

Metric Learning for Hyperspectral Image Segmentation

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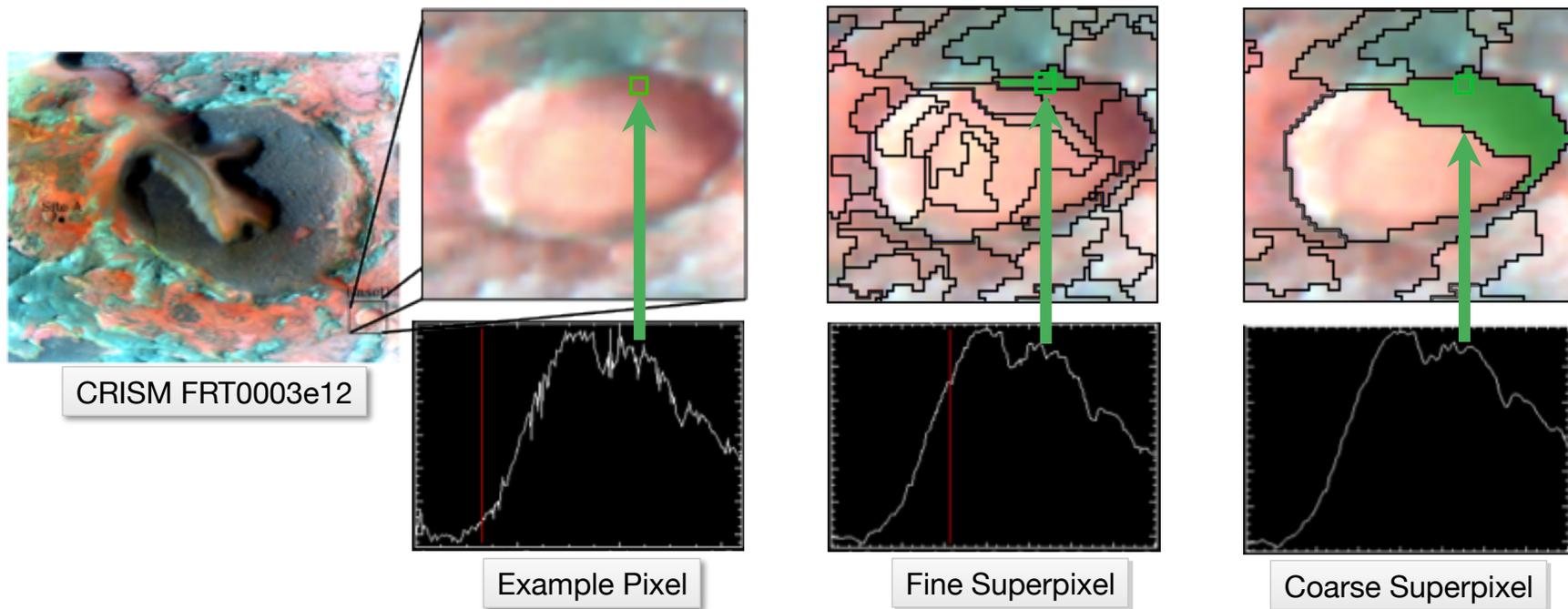
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The work described involves research and development carried out for the AMMOS MultiMission Operations System and MGSS Instrument Operations Subsystem. AMMOS and U.S. Government Support Acknowledged.

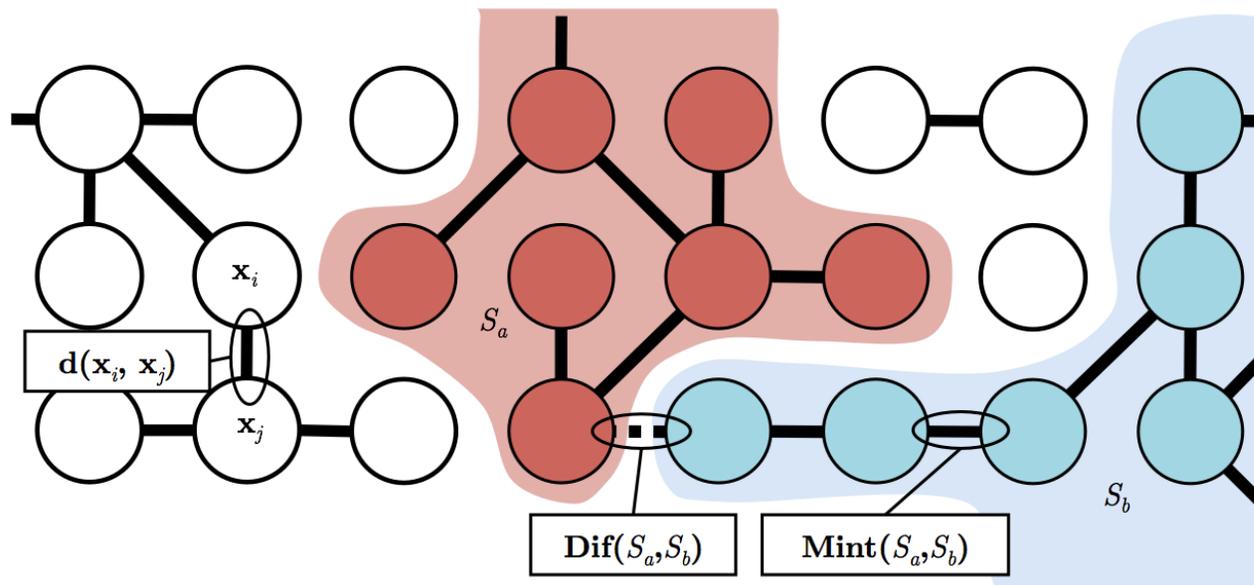
Application: Superpixel Segmentation [Thompson et al., 2010]

- Find spatially contiguous, spectrally homogeneous regions (“superpixels”) corresponding to physical features
- Reduces processing time of subsequent analyses
- Yields theoretical noise improvement of order $n^{1/2}$ for a superpixel of size n



Graph-based Segmentation Algorithm [Felzenszwalb]

- Image = 8-connected graph weighted by distances $d(x_i, x_j)$ between adjacent pixels x_i and x_j
- Agglomerative clustering iteratively connects segments by growing minimum spanning trees



- Segment merging criterion:

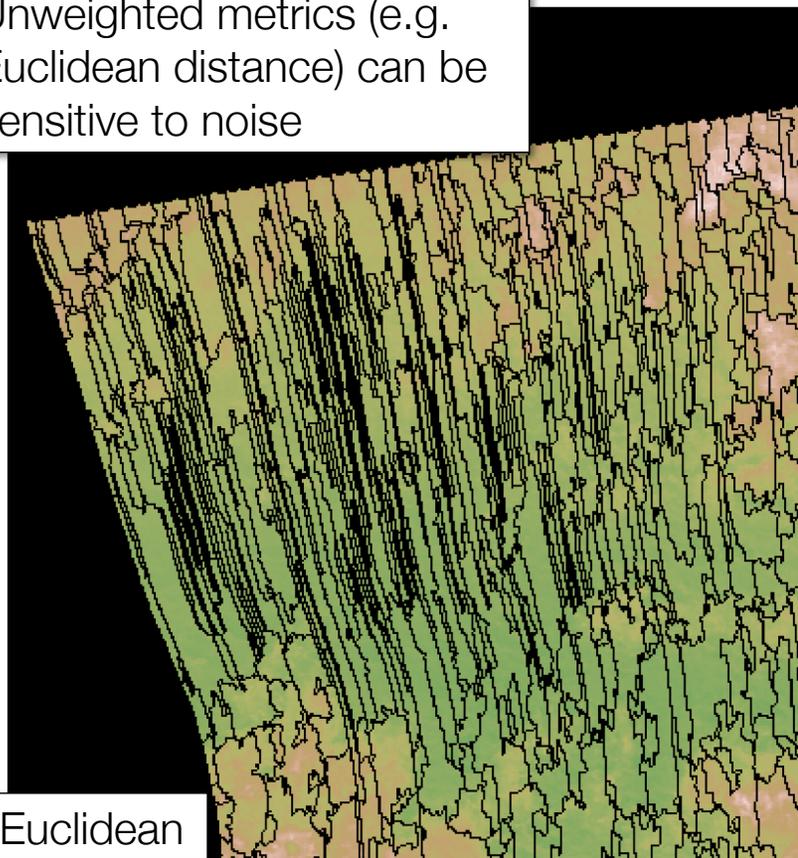
$$\text{Dif}(S_a, S_b) > \text{MInt}(S_a, S_b) = \min \left(\text{Int}(S_a) + \frac{k}{|S_a|}, \text{Int}(S_b) + \frac{k}{|S_b|} \right)$$

- Small k = many segments, large k = few segments, dependant on $d(x_i, x_j)$

Metric Learning for Hyperspectral Image Segmentation

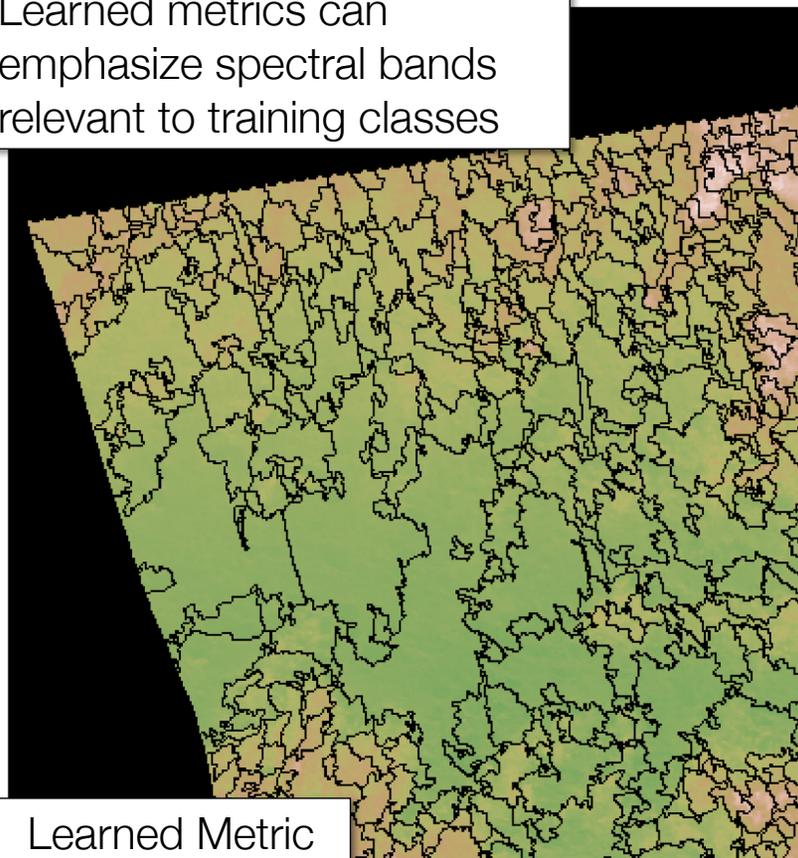
- Segmentation quality dependent on robustness of spectral similarity measure

Unweighted metrics (e.g. Euclidean distance) can be sensitive to noise



Euclidean

Learned metrics can emphasize spectral bands relevant to training classes

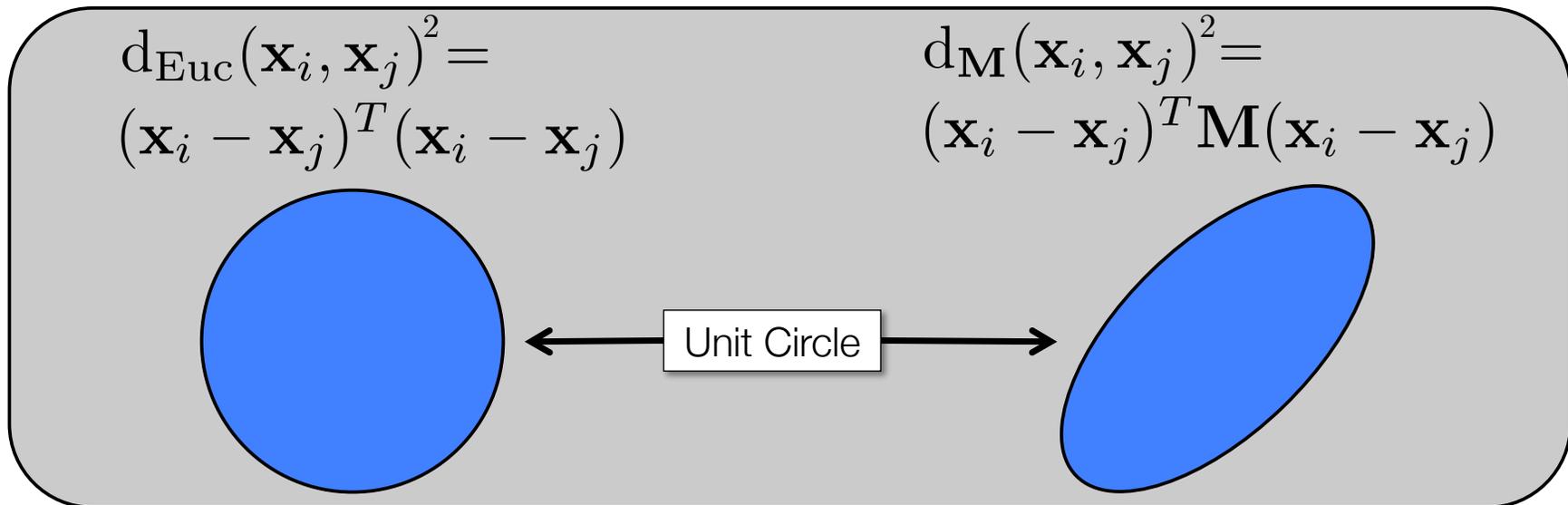


Learned Metric

Image: CRISM FRT000863e

Mahalanobis Metric Learning

- Goal: learn a task-specific Mahalanobis metric given labeled data $\{\mathbf{x}_i, y_i\}_{i=1}^N$ $\mathbf{x}_i \in \mathbb{R}^d$, $y_i \in [1, k]$



- $\mathbf{M} = \mathbf{A}\mathbf{A}^T =$ positive semi-definite transformation matrix
 - Squashes uninformative / emphasizes informative dimensions w.r.t. classes

Image credit: Weinberger et al. NIPS 2010

Multiclass Linear Discriminant Analysis [Fisher. 1934]

- Maximize separation ratio $S = \frac{\alpha^T \Sigma_b \alpha}{\alpha^T \Sigma_w \alpha}$, where:

$$\Sigma_w = \frac{1}{NK} \sum_{i=1}^K \sum_{j=1}^N (\mathbf{x}_j - \boldsymbol{\mu}_i)(\mathbf{x}_j - \boldsymbol{\mu}_i)^T \quad \mu_i = \mathbb{E}[x_j | y_j = i]$$

$$\Sigma_b = \frac{1}{K} \sum_{i=1}^K (\boldsymbol{\mu}_i - \boldsymbol{\mu})(\boldsymbol{\mu}_i - \boldsymbol{\mu})^T \quad \boldsymbol{\mu} = \mathbb{E}[\boldsymbol{\mu}_i]$$

- S maximized when α the top eigenvector of $\Sigma_w^{-1} \Sigma_b$
- A = top $(k-1)$ eigenvectors of $\Sigma_w^{-1} \Sigma_b$
- To prevent degenerate solutions, regularize:

$$\Sigma_w = (1 - \gamma) \Sigma_w + \gamma \mathbf{I}, \quad \gamma \in [0, 1]$$

Information Theoretic Metric Learning (ITML) [Davis et al. 2007]

- Bijection between Mahalanobis distances and multivariate Gaussians

$$\mathcal{N}(x|\mu, \mathbf{M}) = \frac{1}{Z} \exp\left(-\frac{1}{2}d_{\mathbf{M}}(x, \mu)\right) \quad (\text{assume fixed } \mu)$$

- Solve:

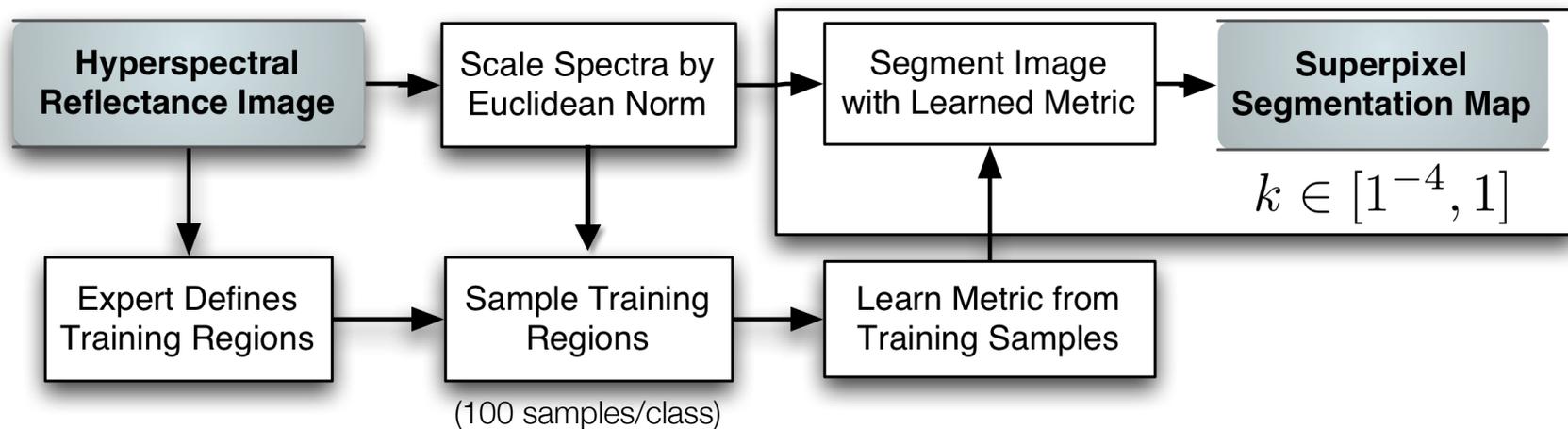
$$\min_{\mathbf{M}} \int \mathcal{N}(x|\mu, \mathbf{M}) \log \left(\frac{\mathcal{N}(x|\mu, \mathbf{M}_0)}{\mathcal{N}(x|\mu, \mathbf{M})} \right) dx$$

- \mathbf{M}_0 = regularization term - known, well-behaved Mahalanobis matrix (e.g., identity or sample covariance matrix)
- Subject to $\mathbf{M} \succeq \mathbf{0}$ and pairwise similarity/dissimilarity constraints:

$$d_{\mathbf{M}}(x_i, x_j) \leq u \rightarrow (i, j) \in S$$

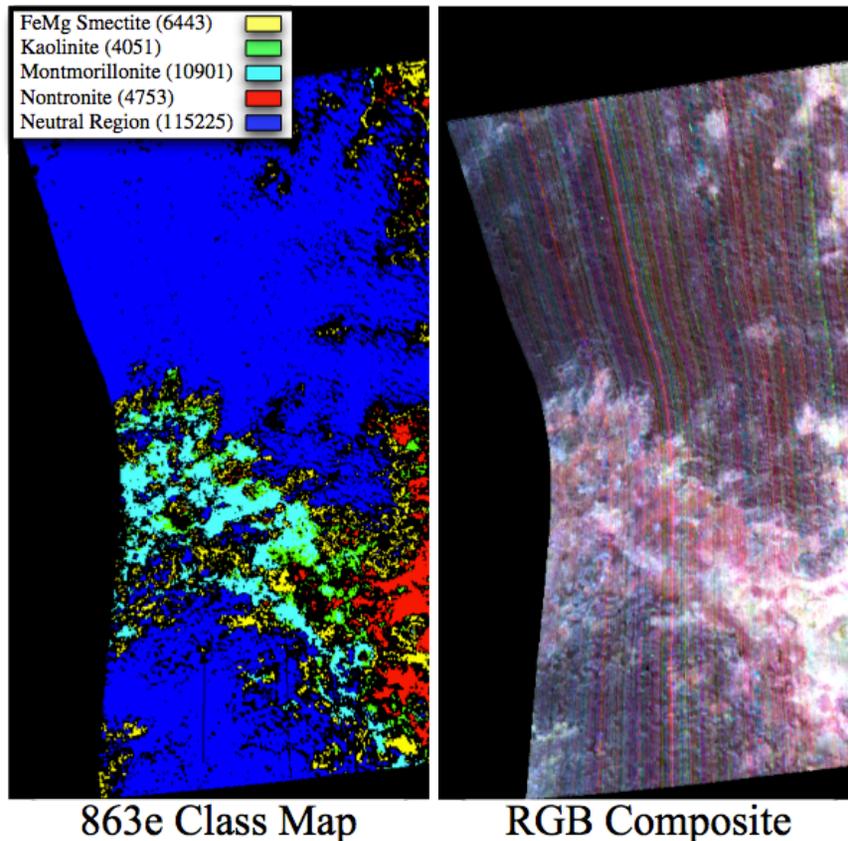
$$d_{\mathbf{M}}(x_i, x_j) \geq l \rightarrow (i, j) \in D$$

Evaluation Methodology

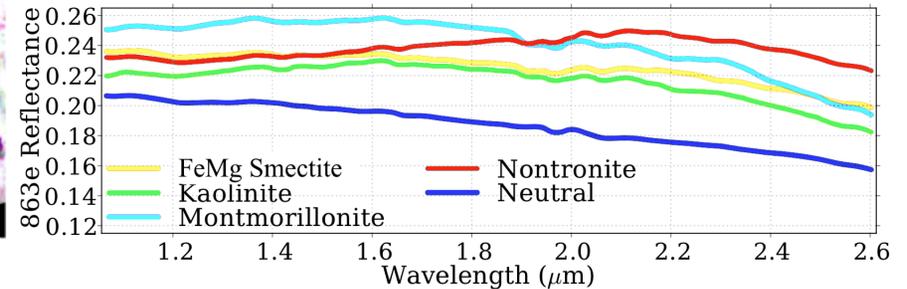


- # of segments (for a fixed image) dependant on (1) similarity metric and (2) segmentation parameter k
 - Vary k to compare segmentation maps with similar # of segments for each measure

Case Study: CRISM Imagery



- Images: FRT 3e12, 3fb9, 863e
- 231 bands in $[1.06, 2.58]$ μm
- Class maps defined and verified by geologist using ENVI Spectral Angle Mapper
- Unlabeled materials excluded from performance analysis



Evaluation Measures

- For a set of classes C and a set of segments S

- $$H(C|S) = \sum_{c \in C, s \in S} p(c, s) \log \frac{p(c)}{p(c, s)}$$

- Measures remaining uncertainty in class map given segmentation partitions
- If segmentation reproduces class map, $H(C|S) = 0$

- $$\text{purity}(S, C) = \sum_{s \in S} \frac{\text{pure}(s, C)}{|s|}$$

- $\text{pure}(s, C) = 1$ if all pixels in segment s belong to a single class c in C

Image 863e Segmentation Results

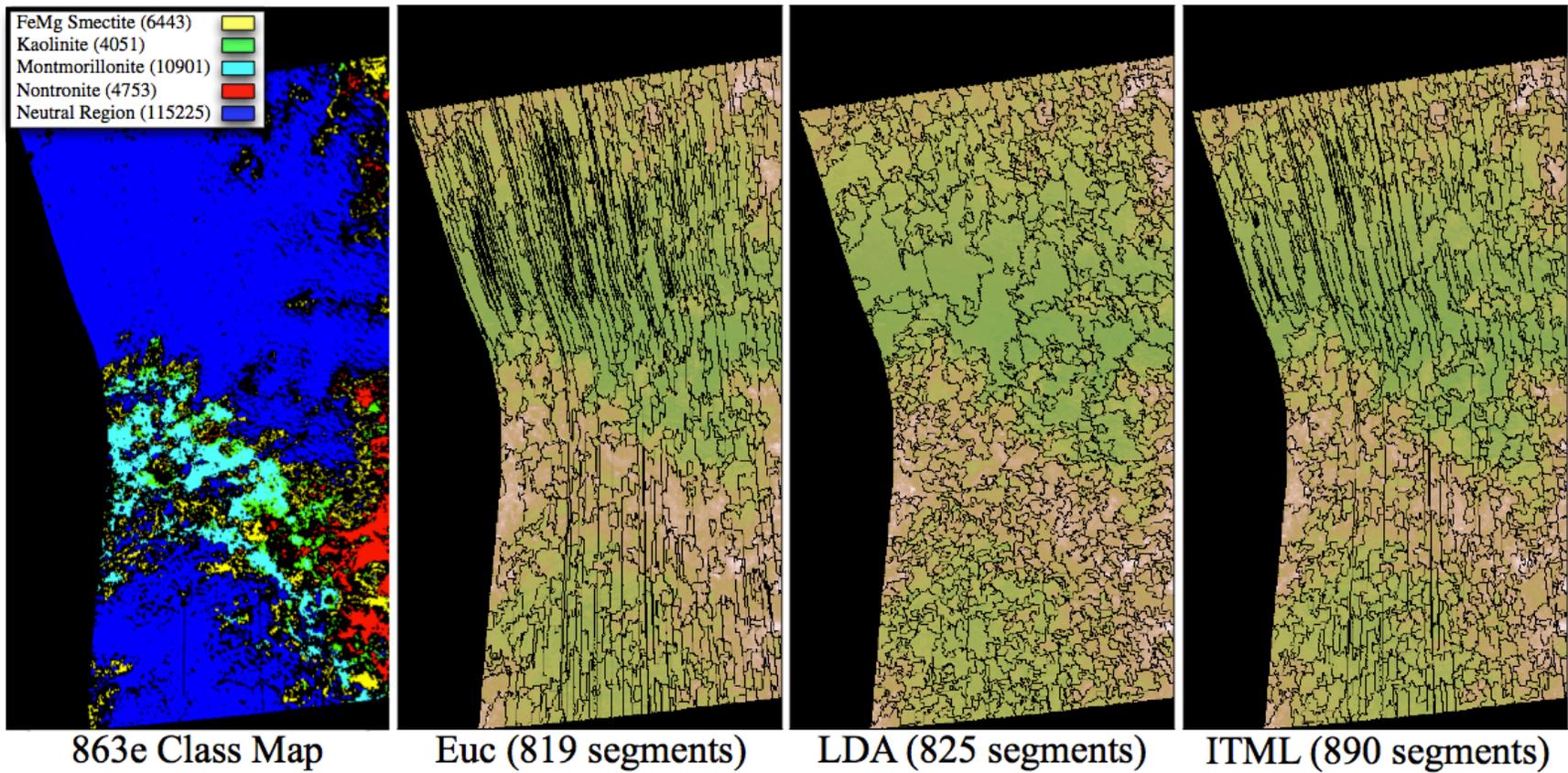
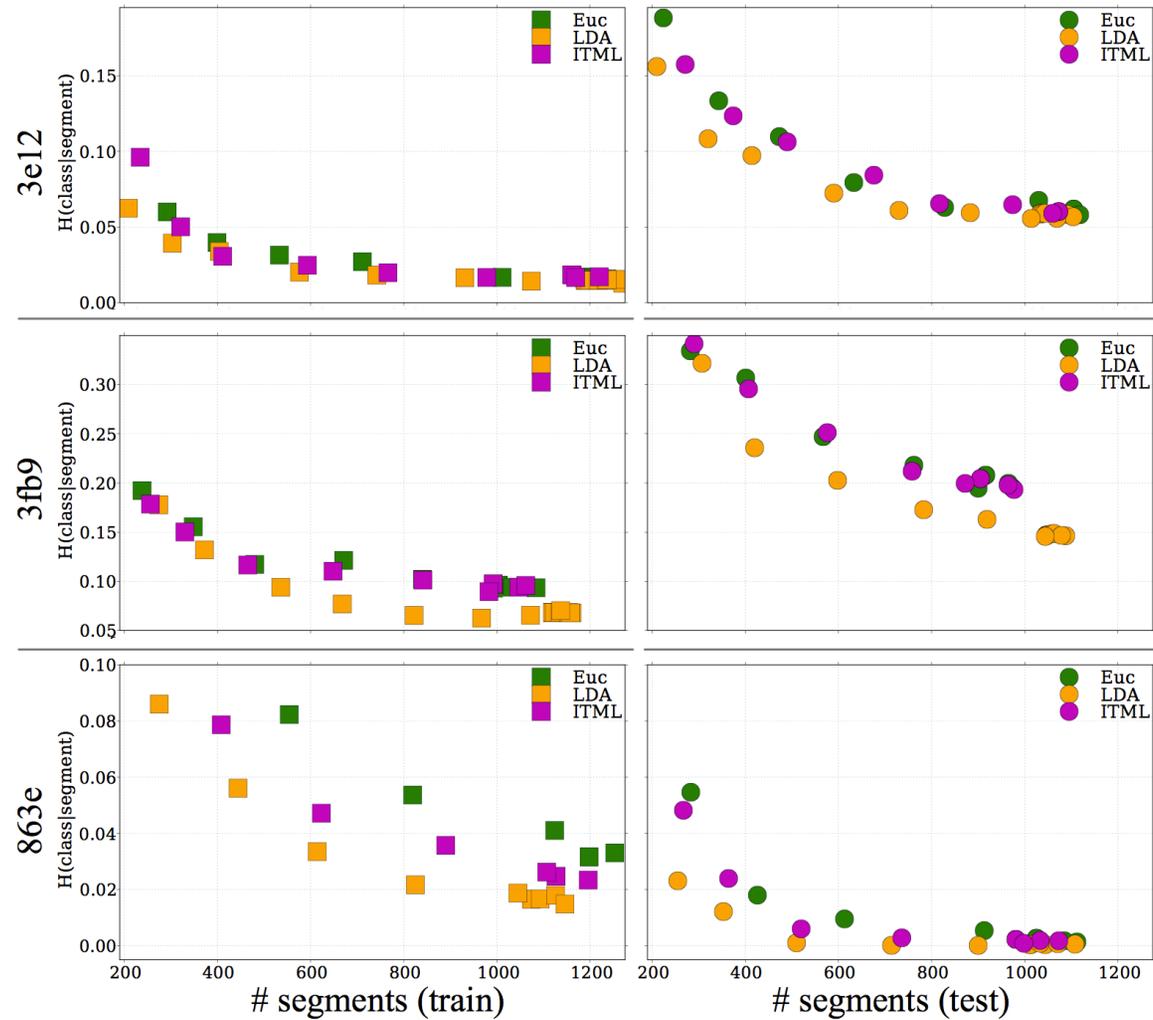


Image 863e Segment Purity Scores

Class (# pixels)	Pure Segments (%)		
	Euc	LDA	ITML
FeMg Smectite (6443)	26	49	48
Kaolinite (4051)	98	99	99
Montmorillonite (10901)	11	31	17
Nontronite (4753)	37	52	40
Neutral Region (115225)	97	99	98
Average (141373)	53	66	60

$H(C|S)$ Results: Images 3e12, 3fb9, 863e



Conclusions / Future Work

- Learned metrics can significantly improve the quality of hyperspectral segmentation results
- Simple techniques (e.g., LDA) with only a few training samples often outperform more computationally expensive metric learning methods
 - Additional samples may improve ITML accuracy
- Future work: comparison to additional metric learning algorithms (neighborhood components analysis, relevant components analysis), and transfer learning scenarios
 - Initial results indicate LDA competitive with state of the art Mahalanobis metric learning algorithms

HiiHAT IDL/ENVI Toolkit

<http://hyperspectral.jpl.nasa.gov>

- ENVI Toolkit for hyperspectral image analysis

- Includes superpixel segmentation, endmember detection, feature enhancement and metric learning functions

The screenshot shows the website for the Hii-Hat Hyperspectral Analysis Toolkit. The header includes the NASA logo, Jet Propulsion Laboratory name, and navigation links for JPL HOME, EARTH, SOLAR SYSTEM, STARS & GALAXIES, and SCIENCE & TECHNOLOGY. The main title is "Hii-Hat Hyperspectral Analysis" with the subtitle "Image Analysis Routines for Planetary Science and Remote Sensing".

Overview

Hyperspectral imagery has provided dramatic new insight into the geology and atmosphere of other planets. However, understanding these images can be quite challenging since scientists can only visualize a small number of bands. The Hyperspectral Image Interpretation and Holistic Analysis Tools (Hii-Hat) is an intelligent assistant to help analysts efficiently browse, summarize, and search hyperspectral images. The software is available as a plugin to the IDL/ENVI environment. The algorithms we have developed are designed for the special challenges of planetary science datasets:

- **High noise levels** Many of the most interesting planetary science questions involve spectral features at the limits of detectability. We emphasize robust strategies capable of detecting subtle spectral features with high levels of noise.
- **Uncertain constituents** Unlike terrestrial remote sensing, we have very few if any samples from the surface. We address this with "unsupervised" analysis that looks for patterns in the observed data itself.
- **Fast turnaround time** Tactical observation planning may require fast decisions, favoring automation where appropriate.

The software toolkit includes automatic procedures to search images for key features and draft analyses for operators. More in-depth studies can benefit from interactive analysis procedures. This page describes these basic functions with examples based on Compact Reconnaissance Imaging Spectrometer (CRISM) data. CRISM has been observing Mars from the Mars Reconnaissance Orbiter spacecraft.

The image also contains two spectral plots and two corresponding images of a crater on Mars. The left plot shows a spectrum with labels for "unanticipated atmospheric distortion", "instrument noise", and "unique & subtle mineralogy". The right plot shows a spectrum with a label for "interpretable absorption features". Below the plots are two images of a crater: the left one is the original image, and the right one is labeled "Detected features" with red arrows pointing to specific areas.

- Free, non-commercial research licenses available

References

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