Segmentation and Classification of Hyperspectral Data Using Watershed

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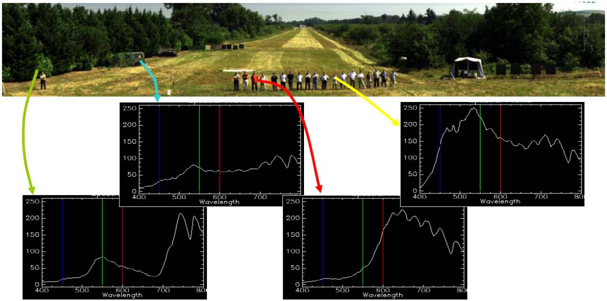
Contents

Hyperspectral image

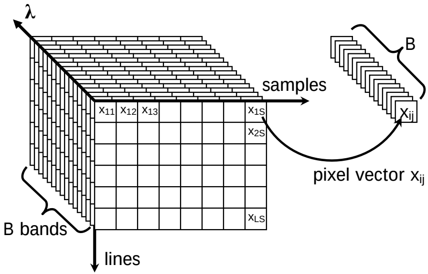
- Every pixel contains a detailed spectrum (>100 spectral bands)
- More information per pixel → increasing capability to distinguish objects



Hyperspectral image

- Hyperspectral image cube (L lines × S samples × B bands)
- Dimensionality increases → classification problem becomes more complex

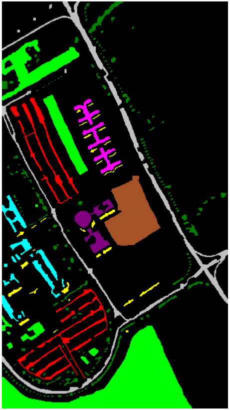
  ⇓
- New algorithmic developments are required



Classification problem

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

Ground-truth data



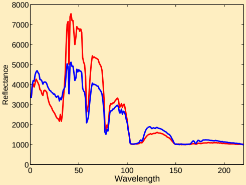
Task

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

- Spectra of each pixel is analyzed
- Directly accessible
- Kernel-based methods (e.g. SVM)
  $\rightarrow$ good classification results



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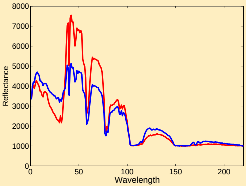
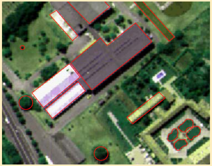


Spectral + spatial information

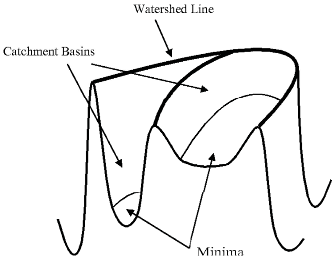
- Info about spatial structures included
- How to define structures?
  - closest neighborhood $\rightarrow$ done before
  - segmentation map
    $\rightarrow$ currently being worked on

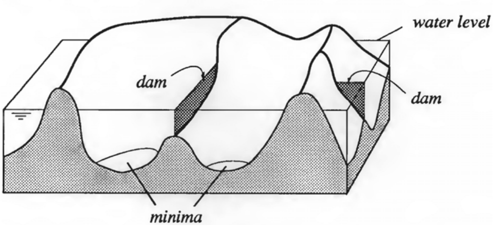


Objective

- Use watershed algorithm to segment a hyperspectral image
- Spectral info + spatial info → classify image

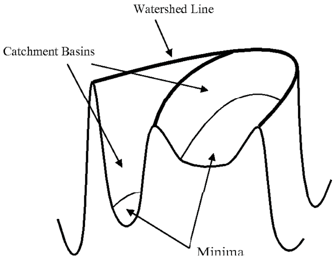
Watershed transformation

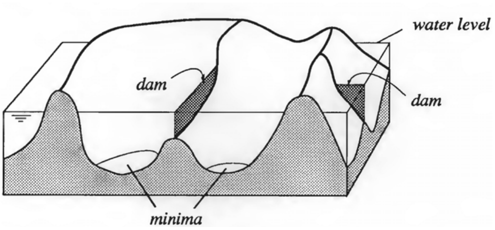




- One-band image on the input
- Value of each pixel = **Elevation** at this point
- Image 2D + Pixel values = **Topographic relief**
- **Minimum** = plateau of pixels from which one can only climb
- **Catchment basin** (associated with a minimum M) = set of pixels whose steepest slope paths reach M
- **Watersheds** = zones separating adjacent catchment basins

Watershed transformation (why to use?)





if **minima** mark relevant image **objects** and **crest lines** correspond to **edges**

$\Downarrow$

Gradient is usually used

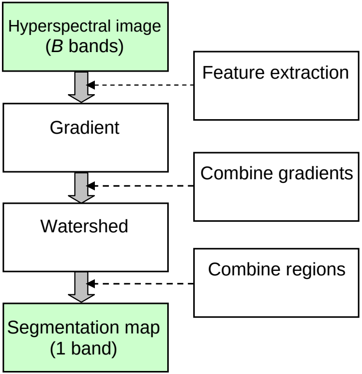
$\Rightarrow$

watershed transformation **partitions** the image into meaningful **regions**

Watershed 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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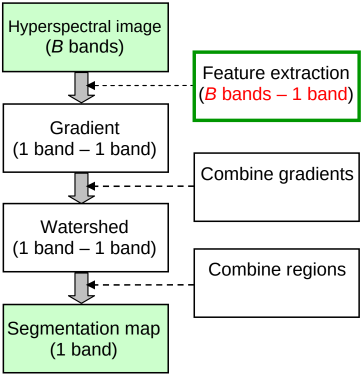

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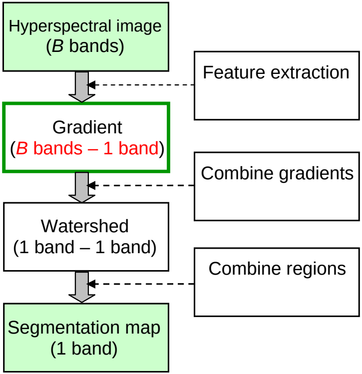

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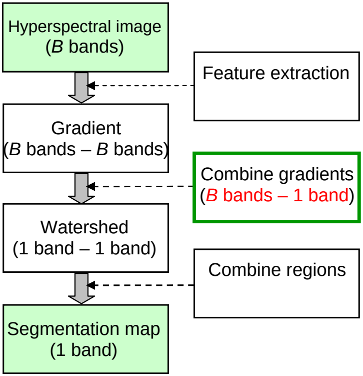

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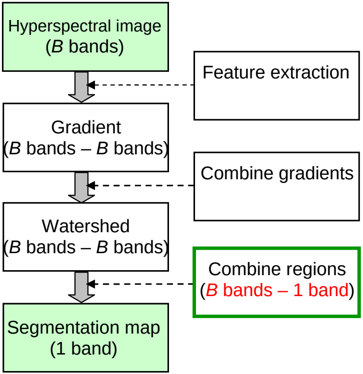
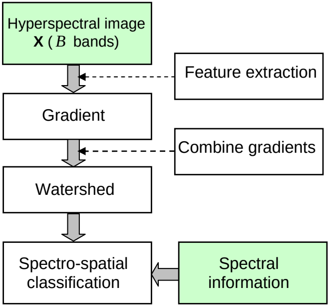


Input

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



Gradient

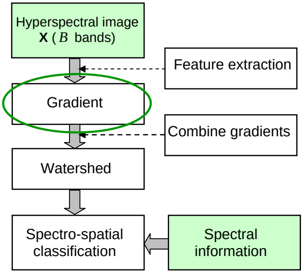
Robust Color Morphological Gradient (RCMG):

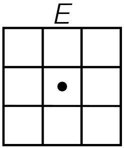
- For each pixel $\mathbf{x}_p$, $\chi = [\mathbf{x}_p^1, \mathbf{x}_p^2, ..., \mathbf{x}_p^e]$ is a set of e vectors within E
- Color Morphological Gradient (CMG):

$$CMG_E(\mathbf{x}_p) = \max_{i,j \in \chi}\{\|\mathbf{x}_p^i - \mathbf{x}_p^j\|_2\}$$

- RCMG:
  - $\mathbf{x}_p^{i\_max}, \mathbf{x}_p^{j\_max}$ - pixels that define the CMG of $\mathbf{x}_p$
  -

$$RCMG_E(\mathbf{x}_p) = \max_{i,j \in [\chi - [\mathbf{x}_p^{i\_max}, \mathbf{x}_p^{j\_max}]]}\{\|\mathbf{x}_p^i - \mathbf{x}_p^j\|_2\}$$





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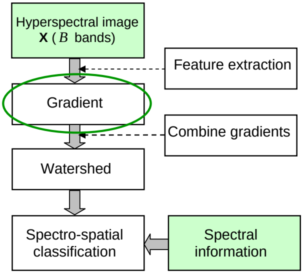

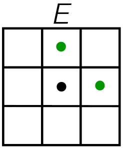

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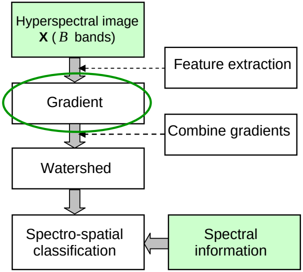
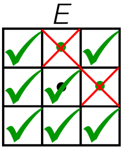




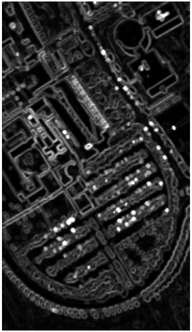
RCMG of University of Pavia image

- B-band image $\rightarrow$ one-band gradient
- Principal borders are defined
- Presence of "noisy" edges
  - Filter image $\rightarrow$ "noisy" borders reduced, but info about details lost

Input image

$\Rightarrow$

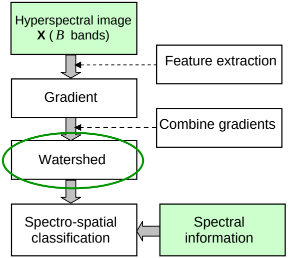
RCMG

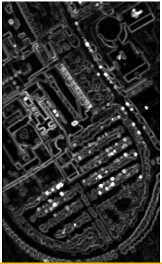


Watershed

- Algorithm of Vincent and Soille(1991)
- For every region **S** Standard Vector Median:

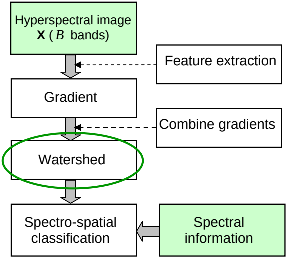
$$\mathbf{s}_{VM} = argmin_{\mathbf{s} \in \mathbf{S}} \left\{ \sum_{j=1}^{m} \|\mathbf{s} - \mathbf{s}_j\|_1 \right\}$$

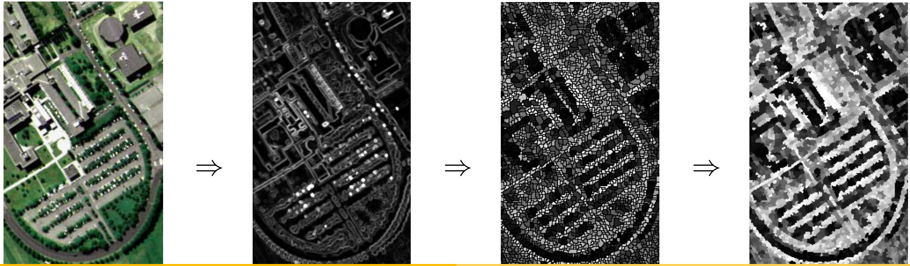


 ⇒  ⇒ 

Watershed

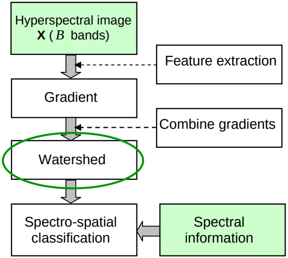
- Every watershed pixel → to the neighboring region with the "closest" median

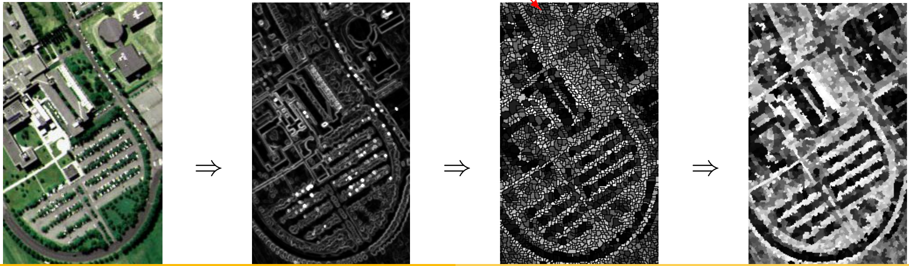




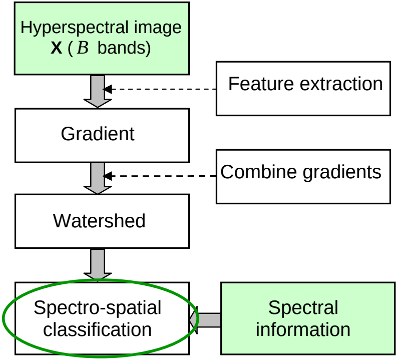
Watershed

- Oversegmentation
  - merging of regions
- Obtained regions $\rightarrow$ to improve classification





Spectro-spatial classification



Spectro-spatial classification

Original image

Spectro-spatial classification

Original image

⇒

SVM classification

Spectro-spatial classification

Original image

⇒

SVM classification

Spectro-spatial classification

Original image

⇒

SVM classification

⇒

Majority vote within the watershed regions

No WHEDs

Spectro-spatial classification

Original image

⇒

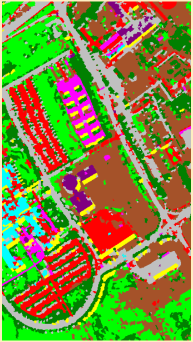
SVM classification

⇒

Majority vote within the watershed regions

No WHEDs

With WHEDs



Spectro-spatial classification

Classification Accuracies (%):

Accuracy	Pixel-wise SVM	SVM + Majority vote	
		No WHEDs	*With WHEDs*
OA	82.08	84.41	**86.64**
AA	89.11	90.70	**92.13**
κ	77.49	80.32	**83.05**
asphalt	85.48	89.82	**94.28**
meadows	71.56	74.03	**76.41**
gravel	**70.70**	69.99	69.89
trees	97.88	98.04	**98.30**
metal sheets	99.55	**99.78**	**99.78**
bare soil	93.46	95.37	**97.51**
bitumen	91.95	94.74	**97.14**
bricks	92.97	96.31	**98.29**
shadows	**98.42**	98.20	97.57

Spectro-spatial classification

- Noise reduced
- Rough borders

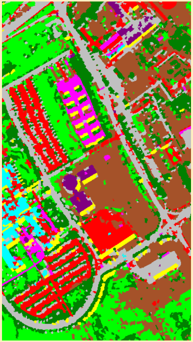
SVM classification

⇒

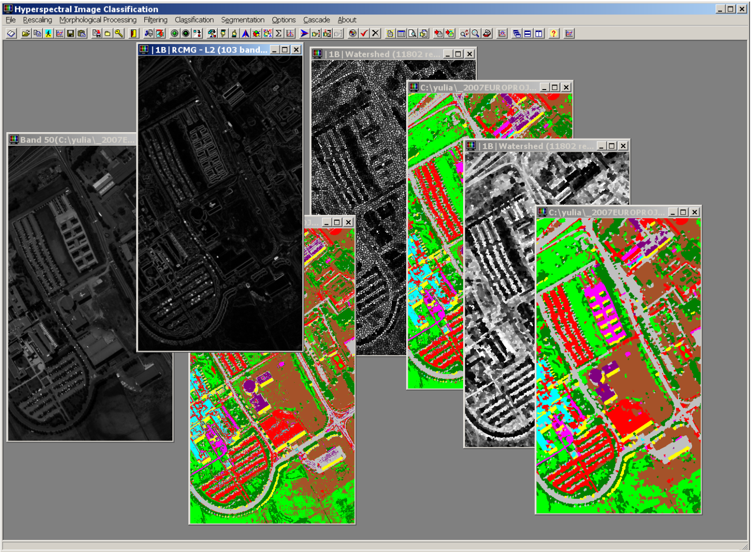
Majority vote within the watershed regions

No WHEDs

With WHEDs



Interactive environment (HyperClas)



Conclusions and perspectives

Conclusions

1. Scheme for spectro-spatial classification of hyperspectral data is presented
2. Watershed is applied for segmentation
3. Results are promising

Perspectives

1. Improve segmentation results
   - filtering
   - merging of regions
2. Explore ways to fuse spectral + spatial info

Thank you for your attention!

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