The Semivariogram in Comparison to the Co-Occurrence Matrix for Classification of Image Texture

James R. Carr and Fernando Pellon de Miranda

Abstract—Semivariogram functions are compared to co-occurrence matrices for classification of digital image texture, and accuracy is assessed using test sites. Images acquired over the following six different spectral bands are used:
1) Spot HRV, near infrared;
2) Landsat thematic mapper (TM), visible red;
3) India Remote Sensing (IRS) LISS-II, visible green;
4) Magellan, Venus, 5-band microwave;
5) Shuttle Imaging Radar (SIR)-C, X-band microwave;
6) SIR-C, L-band microwave.
The semivariogram textural measure provides a larger classification accuracy than a classifier based on a co-occurrence matrix for the microwave images and a smaller classification accuracy for the optical images.

Index Terms—Correlation, covariance analysis, image classification, image texture analysis, pattern classification.

I. INTRODUCTION

TEXTURE information is assumed to be contained in the overall, or average, spatial relationship among gray levels for a particular image [1]. Of primary importance to this work, this spatial relationship is considered to be the covariance of pixel values as a function of distance between pixels. Such textural information can be extracted from an image using gray-tone spatial-dependence matrices [1] or co-occurrence matrices [2], [3]. Alternatively, texture can be extracted using a spatial autocorrelation function [2], [4]. The semivariogram is one example [5]. Classification of texture in microwave imagery based on the semivariogram has yielded compelling, albeit qualitative results, because classification accuracy was not measured [6]–[8]. Computer algorithms [9] are subsequently used to develop quantitative comparisons of textural classifications based on the semivariogram and spatial dependence (co-occurrence) matrices. This comparison is attempted primarily because the spatial co-occurrence matrix method is widely accepted for classifying texture, and the semivariogram is logically compared to it. Such a comparison is not attempted or forwarded as a means for criticizing the use of spatial co-occurrence matrices; in fact, subsequent classification results show that the spatial co-occurrence matrix method is a powerful and accurate textural classifier.

II. SPATIAL AUTOCORRELATION: THE SEMIVARIOGRAM

Let the gray levels comprising a given digital image be represented as \( G(x, y) \). Then, the variogram for these gray levels is written [5] as

\[
2\gamma(h) = \int_x \int_y [G(x, y) - G(x', y')]^2 dy dx
\]

in which \( h \) is the Euclidean distance (lag distance) between the pixel value \( G \) at row \( x \), pixel \( y \), and the pixel value \( G \) at row \( x' \), pixel \( y' \). In practice, this integral is approximated as

\[
2\gamma(h) = \frac{1}{N} \sum_{i=1}^{N} [G(x, y) - G(x', y')]^2
\]

in which \( N \) is the total number of pairs of pixel values \( [G(x, y) \text{ and } G(x', y')] \) that are separated by a distance \( h \); note that this accommodates the compression from a double integral to a single summation. In practice, the semivariogram is computed rather than the variogram

\[
\gamma(h) = \frac{1}{2N} \sum_{i=1}^{N} [G(x, y) - G(x', y')]^2.
\]

The semivariogram often approaches the value of the statistical variance \( s^2 \) of \( G \) as the spatial correlation of \( G \) approaches zero (as separation distance \( h \) becomes large).

Calculation of the semivariogram can be constrained to particular spatial directions, hence, implying a vector calculation. The following four examples show E–W, N–S, NE–SW, and NW–SE calculations, respectively:

E–W:

\[
\gamma(h) = \frac{1}{2N} \sum_{i=1}^{N} [G(x, y) - G(x + h, y)]^2.
\]

N–S:

\[
\gamma(h) = \frac{1}{2N} \sum_{i=1}^{N} [G(x, y) - G(x, y + h)]^2.
\]

NE–SW:

\[
\gamma(h) = \frac{1}{2N} \sum_{i=1}^{N} [G(x + h, y) - G(x, y + h)]^2.
\]
In each of these equations, \( N \) is the total number of pairs of pixel values separated by a distance \( h \) in a particular spatial direction. Moreover, the NE and NW computations assume the pixel distance to be even increments of \( h \), even though technically the actual distance is equal to \( h\sqrt{2} \). The assumption is invoked for simplicity. Moreover, a further simplification uses the absolute value, rather than the square, of pixel difference [9].

When applied for image processing, the semivariogram function is obtained by starting at \( h = 1 \) (a one-pixel offset), then incrementing \( h \) by one through a maximum of 20 increments. This is the present software limitation [9]; such a restriction is arbitrary and can be changed depending on the complexity and spatial extent of a texture (fewer increments for some textures, more increments for others). Some texts on geostatistics show example hand calculations demonstrating the procedure for computing a semivariogram [10].

A semivariogram, either directional or omnidirectional, depending on the nature of the texture, is computed for each class using training sites of size \( M \times M \). Then, classification of texture in an entire image proceeds pixel by pixel. A semivariogram is computed for a region, also of size \( M \times M \), surrounding a pixel to be classified. The essential premise of this classification experiment is to compare the semivariogram for a neighborhood surrounding a pixel to be classified to those for the chosen classes. This comparison necessarily requires semivariograms be computed for similar-sized regions in an effort to match semivariogram signatures of textures as closely as possible. A numerical distance metric is used when comparing these signatures

\[
\text{distance} = \sum_{t=1}^{K} |\gamma(t) - \gamma(p)|
\]

wherein \( K \) is the number of increments of \( h \) allowable given the constraint of the window size \( M \times M \) and the subscripts \( t \) and \( p \) represent the training site and pixel neighborhood semivariograms, respectively. A pixel is assigned to the class for which the value, distance, is a minimum (a minimum-distance algorithm).

**Example:** Given the following 5 × 5 digital image:

\[
\begin{array}{ccccc}
1 & 1 & 2 & 2 & 5 \\
3 & 2 & 3 & 1 & 1 \\
0 & 1 & 1 & 0 & 1 \\
3 & 2 & 4 & 0 & 1 \\
2 & 1 & 1 & 2 & 2 \\
\end{array}
\]

compute semivariogram values for \( h = 1 \) and \( h = 2 \), E–W direction only [assume the simplified procedure based on absolute value]. Solution

For \( h = 1 \) [pairs]:

\[
\begin{align*}
&|1-1| + |1-2| + |2-2| + |2-5| + |3-2| \\
&+ |2-3| + |3-1| + |1-1| + |0-1| + |1-1| \\
&+ |1-0| + |0-1| + |3-2| + |2-4| + |4-0| \\
&+ |0-1| + |2-1| + |1-1| + |1-2| + |2-2| \\
\end{align*}
\]

\[
= 0 + 1 + 0 + 3 + 1 + 1 + 2 + 0 + 1 + 0 + 1 + 1 \\
= 1 + 2 + 4 + 1 + 0 + 1 + 0 \\
= 21/(2N) = 21/40 = 0.53.
\]

For \( h = 2 \) [pairs]:

\[
\begin{align*}
&|1-2| + |1-2| + |2-5| + |3-3| + |2-1| \\
&+ |3-1| + |0-1| + |1-0| + |1-1| + |3-4| \\
&+ |2-0| + |4-1| + |2-1| + |1-2| + |1-2| \\
\end{align*}
\]

\[
= 1 + 1 + 3 + 0 + 1 + 2 + 1 + 1 \\
= 0 + 1 + 2 + 3 + 1 + 1 + 1 \\
= 19/(2N) = 19/30 = 0.63.
\]

Note in this example that the value of the semivariogram increases as \( h \) increases. This is the anticipated behavior if image pixels are spatially correlated; pixels located closer together are more similar in value than pixels spaced farther apart. This change in semivariance with increasing \( h \) is the statistical signature that is relied upon for classifying texture.

### III. CO-OCCURRENCE MATRICES

Co-occurrence (spatial dependence) matrices are widely accepted for the classification of texture [2], [3].

**Example:** Given the 5 × 5 digital image used in the foregoing example, a co-occurrence matrix is developed as follows (E–W direction only). First, the number of different pixel values are determined. Second, these pixel values are ranked, smallest to largest. Third, the digital image is scanned in the direction noted (E–W in this case) to determine the frequency with which one of these pixel values follows another.

With respect to the digital image presented earlier, six different pixel values are observed: 0–5. Hence, the co-occurrence matrix is a 6 × 6 matrix (note that, in this case, the co-occurrence matrix is larger than the input image); let this matrix be called [A]

\[
\begin{array}{cccccc}
0 & 1 & 2 & 3 & 4 & 5 \\
0 & 0 & 0 & 0 & 0 & 0 \\
1 & 1 & 4 & 2 & 0 & 0 \\
2 & 0 & 1 & 2 & 1 & 1 \\
3 & 0 & 1 & 2 & 0 & 0 \\
4 & 1 & 0 & 0 & 0 & 0 \\
5 & 0 & 0 & 0 & 0 & 0 \\
\end{array}
\]

Once this matrix is determined, seven statistical parameters are computed as follows [3] (these seven parameters are chosen for this study; more parameters may be computed.
for higher orders of element difference and inverse element difference).

1) Each entry in matrix \([A]\) is divided by \(n\), the number of pixels that satisfy the algorithm (in this case, one pixel to the right); in this example, \(n = 20\); let this resultant matrix be called \([C]\).

2) Once step 1) is finished, the first statistical parameter is extracted, and it is the maximum value for any entry in \([C]\); in this example, the maximum value is 4/20 or 0.2.

3) First-order element difference moment is computed

\[
\sum_i \sum_j (i-j)c_{ij}.
\]

Notice that if \(\text{ABS}(i-j)\) is used instead of \((i-j)\), the simplified semivariogram computation (Section II) is obtained for a lag distance equal to what is used to develop the co-occurrence matrix (a lag distance \(h = 1\), E–W direction in this example).

4) Second-order element difference moment is computed

\[
\sum_i \sum_j (i-j)^2c_{ij}.
\]

Moreover, this value represents the value of the variogram at a lag distance equal to that used to develop the co-occurrence matrix. Therefore, the co-occurrence matrix and [semi] variogram capture the same information; except, the variogram represents spatial variation over all possible lags, whereas the co-occurrence matrix is developed for a particular lag. Only in the case for which texture obeys a Markov law [2] does the co-occurrence matrix capture spatial variation over all possible lags. We address this issue later when discussing classification results.

5) First-order inverse element difference moment is computed

\[
\sum_i \sum_j \frac{c_{ij}}{(i-j)}.
\]

6) Second-order inverse element difference moment is computed

\[
\sum_i \sum_j \frac{c_{ij}}{(i-j)^2}.
\]

7) Entropy is computed

\[-\sum_i \sum_j c_{ij} \log c_{ij}.
\]

8) Uniformity is computed

\[
\sum_i \sum_j c_{ij}^2.
\]

Once these statistical parameters are computed for an \(M \times M\) training class, a similar sized window is used, centered over pixels to be classified. Similar statistical measures are computed, from which a minimum distance metric is computed to determine to which class, or threshold, pixels are assigned.

IV. APPLICATIONS

Digital images representing the following six different spectral bands are classified:

1) India Remote Sensing (IRS) LISS-II band-2, visible-green image of the Grand Canyon, AZ (Fig. 1);
2) Landsat thematic mapper (TM), band-3, visible-red image of Old Faithful geyser and Shoshone Lake, Yellowstone National Park, WY (Fig. 2);
3) SPOT HRV band-3, near-infrared image of 1989 Brazilian deforestation (Fig. 3);
Fig. 3. 1989 SPOT HRV, band 3 (near-infrared) image of Brazilian rainforest deforestation. Regular geometric patterns mark deforested ground. A 400 row × 400 pixel region is displayed. Copyright CNES/SPOT Image, 1989.

Fig. 4. Magellan, S-band microwave image of Venus. Mass-wasting features are noted in the central portion of the image. These features are near 10 S, 188 E. A 400 row × 400 pixel region is displayed. See Acknowledgment for image source.

4) Magellan, S-band microwave image of mass wasting features on Venus, located near 10 S, 188 E (Fig. 4);
5) shuttle imaging radar (SIR)-C, X-band microwave image of San Francisco, CA (Fig. 5);
6) SIR-C, L-band microwave image, horizontally transmitted and vertically received, of Mt. Rainier, WA (Fig. 6).

Training and test site data are reviewed (Table I). Classification accuracy is summarized for each of the six images using a recommended procedure [11]. A mean digital number (DN) was used with both the semivariogram and co-occurrence matrix methods when computing the minimum distance to each class.

A. IRS LISS-II, Landsat TM, and SPOT HRV Images

Classification accuracy in terms of training site homogeneity and test site accuracy is presented as contingency...
TABLE I
TRAINING AND TEST SITE INFORMATION. ROW AND PIXEL COORDINATES ARE RELATIVE TO IMAGE SIZES REPORTED IN CAPTIONS

<table>
<thead>
<tr>
<th>Image</th>
<th>Class Code</th>
<th>Row # Pixel # Size</th>
<th>Test Site</th>
</tr>
</thead>
<tbody>
<tr>
<td>LISS-II</td>
<td>A</td>
<td>116 271 7x7</td>
<td>119 319 10x10</td>
</tr>
<tr>
<td></td>
<td>B</td>
<td>81 261 7x7</td>
<td>31 281 10x10</td>
</tr>
<tr>
<td></td>
<td>C</td>
<td>281 81 7x7</td>
<td>261 201 10x10</td>
</tr>
<tr>
<td>Landsat-TM</td>
<td>D</td>
<td>240 360 7x7</td>
<td>210 240 9x9</td>
</tr>
<tr>
<td></td>
<td>E</td>
<td>200 320 7x7</td>
<td>200 360 9x9</td>
</tr>
<tr>
<td></td>
<td>F</td>
<td>65 120 7x7</td>
<td>200 25 9x9</td>
</tr>
<tr>
<td></td>
<td>G</td>
<td>6 260 7x7</td>
<td>320 380 9x9</td>
</tr>
<tr>
<td></td>
<td>H</td>
<td>6 260 7x7</td>
<td>180 80 9x9</td>
</tr>
<tr>
<td>SPOC</td>
<td>I</td>
<td>6 6 7x7</td>
<td>305 360 9x9</td>
</tr>
<tr>
<td></td>
<td>J</td>
<td>6 6 7x7</td>
<td>250 300 9x9</td>
</tr>
<tr>
<td></td>
<td>K</td>
<td>120 120 7x7</td>
<td>120 180 9x9</td>
</tr>
<tr>
<td>Magellan</td>
<td>L</td>
<td>244 201 7x7</td>
<td>181 241 9x9</td>
</tr>
<tr>
<td></td>
<td>M</td>
<td>241 241 7x7</td>
<td>260 256 9x9</td>
</tr>
<tr>
<td></td>
<td>N</td>
<td>6 6 7x7</td>
<td>260 380 9x9</td>
</tr>
<tr>
<td>SIR-C, X</td>
<td>O</td>
<td>11 11 7x7</td>
<td>101 331 9x9</td>
</tr>
<tr>
<td></td>
<td>P</td>
<td>111 101 7x7</td>
<td>244 264 9x9</td>
</tr>
<tr>
<td></td>
<td>Q</td>
<td>351 11 7x7</td>
<td>11 171 9x9</td>
</tr>
<tr>
<td>SIR-C, L</td>
<td>R</td>
<td>361 61 7x7</td>
<td>301 81 10x10</td>
</tr>
<tr>
<td></td>
<td>S</td>
<td>91 191 7x7</td>
<td>11 202 10x10</td>
</tr>
<tr>
<td></td>
<td>T</td>
<td>281 281 7x7</td>
<td>241 241 10x10</td>
</tr>
</tbody>
</table>

Codes: A = vegetated (several types); B = canyon; C = native/sparsely vegetated; D = deep water; E = shallow water/silty; F = geyser deposits; G = deforested ground; H = hummocky ground/landslide; I = radar dark; J = radar bright/nonhummocky ground; K = urban; L = nonvegetated volcanics

TABLE II
CONTINGENCY TABLE FOR IRS LISS II IMAGE. CLASSES ARE INDICATED BY NUMBER; T REPRESENTS LOSS TO THRESHOLD

<table>
<thead>
<tr>
<th>Method</th>
<th>Semi-variogram</th>
<th>Co-occurrence</th>
<th>Min Dist</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training</td>
<td>1 2 3 7</td>
<td>1 2 3 7</td>
<td>1 2 3 7</td>
</tr>
<tr>
<td>Test</td>
<td>1 2 3 7</td>
<td>1 2 3 7</td>
<td>1 2 3 7</td>
</tr>
<tr>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>41 36 25</td>
<td>41 36 25</td>
<td>41 36 25</td>
<td>41 36 25</td>
</tr>
<tr>
<td>2 0 98</td>
<td>2 0 98</td>
<td>2 0 98</td>
<td>2 0 98</td>
</tr>
<tr>
<td>average</td>
<td>77</td>
<td>77</td>
<td>50</td>
</tr>
</tbody>
</table>

TABLE III
CONTINGENCY TABLES, LANDSAT TM IMAGE. CLASSES ARE INDICATED BY NUMBER; T REPRESENTS LOSS TO THRESHOLD

<table>
<thead>
<tr>
<th>Method</th>
<th>Semi-variogram</th>
<th>Co-occurrence</th>
<th>Min Dist</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training</td>
<td>1 2 3 7</td>
<td>1 2 3 7</td>
<td>1 2 3 7</td>
</tr>
<tr>
<td>Test</td>
<td>1 2 3 7</td>
<td>1 2 3 7</td>
<td>1 2 3 7</td>
</tr>
<tr>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>41 36 25</td>
<td>41 36 25</td>
<td>41 36 25</td>
<td>41 36 25</td>
</tr>
<tr>
<td>2 0 98</td>
<td>2 0 98</td>
<td>2 0 98</td>
<td>2 0 98</td>
</tr>
<tr>
<td>average</td>
<td>77</td>
<td>77</td>
<td>50</td>
</tr>
</tbody>
</table>

TABLE IV
CONTINGENCY TABLES FOR SPOT HRV IMAGE. CLASSES ARE INDICATED BY NUMBER; T REPRESENTS LOSS TO THRESHOLD

<table>
<thead>
<tr>
<th>Method</th>
<th>Semi-variogram</th>
<th>Co-occurrence</th>
<th>Min Dist</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training</td>
<td>1 2 3 7</td>
<td>1 2 3 7</td>
<td>1 2 3 7</td>
</tr>
<tr>
<td>Test</td>
<td>1 2 3 7</td>
<td>1 2 3 7</td>
<td>1 2 3 7</td>
</tr>
<tr>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>41 36 25</td>
<td>41 36 25</td>
<td>41 36 25</td>
<td>41 36 25</td>
</tr>
<tr>
<td>2 0 98</td>
<td>2 0 98</td>
<td>2 0 98</td>
<td>2 0 98</td>
</tr>
<tr>
<td>average</td>
<td>77</td>
<td>77</td>
<td>50</td>
</tr>
</tbody>
</table>

A simple minimum-distance-to-mean classification based solely on mean DN yields largest accuracy for all three images. It is further noted that, whereas the co-occurrence method yields smaller accuracy in comparison to the semivariogram textural classifier and minimum-distance-to-mean classifier for two of these images, IRS LISS-II (band 2) and Landsat TM (band 3), and yields comparable accuracy to the semivariogram method for the SPOT HRV near-infrared image, it does provide the largest accuracy for the second class of the IRS LISS-II band 2 image of the Grand Canyon. This pertains to both training site
TABLE V  
CONTINGENCY TABLES, MAGELLAN IMAGE. CLASSES ARE  
INDICATED BY NUMBER; T REPRESENTS LOSS TO THRESHOLD

<table>
<thead>
<tr>
<th>Method</th>
<th>Training</th>
<th>Test</th>
</tr>
</thead>
<tbody>
<tr>
<td>Semi-variogram</td>
<td>1 2 3 T</td>
<td>1 2 3 T</td>
</tr>
<tr>
<td>Co-occurrence</td>
<td>1 2 3 T</td>
<td>1 2 3 T</td>
</tr>
<tr>
<td>Min Dist</td>
<td>1 2 3 T</td>
<td>1 2 3 T</td>
</tr>
</tbody>
</table>

homogeneity and test site accuracy. This class represents  
the canyon, and its textural characteristics, as described  
by a co-occurrence matrix, evidently outweigh in importance  
its DN and semivariogram signatures. The co-occurrence  
matrix method also yields largest accuracy for two of  
the classes associated with the Landsat TM image of a portion  
of Yellowstone National Park: class 1, deep water (Shoshone  
Lake); and class 5 (native ground, type II, a subjective  
assignment). The semivariogram method yields accuracy  
comparable to that of the co-occurrence method for class  
1 (deep water), and both yield classification accuracy for this  
class larger than that from the minimum-distance-to-mean  
classifier based solely on DN. In general, minimum-distance- 
to-mean classification based on mean DN yields largest  
classification accuracy for these images acquired in the visible  
and near-infrared portions of the electromagnetic spectrum.  
Occasionally, either the semivariogram or co-occurrence  
matrix methods of textural classification may yield larger  
accuracy for a class.

B. Microwave Imagery

Classification accuracy for the three microwave images is  
summarized as contingency tables (Tables V–VII). Average  
classification accuracy is largest for all three images using  
textural classification based on the semivariogram. In the case  
of the Magellan S-band microwave image of mass-wasting  
features on Venus, all three classes (Table V) are identified  
more accurately using the semivariogram than when using  
the co-occurrence matrix (smallest accuracy) or minimum- 
distance-to-mean classifier based solely on DN. In general, minimum-distance- 
to-mean classification based on mean DN yields largest  
classification accuracy for these images acquired in the visible  
and near-infrared portions of the electromagnetic spectrum.  
Occasionally, either the semivariogram or co-occurrence  
matrix methods of textural classification may yield larger  
accuracy for a class.

TABLE VI  
CONTINGENCY TABLES, SIR-C IMAGE OF SAN FRANCISCO. CLASSES ARE  
INDICATED BY NUMBER; T REPRESENTS LOSS TO THRESHOLD

TABLE VII  
CONTINGENCY TABLES, SIR-C IMAGE OF MT. RAINIER. CLASSES ARE  
INDICATED BY NUMBER; T REPRESENTS LOSS TO THRESHOLD

Co-occurrence  | 1 2 3 T  | 1 2 3 T  |
Min Dist       | 1 2 3 T  | 1 2 3 T  |
average 20

occurrence  | 1 2 3 T  | 1 2 3 T  |
Min Dist       | 1 2 3 T  | 1 2 3 T  |
average 79

Finally, in application to the SIR-C, L-band image (horizontally transmitted and vertically received) of Mt. Rainier,  
the semivariogram method yields largest accuracy for two of  

occurrence  | 1 2 3 T  | 1 2 3 T  |
Min Dist       | 1 2 3 T  | 1 2 3 T  |
average 70

occurrence  | 1 2 3 T  | 1 2 3 T  |
Min Dist       | 1 2 3 T  | 1 2 3 T  |
average 74

occurrence  | 1 2 3 T  | 1 2 3 T  |
Min Dist       | 1 2 3 T  | 1 2 3 T  |
average 26

occurrence  | 1 2 3 T  | 1 2 3 T  |
Min Dist       | 1 2 3 T  | 1 2 3 T  |
average 63
TABLE VIII
CONTINGENCY TABLES, RECLASSIFICATION OF THE MAGELLAN IMAGE USING ALGORITHMS OPERATING IN THE NORTH–SOUTH DIRECTION ONLY. CLASSES ARE INDICATED BY NUMBER; T REPRESENTS LOSS TO THRESHOLD

<table>
<thead>
<tr>
<th>Method</th>
<th>Training</th>
<th>Test</th>
</tr>
</thead>
<tbody>
<tr>
<td>Semi-variogram</td>
<td>1 2 3 4 5 T</td>
<td>1 3 4 5 T</td>
</tr>
<tr>
<td></td>
<td>1 71 6 25 0</td>
<td>68 0 52 0</td>
</tr>
<tr>
<td></td>
<td>2 0 100 0 0</td>
<td>0 0 0 0 0</td>
</tr>
<tr>
<td></td>
<td>3 0 0 100 0</td>
<td>4 0 0 96 0</td>
</tr>
<tr>
<td></td>
<td>average 81</td>
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<tr>
<td>Co-occurrence</td>
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<td>1 2 3 4 5 T</td>
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<td>1 69 0 37 0</td>
<td>5 0 95 0</td>
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<td>25 38 37 0</td>
</tr>
<tr>
<td></td>
<td>3 24 0 76 0</td>
<td>80 11 11 0</td>
</tr>
<tr>
<td></td>
<td>average 47</td>
<td></td>
</tr>
</tbody>
</table>

TABLE IX
CONTINGENCY TABLES, RECLASSIFICATION OF THE LANDSAT TM IMAGE USING ALGORITHMS OPERATING IN THE NORTH–SOUTH DIRECTION ONLY. CLASSES ARE INDICATED BY NUMBER; T REPRESENTS LOSS TO THRESHOLD

<table>
<thead>
<tr>
<th>Method</th>
<th>Training</th>
<th>Test</th>
</tr>
</thead>
<tbody>
<tr>
<td>Semi-variogram</td>
<td>1 2 3 4 5 T</td>
<td>1 2 3 4 5 T</td>
</tr>
<tr>
<td></td>
<td>1 76 24 0 0</td>
<td>0 0 0 0 0</td>
</tr>
<tr>
<td></td>
<td>0 0 69 0 0</td>
<td>0 0 16 26 0</td>
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<tr>
<td></td>
<td>3 0 0 92 0 8</td>
<td>0 0 0 22 0 74 5</td>
</tr>
<tr>
<td></td>
<td>4 0 0 76 24 0</td>
<td>0 0 46 54 0</td>
</tr>
<tr>
<td></td>
<td>5 0 0 92 0 0</td>
<td>0 0 0 14 86 0</td>
</tr>
<tr>
<td></td>
<td>average 95</td>
<td></td>
</tr>
<tr>
<td>Co-occurrence</td>
<td>1 2 3 4 5 T</td>
<td>1 2 3 4 5 T</td>
</tr>
<tr>
<td></td>
<td>1 98 0 0 0 0</td>
<td>0 100 0 0 0 0</td>
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<tr>
<td></td>
<td>2 69 37 0 0 0</td>
<td>0 30 30 7 6 27 0</td>
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<tr>
<td></td>
<td>3 0 0 43 0 57</td>
<td>0 0 51 0 7 42</td>
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<tr>
<td></td>
<td>4 0 0 92 0 0</td>
<td>0 0 0 63 37 0</td>
</tr>
<tr>
<td></td>
<td>5 0 0 6 94 0 0</td>
<td>0 0 1 1 98 0</td>
</tr>
<tr>
<td></td>
<td>average 68</td>
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</tr>
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</table>

three classes (class 1, clear-cut, deforested ground and class 3, nonvegetated volcanics). For class 2, vegetated/river valley, a minimum-distance-to-mean classification based solely on DN yields largest accuracy. The co-occurrence matrix method yields the smallest accuracy; moreover, as with the other two microwave images, a significant number of pixels are lost to thresholding.

V. DISCUSSION

Results (Tables II–VII) pertain only to an E–W classification scheme imposed on the co-occurrence matrix and semivariogram methods. Another analysis of two of the images (Tables VIII and IX) shows the effect when imposing a N–S classification scheme. In the case of the Magellan, S-band microwave image (Table VIII), the semivariogram method for textural classification yields largest accuracy, although its ability to classify the first class (hummocky ground/landslide) is substantially diminished. The co-occurrence classification method still yields smallest accuracy, yet interestingly no pixels are lost to thresholding. With respect to the Landsat TM image (Table IX), the co-occurrence matrix method yields larger accuracy in comparison to the semivariogram method when these methods are applied in the N–S direction only.

An additional aspect to consider with respect to the spatial co-occurrence matrix method is its algorithmic implementation in terms of pixel distance. Results (Tables II–IX) are developed using a one-pixel distance, as was done in the example presented in Section III. Results (Table X) show the change in classification accuracy for this method using a two-pixel distance when applied to two of the three microwave images. Although overall accuracy remains small, substantial increases in accuracy did occur for some classes (class 2, Magellan, and class 1, SIR-C, L-band). Changing the algorithmic design of the co-occurrence matrix method can result in larger classification accuracy for microwave imagery than what is reported herein.

Furthermore, at least with respect to microwave imagery, the fact that the semivariogram textural classifier yields larger accuracy than what is obtained using the co-occurrence matrix method suggests that texture in the microwave domain may not obey a Markov law [2]. The co-occurrence matrix at one spatial distance (one pixel to the east) does not seem to capture the entire autocorrelation function. With respect to Landsat TM, SPOT HRV, and IRS LISS-II data, the co-occurrence and semivariogram textural classifiers yield similar accuracy. This may indicate that a Markov law for texture is valid for visible and near-infrared imagery.

VI. CONCLUSION

The semivariogram function has been applied previously for remote-sensing and image processing applications [12]–[15]. Its application to image classification, however, is relatively new [6]–[9]. Therefore, this method is necessarily compared to the well-known and accepted co-occurrence method [2] for classification of texture. For visible and near-infrared, optically acquired imagery, the semivariogram classifier may yield larger accuracy, but textural classification may not yield as great an accuracy as simple minimum-distance-to-mean
classification based on mean DN. When textural classification is attempted for optically acquired imagery, the co-occurrence matrix method often results in larger accuracy in comparison to the semivariogram method.

Previous studies [6]–[8], although subjective, suggest large accuracy when using semivariogram signatures for classifying microwave imagery. No quantitative assessment was attempted in these early studies. Some quantitative testing as well as extending the semivariogram method to multispectral classification using the notion of the cross semivariogram is presented [9]. These previous studies, as well as quantitative results presented in this present study, suggest that the semivariogram method is particularly useful for classifying texture in microwave imagery.

ACKNOWLEDGMENT

Sincere appreciation is expressed to the two anonymous reviewers, whose suggestions substantially improved this manuscript. Software for semivariogram classification is available for no cost at the International Association for Mathematical Geology anonymous ftp site—ftp.iامg.org (in the directory: \pub\CG\VOL22)—or from J. Carr. A modification was used in this study that includes co-occurrence matrices and is only available (at no cost) from J. Carr. The IRS LISS-II image was obtained from an EOSAT Sample Digital Imagery Product CD-ROM containing Landsat TM and LISS II images of the Grand Canyon, AZ, and central Indiana–northern Kentucky; the Landsat TM image of Yellowstone National Park was taken from the three CD-ROM Joint Education Initiative (JEI) set available from the University of Maryland, College Park; the SPOT HRV image was obtained from the SPOT Satellite Image Library for Schools, NPA Group Ltd., Edenbridge, Kent, U.K.; the Magellan S-band microwave image of Venus was taken from Magellan F-Mosaics CD-ROM MG_0025, directory F-MIDR.10S188:1; two SIR-C images were downloaded from the JPL anonymous ftp site—ftp.jpl.nasa.gov—under \pub\images\browse\ (SC-SFRAN) and \pub\images\hi-res\ (Mt. Rainier image); these images were originally in GIF or JPEG format, were converted by J. Carr to Windows BMP files, and then decoded to raw binary form. The Magellan and SIR-C images are available at no cost from J. Carr.

REFERENCES


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