

Best Merge Region Growing with Integrated Probabilistic Classification for Hyperspectral Imagery

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Outline

- 1 Introduction
- 2 Proposed spectral-spatial classification scheme
- 3 Conclusions and perspectives

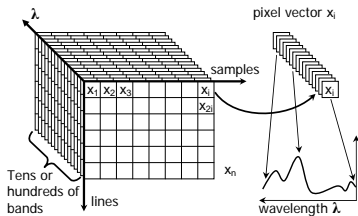
Hyperspectral image

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

- + More information per pixel \rightarrow increasing capability to distinguish objects
- Dimensionality increases \rightarrow image analysis becomes more complex



Advanced algorithms are required!



Supervised classification problem

AVIRIS image

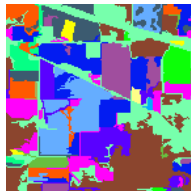
Spatial resolution: 20m/pix
Spectral resolution: 200 bands



Ground-truth data



Task

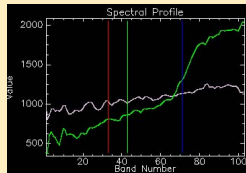


16 classes: corn-no till, corn-min till, corn, soybeans-no till, soybeans-min till, soybeans-clean till, alfalfa, grass/pasture, grass/trees, grass/pasture-mowed, hay-windrowed, oats, wheat, woods, bldg-grass-tree-drives, stone-steel towers

Classification approaches

Only spectral information

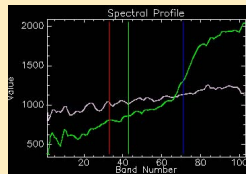
- Pixelwise approach
- Spectrum of each pixel is analyzed
- SVM and kernel-based methods
→ good classification accuracies



Classification approaches

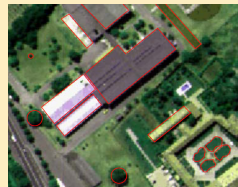
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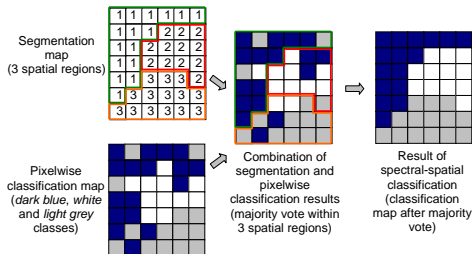
Spectral + spatial information

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



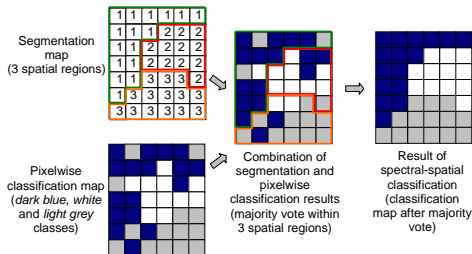
Our previous research

- **Segment** a hyperspectral image into **homogeneous** regions
 - Each region = adaptive neighborhood for all the pixels within the region
- **Spectral** info + **segmentation map** → classify image



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 - Each region = adaptive neighborhood for all the pixels within the region
- **Spectral** info + **segmentation map** → classify image

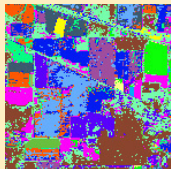


- Unsupervised segmentation: **dependence on the chosen measure of homogeneity**

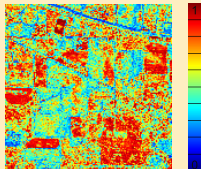
Our previous research: Marker-controlled segmentation

Probabilistic pixelwise
SVM classification

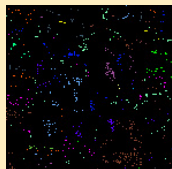
Classification map



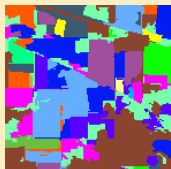
Probability map



Markers = the
most reliably
classified pixels



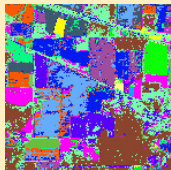
Marker-
controlled region
growing



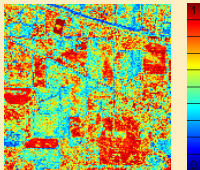
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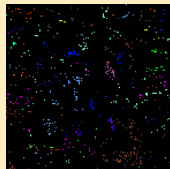
Classification map



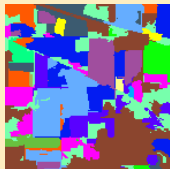
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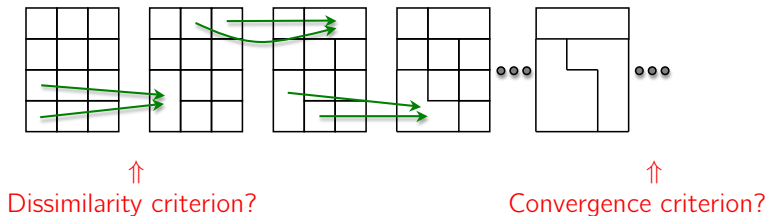
Marker-
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Drawback: strong dependence on the performance of the selected probabilistic classifier

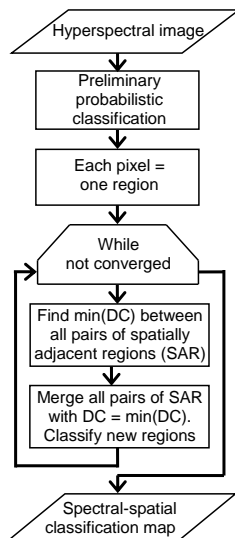
Objective

- Perform segmentation and classification concurrently
→ best merge region growing with **integrated** classification



Input

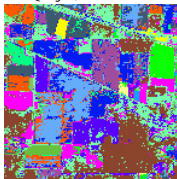
- B -band hyperspectral image
 $\mathbf{X} = \{\mathbf{x}_j \in \mathbb{R}^B, j = 1, 2, \dots, n\}$
- $B \sim 100$



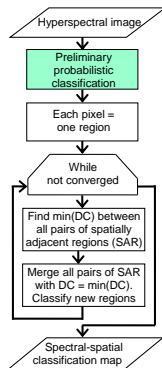
Preliminary probabilistic classification

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

- classification map
 $L = \{L_j, j = 1, \dots, n\}$



- for each pixel \mathbf{x}_j :
a vector of K class probabilities
 $\{P(L_j = k | \mathbf{x}_j), k = 1, \dots, K\}$

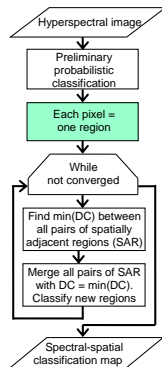


*C. Chang and C. Lin, "LIBSVM: A library for Support Vector Machines," Software available at <http://www.csie.ntu.edu.tw/~cjlin/libsvm>, 2011.

Hierarchical step-wise optimization with classification

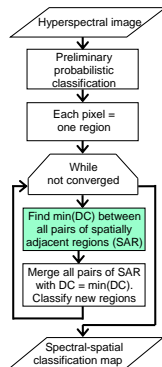
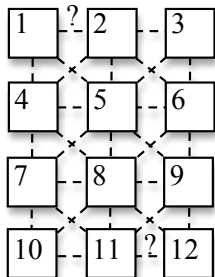
- 1 Each pixel \mathbf{x}_i = one region R_i
 - preliminary class label $L(R_i)$
 - class probabilities
 $\{P_k(R_i) = P(L(R_i) = k | R_i), k = 1, \dots, K\}$

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



Hierarchical step-wise optimization with classification

- 2 Calculate Dissimilarity Criterion (DC) between spatially adjacent regions
 - DC = function of region statistical, geometrical and classification features



Hierarchical step-wise optimization with classification

2 Calculate Dissimilarity Criterion between adjacent regions:

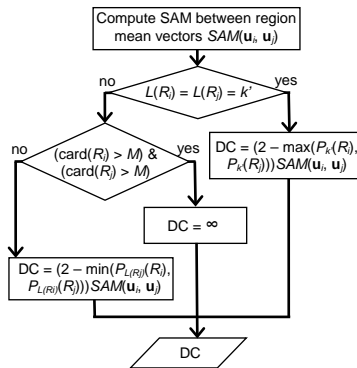
- Compute Spectral Angle Mapper between the region mean vectors u_i and u_j

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

- If adjacent regions have equal class labels \rightarrow they belong more likely to the same region:

$$DC = (2 - \max(P_{k'}(R_i), P_{k'}(R_j))) \cdot SAM(u_i, u_j)$$

- If two large regions are assigned to different classes \rightarrow they cannot be merged together



Hierarchical step-wise optimization with classification

2 Calculate Dissimilarity Criterion between adjacent regions:

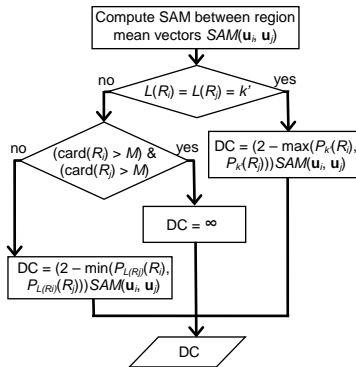
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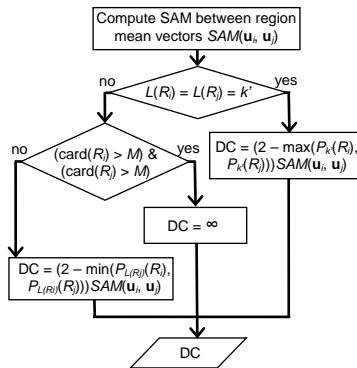
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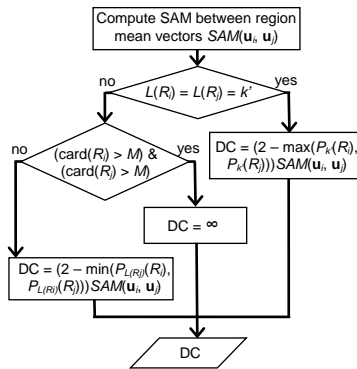
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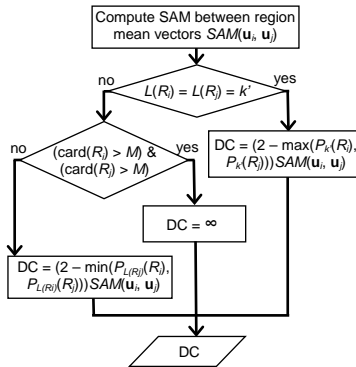
Hierarchical step-wise optimization with classification

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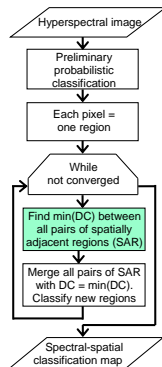
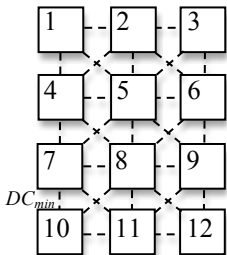
$$SAM(u_i, u_j) = \arccos\left(\frac{u_i \cdot u_j}{\|u_i\|_2 \|u_j\|_2}\right)$$

- If adjacent regions have equal class labels \rightarrow they belong more likely to the same region
- If two large regions are assigned to different classes \rightarrow they cannot be merged together
- If two regions have different class labels \rightarrow DC between them is penalized by $(2 - \min(P_{L(R_j)}(R_i), P_{L(R_i)}(R_j)))$



Hierarchical step-wise optimization with classification

- Find the smallest dissimilarity criterion DC_{min}



Hierarchical step-wise optimization with classification

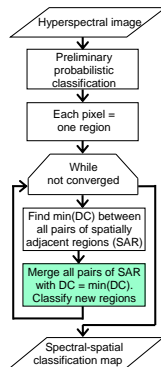
- 4 Merge all pairs of spatially adjacent regions with $DC = DC_{min}$.

For each new region $R_{new} = R_i + R_j$:

$$P_k(R_{new}) = \frac{P_k(R_i)card(R_i) + P_k(R_j)card(R_j)}{card(R_{new})}$$

$$L(R_{new}) = \arg \max_k \{P_k(R_{new})\}$$

All the pixels in R_{new} get a definite class label.



Hierarchical step-wise optimization with classification

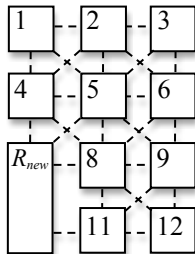
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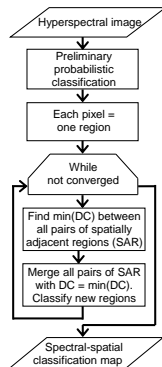
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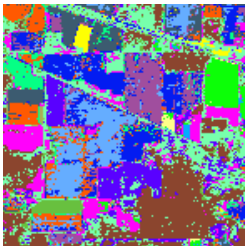


Hierarchical step-wise optimization with classification

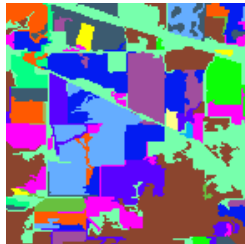
- 2 Calculate Dissimilarity Criterion between adjacent regions
- 3 Find the smallest dissimilarity criterion DC_{min}
- 4 Merge all pairs of spatially adjacent regions with $DC = DC_{min}$
- 5 Stop if all n pixels get a definite class label.
If not converged, go to step 2



Classification maps



SVM



Proposed HSwC method

Classification accuracies (%)

| | No. of Samp. | | SVM | ECHO | SVM MSF | HSeg +MV | HSwC |
|----------------------------|--------------|------|------------|------------|--------------|--------------|--------------|
| | Train | Test | | | | | |
| Overall Accuracy | - | - | 78.17 | 82.64 | 88.41 | 90.86 | 89.24 |
| Average Accuracy | - | - | 85.97 | 83.75 | 91.57 | 93.96 | 94.18 |
| Kappa Coefficient κ | - | - | 75.33 | 80.38 | 86.71 | 89.56 | 87.76 |
| Corn-no till | 50 | 1384 | 78.18 | 83.45 | 90.97 | 90.46 | 93.06 |
| Corn-min till | 50 | 784 | 69.64 | 75.13 | 69.52 | 83.04 | 82.53 |
| Corn | 50 | 184 | 91.85 | 92.39 | 95.65 | 95.65 | 97.28 |
| Soybeans-no till | 50 | 918 | 82.03 | 90.10 | 98.04 | 92.06 | 95.10 |
| Soybeans-min till | 50 | 2418 | 58.95 | 64.14 | 81.97 | 84.04 | 74.36 |
| Soybeans-clean till | 50 | 564 | 87.94 | 89.89 | 85.99 | 95.39 | 96.10 |
| Alfalfa | 15 | 39 | 74.36 | 48.72 | 94.87 | 92.31 | 97.44 |
| Grass/pasture | 50 | 447 | 92.17 | 94.18 | 94.63 | 94.41 | 93.96 |
| Grass/trees | 50 | 697 | 91.68 | 96.27 | 92.40 | 97.56 | 97.85 |
| Grass/pasture-mowed | 15 | 11 | 100 | 36.36 | 100 | 100 | 100 |
| Hay-windrowed | 50 | 439 | 97.72 | 97.72 | 99.77 | 99.54 | 98.86 |
| Oats | 15 | 5 | 100 | 100 | 100 | 100 | 100 |
| Wheat | 50 | 162 | 98.77 | 98.15 | 99.38 | 98.15 | 99.38 |
| Woods | 50 | 1244 | 93.01 | 94.21 | 97.59 | 98.63 | 99.52 |
| Bldg-Grass-Tree-Drives | 50 | 330 | 61.52 | 81.52 | 68.79 | 82.12 | 81.52 |
| Stone-steel towers | 50 | 45 | 97.78 | 97.78 | 95.56 | 100 | 100 |

Conclusions and perspectives

Conclusions

- 1 New spectral-spatial classification method for hyperspectral images was proposed
- 2 New dissimilarity criterion between image regions was defined
- 3 The proposed method:
 - improves classification accuracies
 - provides classification maps with homogeneous regions

Perspectives

- Explore further the choice of:
 - optimal representative features for segmentation regions
 - dissimilarity measures between regions

Thank you for your attention!

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