Characterization of Information Content in Remote Sensing Imagery

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Abstract— Remote sensing imagery acquired at various spatial and radiometric resolutions is used to estimate certain geophysical parameters, gauge the extent of geophysical phenomena, or detect the presence of specific targets. The information content in an image is related to several variables including resolution (both spatial and radiometric), the spatial scale of features to be recognized, the mean radiometric intensity and intensity distribution of various target types, as well as the image statistical characteristics. Textural measures appropriate for specific applications are analyzed in terms of resolution tradeoffs in order to yield the required information content.

INTRODUCTION

Typical examples of the use of remote sensing imagery include estimation of soil moisture, delineation of ice-water boundaries, and identification of targets concealed in clutter backgrounds. The raw image acquired by the sensor is processed using various operations such as filtering, compression, enhancement, etc. In all of these cases, the analyst is attempting to maximize the information content during the processing operation. A variety of issues needs to be addressed in order that the available information content contained within the textural features in the image is enhanced appropriately. The information content in an image must first be quantified and related to the textural parameters. This relationship can then be used to obtain the resolution needed for the required information content. The image information content is a function of several variables, such as the spatial resolution, the radiometric resolution, the scale of variability of the physical parameter of interest, the radiometric separation between two different classes of targets, as well as the ultimate objective of the image analysis (i.e., target detection vs. edge delineation) [1].

This paper seeks to address the above problem. We discuss specific textural parameters used in various remote sensing applications. Radar simulations at different spatial and radiometric resolutions are shown in order to understand the effect of these on the interpretability of the image. The paper concludes with a roadmap for continuing work in this area.

TEXTURAL CHARACTERISTICS OF REMOTE SENSING IMAGERY

Numerous textural measures are used to characterize the local and global variability in a remotely sensed image. These measures include the mean, the standard deviation with respect to windows of various sizes, gradients in different directions, correlations between textural parameters at different locations, etc. [2]-[7]. In most cases, the choice of the textural parameters used for analysis depends upon the end objective as well as the knowledge of the statistical characteristics of specific features within the image.

In this paper, we explore the use of local first and second order statistics for quantifying the information content in an image for the purpose of identifying a target of various spatial extents embedded in a clutter background. We assume that the local mean and/or the local standard deviation can be used in classifying a pixel as belonging to either the target or the background using the distance measure. The use of different window sizes essentially provides varying degrees of spatial resolution.

RADAR IMAGE SIMULATION AND ANALYSIS

Our study focused on being able to quantify the spatial resolution needed to identify a target various spatial extents immersed in a clutter background. The first and second order radiometric contrasts between the target and the clutter background were also varied to study the effect of contrast on interpretability. First order contrast refers to the difference in the mean backscattering coefficient values of the target and the background. Second order contrast refers to the difference between the standard deviations of the backscattering coefficients of the target and the background.

Assumed values of mean values and the standard deviations for the backscattering coefficients for the target and the clutter backgrounds were simulated. Speckle was incorporated in each pixel by sampling the probability distribution for the appropriate backscatter coefficient. Target spatial extents were chosen from small to large values. Targets were also chosen to represent both small as well as large differences between both their mean backscattering coefficients as well as their standard deviations, and that of the clutter background. The total image extent was 256×256 pixels. Three different target sizes were used: 10×10, 20×20, and 50×50. Local windows used were

1×1, 3×3, 5×5, 7×7, 9×9, and 11×11. Various background types were used to simulate high to low contrasts between target and background.

For the target, the three different spatial extents were introduced at known pixel locations within the clutter background. Appropriate values of the backscattering coefficient sampled from an appropriate Gaussian pdf with speckle included were obtained for each pixel. These backscattering coefficients (in dB) were converted to an 8-bit image digital number (DN) in the range 0-255.

Typical images generated in the above manner are shown to provide a clearer understanding of the effect of spatial resolution.

Figure 1 shows the simulated images for a variety of situations. In Fig. 1(a) is seen the image pertaining to a first order contrast between the target and the background of 4 dB, with both target and background backscattering coefficients having the same standard deviation of 1 dB. Thus, the second order contrast between the target and background is zero. This image is shown for a window size of 1×1, i.e., high resolution case. We see that all targets are detectable in this image, despite the low first order contrast. The corresponding image with degraded resolution corresponding to a window size of 9×9 is shown in Fig. 1(b), from which we note that the smallest target is indistinguishable from the background. The medium target has lost some of its detecability, while the large target is somewhat identifiable. On the other hand, if the targets are assumed to have the same mean backscattering value of -10.5 dB, i.e., zero first order contrast, and a difference in the backscattering standard deviations, i.e., second order contrast, of 5.2 dB, the target and background can perhaps be separated by their image variability. Figure 1(c) shows the image pertaining to a window size of 1×1, wherein we note that the three targets are recognizable, albeit weakly. On degrading the resolution to achieve a window size of 9×9 as shown in Fig. 1(d), all three targets have lost their distinguishability from the background, although one can very weakly recognize the largest target. It is to be noted that the target cannot be separated from the background based on its mean backscattering value since the first order contrast is zero.

Figures 2 and 3 show plots of the image information content, calculated in a manner discussed in [8], as a function of first and second order contrasts respectively. Figure 2(a) shows the variation of information content versus contrast at different spatial resolutions for the large 50×50 target. As can be seen, the information content exceeds a value of 50% even for a spatial resolution of 9 pixels for a first order contrast of about 0.5 dB. However, as the target size reduces to 10×10, we see from Fig. 2(b) that the different spatial resolution curves are spaced more apart, and a first order contrast of 1 dB or higher is needed for satisfying the same condition. On the other hand, a spatial resolution of 1 pixel yields an information content of 50% even for first order contrast value as low as 0.3 dB. We would also like to point out that the computation of

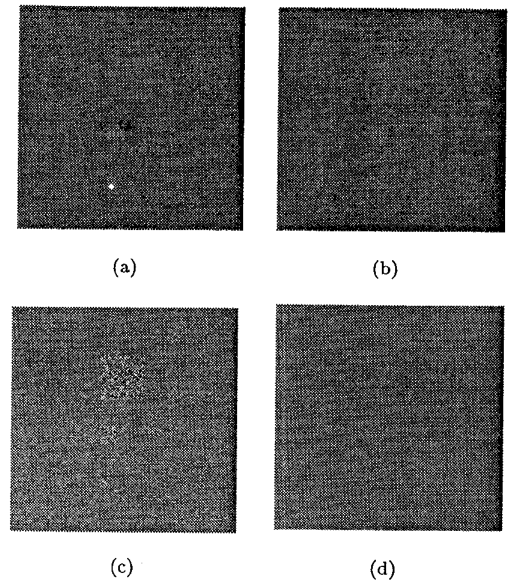


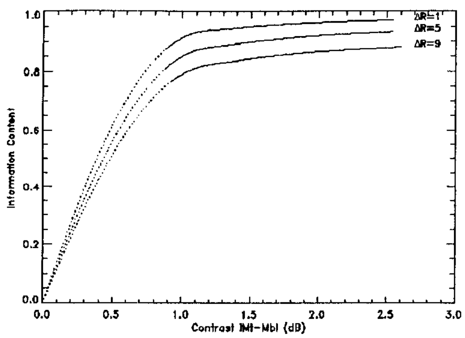
Fig. 1. Effect of varying window size and image statistics on target detectability in a uniform background for following cases: (a) different mean backscattering values, window size 1×1, (b) different mean backscattering values, window size 9×9, (c) different backscattering standard deviaion values, window size 1×1, and (d) different backscattering standard deviation values, window size 9×9.

the information content at contrasts lower than 1 dB was prone to errors, and the dotted lines are merely extrapolations from the corresponding value to the origin, since at zero contrast, we expect zero information content.

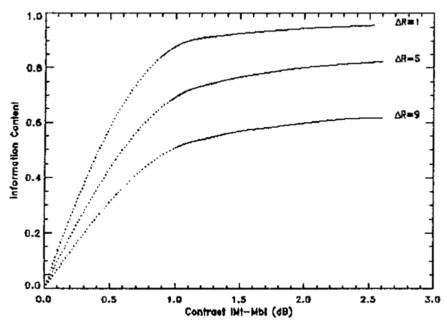
Similar plots for the second order statistics are shown in Fig. 3. It is to be emphasized here that these are plotted for a first order contrast of zero, for which the information content based on mean backscattering values is zero. We observe that the curves for different spatial resolutions are spaced more apart, and also that the curves for the large target, as seen in Fig. 3(a), are similar to the small target, as seen in Fig. 3(b). This leads us to believe that target size is not a factor in identifying it from the background using second order statistics. The second order contrast needed for the 1-pixel spatial resolution case to achieve a 50% or better information content is seen to be approximately 2 dB, while it is much higher for the lower spatial resolution (higher pixel sizes) cases.

CONCLUSIONS

We note that the first and second order contrasts between the target and the backgrouund can be used to characterize image information content for target identification purposes. Simulation results indicate that one can appropriately select the spatial resolution to yield acceptable values of the information content. Future work will focus on combining the first and second order contrasts to further improve the information content for enhancing

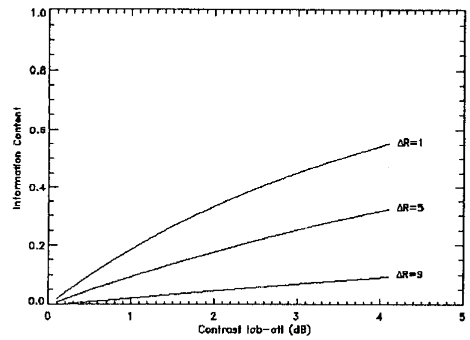


(a)

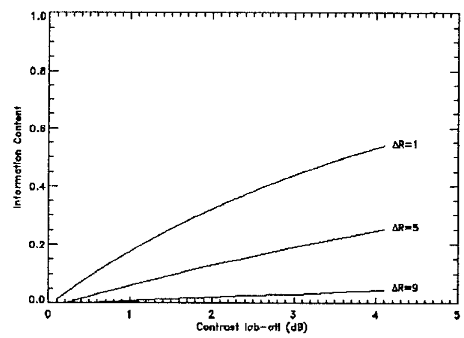


(b)

Fig. 2. Plot of information content as a function of first order contrast at different spatial resolutions for: (a) 50×50 large target, and (b) 10×10 small target.



(a)



(b)

Fig. 3. Plot of information content as a function of second order contrast at different spatial resolutions for: (a) 50×50 large target, and (b) 10×10 small target.

target recognition.

ACKNOWLEDGMENTS

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