LOSSLESS COMPRESSION OF SYNTHETIC APERTURE RADAR
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ABSTRACT

Synthetic Aperture Radar (SAR) has been proven an effective sensor in a wide variety of applications. Many of these uses require transmission and/or processing of the image data in a lossless manner. With the current state of SAR technology, the amount of data contained in a single image may be massive, whether the application requires the entire complex image or magnitude data only. In either case, some type of compression may be required to losslessly transmit this data in a given bandwidth or store it in a reasonable volume. This paper provides the results of applying several lossless compression schemes to SAR imagery.

1. INTRODUCTION

Synthetic Aperture Radar (SAR) is useful in many applications, including oil slick monitoring, terrain mapping and navigation, and automatic target recognition (ATR). Recent advances in technology have resulted in data collections over larger areas and at higher resolutions. A direct result of this is the massive increase in the *amounts* of data being collected. It is important to find ways in which the size of this data can be reduced for storage and transmission purposes. There already exist many readily available, effective techniques for image compression (e.g. JPEG). However, most of these methods are *lossy*; in the area of SAR imagery, some applications cannot tolerate any compression losses, even though the presence of clutter in an image may give the impression of noisy data. Prime examples of this type of application are SAR interferometry (e.g., 3-D terrain mapping) or simply reducing the downlink data rate from a satellite: this data is used in a

variety of research applications, making it impossible to predefine what an acceptable level of information loss would be [1]. Therefore, there is significant interest in the area of *lossless* SAR image compression.

Most lossless compression techniques follow two stages, the first being a "decorrelator" and the second being an entropy coder [2]. In many kinds of two-dimensional data, high correlation exists between neighboring data points, i.e. pixels; the decorrelator serves to produce uncorrelated data points, whose collective entropy should be less than the original data. This is usually accomplished by determining predictions of incoming data points based on past data, and forming as output "error residuals", i.e. differences between predicted and actual values. The entropy coder will then take advantage of this reduction in entropy and will perform a fully-reversible compression of the output of the decorrelator.

The data used for this research is one meter resolution SAR images collected by Sandia National Laboratory's Airborne Multisensor Pod System (AMPS) of the region near Hanford, Washington. Lossless compression techniques were applied to both real (detected/magnitude only) and complex (in-phase and quadrature) data. Both types of data were processed as some applications use only magnitude data (e.g. many ATR systems), while others require complex data.

2. METHODS FOR DECORRELATION

Many methods exist for decorrelation; most of these belong to traditional prediction methods. A few of these methods will be analyzed with respect to SAR imagery. One such method is the recursive least-squares lattice (RLSL) filter [3], which is widely used in adaptive filtering. Rather than using the RLSL for a traditional application such as channel

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equalization, it is used as a one-step predictor. This method should be useful in particular for SAR magnitude images, which have a rayleigh-shaped pixel distribution, as the RLSL is very effective at decorrelating data and providing a residue with gaussian characteristics. The latter is a simpler source model to manipulate. Similarly, a linear predictor (with fixed least-squares coefficients) [4] can be utilized to transform input image data into a residue sequence with gaussian characteristics.

Other methods proposed for lossless image compression involve the frequency domain representation of the image. In [5], the DCT was performed on image blocks, a subset of the DCT coefficients were retained, and then an error residual was formed by taking the difference between the original data block and its lossy reconstruction (formed from the retained coefficients). The DCT itself has proven useful for lossy compression of SAR imagery [6], due to its ability to compact low frequency information into a few coefficients. However, the loss of high frequency detail in lossy DCT schemes (e.g. JPEG) can lead to severe distortion [7]. Therefore, lossless schemes based on the DCT are attractive.

3. ENTROPY CODING

Entropy coding is a useful, fully-reversible method for data compression. The aim of entropy coding is to reduce the size of the input data sequence to its overall entropy, which can be thought of as a theoretical limit to the data sequence's compressibility. One of the most popular methods for entropy coding is arithmetic coding, which basically involves mapping strings of symbols to the interval of real numbers between 0 and 1. The arithmetic coding method proposed in [8] is often used due to its capability for incremental transmission and its lack of overhead in the form of a symbol frequency table. However, as the quantization of the input increases past 12 bits (often seen in SAR imagery), the internal memory requirements for this method become cumbersome. A modification has been proposed in [9] to address this issue, in which an interval frequency table is formed, rather than a symbol frequency table. Arithmetic coding has also been shown to provide near-optimal results for gaussian data [8].

Another type of entropy encoder uses variable-length codewords to reduce entropy, assigning shorter codewords to symbols which have a greater probability of occurrence. One such method under development at Sandia

National Labs for use with complex SAR imagery takes advantage of the gaussian shape of the in-phase and quadrature pixel distribution. An image's clutter standard deviation is estimated; those pixels whose values fall within a certain number of standard deviations of the mean are termed clutter, and those without are non-clutter. This models the data as a 2-state discrete memoryless source. The clutter pixels are encoded with a sufficient number of bits to meet their dynamic range, while the non-clutter pixels are transmitted as is. This method can be employed in a lossless scheme, as it was for this paper, or as a lossy technique when it is necessary to transmit man-made objects (i.e., pixel values farther from the mean) without loss, while clutter may be quantized with fewer than the number of bits necessary.

A third entropy coding technique is bi-level sequence coding, presented in [4]. This method, developed for white gaussian residue sequences, is a type of run-length code. The residue sequence is encoded into an alternating sequence of two different "levels", based on the number of bits required to represent successive consecutive runs of residue values. This should prove useful with SAR images as the vast majority of pixels in an image fall within a small range of low pixel values, which may provide long runs of the lower level.

4. SIMULATIONS

In order to see the effectiveness of different lossless compression techniques on SAR imagery, various techniques were applied to 9 image swaths (820x226 pixels) in the form of either 16-bit magnitude or 32-bit complex (in-phase and quadrature) data. The methods used were the DCT-based method described in [5] (using the arithmetic coder described in [9]), the arithmetic coder from [9] without any preprocessing, the bilevel coding scheme using a linear predictor to generate the gaussian residue sequence described in [4] as well as the linear predictor of [4] followed by the arithmetic coder of [9], the 2-state discrete memoryless source technique (lossless case) and the RLSL method described in [10] (also using the arithmetic coder described in [9]). The criteria used for comparison was the compression ratio, which is simply the size of the input file (in bytes) divided by the size of the output (compressed) file. Also included is the theoretical compression limits, calculated for magnitude data by modeling it as a rayleigh distribution with the rayleigh parameter computed empirically, and by modeling the real

and imaginary data as zero mean gaussian sources with variances computed empirically. These models are then used to compute the entropy [11]. The compression results are given in table 1 for the magnitude images and in table 2 for the complex images.

5. RESULTS AND CONCLUSIONS

Based on the simulations using magnitude data, the compression schemes using a fixed linear predictor followed by an arithmetic encoder slightly outperformed the DCT- and RLSTL-based methods. These three methods do a good job of decorrelating the data, removing more interpixel redundancy and generating a more gaussian distribution for use in the arithmetic encoder. Using a bi-level encoder as the second stage following a linear predictor could not match the compression results of using an arithmetic encoder as the second stage. The arithmetic encoder alone did not perform as well, since its input data was of a rayleigh distribution, vice a gaussian.

For complex data, the linear predictor/arithmetic coder combination also performed the best, providing a noticeable improvement even over the RLSTL-based scheme. In some cases, this scheme achieved a compression ratio slightly in excess of the estimated theoretical limit. This is attributed to both the efficiency of the predictor in generating a nearly gaussian residue and the fact that the entropy estimate is not exact. Even though the input complex images had gaussian shaped distributions, there still was some interpixel redundancy, evident when viewing both the in-phase and quadrature image (some contours and objects are discernible). The RLSTL and linear predictor were both still able to do a good job of decorrelating the input data. The method which models the data as a 2-state DMS did relatively poorly, as this method is not optimized for a completely lossless scheme, but one where only the objects which provide the largest (absolute) valued returns (considered man-made targets) must be transmitted/stored as lossless. The arithmetic encoder alone performed reasonably, as expected with a gaussian input distribution, with the bi-level coding scheme providing comparable results. The DCT-based method did not work as well on complex data as it did on the corresponding magnitude data.

The performance of many compression schemes may depend greatly on the characteristics of the data which is input; some schemes may prove more useful than others for urban SAR scenes, while others may provide better

compression for rural scenes. A similar dependence may hold for the input format: magnitude or complex data. The images tested in this research represented both rural and urban areas, and both magnitude and complex data were tested. In all cases, one of the tested methods provided the best results. Overall then, the method of choice (of those applied) for lossless compression of the tested SAR images is a 2-stage method, using a fixed linear predictor as the first stage to decorrelate the data followed by an arithmetic encoder to entropy encode the residue.

Future work includes testing a 2-D adaptive filter in the 2-stage compression scheme. This as well as other 2-D filters should improve the decorrelation.

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LOSSLESS COMPRESSION RESULTS

Image	Arith. (only)	LP/ Bilevel	DCT/ Arith	RSL/ Arith	LP/ Arith	Theor. Limit
P1-51	1.64	1.72	1.77	1.76	1.86	2.00
P1-52	1.81	1.89	2.00	2.01	2.04	2.13
P1-53	1.87	1.98	2.12	2.09	2.15	2.23
P1-54	1.91	2.03	2.17	2.16	2.19	2.26
P1-55	1.89	2.00	2.14	2.14	2.16	2.24
P1-56	1.91	2.02	2.17	2.17	2.19	2.26
P1-57	1.87	1.97	2.10	2.11	2.12	2.21
P1-58	1.88	1.99	2.12	2.12	2.15	2.23
P1-59	1.92	2.02	2.16	2.15	2.18	2.27

Table 1: Compression Ratios for Magnitude Images

Image	2-State DMS	DCT/ Arith	Arith. (only)	LP/ Bilevel	RSL/ Arith	LP/ Arith	Theor. Limit
P1-51	1.68	1.62	1.71	1.74	1.79	1.92	1.87
P1-52	1.70	1.79	1.88	1.89	2.00	2.07	2.05
P1-53	1.88	1.93	1.98	1.97	2.09	2.16	2.13
P1-54	1.91	1.96	2.03	2.00	2.13	2.19	2.19
P1-55	1.89	1.94	2.01	1.98	2.12	2.18	2.17
P1-56	1.91	1.96	2.04	2.00	2.14	2.19	2.19
P1-57	1.86	1.91	1.98	1.97	2.09	2.15	2.14
P1-58	1.88	1.93	1.99	1.97	2.10	2.17	2.16
P1-59	1.91	1.97	2.04	2.00	2.14	2.20	2.20

Table 2: Compression Ratios for Complex Images

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