WAVELET TRANSFORM BASED COMPRESSION TECHNIQUES FOR RAW SAR DATA

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Abstract

Synthetic aperture radar (SAR) is a sophisticated technique of all-weather radar imaging capable of producing fine detailed images from a moving platform. When such a radar is placed on-board a satellite, compression of the raw SAR signal is necessary to reduce the large amount of collected data for downlink to a ground station within the bandwidth constraints. In this paper we present a transform-based compression system using Haar wavelet, the Battle-Lemarié wavelets (linear and quadratic) and Daubechies wavelets (D-4 and D-20). The transformed data are then quantized using a bit allocation strategy. We take advantage from the multiresolution analysis to use different quantizers in each frequency band of wavelet coefficients. Since the wavelets considered here form orthonormal bases, the reconstruction is guaranteed in each case. Experimental results point out advantages and drawbacks of this approach.

Keywords: *raw SAR data, compression, Haar wavelet, Battle-Lemarié wavelets, Daubechies wavelets.*

1. INTRODUCTION

The *synthetic aperture radar* (SAR) image generation process can be broken up into three basic stages, as shown in Fig. 1. The stages are: (i) sensing of the area target using the imaging radar, (ii) digitalization and compression of the reflected SAR signal for downlink to a ground station, and (iii) processing of the reconstructed SAR signal into image data. This paper focuses on compressing the digitized reflected SAR signal for transmission from a satellite down to a ground station. This digitized reflected SAR signal is known as raw SAR data.

The most widely recognized method of raw SAR data compression is the *block adaptive quantization* (BAQ) [7]. BAQ uses a scalar quantizer controlled by the statistics of the raw SAR data to quantize these data with fewer bits. In order to increase the performance, BAQ combined with other techniques such as vector quantization and trellis-coded quantization, have been proposed in [2].

This work is motivated by our interest in compression algorithms for Radarsat II and III, and their implementations in hardware. In the following section we present a brief introduction to SAR and the SAR signal characteristics. Section 3 discusses the wavelet decomposition and reconstruction algorithms. Bit allocation algorithms and quantization methods are presented in Section 4. Section 5 is devoted to experiments and results.

2. SYNTHETIC APERTURE RADAR

Synthetic aperture radar is a sophisticated remote sensing tool that is capable of providing high resolution images from a moving platform. In imaging radars like SAR, the length of the radar antenna determines the resolution in the azimuth (along-track) direction of the resulting image, thus the longer the antenna, the finer the resolution in this dimension. As it is prohibitively expensive to place a very large radar antenna in space, an alternative approach is to synthesize the aperture.

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In SAR, the radar sends out many pulses very rapidly as it travels over a particular object, and captures the backscattered responses. The ability of the radar antenna to receive many backscattered responses per object, as it moves along its flight track, allows the radar to synthesize a very long antenna. Each echo of the illuminated area can, therefore, be considered as a convolution of the complex ground reflectivities where the received signal can be modelled as

$$S = \sum_{k=1}^{N} a_k e^{j\phi_k} \tag{1}$$

where a_k is the reflectance amplitude, ϕ_k is the phase delay, and the sum is over all elementary phasor contributions, N.

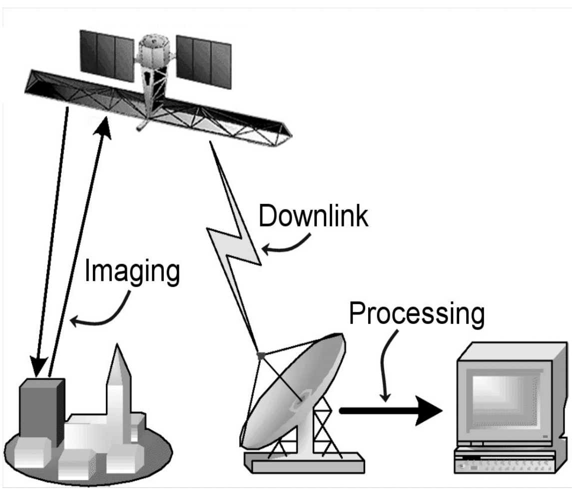


Fig. 1. Basic SAR image generation process.

In communications theory, the independence between the a_k and ϕ_k is assumed, and they are supposed to be uniformly distributed [3]. Thus, according to the central limit theorem, the received SAR signal is a continuous random signal with Gaussian distribution.

This received SAR signal is typically digitized on board the radar into raw SAR data for archiving or transmission. As a high resolution radar can produce hundreds of megabits of data per second, compression of these data is mandatory for transmission from space to a processing station in the available downlink bandwidth.

Since it can be shown that adjacent samples in range and azimuth have low correlation [7], the received signal can be modeled as a complex random process, where its real and imaginary parts are quasi-independent with the same distribution which is a zero mean Gaussian with identical variance. The signal's phase has a uniform distribution while the magnitude is Rayleigh. Another important characteristic which is fundamental in determining the type of compression to be used, is the low variation of the signal power.

The raw SAR signal poses many compression challenges due to its noise like characteristics and high entropy [4]. The raw SAR signal is often compared to noise because signals added incoherently, with random phase, sum in amplitude like a random walk. This makes conventional image compression techniques ill suited to SAR applications. An analysis of raw SAR signal data done by Curlander and McDonough [4] on a NASA DC-8 airborne SAR system shows that the zero-order entropy is 6 to 7 bits per sample. Therefore, if 8-bit quantization is used in the digitalization of the received SAR signal, the maximum achievable compression factor is 1.3. Then a lossy compression is necessary.

3. WAVELET TRANSFORM

We will represent a particular two-dimensional signal by $I(x, y)$ at every point (x, y) in the screen. For normalization convenience, we will work over the global contrast $C(x, y) = I(x, y) - I$ where I is the average over the screen. This is very convenient as wavelets have zero-mean for mathematical reasons [5] and we want to express C as a combination of wavelets.

We consider here a separable two-dimensional dyadic wavelet expansion. Thus, for a given (one-dimensional) *multiresolution analysis* (MRA) determined by a scaling function φ and the associated wavelet ψ, the corresponding 2-dimensional MRA is determined by the scaling function Φ and the three mother wavelets Ψ^0, Ψ^1, Ψ^2 given by [11]

$$\begin{cases} \Phi(x, y) = \varphi(x)\varphi(y) \\ \Psi^0(x, y) = \varphi(x)\psi(y) \\ \Psi^1(x, y) = \psi(x)\varphi(y) \\ \Psi^2(x, y) = \psi(x)\psi(y) \end{cases} \tag{2}$$

The horizontal, vertical and diagonal details, at resolution j are obtained as the inner product of the signal C and a shifted and dilated version of $\Psi^i, i = 0, 1, 2$ respectively, i.e.,

$$\alpha^i_{j,k,m} = \langle C, \Psi^i_{j,k,m} \rangle, \text{ for } i = 0, 1, 2 \tag{3}$$

and the approximation of the signal, at resolution j, is given by

$$\beta_{j,k,m} = \langle C, \Phi_{j,k,m} \rangle \tag{4}$$

where

$$\Phi_{j,k,m}(x,y) = 2^j \Phi(2^j x - k, 2^j y - m) \tag{5}$$

and

$$\Psi^i_{j,k,m}(x,y) = 2^j \Psi^i(2^j x - k, 2^j y - m) \tag{6}$$

The greatest scale is fixed as the unity $1 = 2^0$ (i.e., the corresponding approximation and details are a single point) and the jth scale is then 2^{-j}. Assuming that the scale is of the same order as the dispersion of the wavelet, it is possible to distinguish up to 2^{-2j} different blocks. If the smallest scale is denoted by N (which corresponds to the original signal), then the reconstruction of C is given by [12], [6]

$$C(x,y) = \sum_{j=0}^{N} \sum_{k,m=0\ldots(2^j-1)} \sum_i \alpha^i_{j,k,m} \Psi^i_{j,k,m}(x,y) \tag{7}$$

In this decomposition, where we have neglected the coarsest approximation, the signal is represented in successive levels of details, from the coarsest to the finest details.

Wavelet coefficients-based MRA decomposition can be computed with quadrature mirror filters, consisting of a low-pass filter L and a high-pass filter H [9], [13], [14]. The implementation is as follows: the rows of the input block C are first filtered with L then with H. The filtered output is then down-sampled by 2. Next each column of the row filtered block is again low-pass and high-pass filtered and down-sampled by 2. This is the first level decomposition. We apply the same process to the LL-output recursively to obtain the second level decomposition, and the process continues up to the desired resolution.

4. BIT ALLOCATION AND QUANTIZATION

4.1 Bit Allocation

In the wavelet decomposition of a signal, each coefficient may be quantized using a different number of bits to achieve a minimum distortion of the reconstructed signal.

Let $W_i(b_i)$ be the distortion incurred in quantizing the ith wavelet coefficient $(i = 1, \ldots, K)$ with b_i bits. The bit allocation problem is to find b_i to minimize the overall distortion

$$D(b) = \sum_{i=1}^{K} W_i(b_i) \tag{8}$$

subject to the constraint that

$$\sum_{i=1}^{K} b_i \le B \tag{9}$$

where B is the number of available bits.

Assuming a high resolution quantization and that the distortion measure is the error variance, then the number of bits assigned to each coefficient is given by

$$b_i = \frac{B}{K} + \log \frac{\sigma_i^2}{\left(\prod_{i=1}^{K} \sigma_i^2\right)^{\frac{1}{K}}} \tag{10}$$

where σ_i^2 is the estimated variance of the ith coefficient.

4.2 Quantization

The standard deviation of each coefficient is estimated by the average signal power

$$\sigma = \sqrt{\frac{1}{N} \sum_{i=0}^{N-1} x_i^2} \tag{11}$$

where N is the block size of the coefficient. The standard deviation is then used to determine the optimum quantizer by finding the decision boundaries $\{b_i\}$ and the reconstruction levels $\{y_i\}$ ($i = 1,\ldots,L$ where L is a given number of levels) that minimize the mean squared quantization error. They are the solutions of the Max-Lloyd equations [10]

$$b_j = \frac{y_{j+1} - y_j}{2} \qquad j = 1 \ldots L-1 \quad (12)$$

$$y_j = \frac{\int_{b_{j-1}}^{b_j} x f_x(x) dx}{\int_{b_{j-1}}^{b_j} f_x(x) dx} \qquad j = 1 \ldots L \quad (13)$$

$$f_x(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{x^2}{2\sigma^2}} \quad (14)$$

These parameters are provided in many books for various values of L (e.g. [10]).

5. EXPERIMENTS AND RESULTS

5.1 Wavelets Bases

To conduct our experiment, we have used five orthonormal wavelet bases, namely *Haar wavelet* (HW), the linear and quadratic splines from *Battle-Lemarié* wavelets (BLL and BLQ) which are constructed by orthogonalizing the B-spline functions, and two Daubechies wavelets (D-4 and D-20). The corresponding mother wavelets in one-dimension and their spectra are plotted in Fig 2.

As we can see, the Haar wavelet provides better localization in the spatial domain compared to the Battle-Lemarié ones. However, the opposite is true in the frequency domain. A better trade-off between spatial and spectral localization is provided by Daubechies wavelets. Other important properties like symmetry, number of vanishing moments and regularity can be fruitful for data compression. It was established that [8]:

(a) If the wavelet has enough vanishing moments, then the wavelet coefficients are small at fine scales and can be neglected in a compression application. Haar wavelet has only one vanishing moment, BLL and D-4 have two, BLQ has three while D-20 has ten vanishing moments.

(b) To minimize the number of high amplitude coefficients (which improves the compression) we must reduce the support size of the mother wavelet. Daubechies wavelets have a minimum size support for a given number of vanishing moments.

(c) The regularity of the mother wavelets influences the quantization distortion of the coefficients. Regularity increases with the number of vanishing moments. Haar wavelet is discontinuous, D-4 is Lipshitz 0.55, BLL is continuous, BLQ and D-20 are continuously differentiable.

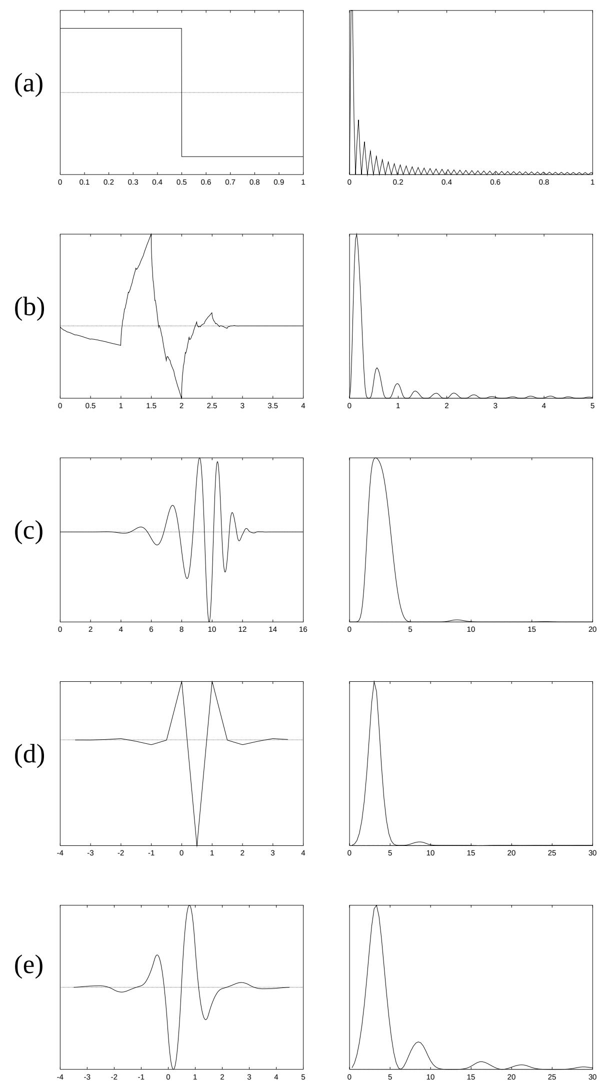


Fig. 2. The mother wavelets and their spectra. (a) HW, (b) D-4, (c) D-20, (d) BLL and (e) BLQ.

To test the performance of the five kinds of wavelets, a set of the ERS-2 mission has been considered. This data frame, of 26624 x 11264 samples in azimuth and range directions, was provided by the *Alaska SAR Facility* (ASF). These raw data were originally quantized with 8 bits. For the evaluation, we consider the *signal-to-noise* *ratio* (SNR) which is the ratio of the original raw data variance to the variance of the error between the original and reconstructed data. This error is the same as the quantization error as long as we consider orthogonal transforms.

5.2 Experimental Results

Figure 3 presents two parts of the original image compared to the corresponding reconstructed ones (for a quantization with 2 bits) obtained after processing the raw data. These two parts were chosen because of their representative features (mountains, river, lake, airport). The error images amplified by 37% shown in Fig. 4 indicate that the reconstructions are of high quality, without any recognizable residual pattern. Notice also that there is no significant difference with respect to the kind of wavelets.

Table 1 presents the SNR (in dB) for a quantization with 1, 2, or 3 bits per sample. The five wavelets performed similarly. This is due to the characteristics of the raw SAR signal which are similar to noise. Further improvement can be obtained by searching for an optimal wavelet able to localize better the important objects.

Table 1: SNR in dB for the five wavelets using 1, 2 or 3 bits

	Haar	BLL	BLQ	D-4	D-20
1 bps	4.35	4.35	4.35	4.36	4.35
2 bps	8.14	8.01	8.00	8.01	8.00
3 bps	14.55	14.52	14.49	14.53	14.50

6. CONCLUSIONS

We have presented in this study a compression of the raw SAR signal using five kinds of wavelets. Our goal to study wavelet-based techniques and their effect on SAR signal, was achieved. The quality reconstruction is very good; however, further improvement of the SNR has to be made. Due to noise like characteristics of the raw SAR signal, the standard wavelets are not very efficient in compacting energy on the transform domain. Hence research has to be oriented to wavelet optimality combined with an efficient quantization strategy.

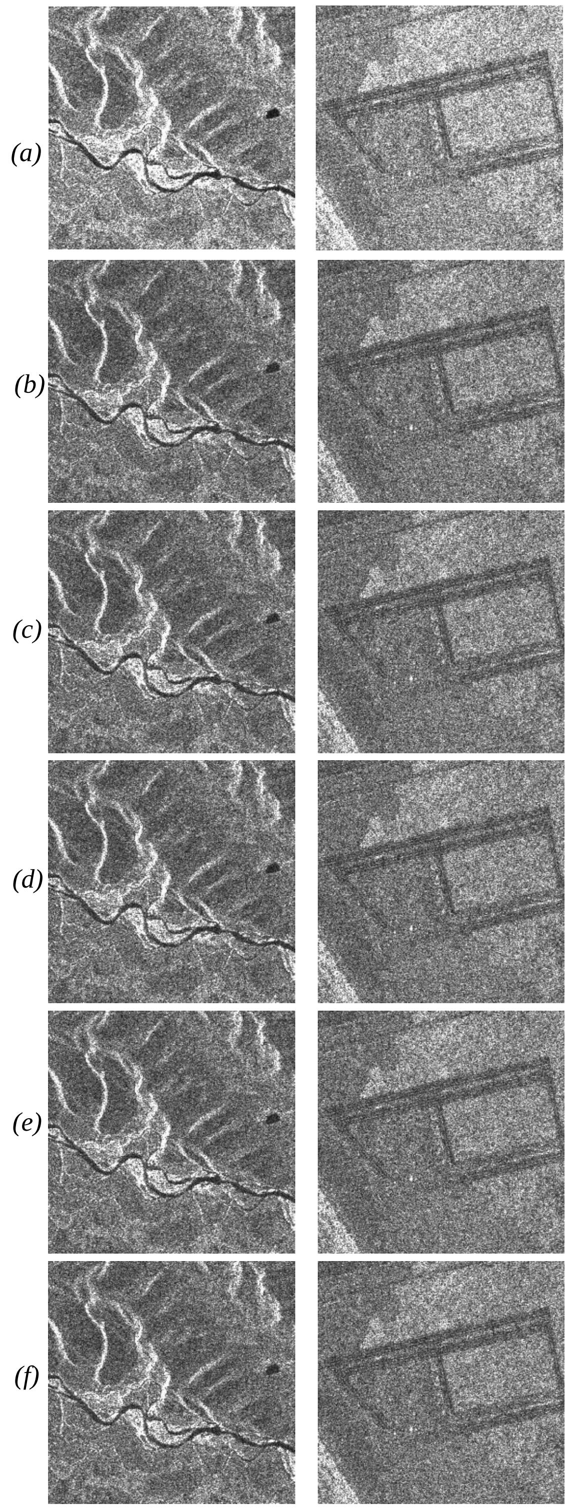
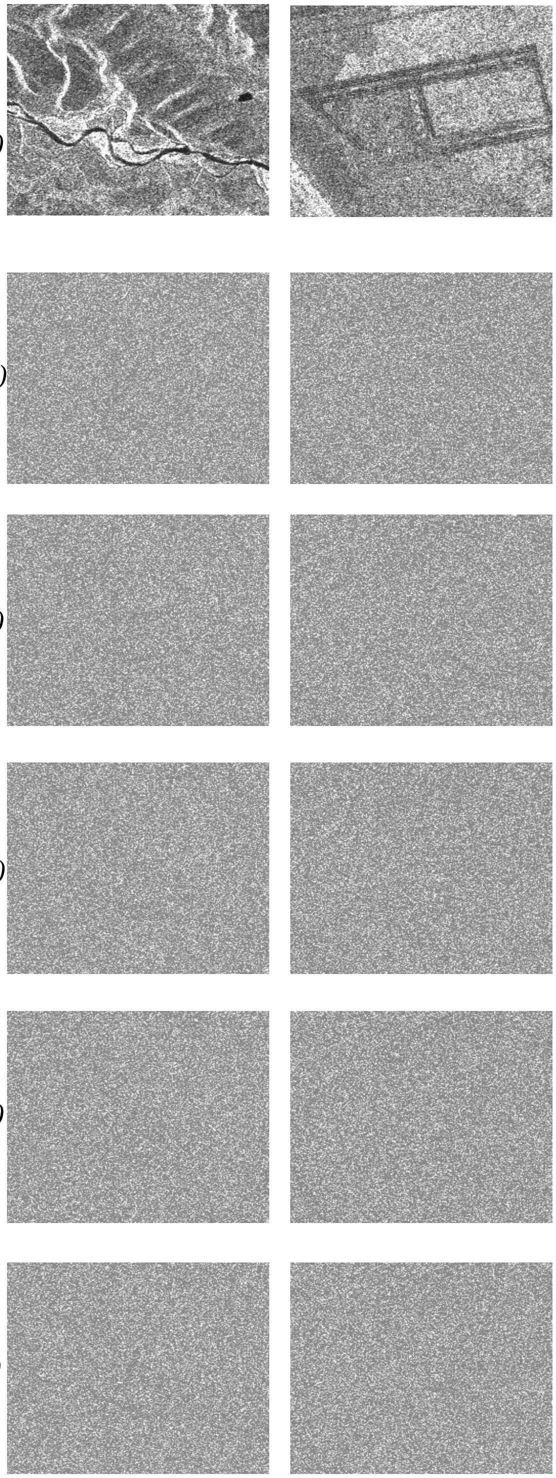


Fig. 3. (a) Original image and reconstructed images using (b) HW, (c) BLL, (d) BLQ, (e) D4 and (f) D20.



(a) (b) (c) (d) (e) (f)

Fig. 4. (a) Original image and error images using (b) HW, (c) BLL, (d) BLQ, (e) D4 and (f) D20.

Acknowledgments

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