Literature Survey
on

Synthetic Aperture Radar (SAR) Image Compression

Güner Arslan and Magesh Valliappan

EE381K

Multidimensional Signal Processing

Prof. Brian Evans

October 1998

1 Introduction

Synthetic Aperture Radar (SAR) is an active remote sensing system which has applications in agriculture, ecology, geology, oceanography, hydrology, military, etc. [1]. SAR systems are mounted on an airplane or satellite which moves in a particular direction with a particular speed. The movement of the airplane or satellite is used to increase the aperture of the SAR system. The main reason which gives SAR systems such diverse applications is that it has the ability to take images in all weather conditions and darkness.

With the improvement of SAR technology larger areas are being imaged and the resolution of the images has increased. This causes larger images to be transmitted and stored. Due to the limited storage and/or down-link capacity on the airplane or satellite the data rate must be reduced. The data rate is proportional to the pulse repetition frequency (PRF), number of samples taken in each echo and the number of quantization bits.

It is possible to reduce data rate by changing these parameters but this decreases the system performance. For example reducing the PRF causes higher azimuth ambiguities, reducing the bandwidth of the system decreases the range resolution and decreasing the the number of quantization bits increases digitization noise [2].

The only remaining choice is to compress the SAR image. SAR data is inherently complex but it is frequently converted to real data for interpretation by human observers or machine algorithms [3]. However, for interferometric purpose the phase information is very important and needs to be preserved accurately.

In order to compress complex data two approaches can be used, the first is to compress magnitude and phase separately. In the second approach, the frequency spectrum of the image is shifted to all positive frequencies. After the inverse Fourier transform, the real part of the complex data carries both phase and magnitude information of the original complex image. This real data can be compressed as usual and after decompression an inverse procedure can be used to get the complex image back [4].

SAR images are different in nature from optical images. The differences can be summarized as follows,

- SAR images are larger in volume. SAR images typically consist of 32 bit complex pixels with large dimensions.

- The entropy of SAR images is higher than that of optical images [4].
- SAR images carry information in low frequency bands as well as high frequency bands. Whereas optical images are generally low-pass with noise in high frequency regions [4].
- SAR images have larger dynamic range than optical images.

Due to these differences, classical image compression techniques do not performance as well when applied to SAR images. More appropriate approaches which take into account these differences, have to be used for SAR image compression. The high entropy and large dynamic range of SAR images result in very low compression ratios when lossless compression techniques are used [1]. Thus if a small amount of information loss is acceptable, lossy compression techniques can be used.

Since some of the information is lost, it is important to decide which feature of the image should be preserved. These features can be one of the following [3],

- Certain pixels of point targets,
- Edges,
- Areas or regions of common texture.

In Section 2 we summarize some lossy image compression techniques applied to SAR images. In section 3 we summarize some commonly used as well as a recently proposed performance measure for SAR image compression. The last section presents the aim of this project.

2 Lossy SAR Image Compression Techniques

In this section we summarize Discrete Cosine transform (DCT), Discrete Wavelet Transform (DWT) and Vector Quantization (VQ) based SAR image compression techniques.

2.1 DCT based SAR Image Compression

DCT is an orthogonal transform which is used widely in optical image compression for its computational efficiency and its energy compaction property. The idea behind orthogonal transforms is to transform the image to new domain where the image is represented ideally by uncorrelated coefficients of which very few carry significant energy and the remaining ones can be quantized to zero.

There are many different forms of the DCT, one of the widely used forms is,

$$C(u,v) = \alpha(u)\alpha(v)\sum_{n=0}^{N-1}\sum_{m=0}^{M-1} x[n,m]cos\left(\frac{(2n+1)u\pi}{2N}\right)cos\left(\frac{(2m+1)v\pi}{2M}\right)$$

and

$$x(n,m) = \sum_{n=0}^{N-1}\sum_{m=0}^{M-1} \alpha(u)\alpha(v)C[u,v]cos\left(\frac{(2n+1)u\pi}{2N}\right)cos\left(\frac{(2m+1)v\pi}{2M}\right)$$

where

$$\alpha(i) = \begin{cases} \sqrt{1/N} & for \quad i = 0 \\ \sqrt{2/N} & for \quad i = 1, 2, ...N-1 \end{cases}$$

DCT is reported as not appropriate for SAR images due to the presence of speckle noise, high entropy, large dynamic range in DCT domain, important information in high frequency and blocking artifacts in SAR images [5][6].

2.2 DWT Based SAR Image Compression

One dimensional DWT can be described as a filter bank followed by a downsampling procedure as shown in Figure 1. This can be extended to the two dimensional case. In Figure 1 h_0 and h_1 are analysis and g_0 and g_1 are sythesis filters respectively. These filters are generally chosen as perfect reconstruction quadrature mirror filters (PR-QMF) [3][7][8]. The advantages of using

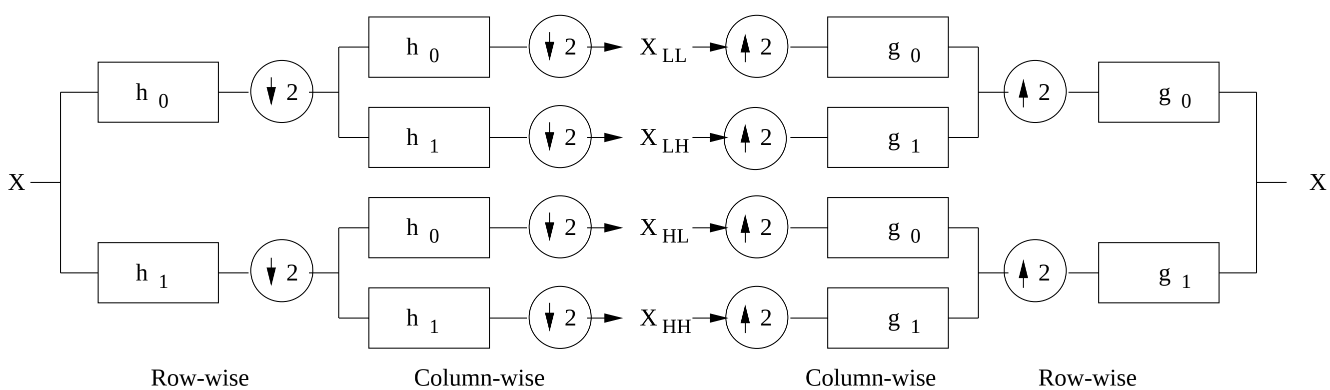

Figure 1: 2-D filter bank implementation of DWT

DWT can be summarized as follows [3],

- DWT allows the allocation of quantization bits to important components both in frequency and time domains.
- Subbands have less dynamic range than the original image.
- Subbands can be used for preview type operations.
- For applications where despeckling is required wavelet based techniques offer built in despeckling [5][8].

2.3 VQ based SAR image compression

Quantization was one of the first approaches to SAR image compression because of its simplicity. The basic idea is to divide the image into small subimages such that the dynamic range of this subimage is small compared to the whole image and quantize the pixels to a lesser number of bits. In addition to the quantized bits the mean value of the subimage needs to be transmitted.

Vector quantization (VQ) is a technique that applies better performance than scalar quantization. VQ based algorithms have been proposed for SAR image compression [2][9]. The first step in VQ based coding is to produce a codebook. This can be done by using clustering algorithms such as k-means and "Linde, Buzo and Gray" (LGB) algorithms. A codebook can be produced using empirical data [2]. After dividing the image into subimages each subimage is compared with the codebook and the code for the nearest subimage is transmitted.

An adaptive VQ based technique called Mixture of Principle Components has also been proposed [9]. In this technique the computational load in the encoder is very high. However the decoder outperforms DCT based methods in terms of both image quality and computational load.

3 Performance Measures

Many different performance measures can be used to compare image compression techniques. When real time operation is crucial as in SAR image compression the computational load is one of the performance measures. Since the aim of image compression is to reduce the number

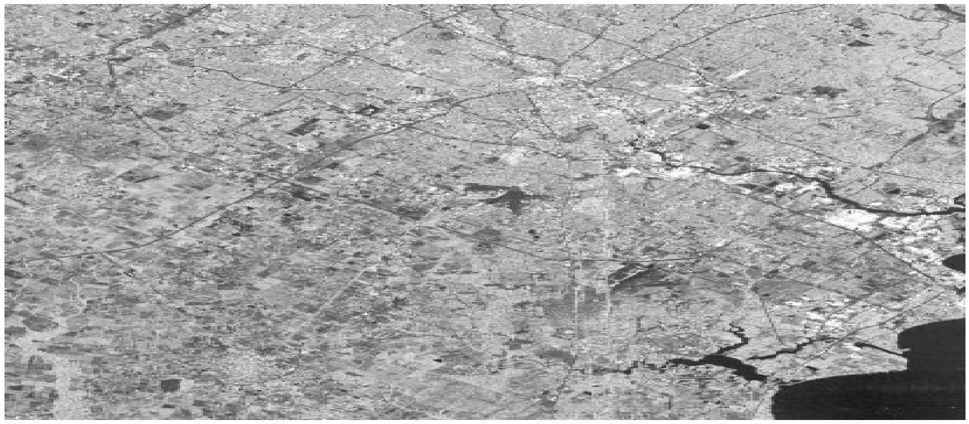

Figure 2: SAR image of Houston from JPL, Pasadena

of bits required to represent a image without visually destroying it, a measure of image quality for a fixed compression ratio is required.

3.1 Commonly used Quality Measures

Although the following performance measures are most commonly used in image processing applications they are not very compliant with subjective quality. Since all of them are global measures they cannot judge local variations of the processed image [4]. Due to the different nature of SAR imgaes, these measures are less useful. For example, consider a compression method (like a DWT based method) which also removes speckle noise. These measures treat the removed noise as error. If a compression technique removes all roads from an image such as in Figure 2, the number of changed pixels is not very high so these measure do not rate this particular technique as poor inspite of a lot of information being lost.

3.1.1 Mean Square Error (MSE)

The mean square error is one of the most commonly used performance measures in image and signal processing. For an image of size $N \times M$ it can be defined as

$$\text{MSE} = \frac{1}{NM} \sum_{n=0}^{N-1} \sum_{m=0}^{M-1} |x[n,m] - \hat{x}[n,m]|^2$$

where $x[n,m]$ is the original image and $\hat{x}[n,m]$ is the decompressed image.

3.1.2 Normalized MSE (NMSE)

MSE is normalized with the variance of the original signal to give NMSE,

$$\text{NMSE} = \frac{\sum_{n=0}^{N-1}\sum_{m=0}^{M-1}|x[n,m]-\hat{x}[m,n]|^2}{\sum_{n=0}^{N-1}\sum_{m=0}^{M-1}|x[n,m]|^2}$$

3.1.3 Signal to Noise Ratio (SNR)

SNR can be defined as

$$\text{SNR} = 10\log_{10}\frac{1}{\text{NMSE}}$$

3.1.4 Peak Signal to noise ratio (PSNR)

PSNR is the most commonly used performance measure for image processing applications. It can be defined as,

$$\text{PSNR} = 10\log_{10}\frac{(\text{ peak-to-peak value of the original image })^2}{\text{MSE}}$$

3.2 Alternative Quality Measures

Since standard measures are not appropriate for SAR images, alternative measures have recently been proposed.

3.2.1 Average Spatial Correlation (ASC)

This quality measure is proposed to decouple the speckle degradation in the original image from the quality assessment of the compression process. ASC is obtained by calculating the spatial correlation of the original and decompressed image on a window (of size 5 for example) around each pixel using

$$c(i,j) = \frac{\sum_n\sum_m y[n,m]\hat{y}[n,m]}{\sqrt{\sum_n\sum_m y^2[n,m]\sum_n\sum_m \hat{y}^2[n,m]}}$$

where $y[n,m]$ is the original image with DC removed and $\hat{y}[n,m]$ is the decompressed image with DC removed.

Then the ASC is defined as

$$\text{ASC} = \frac{1}{NM}\sum_i\sum_j c(i,j)$$

3.2.2 Weighted SNR (WSNR)

Since SAR images are interpreted by humans an important performance measure is the visual quality of the decompressed image. Although the human visual system is a non-linear, shift-variant, non-separable, non-uniform sampled system, aproximate linear models have been proposed. To obtain a quality measure which is correlated with the visual quality of the image the weighted SNR has been proposed as follows,

$$\text{WSNR} \quad = 10\log_{10}\left(\frac{\sum_u\sum_v |X(u,v)C(u,v)|^2}{\sum_u\sum_v |(X(u,v)-\hat{X}(u,v))C(u,v)|^2}\right)$$

where $X(u,v), \hat{X}(u,v)$ and $C(u,v)$ are the discrete Fourier transforms of the original image, decompressed image and the contrast sensitivity function respectiveley [10].

4 Future Work

In this project we are going to compare DCT and DWT based techniques using the performance criterias listed in previous section. Since standard performance measures described in previous section assume additive and uncorrelated noise a preprocessing step is necessary before calculating the MSE, SNR or PSNR. For example the blocking effect in DCT and the mosquito noise in DWT cannot be accepted as uncorrelated additive noise thus a different approach is required to measure these effects. Although SAR images are mostly assessed by humans, standard quality measures do not use any known properties of the the human visual system. For example, the human visual system is not as sensitive to high frequencies as low frequencies, but standard measures give equal importance to all frequencies. Our aim in this project is to simulate the best performance (according to standard measures which have been used in literature) giving DCT and DWT based techniques and compare their performance with more appropriate quality measures such as WSNR.

References

[1] R. W. Ives, *On the Compression of Synthetic Aperture Radar Imagery.* PhD thesis, Dept. of Electrical and Computer Engineering, The University of New Mexico, Albuquerque, New Mexico, May 1998.

[2] U. Benz, K. Strodl, and A. Moriera, “Comparison of several algorithms for SAR raw data compression,” *IEEE Trans. Geoscience and Remote Sensing*, vol. 33, pp. 1266–1276, Sep. 1995.

[3] A. S. Werness, C. Susan, C. Wei, and R. Carpinella, “Experiments with wavelets for compression of SAR data,” *IEEE Trans. Geoscience and Remote Sensing*, vol. 32, pp. 197–201, Jan. 1994.

[4] M. Brandfass, W. Coester, U. Benz, and A. Moreira, “Wavelet based approaches for efficient compression of complex sar image data,” in *Int. Geoscience and Remote Sensing Symposium*, vol. 4, (Singapure, Singapure), pp. 2024–2027, Aug. 1997.

[5] M. Datcu, G. Schwarz, K. Schmidt, and C. Reck, “Quality evaluation of compressed optical and SAR images: JPEG vs. wavelets,” in *Int. Geoscience and Remote Sensing Symposium*, vol. 3, (Richmond, BC, Canada), pp. 1678–1689, Jul. 1995.

[6] G. Staples, S. Rossignol, W. Stevens, and T. Stein, “Data compression effects on SAR image compression,” in *Int. Geoscience and Remote Sensing Symposium*, vol. 3, (Richmond, BC, Canada), pp. 1678–1680, Jul. 1995.

[7] F. Sakarya and S. Emek, “SAR image compression,” in *Proc. Asilomar Conf. Signals, Systems, and Comp.*, vol. 2, pp. 858–862, Nov. 1996.

[8] D. Wei, J. Odegard, H. Gue, M. Land, and C. Burrus, “Simultaneous noise reduction and SAR image data compression using best wavelet packet basis,” in *Proc. IEEE Int. Conf. Image Proc.*, vol. 3, (Washington, D.C.), pp. 200–203, Oct. 1995.

[9] R. D. Dony and S. Haykin, “Compression of SAR images using KLT, VQ and mixture of principal components,” *IEE Proc. Radar, Sonar Navig.*, vol. 144, pp. 113–120, Jun. 1997.

[10] T. Kite, *Design and Quality Assesment of Forward and Inverse Error Diffusion Halftoning Algortihms*. PhD thesis, The University of Texas at Austin, Austin, Texas, Aug. 1998.