Transmission of Images Using SPECK

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Abstract
Compression is the process of representing information in a compact form so as to reduce the bit rate for transmission or storage while maintaining acceptable fidelity or data quality. The objective of this paper is to develop an efficient compression scheme and to obtain better quality and higher compression ratio using Multiwavelet transform with Set Partitioned Embedded block coder algorithm (SPECK). In our tests, we employ Scenes derived from standard AVIRIS hyper spectral images, which possess 224 spectral bands. The performance of the SPECK is compared with SPIHT& JPEG2000.The quality of compression and reconstruction is measured by quantitative measures like PSNR.

Keywords
Hyper spectral imaging, jpeg 2000, SPECK, SPIHT, wavelets.

1. INTRODUCTION

A. Hyperspectral imaging

A hyperspectral image is a dataset which contains a given scene observed through a large number (usually, in the hundreds) of wavelengths. Therefore, such a remote sensing operation produces, for each pixel of the scene; its spectrum [1]. Hyperspectral imaging is a powerful technique and has been widely used in a large number of applications, such as detection and identification of the surface and atmospheric constituents present, analysis of soil type, monitoring agriculture and forest status, environmental studies, and military surveillance[3]. In the case of AVIRIS hyperspectral images, each run of the airborne sensors produces scenes which have 224 spectral bands. The length of a run is not defined a priori but, to keep storage of the raw data manageable, each strip is divided into 512 pixels long scenes. For each band, the value of each pixel is stored as a 16-bit integer[1].

B. Wavelet Transform

The Discrete Wavelet Transform (DWT), which is based on sub-band coding, is found to yield a fast computation of Wavelet Transform. It is easy to implement and reduces the computation time and resources required. In the case of DWT, a time-scale representation of the digital signal is obtained using digital filtering techniques [12]. The signal to be analyzed is passed through filters with different cutoff frequencies at different scales. The discretization is performed by setting a = a0jand b = k a0j b0 for j, k ∈ Z. where, a0 >1 is a dilated step and b ≠ 0 is a translation step. The family of wavelets then becomes

ψjk(t)=a0-j/2ψ(a0-j/2t-kb0) (1)

and the wavelet decomposition of a function f (t) is

$$f(t) = \sum_j \sum_k D_f\ (j,k)\ \psi_{j,k}(t) \quad (2)$$

Where 2-dimensional set of coefficients Df (j,k) is called DWT of given function f(t)

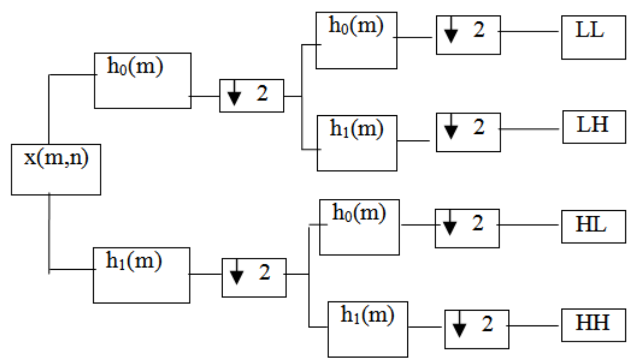

Figure 1. Subband Decomposition of an Image

C.THE PEAK SIGNAL TO NOISE RATIO

PSNR performance is a prerequisite for any modern compression algorithm.PSNR is most easily defined via the mean squared error (MSE). Given a noise-free m×n monochrome image I and its noisy approximation K, MSE is defined as:[15]

$$MSE = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[\mathrm{I(i,j)} - \mathrm{K(i,j)}]^2$$

The PSNR is defined as:

$$psnr = 10.\log_{10}\left(\frac{MAX_I^2}{MSE}\right) = 20.\log_{10}\left(\frac{MAX_I}{\sqrt{MSE}}\right) = 20.\log_{10}(MAX_I) - 10.\log_{10}(MSE)$$

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D. JPEG 2000.

The JPEG committee has recently released its image coding standard, JPEG2000, which will serve as a supplement for the original JPEG standard introduced in 1992. Rather than incrementally improving on the original standard, JPEG 2000 implements an entirely new way of compressing images based on the wavelet transform, in contrast to the discrete cosine transform(DCT)used in the original JPEG standard. The source image is decomposed into components (up to 256). The image components are (optionally) decomposed into rectangular tiles. The tile-component is the basic unit of the original or reconstructed image. A wavelet transform is applied on each tile. The tile is decomposed into different resolution levels. The decomposition levels are made up of sub bands of coefficients that describe the frequency characteristics of local areas of the tile components, rather than across the entire image component. The sub-bands of coefficients are quantized and collected into rectangular arrays of code blocks. The bit planes of the coefficients in a code block (i.e. the bits of equal significance across the coefficients in a code block) are entropy coded. The encoding can be done in such a way that certain regions of interest (ROI) can be coded at a higher quality than the background. Markers are added to the bit stream to allow for error resilience. The code stream has a main header at the beginning that describes the original image and the various decomposition and coding styles that are used to locate, extract, decode and reconstruct the image with the desired resolution, fidelity, region of interest or other characteristics. The state of wavelet-based coding has improved significantly since the introduction of the original JPEG standard. A notable breakthrough was the introduction of embedded zero tree wavelet(EZW) coding by Shapiro .The EZW algorithm was able to exploit the multiresolution properties of the wavelet transform to give a computationally simple algorithm without standing performance . Improvements and enhancements to the EZW algorithm have resulted in modern wavelet coders which have improved

Performance relative to block transform coders. As a result, wavelet-based coding has been adopted as the underlying method to implement the JPEG 2000 standard [16].Prior to JPEG2000,wavelet-based coding was mainly of interest to a limited number of compression researchers . Since the new JPEG standard is wavelet based, a much larger audience including hardware designers, software programmers, and systems designers will be interested in wavelet-based coding.[16]

II. Related Work

A. SPECK Algorithm: Overview

In SPECK, the blocks are recursively and adaptively partitioned such that high energy areas are grouped together into small sets whereas low energy areas are grouped together in large sets. This algorithm makes use of the adaptive quad tree splitting to zoom into high energy areas within a region to code them with minimum significance maps [4, 5]. The algorithm includes encoder and decoder, which implements initialization, sorting pass, refinement pass & quantization steps [6]. Threshold selection & Pixel significance in an entire set (T) of pixels are carried out using equation The algorithm makes use of rectangular regions of image. These regions or sets are called as sets of type S. The dimension of a set S depends on the dimension of the original image and the subband level of the pyramidal structure at which the set lies.

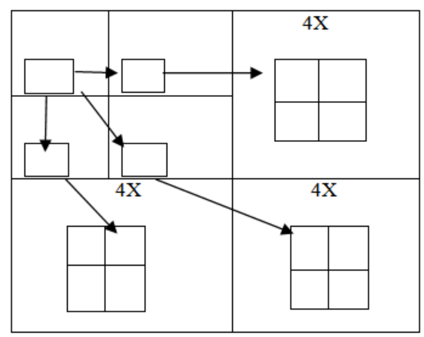

Figure 2. Parent offspring dependencies in tree based organization in wavelet transform.

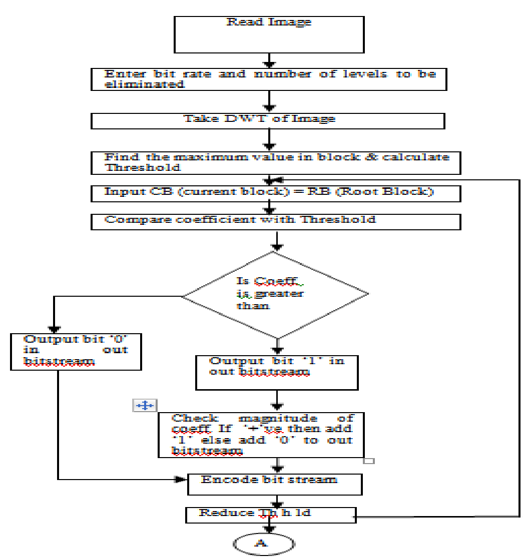

Figure 3.Flow chart of Encoder

During the course of the algorithm, sets of various sizes will be formed, depending on the characteristics of pixels in the original set. Note that a set of size 1consists of just one pixel. The other types of sets used in the SPECK algorithm are referred to as sets of type I. The algorithm maintains two linked lists: LIS - List of Insignificant Sets, and LSP - List of Significant Pixels. The LIS contains sets of type S of varying sizes, which have not found significant against a threshold n while LSP obviously contains those pixels that have tested significant against n. Use of multiple lists will speed up the encoding/decoding process. Following flow chart describes the algorithm [6-11].

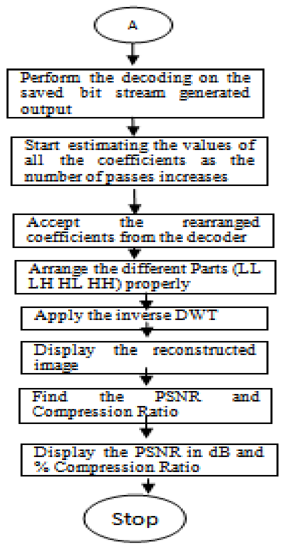

Figure 4.Flow chart of Decoder

B.SPIHT

One of the main features of the proposed coding method is that the ordering data is not explicitly transmitted. Instead, it is based on the fact that the execution path of any algorithm is defined by the results of the comparisons on its branching points. So, if the encoder and decoder have the same sorting algorithm ,then the decoder can duplicate the encoder's execution path if it receives the results of the magnitude comparisons, and the ordering information can be recovered from the execution path.[6]

The SPIHT technique is based on three concepts:

1) partial ordering of the transformed image elements by magnitude, with transmission of order by a subset partitioning algorithm that is duplicated at the decoder,

2) ordered bit plane transmission of refinement bits,

3) exploitation of the self-similarity of the image wavelet transform across different scales.

The partial ordering is a result of comparison of transform element (coefficient) magnitudes to a set of octavely decreasing thresholds.

We say that an element is significant or insignificant with respect to a given threshold, depending on whether of not it exceeds that threshold.

The crucial parts of coding process is that the way subsets of coefficients are partitioned and how the significance information is conveyed.

Algorithm.

- o One of the main features of the proposed coding method is that the ordering data is not explicitly transmitted.
- o Instead, it is based on the fact that the execution path of any algorithm is defined by the results of the comparisons on its branching points.
- o So, if the encoder and decoder have the same sorting algorithm, then the decoder can duplicate the encoder's execution path if it receives the results of the magnitude comparisons, and the ordering information can be recovered from the execution path.
- o One important fact used in the design of the sorting algorithm is that we do not need sort all coefficients.
- o Actually, we need an algorithm that simply selects the coefficients such that $2^n \leqq |c_{i,j}| \leqq 2^{n+1}$, with n decremented in each pass.
- o Given n, if $|c_{i,j}| \geqq 2^n$ then we say that a coefficient is significant; otherwise it is called insignificant.

Algorithm I.

The sorting algorithm divides the set of pixels into partitioning subsets τ_m and performs the magnitude test

$$\max_{(i,j)\in\tau_m}\{|c_{i,j}|\} \geq 2^n$$

- If the decoder receives a "no" to that answer(the subset is insignificant), then it knows that all coefficients in τ_m are insignificant. If the answer is "yes" (the subset is significant), then a certain rule shared by the encoder and the decoder is used to partition τ_m into new subsets $\tau_{m,l}$ and the significance test is then applied to the new subsets. This set division process continues until the magnitude test is done to all single coordinate significant subsets in order to identify each significant coefficient.
- To reduce the number of magnitude comparisons(message bits) we define a set partitioning rule that uses an expected ordering in the hierarchy defined by the subband pyramid.
- The objective is to create new partitions such that subsets expected to be insignificant contain a

large number of elements, and subsets expected to be significant contain only one element.

- To make clear the relationship between magnitude comparisons and message bits, we use the function to indicate $s_n(\tau)=\begin{cases}1, & \max_{(i,j)\in\tau_m}\{|c_{i,j}|\}\geq 2\\ 0, & \text{otherwise}\end{cases}$ the significance of a set of coordinates τ.

III. Results and Analysis.

The results based on previous work; where images taken for the experiment were ‘Lena’, ‘Barbara’, ‘Peppers’, ‘Cameraman’, ‘Mandrill’, ‘Rice’ of size (256 X 256). The wavelet filters used in this experiment are “Haar”. Table 1 and Table 2 represents the corresponding ‘PSNR’ values for different images and different levels of decomposition at 0.2bpp (CR=40) and 0.8bpp (CR=10) using multiwavelets [17].

Table 1. PSNR (dB) for images under various levels of decomposition at 0.2bpp (CR=40).

Multiwavelet (Cardbal3)	PSNR(dB) for Different Levels of Decomposition		
Images	2	3	4
Cameraman	18.27	23.52	24.25
Peppers	20.51	24.50	26.19
Barbara	20.67	24.59	25.73
Lena	21.86	28.80	29.69

Table 2. PSNR (dB) for images under various levels of decomposition using multiwavelet (Cardbal3) at 0.8bpp (CR=10).

Multiwavelet (Cardbal3)	PSNR(dB) for Different Levels of Decomposition		
Images	2	3	4
Cameraman	28.94	30.79	31.07
Peppers	31.09	34.15	34.36
Barbara	29.41	30.77	31.10
Lena	34.98	38.66	39.14
Rice	35.19	33.55	36.28

Table 3.Average SNR (in dB) for SPECK – Cuprite scene 01[1].

	Cuprite			
Rate (bpp)	0.1	0.2	0.5	1
JPEG2000+PC (from [28])	45.30		50.50	54.20
JPEG2000 MC (16-band blocks)	27.37	29.24	32.58	36.27
3D-SPECK (16-band blocks)	35.24	39.50	45.76	49.45
SPECK	27.13	28.92	32.08	35.47

Table 4.PSNR and compression ratio values for different images.

Images	Bit rate	PSNR	MSE	Compression Ratio
COIN (256X256)	0.25	28.82	44.26	84.20
	0.50	29.75	43.17	83.11
	0.75	31.82	42.72	81.12
	1.00	32.81	41.28	78.23
LENA (512X512)	0.25	26.12	42.72	84.27
	0.50	28.02	41.27	82.25
	0.75	29.68	39.98	78.45
	1.00	31.43	36.12	74.20

Table 5.PSNR performance of different coding algorithms.

Bit Rate	EZW PSNR dB	SPIHT PSNR dB	SPECK PSNR dB	EBCOT PSNR dB
0.25	26.84	28.64	28.85	25.93
0.50	27.98	30.23	29.75	26.74
0.75	29.26	31.68	30.89	28.17
1.00	31.53	32.46	32.81	30.18

Figure 5.SPECK compression of ‘Barbara’ image PSNR values [17].

Figure 6.SPECK compression of Peppers image PSNR values. [17]

Figure 7.SPECK compression of mandrill image. [17]

IV.CONCLUSION

In this work, we have successfully analysed an efficient compression scheme to obtain better quality and higher compression ratio using Multiwavelet transform with Set Partitioned Embedded block coder algorithm (SPECK).The performance of the SPECK, is compared with SPIHT& JPEG2000.The SPECK algorithm has some important features which are low complexity, embeddedness, progressive coding, exploits clustering of energy to zoom into high energy areas within a region (block) to code them with minimum significance maps, better visual perception.

REFERENCES

[1] Alessandro J. S. Dutra, IEEE William A. Pearlman, Fellow IEEE, and Eduardo A. B. da Silva Senior Member IEEE, “Successive Approximation Wavelet Coding of AVIRIS Hyperspectral Images” August 2010.

[2] A.N. Netravali and B.G. Haskell, Digital pictures, representation and compression, in Image Processing, Proc. of Data Compression Conference, pp.252-260, 1997. .

[3] Xiaoli Tang and William A. Pearlman Center for Image Processing Research Electrical, Computer and Systems Engineering Department Rensselaer Polytechnic Institute Troy NY 12180-3590, “Lossy to Lossless block based compression of hyperspectral volumetric data”.

[4] Islam A. and William A., “Efficient, Low- Complexity Image Coding with a Set-Partitioning Embedded Block Coder,” IEEE Transactions Circuits and Systems for Video Technology, vol. 14, pp. 1219-1235, November 2004.

[5] Pearlman A., “Efficient, Low-Complexity Image Coding with A Set-Partitioning Embedded Block Coder,” http://www.cipr.~$ltiwavelet_paper. docrpi.edu/~pearlman/papers/speck_example.pdf, IEEE Transactions on Circuits and Systems for Video Technology , vol. 14, no. 11, pp. 1219 – 1235, 2004.

[6] A. Said and W.A. Pearlman, “A new, fast and efficient image codec based on set partitioning in hierarchical trees”, IEEE Transaction on circuits and systems for Video Technology, vol. 6, pp. 243–250, June 1996.

[7] A. Islam and W.A Pearlman, “An embedded and efficient low- complexity hierarchical image coder”, Visual Communications and Image Processing, Proceedings of SPIE, vol.36 No.53, pp. 294–305, Jan.1999.

[8] Grgic S, Grgic M, Zovko-Cihlar B, “Performance analysis of image compression using wavelets”, IEEE Transaction on Industrial Electronics 2002; 48:682-95.

[9] N Sprljan, Sonia Grgic, Mislav Grgic, “Modified SPIHT algorithm for Wavelet packet image coding”, Elsevier Real time Imaging pp 378- 388,11, 2005

[10] Danyali H & Martins A, “Highly scalable, object based wavelet image compression algorithm for network applications”, IEEE proceedings Vision, Image & Signal Processing pp 498-510, 2004

[11] D.Taubman, “High performance scalable image compression with EBCOT”, IEEE Transaction on Image Processing, vol. 9, pp.1158-1170, July 2000.

[12] K Sayood, “Introduction to Data Compression” , Morgan Kaufm ann, San Fransisco, USA, 1996.

[13] R C Gonzalez, R E Woods, “Digital Image Processing”, 2nd ed Pearson Education Inc

[14] Michel Mitsi, Yves Mitsi, G.Opphenheim, J.M.Poggi, “Wavelet toolbox Users Guide”, The Mathworks, Inc Natick

[15] M.Antonini, M.Barlaud, P.Mathieu, and I.Daubechies, “Image coding using wavelet transform”, IEEE Transaction on Image Processing, vol. 1, pp. 205–220, April 1992

[16] Bryan E.Usevitch “A Tutorial on Modern Lossy Wavelet Image Compression”: Foundations of JPEG 2000

[17] The International Arab Journal of Information Technology, Vol. 5, No. 1, January 2008 Novel Image Compression Using Multiwavelets with SPECK Algorithm.