Classification of Hyperspectral Data Using Support Vector Machines and Adaptive Neighborhoods

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Outline

Hyperspectral image

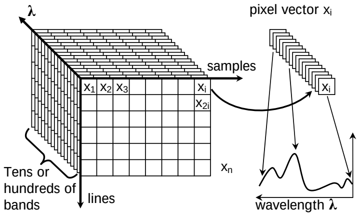
Every pixel contains a detailed spectrum (>100 spectral bands)

+ More information per pixel → increasing capability to distinguish objects

– Dimensionality increases → classification problem becomes more complex

⇓

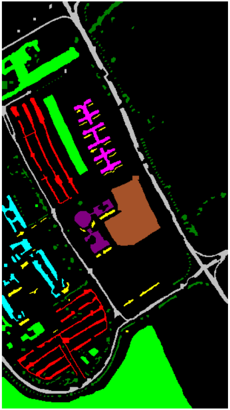
Efficient algorithms for automatic processing are required!



Classification problem

Input ROSIS image
[$610 \times 340 \times 103$]

Ground-truth data



Task

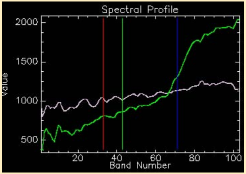
Assign **every** pixel to **one** of the **nine** classes:

alphalt
meadows
gravel
trees
metal sheets
bare soil
bitumen
bricks
shadows

Classification 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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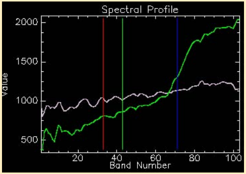
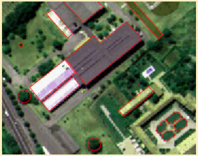


Spectral + spatial information

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



Objective

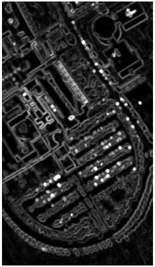
- Segment a hyperspectral image = find an exhaustive partitioning of the image into homogeneous regions
- Spectral info + spatial info $\rightarrow$ classify image

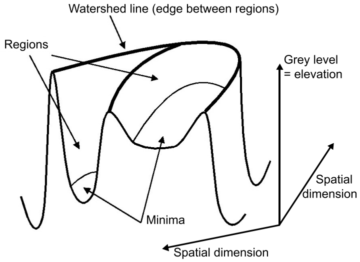
Outline

1. Introduction
2. Spectral-spatial classification of hyperspectral data
   - Segmentation
   - Spectral-spatial classification
3. Conclusions and perspectives

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

Tarabalka, Y., Chanussot, J., Benediktsson, J. A., Angulo, J., Fauvel, M., 2008. Segmentation and classification of hyperspectral data using watershed. In Proc. of IGARSS '08, Boston, USA.

Original image

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Robust Color Morpho Gradient

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Watershed 11802 regions

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Original image

$\Rightarrow$

Robust Color Morpho Gradient

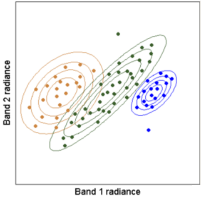
$\Rightarrow$

Watershed 11802 regions

$\Rightarrow$

Edges $\rightarrow$ to adjacent regions

2. Partitional clustering (EM)

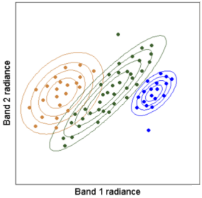


1. Clustering
   - pixels are grouped into C clusters
   - in each cluster $\rightarrow$ pixels drawn from a Gaussian distribution
   - distribution parameters $\rightarrow$ EM algorithm
2. Labeling of connected components

10 clusters

$\Rightarrow$

2. Partitional clustering (EM)



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2. Labeling of connected components

10 clusters $\Rightarrow$ 21450 regions

same cluster, but different regions!

3. Hierarchical image segmentation (HSEG)

- 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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1	2	3
4	5	6
7	8	9
10	11	12

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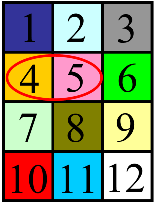

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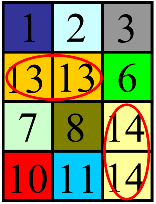

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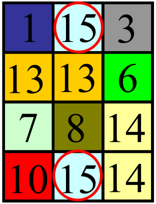

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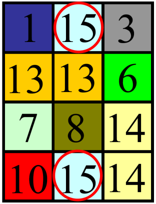

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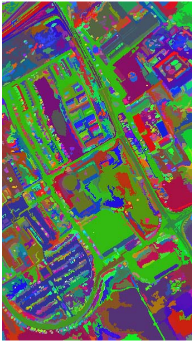

$SCW = 0.0$
7231 regions

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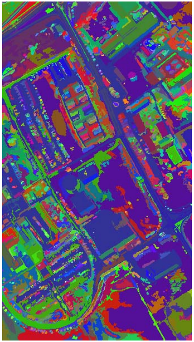
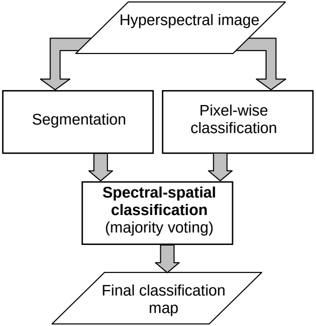
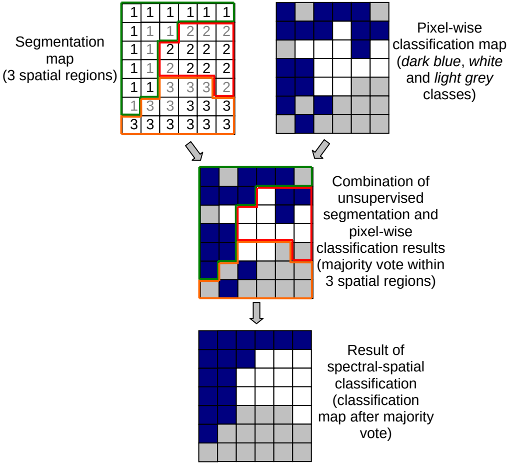


$SCW = 0.1$
7575 regions

Outline

Spectral-spatial classification scheme





Spectral-spatial classification

Original image

Spectral-spatial classification

Original image

$\Rightarrow$

SVM classification

OA = 81.01%
AA = 88.25%

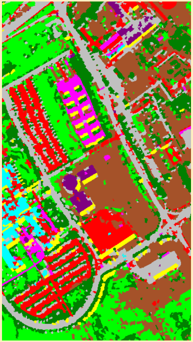
Spectral-spatial classification

SVM classification

OA = 81.01%
AA = 88.25%

$\Rightarrow$

SVM + Watershed

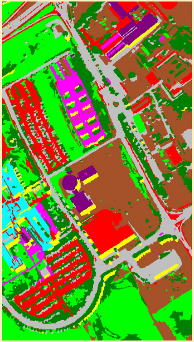


OA = 85.42%
AA = 91.31%

SVM + Partit.clustering

OA = 93.59%
AA = 94.39%

SVM + HSEG ($SCW = 0.1$)



OA = 93.85%
AA = 97.07%

Classification accuracies (%):

	SVM	+Watersh.	+Part.Clus.	+HSEG		EMP[1]
SCW				0.0	0.1	
OA	81.01	85.42	93.59	90.00	**93.85**	85.22
AA	88.25	91.31	94.39	94.15	**97.07**	90.76
κ	75.86	81.30	91.48	86.86	**91.89**	80.86
asphalt	84.93	93.64	90.72	73.33	94.77	**95.36**
meadows	70.79	75.09	**92.73**	88.73	89.32	80.33
gravel	67.16	66.12	82.09	**97.47**	96.14	87.61
trees	97.77	98.56	**99.21**	98.45	98.08	98.37
metal sheets	99.46	99.91	**100**	99.10	99.82	99.48
bare soil	92.83	97.35	96.78	98.43	**99.76**	63.72
bitumen	90.42	96.23	92.46	95.92	**100**	98.87
bricks	92.78	97.92	97.80	98.81	**99.29**	95.41
shadows	**98.11**	96.98	97.74	97.11	96.48	97.68

[1] *A. Plaza et al., 2009. Recent advances in techniques for hyperspectral image processing. Remote Sensing of Environment, accepted for publication.*

Conclusions and perspectives

Conclusions

1. Scheme for spectral-spatial classification of hyperspectral data is presented
2. Several segmentation techniques are investigated
3. The HSEG segmentation map leads to the best classification
4. Obtained classification accuracies $>$ all previous results

Perspectives

- Explore ways to fuse spectral $+$ spatial info

Thank you for your attention!