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Perceptual Compression of Magnitude-Detected Synthetic Aperture Radar Imagery[1]

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Abstract

We present a perceptually-based approach for compressing synthetic aperture radar (SAR) imagery. Key components of the approach are a multiresolution wavelet transform, a bit allocation mask based on an empirical human visual system (HVS) model, and hybrid scalar/vector quantization. Specifically, wavelet shrinkage techniques are used to segregate wavelet transform coefficients into three components: local means, edges, and texture. Each of these three components is then quantized separately according to a perceptually-based bit allocation scheme. Wavelet coefficients associated with local means and edges are quantized using high-rate scalar quantization while texture information is quantized using low-rate vector quantization.

We assess the impact of the perceptually-based multiresolution compression algorithm on visual image quality, impulse response, and texture properties for fine-resolution magnitude-detected SAR imagery and find excellent image quality at bit rates at or above 1 bpp along with graceful performance degradation at rates below 1 bpp.

1 Overview

We present a perceptually-based compression algorithm along with a preliminary evaluation of its performance on fine-resolution synthetic aperture radar (SAR) imagery. Properties of the algorithm are: (i) spatial adaptability to accommodate both the large dynamic ranges and unique image textures seen in SAR imagery, and (ii) the use of perceptually-based design criteria to optimize image quality rather than mean-squared error. Key components of the approach are a multiresolution wavelet transform, a bit allocation method based on an empirical human visual system (HVS) model, and hybrid scalar/vector quantization.

A consistent motivation for the multiresolution decomposition is its conceptual similarity to scene decompositions performed by the human visual system, which set the stage for application of simple, effective HVS bit allocation schemes. Our algorithm is similar in spirit to the wavelet coding techniques described in [1, 7, 11, 16] and the subband coding techniques in [14, 15]. The main distinction between our approach and others is the use of a fixed-weight perceptually-based bit allocation scheme that accounts for both the large dynamic range and texture patterns (speckle) present in SAR imagery.

Wavelet shrinkage techniques [6] are used to segregate wavelet transform coefficients into three components: local means, edges, and texture. Each of these three components is then quantized separately according to a perceptually-based bit allocation scheme. Because edges and low frequency information are perceptually most important [13], wavelet coefficients associated with local means and edges are quantized using high-rate scalar quantization

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while texture information is quantized using low-rate vector quantization. A minimum rate constraint is set for the local mean and edge components so that essential image content is preserved even at bit rates as low as 1/8 bpp.

The perceptually-based bit allocation scheme is implemented by applying a bit-allocation weighting table to the wavelet transform coefficients. Our approach uses a fixed table rather than the weighted mean-squared error approach reported in [14]; in the latter reference, a data-dependent bit allocation table was used, in which each subband weight was scaled by the standard deviation of that subband. Based on empirical evidence collected to date, we find that fixed-weight bit allocation may be more appropriate for SAR imagery.

The remainder of the paper is organized as follows. Section 2 contains a heuristic discussion of SAR image characteristics. We describe the compression algorithm in Section 3. Preliminary results, in terms of qualitative perceptual quality and image quality measures are presented in Section 4.

2 SAR Image Characteristics

SAR imagery is often characterized by a large dynamic range and a characteristic texture, typically referred to as "speckle." As a result, SAR imagery typically has a large data entropy and is often much more difficult to compress than optical or computer-generated imagery. Specifically, electromagnetic scattering properties of man-made objects and natural terrain yield two characteristic features present in typical fine-resolution SAR imagery, *specular glints or flashes* and *speckle*. Specular returns appear as bright points or edges and typically arise from the radar returns from man-made objects, such as buildings and vehicles, and discrete clutter, such as tree trunks or rocks. Figure 1 shows a fine-resolution SAR image of part of a golf course. Present in the image are point-like specular returns from three trihedral reflectors along with edge-like returns from the roofs of two buildings.

Speckle is caused by diffuse scattering from surfaces that are rough compared to the wavelength of the radar [8]. Radar returns from natural terrain are often modeled as having a Rayleigh distribution with a parameter dependent on the mean terrain reflectivity. In Figure 1 one can see the edge between two different types of vegetated terrain.

Image analysts who work with fine resolution SAR imagery focus both on the image patterns caused by specular returns from man-made objects as well as the image texture caused by diffuse returns from natural terrain. In particular, the analyst may be required to perform object recognition, in which case the contextual information provided by the highly textured natural terrain may be just as important as the radar signature of a man-made object. Therefore, in order to preserve the analyst's ability to interpret the imagery, it is important that both the edges and image texture are preserved. The approach we take is to separate the image into its specular and diffuse components and encode each separately using a perceptually-based bit allocation scheme.

2.1 Multiresolution Decomposition and Wavelet Shrinkage

A simple, nonparametric approach for extracting the edge information from imagery is to use wavelet shrinkage [6]. Donoho and Johnstone have shown that the wavelet transforms

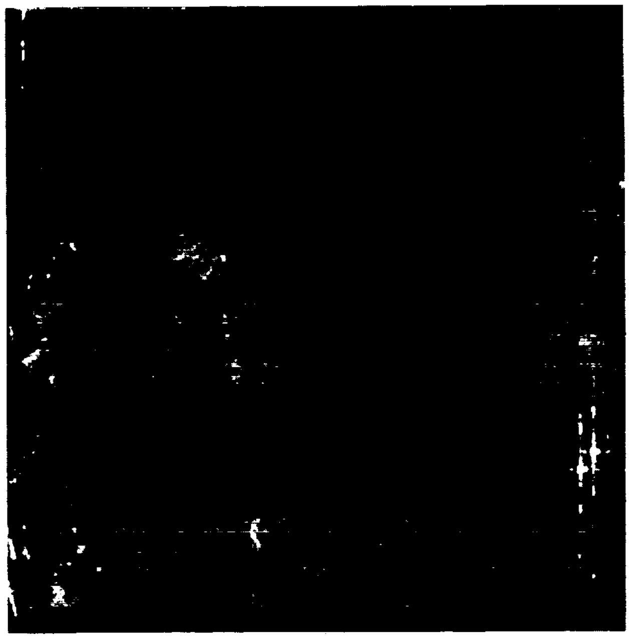


Figure 1: ADTS SAR image of a golf course. Specular returns can be seen from calibration trihedrals and buildings, while natural terrain yeilds diffuse returns (e.g., speckle).

of a broad class of functions, including piecewise-continuous functions, have a compact representation in the wavelet transform domain. On the other hand, an orthogonal discrete wavelet transform applied to white noise yields white noise having the same spectral density as before. Donoho and Johnstone propose a simple scheme for extracting smooth and piecewise-continuous signals from white noise: take the wavelet transform of the sampled noisy signal and apply a soft threshold to remove small wavelet transform coefficients that are likely to be noise.

In our context the speckle, or image texture in a SAR image, can be viewed as a nearly spatially-white but nonstationary noise process, while the edges, or specular returns, can be viewed as smooth or piecewise continuous functions. Figure 2 shows a multiresolution wavelet decomposition of the farm scene along with its decomposition into three components: local means, edges, and texture.

This decomposition is accomplished as follows. The four coefficient Daubechies filter [5] is used to perform a two-dimensional multiresolution wavelet decomposition of the SAR imagery. (Previous empirical evidence has shown that short-length wavelet filters are better than longer length filters for preserving points and edges in SAR imagery [18].) We use the decomposition specified by Mallat [12] to separate the image content according to spatial frequency and orientation. Throughout the remainder of the paper we will use the terminology of [12] and refer to subsets of the 2-D wavelet transform as "detail" images. The *local means* portion of our decomposition corresponds to the "coarse detail," or lowest resolution detail image. The *edges* component consists of all wavelet coefficients exceeding the soft threshold or wavelet coefficient shrinkage operation [6]. Finally, the *texture* component is all of the remaining small coefficients.

3 SAR Image Compression

We use the decomposition shown in Figure 2 as the basis for our compression algorithm. Figure 3 shows a schematic representation of the algorithm, which consists of four stages: a multiresolution wavelet transform (followed by gain normalization of the wavelet coefficients within each detail image), wavelet shrinkage to separate the image data into local means, edges, and textures, perceptually-based bit allocation based on a human visual system model (HVS), and a hybrid scalar/vector quantization operation.

After the 2-D wavelet decomposition has been performed, the coefficients of each detail image in the wavelet decomposition are gain normalized. Gain normalization allows the same vector quantizer to be used for multiple levels of the wavelet decomposition, and increases the efficiency of the vector quantizer. These normalization factors must be transmitted as side information.

Quantization bits are allocated to the wavelet coefficients according to human visual sensitivities to spatial frequency and spatial orientation, and according to whether the coefficients are edges, local means, or texture. The coefficients corresponding to the local means are allotted more bits than the texture coefficients. Moreover, a minimum rate is set for the edge coefficients so that when the overall data rate decreases, the edge coefficients are quantized and transmitted while the texture coefficients may not be transmitted at all. However, when the data rate is high, both edge and texture coefficients are allocated bits based upon

Multiresolution Wavelet Decomposition of a Magnitude-Detected SAR Image Into Three Sources:

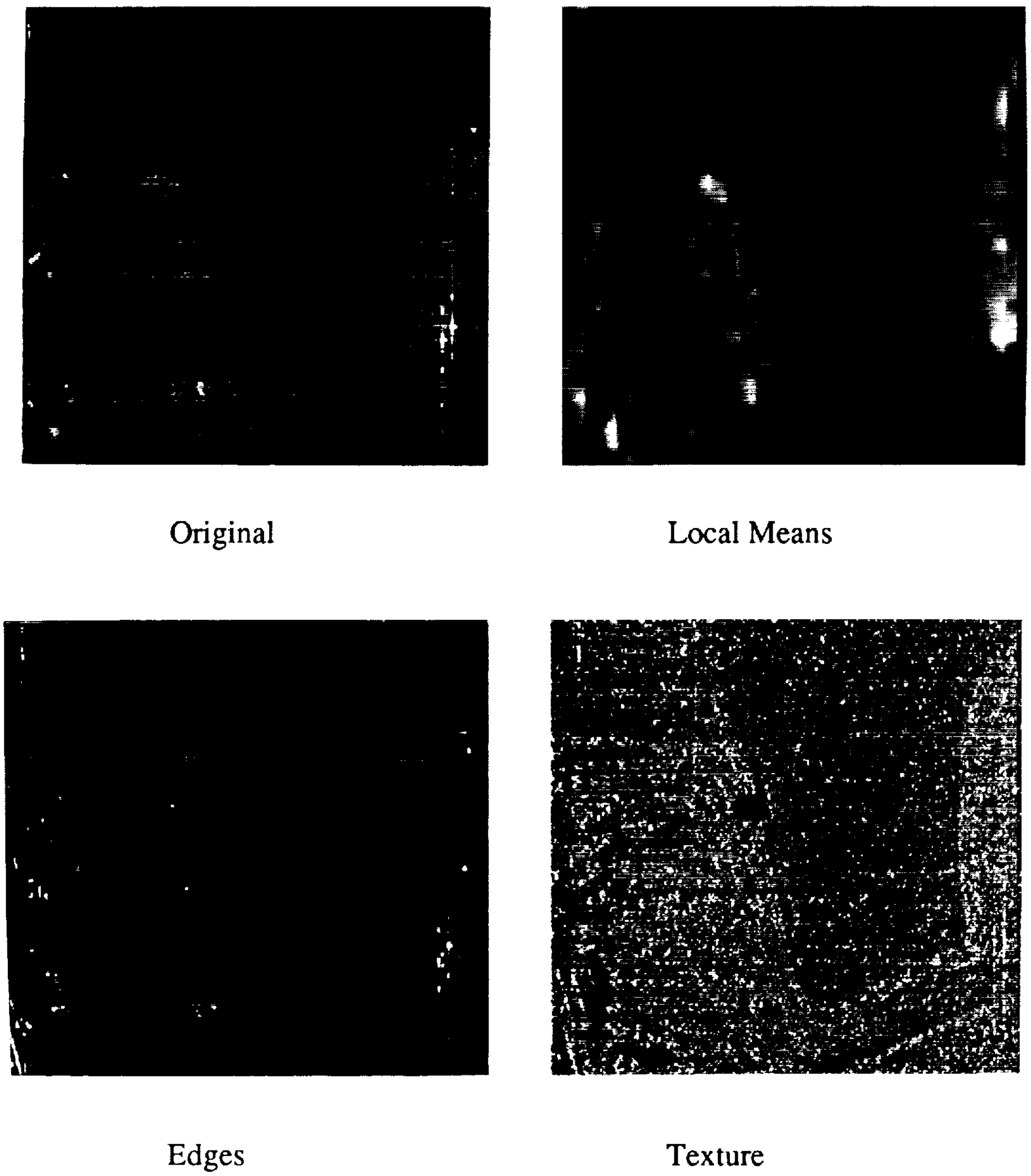


Figure 2: Decomposition of the ADTS image into local means, edges, texture components

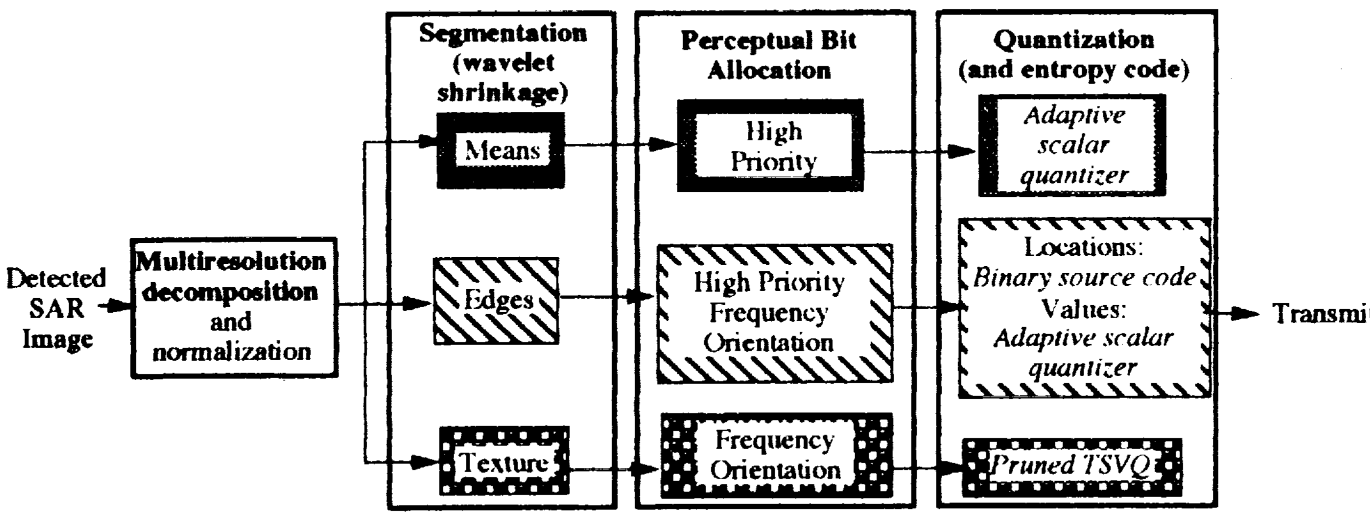


Figure 3: The perceptually-based compression algorithm consists of a wavelet multiresolution transform that is separated into local means, edges, and textures, followed by a hybrid scalar/vector quantizer with perceptually-based bit allocation.

perceptual sensitivity to spatial frequency and spatial orientation.

The bit allocation to spatial frequency and orientation differs from other HVS bit allocation methods in that it is completely independent of the statistics of the wavelet coefficients in each band. In other words, bits are allocated based solely on human visual system sensitivities rather than upon energy or mean-squared error considerations. The spatial frequency weights that are used for bit allocation are derived from equations developed for subband coding [14], which are based upon human contrast sensitivity data acquired by Campbell and Robson [2]. The equation used for bit allocation to each level of the multiresolution decomposition is given by:

$$B(k) = B_{tot} + \frac{1}{2}\log_2\left[\left(W_{HVS}(k)^2/A(k)\right)/\sigma^2_{HVS}\right] \tag{1}$$

where $B(k)$ is the average number of bits allocated to detail image k, B_{tot} is the overall average bit rate, $W_{HVS}(k)$ is the human visual system weight obtained from the equation of Perkins and Lookabaugh [14], $A(k)$ is the relative area of detail image k, and σ^2_{HVS} is a weighted geometric mean of the squared $W_{HVS}(k)$.

Vector quantizers (VQs) for 2×2 texture blocks were combined with adaptive scalar quantizers for edges and local means in a hybrid quantization scheme. The VQs we used were tree-structured variable-rate VQs [9] that were pruned using the optimal pruning algorithm of [4]. To maximize performance of the texture VQs, separate codebooks were created for the vertical, horizontal and diagonal texture components. As mentioned earlier, the edges and local means were quantized using high rate uniform scalar quantizers, while edge locations were coded using an error-resistant binary source coding technique [3]. The scalar quantizer step size was adapted in each detail image with dynamic range and wavelet shrinkage thresholds. Finally, the vector and scalar quantized coefficients were entropy coded.

4 An Example

The perceptual compression algorithm described above was applied to detected SAR imagery (remapped to 8 bpp) obtained from Lincoln Laboratory's Advanced Detection Technology Sensor (ADTS) System [10]. The resolution of this imagery is one foot in both the range and azimuth dimensions. Parameters for the HVS bit allocation and wavelet shrinkage threshold were determined by the viewing geometry, subjective evaluations, and available bit budget.

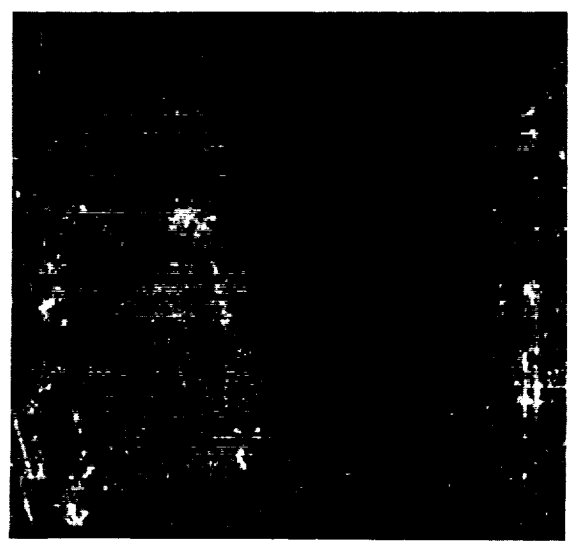
Figure 4 shows compressed versions of the farm scene at rates of 1, 1/2, and 1/4 bits per pixel (bpp). The visual quality of the SAR imagery compressed with the perceptual algorithm is excellent at moderate compression ratios (e.g. 8:1). As the compression ratio increases, the image quality degrades gracefully with minimal smearing of the edges and points. Even at very high compression ratios (e.g. 64:1), the images are recognizable. Also, there are no blockiness artifacts like those that are characteristic of the current version of the JPEG DCT algorithm [17] at rates below 1 bpp.

Finally, Figures 5 and 6 show plots of the measured impulse response (IPR) 3dB widths and image texture, as measured by coefficient of variation, for three different compression rates, 1, 1/2, and 1/4 bpp. Figure 5 contains a summary of several IPR measurements extracted from calibration trihedral signatures within the ATDS imagery. Both the mean

Original (8 bpp)

Compressed to 1 bpp (8:1)

Compressed to 0.5 bpp (16:1)



Compressed to 0.25 bpp (32:1)

Figure 4: ADTS image compressed to 1, 1/2, and 1/4 bpp

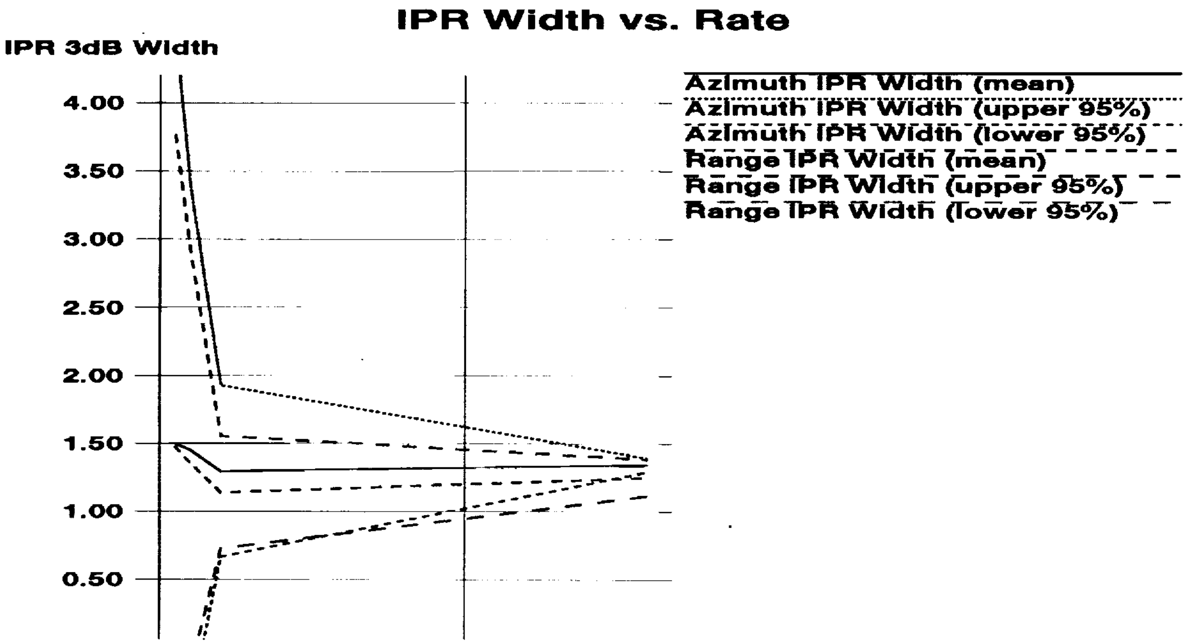


Figure 5: Impulse Response (IPR) 3dB Width Versus Data Rate.

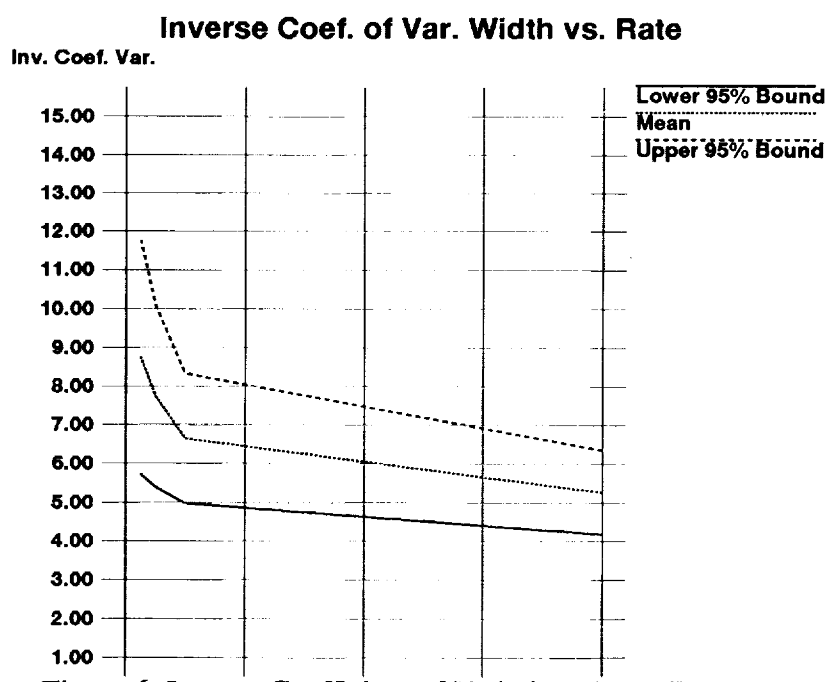


Figure 6: Inverse Coefficient of Variation Versus Data Rate.

IPR measurements in range and azimuth, along with 95% confidence bounds are plotted. What one can observe is that, on average, the IPRs only degrade from an original sampling rate of 1.3 samples per IPR to roughly 1.5 samples per IPR at a compression rate of 32:1 (i.e., 0.25 bpp). On the other hand, the variability of the IPR measurements increases dramatically as the data rate decreases.

Figure 6 shows a plot of the inverse coefficient of variation (mean divided by standard deviation deviation) for a number of local measurements of terrain. Both the mean and upper and lower 95% confidence bounds are plotted for measurements taken over 144 different 15x15 pixel regions containing natural terrain. What we see is that as the data rate is decreased from 8 bpp (no compression) to 0.25 bpp, there is a loss of texture as measured by the increases in the inverse coefficient of variation. At 1 bpp there is a 26% increase in as compared to the original 8 bpp image, however, we observe no significant perceptual degradation. At 0.25 bpp, there is a 66% increase in the inverse coefficient of variation and noticeable smoothing of the image texture.

5 Summary

The perceptually-based multiresolution SAR compression algorithm presented here consists of a wavelet multiresolution decomposition followed by wavelet shrinkage, perceptually-based bit allocation, and hybrid scalar/vector quantization. An important feature that makes this particular approach appropriate for SAR imagery is the use of spatially-adaptive edge detection, via wavelet shrinkage techniques, to separate the image into three components: *local means*, *edges*, and *texture*. Each of these three components is then quantized separately using perceptual bit allocation mask. Based on preliminary results, we find that the algorithm provides excellent image quality at rates at or above 1 bpp and degrades gracefully below 1 bpp.

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