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An Improved Neigh Shrink in Hybrid Wavelet Transform for Image Compression

Naveen Kumr R.
Department of Electronics, KUVEMPU University
Shimoga, Karnataka, India

B. N. Jagadale
Department of Electronics, KUVEMPU University
Shimoga, Karnataka, India

J. S. Bhat
Department of Physics, Karnatak University,
Dharwad, Karnataka, India

Abstract: Rapid progress in mobile communication, demands high-speed multimedia data processing. This has lead the compression technology to speed up the process by reducing the size of data without disturbing image quality. This paper attempts to develop the quality of compression by using improved neigh shrink in hybrid wavelet algorithm to compress an image. After wavelet decomposition, one-dimensional Discrete Cosine Transform is applied to decorrelate approximate coefficients and stored as T-matrix. The detail coefficients are thresholded using 'improved neigh shrink' and Eliminate Zero and Store Data algorithm are applied to eliminate redundancy and stored as reduced array. The compressed approximate and detailed coefficients are encoded by arithmetic coding. The simulated results show that proposed algorithm has significant improvement in image quality in terms of PSNR and SSIM when compared with existed wavelet-based compression methods including JPEG 2000 at high compression rate.

Keywords: Discrete Wavelet Transform (DWT), T-matrix coding, improved Neigh Shrink, EZSD.

I. INTRODUCTION:

A Rapid development of mobile technology with new applications requires large data of high-quality. Processing of such a data leads to a slow transmission and expensive storage, and hence representation of data needs a reduction in a number of bits using image compression techniques [1-3]. Image compression is a technique which reduces the number of bits to represent the large sized image by removing redundant bits[4]. Transform based compression are more preferable to achieve good compression along with the quality of reconstruction. DCT based algorithms are failed in versatility since of its blocking artifacts nature when block sizes are goes on increasing [5,6]. Wavelet based compression suit well for image compression applications because of its multiresolution property. Wavelet-based lossy image compression methods like Embedded Zero-tree wavelet(EZTW)[7], Set Partition Hierarchical Tree (SPIHT)[8],Wavelet difference reduction(WDR)[9] are presently using in some multimedia image compression, which produces an embedded bit-stream of wavelet coefficients with decreasing threshold values to encode the most significant pixels or lists of pixels for reconstruction. But single basis function in wavelet does not meets all its properties, multi wavelets with more than one scaling and wavelet functions are preferable [10,11]. A hybrid compression algorithm proposed by Siddiq et al.[12] achieves high compression ratio with moderate image quality for large size image data. Here the compression is achieved by ignoring first high-frequency subbands at level one and high-frequency subbands at level two are encoded directly by EZSD. The LL subbands are compressed by DCT and encoded By RLE and Arithmetic coding.An enhanced approach for hybrid compression algorithm is proposed in this paper by using an improved neigh shrink as optimal threshold for high-frequency subband at level two and three.

The paper is structured as follows: A hybrid wavelet compression algorithm is explained in section II. The simulation results are tabulated and discussed in section III and followed by the conclusion in section IV.

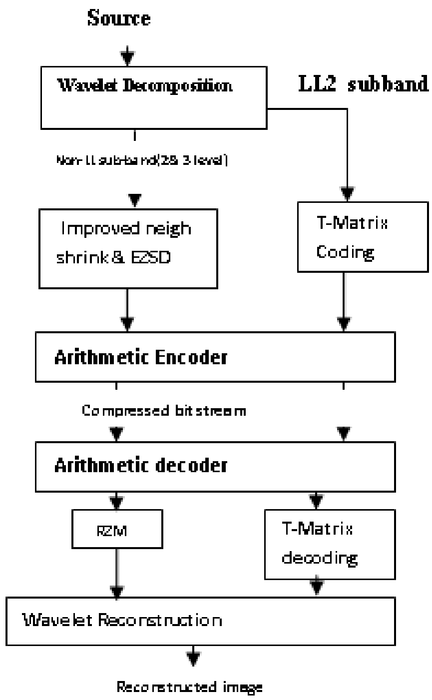

Figure.1: pipelined view of proposed compression algorithm

II. PROPOSED HYBRID WAVELET WAVELET COMPRESSION ALGORITHM:

A. Use of Discrete Wavelet transforms:

The wavelets give the best choice for image analysis due to its multiresolution property. Here decomposition is done by passing source image through a set of low pass and high pass filters to get approximate and detailed coefficients

[13,14]. For each level decomposition of source image produces four sub-bands (LL, LH, HL, and HH). As source image undergoes decomposition, low-frequency sub bands shift towards left corner by becoming more significant. At the same time, high-frequency sub-band shift towards the right bottom corner as insignificant. Hence, by ignoring this insignificant information in high-frequency sub-bands more compression can be achieved.

In this modified approach, the image is subjected to three-level wavelet decomposition. The high-frequency sub-band at first level contains less significant information, and hence it is ignored. While, level two and three high-frequency sub-bands contain some significant information, the direct encoding or ignoring of these sub-bands result in reduced image quality, hence application of an optimal threshold is the key to improving the quality of the reconstructed image.

B. Quantization:

This step is lossy approach and it requires two levels of quantization. The level1 quantization reduces the size of LL_m by, ratio of maximum value of LL_m and Quality factor, as shown below

$$Q1 = Qualityfactor \times \max(LL_m) \qquad (1)$$

$$LL_m = round\left(\frac{LL_m}{Q1}\right) \qquad (2)$$

The Quality factor in eq.1 indicates the quality of the image and is obtained by the maximum value in LL2 divided by all the values in LL2. The process helps LL2 subband coefficients to be more convergent (Quality ranges from 0.005 to 0.01) to get required compression rate. Level2 Quantization is performed on LL2 sub-band after DCT and then divide the matrix by Q2. This eliminates the insignificant coefficients by inserting zeros.

$$Q2(m,n) = \begin{cases} 1, if\ (m=1, n=1) \\ m+n+R, if\ (m \neq 1, n \neq 1) \end{cases} \qquad (3)$$

C. Coding of Low-frequency sub-band using T-Matrix coding:

The DCT uses a small set of values to reconstruct the original signal and also round up the very small values to zero during encoding. Hence it high-quality reconstruction is possible in the compression process.

The decomposed LL2 subband has high energy and more correlated information and DCT is used to compresses the sub-band. The one-dimensional forward and inverse DCT are illustrated as,

$$J_k = S_k \sqrt{\frac{2}{N} \sum_{i=0}^{N-1} G_i \cos\frac{\pi}{N} k\left(i + \tfrac{1}{2}\right)} \qquad (4)$$

$$G_i = \sqrt{\tfrac{2}{N} \sum_{i=0}^{N-1} J_k S_k \cos\frac{\pi}{N} K(i + \tfrac{1}{2})} \qquad (5)$$

$$\text{where } S_k = \begin{cases} \frac{1}{\sqrt{2}}, ifk = 0toN \\ 1, otherwise \end{cases} \qquad (6)$$

The normalization factors $\sqrt{\frac{2}{N}}$ and $\frac{1}{\sqrt{2}}$ makes DCT matrix orthogonal.

Because of the high degree of correlation, the LL2 subband coefficients are difficult to encode directly by arithmetic coding. Therefore, the subband is divided into number of parts and each part is processed by one-dimensional DCT and are quantized by using formula,

$$Q(n) = Q(n-1) + 2 \qquad (7)$$

The transformed values are stored as a row matrix called as Transformed matrix (T-matrix). This process increases the significance of coefficients and de-correlation. Each row of T-matrix has DC values and AC coefficient stream, T-matrix is scanned column-by-column for converting it into a one-dimensional array, and is compressed by The Run Length Encode (RLE) and arithmetic code. The RLE reduces the length of repeated data, and arithmetic code converts reduced data set into bit streams.

D. Coding of high-frequency sub band using improved neigh shrink and EZSD:

After the level two and level three wavelet decomposition redundancy shifted towards in high-frequency sub-bands. Hence application of improved neigh shrink with SURE as optimal threshold possibly increases the compression quality.

For given detailed sub-band, select the wavelet coefficient $K_{i,j}$ need to be shrinking and place a neighboring window $C_{i,j}$ at center.

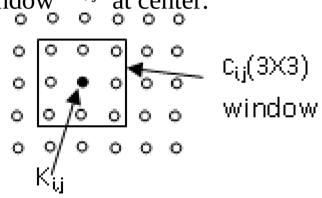

Fig.2 A graphical representation of improved method to shrink wavelet coefficient $K_{i,j}$

Let

$$S_{i,j}^2 = \sum_{(i,j)\in B_{i,j}} K_{i,j}^2 \qquad (8)$$

Where $S_{i,j}^2$ summation has the pixel indices out of the wavelet sub-band range then corresponding term in the summation is to be ignored[15]. The neigh shrink is given by,

$$K_{i,j} = K_{i,j} C_{i,j} \qquad (9)$$

Shrink factor is given by,

$$B_{i,j} = \left(1 - \lambda^2 / K_{i,j}^2\right)_{\oplus} \qquad (10)$$

here the optimal threshold λ and window length L are calculated by stein unbiased risk estimator(SURE) for wavelet coefficients of any sub-band $w_k = k_{i,j} : i, j$

$$(\lambda^s, L^s) = \arg_{\lambda,L} \min SURE(w_k, \lambda, L) \qquad (11)$$

Where as in denoising application noise level is defined with suitable values but in compression, we keep the value of noise level as one. Thresholded and quantized (quality>=0.01) high-frequency sub-bands have a rich number of zeroes, and unnecessary coding of these zeroes make the algorithm assy. Therefore, EZSD is used to eliminate blocks of these zeroes and to store the blocks of non-zero data. It begins with splitting high-frequency sub-bands into non-overlapped blocks (8X8, 16X16) and searches for non-zero blocks. If a non-zero block is found, it will be stored in a reduced array and its position is stored in position array, else it jumps to a next block. The reduced array may contain some more zeroes because some blocks contain more zeroes as compared to the data in them. Therefore, the use of EZSD results in a compact form of reduced array, which helps in the encoding process.

Arithmetic coding is used to compress a stream of data sequence into one-dimensional length code word. The run length encoding helps to avoid coding of repeated coefficients, which reduces the length of the code word. Hence, the arithme tic coding technique converts code word into bit streams.

E. Return Zero Matrix (RZM) algorithm:

During reconstruction this process is used as converse for EZSD method . The reduced array of decoded high-frequency sub-bands is expanded by searching zeros followed by a number in them; the repeated zeros in a new array are counted. The data in an array is replaced by blocks of the matrix and the method applied to all high-frequency sub-bands.

III. RESULTS AND DISCUSSIONS:

The proposed method tested with 8 bit gray scale Boat, Lena, Goldhill, peppers and artificial images (Fig. 3). The table1, shows the PSNR and Structural Similarity Index Mode (SSIM) and comparison of proposed method with SPIHT, WDR and JPEG 2000 at a compression ratio of 80:1.The PSNR and SSIM values of JPEG2000 obtained from [16] and for consistency, same test images are used in the simulation. The figure4, shows that boat image is compressed by SPIHT, WDR, JPEG2000 and proposed method at a compression ratio of 80:1.

The results tabulated in table 1, shows that PSNR and SSIM value of proposed method for boat image is 3.9db and 0.1 are higher than the JPEG2000. But in artificial images,the PSNR and SSIM are lesser in proposed method, this due to the rich significant edge information in images and are not in standard dimension. The quality factor is used to obtain the required compression ratio has some limitation (0.005<Q factor>0.5) and it depends on the use of wavelet family (preferred db5) and encoded array. From the results, we observe that the image quality of proposed method is significantly improved by use of an optimal threshold for the 2nd level high-frequency sub band.

Table.1: Comparison of proposed method with other methods.

Images	***Compression ratio***	***SPIHT***		***WDR***		***JPEG2000***		***Proposed method***	
		PSNR	***SSIM***	***PSNR***	***SSIM***	***PSNR***	***SSIM***	***PSNR***	***SSIM***
Boat	80:1	26.20	0.668	26.96	0.710	26.76	0.740	30.71	0.842
Lena	80:1	29.32	0.803	29.71	0.770	29.62	0.670	31.92	0.902
Goldhill	80:1	27.17	0.660	27.72	0.625	27.69	0.670	27.59	0.672
Peppers	80:1	29.36	0.753	28.93	0.740	29.54	0.783	29.66	0.804
Artificial	80:1	25.25	0.678	23.82	0.620	25.69	0.767	22.02	0.604

(a) (b) (c) (d) (e)

Fig.3 input test images (a)Boat; (b)Lena; (c)Goldhill; (d)peppers

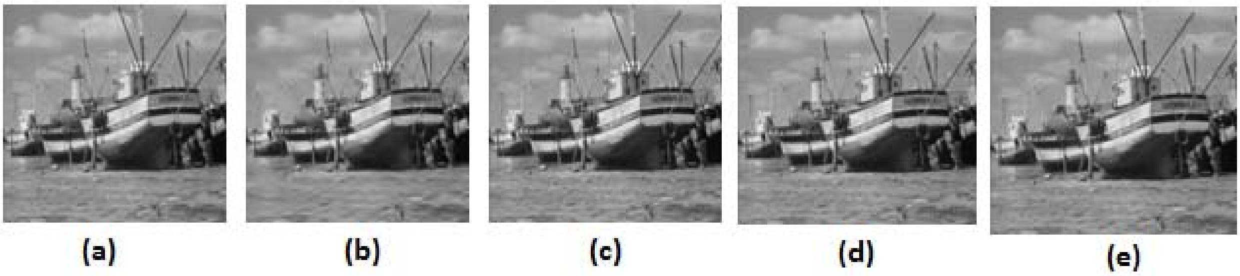

Fig. 4 (a) Original boat image compressed at compression ratio of 80:1 using (b) SPIHT (c)WDR;(d)JPEG2000[16];(e)Proposed method(Q=0.006)

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V. CONCLUSION

In this paper, a new lossy compression algorithm is proposed by using improved neigh shrinks in hybrid wavelet transform. Here, improved neigh shrink efficiently compress the high-frequency sub-bands by using an optimal threshold.At the same time, one dimensional DCT produce lossless coding for low-frequency sub band. The compression ratio is obtained by selecting suitable quality factor and wavelet family. The results obtained by proposed method evidenced that it produce high PSNR and SSIM than existed wavelet-based image compression algorithms.

VI. REFERENCE

[1] H.K.Huang. PACS and Imaging Informatics; Basic Principles and Applications, Wiley, USA, 2010(ISBN:978-0-470-37372-9).

[2] Tim Bruylants, Adrian Munteanu, Peter Schelkens, “Wavelet based volumetric medical image compression”, Signal processing: Image communication, Vol.31,2015,pp. 112-133.

[3] Sayood. K, D. ‘Introduction to Data compression,2nd edition’, Academic press, Morgan Kaufman Publishers, 2000.

[4] ZhiyongZuo, Xia Lan, Lihua Deng, Shoukui Yao, Xiaoping Wang, “An Improved medical image compression with lossless region of interest”, Optik, Vol. 126,2015,pp. 2825-2831.

[5] Al-Haj.A, E. “Combined DWT-DCT Digital image Water marking”, Journal of Computer Science and Network Security, Vol.8, No.10, pp. 44-151.

[6] Tsai.M and Hung. H, K. “DCT and DWT Based Image Watermarking Using Sub-Sampling”, Proceeding of the Fourth International Conference on Machine Learning and Cybern, Guangzhou, pp. 5308-5313.

[7] S.T.Hsiang and J.W.Woods, “Embedded image coding using Zeroblock of subband/wavelet coefficeints and context modeling”, in Proc. Data compress. Conf., Washington, DC, 2001, pp. 83-92.

[8] Amir said and Perlman, W.A. A New, Fast, and Efficient Image Codec based on Set Partitioning in Hierarchical Tree, IEEE Trans. Circuit and systems for Video Technology, Vol. 6, no. 3, pp. 243-250, June 1996.

[9] Jun Tian, Raymond O. Wells Jr, “Embedded Image Coding Using Wavelet Difference Reduction”, Wavelet Image and video compression, International series of engineering and computer science, pp289-301.

[10] Gonzalez RC, Woods RE, Digital Image Processing,3rd ed. , Pearson Education Pvt.Ltd;2009, chapter 8.

[11] Sonja Grgic, MislavGrgic, “Performance Analysis of Image Compression Using Wavelets”, IEEE trans. on Industrial Electronics, Vol.48, (2001) .

[12] Mohammed Mustafa Siddiq, E. “Using two level DWT with limited sequential search algorithm for image compression”,Journal of Signal and Information Processing, Vol.3,2012, pp. 51-62.

[13] Strang. G and Nguyen.T, D. (1996)”Wavelets and Filter Banks”, Wellesly-Cambridge press, Wellesly, MA, http: //www-math. mit. edu /gs/book/wfb.html.

[14] Pizzaman M, Islam1 MR, and Ali MZ, Application of Wavelet Transform and its Advantages Compared to Fourier Transform’, Journal of Physical Sciences,Vol.13,2009, pp.121-134.

[15] Zhou Dengwen, Chen Wengang, E. “Image denoising with an optimal threshold and neighboring window”, pattern Recognition letters, Vol. 29, 2008, pp.1694-1697.

[16] Awwal Mohammed Rufai, GholamrezaAnburjagari, HasamDemirel,” Lossy image compression using singular value decomposition and wavelet difference reduction", Digital signal processing,Vol. 24, 2014, PP:117-123.