A Multiple Classifier Approach for Spectral-Spatial Classification of Hyperspectral Data

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Outline

Hyperspectral image

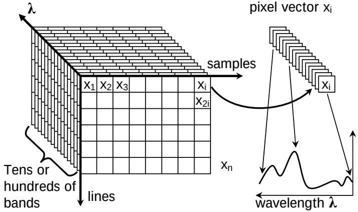
Every pixel contains a detailed spectrum (>100 spectral bands)

+ More information per pixel → increasing capability to distinguish objects

− Dimensionality increases → image analysis becomes more complex

⇓

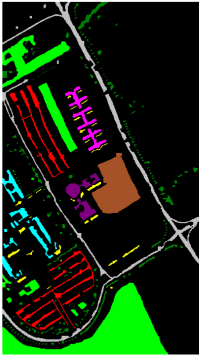
Advanced algorithms are required!



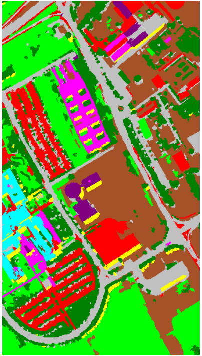
Supervised classification problem

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

Ground-truth data



Task

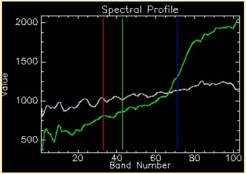


Nine classes: alphalt, meadows, gravel, trees, metal sheets, bare soil, bitumen, bricks, shadows

Classification approaches

Only spectral information

- Pixelwise approach
- Spectrum of each pixel is analyzed
- SVM and kernel-based methods
  $\rightarrow$ good classification accuracies



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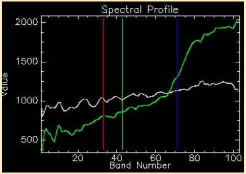
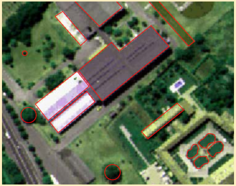


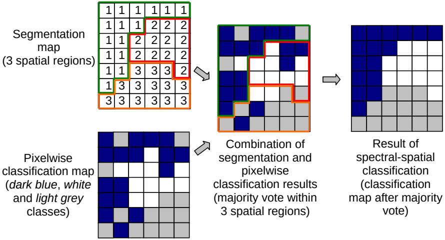
Spectral + spatial information

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



Our previous research

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



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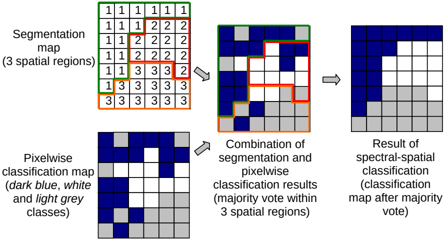


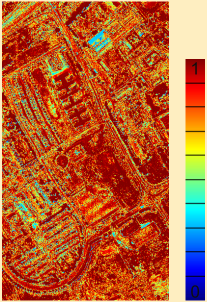
- Unsupervised segmentation: dependence on the chosen measure of homogeneity

Our previous research: Marker-controlled segmentation

Probabilistic pixelwise SVM classification

Classification map

Probability map



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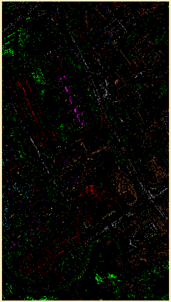
Markers = the most reliably classified pixels



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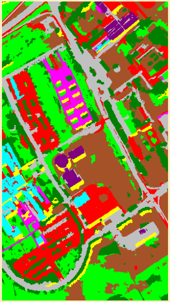
Marker-controlled region growing



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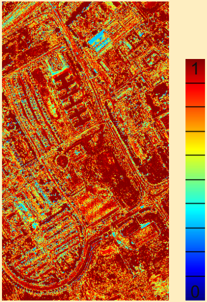

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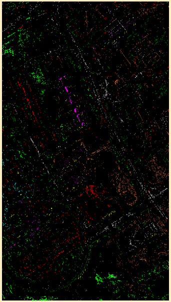

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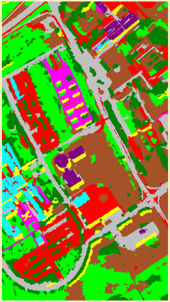

Drawback: strong dependence on the performances of the selected probabilistic classifier

Objective

- Mitigate the dependence of marker selection from the choice of a classifier
  $\rightarrow$ using multiple classifiers

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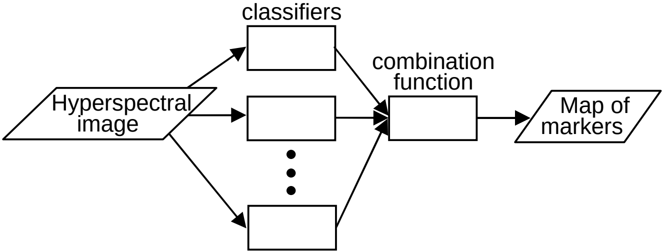

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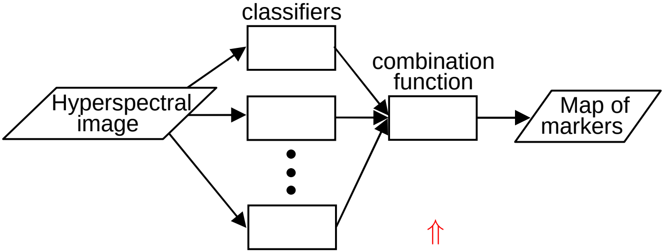
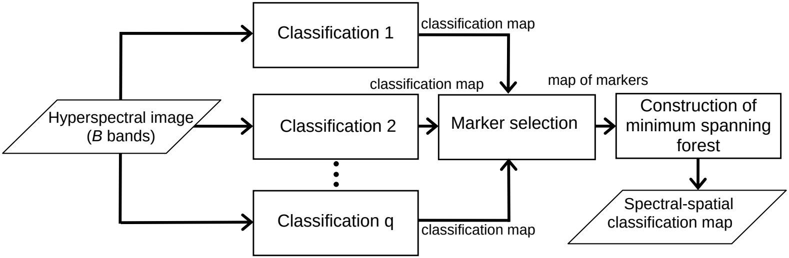


⇑ Which classifiers to use?

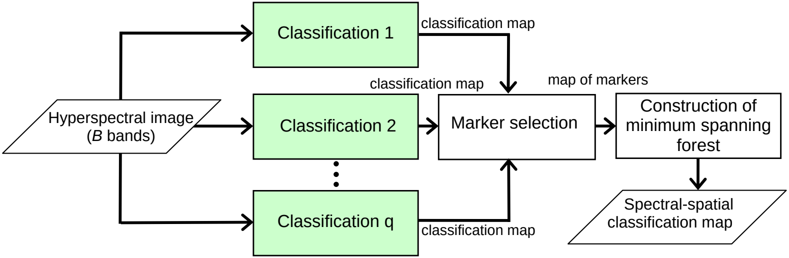
⇑ Rule for combining the classifiers?

Input

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



Multiple classification



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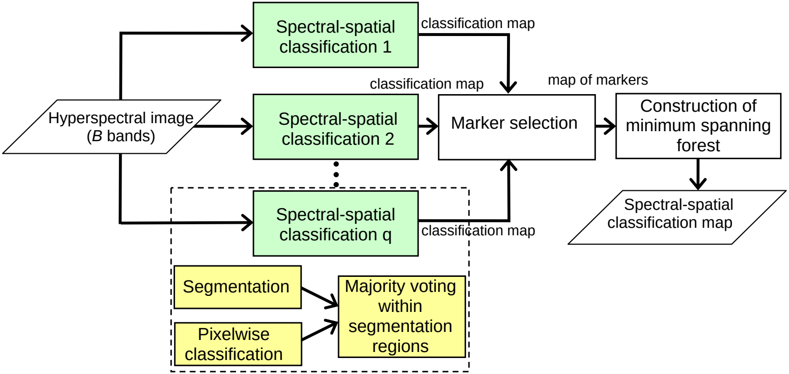

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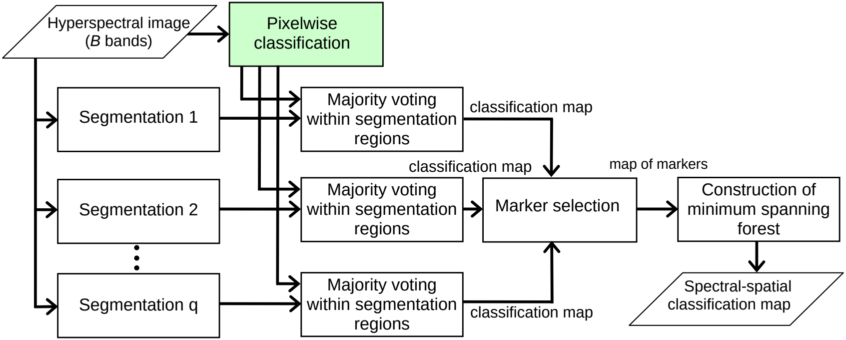

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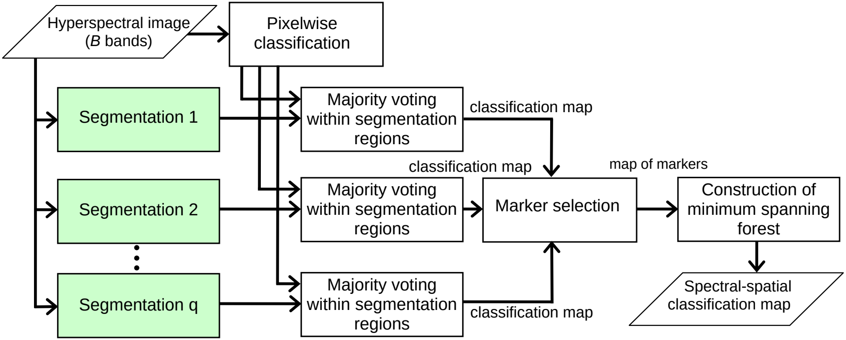

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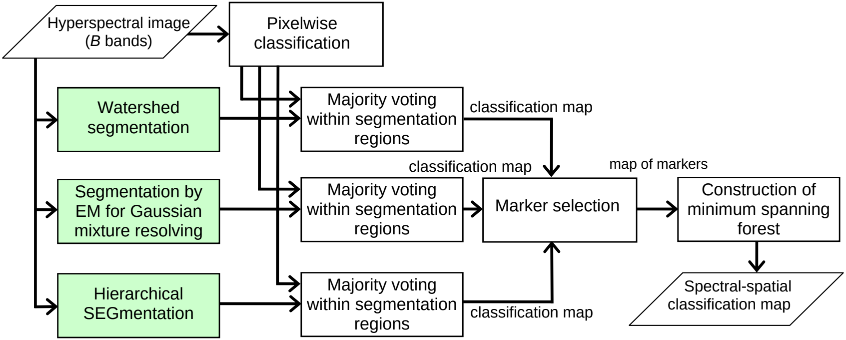

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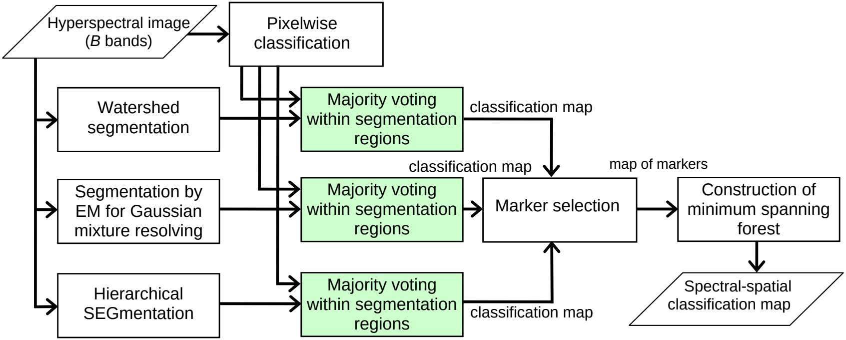


Multiple spectral-spatial classification

Image

⇒

Watershed

Region growing + edge detection

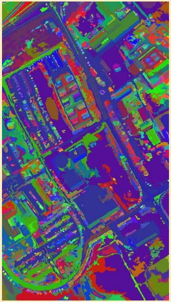
1 region = set of pixels connected to 1 min of the gradient

EM

Spectral clustering approach

In each cluster → pixels drawn from a Gaussian distribution

HSEG



Region growing + spectral clustering

Iterative merging of regions, starting from 1-pixel regions

Multiple spectral-spatial classification

SVM classification

+

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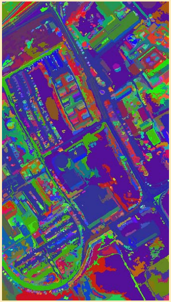

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Multiple spectral-spatial classification

SVM classification

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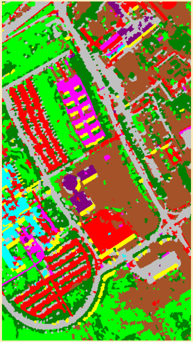
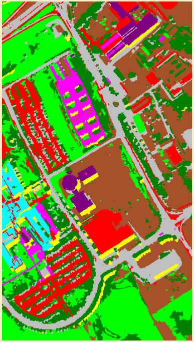
SVM + Watershed



SVM + EM

SVM + HSEG



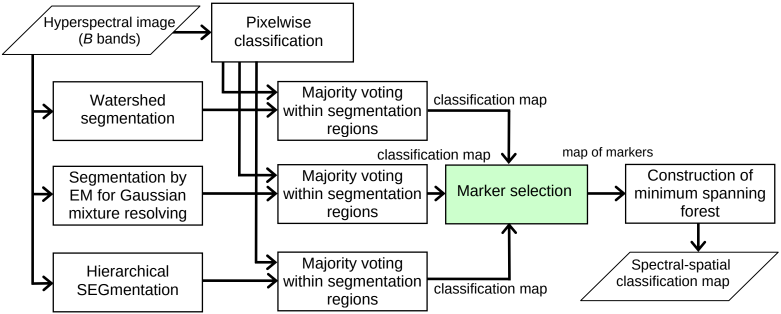
SVM classification: OA = 81.01%, AA = 88.25%

SVM + Watershed: OA = 85.42%, AA = 91.31%

SVM + EM: OA = 94.00%, AA = 93.13%

SVM + HSEG: OA = 93.85%, AA = 97.07%

Marker selection



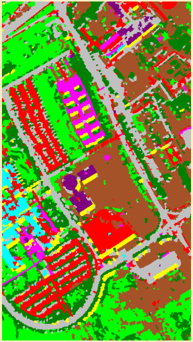
- Pixels assigned by **all** the classifiers to the same class

$\Downarrow$

Map of markers

Marker selection

SVM + Watershed

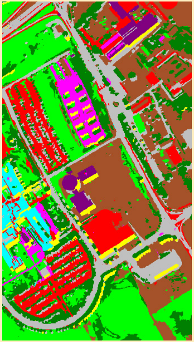


$\wedge$

SVM + EM

$\wedge$

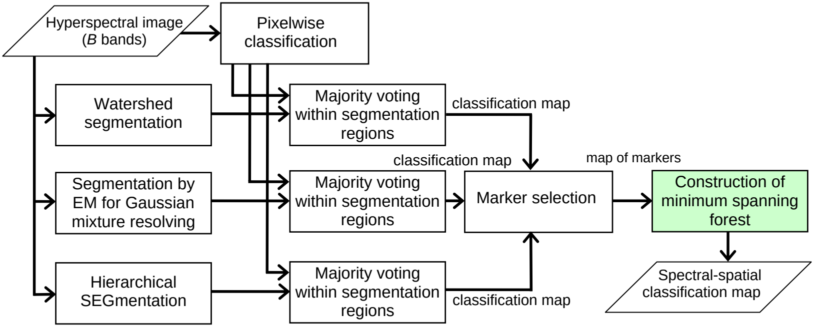
SVM + HSEG



$=$

Map of markers (64% of pixels)

Construction of a Minimum Spanning Forest (MSF)



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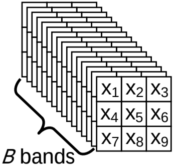

map of markers

1	0	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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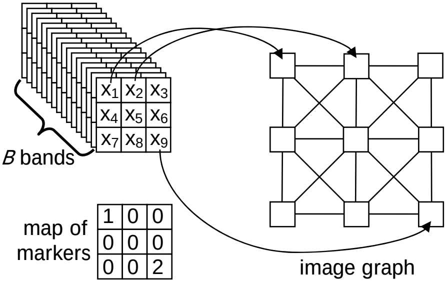

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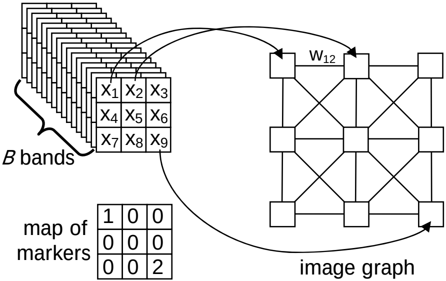

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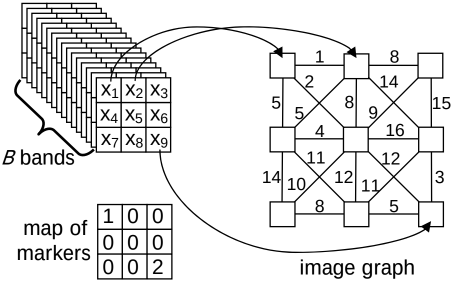

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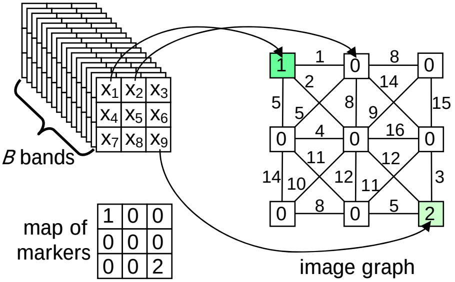

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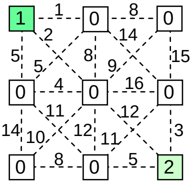

2) Construct a MSF $F^* = (V^*, E^*)$ rooted on $\{t_1, ..., t_m\}$

Initialization: $V^* = \{t_1, t_2, ..., t_m\}$ (marker pixels are in the forest)

1. Choose edge of the image 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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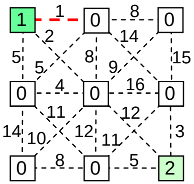

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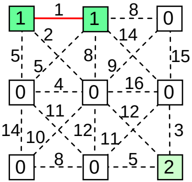

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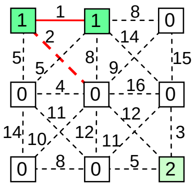

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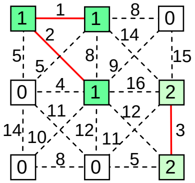

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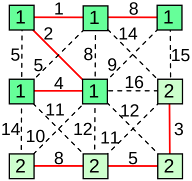

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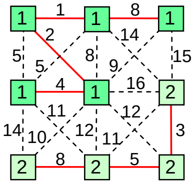

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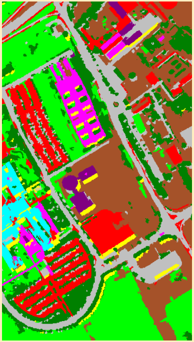
3) Class of each marker $\rightarrow$ class of the corresponding region
(of all the pixels grown from this marker)

MSSC-MSF classification results

Map of MSSC markers

⇒

MSSC-MSF classification map



OA = 97.90%
AA = 98.59%

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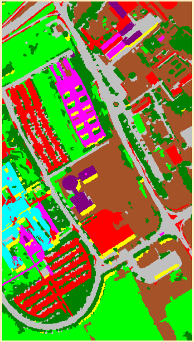


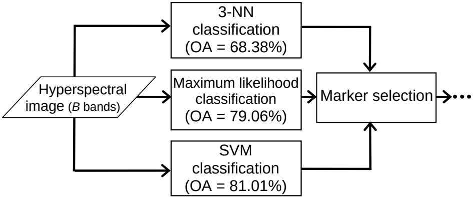
OA = 97.90%
AA = 98.59%

SVM classification map

OA = 81.01%
AA = 88.25%

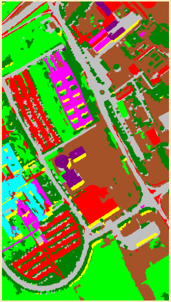
Multiple classification using several pixelwise techniques

- Assess the importance of spectral-spatial approaches for marker selection



MC-MSF map (pixelwise marker selection)

MSSC-MSF map (spectral-spatial marker selection)



OA = 87.98%
AA = 92.05%

OA = 97.60%
AA = 98.59%

Classification accuracies (%):

	SVM	ECHO	Spectral-spatial results used for marker selection			Marker-based classification		
			SVM +WH	SVM +EM	SVM+ HSEG	Prev.* method	MC-MSF	MSSC-MSF
Over.Acc.	81.01	87.58	85.42	94.00	93.85	91.08	87.98	**97.90**
Aver.Acc.	88.25	92.16	91.31	93.13	97.07	94.76	92.05	**98.59**
Coef. κ	75.86	83.90	81.30	91.93	91.89	88.30	84.32	**97.18**
Asphalt	84.93	87.98	93.64	90.10	94.77	93.16	87.01	**98.00**
Meadows	70.79	81.64	75.09	95.99	89.32	85.65	83.24	**96.67**
Gravel	67.16	76.91	66.12	82.26	96.14	89.15	75.37	**97.80**
Trees	97.77	**99.31**	98.56	85.54	98.08	91.24	98.97	98.83
Metal sh.	99.46	99.91	99.91	**100**	99.82	99.91	99.91	99.91
Bare soil	92.83	93.96	97.35	96.72	99.76	99.91	93.24	**100**
Bitumen	90.42	92.97	96.23	91.85	**100**	98.57	95.11	99.90
Bricks	92.78	97.35	97.92	98.34	99.29	99.05	97.00	**99.76**
Shadows	98.11	**99.37**	96.98	97.36	96.48	96.23	98.62	96.48

**Y. Tarabalka, J. Chanussot, and J. A. Benediktsson, "Segmentation and classification of hyperspectral images using Minimum Spanning Forest grown from automatically selected markers," IEEE Trans. on Systems, Man, and Cybernetics, Part B: Cybernetics, 2010.*

Conclusions and perspectives

Conclusions

1. Multiple classifier approach for automatic selection of markers was proposed
2. Scheme for classification of hyperspectral images was developed
3. The proposed method:
    - improves classification accuracies
    - provides classification maps with homogeneous regions

Perspectives

- Explore further the integration of spectral-spatial approaches in multiple classifier systems

Thank you for your attention!

A Multiple Classifier Approach for Spectral-Spatial Classification of Hyperspectral Data

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