Application of Pixel Segmentation to the Low Rate Compression of Complex SAR Imagery

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ABSTRACT

This paper describes a technique to identify pixels within a subregion ("chip") of a complex or detected SAR image which are to be losslessly compressed while the remainder of the image is subjected to a high compression ratio. This *multi-modal* compression is required for the *intelligent* low rate compression of SAR imagery, which addresses the problem of transmitting massive amounts of high resolution complex SAR data from a remote airborne sensor to a ground station for exploitation by an automatic target recognition (ATR) system, in a real time environment, over a narrow bandwidth. The ATR system results might then be presented to an image analyst who, using the contextual information from the SAR image, makes final target determination.

1. INTRODUCTION

The term *multi-modal* compression refers to compression performed which is a combination of lossless and lossy techniques. This problem is currently under study at Sandia National Laboratories in a Defense Advanced Research Projects Agency (DARPA) funded project called "Intelligent Bandwidth Compression" (IBC) [1]-[3]. At the ratios desired, the compression can be achieved by applying one of several existing lossy techniques to the entire image: however, at such high ratios (and possibly even at low compression ratios), an intolerable amount of vital information can be lost and/or unacceptable coding artifacts introduced. These two effects may severely degrade the ATR system's performance, not to mention the perceptual quality of the image from the analyst's perspective.

The term "intelligent" is utilized to signify the presence of an external cuer to designate regions of interest ("chips" of size 32x32 for one meter resolution imagery) within the SAR scene. The use of this cuer allows division of the image into two segments, "background" and "target", which are subjected to different compression algorithms. The constraints imposed by the problem under consideration demand a background compression on the order of 100:1, chip compression on the order of 7:1, and a chip rate not to exceed approximately 67 chips per million pixels. The chips could individually be processed losslessly using one of the methods in [3], achieving a compression ratio on the order of 2:1. However, for the overall compression ratio required in this scenario, this is not sufficient. Therefore, the chips must be compressed with some loss overall: either (1) only a certain percentage of the pixels on the chip are transmitted losslessly ("pixel segmentation") or (2) the entire chip is compressed with minimal acceptable loss. The latter technique is described in [3]: the method of pixels segmentation is presented herein.

Here "target" implies a group of pixels within a chip, while "background" is the entire image as a whole. The targets are compressed losslessly with an arithmetic coder [4], while the background is significantly compressed using a wavelet coder. The use of a cuer with these two distinct modes of compression allows high fidelity coding where it is needed, and very low rate coding where it is not needed, yielding low overall rate while maintaining high quality on regions of interest.

2. PIXEL SEGMENTATION

Given an external cuer, specific chips have been designated as possible targets in the SAR image. It is the man-made objects (specular targets) which generally give the largest magnitude returns to the radar. Accordingly, for an ATR system which attempts to locate and identify man-made objects (such as buildings or vehicles), collections of large magnitude pixels within this chip would tend to belong to the possible target. A simplistic approach to locating target pixels would then be to find the largest magnitude pixels, the number of pixels which may be designated as target pixels dependent on the number of chips and the required compression ratio. These pixel values will be transmitted losslessy, along with a compressed bit map

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of the entire image to keep track of their locations. Note that such a bit map, with small patches of ones in chip locations and zeros over the vast majority is well suited for compression by the modified CCITT run-length coding [5]. Simply using the largest magnitude pixels, however does not take advantage of the correlation which exists between pixels on a target, and may call out large-valued clutter as target pixels, wasting bandwidth.

A better method of pixel segmentation would measure the correlation between pixels on the chip, then preserve those pixel values corresponding to the highest correlation. This has been achieved with both the two-dimensional adaptive correlation enhancer (2DACE) [6] and using two-dimensional higher order statistics based enhancement (2DHOSE) [7]. Both algorithms are described in what follows. The input to each of these will be detected chips.

2-Dimensional Adaptive Correlation Enhancer (2DACE)

The 2DACE provides a recursive estimate of spatial correlation within a chip. For each pixel within the input chip, the correlation coefficients, $w(l,k)$, are computed within a local neighborhood. The correlation coefficients update equation is given by:

$$w(l,k) = \beta \cdot w(l,k) + \frac{(1-\beta)\cdot X(m+1-L, n+k-L)\cdot x(m,n)}{2\cdot L^2 \cdot P(m,n)} \quad (1)$$

where β is the convergence factor (range 0.0 to 1.0), L is the maximum lag value, w is the weight matrix (kernal) of size $2L+1$ by $2L+1$, l is the kernal row index, ranging from 0 to $2L$, k is the kernal column index, ranging from 0 to $2L$, m is the row index in the input chip, n is the column index in the input chip, x is the input chip, and X is a neighborhood about x of size $2L+1$ by $2L+1$. $P(m,n)$ is a recursively defined power estimate of the input chip at row m and column n. Its update equation is given by:

$$P_{new}(m,n) = \beta_v \cdot P_{old}(m,n) + (1-\beta_v)\cdot x^2(m,n) \quad (2)$$

where β_v is a variance update factor. Equation (1) represents a recursive estimator which uses an exponentially damped window in a neighborhood about each pixel location. With β as a spatial convergence factor, it has an approximate spatial recall memory of $1/(1-\beta)$. Making the spatial correlation factor too close to 0.0 or too close to 1.0 tends to reduce estimate reliability. For each pixel in the input image, once the correlation estimates within its neighborhood has been computed, the local measure of correlation at that location is obtained by squaring and summing all of the $w(l,k)$ within the neighborhood. For this research, the parameter values which provided best results were with lag value $L=2$ (a 5x5 neighborhood size) and spatial convergence factor $\beta=0.4$. Computations were performed without scaling. The output of the 2DACE is a correlation "map" from which a given number of pixels with the highest correlation values may be identified.

2-Dimensional Higher Order Statistics Based Enhancement (2DHOSE)

The 2DHOSE outputs an enhanced version of its input based on higher order cumulants. The algorithm has a similar structure to the 2DACE, but the coefficient updates are based on a computation of third and fourth order moments. The update is given as:

$$w(l,k) = \beta \cdot w(l,k) + \frac{(1-\beta)\cdot X(m+1-L, n+k-L)}{2\cdot L^2} \cdot \left(\frac{x(m,n)\left[x^2(m,n) - 3\cdot P(m,n)\right]}{\left[\gamma(m,n) - 3P^2(m,n)\right]}\right) \quad (3)$$

with all variables defined as in the 2DACE update equation, except that

$$P_{new}(m,n) = \alpha \cdot P_{old}(m,n) + (1-\alpha)\cdot x^2(m,n) \quad (4)$$

where α is an update parameter for the HOSE equations and $\gamma(m,n)$ is the recursively defined fourth order moment value for the pixel located in row m and column n. The recursive update for $\gamma(m,n)$ is given by:

$$\gamma_{new}(m,n) = \alpha \cdot \gamma_{old}(m,n) + (1-\alpha)\cdot x^4(m,n) \quad (5)$$

In equation (3), the denominator, if required, is used to scale the input to control dynamic range of the output. If not needed, the denominator is set to unity. Again, for this research, the spatial convergence factor was set to 0.4 and a 5x5 neighborhood was used, without scaling.

As with the 2DACE, the 2DHOSE will output a "map" from which a given number of pixels with the largest values are identified as "targets".

3. BACKGROUND COMPRESSION

In the IBC program, the background is subjected to a high rate of compression using Shapiro's embedded zerotree wavelet compression scheme [8]. This compression is

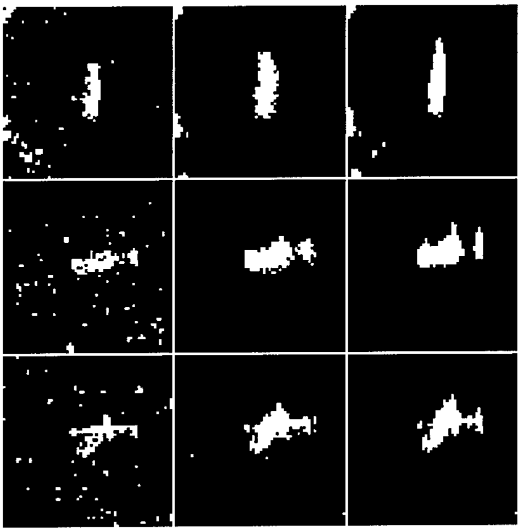


Figure 1: Location of 200 Target Pixels w/in 3 Tactical Vehicles using Largest Magnitude (left), 2DACE (middle) and 2DHOSE (right).

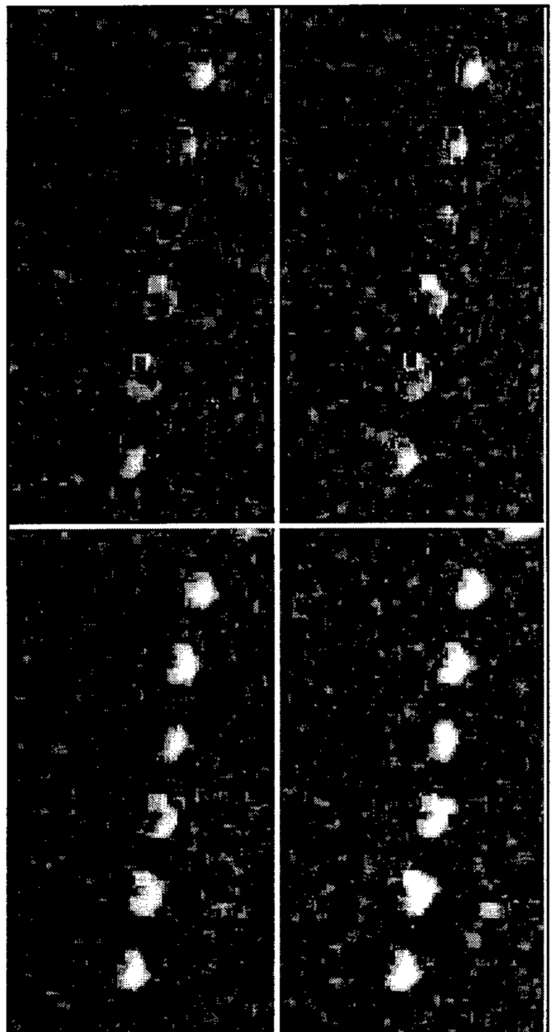
carried out in such a way that the statistics of the speckle is accurately carried in the compressed data stream and the final complex (or detected) image may be respeckled and targets reinserted seamlessly [2]-[3].

4. RESULTS AND CONCLUSIONS

Fig. 1 demonstrates the performance of each type of pixel segmentation on three actual target vehicles. For each vehicle, the figure shows a bit map representing the 200 pixels (in white) from the 64x64 chip whose values would be transmitted losslessy using each method of pixel segmentation. Using the 2DACE or 2DHOSE gives similar performance in terms of locating pixels on target, while the largest-magnitude pixels approach tends to preserve too many high-valued speckle pixels. The 2DACE is currently the segmenter in the IBC project, due to its lower complexity than the 2DHOSE albeit with similar performance.

A measure of image quality is given by the complex correlation coefficient, computed in small neighborhoods (5x5 in this case) about each pixel as [9]:

$$c(x,y)=\frac{\left|\sum_i\sum_j f(i,j)\cdot g^*(i,j)\right|}{\sqrt{\sum_i\sum_j\left\|f(i,j)\right\|^2\cdot\sum_i\sum_j\left\|g(i,j)\right\|^2}}. \qquad (6)$$



Number of Target Pixels/Chip: From Top Left (Clockwise): 50; 100; 200; 300

Figure 2: Complex Correlation Maps with Various Numbers of Pixels

In equation (6) f and g are the original and decompressed images respectively and the summations are computed in the local neighborhood about each location (x,y). Correlation values fall in the range [0.0,1.0] with perfect correlation (a value of 1.0) indicating that all pixels within the neighborhood are equal in the original and decompressed image. Fig. 2 shows the effects of varying the number of pixels/chip designated as targets. This figure is a series of complex correlation maps between an original and decompressed tactical image processed with the IBC system using the 2DACE pixel segmentation on the target chips.

In Fig. 2, obviously as the number of pixels which are segmented as targets increases, the target vehicles become more "filled in" and the quality of the correlation increases. Improved correlation does come however at a cost in compression ratio: more pixels on each target chip means that fewer chips may be processed. The balance depends on the compression effects on the downstream ATR system: the IBC system allows approximately 150-200 pixels/chip depending on resolution.

Fig. 3 is an example of an IBC compression product. This image of the Pentagon was collected with the Sandia SAR system carried onboard the U.S. Department of Energy's Airborne Multisensor Pod System (AMPS). For this example, six random locations were labeled as chips. This figure shows the seamless integration of the targets into the highly compressed background: Fig. 4 shows the actual chip locations. Overall, the IBC system provides a high quality output at low overall bit rate, and pixel segmentation has proven useful in identifying target pixels.

Figure 3: Original Pentagon Image (top) and IBC Decompressed (bottom)

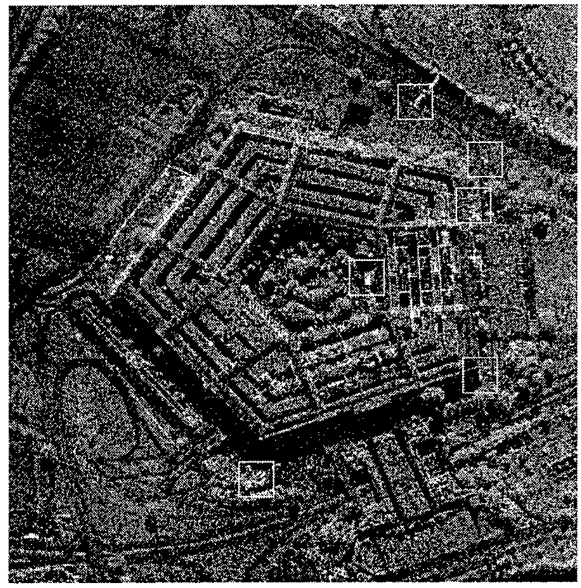


Figure 4: Locations of 6 Chips in Pentagon Image

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