Marker-Based Hierarchical Segmentation and Classification Approach for Hyperspectral Data

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Introduction

- Hyperspectral imaging records a detailed spectrum for each pixel, opening new perspectives in classification.
- Recent studies have shown the advantage of performing a spatial segmentation-based analysis for accurate classification [1, 2].
- Hierarchical Segmentation (HSeg) has shown good performance for spatial analysis of hyperspectral images [3].

3. Marker-based HSeg



- HSeg is a combination of hierarchical step-wise optimization and spectral clustering:
- 1. Each pixel = one region.
- 2. Find the smallest dissimilarity criterion DC_{min} between adjacent regions.
- 3. Merge adjacent regions with $DC = DC_{min}$ and non-adjacent regions with $DC \le S_{wght}DC_{min}$.
- 4. If not converged, go to step 2.



We propose and investigate the use of markers, or region seeds, for this purpose.
Markers are automatically selected by analyzing probabilistic classification results.

Hyperspectral data

The Indian Pines image:

is recorded by the Airborne Visible/Infrared Imaging Spectrometer over the vegetation area,
is of 145 by 145 pixels, with a spatial resolution of 20 m/pixel and 200 spectral channels.



Three implementations of the marker-based HSeg



region w

marker 1

region y

marker 2

M-HSeg^p

region x

marker 1

At initialization, each marker = one region
Two regions with different markers have DC = ∞

each pixel = one region

markers have DC = 0

• Two regions with different

markers have $DC = \infty$

• Two regions with equal



• Sixteen classes of interest are considered.

Proposed classification method

1. Probabilistic pixelwise classification

• Perform a probabilistic Support Vector Machines (SVM) classification [1], in order to obtain:



2. Marker selection

Select the most reliably classified pixels as markers of spatial regions:
Apply a connected component labeling on the classification map.



region z

marker 2

• At initialization,

• At initialization,

each pixel = one region, each marker pixel obtains a new marker label
Two regions with different markers have DC = ∞
At the end, regions with the same initial marker are merged

> $S_{wght} = 0.0, DC = SAM$ between region mean vectors

Classification accuracies in percentage (*DC* = *SAM* between region mean vectors)

	M-HSeg ^r M-HSeg ^p			M-HSeg ^{op}		SVM	SVMMSF
S _{wght}		0.0		0.2	0.5		[1]
Overall Accuracy	77.53	81.59	89.23	88.72	84.74	78.17	89.65
Average Accuracy	84.54	87.09	93.44	93.40	90.50	85.97	93.48
Kappa coefficient	74.48	79.10	87.72	87.15	82.64	75.33	88.19

Conclusions

• A new marker-based HSeg method for spectral-spatial classification of hyperspectral images is proposed.

• The proposed method yields accurate segmentation and classification maps.

The M-HSeg^{op} implementation significantly outperforms M-HSeg^r and M-HSeg^p implementations in terms of accuracies → A region mean vector may be not an accurate representative of image regions.
The best results for this image are obtained with S_{wght} = 0.0, i.e., when Hseg = Hierarchical Step-Wise Optimization [4].

Analyze each connected component:

a) If it is large (>20 pixels) → use P% (40%) of its pixels with the highest probabilities as a marker.
b) If it is small → its pixels with probabilities > T% (90%) are used as a marker.



• Each connected component \rightarrow 1 or 0 marker (2250 regions \rightarrow 107 markers)

A marker is not necessarily a connected set of pixels



• Each marker has a class label

• In the future, we plan to explore the choice of optimal representative features for segmentation regions.

References

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