Texture Region Extraction from Multispectral and Hyperspectral Images by Classifying Local Spectral Histograms

Jiangye Yuan[1], DeLiang Wang[2], Jung-kuan Liu[1], Lin Yan[1], Ron Li[1]

[1] *Dept. of Civil & Env. Engineering & Geodetic Science, The Ohio State University*

[2] *Dept. of Computer Science Engineering, The Ohio State University*

Presented by: Jiangye Yuan

ASPRS 2011 Annual Conference
May 1-5, 2011
Milwaukee, WI

Outline

- Introduction
- Local spectral histogram
- Texture region extraction
- Experimental results
- Conclusions

Introduction

- **Multispectral and hyperspectral imagery provide rich information for the characterization, identification, and classification of land covers**

- **Spatial structure (texture) information is important for analyzing remote sensing images**

- **Spectral histograms, which consist of marginal distributions of filter responses, can effectively capture spatial patterns**

- **We use local spectral histograms as features to extract the regions with a spatial pattern similar to the given seeds from multi-/hyper-spectral images**

Local spectral histogram

- **Given an image window W and a bank of filters $F^{(\alpha)}$, $\alpha = 1, \ldots, K$, a spectral histogram consists of histograms of filter responses**

$$H_{\mathbf{W}} = \frac{1}{|\mathbf{W}|}\left(H_{\mathbf{W}}^{(1)}, H_{\mathbf{W}}^{(2)}, \ldots, H_{\mathbf{W}}^{(K)}\right)$$

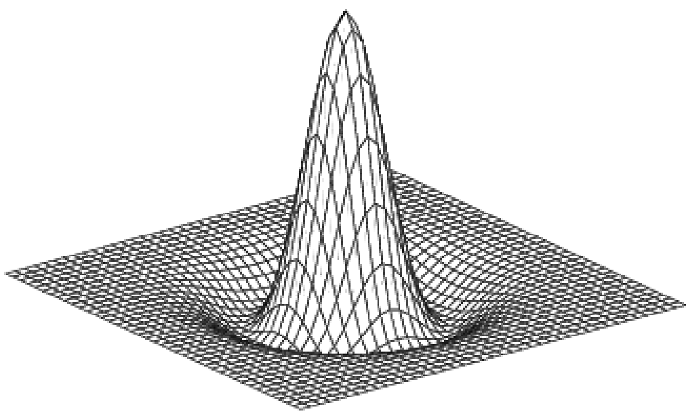
  - $H_{\mathbf{W}}^{(\alpha)}$ **is the histogram of a filter response**

- **The local spectral histogram is computed from a window centered at a pixel. The size of the window is called integration scale**

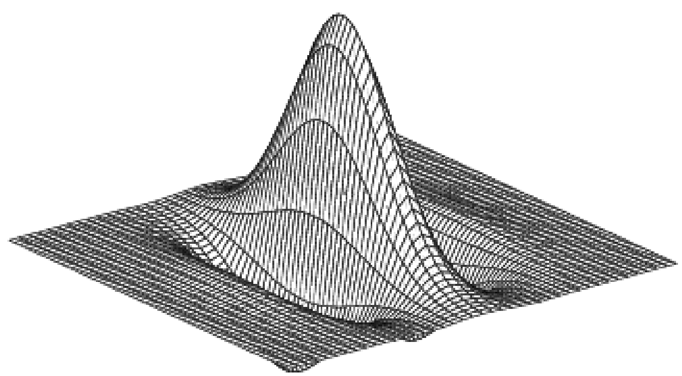
- **When the filters are selected properly, the spectral histogram is sufficient to capture texture appearance**

Local spectral histogram - continued

- **Choice of filters**
  - **Laplacian of Gaussian (LoG) filters: a combination of a Laplacian and Gaussian functions**
  - **Gabor filters: a Gaussian kernel function modulated by a sinusoidal plane wave**



LoG filter

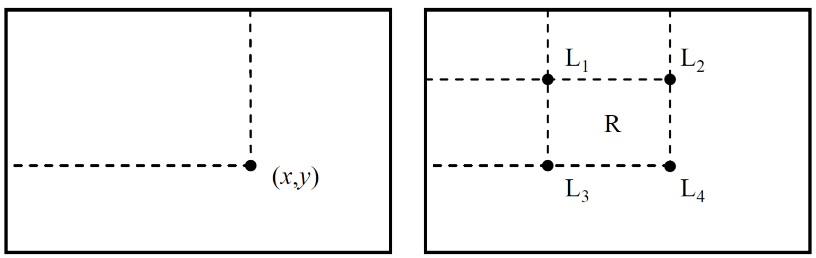


Gabor filter

Fast implementation

- **Local windows should be relatively large in order to characterize textures; therefore fast implementation is needed**

- **Integral histogram image**



  - **The histogram of region R can be computed using four references:** $L_4 + L_1 - L_2 - L_3$

- **Integral histogram images can be computed in one pass over the image. Only three vector arithmetic operations is needed to obtain any local spectral histogram regardless of window size**

Extension to MS/HS imagery

- **By applying filters to each band and concatenating all the local histograms, local spectral histograms can be extended to multispectral and hyperspectral imagery**

- **Dimensionality reduction is necessary**

- **Principle component analysis of filter responses**
  - **Apply a filter to each band of the multidimensional image stack**
  - **Compute the principal components. Select the first several components as the filter responses for computing local spectral histograms**
  - **All the chosen filters are applied to the images in the same manner. The local spectral histogram at each pixel location can be computed using the resulting filter responses**

Texture region extraction

- **A seed window is placed within the target region. The pixels with similar spectral histograms to that of a seed are classified as targets. χ^2-statisics is employed as the distance metric**

$$\chi^2(H_{W_1}, H_{W_2}) = \frac{1}{|\mathbf{W}|} \sum_{\alpha=1}^{K} \sum_{z} \frac{\left(H_{W_1}^{(\alpha)}(z) - H_{W_2}^{(\alpha)}(z) \right)^2}{H_{W_1}^{(\alpha)}(z) + H_{W_2}^{(\alpha)}(z)}.$$

- **A histogram is derived based on the distances between the feature vector of the seed and those at the other pixel locations. The first (smallest) local minimum position provides a natural separation, which can be used as a threshold**

Experimental data

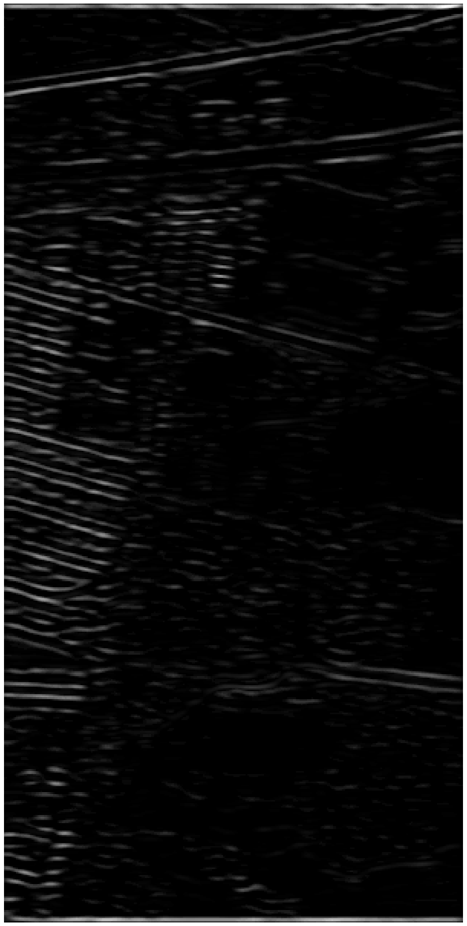
- **Data tested consist of HYDICE hyperspectral imagery with 3 m spatial resolution taken at Copperas Cove, Texas.**

- **The original data contain 210 bands covering a 399nm-2499nm spectral range; 139 bands were manually selected by removing the noisy bands**

false color image

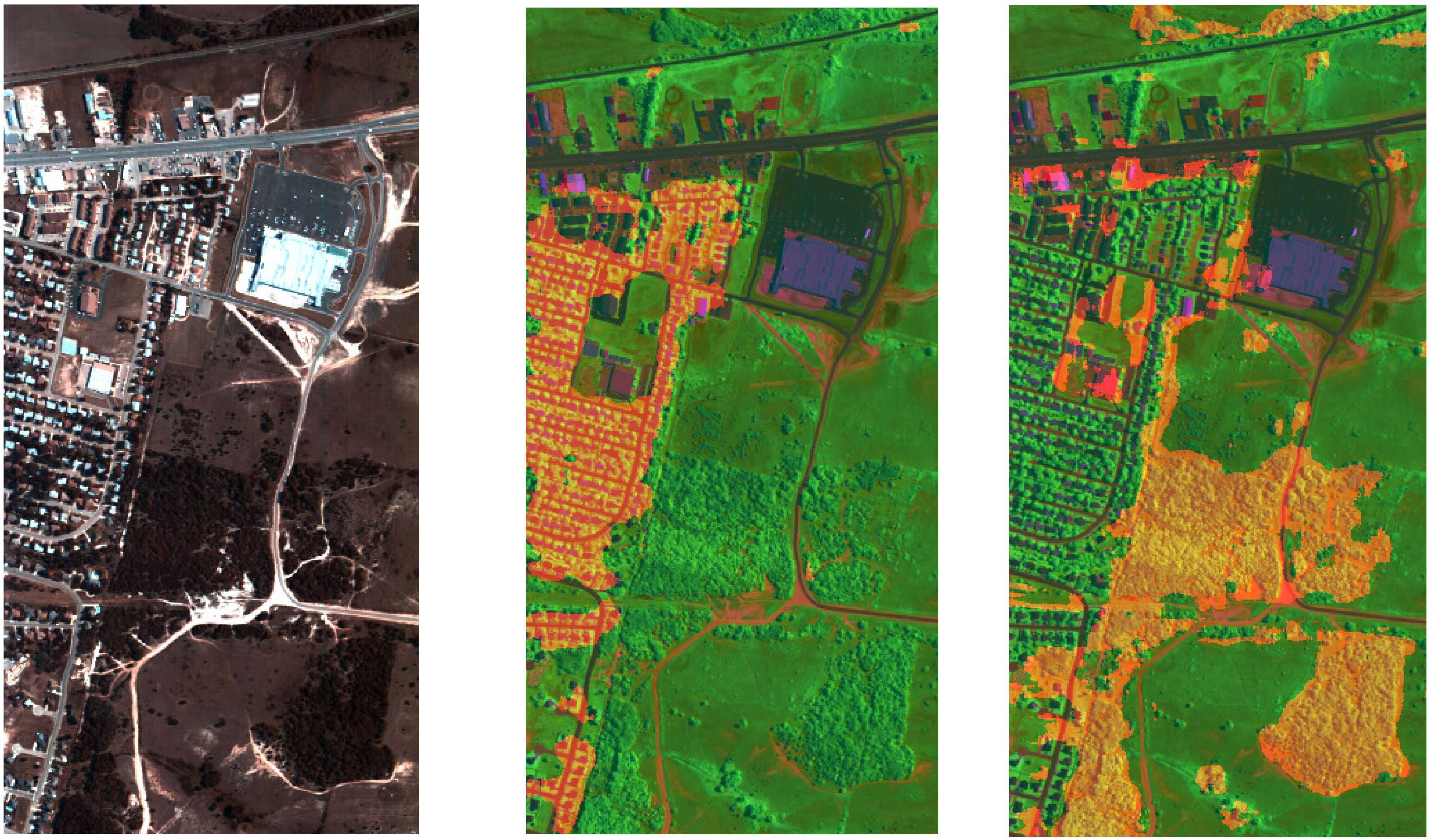
PCA of filter responses

LOG filter



Gabor filter

Experimental result



Building
(Accuracy 91.48%)

Vegetation
(Accuracy 86.21%)

Conclusions

- **The proposed method can effectively extract texture regions from multi-/hyper-spectral imagery**
- **The method is computationally efficient**
- **Although in the current version the filters and integration scales are assumed to be given, future work should include automatic selection of filters and integration scales**
- **Local spectral histograms computed near boundaries do not give an accurate feature, which tends to introduce errors on boundaries. Boundary refinement needs to be addressed**