EDGE DETECTION IN MULTISPECTRAL IMAGERY VIA MAXIMUM ENTROPY

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Abstract - In this paper, a modern spectral analysis method, based on the maximum entropy, for edge detection in multispectral imagery is presented. This technique is shown to be simple and easy to implement. Due to its distinct features, the maximum entropy is proven advantageous when compared to other conventional multidimensional edge detection methods. This method does not involve a smoothing filter and hence there would be no blurring of edges in the processing. Moreover, the problem dealing with sharp corners is eliminated due to the absence of any gradient operations. The application of this method to multispectral imagery to mainly extract roads and highways is shown to be robust in terms of its simplicity and performance evaluation.

Keywords: Edge detection, multispectral, spectral analysis, maximum entropy.

1. INTRODUCTION

Multispectral image analysis has been of interest to the remote sensing community for many years due to its wide applications in areas such as forestry, oceanography, water resources, agriculture, roadmap analysis, and environmental monitoring. In many cases, such applications are based on extracting information by detecting the edges in multispectral imagery. Thus, the process of edge detection is of prime importance in remote sensing technology [1]. Its importance has been observed in automated pattern recognition systems used for target identification, change detection, and classification.

Edges in an image can be defined as the abrupt discontinuities in the intensity values of the pixels in the image. Moreover, edges play a vital role in human perception and vision. The information derived from the edges of an image forms the basis for automated image analysis. The importance of edge detection in various fields has resulted in an exhaustive research in recent years [2-4].

Traditional edge detection schemes are based upon differential operators. The two most popular differential operators are the Laplacian operator and the directional derivative operator [5]. In general, these operators are very efficient due to their time-invariance property with respect to translations and rotations of the image plane. However, their efficiency is not well preserved once they are subjected to the analysis multispectral images.

In this paper, a spectral analysis method, based on the maximum entropy, for edge detection in multispectral imagery is presented.. Due to its distinct features, the maximum entropy is proven advantageous when compared to other conventional multidimensional edge detection methods. This method does not involve a smoothing filter and hence there would be no blurring of edges in the processing. Moreover, the problem dealing with sharp corners is eliminated due to the absence of any gradient operations. The application of this method to multispectral imagery to mainly extract roads and highways is shown to be robust in terms of its simplicity and performance evaluation.

2. METHODOLOGY

2.1 MAXIMUM ENTROPY

Introduced first by Burg, the maximum entropy spectral estimation (MESE) is established based on an explicit extrapolation of a finite known autocorrelation function (ACF) for the unknown samples [6]. The extrapolation process is performed such that the random process characterized by the extrapolated ACF is the most random one. The randomness is measured by evaluating the entropy of the random process. The MESE produces a minimum bias solution because this criterion imposes the fewest constraints on the unknown time series by maximizing its randomness. If a Gaussian random process is assumed, the corresponding power spectral density can be represented by [7]:

$$\hat{P}_{xx}(\omega) = \frac{\sigma^2}{\left|1 + \sum_{k=1}^{P} a(k)e^{-j\omega k}\right|^2}, \qquad (1)$$

where $\{a[1], a[2], ..., a[p], \sigma^2\}$ are obtained by solving the Yule-Walker equations from a known ACF samples.

2.2 2-D MAXIMUM ENTROPY SPECTRAL ESTIMATION

The evaluation of the 2-D MESE is not a simple extension of the 1-D MESE due its the non-linear formulation [7]. Various algorithms have been used for obtaining the power spectral density estimate of a 2-D data based on the maximum entropy method [8-11]. However, most of the algorithms are computationally inefficient and convergence is not always guaranteed. Due to the utilization of the fast Fourier transformation (FFT), the algorithm proposed by Lim and Malik is implemented in this study [12]. This iterative algorithm is computationally simple to implement.

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The two-dimensional autocorrelation function $R_x(n_1, n_2)$ is initially evaluated for the given 2-D data. A unique estimate of the power spectrum of the data, $\hat{P}_x(\omega_1, \omega_2)$ can be calculated by expressing the power spectrum, $P_y(\omega_1, \omega_2)$, as:

$$P_y(\omega_1,\omega_2)=\sum_{n_1=-\infty}^{\infty}\sum_{n_2=-\infty}^{\infty}R_y(n_1,n_2)\,e^{-j\omega_1 n_1}\;e^{-j\omega_2 n_2}\;, \quad (2)$$

and

$$\frac{1}{P_y(\omega_1,\omega_2)}=\sum_{n_1=-\infty}^{\infty}\sum_{n_2=-\infty}^{\infty}\lambda(n_1,n_2)\,e^{-j\omega_1 n_1}\;e^{-j\omega_2 n_2} \quad (3)$$

It can be observed from Equation (3) that $R_y(n_1, n_2)$ can be directly obtained from $\lambda(n_1, n_2)$ via Fourier transformation. Note also that $P_y(\omega_1, \omega_2)$ is the unique maximum entropy power spectral estimate if and only if $\lambda\ (n_1, n_2) = 0$ and $R_y(n_1, n_2) = R_x(n_1, n_2)$ over the entire two-dimensional space. Based upon this criterion, an iterative algorithm is performed. For an initial estimate of $\lambda\ (n_1, n_2)$, an estimate for $R_y(n_1, n_2)$ is obtained and this estimate is corrected by comparing it with the initial $R_x(n_1, n_2)$. The updated $R_y(n_1, n_2)$ is used to obtain a new $\lambda\ (n_1, n_2)$. This iterative process is repeated until a convergence is reached. The resulting Lagrange's coefficients, $\lambda\ (n_1, n_2)$, are used to evaluate the 2-D MESE via [7]

$$\hat{P}_{xx}(\omega_1,\omega_2)=\frac{1}{\displaystyle\sum_{i=-p1}^{p1}\sum_{k=-p2}^{p2}\lambda_{i,k}\,e^{-j2\pi(\omega_1 i+\omega_2 k)}} \quad (4)$$

3. EDGE DETECTION PROCESSING

The entire process of the edge detection scheme is represented as a flow chart in Figure 1. In general, remote sensing images are usually corrupted with high frequency noise. Therefore, the images are passed through a low pass filter in order to eliminate high frequency noise. The reduction of high frequency noise is one of the most critical steps in the process of edge detection. An inefficient low pass filtering may cause the edges in the image to be blurred. A Gaussian low pass filter with an optimal width is used as a pre-processing tool. The width of the Gaussian filter is chosen such that the noise removal is maximized while minimizing the blurring of the edges in the image.

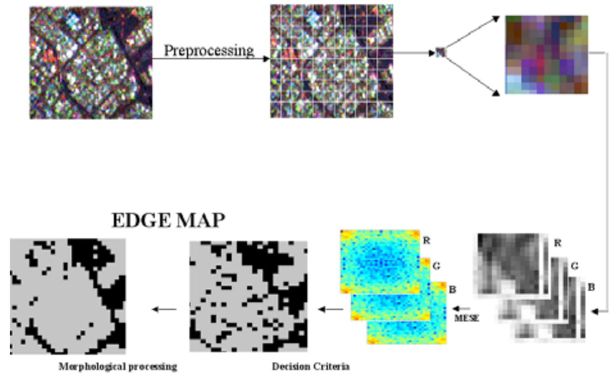

Figure 1: Flow chart for the MESE edge detection technique for multispectral images

The pre-processed image is then divided into sub-images based upon a chosen size. The selection of the size of the sub-image depends on various factors. For very high-resolution images, a sub-image size can be chosen relatively smaller than that in the case of low- resolution images. The increase in a sub-image size may reduce the probability of detecting any false edges, but at the cost of reducing the quality of the edge map. The final edge map appears more 'blocky' when the sub-image size is very large.

Each sub-image is then processed separately. Since the images under consideration are multispectral RGB images, each sub-image consists of three bands, *red*, *green,* and *blue*. Therefore, each sub-image can be further separated into three layers. The PSD estimate of each layer of the sub-image is evaluated individually using the 2-D MESE algorithm. The resulting PSD estimate is subject to proper analysis and a decision criterion is adapted to classify the sub-image as an edge or a non-edge. The design of a proper decision criterion is an important step in this process.

The edge can be considered as a *very high frequency* feature of an image. Whenever an edge is present in any sub-image, the energy of its spectrum is concentrated in the higher frequency areas. In a similar manner, for a non-edge sub-image, the spectral energy is concentrated in the lower frequency areas. This distinctness in the power spectra of an edge sub-image and a non-edge sub-image can be a good metric to distinguish one from the other. The resulting 2-D MESE is observed for all the three layers of the sub-image. The sub-image is labeled as an edge if the energy of the power spectrum of at least one layer of the sub-image is concentrated in the high frequency region and vice-versa. Figure 2 represents the decision criterion.

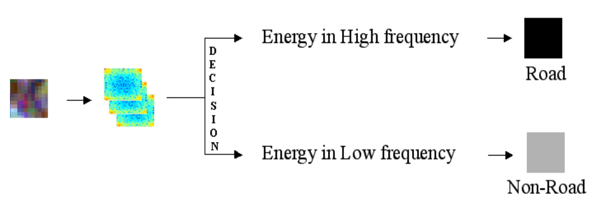

Figure 2: Decision criterion for the MESE edge detection technique for multispectral images

The entire multispectral image is subject to similar classification and a final labeled output image is obtained. The obtained *binary* output image consists of some isolated false alarms, which can be eliminated by implementing certain morphological processing techniques on the edge map. Consistent erosion followed by a suitable dilation eliminates most of the false alarms in the edge map there by enhancing the quality of the edge map.

4. EXPERIMENTAL RESULTS

A multispectral remotely sensed RGB color image consisting of roads and highways is considered to test the performance of the designed 2-D MESE edge detector. The test image is obtained from the NASA web site [21] and is illustrated in Figure 3.

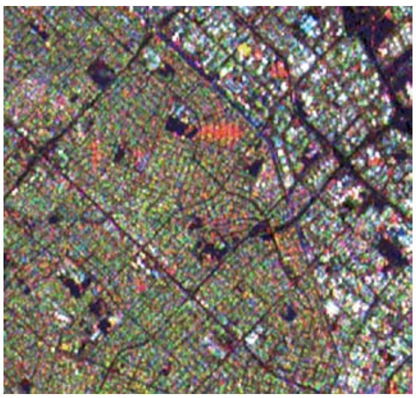

Figure 3: Input multispectral RGB image [21]

Typical PSD estimates obtained using the 2-D MESE of sub -images containing *edges* and *non-edges* are shown in Figures 4 and 5 respectively. It can be clearly observed from these figures that the energy of the power spectrum is concentrated in the higher frequency areas for the *edge* sub-image, while the majority of the signal energy is concentrated in the low frequency areas for the *non-edge* sub-image. This distinction in the energy concentration in lower and higher frequencies represents an excellent basis for classifying *edges* from *non-edges*.

The final edge map is obtained by implementing the designed 2-D MESE on the given input image as shown in Figure 6. It can be observed that all the prominent edges are detected quite accurately. The weak edges, however, are detected less efficiently. From Figure 6, it can be observed that the intersection of the roads is clearly detected. Finally, morphological processing techniques, such as dilation, erosion, etc, are implemented as post-processing tools to enhance the edge map by reducing some of the false alarms in the original edge map, as illustrated in Figure 7.

The algorithm is also tested by passing other RGB mutispectral images having different resolutions. The resulting edge map outputs are shown in Figure 8. The performance and efficiency of the 2-D MESE edge detector are statistically measured by calculating the *probability of detection* (P_D) and *probability of false alarm* (P_{FA}). The results are compared with the ones obtained from conventional edge detectors (Laplacian and directional derivative). This is ahown in Table I. It can be observed that the 2-D MESE edge detector outperformed the conventional edge detectors by a significant margin. However, the efficiency of the MESE edge detector depends upon the resolution of the image.

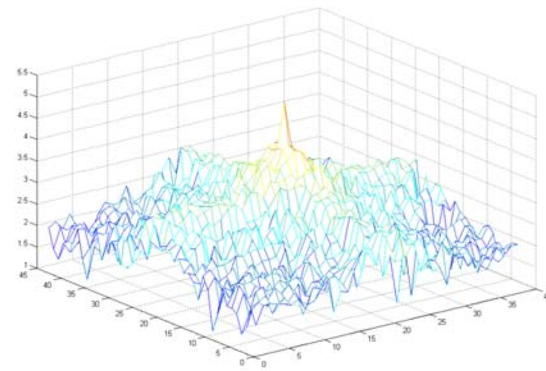

Figure 4: 2-D MESE for an *edge* sub-image

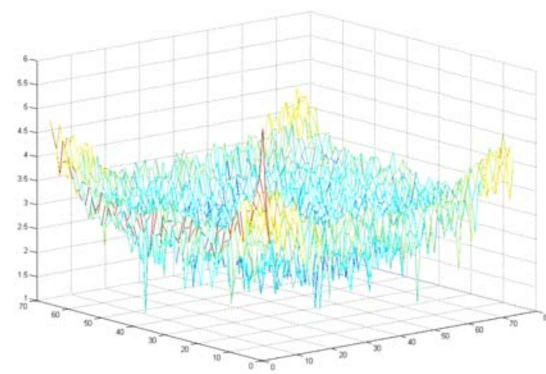

Figure 5: 2-D MESE for a *non-edge* sub-image

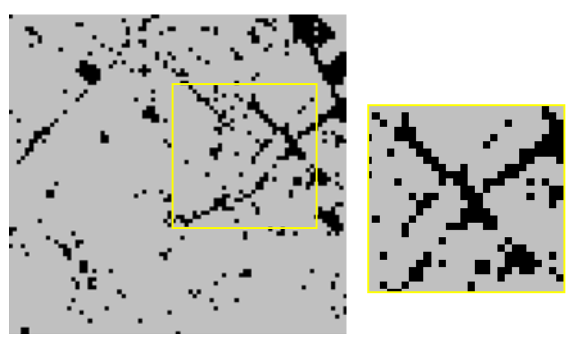

Figure 6: Final edge map of the input image (Zoomed out insight of the intersection)

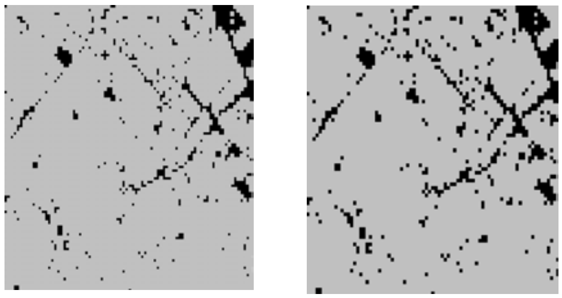

Figure 7: Labeled binary output image obtained after morphological processing

Table I: Performance comparison

	Laplacian		Directional Derivative Operator		MESE	
	P_D	P_{FA}	P_D	P_{FA}	P_D	P_{FA}
Image 1	0.35	0.75	0.45	0.70	0.60	0.35
Image 2	0.50	0.60	0.50	0.60	0.75	0.20
Image 3	0.40	0.60	0.50	0.65	0.70	0.25

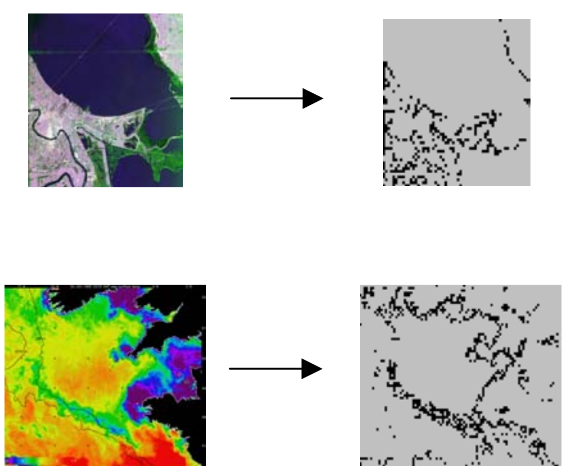

Figure 8: Multispectral input images [21] and their corresponding labeled output

5. CONCLUSION

A 2-D maximum entropy spectral estimation method is implemented and efficiently applied to detect the edges of multispectral images. Preliminary results indicate that prominent edges in multispectral imagery are detected more efficiently when compared to weaker edges detection. However, by taking a proper sub-image size, the weak edges can also be detected efficiently. It is also observed that the efficiency of the 2-D MESE edge detector depends on the resolution of the images. The edge detection algorithm works well when a low-resolution image is used. Proper morphological image processing techniques must be applied to reduce the false alarms and thereby enhancing the final edge map. In addition, a statistical performance comparative study with conventional methods (Laplacian and directional derivative), in terms of probability of false alarm and probability of detection, clearly illustrates the robustness of the presented method.

6. REFERENCES

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