An Improved SPIHT Algorithm for Image Compression in Low Bit Rate

Sonam Mishra[1], Zainab Aizaz[2], Sanjay Sharma[3]

Research Scholar[1], Professor[2], Head Professor[3]

Oriental Institute of Science and Technology, Bhopal M.P. India

Abstract - Wavelet transform has a good locality character of time-frequency domain, overcome the limitations of Fourier transform in dealing with the smooth complex image signal effectively, the sub-image after transformation has strong comparability. It is convenient for coding the sub sequent, made the wavelet transform widely used in image compression field. J. M. Shapiroproposed EZW (Embedded Zero-tree Wavelet) [1] algorithmin1993, the complexity of this algorithm is not high, and the streaming is embedded. It is easy to control compression ratio and realize scalable coding. A.Saidand and W.A.Pearlman proposed a new efficient improvement method in 1996, namely SPIHT (Set Partitioning In Hierarchical Tree) [2,3], using the spatial direction tree, this method shows wavelet coefficient so f zero-tree structure efficient and accurate, which increased the compression efficiency and reduced the complexity of the coding. SPIHT algorithm treat the lowest frequency sub-band coefficient the same importance, so when sorting and scanning process using LIP determine the importance of the wavelet coefficients, only a small part of the bits are used for coding important information, especially in low bit rate, it will inevitably lead to the quality of the recovery image descend. Need a lot of storage space, and exists the disadvantage of repeating problem, this paper focused on the problems of SPIHT algorithm and proposed an improved scheme, combined with the human visual characteristics.

Keywords: Wavelet filter, DWT (discrete wavelet transform), SBC (sub-band coding), SPECK (set partitioned embedded block coder), PSNR, QMF (Quadrature mirror filter).

I. INTRODUCTION

Process of representing information in a compact form so as to reduce storage or the bit rate for transmission with maintaining acceptable fidelity or data quality is compression. During past decade, the success of wavelets in solving many different problems has contributed to its unmatched popularity. For image compression to perform best, wavelet transforms require filters that combine a number of desirable properties, such as orthogonality and symmetry. Due to implementation limitation scalar wavelets do not possess all the properties which are needed for better performance in compression. To overcome this problem new class of wavelets called, Multiwavelets which possess more than one scaling filters. The objective of this thesis is to develop an coherent compression scheme and to obtain higher compression ratio with better quality by using Multiwavelet transform with Set Partitioned Embedded block coder algorithm (SPECK). In SPECK, the blocks are repeatedly and adaptively partitioned such that grouping of high energy areas are done into small sets whereas grouping of low energy areas are done in large sets. This algorithm makes use of the adaptive breaking of quad tree to zoom into high energy areas within a region to code them with minimum significance map. The algorithm includes encoder and decoder, which implements initialization, sorting pass, refinement pass & quantization steps and make use of rectangular regions of image. The set S dimension depends on the original image dimension and the sub band level of the pyramidal structure at which the set lies. In our tests, we have employed scenes derived from the standard AVIRIS hyper spectral images, which is having 224 spectral bands. The objective of this paper is to develop a valuable compression pattern and to obtain better quality and higher compression ratio using Multiwavelet transform with Set Partitioned Embedded block coder algorithm (SPECK).The SPECK performance is compared with SPIHT& JPEG2000. The quantitative measures like PSNR are used to measure the quality of compression and reconstruction.

Image Compression

Image compression deals with the problem of reducing the volume of data required to represent a digital image. It is a procedure which yields a compact representation of an image, which results in reducing the image storage/transmission requirements. Removal of one or more of the three basic data redundancies results into Compression

1. Coding Redundancy

2. Interpixel Redundancy

3. Psychovisual Redundancy

Wavelet Transform

Wavelets are functions defined over a finite interval and having an average value of zero. The basic idea of the wavelet transform is to represent any arbitrary function (t) as a superposition of a set of such wavelets or basis functions. These basis functions or baby wavelets are obtained from a single prototype wavelet called the mother wavelet, by dilations or contractions (scaling) and translations (shifts). The Discrete Wavelet Transform of a finite length signal x (n) having N components, for example, is expressed by an N x N matrix. Wavelets are mathematical functions f(t) such that: (1) They integrate to zero. So they oscillate. (2) They have unit energy. (3) They have compact support. This stems from the fact that a shorter support in time is required for good time resolution. (4) An additional property is that the DC component

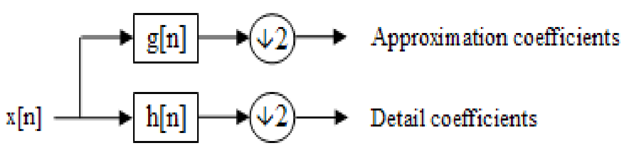

Fig.1 Wavelet Filter

is zero. This comes from the admissibility condition, which is necessary to develop the inverse wavelet transform. These conditions help us visualize a wavelet as “small” wave. The DWT of a signal x is calculated by passing it through a series of filters. First the samples are passed through a low pass Filter with impulse response resulting in a convolution of the two. The signal is also decomposed simultaneously using a high-pass filter h. The outputs giving the detail coefficients (from the high-pass filter) and approximation coefficients (from the low-pass). It is important that the two filters are related to each other and they are known as a quadrature mirror filter.

$$\mathbf{H_i} = \sum_{\mathbf{m=0}}^{\mathbf{k-1}} \mathbf{x_{2i-m}} \cdot \mathbf{s_m(z)} \qquad (1)$$

$$\mathbf{L_i} = \sum_{\mathbf{m=0}}^{\mathbf{k-1}} \mathbf{x_{2i-m}} \cdot \mathbf{t_m(z)} \qquad (2)$$

Into low and high frequencies. Due to the decomposition process the input signal must be a multiple of 2^n where *n* is the number of levels. Discrete wavelet transform (DWT), transforms a discrete time signal to a discrete wavelet representation. It converts an input series x_0, x_1, ..x_m, into one high-pass wavelet coefficient series and one low-pass wavelet coefficient series (of length n/2 each) given by:

II. SPECK (Set Partitioned Embedded Block Coder)

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. The algorithm includes encoder and decoder, which implements initialization, sorting pass, refinement pass & quantization steps. Threshold selection & Pixel significance in an entire set (T) of pixels are carried out 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

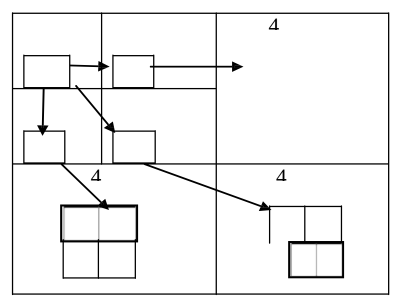

Fig.2 Parent offspring dependencies in tree based organization in wavelet transform

SPECK Algorithm

In this paper we introduce the LVQ-SPECK algorithm, which enlarge the concepts of block set partitioning present in SPECK to simultaneously encode a number of consecutive spectral bands in a hyper spectral image volume. This is accomplished with the use of a lattice vector quantize applied in the spectral direction. The two types of sets used by SPECK are referred to as S and I sets. S sets are rectangular blocks of the image (hence the name *Block Coder*), of varying dimensions, that depend on the size of the original image and the level of the pyramid decomposition to which the set belongs.

1) Initialization:

- Partition image transform X into S and I =X −S sets.
- The initial threshold T0 and the threshold scaling factor α

are transmitted.

- Add S to the LIS, and set LSP = ∅

2) Sorting pass:

for each set S ∈ LIS, and in increasing order of size |S|, do ProcessS(S).

if I = ∅ , ProcessI()

3) Refinement pass:

- for each (x, y) in the LSP, if the residual norm is larger than the current threshold, output the index of the codeword that best represents it. Otherwise, output the zero-codeword index, since there is no refinement to take place.

4) Quantization step:

- update the encoding threshold, i.e., set $T_n = \alpha \times T_{n-1}$, and go to step 2.

III. METHODOLOGY

The objective of this work 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).A comparison of the best known multiwavelets is made to the best known scalar wavelets. Extensive experimental results demonstrate that our techniques exhibit performance equal to, or in several cases superior to, the current wavelet filters.

The SPECK image coding scheme has all the properties that characterizes the scalar quantized significance testing schemes. It shows the following properties in particular:

- Completely embedded: A certain coded bit stream can be used to decode the image at any rate less than or equal to the coded rate. It gives the finest reconstruction possible with the particular coding scheme.

- Employs progressive transmission: Source samples are encoded in decreasing order of their information content.

- Low computational complexity: The algorithm is very simple and does not require any complex computation. Fast encoding/decoding: due to the low computational complexity of the algorithm

- Low dynamic memory requirements: During the coding process, at any given time, only one connected region, lying completely within a subband is processed. After processing this region, the next region is considered for processing.

- High efficiency: Its performance is comparable to the other low-complexity algorithms available today.

Here two linked lists: LIS - List of Insignificant Sets, and LSP - List of Significant Pixels, are maintained. The LIS contains sets of type S of varying sizes which have not yet been found significant against a threshold n while LSP contains those pixels which have tested significant against n. Two types of set partitioning are used in SPECK: quad tree partitioning and octave band partitioning.

Pseudo Code of the Algorithm

A. Initialization

Partition image transform X into two sets: S= root and I= X-S Output n = floor (log2 (max $|C_{i,j}|$))

Add S to LIS and set LSP=Φ

B. Sorting pass

In increasing order of size C of sets

For each set S € LIS,

* Process S (S) Process I ( )

C. Refinement pass

For each (i,j) € LSP, except those included in the last sorting pass, output the nth MSB of $|C_{i,j}|$.

D. Quantization step

Decrement n by 1, and go to step 2

III. RESULTS AND DISCUSSION

PSNR analysis for modified SPECK algorithm

It is important to observe that the bit rates are not entropy estimates- they were calculated from the actual size of the compressed file. Furthermore, by using the progressive transmission ability, the sets of distortion are obtained from the same file, that is, the decoder read the first bytes of the file (up to the desire rate), calculated the inverse sub band transformation , and then compare the recovered image with the original image. The distortion is measured by the peak signal to noise ratio:

The PSNR is defined as

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

The PSNR (in dB) is defined as:

$$\begin{aligned} PSNR &= 10 \cdot \log_{10}\left(\frac{MAX_I^2}{MSE}\right) \\ &= 20 \cdot \log_{10}\left(\frac{MAX_I}{\sqrt{MSE}}\right) \\ &= 20 \cdot \log_{10}(MAX_I) - 10 \cdot \log_{10}(MSE) \end{aligned}$$

Table 1: *PSNR performance of different coding algorithms*

Bit Rate	SPIHT PSNR dB	SPECK PSNR dB
0.25	28.64	73.19
0.50	30.23	75.03
0.75	31.68	75.04
1.00	32.46	75.21

Fig.3 compression of image 1 at 0.25 bb

Table 2: PSNR and compression ratio values for different images

Images	Bit rate	PSNR	Compression Ratio
GROUP IMAGE(150 X150)	0.25	73.19	52.21
	0.50	75.03	83.79
	0.75	75.04	88.77
	1.00	75.21	90.65
LENA (256X256)	0.25	73.06	42.04
	0.50	73.62	81.18
	0.75	74.91	87.72
	1.00	75.70	90.18

IV. CONCLUSION

In this work, we have successfully analyzed an efficient compression scheme to obtain better quality and higher compression ratio using Multi wavelet 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

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