A Novel Hybrid HVS Based Embedded Image Coding Algorithm Using DTT and SPIHT

Ranjan K Senapati, Umesh C Pati, Kamala K Mahapatra.

Department of Electronics and Communication Engineering
National Institute of Technology, Rourkela.
India, Orissa, 769008
rksphd@gmail.com, ucpati@nitrkl.ac.in, kkm@nitrkl.ac.in.

***Abstract*—This paper presents a Discrete Tchebichef Transform (DTT) based hybrid embedded coder for image compression applications. In this coder, DTT is coupled with Set partitioning in hierarchical coding techniques (SPIHT). Further, human visual system (HVS) with appropriate perceptual weights are applied to improve the perceptual quality of the reconstructed image. The compression and image reconstructon performance is compared with some the state-of-the-art coders in the literature. Extensive simulations on various kinds of images shows convincingly that, the proposed coder outperforms most of the coders.**

***Index Terms*—Discrete Tchebichef Transform, Discrete Cosine Transform, Image Compression, Embedded Coder, Human Visual Systems.**

I. Introduction

In recent years, most of the research activities are focused on wavelet based image coders rather than DCT based image coders. This is mainly attributed due to innovative strategies of data organisation and representation of wavelet transformed coefficients. There are several representatives of wavelet based image coders such as: Embedded zerotree wavelet coder (EZW) [1], Set partitioning in hierarchical trees (SPIHT) [2], Morphological representations of wavelet data (MRWD) [3] and Significance-linked connected component analysis (SLCCA) [4]. These methods provide excellent rate-distortion performances.

Although wavelets are capable of more flexible space-frequency resolution trade offs than DCT, DCT is still widely used in many practical applications because of its compression performance and computational advantages. Recently, DCT-based coders with innovative data organisation strategies and representations of DCT coefficients have been reported with high compression efficiency. Some of these representatives are: Xiong *et al.*'s [5] embedded image coder based on DCT. They introduced a wavelet-like tree structure of DCT coefficients and applied embedded zerotree quantizer to the DCT coefficients as in EZW coder, which yielded a better performance than wavelet based EZW. Monoro *et al.* [6] applied sorting algorithm of EZW. Junqiang *et al.* [7] applied SLCCA wavelet-based image coder to DCT subbands. Davis and Chawla [8] proposed significance tree quantization (STQ) optimized for a given class of images.

A new class of transform known as Discrete tchebichef transform (DTT), which is derived form orthonormal tchebichef ploynomials has similar energy compaction properties like DCT [9]–[11]. Recently, DTT has been found excellent rate-distortion trade-off like DCT and outperforms DCT for image having high intensity gradiations [11]. Therefore, we proposed to use DTT as a substitute for DCT in an embedded coder. Further, human visual system [12] is applied to increase the subjective quality of the image. The proposed embedded coder consists of HVS with DTT and SPIHT coding technique. The preformance of this kind of coder is evaluated and is compared with DCT based embedded coders, JPEG, improved JPEG, STQ and STQ+Haar. It has been found that, the proposed coder outperforms most of the coders.

The organisation of the paper is as follows: Section II describes the concept of embedded image coding. Section III reviews the discrete tchebichef transorm algorithm. The proposed HVS based hybrid DTT-SPIHT algorithm is presented in section IV. Simulation results and analysis are presented in section V. The last section concludes the paper.

II. Embedded Image Coding

The Shapiro's EZW coder exploits the self similarity of the wavelet transformed image across different scales by using a hierarchical tree structure [1]. The parent child relationships of a 3-level wavelet decomposition structure is shown in Fig.1. The coefficient in LL_3 band (root), doesn't have any children. The coefficients in HL_3, LH_3 and HH_3 have four children each. A coefficient c_{ij} is called significant with respect to a given threshold T, if $|c_{ij}|\geq$T. otherwise it is insignificance. Meaningfull image statistics have shown that, if a wavelet coefficient is insignificant at a particular threshold T, it is very likely that it's descendents are insignificant with respect to the same threshold.

An embedded image zerotree quantizer refines each input coefficients sequentially using a bitmap type of encoding scheme, and stops whenever the size of the encoded bit stream reaches exact target bit rate [1], [2]. By exploiting the parent-child relationship across different scales in a wavelet transformed image, progressive wavelet coders can effectively order the coefficients by bitplanes and transmit most significant information first. Therefore, it results an embedded bit stream with advantages like progressive transmission and precise rate control, which are absent in JPEG.

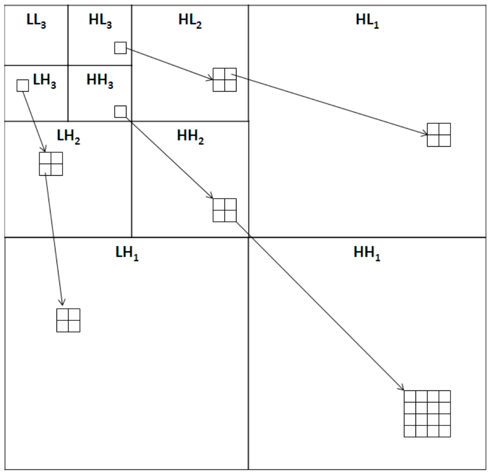

Fig. 1. Parent-child relationship of wavelet coefficients of a 3-level wavelet decomposition pyramid.

III. Discrete Tchebichef Transform

The Discrete Tchebichef Transform (DTT) is relatively a new transform that uses the Tchebichef moments to provide a basis matrix. As with DCT, the DTT is derived from the orthonormal Tchebichef polynomials [10]. For image of size $N \times N$, the forward Discrete Tchebichef Transform of order $u+v$ is defined as:

$$T_{uv} = \sum_{x=0}^{N-1} \sum_{y=0}^{N-1} t_u(x) t_v(y) f(x,y) \tag{1}$$

where, $u, v, x, y = 0, 1, 2.....N-1$. The inverse transform of DTT is defined by:

$$f(x,y) = \sum_{u=0}^{N-1} \sum_{v=0}^{N-1} T_{uv} t_u(x) t_v(y) \tag{2}$$

where, $x, y, u, v = 0, 1, 2......N-1$. From (1) and (2), $t_u(x)$ and $t_v(y)$ are u^{th} and v^{th} order Tchebichef polynomials respectively. In general, n^{th} order Tchebichef polynomial is defined using following recurrance relation as:

$$t_n(i) = (A_1 i + A_2) t_{n-1}(i) + A_3 t_{n-2}(i) \tag{3}$$

where,

$$A_1 = \frac{2}{n} \sqrt{\frac{(4n^2-1)}{(N^2-n^2)}} \tag{4}$$

$$A_2 = \frac{1-N}{n} \sqrt{\frac{(4n^2-1)}{(N^2-n^2)}} \tag{5}$$

$$A_3 = \frac{n-1}{n} \sqrt{\frac{2n+1}{2n-3}} \sqrt{\frac{N^2-(n-1)^2}{N^2-n^2}} \tag{6}$$

The initial values of $t_n(i)$ for $n = 0, 1$ is defined as:

$$t_0(i) = 1/\sqrt{n} \tag{7}$$

$$t_1(i) = (2i + 1 - N)/\sqrt{3/N(N^2-1)} \tag{8}$$

Equation (2) can be expressed using a series representation involving matrices as follows:

$$f(x,y) = \sum_{u=0}^{N-1} \sum_{v=0}^{N-1} T_{uv} G_{uv} \tag{9}$$

where, $u, v, x, y = 0, 1, 2......N-1$ and G_{uv} is called basis matrix. The basis matrix G_{uv} in (9) can be defined as follows:

$$G_{uv} = \begin{bmatrix} t_u(0)t_v(0) & t_u(0)t_v(1) & .. & t_u(0)t_v(7) \\ t_u(1)t_v(0) & t_u(1)t_v(1) & .. & t_u(1)t_v(7) \\ .. & .. & .. & .. \\ t_u(7)t_v(0) & t_u(7)t_v(1) & .. & t_u(7)t_v(7) \end{bmatrix} \tag{10}$$

IV. The Proposed DTT-SPIHT Embedded Coder

The proposed DTT-SPIHT embedded coder is shown in Fig. 2. The input image is divided into non-overlapping 8x8 blocks. Each block is transformed using discrete tchebichef transform. The coefficients are arranged into 3 level wavelet pyramid structure.The coefficients are quantized by SPIHT coding algorithm. The next stage is to use entropy coding which is optional. The proposed algorithm does not use entropy coding.

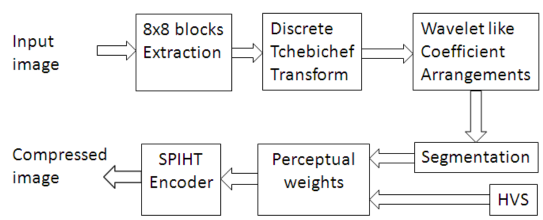

Fig. 2. Block Diagram of HVS based DTT-SPIHT embedded image coder

A. Rearrangement Algorithm of Transformed Coefficients

Fig.3 shows the arrangement of 8x8 DTT coefficients in a 3-level wavelet pyramid structure. After labeling 64 coefficients in each block, the parent child relationship is defined as follows: The parent of coefficient i is $\lfloor \frac{i}{4} \rfloor$ for 1≤i≤ 63, while the set of four children associated with coefficient j is $\{4j, 4j+1, 4j+2, 4j+3\}$ for 1 ≤j≤ 15. The DC coefficient 0 is the root of DTT coefficients tree, which has only three children: coefficients 1,2 and 3. In the proposed structure, offsprings corresponds to direct descendants in the same spatial location in the next finer band of the pyramid. A tree corresponds to a node having 4 children which always form a group of 2x2 adjcent pixels. In Fig. 3, arrows indicate that the same index coefficients of other 8x8 blocks are grouped together so that the entire image can form an overall 3-level pyramid structure.

In the proposed decomposition method, we further decompose LL_3 band into a 3-level pyramid so that, the coarest level will be a 8x8 band. The overall level of decomposition is now six. Then SPIHT encoding algorithm is applied to the overall structure.

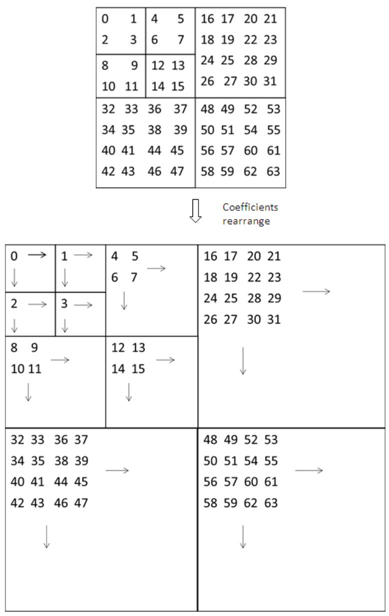

Fig. 3. Rearrangement algorithm of 8x8 transformed coefficients.

B. Human Visual System (HVS)

In the proposed coder, different perceptual weights have been added across the subbands. It is found from the research in vision psychophysics that sensitivity of human eyes to the distortion reduces in order from edge block, smooth block and texture block. Different sensitivities suggest that different perceptual weights should be assigned to different blocks [12]. These perceptual weights decreases from coarse to fine scale in accordance with the energy decreasing characteristics of the wavelet coefficients. On the otherhand, this ensures most significant coefficients transferred with highest priority. Therefore it can improved the reconstructed image quality. Table I shows the perceptual weights applied to high frequency sub-bands at the coarest scale.

The segmentation process determines the type of image block. Entropy and variance values of different blocks play an important role during segmentation. The entropy value of smooth block is smaller than the edge and textured block. The variance of textured block is smaller than edge and smooth block.

TABLE I
PERCEPTUAL WEIGHTS APPLIED TO HIGH FREQUENCY SUB-BAND AT COAREST SCALE

Image block	Texture image	Edge image	Smooth image
Texture	0.5	1	1
Edge	2	2	2
Smooth	1.5	1.5	1.8

C. SPIHT Algorithm

SPIHT algorithm [2] keeps track of the state of sets by means of three lists, i.e, list of insignificant sets (LIS), list of significant pixels (LSP) and lists of insignificant pixels (LIP). The algorithm uses the following sets to code a bitmap effectively: $O(i,j)$ is the set of coordinates of all offspring of node (i,j),$D(i,j)$ is set of coordinates of all descendents of node (i,j), $L(i,j)$ is the set of coordinates defined as $D(i,j) - O(i,j)$, $H(i,j)$ is set of all tree roots. The significance test of the a wavelet coefficient is defined as follows:

$$S_n(\Gamma) = \begin{cases} 1, \max\limits_{(i,j\epsilon\Gamma)} \mid (T(i,j) \mid \geq 2^n \\ 0, otherwise. \end{cases} \tag{11}$$

where, $T(i,j)$ is the coefficient at node (i,j). Γ is the testing coordinate set in (11). Briefly, SPIHT coding method is described in the following two passes:

1. Initialization: LSP=ϕ. LIP contains all tree roots at coarsest scale. LIS contains all tree nodes. choose the threshold according to (11).

2. Sorting pass: Output $S_n(i,j)$ for all the nodes (i,j) of LIP. If $S_n = 1$, move the node (i,j) to the LSP and output the sign of $T(i.j)$. For all the nodes of (i,j) of LIS, if the nodes belongs to type A, output $S_n(D(i,j))$. If $S_n(D(i.j)) = 1$, output $S_n(k,l)$ for any node $(k,l)\ \epsilon\ O(i,j)$. If $S_n(k,l) = 1$, append node (k,l) to the LSP and output its sign. Otherwise, move (k,l) to the LIP. If $L(i,j) \neq \phi$, then move (i,j) from LIS, while marking as type B. Otherwise, remove the node (i,j) from LIS. If the node belongs to type B, then output $S_n(L(i,j))$. If $S_n(L(i,j)) = 1$, append the four direct subsequent nodes to the LIS as type A.

3. Refinement pass: For each elements (i,j) in the LSP, output the n-th most significant bit except those added above.

4. Update: Decrement n by 1, and go to sorting pass.

V. SIMULATION RESULTS AND ANALYSIS

To evaluate the performance of proposed hybrid image coding algorithm, experiments are conducted on Lena, Barbara, 256 Level Test Pattern and Ruler images. The size of each image is 512×512. The first image is a smooth image, second one is a texture image, third and fourth are images having sharp edges.

Table II shows a comparison of proposed DTT-SPIHT algotithm with some of the best known algorithms in the literature. Comparing with Improved JPEG, DTT-SPIHT shows a PSNR reduction of 0.2 dB for bit-rates 0.5 and 0.3 dB for bit-rate 0.25 bpp on Lena image. At bit-rate above 0.75 the PSNR values of DTT-SPIHT is high. For Barbara image, DTT-SPIHT shows a PSNR reduction of 0.3 dB between 0.5-0.75 bpp. The

TABLE II
PSNR(dB) COMPARISON OF DTT-SPIHT WITH OTHER ALGORITHMS

Rate(b/p)	JPEG		Improved JPEG		EZDCT		STQ		STQ+Haar		DCT-SPIHT		DTT-SPIHT	
Image	Barbara	Lena	Barbara	Lena	Barbara	Lena	Barbara	Lena	Barbara	Lena	Barbara	Lena	Barbara	Lena
0.25	25.2	31.6	26.0	31.9	25.4	30.7	26.6	31.2	26.8	32.3	26.9	31.8	26.5	31.6
0.50	28.3	34.9	30.1	35.5	29.4	34.8	30.1	35.4	30.7	35.6	30.6	35.6	29.8	35.3
0.75	31.0	36.6	33.0	37.5	32.5	37.1	32.7	37.0	33.4	37.2	33.5	37.7	32.7	37.5
1.00	33.1	37.9	35.2	38.8	34.9	38.7	35.4	38.8	35.6	39.0	36.1	39.3	35.3	39.2

advantage of the proposed method is its simplicity in comparison to improved JPEG. Entropy encoding and decoding processes are not used by our algorithm. By incorporating arithmetic coding stages in the our coder, additional 5-10 percentage compression can be achieved.

Comparing with EZDCT algorithm, proposed DTT-SPIHT shows a PSNR gain upto 1 dB at low bit-rates in Lena and Barbara images. For Barbara image, STQ algorithm shows a PSNR gain of almost 0.1 dB over 0.25 to 1 bit-rates. DTT-SPIHT outperforms STQ at any bit-rate on Barbara image. STQ+Haar shows a maximum of 0.9 dB gain over DTT-SPIHT on Barbara image. For bit-rates between 0.5 and 1 bpp DTT-SPIHT shows a good PSNR gain over STQ+Haar algorithm on Lena image. DCT-SPIHT always outperform the proposed DTT-SPIHT algorithm for Lena and Brabara images.

The performance of propose DTT-SPIHT algorithm can be well judged form table III, which shows a PSNR comparison between DCT-SPIHT and DTT-SPIHT on 256 Level Test Pattern and Ruler images. It is seen that for bit-rates above 0.5 bpp DTT-SPIHT shows a gain of 0.1 to 0.2 dB on 256 Level Test Pattern image. Below 0.5 bit-rate, the PSNR gain is almost same. On Ruler image, the proposed algorithm outperforms DCT-SPIHT at any bit-rates.

Table IV shows the comparison of hybrid DTT-SPIHT with HVS is on and off. It is demonstrated that when HVS is on, it reduces the objective quality of the image between 0.1 to 0.3 dB at lower bit-rates (0.125 to 0.5 bpp) for Lena image. Fig. 4 (a) and (b) shows the reconstructed Lena image at a bit-rate of 0.25 bpp while HVS is on and HVS is off respectively. It has been observed that the shoulder and facial protion of Lena image in Fig. 4(a) is smoother than in Fig. 4(b). Similar kind of performance also noticed for other bit-rates. Therefore, by making HVS on, slightly increases the perceptual quality of the image. Similar perceptual improvement is also observed for Barbara image.

TABLE III
COMPARISON OF PSNR(dB) VALUES OF DCT-SPIHT WITH DTT-SPIHT

Rate(b/p)	DCT-SPIHT		DTT-SPIHT	
Images	256 Level-Test Pattern	Ruler	256 Level-Test Pattern	Ruler
0.125	17.3	13.0	17.3	13.8
0.25	19.1	16.3	19.0	19.3
0.50	21.8	22.9	21.8	23.1
0.75	24.4	26.5	24.5	27.4
1.00	26.6	28.6	26.8	31.0

(a) (b)

Fig. 4. The reconstructed images of Lena using HVS based DTT-SPIHT at a bit-rate of 0.25 bpp (a) HVS on (PSNR=31.5) (b) HVS off (PSNR=31.6).

TABLE IV
COMPARISON OF PSNR(dB) VALUES OF HYBRID DTT-SPIHT WITH HVS ON AND HVS OFF

Rate(b/p)	DTT-SPIHT (HVS off)		DTT-SPIHT (HVS on)	
Images	Barbara	Lena	Barbara	Lena
0.125	24.3	28.5	23.9	28.4
0.25	26.5	31.6	25.9	31.5
0.50	29.8	35.3	29.3	35.0
0.75	32.7	37.5	32.2	37.2
1.00	35.3	39.3	34.7	38.7

VI. CONCLUSION

A novel hybrid HVS based DTT-SPIHT embedded image coding algorithm is proposed. It has been demonstrated that the proposed image coding algorithm shows an impressive PSNR gain over standard baseline JPEG, EZDCT and STQ, almost at all bit-rates but comparable with Improved JPEG, STQ+Haar and DCT-SPIHT on smooth and textured images. For images having sharp edges, DTT-SPIHT consistently outperforms DCT-SPIHT. By incorporating HVS, the perceptual quality of the proposed algorithm has been improved at a little cost of PSNR values. This is especially noticeable at bit-rates between 0.5 to 1 bpp. Future research direction is to use adaptive HVS and modified SPIHT algorithm, which is expected to improve the image quality at low bit-rates both subjectively and objectively.

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