Classification of natural scenes via multispectral Imaging

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Scene Recognition and Goal

• Two week project with the University of Houston
  – Submitted to ICIP

• Scene understanding and object recognition is important in many computer vision applications
  – Robot navigation, remote sensing, medical imaging, etc.

• Classification performance improves if hyperspectral images are used
  – At the expense of time, convenience, and money

• Goal: Achieve similar accuracy using far fewer measurements
Hyperspectral Images of Natural Scenes

Hyperspectral data captured using Headwall Photonics hyperspectral imager

Image Resolution: $1004 \times 2500 \times 325$

Rendered in RGB using Flea3 sensor Response
Hyperspectral Images of Natural Scenes

Hyperspectral data captured using Headwall Photonics hyperspectral imager

Image Resolution: $1004 \times 2500 \times 325$

Rendered in RGB using Flea3 sensor Response
Object Labeling

Objects of Interest
- Vegetation
- Metal
- Concrete
- Pathway
- Skin
- Fabric
- Rubber

Image Resolution: 1004 × 2500 × 325
Rendered in RGB using Flea3 sensor Response
Object Classification using SVM

• Image classification is a well-studied research topic \[^1\]

• We adapt a commonly used classifier
  – Not interested in designing a new classifier
  – Trying to show the value of the acquisition method, not classifier

• We use a simple SVM classifier with a radial basis function kernel
  – Non-linear mapping improves results for low-dimensional data
  – Only two degrees of freedom \(C, \gamma\)

RGB & Hyperspectral Classification

Training Scene

Testing Scene

<table>
<thead>
<tr>
<th></th>
<th>Training</th>
<th>Testing</th>
</tr>
</thead>
<tbody>
<tr>
<td>RGB</td>
<td>75.3</td>
<td>71.0</td>
</tr>
<tr>
<td>Hyperspectral</td>
<td>95.1</td>
<td>87.7</td>
</tr>
</tbody>
</table>
Reducing Spectral Measurements

• Adding spectral measurements improves classification performance
  – RGB (3 channels): 71%
  – Hyperspectral (325 channels): 87.7%

• How much benefit is one additional channel over RGB? Three additional channels?

• Acquisition schemes
  – RGB + Near-infrared
  – RGB + 3 narrowband channels
  – 6 narrowband channels
  – 6 common optical filters
Channel Selection

- Accuracy of 325 bands: 87.7%
- Accuracy of 6 uniformly distributed bands: 84.9%
  - 97% as accurate
  - 50x fewer bands
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![Classification Accuracy vs # of bands graph](image)
RGB+NIR

- Three color filters
- One broadband NIR channel
- Classification accuracy – 79.7%

Classification Accuracy (Testing)

- RGB: 71.0%
- RGB+NIR: 79.7%
- Hyperspectral: 87.7%
RGB+3 Narrowband Channels

• Narrowband channels picked using greedy algorithm

• Classification accuracy
  – 84.9%
6 Narrowband Channels

• Channels picked using greedy algorithm as before

• Classification accuracy
  – 85.1%
6 Optical Filters

- Inspired by available shortpass, longpass, bandpass, band reject filters
  - Placed every 25nm, bandwidths of 25, 50, 75nm (where applicable)

- Classification accuracy
  - 86.4%
Future Work

• These preliminary results merit further investigation using a diverse dataset of natural scenes (captured with a hyperspectral imager)

• If the results hold for the full dataset:
  – Investigate optimal filter selection
  – Quantify the tradeoff between accuracy and number of channels