A NEW METHOD FOR EXTRACTING TOPOGRAPHIC INFORMATION FROM A SINGLE MULTISPECTRAL IMAGE

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Abstract -- A new method for extracting the variation in brightness due to topography (topographic component) from multispectral imagery is described. A lookup table relates multispectral brightness values within a training area to the topographic component computed from elevation data for a given reflectance model. The lookup table can then be used to determine the topographic component directly from the imagery in areas where elevation data does not exist.

INTRODUCTION

Techniques which estimate topography from a single image (shape-from-shading, or photoclinometry) convert shading information into slope that is, in turn, integrated to form an elevation surface. If we assume that atmospheric effects have been removed, the brightness in a multispectral image at pixel (i,j) in band n is given by

$$b(i,j,n) = a(i,j,n)t(i,j) \tag{1}$$

where $a(i,j,n)$ is the spectral albedo and $t(i,j)$ is the brightness due to the topography (topographic component). It is usually assumed that the topographic component does not depend on wavelength. When the albedo of the surface is constant over the area brightness is related to slope by the reflectance map [1]. Except in limited situations (e.g., planetary surfaces, terrestrial deserts and snow), surfaces are covered by different materials so the albedo must also be treated as a variable. In a previous approach [2], multispectral imagery is clustered into regions with similar spectral properties using band ratios. Under certain conditions, the average value of a band over each region can be used as an estimate of the albedo of the region. The topographic component can then be estimated by dividing a band by its albedo. The performance of this approach depends critically on the clustering.

METHOD

We estimate the topographic component directly from multispectral imagery without clustering. It is assumed that surface reflectance function is known (or can be assumed), and that elevation data is available over a representative portion of the image (training area). Over the training area elevation data is coregistered to the image and used to compute a lookup table that can be used to estimate the topographic component directly from the multispectral image over areas where elevation data does not exist.

For a Lambertian surface the topographic component is

$$t(i,j) = \max\left\{ \frac{1 + p(i,j)p_0 + q(i,j)q_0}{\sqrt{\left[1 + p^2(i,j)q^2(i,j)\right]\left[1 + p_0^2 + q_0^2\right]}}, 0 \right\} \tag{2}$$

where p_0 and q_0 are the i- and j-gradients in the direction of the sun. The i- and j-gradients of the surface at (i,j) are

$$\begin{aligned} p(i,j) &= \left[e(i,j) - e(i-1,j)\right]/\Delta_i \\ q(i,j) &= \left[e(i,j) - e(i,j-1)\right]/\Delta_j \end{aligned} \tag{3}$$

where $e(i,j)$ is the elevation, and Δ_i and Δ_j are the sizes of an elevation cell (i.e., its resolution) in the i and j directions.

Instead of using elevation data, we seek an estimate of the topographic component as a function of the brightness values:

$$\hat{t}(i,j) = f\left[b(i,j,1), \ldots b(i,j,N)\right] = f\left[\mathbf{b}(i,j)\right] \tag{4}$$

Assume that a relationship exists between the brightness values and the topographic component. Let $\mathbf{b}_K = \left[b(1), \ldots b(N)\right]$ denote the k-th unique combination of the N brightness values within the training area. The joint probability distribution $p(t, \mathbf{b}_K)$ is proportional to the number of times the t-th value of the topographic component (Eq. 2) occurs together with the k-th combination of brightness values. The function that minimizes the mean-square error between the topographic component derived from the elevation (Eq. 2) and topographic component estimated from the brightness (Eq. 4) is given by the conditional expected value [3]

$$f\left[\mathbf{b}_k\right] = \frac{\sum\limits_{(i,j)\in R_k} t(i,j)p\left(t(i,j), \mathbf{b}_k\right)}{p\left(\mathbf{b}_k\right)} \tag{5}$$

where $p\left(\mathbf{b}_k\right) = \sum\limits_t p\left(t, \mathbf{b}_k\right)$ and R_k is the region in the image occupied by the k-th combination of brightness values, i.e., the (i,j) where $\mathbf{b}(i,j) = \mathbf{b}_k$.

The above function can readily be implemented as a lookup table. The topographic component for brightness value combinations not in the training area and thus not represented in the lookup table are interpolated to the nearest value in the table.

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EXPERIMENTAL RESULTS

Our method has been evaluated using Landsat TM imagery and USGS digital elevation models (DEMs). In order to reduce the complexity of the algorithm and the size of the lookup table, we used the first three Landsat TM principal components. Figure 1a shows the first principal component over a study area that includes the eastern portion of Albuquerque, NM and the Sandia Mountains. The full image is 1361 x 1285 pixels. This area is particularly challenging for shape-from-shading due to the variety of land cover categories. The DEM was resampled to 25 meters and registered to the imagery (Figure 1b).

A 200 x 200 pixel training area extracted from near the center of the study area is shown in Figure 2a. Figure 2b is the topographic component computed from the DEM using a Lambertian reflectance map. Within the training area, 14,538 unique combinations of the three principal component values were found. Figure 2c is the topographic component estimated from the three principal component images by our method.

We then used the lookup table to estimate the topographic component from the Landsat imagery outside of the training area. Figure 3a shows the topographic component derived from the DEM over the full study area. Figure 3b is the topographic component estimated from the imagery using the lookup table derived over the training area. The full study area contained 133,213 unique combinations of the three Landsat TM principal component values. Thus within the study area only about 10% of the spectral diversity of the image is represented. Results over a 200 x 200 pixel area south-southeast of the training area are shown in Figure 4.

CONCLUSION

A new method for extracting topographic information from multispectral imagery has been described. Within the training area, the method is able to spatially enhance the topographic component, revealing subtle detail not visible in the lower resolution DEM. On average, the value of the topographic component computed from the imagery is about the same as that computed from the DEM. Outside of the training area the topographic component can be extracted from multispectral imagery over areas where elevation does not exist. However, the value of the topographic component computed from the imagery was lower on average than that computed from the DEM. We have found that this bias can be reduced by increasing the size of the training area. Better understanding the training requirements of the algorithm is an area of future work.

References

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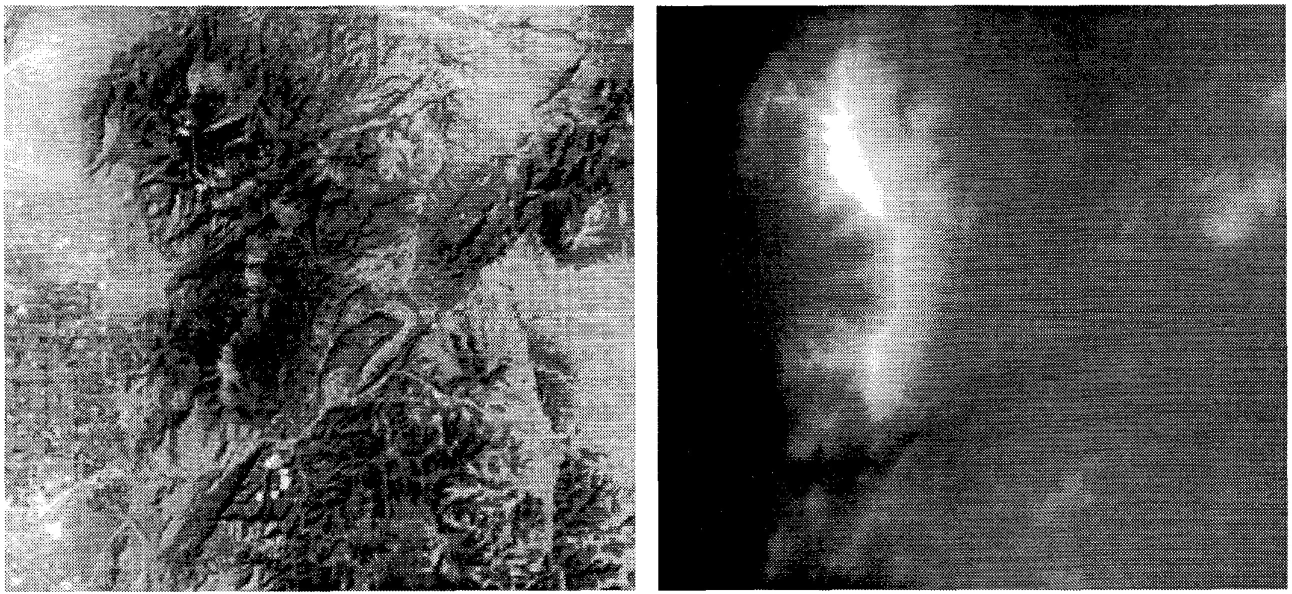
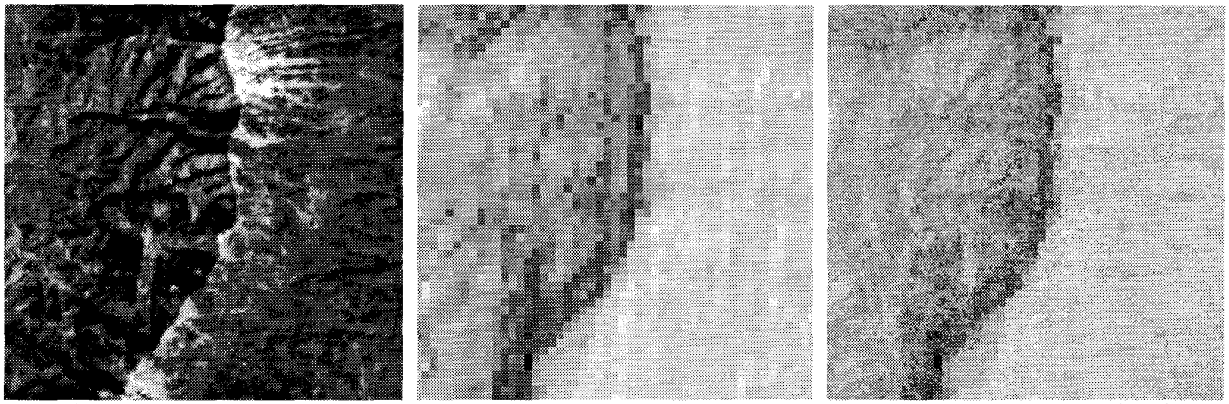
[3] A. Papoulis, *Probability, Random Variables and Stochastic Processes,* McGraw-Hill, 1965.



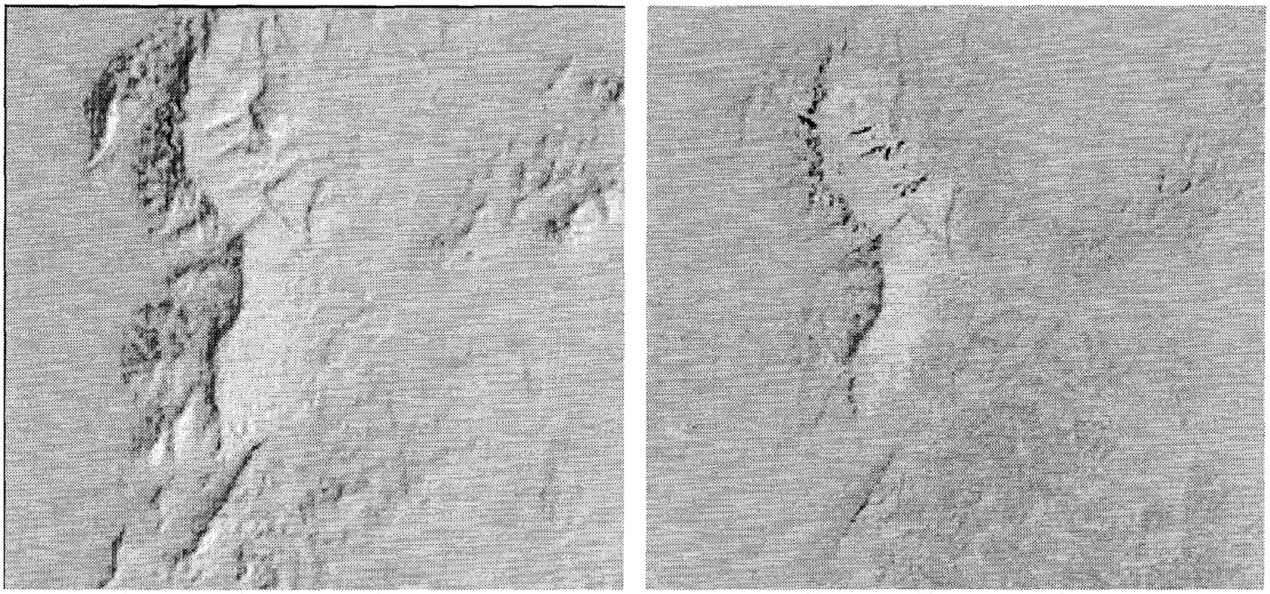
a) Landsat TM (first principal component) b) USGS Digital Elevation Model

Figure 1 Full study area -- Albuquerque and Sandia Mountains



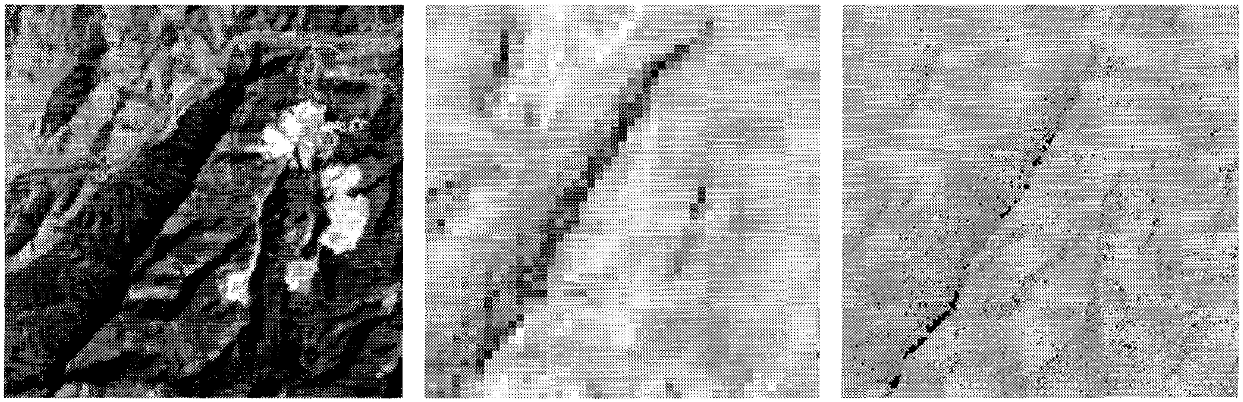
a) First principal component b) Topographic component from DEM c) Topographic component from image

Figure 2 Training area



a) Topographic component from DEM b) Topographic component from image

Figure 3 Results comparison over full study area



a) First principal component b) Topographic component from DEM c) Topographic component from image

Figure 4 Evaluation outside of training area