Automated large area tree species mapping and disease detection using airborne hyperspectral remote sensing

William Oxford

Neil Fuller, James Caudery, Steve Case, Michael Gajdus, Martin Black
Outline

- About 2Excel Aviation, BioSystems
- Context
- Case Study 1: Tree Species Identification
  - Data Sources
  - Methods
  - Results
  - Conclusions and Future Research
- Case Study 2: Tree Disease Detection
  - Data Sources
  - Methods
  - Results
  - Conclusions and Future Research
About Us
Context

• Knowledge on tree species is relevant for biomass estimation, habitat quality assessment and biodiversity characterization

• Tree health assessment is relevant to monitor spread of disease and to inform management intervention

• Hyperspectral data has been proven to have a high potential for the mapping of tree species composition

• This presentation will address the following:
  • How do techniques, proven in Defence and Security, compare with published approaches for tree species mapping?
  • Do these techniques have application to detect Ash die back?
Hyperspectral data acquisition and interpretation

Data acquisition
Rate of data capture relates to operational altitude, forward speed and Field of View.

Spatial resolution
Number of pixels in the Instantaneous Field of View
1600 for VNIR
384 for SWIR

Data cube
Each pixel generates data from every band width relative to spectral resolution

Hyperspectral signature
Each pixel shown as intensity against wavelength

Reflectance
Spectral resolution
Number of bands or band width within the spectrograph

Pixel grid
Data cube
1000 m
2500 – 5000 Ha per hour

Data acquisition
Rate of data capture relates to operational altitude, forward speed and Field of View.

Spatial resolution
Number of pixels in the Instantaneous Field of View
1600 for VNIR
384 for SWIR

Data cube
Each pixel generates data from every band width relative to spectral resolution

Hyperspectral signature
Each pixel shown as intensity against wavelength

Reflectance
Spectral resolution
Number of bands or band width within the spectrograph

Pixel grid

Reflectance
Case Study 1
Tree Species Identification
Data and study area

• Hyperspectral data collected
  • 24SEPT15 over BRAMPTON, 5 lines
  • 0.3m GSD VNIR, 0.6m GSD SWIR, 192 bands

• MOD Tree Survey
  • Hand selected 9 common species, 56 trees

- Ash
- Common Lime
- Horse Chestnut
- Norway Maple
- Pedunculate Oak
- Silver Birch
- Sycamore
- Wild Cherry
- Yew
Comparison of Feature Reduction Algorithms for Classifying Tree Species With Hyperspectral Data on Three Central European Test Sites
Fabian E. Fassnacht et.al.

Automatic Forest Area Extraction From Imaging Spectroscopy Data Using An Extended NDVI Fabian Fassnacht, et.al.

CORRECTION OF SHADOWING IN IMAGING SPECTROSCOPY DATA BY QUANTIFICATION OF THE PROPORTION OF DIFFUSE ILLUMINATION Daniel Schläpfer et.al.

Method

Reflectance cube

Tree index

Tree & Shadow mask

Common MNF transform

SVM (RBF)

Rule Images

Class map

Validation pixels

Confusion matrix

Training pixels

Spectral libraries

Target detection

Standard PCA transform
Results – Support Vector Machine

- Target detection results very poor, not shown
- SVM shows excellent overall classification (98%) using pixels from all five images
- However, performance falls significantly (species dependent) using training pixels drawn from only one image
  - Observe that this is not purely due to number of training pixels

<table>
<thead>
<tr>
<th>Ash</th>
<th>1245</th>
<th>3</th>
<th>3</th>
<th>0</th>
<th>12</th>
<th>0</th>
<th>13</th>
<th>5</th>
<th>1</th>
<th>1282</th>
<th>0.971</th>
</tr>
</thead>
<tbody>
<tr>
<td>Common Lime</td>
<td>1</td>
<td>368</td>
<td>0</td>
<td>0</td>
<td>2</td>
<td>0</td>
<td>4</td>
<td>1</td>
<td>2</td>
<td>378</td>
<td>0.974</td>
</tr>
<tr>
<td>Horse Chestnut</td>
<td>0</td>
<td>0</td>
<td>863</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>863</td>
<td>1</td>
</tr>
<tr>
<td>Norway Maple</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>756</td>
<td>1</td>
<td>0</td>
<td>6</td>
<td>0</td>
<td>0</td>
<td>764</td>
<td>0.99</td>
</tr>
<tr>
<td>Pedunculate Oak</td>
<td>20</td>
<td>4</td>
<td>0</td>
<td>1</td>
<td>2878</td>
<td>0</td>
<td>19</td>
<td>10</td>
<td>1</td>
<td>2933</td>
<td>0.981</td>
</tr>
<tr>
<td>Silver Birch</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>741</td>
<td>0</td>
<td>0</td>
<td>2</td>
<td>744</td>
<td>0.996</td>
<td></td>
</tr>
<tr>
<td>Sycamore</td>
<td>16</td>
<td>4</td>
<td>0</td>
<td>3</td>
<td>15</td>
<td>0</td>
<td>2169</td>
<td>0</td>
<td>0</td>
<td>2207</td>
<td>0.983</td>
</tr>
<tr>
<td>Wild Cherry</td>
<td>4</td>
<td>6</td>
<td>0</td>
<td>0</td>
<td>7</td>
<td>2</td>
<td>1</td>
<td>644</td>
<td>1</td>
<td>665</td>
<td>0.968</td>
</tr>
<tr>
<td>Yew</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>2</td>
<td>0</td>
<td>0</td>
<td>422</td>
<td>0.995</td>
<td></td>
</tr>
<tr>
<td></td>
<td>1286</td>
<td>387</td>
<td>866</td>
<td>760</td>
<td>2915</td>
<td>745</td>
<td>2212</td>
<td>660</td>
<td>427</td>
<td>10258</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.968</td>
<td>0.951</td>
<td>0.997</td>
<td>0.995</td>
<td>0.987</td>
<td>0.995</td>
<td>0.981</td>
<td>0.976</td>
<td>0.984</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Details of SVM; radial basis function kernel, samples divided into training (2/3, max 10000 samples) and test (1/3), parameters optimised using k-5 fold cross-validation on training data
Conclusions and Future Research

• Target detection was not successful; potential that the mean spectrum is not discriminatory (in high dimensions)
• SVM classification results are similar to published results
• Transfer of training data across strips is not robust, even when imagery is of consistent quality
  • Is tree phenomenology robust over scale?
  • Implications for operational production
• Future directions, drive towards automation, include:
  • Improved tree mask
  • Explore target detection performance
  • Sensitivity to training samples/species/resolution
  • Thresholds for empty classes
Tree Species Mapping
Case Study 2
Tree Disease Detection
Data and study area

- Hyperspectral data collected
  - 08AUG15 over LOWICK, single line
  - 0.3m GSD VNIR, 0.6m GSD SWIR, 198 bands
- Observations of ASH tree disease
  - % of total canopy that displays the "angst twig" symptomology induced by the anamorphic stage
  - Hand selected 45 trees, 15912 pixel samples
Comparison of Feature Reduction Algorithms for Classifying Tree Species With Hyperspectral Data on Three Central European Test Sites
Fabian E. Faßnacht et.al.

Automatic Forest Area Extraction From Imaging Spectroscopy Data Using An Extended NDVI Fabian Faßnacht, et.al.

Correction of Shadowing in Imaging Spectroscopy Data by Quantification of the Proportion of Diffuse Illumination Daniel Schläpfer et.al.

Method

Reflectance cube

Tree index

Tree & Shadow mask

MNF transform

Validation pixels

Linear Regression

Plots v disease

Rule Images

Training pixels

Spectral libraries (high disease)

Target detection

Standard PCA transform

Vegetation indices

Validation pixels
Results – Scatterplots

Indices as defined in ENVI 8.5
Target detection scatterplot using ACE detection,
95% disease signature from IMNF image
Results – Scatterplots

Indices as defined in ENVI 8.5
Target detection scatterplot using ACE detection,
95% disease signature from IMNF image
Results – Regression

Details of regression; stratified sampling into 10 bins, pixels randomly divided into training (~800 samples) and validation (~500 samples) data, 100 runs

All 198 bands cannot be selected due to potential to over-fit the data
Conclusions and Future Research

• Within crown pixel scatter creates difficulty in data mining for a ‘disease signature’
• Target detection was not successful; the mean spectrum is not diagnostic (in high dimensions)
• Linear band combinations show promise to predict disease amongst a *known ash population*
• Future directions include:
  • Explore target detection performance, reducing spatial resolution
  • Improve disease assessment protocols
  • Alternative machine learning techniques (e.g. SVM-R)
Conclusions

- How do techniques, proven in Defence and Security, compare with published approaches for tree species mapping?
- Do these techniques have application to detect Ash die back?

- Results do not support use of target detection techniques for either application
- Speculate that the ‘signature’ is variable so is neither diagnostic nor robust
  - feature selection and/or reduced resolution may assist