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COMPRESSION OF COMPLEX-VALUED SAR IMAGERY

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Abstract

Synthetic Aperture Radars are coherent imaging systems that produce complex-valued images of the ground. Because modern systems can generate large amounts of data, there is substantial interest in applying image compression techniques to these products. In this paper, we examine the properties of complex-valued SAR images relevant to the task of data compression. We advocate the use of transform-based compression methods but employ radically different quantization strategies than those commonly used for incoherent optical images. The theory, methodology, and examples are presented.

I. INTRODUCTION: COMPLEX SAR IMAGERY

A synthetic aperture radar (SAR) is an active, high-resolution, and coherent microwave imaging system with diverse applications in remote sensing [1]. Modern systems are capable of very high area rates and real-time processing. Coupled with the high spatial resolution, these qualities ensure that the bandwidth requirements for transmission and storage of such data can be daunting. Data compression is a natural consideration for such systems.

Owing to their coherent nature, SAR images exhibit three attributes that set them apart from the incoherent, optical images to which compression algorithms are commonly applied. That is, they are *complex*, with phase as well as magnitude, they possess very high dynamic range, and they exhibit very little spatial correlation.

SAR images are fundamentally complex valued. They are produced by a coherent illuminator, receiver, and image formation processor. Historically, the phase components of SAR images have been discarded, a viewable image generally being produced from the magnitude information only. More recently, several powerful new techniques relying on the full complex nature of the imagery have come to the fore, including autofocus and interferometry [2]. While it might be possible to separately compress the magnitude and phase components of such images, we will shortly show that some special properties of the original complex values can be fruitfully exploited for compression.

The high dynamic range of SAR images is also attributable to the coherent nature of the imaging process. Within a *resolution cell* of an image, the transduced image domain value is related to the radar cross section per unit area of the corresponding patch of illuminated terrain [3]. This *specific cross section* can vary over a considerable range. Most natural terrain, being rough relative to the wavelengths employed, exhibit relatively low values of this parameter, in the vicinity of -15 dBsm/m^2, for example. Flat, smooth surfaces such as dry lakebeds and bodies of water have values many dB lower than this. On the other hand, manmade objects, especially of conducting materials with large flat surfaces and right angles, can have specific cross sections of +60 dBsm/m^2 and higher. It is not unusual for a high resolution SAR system to be designed to accommodate 100 dB and more of dynamic range. This is in contrast to the typical digital optical image for which 50 dB of dynamic range is adequate.

The lack of spatial correlation in SAR image data is also of fundamental importance to compression. Most compression schemes explicitly or implicitly take advantage of spatial correlation in images, removing redundancy to achieve lower data rates. This does not work for SAR imagery. In most natural terrain, the transduced complex reflectivity is the complex sum of the contribution from many small scattering centers in a resolution cell [4]. The number and distribution of scattering centers in adjacent resolution cells are mutually independent. Therefore the image domain complex values are statistically independent. SAR images are often *oversampled* at a rate somewhat higher than Nyquist, however, and this does result in some inter-pixel correlation which we will exploit.

In summary then, SAR images as produced by modern systems are digital, complex valued, exhibit a large (> 100dB) dynamic range, and possess little spatial correlation. Image compression methodologies that offer good performance on optical imagery generally do not produce acceptable performance with this kind of source. In the next section, we will examine a popular family of compression algorithms to further illuminate this problem.

II. TRANSFORM-BASED IMAGE CODING

Transform-based image compression techniques have enjoyed widespread application. The JPEG standard has brought the Discrete Cosine Transform (DCT) into everyday use, and

Wavelet Transform based compression has seen much research activity of late. All transform based techniques attempt to do the same thing: using a reversible, linear transform, they change the data from the image domain, where it is highly correlated, into a domain where the transform coefficients are uncorrelated, or nearly so, and the variances of those coefficients vary widely [5]. The first property ensures that the coefficients themselves are unique and cannot be predicted from the rest of the data. The second results from the all-important property of *energy compaction.*

Distributing the image energy in the transform domain in a highly non-uniform manner allows for the rate compression. Few transmitted bits are allocated to the low-energy coefficients, while more are devoted to the high-energy ones. Thus, the visually important high-energy coefficients are subjected to very little quantization noise and vice versa. The resulting decompressed image can be made to closely resemble the original, while still reducing the data rate by a factor of 8 or 16 or more. Obviously, the better the energy compaction, the higher the compression ratio for a given fidelity. The best transforms compact the image energy into the fewest coefficients. Sophisticated quantization schemes, which may be non-uniform and/or adaptive, then realize the actual rate reduction by discarding the most information in the least important coefficients. Note that these schemes are always *information lossy* in that the original image can never be reconstructed *exactly.* This is the price paid for the more impressive compression ratios achieved.

Various linear transforms can be employed in this way. Perhaps the best, from the standpoint of energy compaction is the Karhunen-Loeve [5]. However, as it involves the computation and inversion of a very large autocorrelation matrix, the K-L transform is computationally burdensome. In practice, nearly as good a performance can be achieved with much faster algorithms based on Fourier, Hadamard, Cosine, and Wavelet transforms. For a number of reasons, the Discrete Cosine Transform was chosen as the basis for the JPEG compression standard [6].

By way of example, Figure 1 shows the standard image "Lena" from the image processing literature. We compute its two dimensional Fourier transform, and the logarithm of the coefficient magnitudes are displayed in Figure 2. Here, the dc coefficient is in the center of the figure. The conjugate symmetry (owing to the fact that the source image is real) is easily seen. It is quite clear that much of the image's energy is compacted into a rather small number of coefficients near dc and along the coordinate axes. Hence the effectiveness of transform coding as it is usually applied.

III. TRANSFORMED SAR IMAGERY

The experiment just described has a very different outcome with complex SAR imagery. Figure 3 shows a portion of a high-resolution (1 meter) SAR image of the Solar Test Facility at Sandia National Laboratories in Albuquerque. The bright squares in the image are an array of solar reflectors. Shown is the magnitude of the complex data after being log-mapped for display purposes.

This time, after computing the 2-D Fourier transform of the image, we obtain a set of Fourier coefficients whose magnitudes are displayed in Figure 4. Bear in mind that Figure 4 is *linearly* mapped, while Figure 2 is *log* mapped. Comparing this result to Figure 2, we notice a much different situation. Around the outside of the Fourier domain, there is a band of extremely small coefficients. Actually, were it not for numerical effects, this region would have all zero coefficients. This *zero-padded* region was added at the time of image formation to accomplish a specified image domain oversample ratio, a common practice in high resolution SAR [7].

Inside the zero-padded region, we see a region of non-zero coefficients. We notice a gradual roll-off in coefficient magnitude with distance from the origin. This is due to a windowing function that was imposed during the image formation process. SAR image formation usually includes this step in order to suppress the image domain impulse response sidelobes. The precise window function is usually known. Since common functions are strictly positive, they may be divided out. When this step has been applied to Figure 4, the resulting *dewindowed* Fourier domain data is shown in Figure 5.

What is astonishing in Figure 5 is the complete lack of energy compaction, whatsoever. In fact this is a characteristic of SAR imagery. It can be shown that lines through the data in this domain are equal to projection functions of the ground reflectivities [8]. Because the projection functions are obtained by integrating over the entire illuminated terrain patch, the notion of the central limit theorem would suggest that samples in this domain are drawn from *the same* probability distribution and that distribution is 2-D Gaussian. Thus, all coefficients have the same energy and in fact are independent and identically distributed (iid) Gaussian. This is precisely what we see with the real data of Figure 5.

IV. COMPRESSION METHODOLOGY

The observations of the previous paragraph with respect to the Fourier domain coefficients shown in Figure 5 suggest a new methodology to compress SAR images. Most obviously, we can discard the zero-padded region of the coefficients. This could be equivalently accomplished in the image domain by removing the 2-D pixel correlation, but is more easily and precisely achieved in this domain. Next, the remaining coefficients can be readily quantized, since they are all drawn *from the same distribution.* Instead of energy compaction, as in the case of optical images, we have just the opposite situation. The energy is spread evenly throughout the domain and the coefficient variance, instead of varying widely, does not vary at all. The fact that the coefficient variance is uniform means that the dynamic range of the data in this domain is much smaller than in the image domain from which it was derived. Hence, we may use a smaller word length to represent this data than was used for the image, yielding the bandwidth compression we seek. Quantization noise introduced at this step will be spread evenly in the reconstructed image, without the tendency to introduce blocking and Gibbs effect artifacts as occurs with JPEG-like quantizers.

The fact that the transform coefficients are iid makes the quantizer design simple: complicated adaptive schemes are no longer necessary. We have investigated the use of both uniform and Lloyd-Max optimal quantizers. Since the coefficients are known to possess a 2-D Gaussian distribution, the latter is straightforward to specify. The only parameter that needs to be estimated from the data for either quantizer is its variance.

The SAR image of Figure 3 is composed of 512x512 pixels, the complex values of which are represented as in-phase and quadrature (I-Q) components. These components in turn are each formatted as 16-bit integers, allowing for 96 dB of dynamic range. Thus, the original image is comprised of $512 \cdot 512 \cdot 4 = 1$ Mbyte.

After 2-D Fourier transformation of the image we may likewise represent the complex Fourier domain coefficients as 16-bit I and Q values, the total data set again being of size 1 Mbyte. For this SAR image, the zero-padded portion of the Fourier domain represents 59% of the coefficients (see Figure 5). By discarding these coefficients, a compression factor of 2.4 is realized. Then, capitalizing on their small dynamic range, the Fourier coefficients can be quantized to fewer bits, as discussed above. If, for example, the I and Q components of the coefficients are quantized to 4 bits each, an overall compression ratio of: $2.4 \cdot (16/4) = 9.6$ is realized. This overall ratio can be improved modestly by entropy coding of these quantized coefficients. We experimented with the Said and Pearlman implementation of the Witten, Neal, and Cleary arithmetic encoder [9]. With this in use, the overall compression ratio for this example was 10.4:1.

Reconstruction is a simple matter of decoding and rescaling the quantized coefficients, multiplying by the window function, zero padding, and 2-D transformation. Figure 6 shows the reconstructed example of Figure 3 after compression by a factor of 10.4 as described. We note in particular a complete lack of visible coding artifacts in Figure 6.

V. QUANTIZATION EFFECTS

In the compression scheme just outlined, the only step that incurs information loss is the quantization of the transform coefficients. We have explored the effects of various quantizers in a quantitative fashion. The metric used for this purpose is the sample complex spatial correlation coefficient between the original and decompressed complex images. This metric was used in place of the more common mean squared error, as it more accurately measures the quality of complex-valued SAR images in their most frequent application: interferometry. In particular, it is very sensitive to inaccurate reproduction of phase.

The spatial correlation measure is calculated over a small local neighborhood of each pixel in the image. For two images f and g, the measure at pixel location (i,j) is defined to be [10]:

$$\alpha(i,j) = \frac{\left|\Sigma_k \Sigma_l f(k,l) g^*(k,l)\right|}{\sqrt{\Sigma_k \Sigma_l \left|f(k,l)\right|^2 \Sigma_k \Sigma_l \left|g(k,l)\right|^2}} \quad (1)$$

where k and l range over a small neighborhood of (i,j). The coefficient of Equation 1 lies in the interval [0,1], with a value of 1.0 reached when $f(k,l) = g(k,l)\ \forall\ k,l$, i.e. the images are identical in the neighborhood.

A representative image of the spatial correlation coefficient between the image of Figure 3 and that of Figure 6 is shown in Figure 7. Notice that the correlation is highest (and near unity) for strong scatterers, and smallest in low return areas. This is consistent with our earlier observation that the effect of quantization noise introduced in the Fourier domain is to evenly raise the noise floor in the image domain.

Armed with this quality metric, we have examined the effects of quantizing the Fourier coefficients in both the I-Q and magnitude-phase formats, and the effects of optimal Lloyd-Max [11] and uniform quantizers. Table 1 shows the average correlation values for the two I-Q quantizers (top row) and the two magnitude-phase quantizers (bottom row). All four results were obtained with a quantizer word length of 8 bits per complex sample (achieving an overall compression ratio of 10.4:1).

From these results, we conclude that there is no advantage gained by converting the transform domain data to a magnitude-phase format. The advantage of an optimal Lloyd-Max quantizer over a simple uniform quantizer is slight but noticeable. This is consistent with known results for Gaussian distributions. Of course, longer word lengths yield universally better results, and vice versa. Eight bits per complex sample yields acceptable phase preservation for most applications.

ACKNOWLEDGMENTS

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Figure 1

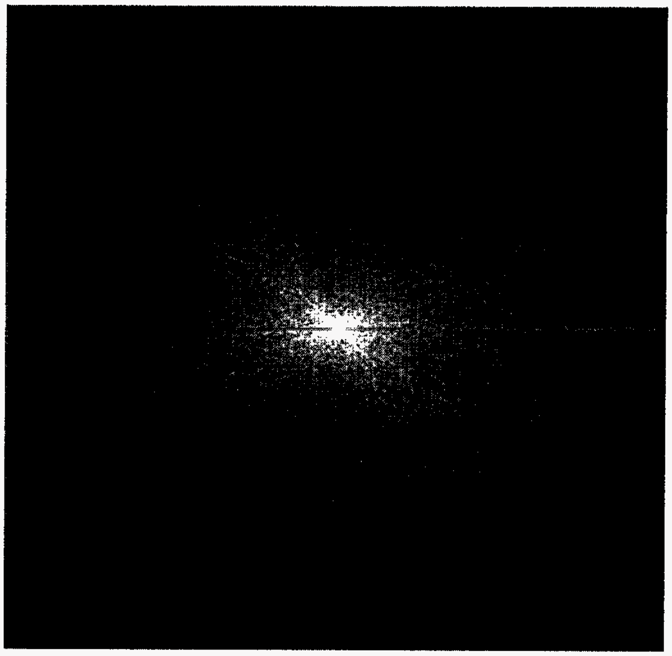

Figure 2

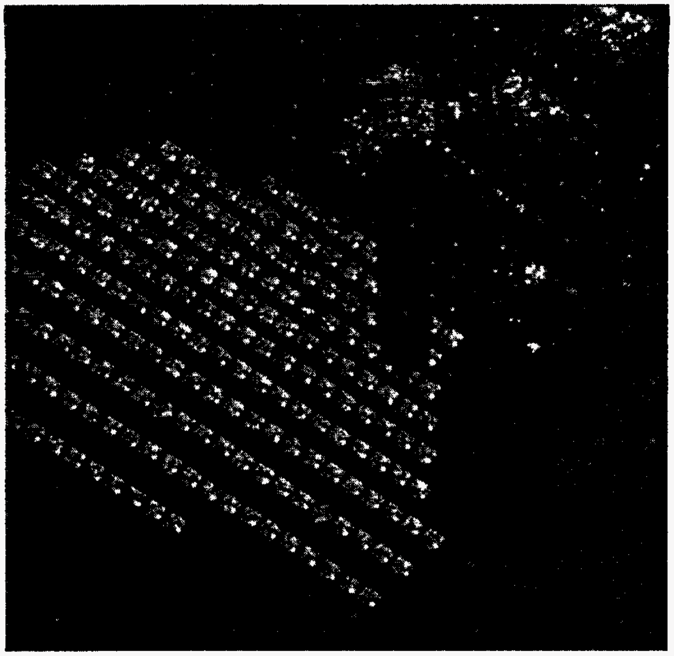

Figure 3

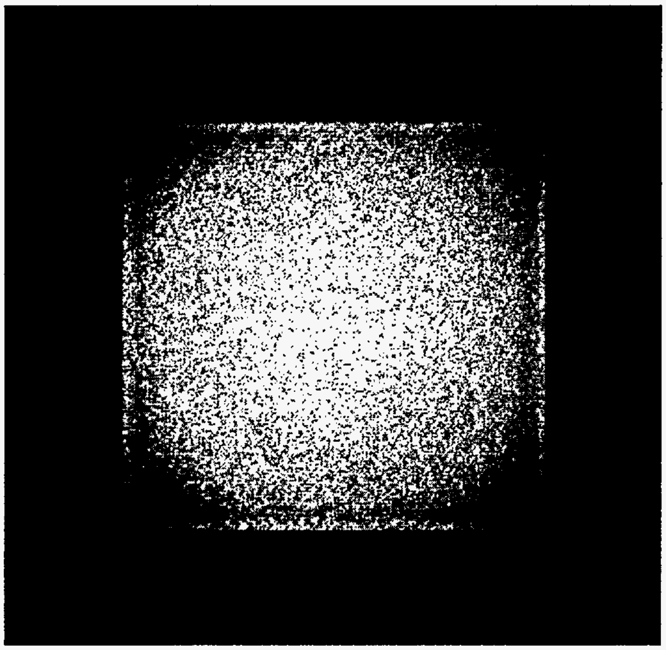

Figure 4

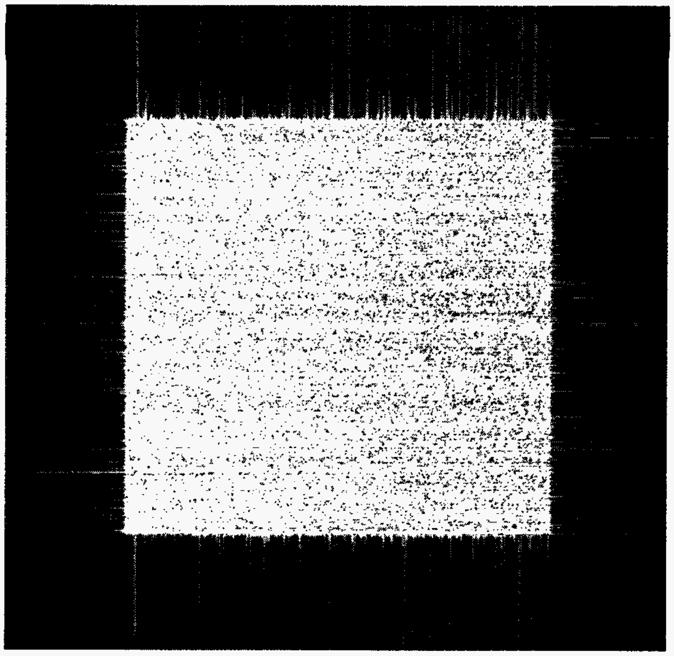

Figure 5

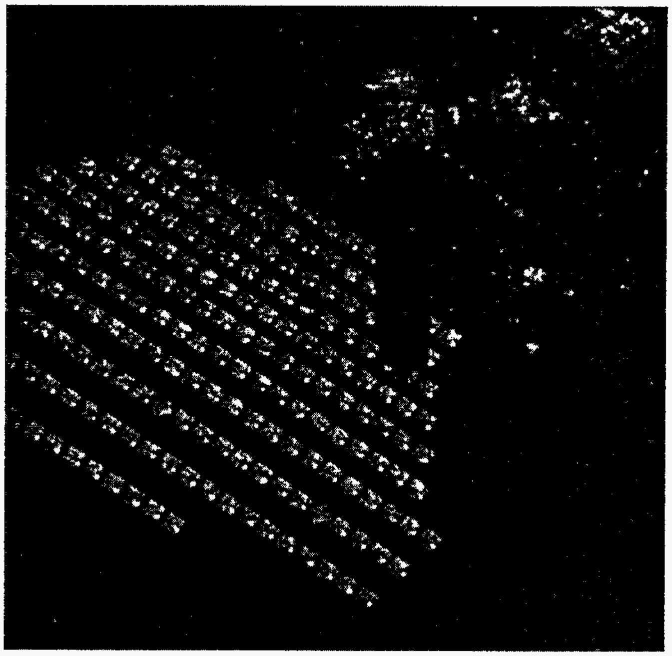

Figure 6

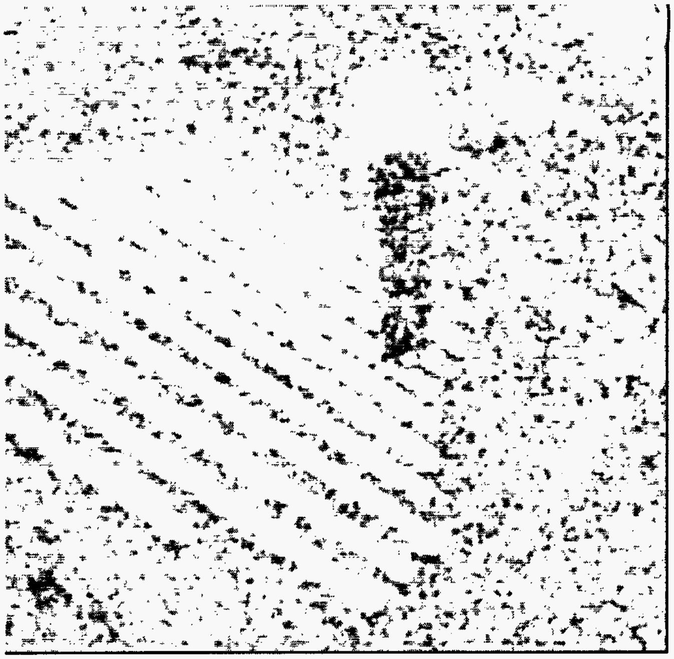

Figure 7

	Lloyd-Max Quantizer	Uniform Quantizer
I-Q	0.906	0.864
Mag-Phase	0.896	0.883

Table 1