Very low rate compression of speckled SAR imagery

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ABSTRACT

Synthetic Aperture Radars produce coherent, and speckled, high resolution images of the ground. Because modern systems can generate large amounts of imagery, there is substantial interest in applying image compression techniques to these products. In this paper, we examine the properties of speckled imagery relevant to the task of data compression. In particular, we demonstrate the advisability of compressing the speckle mean function rather than the literal image. The theory, methodology, and an example are presented.

Keywords: synthetic aperture radar, image compression, wavelets, speckle

1. SPECKLED IMAGERY

Speckled imagery arises in a number of areas of interest. For example, a synthetic aperture radar (SAR)[1] is a remote sensing system that can be used to produce a two-dimensional image of the ground. Because the system is coherent and because natural terrain is generally rough relative to the wavelengths usually employed, the resulting imagery exhibits the phenomenon of speckle[2].

Because SARs can be amazing data sources, generating many megabytes of imagery per second and in realtime, the issue of image compression is an important one to many systems. However, several characteristics of coherent, speckled images make them problematical subjects of traditional image compression techniques. These problems include the entropy of speckle, dynamic range, and the lack of inter-sample correlation. We will note at the outset that in all cases we are dealing with sampled, digital data sets.

One of the biggest obstacles to compressing speckled images is the entropy of speckle processes. Entropy is a measure of the "randomness" of a stochastic process, and the entropy of a source represents the minimum channel rate required to convey the source information without distortion[3]. A higher source entropy necessitates more bits per sample channel capacity. By this measure, coherent speckle is a fairly high entropy data source. If the object being illuminated is truly rough on the scale of the wavelength used, the reconstructed complex image samples have a first order distribution that is circular complex Gaussian[4]. Upon detection, the magnitude squared of these samples has a negative exponential distribution:

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$$p(I) = \frac{1}{2\sigma^2} e^{-I/2\sigma^2} \quad I \geq 0 \tag{1}$$

As distributions go, this represents a poor choice as far as compression is concerned, since its entropy:

$$H(I) = \int p(I) \log \frac{1}{p(I)} dI = \log(2\sigma^2 e) \tag{2}$$

is quite high. The second order statistics of speckle are no more encouraging. Compression algorithms can take advantage of high spatial correlations in imagery, but such is not the case with speckled images. In the general optical case, the power spectral density of speckle is shaped as the autocorrelation function of the pupil. In SAR imagery, the return from any two resolution cells is independent, since for rough terrain the complex scattering from one patch of ground is independent of that from any other. Although SAR images are generally produced with a small oversample ratio, for diffuse scatterers there is little practical inter-sample correlation to be exploited.

Finally, there is the question of dynamic range. Again the coherent nature of SAR images, in particular, exacerbates the situation. Although the background clutter does not exhibit a large dynamic range, *specular* returns add a very large dynamic range to the whole data set. This is because the backscatter energy for speculars is coherently summed over the aperture.

In summary, speckled coherent images, especially those produced by a SAR, possess a highly random first order intensity distribution, have very little spatial correlation between samples, and have a large dynamic range. These attributes all work against one's ability to compress the data.

2. SOME PROPERTIES OF SPECKLE

When a rough surface is illuminated by a monochromatic source, the backscattered energy consists of the superposition of returns from a great many small scattering centers. A coherent image of such a surface exhibits the highly complex interference pattern (speckle) that results from summing the impulse response functions for the many scattering centers. SAR images of natural terrain therefore demonstrate this classical speckle noise. A SAR image function is thus a sample from a stochastic process. The image pixels are random variables which have a circular complex Gaussian distribution. They are independent from *resolution cell* to *resolution cell*, but because SAR images are frequently spatially sampled at a rate somewhat in excess of the Nyquist rate, some pixel correlation exists.

The SAR image, which we will denote as $f(x, y)$, is a sample of the complex terrain reflectivity function. We are normally interested in a local estimate of the backscatter coefficient[1]:

$$\sigma^0(x, y) = \mathcal{E} \mid f(x, y) \mid^2 \tag{3}$$

where the position argument (x, y) is included making the spatial variation of the terrain backscatter explicit. The viewed image is therefore the intensity of $f(x, y)$:

$$I(x,y) = |\, f(x,y)\, |^2 \tag{4}$$

whose pixels have a probability distribution given by Equation (1). In that equation, σ^2 is the variance of the real and imaginary Gaussian distributed components. The mean of the intensity image is:

$$I_0(x,y) = \mathcal{E}I(x,y) = 2\sigma^2(x,y) \tag{5}$$

An important point to note is that, for any given image, the particular speckle pattern observed is simply one sample from the ensemble. There is no information about the terrain to be derived from this pattern. Only the *mean* of the random variables contains relevant information. Indeed, if we form another SAR image of the same terrain with a second independent aperture, the two speckle patterns will be found to be uncorrelated. This is the origin of *multi-look* processing, where several "looks" at the same terrain are averaged to reduce the speckle noise[5].

From the point of view of image compression, it would therefore be extremely wasteful to expend bandwidth in trying to capture the significant fluctuations of the speckle noise itself. Since only the *mean* of the intensities rather than the intensities themselves contain useful information, it is clear that we ought to compress that information and not the literal image. Furthermore, for much of the image content of typical scenes, the mean function is slowly varying relative to the sample rate. This implies that compressing the mean function can take advantage of inter-sample correlation, which cannot be done for the literal data.

We conclude that a complete statistical description of a speckled SAR image of a distributed scattering surface is given by the real, nonnegative 2-D function $I_0(x,y)$ and the sampling over-sample ratios in the X and Y directions. This description holds for all pixels of distributed, rough reflectors but not for specular reflectors. We are careful to point out that for certain specialized applications of SAR imagery (for example *interferometry*), the precise speckle pattern of a *single* sample from the ensemble is crucial. The particular magnitude and phase values *of the speckle* are vital to subsequent processing steps and the above arguments are therefore not valid[6].

3. PARAMETER ESTIMATION

The above considerations argue that we ought to compress not the detected intensity image with its attendent but unimportant speckle noise, but rather the speckle mean function, $I_0(x,y)$. This function will exhibit both a lower entropy and higher spatial correlation than the intensity image, while throwing away nothing of consequence.

A maximum likelihood estimator for $I_0(x,y)$ is straightforword to derive. For every pixel in the intensity image $I(x,y)$, we imagine a small 2-D neighborhood of surrounding pixels and assume that the same distribution applies to all the pixels of the neighborhood. That is, we assume that the mean, I_0, is constant over this small local region. (We will return to this assumption shortly.) With the density function for the pixels $[I_i]$ of the neighborhood given by Equation (1), (and with $I_0 = 2\sigma^2$ from Equation (5)), we form the likelihood function:

$$
\begin{aligned}
L(I_1, ..., I_n; I_0) &= \prod_{i=1}^{n} p(I_i; I_0) \\
&= \prod_{i=1}^{n} \frac{1}{I_0} e^{-I_i/I_0} \\
&= I_0^{-n} e^{-1/I_0 \sum I_i}
\end{aligned}
\tag{6}
$$

Taking the logarithm of the likelihood function,

$$
\ln L = -n \ln I_0 \; - \; \frac{1}{I_0} \sum I_i \tag{7}
$$

To find the value of I_0 that maximizes this function, we differentiate with respect to that parameter and set the derivative equal to 0:

$$
nI_0 - \sum_{i=1}^{n} I_i = 0 \tag{8}
$$

the solution of which is obviously the arithmetic mean:

$$
\hat{I}_0 = \frac{1}{n} \sum_{i=1}^{n} I_i \tag{9}
$$

This is a very advantagous result. We need only compute the average intensity value over a small (say 3X3) window that slides over the image. This speckle mean or backscatter coefficient "image" is then passed to an image compression engine where the actual data compression occurs. A higher compression ratio can be achieved on this image than on the original intensity image at a comparable level of distortion.

There is, however, one important consideration to be addressed. In deriving the above maximum likelihood estimator, we assumed that I_0 and therefore the backscatter coefficient was constant over the local neighborhood. While this assumption may hold to a degree in natural terrain, it is decidedly false in the presence of man-made specular reflectors. These targets are typically pointlike with a significantly higher, sometimes much higher, radar cross section than the surrounding terrain. If these pixels are subjected to the same averaging filter of Equation (9), the compressed / decompressed pixels will be severely suppressed. Furthermore, the very assumption that the target itself is distributed and rough relative to the wavelength of the radar is suspect in this case.

For the case of specular target pixels, then, we would rather *not* treat them as speckled and attempt to compute I_0. Instead, we merely pass these pixels straight on to the compression engine. Our means of deciding which pixels belong in this category is based on an intensity threshold. The mean and variance of the entire intensity image is computed. Since ground clutter virtually always dominates this computation, we can pick a threshold above which any intensity value is called specular. In practice, threshold values of 4 or 5 standard deviations above the mean perform well.

4. COMPRESSION METHODOLOGY AND AN EXAMPLE

Compression of speckled SAR images by this method is a four step process. First, the mean and variance of the intensity image is computed. From the mean, a scale factor is computed such that, after scaling, the range of intensity values are most suited to the compression engine. The mean and variance values are also used to compute a specular target threshold as discussed above. Next, the intensity data is multiplied by the scale factor.

Third, a small moving window is used to estimate the speckle mean function using Equation (9). For intensity values above the specular threshold, the intensity value is substituted for the speckle mean. Finally, the mean function (with occasional substitutions) is passed to an image compression engine. This compressor can take many forms. We have experimented with DPCM, JPEG, and wavelet based image compression schemes. By far, the best result is obtained with the embedded zerotree wavelet (EZW) compression scheme of Shapiro[7]. The example shown in Figure 1 was compressed using the length 2/6 biorthogonal wavelets[8] in the EZW algorithm to a compression ratio of 100:1.

Decompression is largely the inverse of compression. An image decompression engine regenerates the speckle mean function from the compressed data. Since the speckle statistics are wholely determined by the mean and the X and Y direction oversample ratios, a new sample from the speckle ensemble can be synthetically generated from the speckle mean function. That is, a random number generator with the proper density function (Equation (1)) and whose impulse response function has the proper oversampling will produce a new speckle field whose statistics, both locally and globally, are the same as that of the original image. This is an optional step, since some applications would rather output the mean function itself. Finally, the reconstructed intensity image is rescaled by the inverse of the scale factor used in compression. Note that no nonlinear companding of the data (such as log mapping) is performed. The output intensity image has the same dynamic range and linearity as the input image and the same statistics. Indeed all of the higher cross section pixels have not been affected at all except for the distortion introduced by the compression engine.

Figure 1 shows a 1m resolution SAR image of the Pentagon building in Arlington, VA with some surrounding trees, roads, bridges, and parking lots. This image was produced by the Dept. of Energy's AMPS platform during Mission 3[9]. For the purposes of display, the 60dB of dynamic range in this image has been log mapped to eight bits per pixel. After compression to a ratio of 100:1 and decompression, the output image is shown in Figure 2. That figure was also log mapped by the same mapping function as used in Figure 1. While there has certainly been information lost in the compression process, the output image bears a remarkable resemblance to the input in detail, dynamic range, and texture. This is a better result than is obtained by passing the same input image directly into the compression engine, the output of which is seen in Figure 3. Notice the substantial coding artifacts and lack of texture in this image, as compared to Figure 2.

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Figure 1: Original 1-m SAR image of Pentagon.

Figure 2: Reconstructed image of Pentagon. The original image was compressed by a ratio of 100:1.

Figure 3: Reconstructed image of Pentagon, without pre- and post- processing. Compression ratio 100:1.

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