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Haralick Texture Features Expanded Into The Spectral Domain

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ABSTRACT

Robert M. Haralick, et. al., described a technique for computing texture features based on gray-level spatial dependencies using a Gray Level Co-occurrence Matrix (GLCM)[1]. The traditional GLCM process quantizes a gray-scale image into a small number of discrete gray-level bins. The number and arrangement of spatially co-occurring gray-levels in an image is then statistically analyzed. The output of the traditional GLCM process is a gray-scale image with values corresponding to the intensity of the statistical measure. A method to calculate Spectral Texture is modeled on Haralick's texture features. This Spectral Texture Method uses spectral-similarity spatial dependencies (rather than gray-level spatial dependencies). In the Spectral Texture Method, a spectral image is quantized based on discrete spectral angle ranges. Each pixel in the image is compared to an exemplar spectrum, and a quantized image is created in which pixel values correspond to a spectral similarity value. Statistics are calculated on spatially co-occurring spectral-similarity values. Comparisons between Haralick Texture Features and the Spectral Texture Method results are made, and possible uses of Spectral Texture features are discussed.

Keywords: Spatial-spectral, Haralick texture features, spectral texture, co-occurrence matrix

1. INTRODUCTION

The goal of this research is to find a method of utilizing the spatial information that is typically ignored in spectral image processing routines. Significant effort is spent on converting remotely sensed data into a spatially recognizable form, and therefore analysis routines can be designed to utilize this information.

Information about the materials in an image can be deduced based on their textures. A human analyst is able to distinguish manmade features from natural features in an image based on the 'regularity' of the data. Straight lines, and regular repetitions of features hint at manmade materials. This spatial information is useful in distinguishing an agricultural field from a prairie, for example. Using a purely spectral image processing routine, the prairie would not be distinguished from the agricultural field.

Haralick described methods for measuring texture in gray-scale images, and statistics for quantifying those textures. It is the hypothesis of this research that Haralick's Texture Features and statistics as defined for gray-scale images can be modified to incorporate spectral information, and that these Spectral Texture Features will provide useful information about the image. It is shown that texture features can be used to classify general classes of materials, and that Spectral Texture Features in particular provide a clearer classification of land cover types than purely spectral methods alone.

The dataset used to demonstrate the ideas in this paper is an AVIRIS image collected over the area surrounding Moffett Field, CA (Figure 1a). This scene was chosen because it contains a variety of land cover types, including agricultural areas, water, light urban and heavy urban areas. The original AVIRIS image is 614 x 512 pixels. The pixels have roughly 20 m spatial resolution. The AVIRIS image has 224 spectral bands covering a spectral range of 400 to 2500 nm. Regions of interest were drawn to define the general land cover classes (Figure 1b). Each region may contain multiple distinguishable materials, but a human analyst is able to easily combine the separate materials into classes. In Figure 1b, the red regions represent the areas of light/heavy urbanization. The yellow areas are agricultural/vegetated areas, the green regions are salt ponds, and the blue region is water.

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Figure 1a: AVIRIS RGB image (Bands 36, 23, 10).

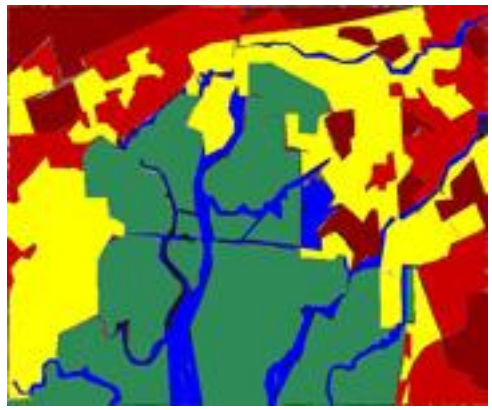

Figure 1b: A very general land cover classification.

In order to compare the results using HSI and MSI data, an MSI image was simulated from the original HSI dataset. The MSI image was created using a sampling of the original AVIRIS spectral bands. A Gaussian distribution was defined for each simulated MSI band using the band-centers and FWHM information of the Quickbird sensor. The simulated MSI image contains 4 bands, with bands centers and bandwidths according to the table below[2].

Band	Bandwidth at FWHM (nm)	Center (nm)
Blue	71.3	480.3
Green	88.6	550.7
Red	65.8	664.8
VNIR	95.4	805.0

Table 1: Bandwidth and band center information for the Quickbird Multi-spectral sensor.

The paper is organized as follows: Section 2 defines the Quantization Level Co-occurrence Matrix (QLCM), and describes methods of creating this matrix for the Haralick Texture Method, and the new Spectral Texture Method. Section 3 contains definitions and examples of Texture Features as defined for Haralick's Method and the Spectral Texture Method. Section 4 contains results and analyses. Conclusions and future work are outlined in Section 5.

2. THE QUANIZATION LEVEL CO-OCCURRENCE MATRIX (QLCM)

Texture is defined by quantifying the spatial relationship between materials in an image. In the Haralick Texture Method, materials are distinguished based on differences in reflectance values in one spectral band. Each pixel's gray-level is compared to the gray-levels of surrounding pixels. The Spectral Texture Method distinguishes materials based on the spectral angle distance between pixels, but the process for defining the spatial relationship of materials in the image is the same for both methods. Haralick defined a Gray Level Co-occurrence Matrix (GLCM) in his technique. The method to calculate Spectral Texture uses the same type of matrix for defining the spatial relationship of materials, however, the matrix depends upon the number of co-occurrences of spectrally similar pixels, rather than similar gray-levels. Since the co-occurrence matrix is defined in the same way for both methods, we will call it a Quantization Level Co-occurrence Matrix, and show the definition below.

The first step in creating the Quantization Level Co-occurrence Matrix, or QLCM, is to quantize the image. This quantization compresses all of the information in the image into one band. While the Haralick method quantizes the original image according to gray-levels in one spectral band, the Spectral Texture method uses a spectral distance measure to incorporate relative spectral information about the image by comparing each pixel in the image to an exemplar spectrum. The quantization image has the same spatial dimensions as the original image. The quantization depends on the range of values to be quantized, and number of quantization levels or quantization step-size. These parameters are defined for each method below.

2.1 Quantizing the image using the Haralick Texture Method

In the Haralick Texture Method, the quantization range is defined as the range of reflectance values in a particular spectral band. The user sets the number of quantization levels. Sixty-four quantization levels were used when calculating Haralick Textures for the examples in this paper. This is the maximum number of levels currently available in the commercial ENVI software. In the Haralick Method, quantizing the data simply reduces the radiometric sensitivity of the data. The larger the number of quantization levels used, the greater the amount of radiometric detail that is preserved. Rather than choosing one spectral band, a simulated panchromatic image was created by summing all of the spectral bands. The darkest pixels in the panchromatic image are given a value of 0, and the brightest are given a value of 63. Using 64 quantization levels appears to preserve most of the detail contained in the original image.

2.2 Quantizing the image using the Spectral Texture Method

An effort was made to mirror the Haralick Texture Method and traditional GLCM process as closely as possible. Quantization values for the Spectral Texture Method are based on spectral angle distances between each pixel in the image and an exemplar 'dark' (i.e., low total reflectance) spectrum taken from the image. Each pixel in the image is compared to the exemplar spectrum by means of a spectral angle distance measure.

$$\text{Spectral Angle } \theta = \arccos\left(\frac{\overline{V}_1 \bullet \overline{V}_2}{|\overline{V}_1||\overline{V}_2|}\right)$$

Rather than define a range of possible spectral angle distances, a quantization step-size was defined. For the examples in this paper, this 'unit' spectral angle range was chosen to be 3 degrees. This step-size choice is somewhat arbitrary, but was based on the assumption that materials separated by less than 3 degrees are actually the same class of material.

The quantization levels are numbered from 0 to N, with 0 being the 3-degree range most similar to the exemplar spectrum, and N being the 3-degree range most dissimilar to the exemplar spectrum. The spectral angle distance between each pixel in the image and the exemplar spectrum is calculated, quantized and stored in the quantization image.

The 'dark' exemplar spectrum was found by adding ten percent of the image reflectance range to the total reflectance of the darkest pixel, and choosing a pixel that has a total reflectance within half a percent of this value. This means the exemplar spectrum is a relatively dark pixel, but not necessarily the darkest in the image.

Example quantization images for both Texture Methods are shown below (Figures 2a-d). Note the features highlighted by each method. These quantization images are used to calculate the QLCM and associated texture statistics.

Figure 2a: Haralick Method Quantization image created for the HSI image. All 224 HSI bands were summed to simulate a panchromatic image.

Figure 2b: Spectral Texture Quantization image created from the HSI image.

Figure 2c: Haralick Method Quantization image for the simulated MSI image. The 4 simulated MSI bands were summed to create a panchromatic image band.

Figure 2d: Spectral Texture Quantization image created from the simulated MSI image.

2.3 Calculating the QLCM

Once the quantization image has been created, the next step is to create the QLCM. The QLCM is an N x N matrix, where N is the number of quantization levels. The elements of the QLCM represent the number of co-occurring quantization levels. Each pixel in the quantized image has an associated QLCM, which is based on the number of co-occurring quantization levels in a pixel neighborhood. The user defines the size of the pixel neighborhood. The size and shape of the pixel neighborhood can be adjusted if the user has *a priori* knowledge of the scale and size of objects within the image. The direction of co-occurrence is another parameter that can be manipulated by the user if there is a predominant directional arrangement of textures in the image. In this paper, a co-occurrence was defined as occurring between a pixel and it's neighbor immediately to the right. The examples in this paper are only meant to demonstrate the feasibility of incorporating spectral information in the Haralick Texture Method. Changing the direction and distance between co-occurrences would affect both texture methods similarly, so no effort was directed towards manipulating these parameters in order to improve results. A subset of an example quantization image, with a 3 x 3 pixel neighborhood, and the associated QLCM using 4 quantization levels is shown below (Figures 3a-b).

2	2	3	0	1	…
0	2	2	0	1	…
3	3	2	3	1	…
0	1	1	2	2	…
2	3	2	1	3	…
:	:	:	:	:	

Figure 3a: Sample quantization image, with a 3 x 3 neighborhood defined around pixel (1, 1).

	0	1	2	3
0	0	0	1	0
1	0	0	0	0
2	1	0	2	1
3	0	0	1	1

Figure 3b: Sample QLCM. Element (0, 1) contains the number of times 0 occurs next to 1 in the quantization image 3 x 3 neighborhood centered on pixel (1, 1) of the quantization image.

Statistics that define properties of the texture are calculated on each QLCM matrix. These statistics, originally defined by Haralick, are described in detail in Section 3. For each pixel in the quantized image, a QLCM is created, and a texture statistic is calculated. The output of each method is a texture image, which contains the texture statistic associated with each pixel in the original image.

3. HARALICK TEXTURE FEATURES

The Haralick Texture Features explored in this study are: Angular Second Moment (ASM), Contrast, Correlation, Entropy, and Variance. The definitions of these texture statistics were taken directly from Haralick[1]. The words 'gray tone' in the original definition were replaced with 'quantization level' in order to make the definitions apply to the Spectral Texture Method as well. A Mean Texture feature was also created (Section 3.6).

Notation:

$p(i,j)$	(i,j)th entry in a normalized quantization-level spatial-dependence matrix.
N_q	Number of distinct quantization levels in the quantized image.

3.1 Angular Second Moment (ASM)

Haralick defined the ASM as a measure of homogeneity of the image.

$$f_1 = \sum_i \sum_j \{p(i,j)\}^2$$

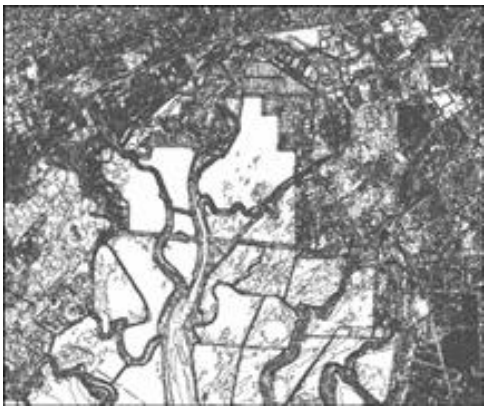

Figure 4a: Haralick Method ASM texture feature for HSI image cube.

Figure 4b: Spectral Texture Method ASM texture feature for HSI image cube.

Figure 4c: Haralick Method ASM texture feature for simulated MSI image cube.

Figure 4d: Spectral Texture Method ASM texture feature for simulated MSI image cube.

3.2 Contrast

$$f_2 = \sum_{n=0}^{N_{q-1}} n^2 \left(\sum_{\substack{i=1 \\ |i-j|=n}}^{N_q} \sum_{j=1}^{N_q} p(i,j) \right)$$

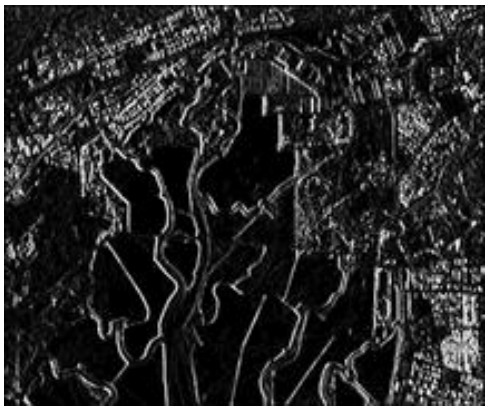

Figure 5a: Haralick Method Contrast texture feature for the HSI image cube.

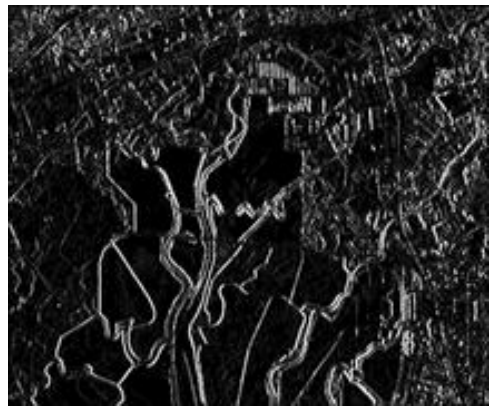

Figure 5b: Spectral Texture Method Contrast texture feature for the HSI image cube.

Figure 5c: Haralick Method Contrast texture feature for the simulated MSI image cube.

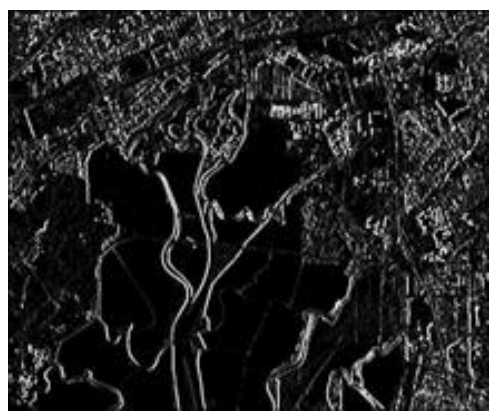

Figure 5d: Spectral Texture Contrast texture feature for the simulated MSI image cube.

3.3 Correlation

$$f_3 = \frac{\sum_i \sum_j (ij) p(i,j) - \mu_x \mu_y}{\sigma_x \sigma_y}$$, where μ_x, μ_y, σ_x and σ_y are the means and standard deviations of p_x and p_y.

$p_x(i) = i^{th}$ entry in the marginal-probability matrix obtained by summing the rows of $p(i,j)$.

Figure 6a: Haralick Method Correlation texture feature for the HSI image cube.

Figure 6b: Spectral Texture Method Correlation texture feature for the HSI image cube.

Figure 6c: Haralick Method Correlation texture feature for the simulated MSI image cube.

Figure 6d: Spectral Texture Method Correlation texture feature for the simulated MSI image cube.

3.4 Entropy

$$f_9 = -\sum_i \sum_j p(i,j)\log(p(i,j))$$

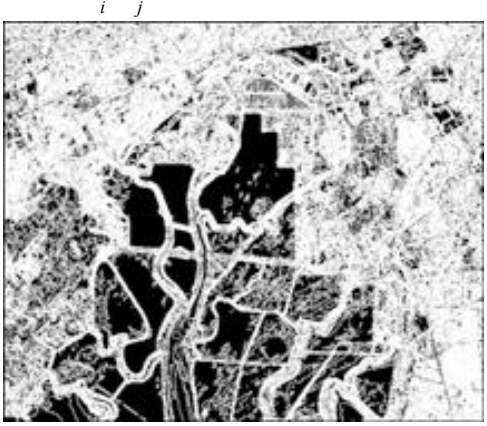

Figure 7a: Haralick Method Entropy texture feature for the HSI image cube.

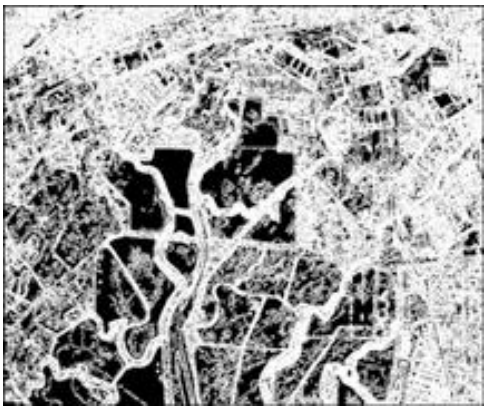

Figure 7b: Spectral Texture Method Entropy texture feature for the HSI image cube.

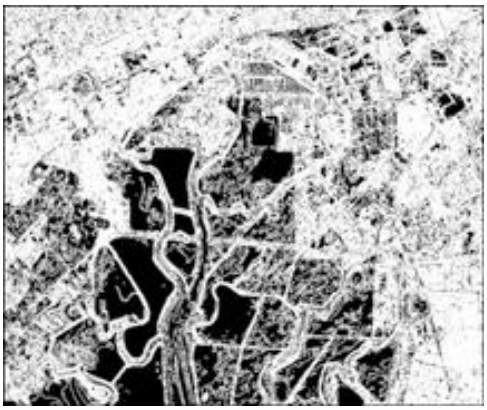

Figure 7c: Haralick Method Entropy texture feature for the simulated MSI image cube.

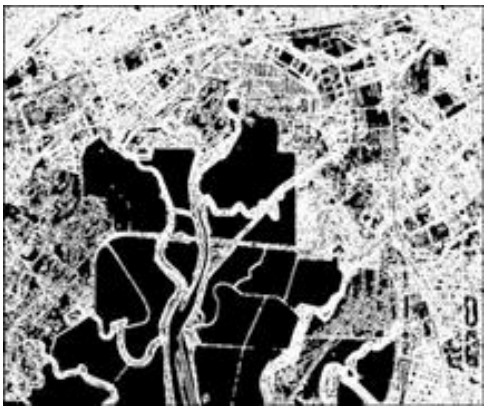

Figure 7d: Spectral Texture Method Entropy texture feature for the simulated MSI image cube.

3.5 Variance

$$f_4 = \sum_i \sum_j (i-\mu)^2 p(i,j)$$

Figure 8a: Haralick Method Variance texture feature for the HSI image cube.

Figure 8b: Spectral Texture Method Variance texture feature for the HSI image cube.

Figure 8c: Haralick Method Variance texture feature for the simulated MSI image cube.

Figure 8d: Spectral Texture Method Variance texture feature for the simulated MSI image cube.

3.6 Mean

$$f = \left(\sum_{i=1}^{N_q} \sum_{\substack{j=1 \\ i+j=n}}^{N_q} p(i,j) \right) / M$$ where M = the number of non-zero elements in the QLCM.

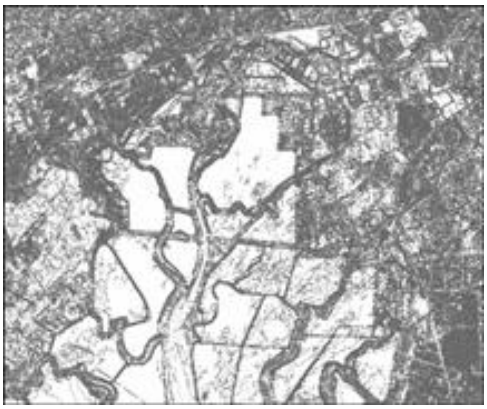

Figure 9a: Haralick Method Mean texture feature for the HSI image cube.

Figure 9b: Spectral Texture Method Mean texture feature for the HSI image cube.

Figure 9c: Haralick Method Mean texture feature for the simulated MSI image cube.

Figure 9d: Spectral Texture Method Mean texture feature for the simulated MSI image cube.

4. RESULTS AND ANALYSIS

It is interesting to look at each of the texture features, and it is apparent that the Spectral Texture Method distinguishes classes of materials better than the traditional Haralick Texture Method in some cases. The texture features were combined into 'image cubes' and analyzed. The results of the Principal Components analysis, and the ISODATA unsupervised image classification algorithm are shown below.

4.1 Principal Components Analysis

The texture feature bands for the Haralick Method and the Spectral Texture Method were combined to form two image cubes. By looking at the first three principal components of the original image, the Haralick Texture Features image,

and the Spectral Texture Features image respectively, we can see that the Spectral Texture Method captures unique information about the image.

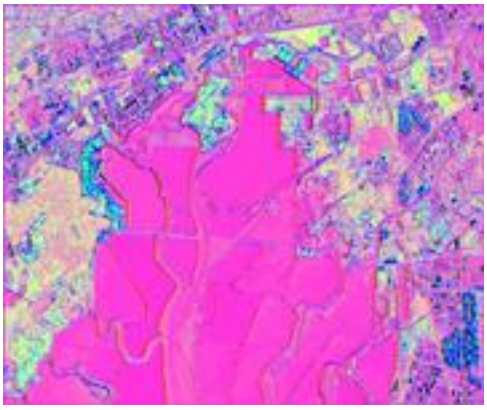

Figure 10a: RGB image of Principal Components 1-3; Haralick Method Textures from HSI image cube.

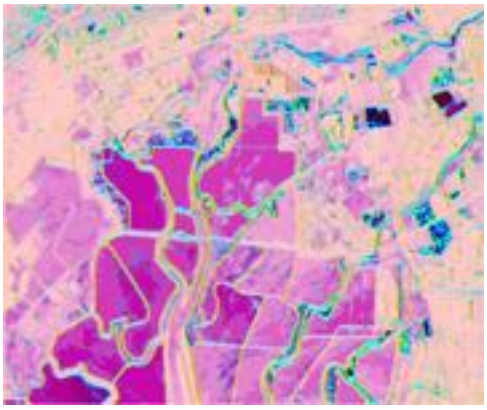

Figure 10b: RGB of PC1, 2, 3; Spectral Texture Method features from HSI image cube.

Figure 10c: RGB of PC1, 2, 3; Haralick Method Textures from simulated MSI image cube.

Figure 10d: RGB of PC1, 2, 3; Spectral Texture Method features from simulated MSI image cube.

4.2 Image Classification Analysis

The ISODATA unsupervised classification algorithm was used to classify the original HSI, the simulated MSI image, and the Texture Feature images created using each Texture Method. The ISODATA algorithm classifies data by calculating class means evenly distributed in the data space, and minimum distance techniques to cluster pixels[3]. The parameters for the ISODATA unsupervised classification were kept the same for all cases. The algorithm was allowed to choose 4 to 10 classes.

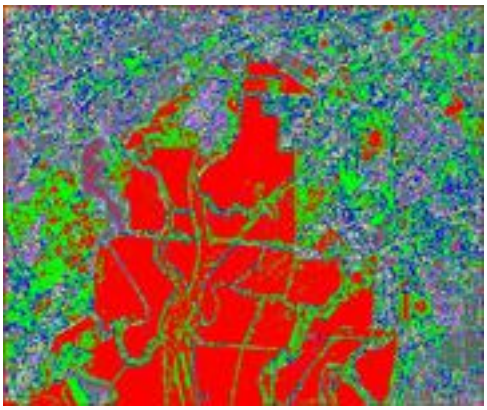

Figure 11a: ISODATA classification of Haralick Method Texture features from HSI image cube.

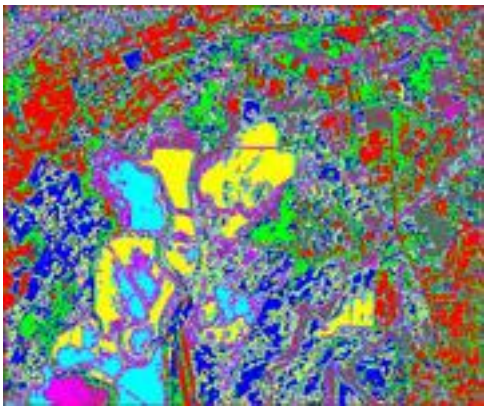

Figure 11b: ISODATA classification of Spectral Texture Method features from HSI image cube.

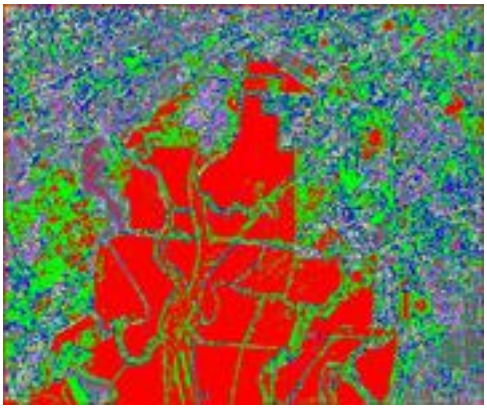

Figure 11c: Classification of Haralick Method texture features from simulated MSI image cube.

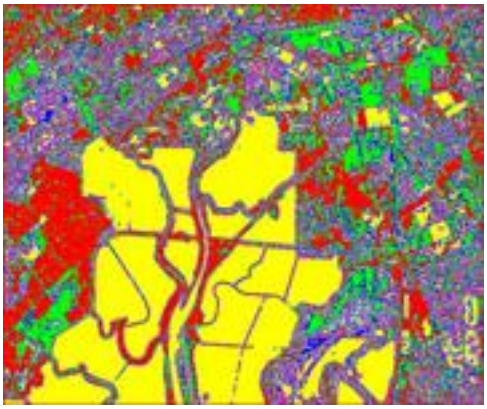

Figure 11d: Classification of Spectral Texture Method features from simulated MSI image cube.

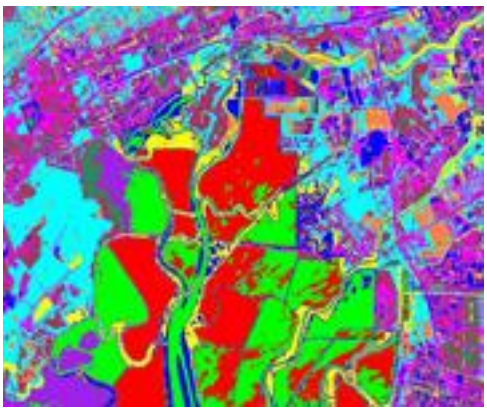

Figure 11e: ISODATA classification of original AVIRIS 224-band HSI image cube.

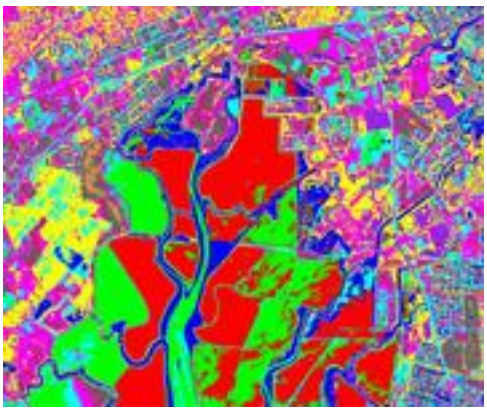

Figure 11f: ISODATA classification of simulated 4-band MSI image cube.

When these results are compared to the land cover classification in Figure 1b, we can see that a classification using Texture Features provides a clearer classification of land cover types, especially in the MSI case. The effect is most obvious in the region containing the salt ponds. The classification result from the Spectral Texture Method using the

HSI image is very unclear, but this could most likely be improved by discarding 'garbage' bands. All 224 spectral bands were used in the analysis.

5. CONCLUSIONS AND FUTURE WORK

A method to incorporate relative spectral information into the Haralick Texture Method has been developed. Spectral information is used in the Spectral Texture Method by measuring the spectral angle between each pixel in a spectral image and an exemplar spectrum.

Examples show that quantizing a spectral image based on spectral angle values yields texture features that highlight unique information about an image. The spectral angle quantization tends to highlight classes of materials, whereas the traditional gray-level quantization highlights materials that are visually different in a certain spectral band. While both texture methods can be used to create an image classification that distinguishes land cover types, the Spectral Texture Method appears to offer an improvement over the Haralick Texture Method.

Future work efforts could be directed at studying other methods of compressing the spectral information in an image. It might be interesting to look at different ways of measuring spectral similarity (such as Euclidean distance). The classification results using the Spectral Texture Method approach a land cover classification map, but there is still huge room for improvement in this area.

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