



Remote Sensing Image Compression Using 3D-SPIHT Algorithm

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Abstract

To measure the characteristics of an object from a distance, the technique of remote sensing is used. By this technique we can collect all information about an object without making any physical contact with that object. 3D SPIHT algorithm to code objects with arbitrary shape and adds spatial and temporal scalability features to it. It keeps important features of the original 3D SPIHT coder such as compression efficiency, full embeddedness and rate scalability. Set Partitioning in hierarchical trees (SPIHT) algorithm to remote sensing images, using a wavelet decomposition method. The wavelet decomposition is accomplished with wavelet filters implemented with the lifting method. Result show that our algorithm with filters performs as well and better in lossless coding systems using 3D SPIHT and wavelet transforms on remote sensing images.

Keywords: Remote Sensing Image, Wavelet Decomposition, JPEG2000, 3D-SPIHT

1. Introduction

Remote sensing in its broadest sense is simply defined as the observation of an object from some distance. Earth observation and weather satellites, medical x-rays for bone fractures are all examples of remote sensing. Remote sensing devices make use of emitted or reflected electromagnetic radiation from the object of interest in a certain frequency domain (infrared, visible light, microwave). Remote sensors are classified as either; active sensors or passive sensors. Active sensors provide their own source of radiation to send out to an object and record the magnitude of radiation returns. Passive sensors record incoming radiation that has been scattered, observed and transmitted from the earth in transmit from its original source, the sun.

In the recent years, operators are getting much more information than ever before due to the development of image sensors. The essential development of sensors has also resulted in the augmentation of the human observer workload. To deal with these situations, there is a strong need of developing an image processing technique which integrates the information from different sensors. It greatly improves the

capability of image interpretation and the reliability of image judgment which resulted in enhancing the accuracy of classification and target recognition. A number of techniques have been proposed in the last few years for the compression of remote sensing images. The entire try to take advantage, in various degrees, of the peculiarities of these images. The techniques based on quantization and transform coding.

Quantization [1], [2] is theoretically the optimal block coding strategy. Indeed it is the direct application of the principles of information theory, and all other block coding techniques (e.g., transform coding) can be seen as structurally constrained forms of quantization. However, unconstrained quantization is characterized by a computational complexity that grows exponentially with the block size. As a consequence, practical coding schemes based on quantization are forced to use small block, thereby exploiting the statistical dependencies among only a small number of pixels and/or spectral bands. To obtain good encoding performance with limited complexity, many researchers rely on transform coding techniques [3], where a linear transform decorrelates the input data concentrates most of the power in a few coefficients so that subsequent quantization is more efficient.

In the transform coding framework, wavelet transform [4], [5] deserves a special treatment because of its peculiar characteristics. Indeed due to its implementation as a recursive filtering procedure, it can easily work on large blocks there by providing an excellent power concentration. After transform and quantization both use the zerotree coding approach by applying suitably modified versions of the SPIHT on the resulting images. The Set Partitioning in Hierarchical Trees (SPIHT) algorithm [6] is one of the best wavelet based coding

Compression is a commonly used process to reduce the amount of initial data to be stored or transmitted by a channel to a receiver. 3D SPIHT use lists (list of significant and insignificant pixels, list of insignificant sets) which grow very fast compared to list of 2D SPIHT (each pixels has eight children for the 3D version and only four in 2D). 3D SPIHT is necessary to have a wavelet decomposition output corresponding to the input of 3D SPIHT encoder. In this paper we compare proposed work using wavelet with the original scheme using 3D SPIHT algorithm.

2. Methodology

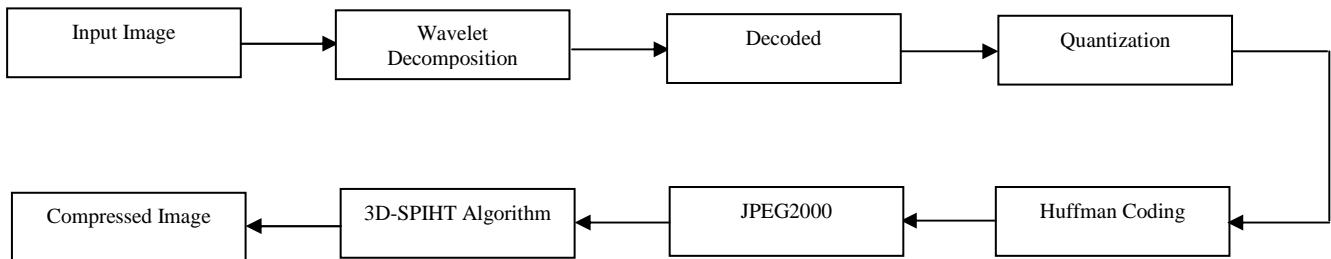


Fig. 1 System Architecture

3. The 3D-SPIHT Compression

SPIHT (Set Partitioning in Hierarchical Trees) algorithm is a sophisticated version of the EZW algorithm. The highest PSNR values for a given compression ratios for a wide variety of images have been obtained with SPIHT. Therefore, it is probably the most widely used wavelet based algorithm for image compression, providing a basic standard of comparison for all subsequent algorithms. The term Hierarchical trees refers to the quadtrees, Set Partitioning refer to the way these quadtrees divide up, partition, the wavelet transform values at a given threshold. The SPIHT algorithm proposed in this paper solves the spatial and temporal scalability through the introduction of multiple resolutions dependent lists and a resolution dependent sorting pass. It keep important feature of the original SPIHT coder such as compression efficiency, full embeddedness, and rate scalability. The full scalability of the algorithm is achieved through the introduction multiple resolution dependent lists of the sorting stage of the algorithm. The idea of bitstream transcoding without decoding to obtain different bitstreams for various spatial and temporal

algorithm for remote sensing images. It is very efficiently exploits the self-similarity between different levels in the wavelet pyramid and provides an embedded bit stream which support PSNR, MSE scalability. The excellent performance of SPIHT for remote sensing image makes it an attractive coding strategy. A 3D extension of SPIHT has been proposed by Kim and Pearlman in [7, 8]. They applied 3D wavelet transform and coded the wavelet coefficients by the 3D SPIHT algorithm.

Image Compression is one of the techniques in image processing. There are various types of Algorithms and techniques are used for compressed the images. Some of the Algorithms and techniques are SPECK Algorithm, SPIHT Algorithm, ASWDR Algorithm, LZW Coding, Fractal Coding. Here the proposed work is represented the architecture as shown the fig.1.

resolutions and bit rates is completely supported by the algorithm.

SPIHT coding is applied on each band of the wavelet transform results to achieve compression. In order to take this fact into account, it is preferable to weight each band. As weight we use the energy $E = \sqrt{\sum_{x,y} I_\lambda(x,y)^2} / X,Y$, where

I_λ is the image band at the λ wavelength, X and Y and its dimension, and x and y are the position of a pixel in the band. Depending on energy band, we allocate proportional number of bits for the output of the SPIHT algorithm. The 3D approach consists in considering the whole remote sensing image as an input for full 3D decomposition. To achieve compression 3D SPIHT [9] is then applied.

The 3D SPIHT algorithm of [8] considers set of coefficients that are related through a parent offspring like the one depicted in **Fig: 1**. In its bitplane coding process, the algorithm deals with the wavelet coefficients as either a root of an insignificant set, an individual insignificant pixel, or a

significant pixel. It sorts these coefficients in three ordered lists: the list of insignificant sets (LIS), the list of insignificant pixels (LIP), and the list of significant pixels (LSP). The main concepts of the algorithm is managing these lists in order to efficiently extract insignificant sets in a hierarchical structure and identify significant coefficients which is the core of its high compression performance.

The 3D wavelet decomposition provides a multiresolution structure that consists of different spatio-temporal subbands that can be coded separately by a scalable encoder to provide various spatial and temporal scalabilities. In general by applying N_t levels of 1D temporal decomposition and N_s levels of 2D spatial decomposition, at most $N_s + 1$ levels of spatial resolution and $N_t + 1$ levels of temporal scalability are achievable. The total number of possible spatio-temporal resolution in this case is $(N_s + 1) + (N_t + 1)$. To distinguish between different resolutions levels, we denote the lowest spatial resolution levels as level $N_s + 1$ and the lowest temporal resolution level as $N_t + 1$. Algorithm provides full spatial and temporal scalability would encode the different resolution resolutionsubbands separately, allowing a transcoder or a decoder to directly access the data needed to reconstruct a desired spatial and temporal resolution.

4. JPEG2000

JPEG-2000 is an emerging standard for still image compression. JPEG-2000 image compression system has a rate distortion advantage over the original JPEG. JPEG-2000 [10][11] image compression standard which has replaced the commonly used DCT based JPEG. More importantly, it also allows extraction of different resolutions, pixel fidelities, regions of interest, components, and more, all from a single compressed bitstream. The coding mechanisms themselves are more efficient and support more flexible, finely embedded representations of the image. JPEG 2000 employs a discrete wavelet transform (DWT). The JPEG 2000 algorithm also inherently supports good lossless compression, competitive compression of bi-level and low bitdepth imagery, and bit-streams which embed good lossy representations of the image within a lossless representation. The DWT is an important tool in the construction of resolution-scalable bitstreams. As shown in Fig. 1, a first DWTstage decomposes the image into four subbands, denoted LL1, HL1 (horizontally high-pass), LH1 (vertically high-pass) and HH1. The next DWT stage decomposes this LL1 subband into four more subbands, denoted LL2, LH2, HL2 and HH2. The process continues for some number of stages, D; producing a total of $3D + 1$ subbands whose samples represent the original image.

JPEG-2000 It is a wavelet-based compression technique that adds/improves features such as coding of regions of interest, progressive coding, scalability etc. The entire coding can be divided into four stages: tiling, discrete wavelets transform (DWT), scalar quantization and block coding. The image is divided into rectangular regions called tiles, each tile gets encoded separately. The purpose of dividing images into tiles

is that the decoder needs to decode only certain parts of the image on demand, instead of decoding the entire image and also less memory will be needed by the decoder to decode the image. After dividing the image into tiles, a wavelet transform is applied to each tile. The wavelet transform is followed by scalar quantization to quantize the subbands. The scalar quantized subbands representing different scales are coded using Embedded Block Coding with Block Truncation (EBCOT) [29-32, 36] scheme. For the case of hyperspectral imagery the Part II of JPEG2000 [32] is implemented to allow multi-component image compression which involves grouping of arbitrary subsets of components into component collections and applying point transforms along the spectral direction like wavelet transform. The post-compression rate-distortion optimizer of EBCOT is simultaneously applied to all code blocks across all the components.

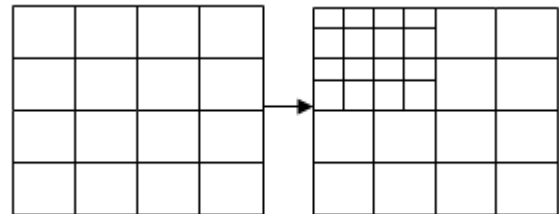


Fig. 2 Iteration of Wavelet Decomposition

The DWT's multi-resolution properties arise from the fact that the LL_d subband is a reasonable low resolution rendition of LL_{d-1} ; with half the width and height. Here, the original image is interpreted as an LL_0 subband of highest resolution, while the lowest resolution is represented directly by the LL_d subband. The LL_d subband, $0 \leq d < D$; may be recovered from the subbands at levels $d + 1$ through D by applying only $D - d$ stages of DWT synthesis. So long as each subband from DWT stage d ; $0 < d \leq D$, is compressed without reference to information in any of the subbands from DWT stage $s < d'$; $0 \leq d' < d$; we may convert a compressed image into a lower resolution compressed image, simply by discarding those subbands which are not required. The number of resolutions available in this way is $D + 1$.

5. Problem Description

5.1 Mean Square Error (MSE)

The simplest of image quality measurement is Mean Square Error (MSE). The large value of MSE means that image is poor quality [12]. MSE is defined as follow:

$$MSE = \frac{1}{MN} \sum_{m=1}^M \sum_{n=1}^N (x(m, n) - \hat{x}(m, n))^2$$

5.2 Peak Signal to Noise Ratio (PSNR)

The small value of Peak Signal to Noise Ratio (PSNR) means that image is poor quality. In general, a good reconstructed

image is one with low MSE and high PSNR [12]. PSNR is defined as follow:

$$PSNR = 10 \log \frac{255^2}{MSE}$$

5.3 Correlation

Correlation coefficient quantifies the closeness between two images. The correlation coefficient is computed by using the following equation [13].

$$Corr \left(\frac{A}{B} \right) = \frac{\sum_{i=1}^M \sum_{j=1}^N (A_{i,j} - \bar{A})(B_{i,j} - \bar{B})}{\sqrt{\sum_{i=1}^M \sum_{j=1}^N (A_{i,j} - \bar{A})^2 \sum_{i=1}^M \sum_{j=1}^N (B_{i,j} - \bar{B})^2}}$$

A correlation is a number between -1 and +1 that measures the degree of association between two variables (call them X and Y). A positive value for the correlation implies a positive association (large values of X tend to be associated with large values of Y and small values of X tend to be associated with small values of Y). A negative value for the correlation implies a negative or inverse association (large values of X tend to be associated with small values of Y and vice versa).

5.4 Structural Similarity Measures

The structural similarity (SSIM) index is a method for measuring the similarity between two images [14]. The measure between two windows x and y of common size N×N is:

$$SSIM(x, y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)}$$

where μ_x is the average of x, μ_y is the average of y, σ_x^2 is variance of x, σ_y^2 is variance of y, σ_{xy} represents the covariance of x and y, $C_1 = (k_1 L)^2$, $C_2 = (k_2 L)^2$ two variables to stabilize the division with weak denominator.

5.5 Execution Time

The execution time for all the images are tested and compared with JPEG2000 and 3D-OWT which are used. The 3D-OWT gives the higher results for all the ten Remote Sensing Images. Execution time is calculated using tic toc method.

6. Parameters for Evaluation

Remote sensing image is defined as an image produced by a recording device that is not in physical or intimate contact with the object under study. Remote sensing image is used to obtain information about a target or an area or phenomenon through the analysis of certain information which is obtain by the remote sensing imagery generally

require correction of undesirable sensor characteristics and other disturbing effects before performing data analysis. Images obtained by satellite are useful in many environmental applications such as tracking of earth resources, geographical mapping, prediction of agriculture crops, urban growth, weather, flood and fire control etc. When capturing image using sensors, the resulting image may contain Noise from dirtiness on the image data acquisition process. So in this paper, we have analysed a remote sensing image. It is downloaded from Google sites.

7. Results

The figure2 shows the experimental results of the proposed work. The test image is taken as Input image. It has very high frequency components, so the JPEG2000 and 3D-SPIHT algorithmis used to compress the Image. Both of the Algorithms compress the image. When compared to the JPEG2000, 3D-SPIHT produces better compression when compared to JPEG2000 which is shown in fig2. This shows that the 3D-SPIHT Algorithm has shown good efficiency for image compression. The proposed work is done using MATLAB. 2010version.

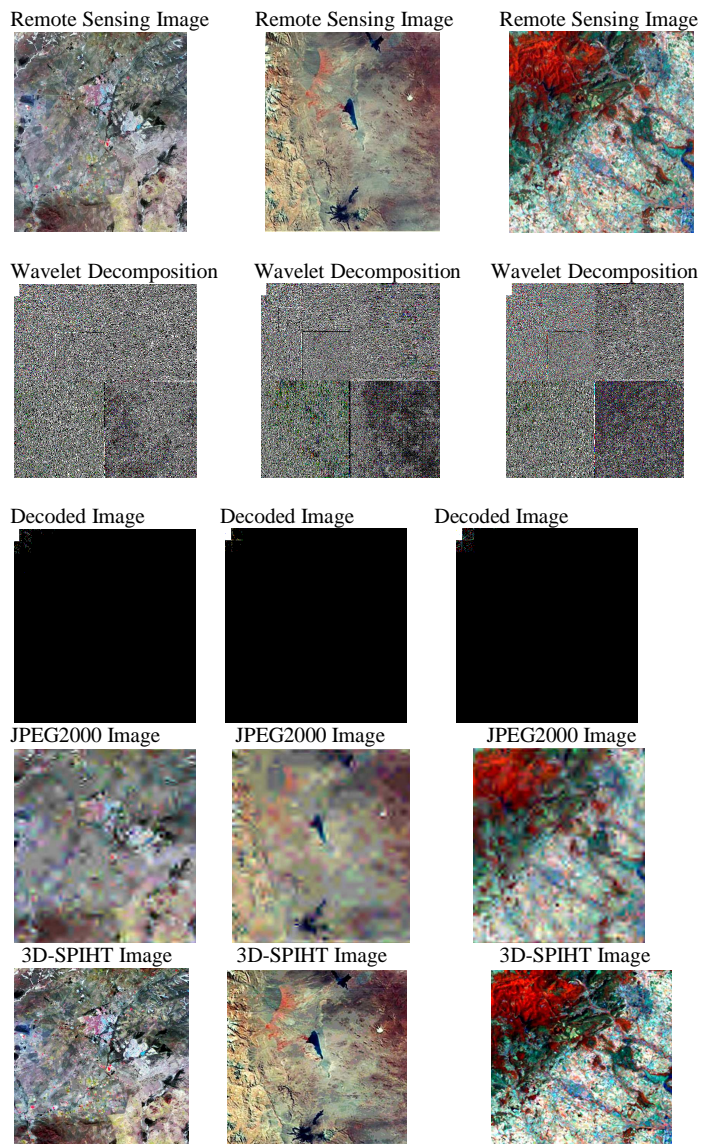


Table 1 Results of CR, PSNR, MSE, CORRELATION, SSIM, EXECUTION TIME Value for JPEG20000

JPEG2000						
IMAGES	CR	PSNR	MSE	CORRELATION	SSIM	EXEC. TIME
Image 1	0.8961	19.4788	733.1585	0.8851	0.3014	9.3918
Image 2	0.8959	20.3757	596.3580	0.9005	0.4096	9.2444
Image 3	0.8909	19.0632	806.7978	0.9308	0.3481	9.1297
Image 4	0.9529	17.2663	611.5435	0.9579	0.9579	9.1845
Image 5	0.8917	19.4169	743.6823	0.8755	0.2442	9.3745

Table 2 Results of CR, PSNR, MSE, CORRELATION, SSIM, EXECUTION TIME Value for 3D-SPIHTAlgorithm

3D-SPIHT ALGORITHM						
IMAGES	CR	PSNR	MSE	CORRELATION	SSIM	EXEC. TIME
Image 1	0.9993	29.7236	69.2972	0.9917	0.8602	35.2268
Image 2	1.0023	28.5517	90.7633	0.9912	0.8297	11.9705
Image 3	0.9977	29.4443	73.9008	0.9958	0.8815	12.6236
Image 4	1.2095	28.5629	90.5297	0.9968	0.8326	29.4804
Image 5	1.0046	31.3066	48.1310	0.9890	0.8502	41.4331

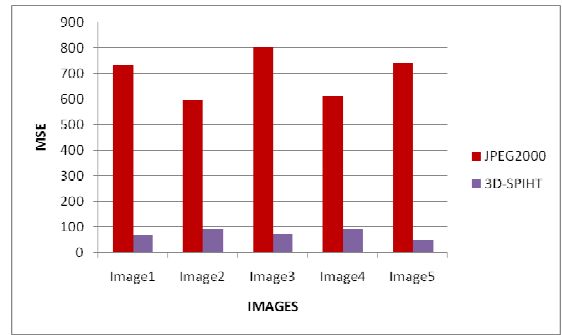


Fig. 6 Comparison of MSE in JPEG2000 and 3D-SPIHT

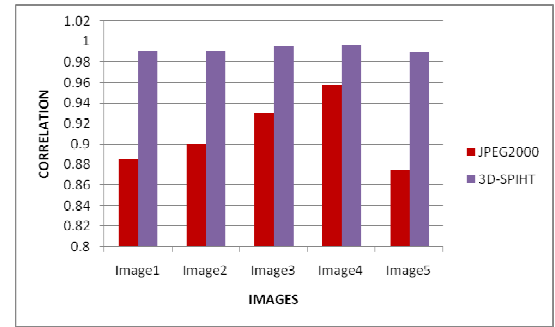


Fig. 7 Comparison of CORRELATION in JPEG2000 and 3D-SPIHT

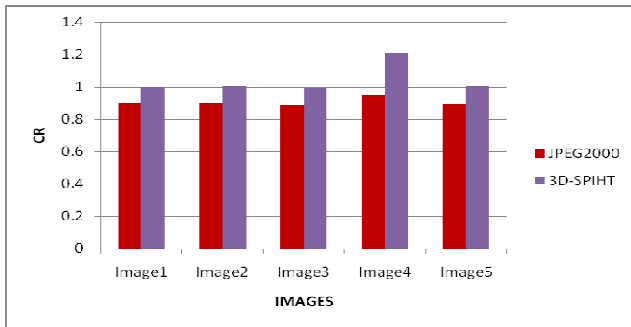


Fig. 4 Comparison of CR in JPEG2000 and 3D-SPIHT

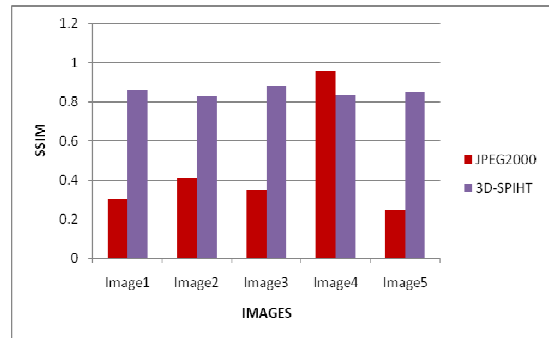


Fig. 8 Comparison of SSIM in JPEG2000 and 3D-SPIHT

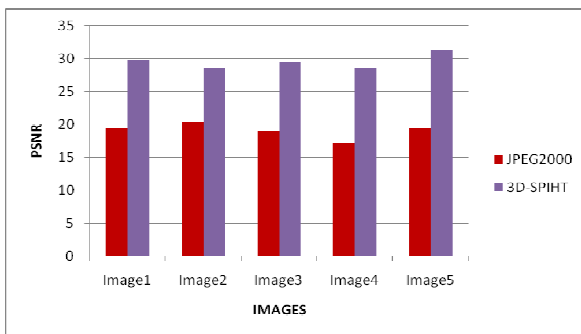


Fig. 5 Comparison of PSNR in JPEG2000 and 3D-SPIHT

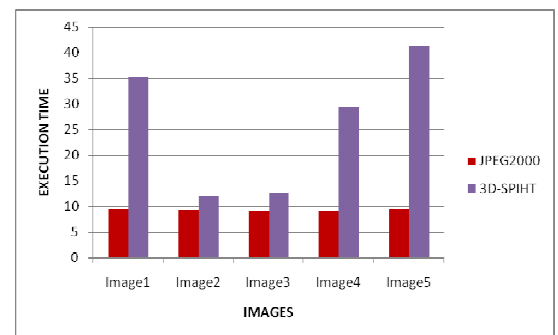


Fig. 9 Comparison of EXECUTION TIME in JPEG2000 and 3D-SPIHT

8. Conclusion

In this paper, we compared 3D-SPIHT algorithm and JPEG2000 for the compression of remote sensing images. The interesting features of the original 3D-SPIHT algorithm such as high compression efficiency, embeddedness and very fine granularity of the bitstream are kept. Our experiment shows as 3D-SPIHT algorithm seems to be preferable for compression than JPEG2000 because of its quality of image. Results show that 3D-SPIHT algorithm maintaining the full embeddedness required by color image compression and gives better performance in terms of the PSNR and compression ratio than the JPEG 2000.

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