Multiple Classifiers and Graph Cut Method for Spectral-Spatial Classification of Hyperspectral Image

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Introduction

- Hyperspectral images
  - Hyperspectral image is captured across EM spectrum, typically in 0.4-2.5 µm in very narrow contiguous bands
  - Due to imaging in the very narrow bands, it takes into new range of applications such as
    - environmental monitoring
    - vegetation health monitoring
    - mineral exploration
    - military and defense

Challenges:
The advantage of hyperspectral image itself will be a limitation of hyperspectral image

Source: www.hypermed-inc.com/page_id=35
Challenges of HSI

- Challenges
  - the dimension of image are huge
  - often information are correlated
  - the spectral variability of the pixels of same classes
  - limited reference samples than required (Difficult to obtain)

- These limitation separates from the other pattern recognition problems

- Numerous work have been appeared → overcome challenges
  - Proposing feature reduction/selection methods
  - Advance classifiers to take care of data complexity

Choosing the best classifier is a challenging task → given numerous possibilities

Accuracy of single classifier could not be extended beyond hard limit

- there is no single best classifier → acceptable for wide range of application
Multiple Classifier System (MCS)

- Alternative way to increase accuracy and reliability

The classifier which performs better is known as single best (SB) classifier

Input patterns → Classifier I → Rule image I → Combination function → result

Condition: Accurate and diverse

MCS has shown its effectiveness to increase the classification accuracy of the hyperspectral image.

However it includes only the spectral information.
Objective

- Apart from high spectral content, hyperspectral image is also rich in spatial information.
- So, incorporating spatial contextual information is necessary in the classification framework → otherwise result in salt and pepper noise effect
- Hence modeling spatial contextual information is essential to obtain state of art classified maps.

- The objective is to design a method to exploit the spectral and spatial information in a unified framework
Proposed Spectral-Spatial Classification Approach

- The spectral information is extracted from the multiple classifier system.
- The spatial contextual information is modelled using Markov random field.
- In other words, the proposed problem is modelled as the energy minimization problem on the graph of image pixels.

\[ E = E_{\text{data}} + E_{\text{smooth}} \]

- MCS
- Potts model (MRF)
Random subspace method (RSM) is used to generate MCS

Decision profile matrix

$$DP(x) = \begin{bmatrix}
    d_{1,1}(x) & \cdots & d_{1,j}(x) & \cdots & d_{1,c}(x) \\
    d_{2,1}(x) & \cdots & d_{2,j}(x) & \cdots & d_{2,c}(x) \\
    \vdots & \vdots & \vdots & \ddots & \vdots \\
    d_{L,1}(x) & \cdots & d_{L,j}(x) & \cdots & d_{L,c}(x)
\end{bmatrix}$$

Support from the classifiers \(\psi_1, \ldots, \psi_L\) for class \(\omega\)

Bayesian average rule

$$P \left( \frac{\omega_j}{x} \right) = \sum_{l=1}^{L} d_{l,j}(x), \ j = 1, 2, \ldots, M$$

\(x \in \omega_m, m = \text{arg max}_j P \left( \frac{\omega_j}{x} \right)\)
Proposed Method

Spectral-Spatial Model

\[ E(\omega) = E_{data} + E_{smooth} = \sum_{i=1}^{N} D_i(\omega_i) + \sum_{j \in Z} W_{i,j}(\omega_i, \omega_j) \]

Where \( N \) is number of pixels in image, \( D_i(\omega_i) \) is the potential term which measures the cost of assigning the label \( \omega_i \) for the \( i \)th pixel. \( Z \) is the spatial neighbourhood of \( i \)th pixel, and \( W_{i,j} \) is the interaction term between the adjacent pixels \( i \), and \( j \).

- The data energy term is derived from the class posterior probabilistic values of MCS

\[ D_i(\omega_i) = -\ln \left( P \left( \frac{\omega_i}{x_i} \right) \right) \]

- This is regarded as the spectral information
Proposed Method

Spectral-Spatial Model

\[ E(\omega) = E_{\text{data}} + E_{\text{smooth}} = \sum_{i=1}^{N} D_i(\omega_i) + \sum_{j \in \mathbb{Z}} W_{i,j}(\omega_i, \omega_j) \]

- The spatial energy (interaction) term is expressed using Potts (Ising) model as

\[ W_{i,j}(\omega_i, \omega_j) = \beta(1 - \delta(\omega_i, \omega_j)) \]

The interaction term penalizes the spatial transitions among the neighbouring pixels with different class labels.

where \( \delta(.) \) is the kronecker function

\[ \delta(\omega_i, \omega_j) = \begin{cases} 
1 & \text{for } \omega_i = \omega_j \\
0 & \text{for } \omega_i \neq \omega_j 
\end{cases} \]

The energy equation is solved using \( \alpha \)-expansion based graph cut method.
Hyperspectral Datasets

- We have adopted two benchmark hyperspectral images with land cover settings (ROSIS University image, AVIRIS Indian Pines image)

ROSIS University image
No of bands: 115
Spatial resln : 1.3 m
No of classes : 9

AVIRIS Indian Pines image
No of bands: 220
Spatial resln : 20 m
No of classes : 16
Experimental Design

- From the ground truth reference samples, 50 samples are used for training and remaining are used for testing.
- If the available reference samples are less than 50 then, 50% of samples are used for training and remaining for testing.
- In order to avoid the bias induced by the random sampling of training samples, 10 independent Monte Carlo runs are performed and accuracies are averaged.
- The parameters of the RBF kernel function are tuned using 5-fold cross validation using grid search method.
- RSM is partitioned into five subspaces.

Table 1: Number of reference samples considered for the experiment of University image

<table>
<thead>
<tr>
<th>Class name</th>
<th>Reference samples</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Asphalt</td>
<td>6631</td>
</tr>
<tr>
<td>2. Meadows</td>
<td>18649</td>
</tr>
<tr>
<td>3. Gravel</td>
<td>2099</td>
</tr>
<tr>
<td>4. Trees</td>
<td>3064</td>
</tr>
<tr>
<td>5. Metal sheets</td>
<td>1345</td>
</tr>
<tr>
<td>6. Bare soil</td>
<td>5029</td>
</tr>
<tr>
<td>7. Bitumen</td>
<td>1330</td>
</tr>
<tr>
<td>8. Bricks</td>
<td>3682</td>
</tr>
<tr>
<td>9. Shadows</td>
<td>947</td>
</tr>
<tr>
<td>Total</td>
<td>42776</td>
</tr>
</tbody>
</table>

Table 2: Number of reference samples considered for the Indian pines image

<table>
<thead>
<tr>
<th>Class name</th>
<th>Reference samples</th>
<th>Class name</th>
<th>Reference samples</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Alfalfa</td>
<td>46</td>
<td>9. Oats</td>
<td>20</td>
</tr>
<tr>
<td>2. Corn-notill</td>
<td>1428</td>
<td>10. Soybeans-notill</td>
<td>972</td>
</tr>
<tr>
<td>Total</td>
<td>10249</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Results and Discussion-MCS

MCS Results

- the classifier which produces maximum classification accuracy is single best classifier (SBC)
- RSM produced diverse results
- the maximum OA produced by RSM is 82.1%, and 74.7% for University and AVIRIS image
- MCS has improved OA significantly up to 5% over the SBC
- This concludes MCS provides better probability estimates than single classifier

Overall accuracy (OA) of base classifiers and MCS

However, MCS lacks spatial information and the resulting classified map is not smooth
Results and Discussion-Proposed Method

- When the spatial information is incorporated in the MCS using Potts (MRF) method, the accuracy has been increased significantly.

<table>
<thead>
<tr>
<th>Image</th>
<th>Proposed method (MCS+GC)</th>
<th>MCS</th>
</tr>
</thead>
<tbody>
<tr>
<td>University</td>
<td>96.3%</td>
<td>84.47%</td>
</tr>
<tr>
<td>AVIRIS</td>
<td>90.2%</td>
<td>79.5%</td>
</tr>
</tbody>
</table>

- There is about 11-12% increase in classification accuracy over the pixel wise classification (MCS) result.
Results and Discussion-Classified Images

Classified images of University image

SBC
MCS
MCS+GC (proposed method)

Legend:
- Asphalt
- Meadows
- Gravel
- Trees
- Metal Sheets
- Bare soil
- Bitumen
- Bricks
- Shadows
Results and Discussion - Proposed Method

Classified images of AVIRIS Indian Pines image

SBC

MCS

MCS+GC (proposed method)
Results and Discussion-Comparison with state-of-the-art methods

- In order to highlight the potential of our approach, the classification results are compared with the state-of-the-art pixel wise and spectral-spatial classification methods.

<table>
<thead>
<tr>
<th>Image</th>
<th>MCS</th>
<th>SBC</th>
<th>Full band SVM</th>
<th>Full band SVM +GC</th>
<th>SBC+GC</th>
<th>Proposed method (MCS+GC)</th>
</tr>
</thead>
<tbody>
<tr>
<td>University</td>
<td>84.47%</td>
<td>82.05%</td>
<td>83.8%</td>
<td>93.7%</td>
<td>94.2%</td>
<td>96.3%</td>
</tr>
<tr>
<td>AVIRIS</td>
<td>79.5%</td>
<td>74.6%</td>
<td>73.5%</td>
<td>86.2%</td>
<td>87.1%</td>
<td>90.2%</td>
</tr>
<tr>
<td>University</td>
<td>11</td>
<td>10</td>
<td>18</td>
<td>996</td>
<td>980</td>
<td>981</td>
</tr>
<tr>
<td>AVIRIS</td>
<td>31</td>
<td>30</td>
<td>103</td>
<td>120</td>
<td>48</td>
<td>47</td>
</tr>
</tbody>
</table>

- When compared with pixel wise classification method → 12-14%, 11-16% improvement
- Spectral-spatial classification method → 3-4% improvement
- The statistical significance test confirms that accuracy of the proposed method is statistically significant.
Conclusion

- MCS is an effective strategy for hyperspectral image classification in terms of both computational time and accuracy.
- The proposed MCS based graph cut method exploits both spectral and spatial information effectively, and produces state-of-the-art classified results.
- The proposed method has the potential to produce high quality classification map for land use/land cover applications.
- Further, our experiments were conducted with few training samples per class.
Thanks for your attention