

An Improved Technique for Complex SAR Image Compression Based on FFT and Discrete Wavelet Transform

Gopal K. Patidar¹, Krishna Patidar², Swapna Pillai³, Tarwar S. Savner⁴, M. Chiranjeevi⁵

M. Tech. Student, Department of ECE, AITR, Indore, India^{1,2,3}

Assistant Professor, Department of ECE, AITR, Indore, India^{4,5}

Abstract: SAR images are different from optical images in many ways. Therefore, the traditional compression methods, which have been used for compression, are not so efficient for the compression of the SAR images. Generally, 2-dimensional Fourier transform (2D-FT) is used for representing a complex SAR image. But, the energy of the coefficients of 2D-FT on the complex SAR image distributes in the whole frequency domain also. Typically, the frequency signals are divided into two parts, i.e., real and imaginary parts. A Wavelet transform gives very strong de correlation ability and can be used for local analysis in time and frequency with different scales. Wavelet transform have also been applied to complex SAR image compression, as it is suitable for non-stationary signal processing. We have embodied the wavelet transform with SPIHT for compression of SAR images. Also FFT is used for converting the complex SAR image into a real image before applying it to DWT. In particular, we have used Le Gall 5/3 biorthogonal wavelet for calculating the wavelet transform.

Keywords: Discrete Wavelet Transform (DWT), Fast Fourier Transform (FFT), Synthetic Aperture Radar (SAR), SPIHT, Image Compression, PSNR.

I. INTRODUCTION

Synthetic Aperture Radar (SAR) is a remote sensing system, having applications in geology, oceanography, agriculture, ecology, military, hydrology etc. [14]. These systems are mounted on a satellite or airplane which moves with a particular speed, in a particular direction. This Movement of the airplane or satellite is used for increasing the aperture of the SAR system. The main reason behind the diverse applications of SAR systems is that it can take images in darkness as well as in all weather conditions.

As the SAR technology matured, larger areas are being imaged and the images with high resolutions are being produced. Thus it creates a necessity of transmitting and storing large images. However, the data rate must be reduced due to the limited down-link capacity and /or limited storage on the airplane or satellite. As the data rate is proportional to the pulse repetition frequency (PRF), and thus to the number of samples taken in each echo and the number of quantization bits. One may reduce the data rate by changing these parameters but this decreases the system performance. For an example, if PRF is reduced, it will causes higher azimuth ambiguities, and reducing the bandwidth of the system will decreases the range resolution. Also, decreasing number of quantization bits will increases the digitization noise [1]. Then we are left with only choice of compressing the SAR images. Since, SAR data is inherently complex but it can be frequently converted to real data for its interpretation by human or machine algorithms [2]. Note that, for inter ferometric purposes, the phase information is very crucial. The rest of the paper is organized as follows: In Section II, We

study the previous work related to our problem. In Section III, we give sufficient theory related to this works and the discretion of proposed algorithm is given Section IV.. The simulation results are presented in Section V. The scope of future research and concluding remarks are given in Section VI.

II. LITERATURE SURVEY

Traditional wavelet transform methods have been applied for the compression of SAR images [2]-[4]. In [15], authors have proposed an algorithm employing wedgelet transform for extracting edges of SAR images and then encoded the edges and textures separately. 2-D wavelet transform have been applied in remote sensing compression by Li *et al.* in [16]. Recently, directional lifting transform have also been applied in SAR image compression by authors in [14]. However, the complexity of algorithm also increased significantly.

In this paper, we propose an algorithm for efficient representation of SAR images using DWT-FFT method. The complex image is first converted into a real image before the wavelet transform is applied. The FFT program is first applied on the complex SAR image and then we shift the negative frequency band to the positive side. The original signal band width gets doubled in this process, concentrated in the positive side. Secondly, the IFFT transform is performed to obtain a complex signal with data volume doubled. Finally, the complex signal is represented with its real part because the real part and imaginary part of the complex signal satisfy the Hilbert transform [14].

III. PRELIMINARIES AND BACKGROUND

In this section, we review the basics related to the work presented in this paper. However, due to the limitation of space, it not possible to go through the rigours mathematical theory involved behind the algorithm. For detailed information, readers may refer to the references cited in the document at suitable places.

A. Discrete Wavelet Transform (DWT)

In the discrete wavelet transform, an image signal can be analyzed by passing it through an analysis filter bank followed by a decimation operation. This analysis filter bank, which consists of a low pass and a high pass filter at each decomposition stage, is commonly used in image compression [8].

A two-dimensional transform is done by performing two separate one-dimensional transforms. First, the image is filtered along the x-dimension and decimated by two. Then, it is followed by filtering the sub-image along the y-dimension and decimated by two. Finally, we have split the image into four bands denoted by LL, HL, LH and HH after one-level decomposition [14].

The reconstruction of the image can be carried out by the following procedure. First, we will up sample by a factor of two on all the four sub bands at the coarsest scale, and filter the sub bands in each dimension. Then we sum the four filtered sub bands to reach the low-low sub band at the next finer scale. We repeat this process until the image is fully reconstructed. See Fig. ?? For more details on Fast Fourier transform (FFT), wavelets and image processing, readers are referred to [8][9][11][14].

B. Le Gall 5/3 Wavelet

We have used the popular Le Gall 5/3, also known as biorthogonal CDF-5/3 wavelet for computing the discrete wavelet transform [12]. The Le Gall 5/3 wavelet is also being used in JPEG 2000, lossless image compression standard. The same standard uses CDF-9/7 for lossy image compression. Figure 1 shows an Le Gall 5/3 wavelet.

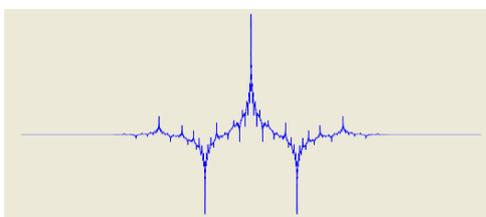


Fig.1. Le Gall 5/3 Wavelet

C. SPIHT Algorithm

Set partitioning in hierarchical trees (SPIHT)[5][6], is an image compression algorithm. This algorithm takes advantage of inherent similarities in the sub bands in a wavelet decomposition of an image. Firstly, the algorithm encodes the most important wavelet transform coefficients, and then transmits the bits to get an increasingly refined copy of the original image, progressively. The SPIHT algorithm exploits the properties, present in a wide variety of images. People

have successfully tested SPIHT in natural (portraits, landscape, weddings, etc.) and medical (X-ray, CT, etc.) images. Its embedded coding process proved to be effective in a variety of reconstruction qualities.

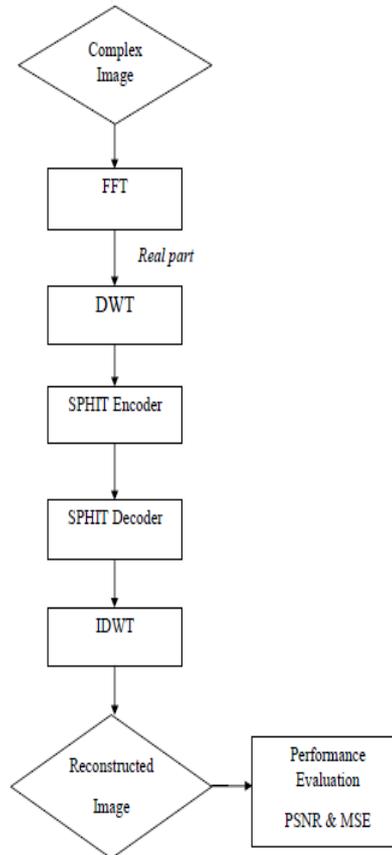


Fig.2. A flow chart of proposed algorithm



Fig.3. Complex to real image conversion process

SPIHT has also been proved efficient for some less usual purposes, like elevation maps, scientific data, and others. SPIHT follows a bit-plane sequence and codes the individual bits of the coefficients of wavelet transform. Thus, it is capable of recovering the image perfectly since it codes all bits of the transform. However, theoretically, wavelet transform will reconstruction the image perfectly, only if the numbers are stored as infinite-precision numbers. Practically, it is possible to recover the image perfectly by rounding after recovery, however, this is not the most efficient approach.

D. Performance Metrics

We also measure the performance of the compression algorithm. In measuring the quality of the reconstructed image, these two mathematical metrics are used. One of them is MSE, which measures the cumulative square error between the original and the compressed image. The formula for MSE is giving as;

$$MSE = \frac{1}{MN} \sum_{i=1}^M \sum_{j=1}^N [I(i,j) - I'(i,j)]^2 -$$

The second metric is “Peak signal to noise ratio”, i.e., PSNR, given as;

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

Due to the fact that, various signals have a very extensive dynamic range, it is worthy to represent PSNR in terms of the logarithmic or decibel scale. PSNR is an engineering term which represents the ratio between the greatest likely power of a signal and the power of corrupting noise which affects the fidelity of its representation. The PSNR is commonly used to measure the quality of reconstruction by lossless compression code (e.g., for image compression). While these two measurements may not be the best approach for measuring an image compression performance, but they provide a guide to the quality of the reconstructed image. A lower value of MSE and higher value of PSNR, shows a good reconstructed image, i.e., the image has low error and high image fidelity.

IV. PROPOSED ALGORITHM

We embodied the fast Fourier transform (FFT) and discrete wavelet transform (DWT) for the compression of complex SAR image. We name it as DWT_FFT algorithm.

Since, complex SAR images can generally be compressed in two kinds of images: real and imaginary part of original complex SAR image, and real image with FFT converted from original complex SAR image. It was shown by Brandfass *et al.* in [3] that a complex SAR image can be first converted into a real image of the same amount and without loss of any phase information then performed wavelet representation and zero-tree encoding on the real image. The real image achieved through FFT scheme is equivalent to the interpolation image of the real-part image of complex SAR image. Both the real image and the real part/imaginary part of the complex SAR image are rich in edges. The Figure 3 give necessary steps taken for the obtaining a real image from a complex SAR image. The flow chart, given in figure 2 explains the whole procedure, which is as follows;

1. First of all, the complex SAR image is converted into a real image by taking its FFT, and then shifting the spectrum to positive frequencies.
2. Then we perform the discrete wavelet transform (DWT) on this real image. We have used popular Le Gall 5/3 wavelet for computing wavelet transform.
3. Now we encode these wavelet coefficients using SPIHT algorithm. The MATLAB implementation of SPIHT codec used here is downloaded from website: <http://www.mathworks.com/matlabcentral/fileexchange/4808-spiht>.
4. In order to reconstruct the image from the encoded one, we first decode the encoded image, and then perform inverse DWT.
5. Then we calculate the performance metric of this reconstructed image, i.e., MSE and PSNR.

We have applied our algorithm on six SAR images obtained from the website of “Sandia National Laboratories”, given in Figure 4-9. The simulation results are presented in the Section V.

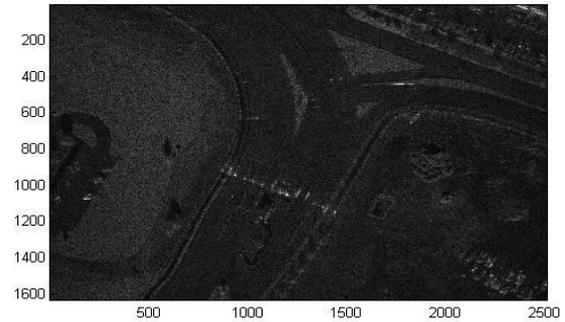


Fig.4. Complex SAR Image 1

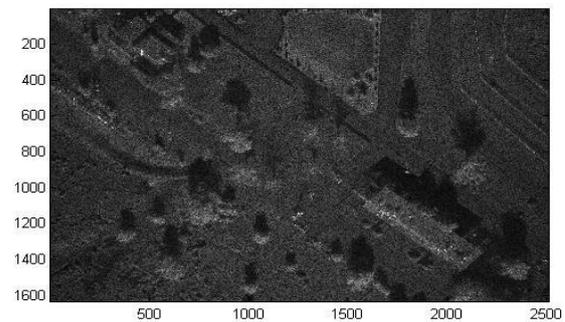


Fig.5. Complex SAR Image 2

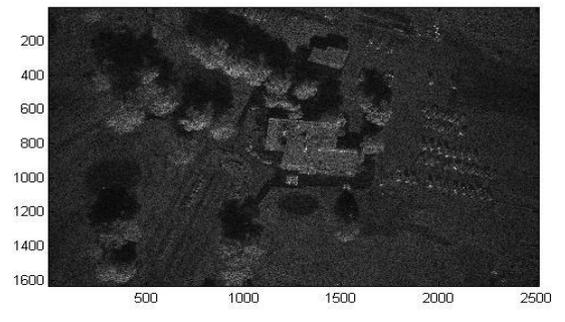


Fig.6. Complex SAR Image 3

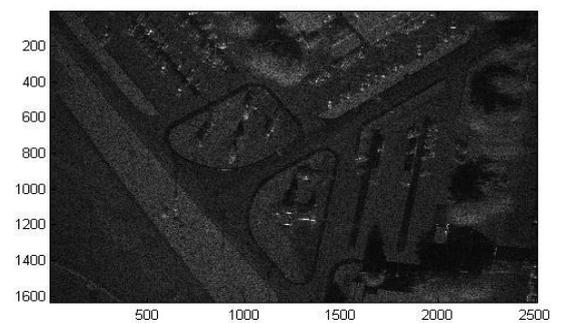


Fig.7. Complex SAR Image 4

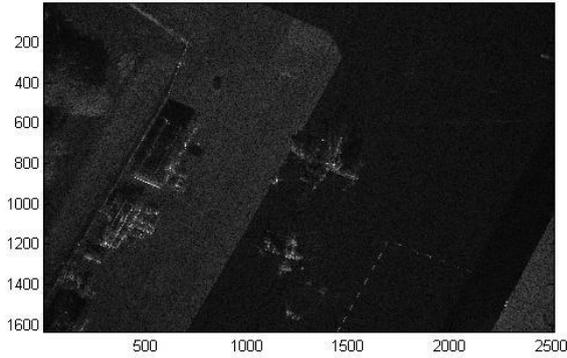


Fig.8. Complex SAR Image 5

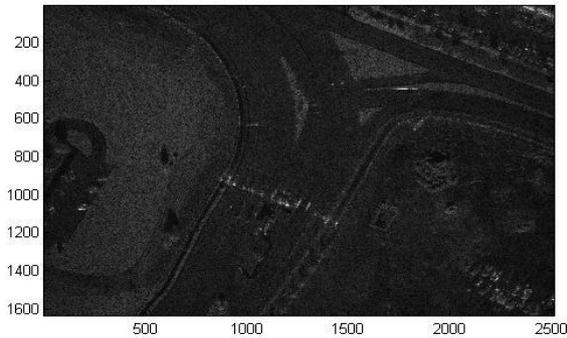


Fig.9. Complex SAR Image 6

V. RESULTS

In this section, we present few simulation results to show the effectiveness of the proposed image compression algorithm. We have performed extensive simulations on six complex SAR images obtained from “Sandiya National Laboratories” [7]. The values of metrics obtained are tabulated in the Table I. In view of the size of the manuscript, we have given histograms only for Image 1 only, out of total six images.

TABLE I
OBTAINED VALUES OF METRICS

SAR	1.0 BPP		3.0 BPP		5.0 BPP	
	PSNR	MSE	PSNR	MSE	PSNR	MSE
1	75.22	128.8	87.49	7.652	98.11	0.662
2	72.37	248.7	83.42	19.51	95.49	1.212
3	73.40	196.2	84.17	16.40	96.39	0.985
4	74.07	168.0	86.09	10.54	97.84	0.705
5	85.08	13.30	95.61	1.179	107.6	0.073
6	75.22	128.8	87.49	7.652	98.11	0.662

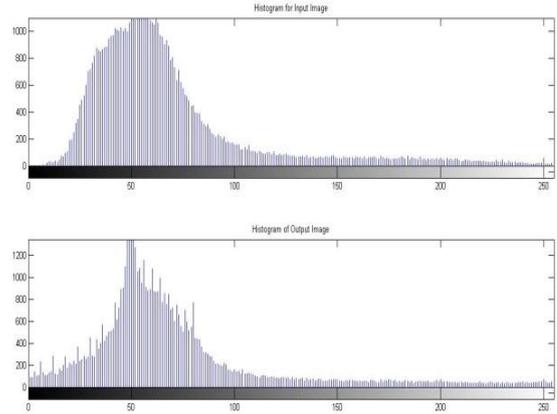


Fig.10. Histogram for SAR Image 1 at bpp 1.0

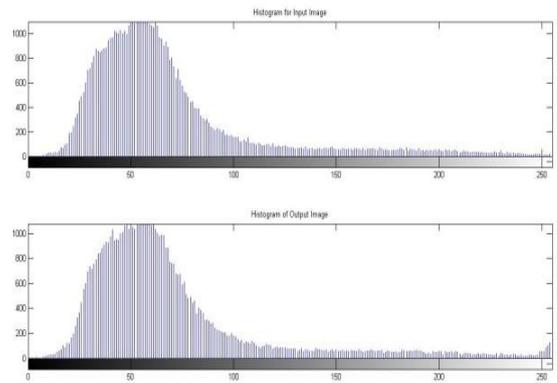


Fig.11. Histogram for SAR Image 1 at bpp 3.0

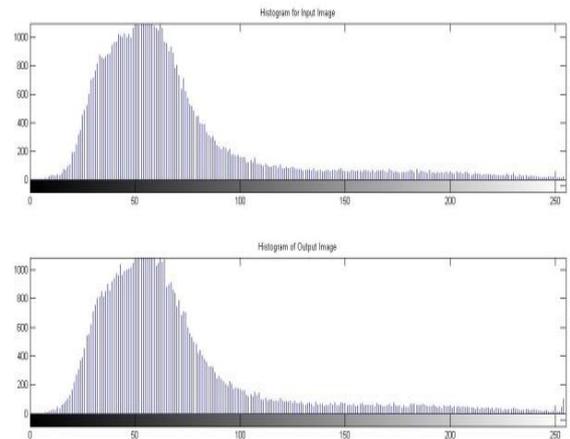


Fig.12. Histogram for SAR Image 1 at bpp 5.0

VI. CONCLUSION

The DWT–FFT scheme performs better than SPIHT in compression of SAR images. The proposed algorithm shows significant improvement in PSNR and MSE as compared to SPIHT. We also note the improvement in metrics with increase in BPP. We analyze mainly the SAR data from various satellite projections. These results may prove useful in further analysis of non-stationary signals, time series, etc.

ACKNOWLEDGMENT

Authors gratefully acknowledge the support received from the department of Electronics and Communication Engineering, Acropolis Institute of Technology and Research, Indore (M.P.) towards the preparation of the paper. We also thank “Sandiya National Laboratories” for allowing us to use SAR image for analysis.

REFERENCES

- [1] U. Benz, K. Strodl and A. Moreira, “A comparison of several algorithms for SAR raw data compression,” *Geosciences and Remote Sensing, IEEE Transactions on*, vol. 33, no. 5, pp. 1266-1276, 1995.
- [2] S. Werness, S. C. Wei, and R. Carpinella, “Experiments with wavelets for compression of SAR data,” *Geosciences and Remote Sensing, IEEE Transactions on*, vol. 32, no. 1, pp. 197-201, 1994.
- [3] M. Brandfass, W. Coster, U. Benz, and A. Moreira, “Wavelet based approaches for efficient compression of complex SAR image data,” in *Geosciences and Remote Sensing, 1997. IGARSS'97. Remote Sensing-A Scientific Vision for Sustainable Development. 1997 IEEE International*, vol. 4. IEEE, 1997, pp. 2024-2027.
- [4] R. Ives, N. Magotra, and C. Kiser, “Wavelet compression of complex SAR imagery using complex-and real-valued wavelets: a comparative study,” in *Signals, Systems & Computers, 1998. Conference Record of the Thirty-Second Asilomar Conference on*, vol. 2. IEEE, 1998, pp. 1294--1298.
- [5] A. Said and W. A. Pearlman, “A new, fast, and efficient image codec based on set partitioning in hierarchical trees,” *Circuits and Systems for Video Technology, IEEE Transactions on*, vol. 6, no. 3, pp. 243-250, 1996.
- [6] S. Mustafa and A. P. William. Set Partitioning in Hierarchical Trees (SPIHT) Algorithm. [Online]. Available: <http://www.cipr.rpi.edu/research/SPIHT>. Sandia National Laboratories, Sandia SAR data. [Online]. Available: <http://www.sandia.gov/radar/sar-data.html>
- [7] G. Strang and T. Nguyen, *Wavelets and filter banks*. Wellesley-Cambridge Press, 1997.
- [8] A. V. Oppenheim, R. W. Schaffer, and Buck, *Discrete-time signal Processing*. Prentice Hall Upper Saddle River, 1999.
- [9] P. Eichel and R. W. Ives, “Compression of complex-valued SAR images,” *Image Processing, IEEE Transactions on*, vol. 8, no. 10, pp. 1483-1487, 1999.
- [10] MATLAB, version 7.7.0 (R2008b). Natick, Massachusetts: The MathWorks Inc., 2008.
- [11] I. Daubechies, *Ten lectures on wavelets*. Philadelphia, PA, USA: Society for Industrial and Applied Mathematics, 1992.
- [12] J. M. Shapiro, “Embedded image coding using zero trees of wavelet coefficients,” *Signal Processing, IEEE Transactions on*, vol. 41, no. 12, pp. 3445-3462, 1993.
- [13] X. Hou, J. Yang, G. Jiang, and X. Qian, “Complex SAR image compression based on directional lifting wavelet transform with high clustering capability,” *Geosciences and Remote Sensing, IEEE Transactions on*, vol. 51, no. 1, pp. 527-538, 2013.
- [14] Dong, Ruchan, et al. "SAR image compression based on wedgelet-wavelet." *Signal Processing for Image Enhancement and Multimedia Processing*. Springer US, 2008. 67-75.
- [15] Li, Bo, Rui Yang, and Hongxu Jiang. "Remote-sensing image compression using two-dimensional oriented wavelet transform." *Geoscience and Remote Sensing, IEEE Transactions on* 49.1 (2011): 236-250.