Modified SPIHT Algorithm for Coding Color Images using Inter-color Correlation

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Summary
Most of the color image compression techniques reduce the redundancy between color components (R, G, B) by transforming the color primaries into a de-correlated color space, such as YIQ or YUV. As the human visual system is more sensitive to details in luminance than to details in chrominance, the chrominance components can be compressed at high rate. Instead of de-correlating the color planes, high regional correlation between the components of color images is used as a basis for a new coding technique. The high correlation of color channels implicitly suggests a localized functional relation between the components. It could be used in an alternative compression approach, by approximating subordinate colors as functions of the base color instead of coding each color planes. The 9 by 7 wavelet filter and Set Partitioning in Hierarchical Tree (SPIHT) coding for encoding the base color are used. The linear three channel Discrete Hartley Transform (DHT) is applied to the RGB image to obtain the color channels C1C2C3. Taking C1 as base color and the other two channels are approximated as linear functions of the base color. Only two parameters are transmitted for each block N*N of C2 and C3. A significant Peak Signal to Noise Ratio improvement is achieved compared to the traditional coding scheme for the same compression rate.

Key words:
Color image coding, Linear color component transform, inter-color correlation, segmentation, linear approximation, wavelet filter, SPIHT coding.

1. Introduction

The objective of an image compression algorithm is to exploit the redundancy in an image such that a smaller number of bits can be used to represent the image while maintaining an "acceptable" visual quality for the decompressed image. The redundancy of an image resides in the correlation of neighboring pixels. For a color image, there also exists correlation between the color components.

Uncompressed multimedia (graphics, audio and video) data requires considerable storage capacity and transmission bandwidth. Despite rapid progress in mass-storage density, processor speed and digital communication system performance, requirements for data storage capacity and data transmission bandwidth continue to exceed the capabilities of available technologies. One key problem in image compression is to analyze the statistical characteristics of source data for better entropy coding. For example, in the embedded zero-tree wavelet (EZW) coder [1], coefficients after discrete wavelet transform (DWT) can be represented by a zero tree structure. In the set partitioning in hierarchical trees (SPIHT) coder [2], a spatial orientation tree (SOT) is adopted. And in JPEG2000 [3], the values of neighboring pixels are used as context when modeling the statistics of current pixel.

The above methods were designed and optimized for monochrome images. However, most digital images are color images. When coding color images, each component is usually coded independently without any inter-color prediction [4]. Most chrominance changes in a real scene are accompanied by a luminance change [5]. Having noticed the inter-color correlation among different color components, some researchers began placing their attention on correlation based compression algorithm. For example, color EZW (CEZW) [6] and color SPIHT (CSPIHT) [7] were proposed to exploit underlying inter-color correlation by expanding the existing zero tree or SOT structure across the spectral planes. By using the inter-color correlation these methods obtain a better performance than the traditional coding schemes.

A new algorithm for coding color images based on inter color correlation is introduced here. This algorithm utilizes the high inter color correlations between color components of natural images [8, 9, 10, 11] after transforming them into another color domain. It does by dividing the image into square blocks, expanding two of the color component (the dependent colors) as a polynomial function of the third (base) color for each block. This way only the polynomial coefficients are encoded for each block of the dependent colors, whereas the base color component is encoded by monochromatic compression technique.

The paper is organized as follows. Section 3.1 analyzes the method of the selection of the base color for coding the color images based on inter-color correlation. Based on this analysis, a new color image coder is presented in section 3.2. The experimental results are reported and discussed in section 3.3. Conclusions drawn are given in section 3.4.

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2. Tables, Figures and Equations

2.1 Tables and Figures

Table 1: Measure of Entropy of color channels in three channel DHT

Image	*Entropy of C1 Channel*	*Entropy of C2 Channel*	*Entropy of C3 Channel*
Lena	7.6353	6.9382	7.2657
Peppers	7.4399	7.4092	7.4151
Tree	7.4170	7.1225	6.6594
Tomato	7.6858	7.1246	6.6880
Hibiscus	7.4644	6.1049	6.3582
Carrots	6.1667	5.3678	5.7231
House	7.5930	6.5162	6.4704
Igloo	6.9455	6.1539	5.1701
Banyan tree	7.6194	7.0565	6.6678

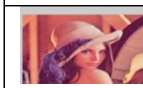
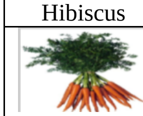
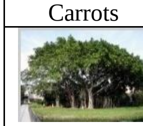
Table 2: Summary of inter-color correlation for various color images

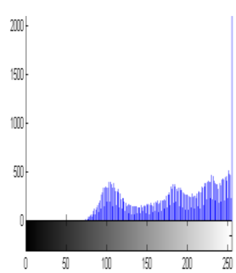
Image	*Correlation between C1C2*	*Correlation between C1C3*	*Correlation between C2C3*
Lena	0.4275	0.5766	0.0917
Peppers	0.2942	0.5207	0.2761
Tree	0.6477	0.5211	0.1656
Tomato	0.4605	0.3733	0.3168
Hibiscus	0.3744	0.5269	0.3683
Carrots	0.3140	0.1627	0.0940
House	0.1265	0.2703	0.0483
Igloo	0.7463	0.1837	0.1038
Banyan tree	0.7575	0.6098	0.5615

Table – 3 Analysis and Synthesis filter coefficients of CDF 9/7 wavelet

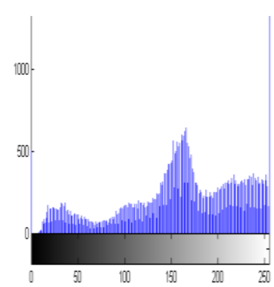
k	*Analysis low pass filter*	*Analysis high pass filter*	*Synthesis low pass filter*	*Synthesis high pass filter*
-4	0.02674876	0	0	0.0267488
-3	-0.01686414	0.0912718	-.0912717	0.0168641
-2	-0.07822333	-.0575435	-.0575435	-0.078223
-1	0.26686412	-.5912718	0.5912717	-0.266864
0	0.60294902	1.1150870	1.1150871	0.6029490
1	0.26686412	-0.591272	0.5912718	-0.266864
2	-.078223266	-.0575435	-.0575435	-.0782234
3	-.016864118	0.0912718	-.0912718	0.0168641
4	0.02674876	0	0	0.0267480

Table – 4: PSNR values for the proposed Algorithm and SPIHT Algorithm

Image	PSNR for the Proposed Algorithm	PSNR for SPIHT Algorithm	Rate bpp		PSNR GAIN
			C2	C3	
 Lena	33.1900	30.6548	0.1016	0.0938	2.5352
 Tree	31.7838	26.5987		0.0859	5.1851
 Peppers	26.7274	26.1347	0.1016	0.0938	0.5927
 Tomato	26.5515	24.9537	0.0938	0.0859	1.5978
 Hibiscus	25.7410	24.8782	0.0859	0.0859	0.8628
 Carrots	27.2852	26.6773	0.1094	0.1016	0.6079
 Banyan tree	29.2025	28.2019	0.1094	0.1016	1.0006
 Igloo	33.6661	31.6925	0.1094	0.1094	1.9736
 House	28.2869	28.0141	0.0938	0.0938	0.2728
Mean	29.1594	27.5340	0.0999	0.0946	1.6254



(a)



(a)

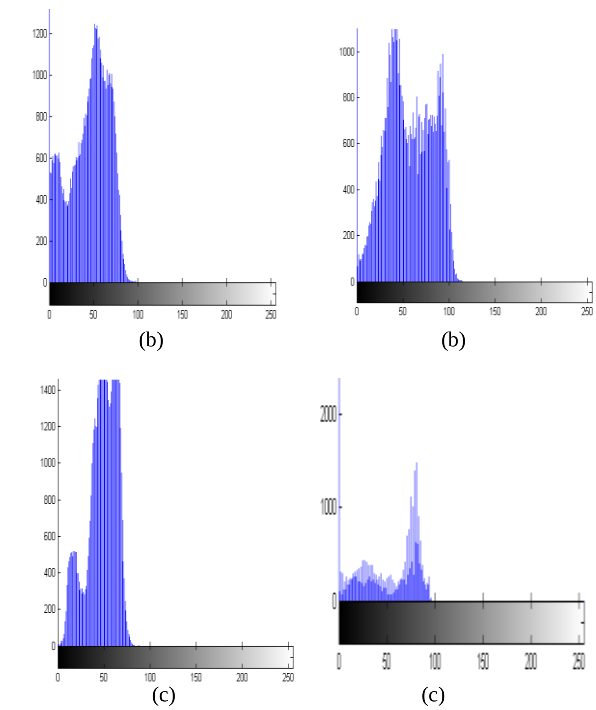


Fig 1: Histogram of color channels of the images Lena and Peppers respectively after DHT color transforms. (a) C1 channel (b) C2 channel (c) C3 channel

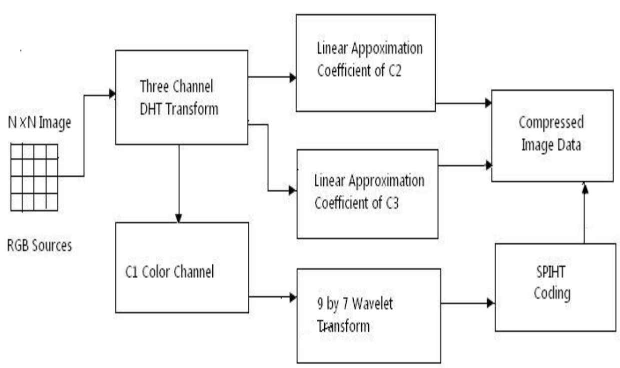


Fig 3: Block diagram of Encoder

(a) (a)

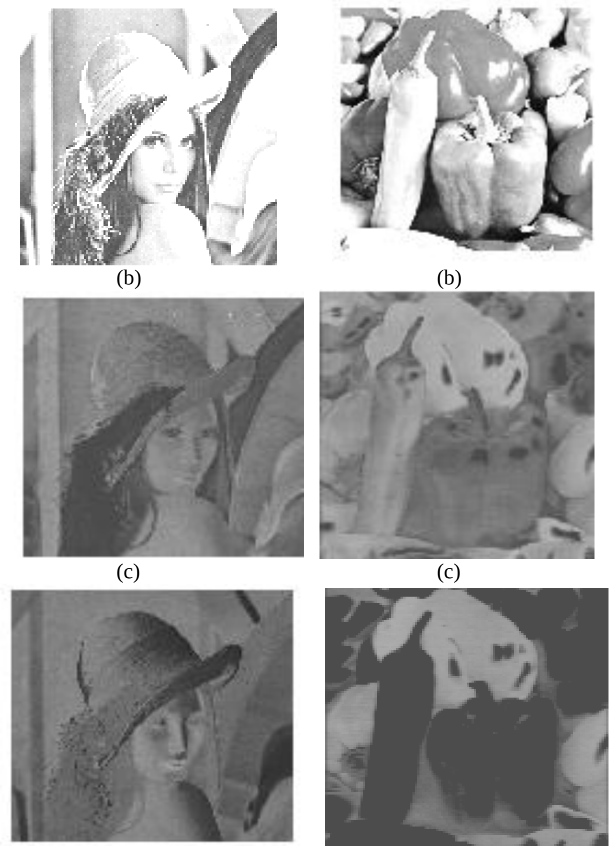


Fig 2: Inter-band correlation of C1, C2, C3 components of the images Lena and Peppers respectively (a) The original image (b) C1 Component (c) C2 Component and (d) C3 Component

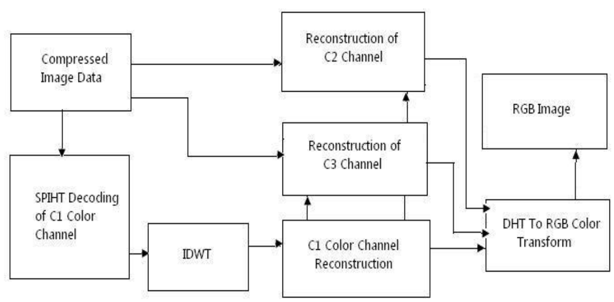
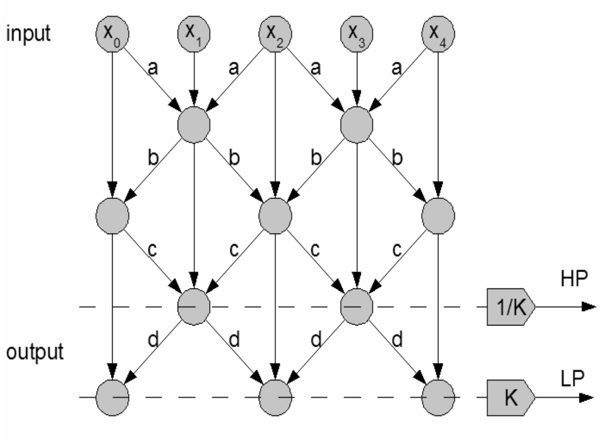
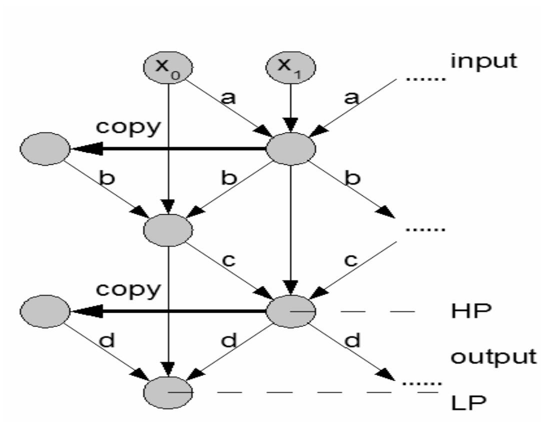


Fig 4: Block diagram of Decoder



(a)



(b)

Fig 5: (a) Data dependency diagram showing the data flow according to CDF9/7 lifting scheme implementation. Source signal is defined as X, the result is taken from HP and LP branches for high-pass and low-pass coefficients respectively; a, b, c, d and K are constants computed by filter factorization process. (b) Demonstrating boundary handling

(a)

(b)

(c)

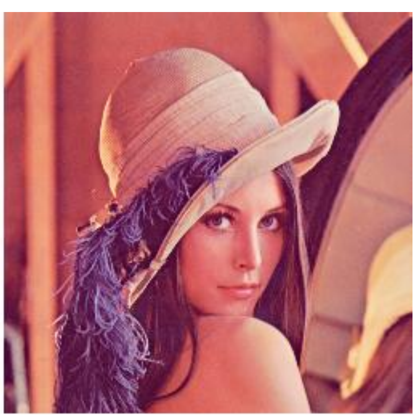
Fig 6: House Image (a) The original image (b) Compressed by the proposed Algorithm and (c) Compressed by the SPIHT algorithm.

(a)

(b)

(c)

Fig 7: Peppers Image (a) The original image (b) Compressed by the proposed Algorithm and (c) Compressed by the SPIHT algorithm.



(a)

(b)

(c)

Fig 8: Lena Image (a) The original image (b) Compressed by the proposed Algorithm and (c) Compressed by the SPIHT algorithm.

2.2 Equations

$$I_{total} = p_1 MN \log_2(1/p_1) + p_2 MN \text{iog}_2(1/p_2) + ... \quad (1)$$

$$H = I_{total}/MN = p_1 \log_2(1/p_1) + p_2 \log_2(1/p_2) + ... (2)$$

$$\rho_{\text{a, b}} = \Lambda_{ab} / \sqrt{\Lambda_{aa}\Lambda_{bb}} \quad (3)$$

Where a and b are color planes.

$$\Lambda_{ab} = (1/MN) \sum_{i=1}^{M} \sum_{j=1}^{N} (X_a(i, j) - \mu_a)(X_b(i, j) - \mu_b \quad (4)$$

$$\mu_a = (1/MN) \sum_{i=1}^{M} \sum_{j=1}^{N} X_a(i, j) \quad (5)$$

$$\mu_b = (1/MN) \sum_{i=1}^{M} \sum_{j=1}^{N} X_b(i, j) \quad (6)$$

$$\begin{bmatrix} C1 \\ C2 \\ C3 \end{bmatrix} = \begin{bmatrix} 0.5774 & 0.5774 & 0.5774 \\ 0.5774 & 0.2113 & -0.7887 \\ 0.5774 & -0.7887 & 0.2113 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad (7)$$

$$C2 = a_k C1^{k} + a_{k-1} C1^{k-1} + \ldots\ldots + a_1 C1 + a_0 \quad (8)$$
$$C3 = b_k C1^{k} + b_{k-1} C1^{k-1} + \ldots\ldots + b_1 C1 + b_0 \quad (9)$$

$$\tilde{C2} = a_{r1} * C1 + b_{r0} \quad (10)$$

$$\tilde{C3} = a_{b1} * C1 + b_{b0} \quad (11)$$

$$E[(C2-\tilde{C2})^2] = E[(C2 - a_{r1} * C1 - b_{r0})^2] \quad (12)$$

$$E[(C3-\tilde{C3})^2] = E[(C3 - a_{b1} * C1 - b_{b0})^2] \quad (13)$$

The optimal coefficients are

$$a_{r1} = \frac{\mathrm{Cov}(C1, C2)}{\mathrm{var}(C1)} \quad (14)$$

$$b_{r0} = E(C2) - \frac{\mathrm{Cov}(C1, C2)}{\mathrm{var}(C1)} E(C1) \quad (15)$$

$$a_{b1} = \frac{\mathrm{Cov}(C1, C3)}{\mathrm{var}(C1)} \quad (16)$$

$$b_{b0} = E(C3) - \frac{\mathrm{Cov}(C1, C3)}{\mathrm{var}(C1)} E(C1) \quad (17)$$

$$(1-X/2)^{A} Q_{A}(X) + (X/2)^{A} Q_{A}(2-X) = 1 \quad (18)$$

$$a_{\mathrm{prim}}(Z) = 2Z^{d} \left(\frac{1+Z}{2}\right)^{A} q_{\mathrm{prim}}(1-(Z+Z^{-1})/2) \quad (19)$$

$$a_{\mathrm{dual}}(Z) = 2Z^{d} \left(\frac{1+Z}{2}\right)^{A} q_{\mathrm{dual}}(1-(Z+Z^{-1})/2) \quad (20)$$

$$a_{\mathrm{prim}}(X) = 1 - cX \quad (21)$$
$$a_{\mathrm{dual}}(X) = 1 + (c+2)X + (c^2 + 2c + 5/2) X^2 \quad (22)$$

$$\mathrm{PSNR} = 10\log_{10} \frac{255*255}{(\mathrm{MSE(R)} + \mathrm{MSE(G)} + \mathrm{MSE(B)})/3} \quad (23)$$

3. Paragraphs and Itemizations

3.1 Selection of base color

Base color for coding the color images using correlation based approach can be selected by considering two points. The first one considers the entropy of the color bands after linear color component transform. The second one considers the correlation between the planes.

3.1.1 Study of Entropy of color channels

In a color channel, suppose there are M different and independent messages m_1, m_2, m_3…, with probabilities of occurrence p_1, p_2, p_3….. Suppose that for an image size of M x N, a sequence of MN messages can be generated. A color plane consists of p_1MN messages of m_1, p_2MN messages of m_2, etc. The total information in such a color plane is given in equation 1.The average information or entropy is represented by the symbol H and is given by equation 2.

The entropy of each plane is measured and the color plane which has more entropy (information) is selected as base color for coding. The other two are considered as sub-ordinate color planes. To determine the entropy the Histogram of the digital image of each color plane is calculated.

Histogram of a digital image with gray levels in the range [0, L-1] is a discrete function h $(r_k) = n_k$, where r_k is the k^{th} grey level and n_k is the number of pixels in the image having grey level r_k. It is common practice to normalize a histogram by dividing each of its values by by the total number of pixels in the image, denoted by n. The normalized histogram is given by p $(r_k) = n_k/n$, for k = 0, 1, 2 …L-1. P (r_k) gives an estimate of the probability of occurrence of grey r_k. The Histogram of the three channels C1, C2, and C3 of the DHT transformed Lena and Peppers images are shown in figure 1.

The entropy measures of each plane of various images after taking the linear three channel DHT color transform is tabulated in table -1. It suggests that in almost all color images after DHT transform the C1 channel has more entropy. That is the channel C1 contains more information than the other two channels. So the best selection of the base color for correlation based approach coding is the channel C1.

3.1.2 Study of Correlation between color channels

Correlation is a measure of the relation between two or more variables. Correlation co-efficient can range from -1.00 to +1.00. The value of -1.00 represent a perfect negative correlation while a value of +1.00 represents a perfect positive correlation and a value of zero represents no correlation. The most widely used type of correlation co efficient is Pearson also called linear correlation as given in equation 3.

Where is the covariance which measures the extent to which two random variables (color planes in our case) are related to each other. It is the measure of the interaction between brightness values in two bands of the image. Where μ_a and μ_b are the mean values which is an arithmetic average and defined as in equation 5 and 6 respectively.

Even after the application linear color component transform there exist correlation between the color channels. The three channel Discrete Hartley Transform is applied to the RGB image as the first step. The RGB image is converted into C1C2C3. The inter-color correlations of C1, C2 and C3 components in various color images are calculated. The correlation co-efficient is calculated according to equation-3. The local correlation, which is the correlation of color components in an N x N block, is calculated. Afterwards the mean value of correlations of all sub-blocks in an image is calculated. For three primary color components C1, C2 and C3, three pairs of cross correlation are calculated as correlation of C1 and C2 colors, C1 and C3 colors and C2 and C3 colors. The results are summarized in table 2. The following observations are made:

1. Among three cross correlations between C1-C2, C1-C3, C2-C3 components the cross correlation of C2-C3 tends to be smaller. In other words, C2 and C3 color components are the most uncorrelated colors.
2. The following relation holds generally
   a) C2-C3 cross correlation < C1-C2, C1-C3 cross correlation
   b) Sum of cross correlation of C1-C2 and C1-C3 > C1-C2+ C2-C3 > C1-C3 + C2-C3

In other words, the C1 component is more correlative than the other two color components. The most correlated color channel as well as containing more information, the channel C1 is selected as base color and the other two color bands are considered as sub-ordinate colors. The visual correlations of these channels are shown in figure 2 for the images Lena and Peppers.

3.2 Color-correlation based Compression Algorithm

The color correlation based compression algorithm [10] is an alternative method of taking advantage of high inter-band correlation in C1C2C3 color planes. High color correlation suggests that one of the primary colors is an independent variable and two others are functions of this base color. Due to the limited sensitivity of the visual system to chrominance information, only rough approximation is required without a significant reduction in image quality. The processing steps in the proposed encoder and decoder for color images are described in figure 3 and figure 4.

3.2.1Coding Algorithm

(i) Linear Color Component Transform

The orthogonal linear transforms can be applied for color de-correlation, such as three channel Discrete Cosine Transform (DCT) and Discrete Hartley Transform (DHT). There are 11 published color transforms (YCrCb, NTSC, PAL, HDTV, UVW, DCT, DHT, two approximate K-L transforms (K1K2K3 and KLT), the original reversible color transform (ORCT) adopted in JPEG-2000, CIE X-Y-Z primary color coordinate system) to de-correlate the color channels. Out of 11 linear color transforms for correlation based coding algorithm the DHT performs better than the other transforms in terms of PSNR. It is observed from Table -2, even after linear color component transform, there exist correlation between color channels. The three channel DHT transform is used to transform the RGB components into an efficient set of color components suitable for correlation based coding algorithm. The three channel DHT is expressed as in equation 7.Based on the study of entropy of the channels and correlation, the channel C1 is selected as base color.

(ii)Linear Approximation of C2 and C3 Color Components

The steps of the coding algorithm are as follows

1. Group the pixel values of each color components into N x N blocks.
2. Encode the C2 and C3 colors using polynomial expansion of these colors as a function of the C1 as stated in equations 8 and 9. Where k is the order of the polynomial expansion and a_k and b_k are the coefficients of polynomial expansion. Only the reduced set of coefficients a_k and b_k are transmitted to the receiver.

Linear approximation for the dependent colors in each block is used. The motivation for this is that two color components in the image domain are highly correlated in a small neighborhood whereas high correlation suggests a linear dependency. Hence the two color channels C2 and C3 are approximated according to equation 10 and 11.

The least squares (LS) a MSE (mean square error) criterion is used to find the coefficients, i.e., for a_{r1} and b_{r0} by minimizing the error between actual C2 and linear approximated C2 and the same for C3 as given in equation 12 and 13

The optimal coefficients are a_{r1}, b_{r0} ,a_{b0} and b_{b0} are calculated as shown in equations 14, 15,16 and 17.

For encoding the base color C1, the 9 by 7 wavelet filter and SPIHT coding are used.

(iii) The 9 by 7 Wavelet Filter

There exists two ways to implement the computation of discrete wavelet transform. The first approach uses convolution (filtering) with appropriate boundary handling. The second is the fast lifting approach, a refined system of very short filters which are applied in a way that produces the same result as the first approach, introducing significant computational and memory saving. Lifting scheme is derived from a polyphase matrix representation of the wavelet filters, a representation that is distinguishing between even and odd samples. Using the algorithm of filter factoring, the original filter is split into a series of shorter filters (typically Laurent polynomials of first degree). Those filters are designed as lifting steps. In each step one group of coefficients are lifted (altered) with the help of the other one (classical dyadic transform always leads to two groups of coefficients, low pass and high pass). Data flow in the final algorithm is presented in figure 5.

The most widely used image processing wavelet filters, are the Cohen-Daubechies-Feauveau 9/7-tap filters (CDF 9/7). The Cohen-Daubechies-Feauveau wavelet are historically first family of biorthogonal wavelets. The JPEG 2000 compression standard uses the biorthogonal CDF 5/3 wavelet for lossless compression and a CDF 9/7 wavelet for lossy compression. For every positive integer A there exists a unique polynomial $Q_A(X)$ of degree A-1 satisfying the identity as in equation 18.

This is the same polynomial as used in the construction of the Daubechies wavelets. But, instead of a spectral factorization, here this is factored into $Q_A(X) = a_{prim}(X)\, a_{dual}(X)$, where the factors are polynomials with real coefficients and constant coefficient 1. Then,

$A_{prim}(Z)$ and $a_{dual}(Z)$ which are given in equations 19 and 20 form a biorthogonal pair of scaling sequences. Where d is some integer used to center the symmetric sequences at zero or to make the corresponding discrete filters causal. Depending on the roots of $Q_A(X)$, there may be up to 2^{A-1} different factorizations. A simple factorization is $q_{prim}(X) = 1$ and $q_{dual}(X) = Q_A(X)$, then the primary scaling function is the B-spline of order A-1. For A=1 one obtains the orthogonal Harr wavelet. The 9/7-CDF wavelet can be obtained by setting A=4 and $Q_4(X) = 1+ 2X + 5/2\, X^2 + 5/2\, X^3$. This polynomial has exactly one real root, thus it is the product of a linear factor (1-cX) and a quadratic factor. The coefficient c, which is the inverse of the root, has an approximate value of -1.4603482098.The $a_{prim}(Z)$ and $a_{dual}(Z)$ are given the equations 21 and 22.

For the coefficients of the centered scaling and wavelet sequences, the numerical values in an implementation-friendly form are tabulated in table – 3. Computational savings of the scheme are gained from the length of the filters (convolution with a 9-tap filter is slower than with a series two-tap filters) and due to a minimum dependency between the coefficients, the whole computation can be done in one memory block of the original signal size. The problem of boundary effect is handled easily by copying one missing sample on each side using half-sample symmetry as shown in figure 7-b. Since images are two dimensional signals, the scheme is extended to 2D space by applying the transform row-and column-wise, respectively (taking separable of the transform into account). As a consequence four sub bands arise from one level of the transform. One low-pass sub bands containing the coarse approximation of the source image called LL sub band, and three high-pass sub bands that exploit image details across different directions. They are HL for horizontal, LH for vertical and HH for diagonal details. In the next level of the transform, the LL band is used for further decomposition and replaces it with respective four sub bands. This forms the decomposition image.

(iv) SPIHT Coding Scheme

When the decomposition image is obtained, the next step is to find a way how to code the wavelet coefficients into an efficient result, taking redundancy and storage space into consideration. SPIHT [2] is one of the most advanced schemes available, even outperforming the state-of-the-art JPEG 2000 in some situations.

The basic principle is the same; a progressive coding is applied, processing the image respectively to a lowering threshold. The difference is in the concept of zero trees (spatial orientation trees in SPIHT). This is an idea that takes bounds between coefficients across sub bands in different levels into consideration. If there is a coefficient in the highest level of transform in a particular sub band considered insignificant against a particular threshold, it is very probable that its descendants in lower levels will be insignificant too, so we can code quite a large group of coefficients with one symbol.

SPIHT makes use of three lists – the List of Significant Pixels (LSP), List of Insignificant Pixels (LIP) and List of Insignificant Sets (LIS). These are coefficient location lists that contain their coordinates. After the initialization, the algorithm takes two stages for each level of threshold – the sorting pass (in which lists are organized) and the refinement pass (which does the actual progressive coding transmission). The result is in the form of a bit stream.

The algorithm has several advantages. The first one is an intensive progressive capability –the decoding (or coding) can be interrupted at any time and a result of maximum possible detail can be reconstructed with one-bit precision. This is very desirable when transmitting files over the internet, since users with slower connection speeds can download only a small part of the file, obtaining much more usable result when compared to other codec such as progressive JPEG. Second advantage is a very compact output bit stream with large bit variability – no additional entropy coding or scrambling has to be applied.

But SPIHT coding also have some disadvantages. SPIHT is very vulnerable to bit corruption, as a single bit error can introduce significant image distortion depending of its location. Much worse property is the need of precise bit synchronization, because a leak in bit transmission can lead to complete misinterpretation from the side of the decoder. For SPIHT to be employed in real-time applications, error handling and synchronization methods must be introduced in order to make the codec more resilient.

3.2.2Decoding Algorithm

The steps of decoding algorithm are as follows.

- Reconstruct the base color by using SPIHT decoder and inverse wavelet transform.

- Reconstruct the C2 and C3 color components by using the C1 color component and the linear approximation co-efficient.

- C2 = a_{r1}*C1 +b_{r0}
- C3 = a_{b1}*C1 +b_{b0}
- Apply the inverse linear color component transform to obtain RGB image from C1C2C3.

3.3. Experimental Results

The proposed algorithm is implemented using MATLAB 7.0: the language of technical computing. The Intel Pentium – IV Processor is used to run the program. Nine 24 bit color images Lena, Peppers, Tree, Tomato, Hibiscus, Carrots, Banyan tree, Igloo, and House are taken as test images. The performance of the proposed coding algorithm using inter-color correlation is evaluated. As a comparison benchmark the peak signal to noise ratio (PSNR) values, based on mean square error (MSE) are calculated for the proposed algorithm and SPIHT algorithm as in equation 23. From the results listed in table-4, it is observed that about 0.2728 dB to 5.1851 dB gains in PSNR is obtained with the proposed algorithm compared to SPIHT coding for same bit rate. The visual comparison of the quality of the proposed algorithm and the SPIHT algorithm are shown in the figures 6, 7 and 8 for the images House, Peppers, and Lena. A better quality improvement is observed with the correlation based approach algorithm than the traditional SPIHT coding.

3.4. Conclusion

A new Algorithm to color image compression is considered. This Algorithm is based on exploiting the inter-color correlations between the color primaries instead of transforming them into a de correlated color space. The algorithm is implemented, by employing the 9 by 7 wavelet filter and SPIHT coding for coding the primary color C1. The first-order linear approximation (y = a*x + b) of the two of the color components (C2 and C3) based on the third color component C1 is used. This algorithm allows the reduction of complexity for both coding and decoding of color images. It is concluded that a significant PSNR gain varies from 0.2728 dB (for House image) to 5.1851 dB (for Tree image) is obtained with reduced complexity in algorithm. Also it is concluded that in color image coding, a correlation based approach is superior to the traditional de-correlation methods.

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