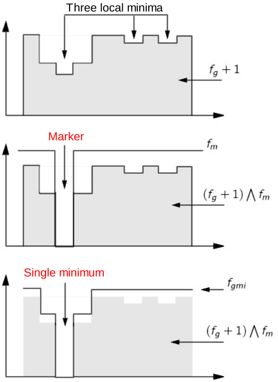
   - Compute $(f_g + 1) \bigwedge f_m$
   - Perform minima imposition: morphological reconstruction by erosion of $(f_g + 1) \bigwedge f_m$ from f_m:

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



1. Marker-controlled watershed

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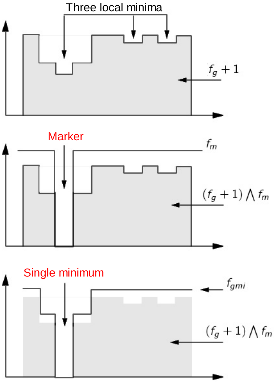

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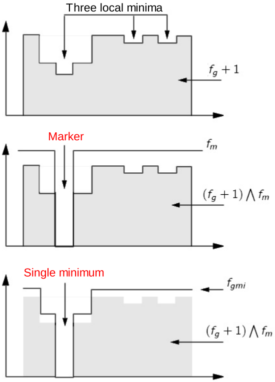

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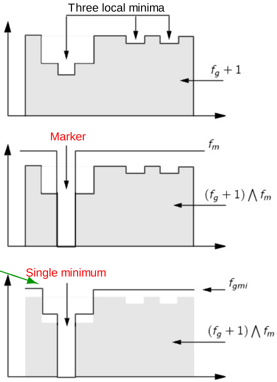
1. Transform the gradient f_g $\rightarrow$ markers are the only minima
2. Apply watershed on the filtered gradient image f_{gmi} (Vincent and Soille, 1991)



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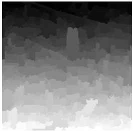
3. Assign every watershed pixel to the spectrally most similar neighboring region

⇓



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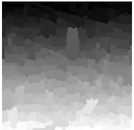
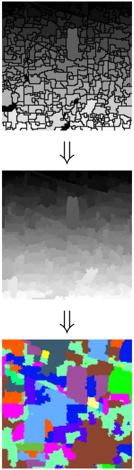
$\Downarrow$



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

1. Marker-controlled watershed

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
4. Merge regions belonging to the same marker



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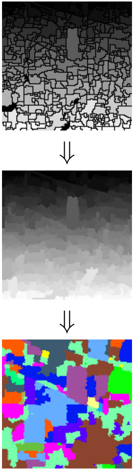
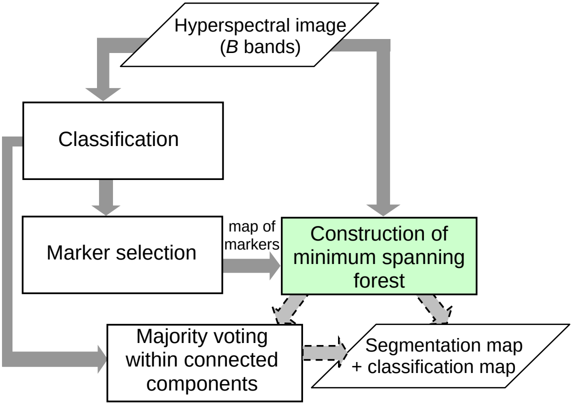
2. Apply watershed on the filtered gradient image f_{gmi} (Vincent and Soille, 1991)
3. Assign every watershed pixel to the spectrally most similar neighboring region
4. Merge regions belonging to the same marker
5. Class of each marker $\rightarrow$ class of the corresponding region



Construction of a Minimum Spanning Forest

2. Construction of a Minimum Spanning Forest (MSF)



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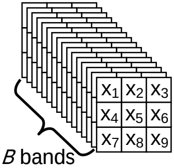

map of markers

1	1	0
0	0	0
0	0	2

1) Map an image onto a graph

- Weight $w_{i,j}$ indicates the degree of dissimilarity between pixels $\mathbf{x}_i$ and $\mathbf{x}_j$. Spectral Angle Mapper (SAM) distance can be used:

$$w_{i,j} = SAM(\mathbf{x}_i, \mathbf{x}_j) = \arccos\left(\frac{\sum_{b=1}^{B} x_{ib}x_{jb}}{[\sum_{b=1}^{B} x_{ib}^2]^{1/2}[\sum_{b=1}^{B} x_{jb}^2]^{1/2}}\right)$$

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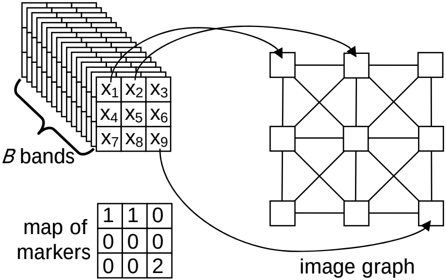

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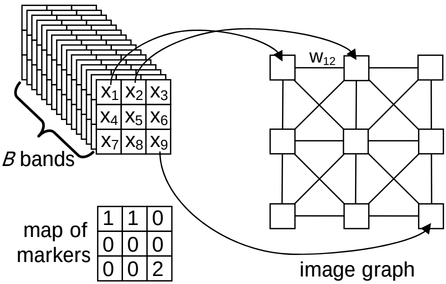

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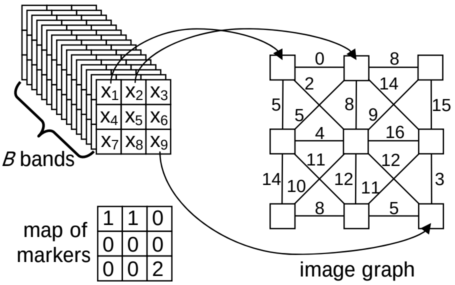

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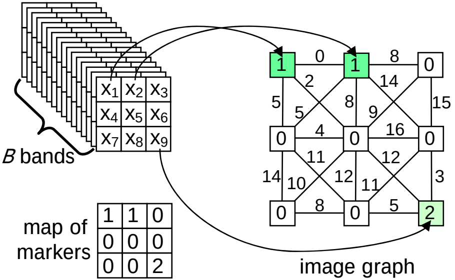

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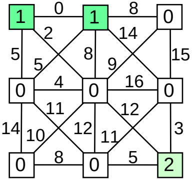
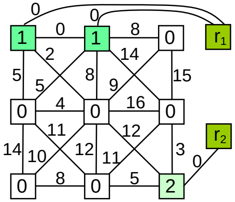


image graph

Given a graph G, a **MSF** F^* rooted on vertices $\{r_1, ..., r_m\}$ is:

- a non-connected graph without cycles
- contains all the vertices of G
- consists of connected subgraphs, each subgraph (tree) contains (is rooted on) one root r_i
- sum of the edges weights of F^* is minimal

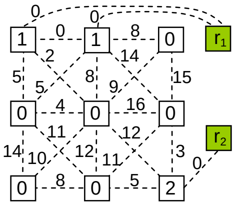
2. Construction of a Minimum Spanning Forest (MSF)



modified graph

2) Add m extra vertices $r_i, i = 1, ..., m$ corresponding to m markers

2. Construction of a Minimum Spanning Forest (MSF)



3) Construct a MSF $F^* = (V^*, E^*)$

Initialization: $V^* = \{r_1, r_2, ..., r_m\}$ (roots are in the forest)

1. Choose edge of the modified graph e_{ij} with minimal weight such that $i \in V^*$ and $j \notin V^*$
2. $V^* = V^* \cup \{j\}$, $E^* = E^* \cup \{e_{i,j}\}$
3. If $V^* \neq V$, go to 1

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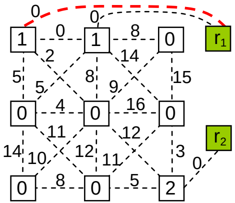

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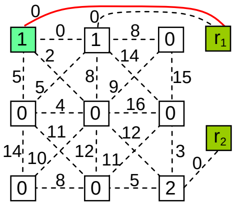

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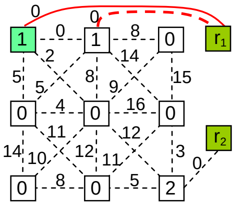

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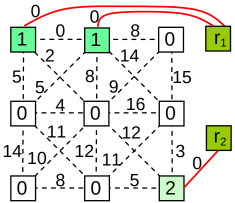

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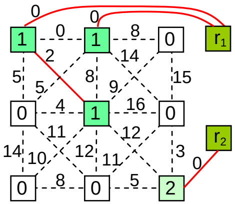

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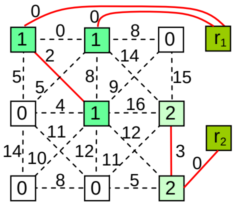

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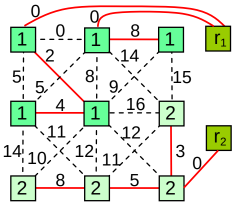

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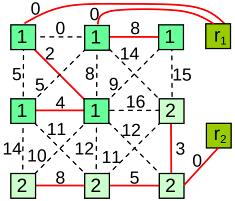
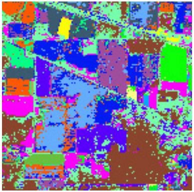


3) Construct a MSF $F^* = (V^*, E^*)$

4) Class of each marker $\rightarrow$ class of the corresponding region
(of all the pixels grown from this marker)

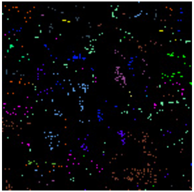
2. Construction of a Minimum Spanning Forest (MSF)

Pixel-wise classification map



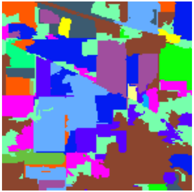
⇒

Map of 107 markers



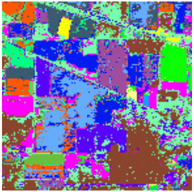
⇒

MSF-based classification map



2. Construction of a Minimum Spanning Forest (MSF)

Pixel-wise classification map



⇒

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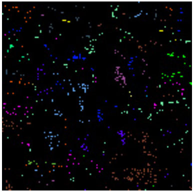
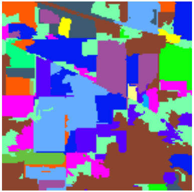


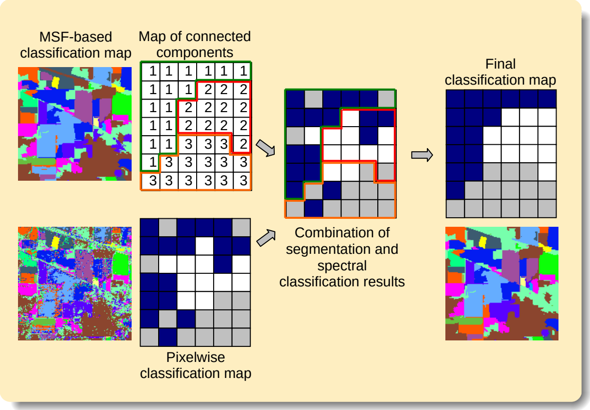
⇒

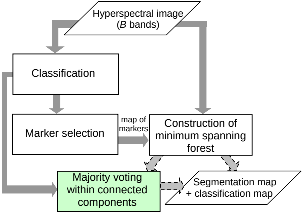
MSF-based classification map



If a marker is classified to the wrong class ⇒ The whole region grown from this marker risks to be wrongly classified!

2. Construction of a Minimum Spanning Forest / Post-processing





Classification accuracies for the Indian Pines data (%)

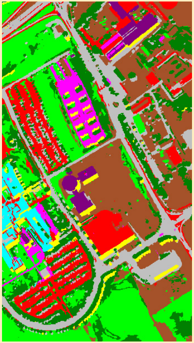
	SVM	ECHO	Strategy 2	Strategy 3: Marker-based classification			
			SVM+ Waters.	SVM- Waters.	SVM- MSF	SVM- MSF+MV	MSSC- MSF
Overall Accuracy	78.17	82.64	86.63	85.99	88.41	91.80	**92.32**
Average Accuracy	85.97	83.75	91.61	86.95	91.57	**94.28**	94.22
Kappa Coef. κ	75.33	80.38	84.83	83.98	86.71	90.64	**91.19**
Corn-no till	78.18	83.45	**94.22**	80.35	90.97	93.21	89.74
Corn-min till	69.64	75.13	78.06	71.94	69.52	**96.56**	86.99
Corn	91.85	92.39	88.59	73.37	**95.65**	**95.65**	95.11
Soybeans-no till	82.03	90.10	96.30	**98.91**	98.04	93.91	91.84
Soybeans-min till	58.95	64.14	68.82	80.48	81.97	81.97	**89.16**
Soybeans-clean till	87.94	89.89	90.78	84.75	85.99	97.16	**97.34**
Alfalfa	74.36	48.72	**94.87**	**94.87**	**94.87**	**94.87**	**94.87**
Grass/pasture	92.17	94.18	95.08	**95.30**	94.63	94.63	94.63
Grass/trees	91.68	96.27	**97.99**	92.97	92.40	97.27	97.85
Grass/pasture-mow	**100**	36.36	**100**	**100**	**100**	**100**	**100**
Hay-windrowed	97.72	97.72	99.54	99.54	**99.77**	**99.77**	**99.77**
Oats	**100**	**100**	**100**	**100**	**100**	**100**	**100**
Wheat	98.77	98.15	**99.38**	**99.38**	**99.38**	**99.38**	**99.38**
Woods	93.01	94.21	97.11	99.36	97.59	**99.68**	99.44
Bldg-Grass-Tree-Dr	61.52	**81.52**	69.39	55.45	68.79	68.79	73.64
Stone-steel towers	**97.78**	**97.78**	95.56	64.44	95.56	95.56	**97.78**

Classification of the Pavia image

SVM classification

OA = 81.01%
AA = 88.25%

Strategy 2: SVM + HSEG

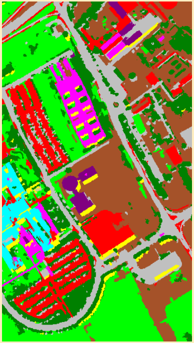


OA = 93.85%
AA = 97.07%

Strategy 3: SVM-MSF+MV

OA = 91.08%
AA = 94.76%

Strategy 3: MSSC - MSF



OA = 97.90%
AA = 98.59%

Classification accuracies for the Pavia image (%):

	SVM	ECHO	Strategy 2		Strategy 3: Marker-based classif.		
			SVM+ Waters.	SVM+ HSEG	SVM-MSF	SVM-MSF+MV	MSSC-MSF
Overall Accuracy	81.01	87.58	85.42	93.85	84.14	91.08	**97.90**
Average Accuracy	88.25	92.16	91.31	97.07	92.35	94.76	**98.59**
Kappa Coef. κ	75.86	83.90	81.30	91.89	79.71	88.30	**97.18**
Asphalt	84.93	87.98	93.64	94.77	93.05	93.16	**98.00**
Meadows	70.79	81.64	75.09	89.32	72.30	85.65	**96.67**
Gravel	67.16	76.91	66.12	96.14	89.15	89.15	**97.80**
Trees	97.77	**99.31**	98.56	98.08	87.02	91.24	98.83
Metal sheets	99.46	**99.91**	**99.91**	99.82	**99.91**	**99.91**	**99.91**
Bare soil	92.83	93.96	97.35	99.76	97.11	99.91	**100**
Bitumen	90.42	92.97	96.23	**100**	98.57	98.57	99.90
Bricks	92.78	97.35	97.92	99.29	95.66	99.05	**99.76**
Shadows	98.11	**99.37**	96.98	96.48	98.36	96.23	96.48

Outline

1 Introduction

2 Classification using segmentation-derived adaptive neighborhoods
- Segmentation
- Spectral-spatial classification
- Concluding discussion

3 Segmentation and classification using automatically selected markers
- Marker selection
- Classification using marker-controlled region growing
- Concluding discussion

4 Conclusions and perspectives

1. Classification using automatically selected markers:
    - significantly decreases oversegmentation
    - improves classification accuracies
    - provides classification maps with homogeneous regions
2. Marker selection: it is advantageous to use
    - SVM classifier
    - spatial information
    - multiple classifier approaches
3. Marker-controlled region growing
    - MSF-based method has proven to be efficient and robust

Contributions

- **Three spectral-spatial classification strategies:**
  1. Using SVM and MRF models
  2. Using adaptive neighborhoods derived from unsupervised segmentation
     - Segmentation techniques working both in the spatial and spectral domain → good performances
     - Pixelwise classification + majority voting within regions → simple and fast technique
  3. Using marker-based region growing segmentation
     - Analyzing probabilistic classification results for marker selection
     - Interest of using spatial information and multiple classifier approaches for marker selection
     - MSF-based marker-controlled region growing → efficient and robust
- Possibilities of high-performance parallel computing using commodity processors

Perspectives

1. Spectral-spatial image analysis
   - Develop new similarity measures
   - Automatically select results in segmentation hierarchies
   - Perform segmentation and classification concurrently
2. Further explore parallel strategies using commodity processors
3. Apply and adapt the proposed methods for other types of data/applications
   - medical imaging

Classification of Hyperspectral Data Using Spectral-Spatial Approaches

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May 13, 2010