DATA EXPLOITATION OF HYSPIRI OBSERVATIONS FOR PRECISION VEGETATION MAPPING

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Background and Project Team

- Project Title: "Applying NASA HyspIRI satellite observations to precision vegetation mapping for ecological forecasting applications," NASA, 2009-2011.

- PIs:
  - Dr. Lori M. Bruce (Electrical Engineering, Mississippi State University)
  - Dr. Saurabh Prasad (Electrical Engineering, Mississippi State University) (*Technical Lead - Statistical Pattern Recognition*)

- Collaborator:
  - Dr. Wilfredo Robles (Department of Plant and Soil Sciences, University of Puerto Rico) (Dataset provider – providing us with a library of hyperspectral samples from a variety of aquatic plant species).
Outline of this presentation

- Background – Pattern classification in the context of high-dimensional feature spaces (Direct relevance to Hyperspectral image analysis)
- Review of conventional methods
- The divide-and-conquer paradigm – a Multi-Classifier, Decision Fusion (MCDF) Framework
- Experimental analysis with:
  - Simulated/Proxy-HyspIRI data
- Conclusions and ongoing work
Some examples: Face recognition, target recognition and land cover classification in remote sensing applications, CAD medical applications, speech and speaker recognition ...
Hyperspectral Remote Sensing Systems

CCD Detector

On-Ground Scene

Form Hyperspectral Cube

Per Pixel Extract Hyperspectral Signature

Reflectance

350 2500 nm

Components of Spectrum

Vegetation

Soil

Water

Hyperspectral Cube

Hyperspectral Remote Sensing Systems

5
The Proposed Framework – Multi-classifiers and Decision Fusion (MCDF)

Mutual Information

Approximately independent subspaces ↔ diverse classifiers
Diverse classifiers ↔ Better decision fusion
The Proposed Framework – Multi-classifiers and Decision Fusion (MCDF)

PP: An appropriate pre-processing
Multi-Classifiers and Decision Fusion: Subspace Identification

- Use training data for Band-Grouping
- Identify subspaces by maximizing some performance metric
Multi-Classifiers and Decision Fusion: Decision Fusion Strategies

- **Hard Decision Fusion**
  - Majority Vote:
    \[ N(i) = \sum_{j=1}^{n} I(w_j = i) \]
    \[ w = \arg \max_{i \in \{1,2,...C\}} N(i) \]
  - Weighted Majority Vote:
    \[ N(i) = \sum_{j=1}^{n} \alpha_j I(w_j = i) \]
    \[ w = \arg \max_{i \in \{1,2,...C\}} N(i) \]

Confidence score in the \( j \)'th subspace.
Multi-Classifiers and Decision Fusion: Decision Fusion Strategies

- Soft Decision Fusion
  - Linear Opinion Pool

\[
C(w_i \mid x) = \sum_{j=1}^{n} \alpha_j p_j(w_i \mid x)
\]

\[
w = \arg \max_{i \in \{1,2\ldots C\}} C(w_i \mid x)
\]

- Logarithmic Opinion Pool

\[
C(w_i \mid x) = \prod_{j=1}^{n} p_j(w_i \mid x)
\]

\[
\Rightarrow \log C(w_i \mid x) = \sum_{j=1}^{n} \alpha_j \log p_j(w_i \mid x)
\]

Confidence score in the \(j\)’th subspace
Multi-Classifiers and Decision Fusion: Adaptive Weight Assignment

- Band-Grouping (Subspace Identification)
- Pre-Processing and Multi-Classifier System
- Training Accuracy Assessment
- Decision Fusion

Input:
- Training Signatures
- Test Signatures

Output:
- Class Labels
- Confidence Scores
- Class Labels for Test Signatures

Steps:
1. Band-Grouping (Subspace Identification)
2. Pre-Processing and Multi-Classifier System
3. Decision Fusion
4. Training Accuracy Assessment
Experimental hyperspectral dataset

Mild pixel mixing

Moderate pixel mixing

Severe pixel mixing

Target

Background
Practical Classification Tasks

Invasive Species Classification

HyspIRI VSWIR Specifications:

- Spectral range: 380 to 2500 nm, Uniformly sampled @ 10nm
- A spatial resolution of 60 m.
- Temporal revisit: 19 days (Global land coast), 3 days (Rapid response)

Proxy HyspIRI Signatures

Precision mapping of aquatic vegetation
Practical Classification Task 1

Invasive Species Classification – Waterhyacynth vs. American Lotus

A possible remote sensing application for such species may involve detecting and mapping Waterhyacinth in aquatic environments for appropriate chemical treatment and removal. The two aquatic species were grown under well-regulated environmental conditions at the R. R. Foil Plant Research Center at Mississippi State University. Data was collected in the range of ±2 hours of solar noon, every week from 24th June 2005 to 26th October 2005, for a total of twenty signatures per class per date.
Practical Classification Task 1

Invasive Species Classification – Waterhyacynths vs. American Lotus

Performance of classification algorithms as a function of SNR using proxy-HyspIRI data
Practical Classification Task 1

Invasive Species Classification – Waterhyacynth vs. American Lotus

Performance of classification algorithms as a function of target abundance using proxy-HyspIRI data
Practical Classification Task 2

Another aquatic species classification task: Duckweed; Hydrilla; American Lotus; Eurasian watermilfoil; Salvinia; Waterhyacinth Water
Practical Classification Task 2

Another aquatic species classification task: Duckweed; Hydrilla; American Lotus; Eurasian watermilfoil; Salvinia; Waterhyacinth; Water

Performance of FLDA+ML as a function of target abundance using proxy-HyspIRI data
Practical Classification Task 3

Detection and Classification of Chemical Induced Crop Stress

Ground-Truthing with Handheld (ASD) Spectroradiometers and GPS units
Practical Classification Task 3
Detection and Classification of Chemical Induced Crop Stress

Increasing chemical stress (~dosage) on the crop
Practical Classification Task 3
Detection and Classification of Chemical Induced Crop Stress

Performance of classification algorithms as a function of target abundance using proxy-HyspIRI data
## Practical Classification Task 3

**Detection and Classification of Chemical Induced Crop Stress**

<table>
<thead>
<tr>
<th>Temporal Misalignment</th>
<th>Overall Classification Accuracy (%)</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>PCA</td>
</tr>
<tr>
<td>±1 week</td>
<td>60.5 (1.6)</td>
</tr>
<tr>
<td>±2 week</td>
<td>58.6 (1.6)</td>
</tr>
<tr>
<td>±4 week</td>
<td>56.7 (1.7)</td>
</tr>
<tr>
<td>±6 week</td>
<td>52.8 (1.7)</td>
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<tr>
<td>±8 week</td>
<td>46.6 (1.7)</td>
</tr>
</tbody>
</table>

Performance of classification algorithms with temporal misalignments between training and testing using proxy-HyspIRI data.
Question / Comments

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