Progressive SAR Image Compression Using Low Complexity Bandlet Transform and Modified EZBC

Maryam Kuchakzadeh, Habibollah Danyali and Sadegh Samadi

Abstract. In this paper, we introduce a progressive SAR image compression based on Bandlet transform (BT) and a modified Embedded Zero-Block Coding (EZBC) algorithm. Bandlet transform as a new developed adaptive multiresolution geometry analysis tool exhibits enormous potential in compression based on geometric regularity. Since in SAR images, important information is spread in the entire frequency spectrum, discrete wavelet transform (DWT) cannot provide optimal representation and instead Bandlet transform is employed to provide a sparse representation of the image. A modified version of EZBC algorithm is introduced to efficiently encode the Bandlet coefficient in a progressive manner in which fidelity of the reconstructed image in the decoder gradually improves as more bits are received and decoded. Numerical tests show that our method provide a significant improvement particularly for low bit rate SAR image compression.

Keywords: SAR, DWT, Bandlet transform, EZBC, progressive image coding.

1. Introduction

Remote sensing is the collection of information relating to remote targets without being in physical contact with them for further processing. Today, Synthetic Aperture Radar (SAR) has evolved as a powerful tool that accomplishes the necessities of imaging remote sensing systems and provides high-resolution images from the earth surface [1].

The performance of SAR is same in all weather conditions and all times, thus SAR images have an important role in military and civilian applications. With the improvement of SAR technology, larger areas and higher resolution sensors are considered. This causes the volume of data associated with SAR images to be extremely large [2]. To reduce the burden of data storage and transmission, there is a strong interest in developing SAR image compression algorithms without significant loss of perceptual image quality.

Use of transform domain for image coding and image compression has the most applicable and has been widely used in recent systems. Any transform by which image energy can be embedded in less coefficients will be able to improve coding results. Up to now, DWT has been used in many image coding systems [3]. In the field of SAR images compression, DWT also become more common [4]. However, DWT is isotropic and has poor directionality, so it fails to provide a sparse representation of oriented 1-D (one dimensional) discontinuities in images such as contours [5]. To resolve the defect of DWT, a set of representations has been proposed which called X-Lets or directional wavelets [6]. Ridgelet [7], Curvelet [8], Contourlet [9] and BT [10-11] are some members of this family.

The optimal representation with Ridgelet, Curvelet and Contourlet can only be obtained when the geometry structures are ideal, i.e. strictly lines or curves [7-9]. Since there are many edges or geometric structures in image that their directions cannot be predicted, so these transforms are not good and an adaptive geometric representation tool is more reasonable [10].

Bandlet which is proposed by Pennec, Peyre and Mallat, can implement a sparse approximation of image geometry when geometric regularity is unknown by an adaptive segmentation and a local geometric flow [10-11]. Many researchers have demonstrated the efficiency of BT for the SAR images compression [12-13]. However, this improvement is achieved at the expense of a substantial increase in high computational complexity in time and space.

In a typical image coding system, after determination of transform type, a proper algorithm based on transform domain is required to both reducing transform coefficients and arranging them in a binary stream for transmitting over a transfer channel. Algorithms such as EZW (Embedded Zero-tree Wavelet) [14], SPIHT (Set Partitioning in Hierarchical Trees) [15], EZBC [16], EBCOT (Embedded Block Coding with Optimized Truncation) [17] and SPECK (Set Partitioning Embedded bloCK) [18] have been introduced as the most applicable strategies for compression and coding in DWT domain. Since BT domain structurally is similar to DWT domain, therefore wavelet based coding algorithms can be used for Bandlet coefficients as well.

The performance of SPIHT and EZW is based on a Treestructure, and their efficiency is dependent on large trees. Since existing energy in the high frequency component causes the loss of large trees, their efficiency reduces for the textured images [14-15]. To overcome this problem, algorithms based on Block-structure such as EZBC, EBCOT and SPECK have been introduced [16-18].

In this paper for two reasons, EZBC algorithm uses to SAR images compression. First for simplicity, while EBCOT algorithm is high complexity. Second, due to its ability in a region of interest (ROI) compression with higher bit rate than background, while SPECK algorithm is

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disabled in ROI compression due to lack of random access to data.

Several papers have been published to compress SAR images using BT [12-13] in which segmentation optimization and geometric flows optimization in Bandlet, causes the representation to be sparser and consequently improves the compression ratio. However, they ignore Block-structure of BT and use entropy coding to code resultant coefficients. Thus, they could not provide an efficient coding method.

Our goal firstly is to reduce consumed bits by modification of the BT and secondly is to focus our attention on Block-structure of this transform and finally provide an efficient algorithm for it. In our proposed approach, Bandlet is performed in Wavelet Packet Transform (WPT) domain, whereas the conventional Bandlet is applied on DWT domain. We also introduce a modification of EZBC algorithm to code BT coefficients, which can further improve the SAR image compression results in compare with Tree-structure based coding algorithms.

2. Low Complexity Bandlet and EZBC Algorithm

2.1. Low Complexity BT on WPT Domain

Providing an effective transform-based representation is an important problem in the area of image compression. Despite DWT is widely used in compression algorithms, existing spatial and geometric redundancy among wavelet coefficients reduces its performance in low bit rate. To remove this redundancy, Pennec and Mallat introduced geometric flow to represent the image regularity and presented the first generation BT [10]. Unfortunately, the resulting transform was non-orthogonal and produced blocking artifacts due to piecewise-constant nature of basis functions. Instead, they introduced the second generation BT (2G-BT) [11] that was simpler and orthogonal and had no border effect.

The BT computes the projection of a function x (image) on basis $\mathfrak{B} = \left\{ b_{\mu} \right\}_{\mu}$. Thus, a complete Bandlet representation is composed of:

• A quadtree segmentation for each scale of wavelet.

• For each scale and each dyadic square in the quadtree:

 \circ The direction *d*,

• The Bandlet coefficients.

The best approximation x_R of a function x with obtained coefficients in an orthogonal basis $\mathfrak{B} = \{b_\mu\}_\mu$ is computed using the coefficients larger than some threshold T. The function restored from quantized Bandlet coefficients is:

$$x_{R} = \sum_{\left| \left\langle \mathbf{x}, \mathbf{b}_{\mu} \right\rangle \right| > T} \left\langle \mathbf{x}, \mathbf{b}_{\mu} \right\rangle b_{\mu} \tag{1}$$

and the approximation error is:

$$\|x - x_R\|^2 = \sum_{|\langle \mathbf{x}, \mathbf{b}_\mu \rangle| \le T} |\langle \mathbf{x}, \mathbf{b}_\mu \rangle|^2$$
(2)

Therefore, an image is compressed in a Bandlet frame by coding the segmentation of the wavelet domain, a geometric flow in each region of the segmentation and the decomposition coefficients. Note that there might exist some dyadic squares in which we do not have geometry because the square does not contain any geometric singularity. In these cases we simply keep the original wavelet coefficients.

By R, we denote the number of needed bits to code both the Bandlet basis and the coefficients in this basis. It can be decomposed into:

$$R = \sum_{j} R_{j} = \sum_{j} \left(R_{Sj} + R_{Fj} + R_{Bj} \right),$$
(3)

where, for each scale (denoted by j):

 R_{sj} is the number of bits needed to encode the dyadic segmentation.

 R_{Fj} is the number of bits that need to code the optimal geometric flow d in each square of segmentation.

 R_{B_j} is the number of bits needed to encode the quantized Bandlet coefficients.

In order to approximate the function (image) by the BT, the set of wavelet coefficients segments in squares. For each scale and orientation of the DWT, this segmentation is obtained using a recursive subdivision in dyadic squares of various sizes. Finally for each square in the obtained quadtree, the optimal geometrical direction d is computed by the minimization of a Lagrangian \mathcal{L} for a given quantization step T [10-11]:

$$\mathcal{L}(x, R, \mathfrak{B}) = \|x - x_R\|^2 + \frac{3}{4} T^2 \sum_{j} (R_{sj} + R_{Fj} + R_{Bj})$$
(4)

This minimization determines the best geometric direction that achieves the best approximation of the original signal and the number of needed bits to code the approximated signal.

Although BT provides an efficient and more effective representation than wavelet but its drawback is high complexity due to pruning the quadtree and computing best direction. By taking the advantage of the fixed size segmentation, our proposed method is low complexity and thus can be implemented rapidly when compared with the conventional BT. Since by using of fixed partition size, we do not need to address the quadtrees, it saves the coding bits. Thus the number of bits required for coding Bandlet basis be summarized as follows:

$$R = \sum_{j} R_{j} = \sum_{j} \left(R_{Fj} + R_{Bj} \right)$$
(5)

This low complexity BT superiority is remarkable in low bit rate. More details of this transform can be found in [9].

As mentioned, conventional Bandlet is implemented on DWT domain. Since, there are important information distributed in all over the spectrum of SAR images, by use of DWT we are unable to provide optimal representation. Applying wavelet to different frequency bands according to their energy levels is a good way to more energy compaction in SAR Images. In other words, we should use WPT. Kuchakzadeh et al.: Progressive SAR Image Compression Using Low Complexity Bandlet Transform and Modified EZBC

2.2. EZBC Algorithm

The algorithm based on the Block-structure have better performance than algorithms based on Tree-structure for compressing images with complex structures and details textures. So coding algorithms such as EZBC provides better performance for compressing the images with high frequency components. Since in SAR images, high frequency bands have remarkable energy (information) like low frequency band, so for compressing these kind of images can use EZBC compression algorithm [16].

One of the bit-plane coding algorithms is EZBC which in each level sends bits of transform coefficients according to their significance. In this algorithm, each subband of the wavelet decomposed image is considered as a block and then each block is coded separately from the lowest frequency subband (in the coarser scale) to the highest frequency subband (in the finest scale). This strategy could encode a whole insignificant block according to the coding threshold with only one bit and thus efficiently compress the image especially at very low bit rates.

If EZBC be employed in WPT domain, each band of transform should be considered as a block and then these blocks are coded separately. Because of increasing number of WPT bands in compare with DWT, if we send a code for each threshold, to distinguish significant blocks from insignificant ones, we must spent a lot of bits. Whereas large number of blocks is insignificant in compare with thresholds, they take bits. Thus, the quality of reconstructed image is severely reduced. In order to reduce the bit consumption and consequently to increase efficiency of compression method, we purpose that subbands are coded according to their significance in EZBC algorithm.

3. Modified EZBC Based on Bandlet for SAR Image Compression

By modifying the EZBC for WP based Bandlet, the algorithm can be improved for SAR image compression. Block diagram of the proposed methods depicted in Fig. 1 that its steps are as follows:

Step 1) Apply WPT to SAR image in order to more energy compaction

The WPT is as follows:

- Perform one level DWT (Image divide into four bands)
- Calculate the average energy for each resulted band according to the following equation:

$$E = \frac{1}{M \times N} \sum_{m=1}^{M} \sum_{n=1}^{N} |x(m,n)|^{2}$$
(6)

where $M \times N$ is the size of the band, and x(m, n) are the wavelet coefficient in the same subband.

• For each band, if the energy is lower than the obtained average energy, the decomposition process stops, because there is little information in it. Otherwise, the bands are named significant and the above steps will repeat for it.

Step 2) Partitioning of obtained transform domain into some squares with the same size

Step 3) Calculation of optimum geometric flow according to cost function

Step 4) Applying 1-D wavelet transform along to geometric flow in order to generation of Bandlet coefficients

Step 5) Rearranging Bandlet coefficients along the geometry in each square

Step 6) Ordering bands of Bandlet domain based on the largest amount of energy or greatest coefficient

Note that reordering bands in descending form, according to greatest coefficient of each block, causes the important and high energy careering blocks to be coded before other blocks. This strategy leads to reduction in consumed bits and consequently increases algorithm efficiency at low bit rates. For this purpose, we need to assess and identify the blocks if they could be decomposed further. Now we should provide a list and place the address of important subbands at first, followed by the address of the rest of the blocks (containing low energy level and less information).

Step7) Perform EZBC algorithm to bands according to their energy



Fig. 1. Block diagram of the proposed method for SAR image compression.

• In the previous step we obtained a list of the addresses of all bands. Now, according to this list, the bands respectively are coded based on EZBC algorithm. Since bands are sorted and numbered by importance, so more important bands are coded sooner. This process will continue until the number of bits for image encoding is finished.

4. Experiments and Performance Evaluation

In this section to investigate the performance of the proposed method, we compare the compression results of SPIHT, EZBC and our method applied on a SAR test image (512×512 pixels) shown in Fig 2. Since our proposed method has been implemented in WPT based BT domain, therefore it is expected that results are compared with [19] and [20]. Unfortunately, goal of [20] is improvement of reconstructed image quality for high bit rates, while our goal is to improve outcomes for low bit rates. In addition, our proposed SAR image coding system is designed without speckle noise reduction, while in paper [19], first speckle noise of SAR images is removed by soft thresholding in MP domain and then, the coding step is done by modified SPIHT algorithm. So, we cannot compare our results with [19] and [20].

In our experiment, we compared the performance of three level DWT followed by SPIHT coding, two level DWT followed by EZBC coding and two level Bandlet on WP domain followed by modified EZBC coding (our method). It should be noted that the coding of our proposed method consists of two sections: coding of the optimal geometric flows and the Bandlet coefficients. For the optimal geometric flows, we adapt an entropy coding and for the Bandlet coefficient, we apply the modified EZBC coding.

At first we compare the implementation time of the 2G-BT and modified Bandlet. The obtained result are shown in Table 1. Ten independent experiments are taken on a PC with Intel Core i5-2.50 GHz and 8.00 GB RAM, and the average time is calculated. The results show that modified Bandlet is remarkably faster than the 2G-BT because our BT employed the fixed partition way of the images, which can avoid the bottom to top pruning algorithm of wavelet quadtree and the exhaustive searching of geometric flows in the 2G-BT.



Fig. 2. A SAR test image (512×512 pixels).

Table 1. The Required Time of 2G-BT and Modified BT for Sar Test Iamge

Average Running Time (In Second)	
2G-BT	Modified Bandlet
1470.22 s	35.98 s

PSNR criterion is employed to evaluate the performance of the compression methods that define as:

$$PSNR = 10 \log_{10} \frac{255^2}{\frac{1}{MN} \sum_{m} \sum_{n} (x(m,n) - \hat{x}(m,n))^2} dB$$
(7)

where $M \times N$ present the size of image and x, \hat{x} represent the original and compressed images respectively.

In addition to it, we also use the *SSIM* (Structural SIMilarity) index [21], an appropriate method for evaluating the similarity between the reconstructed SAR image and the original one. SSIM is defined as:

$$SSIM(x,\hat{x}) = l(x,\hat{x})C(x,\hat{x})S(x,\hat{x})$$
(8)

where $l(x, \hat{x})$ is the luminance comparison, $C(x, \hat{x})$ is the contrast comparison, and $S(x, \hat{x})$ is the structure comparison. The value of $SSIM(x, \hat{x})$ should be between 0 and 1. The higher the value of $SSIM(x, \hat{x})$ is the more similarity between images x and \hat{x} . With $SSIM(x, \hat{x}) = 1$ we can say x and \hat{x} are the same.

Figure 3 shows the obtained *PSNR* and *SSIM* respectively at different bpp for the SAR test image of Fig. 1. It can be seen that our proposed method outperforms at low bit rate.

The resultant compressed images of the three methods are shown in Fig. 4 (a) to (c), the results of SPIHT, EZBC and our method at 0.4 bpp. We can see that, the reconstructed image in our method has a better visual quality especially in preservation of edges and textures.

5. Conclusion

In this paper a low complexity Bandlet transform based on a fixed size image partition was proposed for SAR image compression. In contrast to optical images, SAR images have both low and high frequency components. In the proposed method, in order to perform BT, we used WPT instead of DWT. To encode the transformed coefficients, a modified EZBC algorithm was introduced. Our method can utilize the geometrical regularity and preserve textures in the compressed SAR image well even at very low bit rates. The experimental results showed that this method is an effective algorithm for SAR images compression and has a better visual effect especially at low bit rates in compared with the existing progressive coding algorithms. The proposed method has the potential to be extended for region of interest coding in SAR images.



Fig. 3. (a) PSNR values and (b) SSIM values at different bit-rates for the test image.



Fig. 4. The reconstructed test image at 0.4 bit per pixel by (a) SPIHT(PSNR=18.05dB) (b) EZBC (PSNR=21.35dB) (c) our method (PSNR=22.33dB).

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