DETECTING MAN-MADE FEATURES IN SAR IMAGERY

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Abstract -- A method for detecting man-made features in synthetic aperture radar (SAR) imagery is described. The method is based on matching the local histogram against a family of Weibull densities. The Weibull density is defined by two parameters, the median and the skewness (Weibull parameter). Regions containing man-made objects have Weibull parameter values that are smaller than those containing natural features. In experiments performed with aircraft SAR imagery, man-made features are effectively discriminated from natural features using this method.

INTRODUCTION

Object detection techniques generally rely on edges or specific textures to indicate the presence of man-made objects in optical imagery. Instead of attempting to detect man-made objects directly, fractal techniques [1,2] model and remove the natural background. Certain sensors provides other opportunities to detect man-made features. For example, in multispectral imagery surface materials associated with man-made features can often be identified by their spectral signature. SAR texture modeling and discrimination approaches based on a variety of methods have been developed and evaluated [3].

In SAR clutter statistics provide an indication of type of surface material present [4]. Areas containing natural features (e.g., sparse vegetation, forested areas, and water) can often be modeled by the Rayleigh density. On the other hand in areas containing man-made features the clutter density has heavy tails and is better modeled by the log-normal density. Our method exploits the probability density of the clutter in SAR to detect man-made features. In particular we model the clutter by a family of densities and pick the density that best describes the clutter on a local basis.

METHOD

The image $X = \{x(i,j)\}$ is divided into non-overlapping regions. Let $p_{i,j}(x)$ denote the local histogram computed over the $r \times r$ pixel region $R(i,j)$ centered at pixel (i,j). We use the local histogram normalized to unit area as an estimate of the density in $R(i,j)$. Within each region, a family of Weibull densities for a range of parameter values are generated. The Weibull density [5] is given by

$$p_\alpha(x) = \frac{\alpha}{x_m}\left(\frac{x}{x_m}\right)^{\alpha-1} \exp\left[-\left(\frac{x}{x_m}\right)^{\alpha}\right] \quad (1)$$

where α is the Weibull parameter which relates to the skewness of the distribution and x_m is the median value. The power of the Weibull is that it becomes different densities by changing the Weibull parameter. For $\alpha = 2$ it becomes the Rayleigh density, for $\alpha = 1$ it becomes the exponential density. Between the two the Weibull can approximate a log-normal density. Thus a single parameterized model can be used to model the clutter in regions containing natural features as well as in regions containing man-made features.

Figure 1 plots a family of Weibull densities for x_m=128 and $1 \le \alpha \le 4$. We use the median value of the local histogram computed over $R(i,j)$ as an estimate of x_m. In effect we are adjusting the model locally based on the brightness values within the window. This should also compensate for variations in brightness caused by changes in slope in the direction of the illumination.

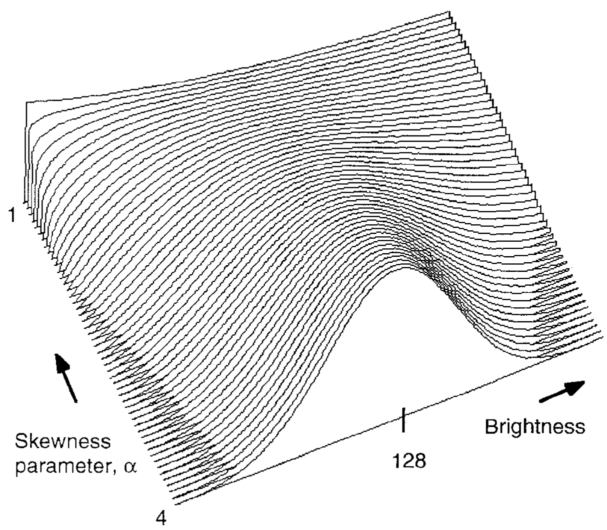

Figure 1 Family of Weibull densities

The model densities $p_\alpha(x)$ are then compared to the normalized local histogram. Let $P_\alpha(x)$ and $P_{i,j}(x)$ denote the cumulative distributions of the model densities and normalized local histogram. We use the maximum difference between cumulative distributions to find the model density that is most similar to the local histogram [5]. The maximum differences are

$$D(i,j,\alpha) = \max_x \left| P_{i,j}(x) - P_\alpha(x) \right| \quad (2)$$

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The Weibull parameter with the smallest maximum difference

$$\alpha = \arg\min_{\alpha'} D(i,j,\alpha') \tag{3}$$

is output in the form of a parameter image $\alpha(i,j)$. The parameter image indicates which of the model densities best matches the image in each region. We also output the smallest maximum difference

$$D = \min_{\alpha'} D(i,j,\alpha') \tag{4}$$

as a "model fit" image $D(i,j)$. The model fit image identifies those regions that are not described well by any of the model densities.

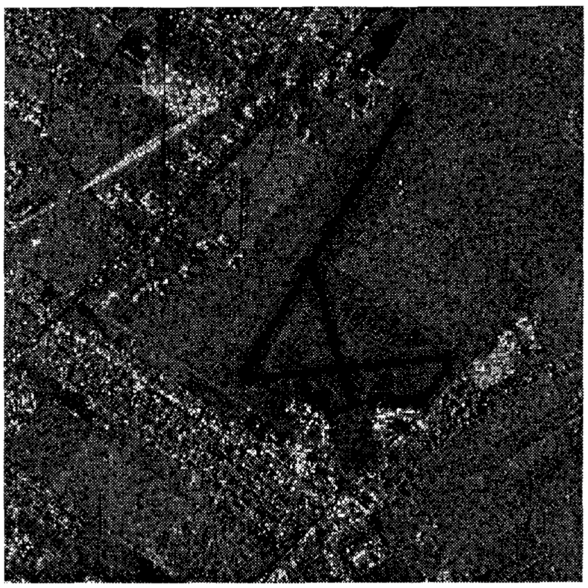


Figure 2 Aircraft SAR image (Courtesy ERIM)

EXPERIMENTAL RESULTS

Figure 2 is a 512 x 512 pixel aircraft SAR image over Willow Run Airport in Michigan. Figure 3 shows the computed parameter image for an 8 x 8 pixel window. The range of parameter values used was $1 \le \alpha \le 4$ in 32 discrete steps. Built up areas have low Weibull parameter values. These are the darker areas in Figure 3. A histogram over a built up area in this image is shown in Figure 4a. In built up areas, the histograms have very heavy tails and are thus better modeled by log-normal or even exponential densities. Natural features (e.g., sparse vegetation, forested areas, and water) on the other hand are better modeled by Rayleigh densities. In regions containing natural features the Weibull parameter values are higher. These are the brighter areas in Figure 3. Histograms over wooded and grassy areas in this image are shown in Figure 4b and c.

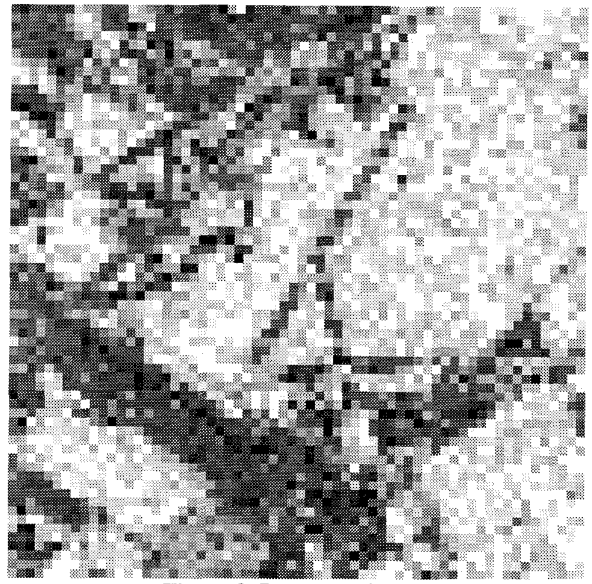
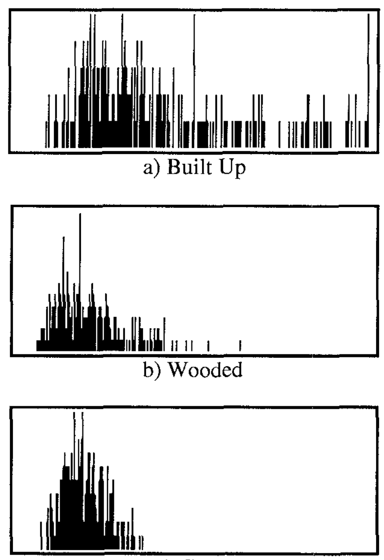


Figure 3 Parameter image



a) Built Up

b) Wooded

c) Grass

Figure 4 Selected histograms from image

Figure 5 depicts the model-fit errors, i.e., areas in the image that did not match any of the model densities. In many of these areas the densities have more than one mode thus indicating a mixture of two or more materials. This effect is particularly evident near features that are about the size of the processing window (e.g., the roads and the runways).

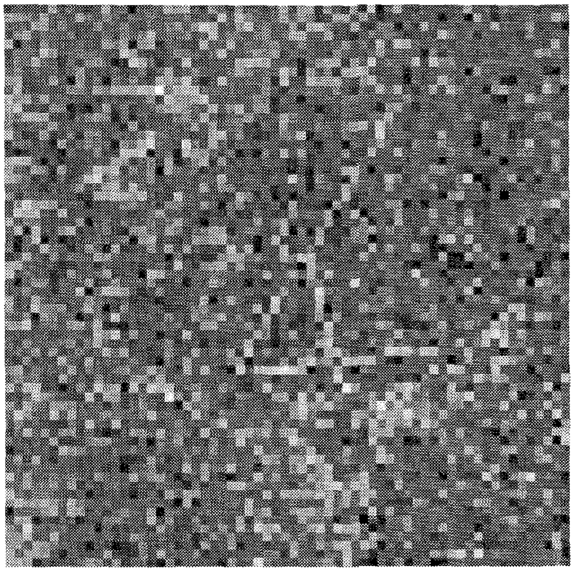


Figure 5 Model-fit image

Man-made and natural features are separated by thresholding the parameter image (Figure 3). The threshold value used ($\alpha = 2.7$) was between the two modes in the parameter image histogram (Figure 6). Values less than the threshold are classified as man-made. Regions containing man-made and natural features are shown in Figures 7 and 8.

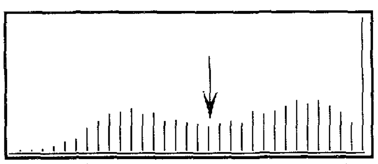


Figure 6 Histogram of the parameter image

CONCLUSION

A method for detecting man-made features in SAR imagery has been described and demonstrated. Additional testing is underway to determine the stability of the threshold for discriminating between man-made and natural features for a given SAR sensor. We are also determining the extent to which the method is insensitive to the topographic modulation of brightness mentioned in the paper. Future applications include the detection of man-made changes in imagery and use together with other texture measurements for land use classification.

References

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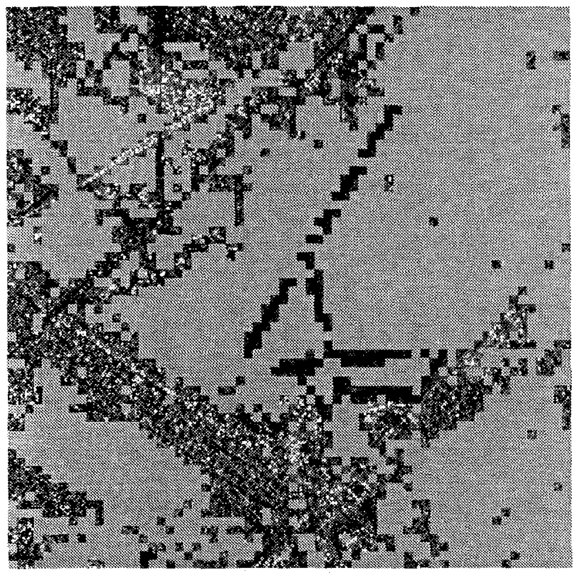

Figure 7 Man-made features

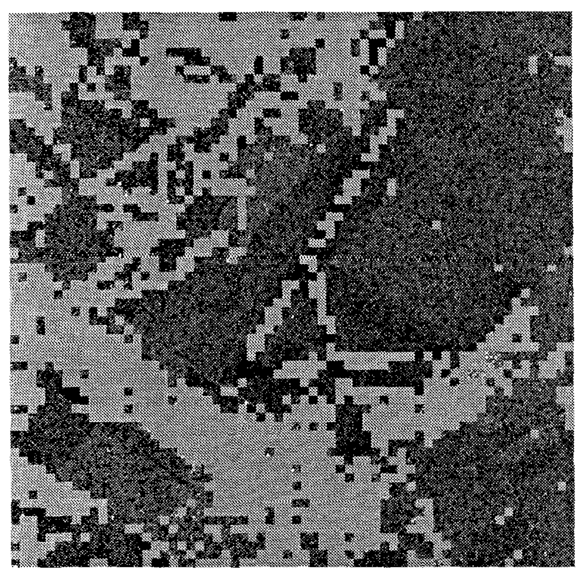

Figure 8 Natural features