



Directional lifting wavelet transform based SAR Image Compression

B.Dheepa¹, R.Nithya², N.Nishavithri³, K.Vinoth⁴, K.Balaji⁵

¹Mailam Engineering College, India, dheepa.ece@gmail.com

²Mailam Engineering College, India, nithirama@gmail.com

³Mailam Engineering College, India, nishanat19@gmail.com

⁴Mailam Engineering College, India, vinoxons@gmail.com

⁵Mailam Engineering College, India, ksbalajiout@gmail.com

ABSTRACT

Data compression technology is an effective way to alleviate the pressure of transmission and storage on SAR system. The complex SAR image consists of amplitude and phase, the first-level image data of the SAR system. The information fidelity in SAR image is crucial to some special applications, such as interferometers and moving target detection. The objective of this scheme is to assess the potential of the Contourlet Transform (CT) in relation to the issue of noise removal in SAR intensity images. The contourlet transform can be seen as a filter bank implementation of the curvelet transform. This novel approach to non linear approximation aims at providing a better representation of the geometrical content of natural images. Recently, a stationary version has been proposed that preserves translation invariance. We compare the CT performances against the curvelet transform and the stationary wavelet transform for two different noise reduction techniques. Results indicate a better compromise between noise removals and also the proposed scheme significantly outperforms DLWT based scheme in terms of higher PSNR and compression ratio with better representation of SAR image.

Key words: DLWT, Image compression, PSNR ratio, SAR image.

1. INTRODUCTION

Synthetic Aperture Radar (SAR) is an active remote sensing system which has applications in agriculture, ecology, geology, oceanography, hydrology, military, etc. 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[1]. 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 number of quantization bits increases digitization noise. 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.

2. DIGITAL IMAGE PROCESSING

Digital image is defined as a two dimensional function $f(x, y)$, where 'x' and 'y' are spatial (plane) coordinates, and the amplitude of 'f' at any pair of coordinates (x, y) is called intensity or grey level of the image at that point. The field of digital image processing refers to processing digital images by means of a digital computer. The digital image is composed of a finite number of elements, each of which has a particular location and value. The elements are referred to as picture elements, image elements and pixels. Pixel is the term most widely used. Image processing modifies pictures to improve them (enhancement, restoration), extract information (analysis, recognition), and change their structure (composition, image editing). Images can be processed by optical, photographic, and electronic means, but image processing using digital computers is the most common method because digital methods are fast, flexible, and precise[3]. An image can be synthesized from a micrograph of various cell organelles by assigning a light intensity value to each cell organelle. The sensor signal is "digitized"-- converted to an array of numerical values, each value representing the light intensity of a small area of the cell. The digitized values are called picture elements, or "pixels," and are stored in computer memory as a digital image. A typical size for a digital image is an array of 512 by 512 pixels, where each pixel has value in the range of 0 to 255.

The digital image is processed by a computer to achieve the desired result. Image processing technology is used by planetary scientists to enhance images of Mars, Venus, or other planets. Doctors use this technology to manipulate CT scans and MRI images. Image processing in the laboratory can motivate students and make science relevant to student learning. Image processing is an excellent topic for classroom application of science research techniques.

2.1 Sampling

In order to use an analog signal on a computer it must be digitized with an analog-to-digital converter. Sampling is usually carried out in two stages, discretization and quantization. In the discretization stage, the space of signals is partitioned into equivalence classes and quantization is carried out by replacing the signal with representative signal of the corresponding equivalence class. In the quantization stage the representative signal values are approximated by values from a finite set. The Nyquist–Shannon sampling theorem states that a signal can be exactly reconstructed from its samples if the sampling frequency is greater than twice the highest frequency of the signal; but requires an infinite number of samples. In practice, the sampling frequency is often significantly more than twice that required by the signal's limited bandwidth.

2.2 Image enhancement

Image enhancement is one of the most important issues in low-level image processing. Its purpose is to improve the quality of low contrast images, i.e., to enlarge the intensity difference among objects and background. Local methods employ feature-based approach and the local features can be gained by using edge operators or by computing local statistics such as local mean, standard deviation, etc. the original image may be changed greatly. Global methods are mainly implemented by using histogram modification approaches. One of the most commonly used methods is histogram equalization (HE).

2.3 Image segmentation

Technically speaking, image segmentation refers to the decomposition of a scene into different components. Major problems of image segmentation are result of noise in the image.

2.4 Image restoration

The purpose of image restoration is to restore a degraded/distorted image to its original content and quality. It is to improve the quality of a digital image which has been degraded due to various phenomena like:

- Motion
- Improper focusing of Camera during image acquisition.
- Atmospheric turbulence
- Noise

3. IMAGE COMPRESSION

When transmitting or storing picture information, compression must be employed to maintain picture resolution while making best use of limited channel bandwidth. Compression is defined as lossless if full recovery of the original is available from the channel without any loss of information; otherwise, it is lossy. Standards are required to ensure interoperability. JPEG 2000 is the only standard compression scheme that provides for both lossless and lossy compression [4]. Communications equipment like modems, bridges, and routers use compression schemes to improve throughput over standard phone lines or leased lines. Compression is also used to compress voice telephone calls transmitted over leased lines so that more calls can be placed on those lines [5]. In addition, compression is essential for videoconferencing applications that run over data networks. Compression has become critical in the move to combine voice and data networks. Compression techniques have been developed that reduce the data requirements for a voice channel down to 8 Kbits/sec. This is a significant improvement over non compressed voice (64 Kbits/sec) and older compression techniques yielding 32 Kbits/sec. If n_1 and n_2 denote the number of information-carrying units in two data sets that represent the same information, the relative data redundancy R_D [2] of the first data set (the one characterized by n_1) can be defined as,

$$R_D = 1 - \frac{1}{C_R}$$

Where C_R called as compression ratio [2]. It is defined as

$$C_R = \frac{n_1}{n_2}$$

In image compression, three basic data redundancies can be identified and exploited: Coding redundancy, inter pixel redundancy, and psychovisual redundancy. Image compression is achieved when one or more of these redundancies are reduced or eliminated. The image compression is mainly used for image transmission and storage. Image transmission applications are in broadcast television; remote sensing via satellite, air-craft, radar, or sonar; teleconferencing; computer communications; and facsimile transmission.

3.1 Image compression types

There are two types of image compression techniques.

1. Lossy Image compression
2. Lossless Image compression

Lossy Image compression: Lossy compression provides higher levels of data reduction but result in a less than perfect reproduction of the original image. It provides high compression ratio. It is useful in applications such as broadcast television, videoconferencing, and facsimile transmission, in which a certain amount of error is an acceptable trade-off for increased compression performance.

Lossless Image compression: Lossless Image compression is the only acceptable amount of data reduction. It provides low compression ratio while compared to lossy. In Lossless Image compression techniques are composed of two relatively independent operations: (1) devising an alternative representation of the image in which its inter pixel redundancies are reduced and (2) coding the representation to eliminate coding redundancies. Lossless Image compression is useful in applications such as medical imaginary, business documents and satellite images.

3.2 Basic Compression Techniques

The most basic compression techniques are described here:

Null compression: Replaces a series of blank spaces with a compression code, followed by a value that represents the number of spaces.

Run-length compression: Expands on the null compression technique by compressing any series of four or more repeating characters. The characters are replaced with a compression code, one of the characters, and a value that represents the number of characters to repeat. Some synchronous data transmissions can be compressed by as much as 98 percent using this scheme.

Keyword encoding: Creates a table with values that represent common sets of characters. Frequently occurring words like *for* and *the* or character pairs like *sh* or *th* are represented with tokens used to store or transmit the characters.

Adaptive Huffman coding and Lempel Ziv algorithms: These compression techniques use a symbol dictionary to represent recurring patterns. The dictionary is dynamically updated during a compression as new patterns occur. For data transmissions, the dictionary is passed to a receiving system so it knows how to decode the characters. For file storage, the dictionary is stored with the compressed file.

3.3 Storage System Compression

Before discussing compression algorithms for file storage, know that hard drives store information using data-encoding techniques that optimize the way bits are stored in the magnetic flux transition states. This encoding is built into the drive and used to store all data on that drive. This encoding provides some compression of data, but it must be discussed separately from the application-level compression that you can choose to apply to individual data files before they are sent to the drive for storage.

DCT (discrete cosine transforms): DCT is a common compression technique in which data is represented as a series of cosine waves. In the case of video, this technique replaces continuous sampling with an equation that represents the data. In the case of a still image, 8×8 blocks of information are converted into a wave that describes the number of color shifts and the extent of change in those color shifts.

Fractal compression: Today, most people are familiar with fractals and fractal geometry in some way. You have no doubt viewed the "growth" of a fractal tree or coastline on a computer screen. Some scientist wondered whether fractal mathematics could be used in the reverse direction to compress an image. Michael Barnsley of Georgia Tech apparently solved this problem, applied for a patent, and started Iterated Systems Incorporated in 1987[7]. Several other patents followed and the company began marketing fractal compression products. The basic idea is to break an image down into smaller and smaller tiles. The compression engine (a dedicated board) searches for matching patterns in the image using a mathematical transformation that manipulates tiles in various ways. Repetitive patterns are saved to reconstruct the original, and unmatched data that is considered unimportant is discarded. More recently, Iterated Systems has integrated wavelet technology, discussed next, in its latest products.

Wavelet transform: When using a wavelet transform to describe an image, an average of the coefficients-in this case, pixels-is taken. Then the detail coefficients are calculated. Another average is taken, and more detail coefficients are calculated. This process continues until the image is completely described or the level of detail necessary to represent the image is achieved[6]. As more detail coefficients are described, the image becomes clearer and less blocky. Once the wavelet transform is complete, a picture can be displayed at any resolution by recursively adding and subtracting the detail coefficients from a lower-resolution version. This technique is used by Iterated Systems. JPEG (Joint Photographic Experts Group) compression is an ITU and ISO standardized method for compressing still images using DCT, which converts three-dimensional color and coordinate image information into a format that is more responsive to compression. Color information is also encoded and some is discarded, depending on the desired end-results resolution. Compression can be lossless or lossy. The resulting information is then compressed using RLE, a special technique that compresses similar regions. In video compression, each frame is an array of pixels that must be reduced by removing redundant information. Video compression is usually done with special integrated circuits, rather than with software, to gain performance. Standard video is normally about 30 frames/sec, but studies have found that 16 frames/sec is acceptable to many viewers, so frame dropping provides another form of compression [6-7]. When information is removed out of a single frame, it is called intraframe or spatial compression. But video contains a lot of redundant inter frame information such as the background around a talking head in a news clip. Inter frame compression

works by first establishing a key frame that represents all the frames with similar information, and then recording only the changes that occur in each frame. The key frame is called the "I" frame and the subsequent frames that contain only "difference" information are referred to as "P" (predictive) frames. A "B" (bidirectional) frame is used when new information begins to appear in frames and contains information from previous frames and forward frames.

3.4 Image Compression Standards

There are many methods available for lossy and lossless, image compression. The efficiency of these coding standardized by some Organizations. The International Standardization Organization (ISO) and Consultative Committee of the International Telephone and Telegraph (CCITT) are defined the image compression standards for both binary and continuous tone (monochrome and Color) images[8]. Some of the Image Compression Standards are

1. JBIG1
2. JBIG2
3. JPEG-LS
4. DCT based JPEG
5. Wavelet based JPEG2000

Currently, JPEG2000 is widely used because; the JPEG-2000 standard supports lossy and lossless compression of single-component (e.g., grayscale) and multi component (e.g., color) imagery. In addition to this basic compression functionality, however, numerous other features are provided, including: 1) progressive recovery of an image by fidelity or resolution; 2) region of interest coding, whereby different parts of an image can be coded with differing fidelity; 3) random access to particular regions of an image without the needed to decode the entire code stream; 4) a flexible file format with provisions for specifying opacity information and image sequences; and 5) good error resilience. Due to its excellent coding performance and many attractive features, JPEG 2000 has a very large potential application base. Some possible application areas include: image archiving, Internet, web browsing, document imaging, digital photography, medical imaging, remote sensing, and desktop publishing. The main advantage of JPEG2000 over other standards, first, it would address a number of weaknesses in the existing JPEG standard. Second, it would provide a number of new features not available in the JPEG standard[9]. The preceding points led to several key objectives for the new standard, namely that it should: 1) allow efficient lossy and lossless compression within a single unified coding framework, 2) provide superior image quality, both objectively and subjectively, at low bit rates, 3) support additional features such as region of interest coding, and a more flexible file format, 4) avoid excessive computational and memory complexity. Undoubtedly, much of the success of the original JPEG standard can be attributed to its royalty-free nature. Consequently, considerable effort has been made to ensure that minimally-compliant JPEG-2000 codec can be implemented free of royalties.

4. DIRECTIONAL LIFTING WAVELET TRANSFORM

4.1 Lifting scheme

The lifting scheme is a technique for both designing wavelets and performing the discrete wavelet transform. These are wavelets that are not necessarily translates and dilates of one fixed function. Such wavelets can be adapted to intervals, domains, surfaces, weights, and irregular samples. We show how the lifting scheme leads to a faster, in-place calculation of the wavelet transform in figure 1. Actually it is worthwhile to merge these steps and design the wavelet filters while performing the wavelet transform. This is then called the second generation wavelet transform [11]. The technique was introduced by Wim Sweldens. The discrete wavelet transform applies several filters separately to the same signal. In contrast to that, for the lifting scheme the signal is divided like a zipper. Then a series of convolution-accumulate operations across the divided signals is applied.

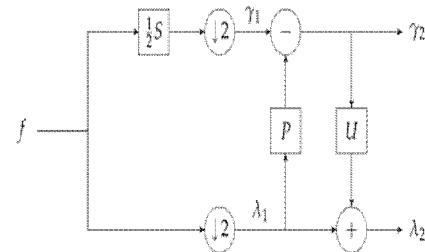


Figure 1: Basic Model of DLWT scheme

The basic idea of lifting is the following: If a pair of filters (h, g) is complementary, that is it allows for perfect reconstruction, then for every filter S the pair (h', g) with $h'(z) = h(z) + s(z^2).g(z)$ allows for perfect reconstruction, too. Of course, this is also true for every pair (h, g') of the form $g'(z) = g(z) + t(z^2).h(z)$. The converse is also true: If the filter banks (h, g) and (h', g) allow for perfect reconstruction, then there is a unique filter S with $h'(z) = h(z) + s(z^2).g(z)$. Each such transform of the filter bank (or the respective operation in a wavelet transform) is called a lifting step. A sequence of lifting steps consists of alternating lifts, that is, once the low pass is fixed and the high pass is changed and in the next step the high pass is fixed and the low pass is changed. Successive steps of the same direction can be merged.

4.2 Properties

Every transform by the lifting scheme can be inverted. Every perfect reconstruction filter bank can be decomposed into lifting steps by the Euclidean algorithm. That is, "lifting decomposable filter bank" and "perfect reconstruction filter bank" denotes the same. Every two perfect reconstructable filter banks can be transformed into each other by a sequence of lifting steps. (If P and Q are polyphase matrices with the same determinant, the lifting sequence from P to Q , is the same as the one from the lazy polyphase matrix I to $P^{-1}.Q$). Speedup by a factor of two [10]. This is only possible because lifting is restricted to perfect reconstruction filter banks. That

is, lifting somehow squeezes out redundancies caused by perfect reconstructability [13]. In place: The transformation can be performed immediately in the memory of the input data with only constant memory overhead. Non-linearities: The convolution operations can be replaced by any other operation. For perfect reconstruction only the invertibility of the addition operation is relevant. This way rounding errors in convolution can be tolerated and bit-exact reconstruction is possible [12]. However the numeric stability may be reduced by the non-linearities. This must be respected if the transformed signal is processed like in lossy compression. Although every reconstructable filter bank can be expressed in terms of lifting steps, a general description of the lifting steps is not obvious from a description of a wavelet family.

4.3 Applications

Wavelet transform with integer values. Fourier transform with bit-exact reconstruction. Construction of wavelets with a required number of smoothness factors and vanishing moments. Construction of wavelets matched to a given pattern. Implementation of the Discrete Wavelet Transform in JPEG 2000.

5. RESULTS AND COMPARISONS

5.1 Quality Measures for Image

5.1.1 Compression ratio

The compression ratio is used to measure the ability of compression by comparing the size of the image being compressed to the size of the original image. It is defined as the ratio between the compressed size and the uncompressed size.

5.1.2 PSNR

It is one of the parameters that can be used to quantify image quality. Larger PSNR will produce better image quality. It is defined as the ratio of maximum signal power to that of the power of corrupting noise that affects the fidelity of its representation. It is used to measure the quality of reconstructed images that have been compressed. It is usually expressed in decibel.

5.1.3 MPE

It is also an important parameter. It is defined as the average phase difference between the current phase set and the phase set obtained from the refined model structure.

5.2 RESULTS

5.2.1 SAR image

Synthetic-aperture radar (SAR) is a form of radar whose defining characteristic is its use of relative motion, between an antenna and its target region, to provide distinctive long-term coherent-signal variations that are exploited to

obtain finer spatial resolution than is possible with conventional beam-scanning means. It originated as an advanced form of side-looking airborne radar (SLAR). Figure 2 taken here is SAR image (i.e) input image which is obtained by collecting the echo returning from radar pulses and processed them into a single image.

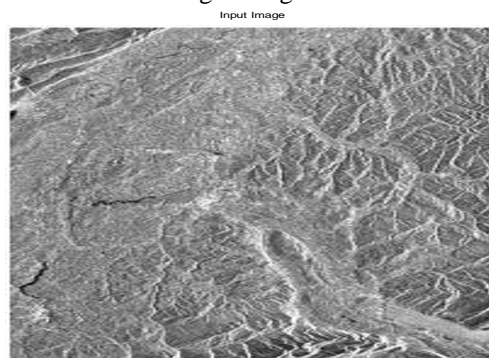


Figure 2: Input image

SAR images have wide applications in remote sensing and mapping of the surfaces of both the Earth and other planets. SAR systems take advantage of the long-range propagation characteristics of radar signals and the complex information processing capability of modern digital electronics to provide high resolution imagery.

5.2.2 Filtered image

In image processing filters are mainly used to suppress either the high frequencies in the image, *i.e.* smoothing the image, or the low frequencies, *i.e.* enhancing or detecting edges in the image. An image can be filtered either in the frequency or in the spatial domain.

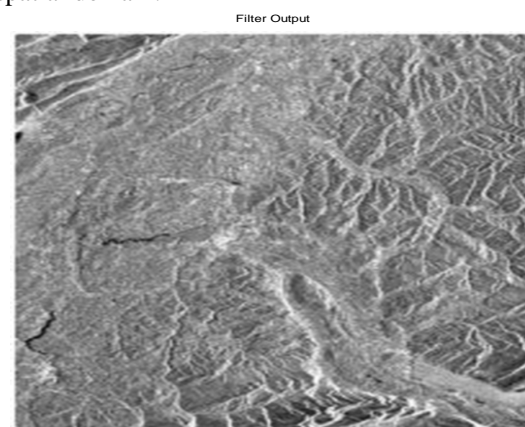


Figure 3: Filtered image

The first involves transforming the image into the frequency domain, multiplying it with the frequency filter function and re-transforming the result into the spatial domain. The filter function is shaped so as to attenuate some frequencies and enhance others. Figure 3 is the filtered output of input image.

5.2.3 DWT decomposition

In numerical analysis and functional analysis, a discrete wavelet transform (DWT) is any wavelet transform for which the wavelets are discretely sampled. As with other wavelet transforms, a key advantage it has over Fourier transforms is temporal resolution: it captures both frequency and location information (location in time).

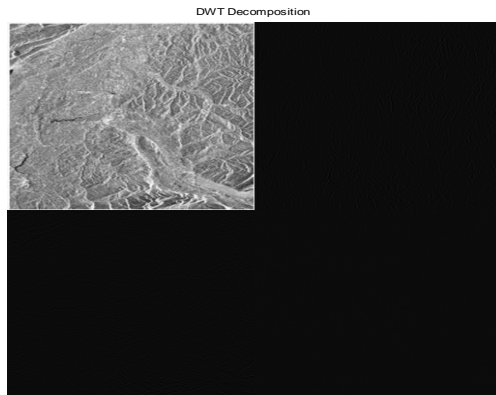


Figure 4: DWT decomposed image

Here figure 4 is divided into vertical and horizontal low pass sub bands. Based on the energy levels the decomposition process can be extended to any levels.

5.2.4 DLWT decomposition

By using directional lifting wavelet transform figure 5 is further decomposed into levels. The decomposition process is mainly in order to remove the unwanted regions in an image and to mainly concentrate on a particular region.

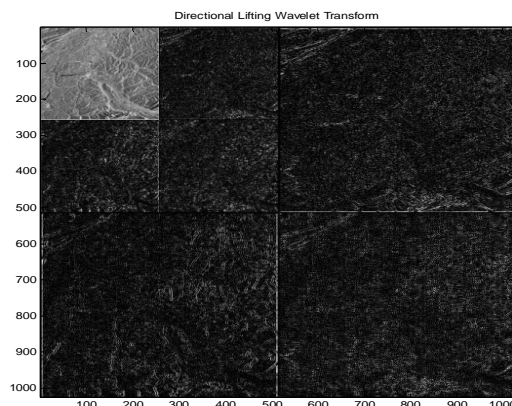


Figure 5: DLWT decomposed image

The lifting technique is an efficient implementation of wavelet transform with low memory and computational complexity. Directional lifting techniques aims at extensively

exploiting the spatial correlation among neighboring pixels in a description.

Compressed image

The objective of image compression is to reduce irrelevance and redundancy of the image data in order to be able to store or transmit data in an efficient form. The images are first compressed and then stored in the local storage or transmitted to the end users.

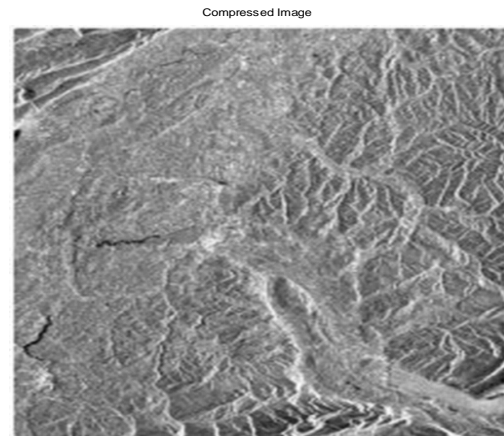


Figure 6: Compressed image

Lossless compression is preferred for archival purposes and often for medical imaging, technical drawings, clip art, or comics. This is because lossy compression methods, especially when used at low bit rates, introduce compression artifacts. The best image quality at a given bit-rate (or compression rate) is the main goal of image compression. Figure 6 is the compressed image of SAR image.

5.2.5 Decompressed image

Figure 7 is decompressed in order to reconstruct the original image from the compressed image.

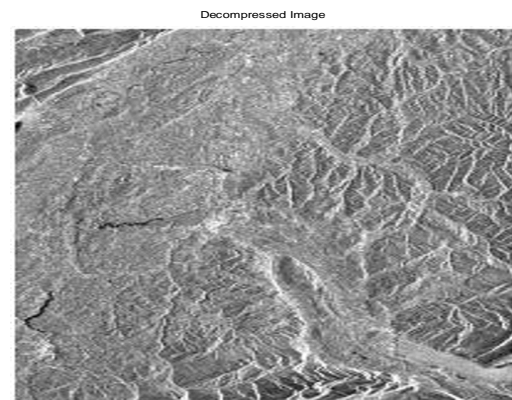


Figure 7: Decompressed image

5.2.6 Comparison of DWT and DLWT

PSNR (PEAK SIGNAL TO NOISE RATIO) is defined as the ratio of maximum signal power to that of the power of signal noise. It is used to measure the quality of the image. It is usually measured in decibel.

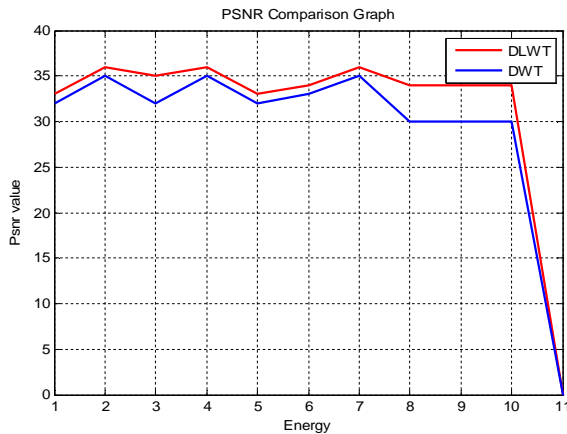


Figure 8: PSNR comparison plot

When compared to ordinary discrete wavelet transform, directional lifting wavelet transform improves the peak signal to noise ratio and reduce the mean phase error. Figure 8 shows the quality of image obtained using DLWT will be better when compared to DWT. Thus the compression ratio can also be increased.

5.2.7 Comparison of coding performance

The performance of DLWT when compared to DWT will be high since which is shown in figure 9, DLWT can encode more number of coefficients at a same bit rate but DWT require different bit rates for different number of coefficients.

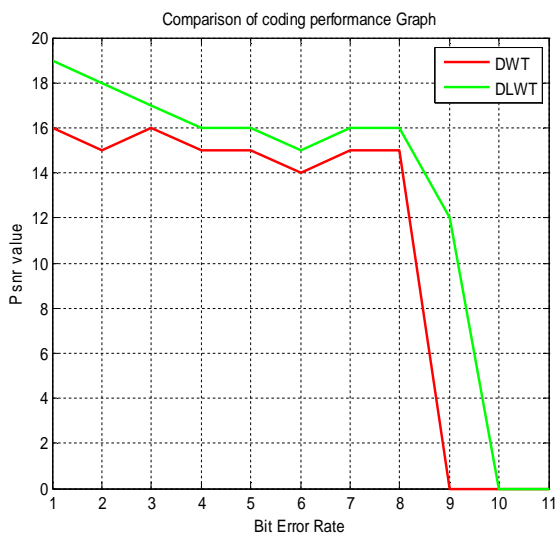


Figure 9: BER comparison plot

Thus DLWT can improve the coding performance and provides high clustering capability.

6. CONCLUSION

Data compression technology is an effective way to alleviate the pressure of transmission and storage on SAR system. 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. There are two main contributions in this paper. First, we propose two compression schemes, DLWT_IQ and DLWT_FFT, for the complex SAR images based on DLWT. The proposed two compression schemes significantly outperform DWT-based schemes in terms of higher PSNR and lower MPE. It is noteworthy that DLWT_FFT outperforms DLWT_IQ at low and middle bit rates, and thus can be applied for website browsing. Furthermore, both schemes preserve phases better than 1° and amplitudes better than 100 dB in PSNR, which is promising for a wide range of applications. Second, we observe a novel phenomenon, that is, for SAR images, DLWT provides higher clustering capability and the clustering capability can be captured by the BPE coding algorithm to improve the rate distortion performance when compared with DWT, even if the K-term approximation of DLWT is not as good as that of DWT. Hence, we may need other measures to assess the performance of representation for coding algorithm in addition to the classical K-term approximation.

REFERENCES

- [1] R. W. Ives, C. Kiser, and N. Magotra, “Wavelet compression of complex SAR imagery using complex-and real-valued wavelets: A comparative study,” in *Proc. IEEE Asilomar Conf. Signals, Syst. Comput.*, Nov. 1998, vol. 2, pp. 1294–1298.
- [2] S. Suganya, M. Selvaganapathy, N. Nishavithri, “Comparison of warping filter banks using MATLAB based Feature Extraction techniques in ASR”, *International Journal of Innovative Research in Computer and Communication Engineering*, Volume 4, Issue 5, May 2016.
- [3] M. Selvaganapathy, R. Kayalvizhi, N. Mahendran, “An Effective optimization for feature extracted image using Particle Swarm Optimization”, *Proceedings of TEQIP – II Sponsored International Conference on Contemporary Topics in Power Engineering and Aiding Technologies (ICCPEAT’2017)*, February 2017.
- [4] Tonny Hidayat, Mohd Hafiz Zakaria and Ahmad Naim Che Pee “Reformat the File Uncompressed into Lossy Based on Audio Compression Method using Huffman Shift Coding Scheme”, *International Journal of Advanced trends in Computer Science and Engineering*, Volume 8, no.1.5, ISSN 2278-3091,2019. <https://doi.org/10.30534/ijatcse/2019/5381.52019>

- [5] Heorhii Kuchuk, Andriy Kovalenko, Bnar Fareed Ibrahim, Igor Ruban “ **Adaptive Compression method for Video Information**”, *International Journal of Advanced trends in Computer Science and Engineering*, Volume 8, No.1.2, ISSN 2278-3091, 2019.
- [6] Noor Huda Ja’afar, Afandi Ahmad, Syazmeer Sabudin “**Implementation of Fast Discrete Curvelet Transform using Field-Programmable Gate Array**”, *International Journal of Advanced trends in Computer Science and Engineering*, Volume 9, no 1.2, ISSN 2278-3091, 2020.
<https://doi.org/10.30534/ijatcse/2020/2591.22020>
- [7] A. M. Atto, D. Pastor, and A. Isar, “**On the statistical decorrelation of the wavelet packet coefficients of a band-limited wide-sense stationary random process,**” *Signal Process.*, vol. 87, no. 10, pp. 2320–2335, Oct. 2007.
- [8] Y. Liu and K. N. Ngan, “**Weighted adaptive lifting-based wavelet transform for image coding,**” *IEEE Trans. Image Process.*, vol. 17, no. 4, pp. 500–511, Apr. 2008.
- [9] B. Li, R. Rui, and H. X. Jiang, “**Remote-sensing image compression using two-dimensional oriented wavelet transform,**” *IEEE Trans. Geosci. Remote Sens.*, vol. 49, no. 1, pp. 236–250, Jan. 2011.
<https://doi.org/10.1109/TGRS.2010.2056691>
- [10] P. Eichel and R.W. Ives, “**Compression of complex-valued SAR images,**” *IEEE Trans. Image Process.*, vol. 8, no. 10, pp. 1483–1487, Oct. 1999.
- [12] M. N. Do and M. Vetterli, “**The contourlet transform: An efficient directional multi resolution image representation,**” *IEEE Trans. Image Process.*, vol. 14, no. 12, pp. 2091–2106, Dec. 2005.
- [13] R. Dong, B. Hou, and S. Wang, “**SAR image compression based on wedgelet-wavelet,**” *Signal Process. Image Enhancement Multimedia Process.*, vol. 31, pp. 67–75, Dec. 2007.
https://doi.org/10.1007/978-0-387-72500-0_7