

SAR Image Compression using Forward Biorthogonal Wavelet Transform Coupled with SPIHT Algorithm

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Abstract: SAR image compression is very important in reducing the costs of data storage and transmission in relatively slow channels. We propose synthetic aperture radar (SAR) complex image compression schemes based on FWT53_FFT with the set partitioning in hierarchical trees (SPIHT) algorithm. The FWT53_FFT (Forward biorthogonal 5/3 wavelet transform) encodes the real images converted by fast Fourier transform (FFT). The performance analysis is observed by changing in BPP(Bit per pixel) for a given image and based on varying BPP peak signal-to-noise ratio (PSNR) and (Mean square Error) MSE.

Keywords: FWT, FFT, BPP, PSNR, MSE, SPIHT.

I. Introduction

Data compression is the technique to reduce the redundancies in data representation in order to decrease data storage requirements and hence communication costs [1]. Reducing the storage requirement is equivalent to increasing the capacity of the storage medium and hence communication bandwidth. Thus the development of efficient compression techniques will continue to be a design challenge for future communication systems and advanced multimedia applications [2] [3]. Data can be called as a combination of information and redundancy. Information is the portion of data that must be preserved permanently in its original form in order to correctly interpret the meaning or purpose of the data. Redundancy is that portion of data that can be removed when it is not needed or can be reinserted to interpret the

data when needed. Most often, the redundancy is reinserted in order to generate the original data in its original form. A technique to reduce the redundancy of data is defined as Data compression [2] [3]. There is two types of data compression lossless and lossy algorithms, lossless algorithm which can reconstruct the original data exactly from the compressed data, and lossy algorithms, which can only reconstruct an approximation of the original message [3]. In our work we have selected SAR image because it has large scope for compression and this image has varied affliction like a security system for defense, for natural climatic etc.

SAR images formed from spatially overlapped radar phase histories are becoming increasingly important in a variety of remote sensing and tactical applications. The capability of SAR sensors to operate in virtually all types of weather conditions, from very long ranges and over wide areas of coverage, makes them extremely attractive for surveillance missions and for monitoring the earth's resources. With the increased popularity and the corresponding abundance of such imagery, the need to compress SAR images without significant loss of image quality has become more urgent. In addition, because SAR images are interpreted for content by humans or by machines, appropriate coding of images enables efficient and effective machine selection and interpretation.

The complex SAR image, which consists of amplitude and phase, is the first-level image data of the SAR system. The phase information fidelity in complex SAR image is crucial to some special applications, such as interferometry and moving target detection. Therefore, complex SAR image compression requires not only reasonable amplitude fidelity but also high phase information accuracy, which is different from the ordinary optical image compression. Currently, most compression algorithms of complex SAR image adopt the traditional wavelet transform. However, for the complex SAR images, which are rich in edges and texture, traditional wavelet transform does not show efficient representation. Dong et al. [4] proposed an algorithm which extracted edges of SAR image with wedge let transform and encoded the edges and texture separately. Li et al. [5] used 2-D oriented wavelet transform for remote sensing compression. The SAR images used in [4], [5] are not complex SAR images. The spatial-domain directional wavelet, such as directional lifting wavelet transform (DLWT), employs direction prediction for wavelet decomposition, which adapts the wavelet transform direction to the image edges. DLWT [6] – [8] integrates spatial direction prediction into the wavelet transform lifting framework, provides an efficient. Mohammed Hamzah Abed et al. use a modified version of SPIHT for two dimensional signals which is lossless [9]. G.Chenchu Krishnaiah et al. performs 9/7 and 5/3 wavelets on photographic images (monochrome and color) and estimated Peak Signal to Noise Ratio (PSNR) [10]. J. Maly et al. Proposes an implementation of discrete-time wavelet transform based image codec using Set Partitioning in Hierarchical Trees (SPIHT) coding in the MATLAB environment. The

results show that the CDF 5/3 perform best results among all tested wavelet families [11].

II. Set Partitioning in Hierarchical Trees encoder

Probably the most successful variation of the ideas of Shapiro was Set Partitioning in Hierarchical Trees (SPIHT) [12]. SPIHT is based on the concept that the wavelet coefficients with higher magnitudes should be transmitted first because they have a more information content.

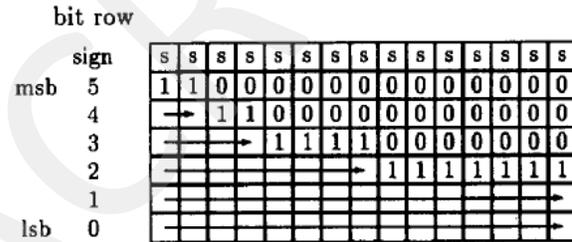


Figure 1: Left: The first stage of a 2-D wavelet transform. Right: after the second stage.

Figure 1 shows how a set of coefficients might be ordered and the information would be represented. The number of coefficients μ_n such that $2^n \leq |c| < 2^{n+1}$ is transmitted along with this information, where c is the coefficient in question. This means that only the bits covered by the arrows in Figure 1 need to be transmitted because all other bits can be inferred from μ_n . Although the coefficients might be ordered in terms of magnitude, in order to recover the image in the decoder, the coefficients will have to be reordered back to their original order. This ordering information is not transmitted explicitly, and instead is reconstructed based on the fact that the decoder duplicates the encoder's execution path. Each decision is denoted by

$$S_n(T) = \begin{cases} 1 & \max_{(i,j)} E_T |c_{i,j}| \geq z^n \\ 0 & \text{otherwise} \end{cases}$$

This indicates the importance of the coordinates in T, where T is a continually updated set of coefficient coordinates used in the algorithm. At each encoding step, the S_n decision is output, and the decoding algorithm looks exactly the same except that S_n is input at each step of the way. This is what allows the execution path to be reconstructed and the ordering information inferred.

SPIHT continually updates a set of internal buffers that contain coefficients that are in various stages of the algorithm. SPIHT was significantly better in terms of SNR than any other published method

The flowchart of SPIHT is presented in figure 2. In the First step, the original image is decomposed into ten sub bands. Then the method finds the maximum and the iteration number. Second step, the method puts the DWT coefficients into sorting pass that finds the significance coefficients in all coefficients and encodes the sign of these significance coefficients. Third step, the significant coefficients that be found in sorting pass are put into the refinement pass that use two bits to exact the reconstruct value for closing to real value. The front, second and third steps are iterative, next iteration decreases the threshold $T_n = T_{n-1}/2$ and the reconstructive value $R_n = R_{n-1}/2$ Forth step, the encoding bits access entropy coding and then transmit [13]. The result is in the form of a bit stream. All of the wavelet-based-image encoding algorithms improve the compression rate and the visual quality, but the wavelet-transform computation is a serious disadvantage of those algorithms.

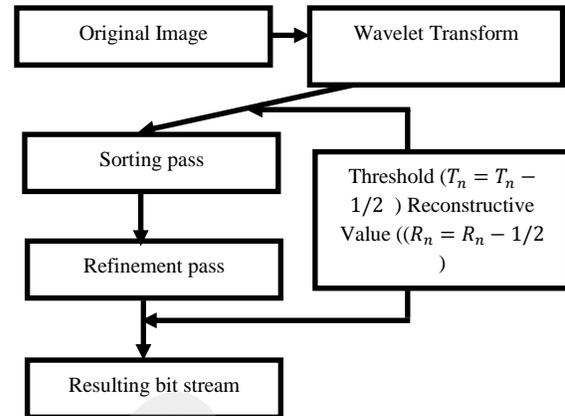


Figure 2: The flowchart of SPIHT [14]

III. Cohen-Daubechies-Feauveau 5/3-tap filters (CDF 5/3)

The Cohen-Daubechies-Feauveau (CDF) 5/3 biorthogonal wavelet is a simple wavelet that has two sets of scaling and wavelet functions for analysis and synthesis, hence bi-orthogonality. The CDF 5/3 wavelet has a 5-tap low-pass analysis filter $h(z)$ and 3-tap high-pass analysis filter $g(z)$, hence 5/3. The CDF 5/3 also has a 3-tap low-pass synthesis filter $\tilde{h}(z)$ and 5-tap high-pass synthesis filter $\tilde{g}(z)$

The CDF 5/3 analysis and synthesis sequences are listed below.

Analysis Filters:

$$h(z) = -\frac{1}{8}z^{-2} + \frac{1}{4}z^{-1} + \frac{3}{4} + \frac{1}{4}z^1 - \frac{1}{8}z^2$$

$$g(z) = -\frac{1}{2}z^{-1} + 1 - \frac{1}{2}z^1$$

Synthesis Filters:

$$\tilde{h}(z) = \frac{1}{2}z^{-1} + 1 + \frac{1}{2}z^1$$

$$\tilde{g}(z) = -\frac{1}{8}z^{-2} - \frac{1}{4}z^{-1} + \frac{3}{4} - \frac{1}{4}z^1 - \frac{1}{8}z^2$$

CDF 5/3 DWT using Lifting Scheme

The low-pass and high-pass analysis filters for the CDF 5/3 are restated below with the high-pass filter translated by z^{-1}

$$h(z) = -\frac{1}{8}z^{-2} + \frac{1}{4}z^{-1} + \frac{3}{4} + \frac{1}{4}z^1 - \frac{1}{8}z^2$$

$$\begin{aligned} z^{-1}g(z) &= z^{-1} \left(-\frac{1}{2}z^{-1} + 1 - \frac{1}{2}z^1 \right) \\ &= -\frac{1}{2}z^{-2} + z^{-1} - \frac{1}{2} \end{aligned}$$

The polyphase matrix $P(z)$ for the CDF 5/3 wavelet is shown below.

$$P(z) = \begin{bmatrix} -\frac{1}{8}z^{-1} + \frac{3}{4} - \frac{1}{8}z^1 & -\frac{1}{2}z^{-1} - \frac{1}{2} \\ \frac{1}{4} + \frac{1}{4}z^1 & 1 \end{bmatrix}$$

$$P(z) = \begin{bmatrix} \frac{3}{4} - \frac{1}{8}(z^1 + z^{-1}) & -\frac{1}{2}(z^{-1} + 1) \\ \frac{1}{4}(1 + z^1) & 1 \end{bmatrix}$$

The polyphase matrix can then be factored into two triangular matrices.

$$P(z) = \begin{bmatrix} 1 & -\frac{1}{2}(z^{-1} + 1) \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ \frac{1}{4}(1 + z^1) & 1 \end{bmatrix}$$

It is apparent that two lift steps are required, one predict and one update step, to perform the CDF 5/3 DWT. The coefficient for the predict step is:

$$\alpha = -1/2$$

and the coefficient for the update step is:

$$\beta = 1/4$$

Predict and update equations for the CDF 5/3 filter are shown below.

$$\begin{aligned} \text{Predict : } odd_{new} &= odd_{old} \\ &+ [-1/2(even_{left} + even_{right})] \end{aligned}$$

$$\begin{aligned} \text{Update : } even_{new} &= even_{old} \\ &+ [1/4(odd_{left} + odd_{right})] \end{aligned}$$

The floor function is used for both predict and update equations to provide an integer-to integer transform. The forward CDF 5/3 DWT using the lifting scheme is shown in Figure 3.

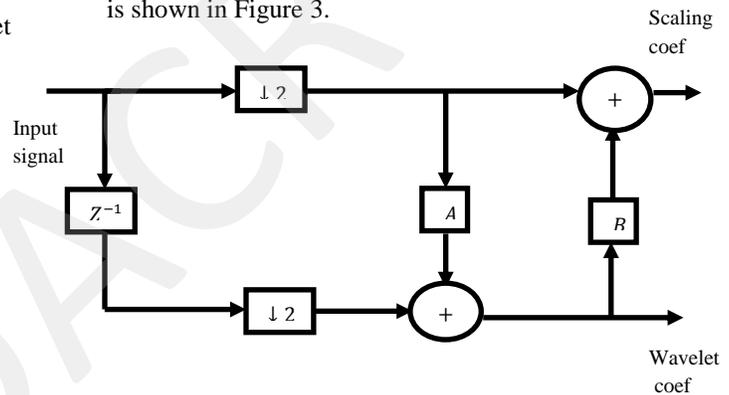


Figure 3: Forward CDF 5/3 DWT using Lifting Scheme

IV. Proposed work

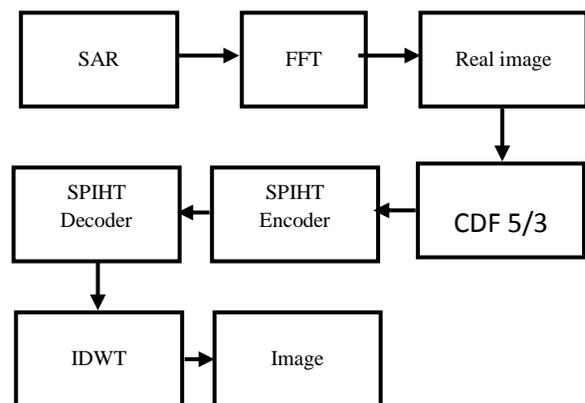


Figure 4: procedure for image compression

Initially, put on 1-D FFT transform on the SAR image and move the negative frequency band to the positive side, this doubles the original signal bandwidth and the original frequency signal focused on the positive side; second, do 1-D IFFT transform and get a complex signal with data volume doubled; lastly, characterize the complex signal with its real part as the imaginary part and the real part of the complex signal fulfill the Hilbert transform. The spectrum movement is corresponding to supplement zeros on the negative side of the frequency signal and creates the bandwidth doubled; so, the complex signal which is the resultant signal of the inverse FFT transform is corresponding to interpolate the complex SAR image by every two pixels on the dimension of transform.

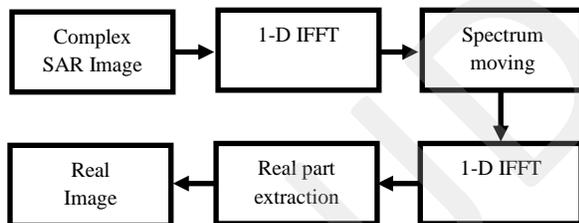
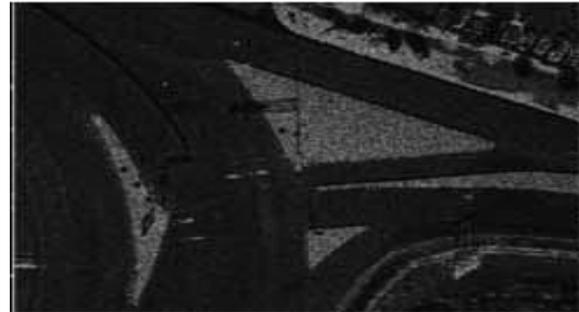


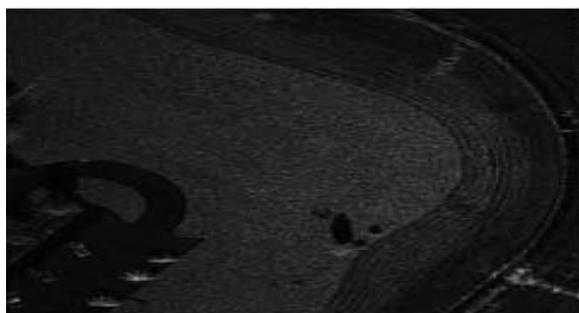
Figure 5: block diagram of FFT



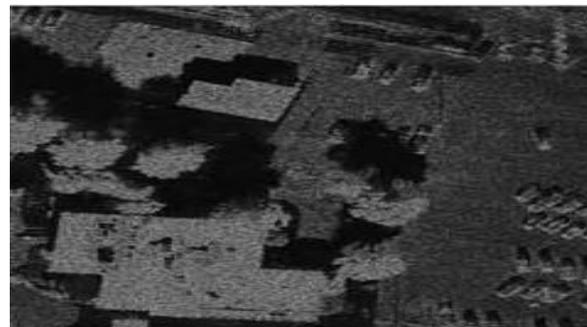
b. Image 2



c. Image 3



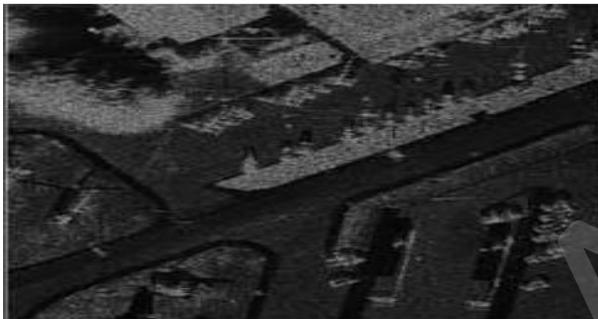
a. Image 1



d. Image 4



e. Image 5



f. Image 6

Figure 6: real part of testing images

A. Mean Square Error

The MSE of an estimator is one of various ways to measure the modification between values created by an estimator and the true values of the quantity being projected. MSE calculates the middling of the squares of the "errors." The error is the quantity by which the value created by the estimator varies from the quantity to be projected. The alteration happens showing to arbitrariness or owing to the estimator doesn't account for data that could yield a more precise estimate.

$$MSE = 1/(M * N) \sum_{i=1}^M \sum_{j=1}^N [x(i,j) - y(i,j)]^2$$

B. Peak Signal in Noise Ratio

PSNR is an engineering term for the ratio between the greatest likely power of a signal and the power of corrupting noise that affects the fidelity of its representation. As various signals have a very extensive dynamic range, PSNR is generally conveyed in terms of the logarithmic decibel scale. The PSNR is most commonly used as a measure of quality of reconstruction by lossless compression code (e.g., for image compression).

When the pixels are represented using 16 bits per sample (16 data type images)

$$PSNR = 10 * \log_{10} \left(\frac{(65535)^2}{MSE} \right)$$

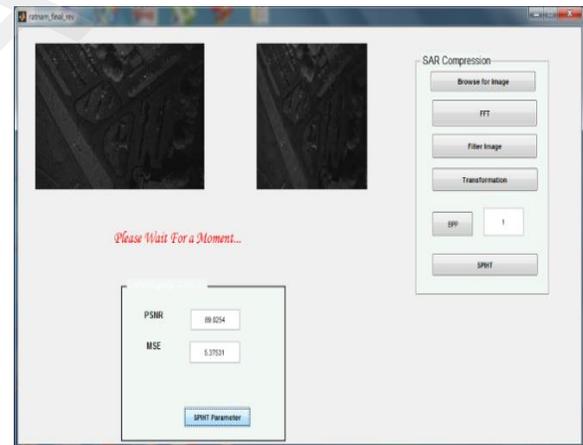


Figure 7: GUI of proposed work

V. Result

Table 1: Comparison of PSNR values obtains using proposed methodology

	1.0BPP	3.0BPP	5.0BPP
	PSNR	PSNR	PSNR
Image1	74.5517	84.8063	97.6415
Image2	75.2299	87.4912	98.1174
Image3	72.3711	83.4255	95.49944
Image4	73.4022	84.1797	96.3942
Image5	76.5757	87.74485	97.9975
Image6	74.0752	86.0985	97.8451

	1.0BPP	3.0BPP	5.0BPP
	MSE	MSE	MSE
Image1	150.585	14.2009	0.739258
Image2	128.813	7.65292	0.662537
image3	248.793	19.5163	1.21201
image4	196.211	84.1797	0.985199
image5	94.4888	7.21271	0.681076
image6	168.045	10.5461	0.705399

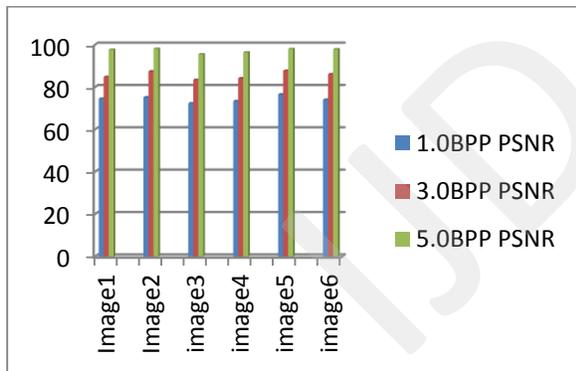


Figure 8: Graph of PSNR

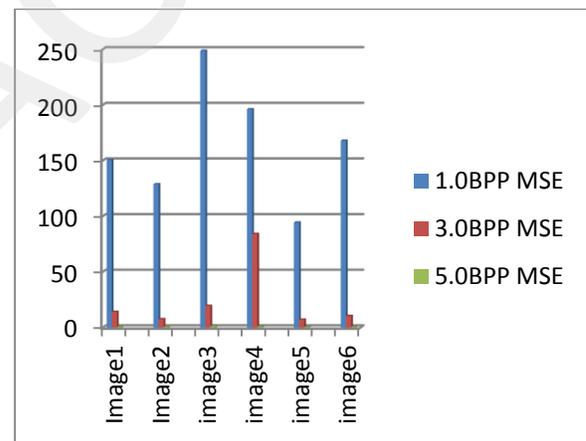


Figure 9: Graph of MSE

Table 2 Comparison of MSE values obtains using proposed methodology

VI. Conclusion

The objective specified is clearly evaluated image compression performance, in accounting PSNR and MSE. The images were evaluated quantitatively and qualitatively assessments are done by metrics in order to establish the impact of wavelet and the need of encoding based approach for image compression. The experimental analysis is mainly performed on SAR data from various satellite projections. In

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ending, the FWT along with SPIHT compression technique allows output as expertly compressed image, with different operative importance without changing the pixel accuracy and image resolution or size. The analysis presented here will prove useful in studies of non-stationary in time series, and the addition of statistical significance tests will improve the quantitative nature of wavelet analysis.

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