

IMPLEMENTATION OF HYBRID DWT-DCT ALGORITHM FOR IMAGE COMPRESSION: A REVIEW

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ABSTRACT

Digital image in their raw form require an enormous amount of storage capacity. Considering the important role played by digital imaging and, it is necessary to develop a system that produces high degree of compression while preserving critical image information. There are various transformation techniques used for data compression. Discrete Cosine Transform (DCT) and Discrete Wavelet Transform (DWT) are the most commonly used transformation. DCT has high energy compaction property and requires less computational resources. On the other hand, DWT is multi resolution transformation. In this paper, we propose a hybrid DWT-DCT algorithm for image compression and reconstruction taking benefit from the advantages of both algorithms. The algorithm performs the Discrete Cosine Transform (DCT) on the Discrete Wavelet Transform (DWT) coefficients. Simulations have been conducted on several natural, bench marks, medical and endoscopic images. Several QCIF, high definition, and endoscopic videos have also been used to demonstrate the advantage of the proposed scheme. The simulation results show that the proposed hybrid DWT-DCT algorithm performs much better than the standalone JPEG-based DCT, DWT, and WHT algorithms in terms of peak signal to noise ratio (PSNR), bit error rate (BER), mean square error (MSE), energy compaction, time taken for processing as well as visual perception at higher compression ratio. The new scheme reduces “false contouring” and “blocking artifacts” significantly. Furthermore, the proposed algorithm is also compared with the some existing hybrid algorithms. The comparison results show that, the proposed hybrid algorithm has better performance and reconstruction quality.

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I. INTRODUCTION

DATA compression is one of the major areas of the research in image and video processing applications. With the development of computer and network technology, more multimedia-based information has been transmitted over the internet and wireless network. The data to be transmitted and stored requires unnecessary space; as a result, it is desirable to represent the information in the data with considerably fewer bits. At a same time, it must be able to reconstruct the data very close to original data. This can be achieved via an effective and efficient compression and decompression algorithm.

The Joint Photographic Expert Group (JPEG) was developed in 1992, based on the Discrete Cosine Transform (DCT). It has been one of the most widely used compression methods [1]. Although hardware implementation for the JPEG using the DCT is simple, the noticeable “blocking artifacts” across the block boundaries cannot be neglected at higher compression ratio. In addition, the quality of the reconstructed images is degraded by the “false contouring” effect for specific images having gradually shaded areas [2]. The main cause of false contouring effect is heavy quantization of the transform coefficients and looks like a contour map. The Discrete Wavelet Transform (DWT) based coding, on the other hand, has been emerged as another efficient tool for image compression [3] mainly due to its ability to display image at different resolutions and achieve higher compression ratio. The Forward Walsh Hadamard Transform (FWHT) is another option for the image and video compression applications which requires less computation as compared to DCT and DWT algorithm. In order to benefit from the respective strengths of individual popular coding schemes, a new scheme, known as hybrid-algorithm, has been developed where two transforms techniques are implemented together. There have been few efforts devoted to such hybrid implementation. The DWT is used for intra-coding and the DCT for inter-coding. Usama presents a scalable hybrid scheme for image coding that combines both the Wavelet and the Fourier transforms [4]. Yu and Mitra in [5] have introduced another form of hybrid transformation coding technique. In [6], Singh et al. have applied similar hybrid algorithm to medical images that uses 5-level DWT decomposition. Because of higher level (5 levels DWT), the scheme requires large computational resources and is not suitable for use in modern coding standards. The hybrid scheme may also be suitable for medical imaging application such as, capsule endoscopic.

In this paper, section II define in section1-features and review of different papers that I read of image compression, section II -DCT, section III-DWT, section IV-Hybrid scene, section V-conclusion.

II. DISCRETE COSINE TRANSFORM (DCT)

The DCT for an $N \times N$ input sequence can be defined as

Follows [1]:

$$D_{DCT}(i, j) = \frac{1}{\sqrt{2N}} B(i)B(j) \sum_{x=0}^{N-1} \sum_{y=0}^{N-1} M(x, y) \cdot \cos\left[\frac{(2x+1)}{2N} i\pi\right] \cos\left[\frac{(2y+1)}{2N} j\pi\right] \quad \text{--- (1)}$$

Where

$$B(u) = \begin{cases} \frac{1}{\sqrt{2}} & \text{if } u = 0 \\ 1 & \text{if } u > 0 \end{cases}$$

$M(x, y)$ is the original data of size $x * y$.

The input image is first divided into 8×8 blocks; then the 8-point 2-D DCT is performed. The DCT coefficients are then quantized using an 8×8 quantization table(7), as described in the JPEG standard. The quantization is achieved by dividing each elements of the transformed original data matrix by corresponding element in the quantization matrix Q and rounding to the nearest integer value as shown in Eq. (2):

$$D_{quant}(i, j) = \text{round}\left(\frac{D_{DCT}(i, j)}{Q(i, j)}\right) \quad \text{---- (2)}$$

Further compression is achieved by applying appropriate scaling factor. In order to reconstruct the data, the rescaling and the de-quantization is performed. The de-quantized matrix is then transformed back using the inverse-DCT.

The entire procedure is shown in Fig. 1.

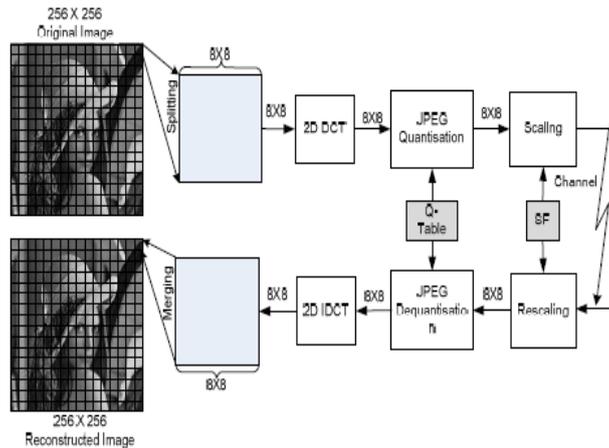


Fig.1. Block diagram of the JPEG-based DCT scheme

III. DISCRETE WAVELET TRANSFORM (DWT)

The DWT represents an image as a sum of wavelet functions, known as wavelets, with different location and scale [8]. The DWT represents the image data into a set of high pass (detail) and low pass (approximate) coefficients. The image is first divided into blocks of 32×32 . Each block is then passed through the two filters: the first level decomposition is performed to decompose the input data into an approximation and detail coefficients. After obtaining the transformed matrix, the detail and approximate coefficients are separated as LL, HL, LH, and HH coefficients. All the coefficients are discarded, except the LL coefficients that are transformed into the second level. The coefficients are then passed through a constant scaling factor to achieve the desired compression ratio. An illustration is shown in Fig. 2. Here, $x[n]$ is the input signal, $d[n]$ is the high frequency component, and $a[n]$ is the low frequency component. For data reconstruction, the coefficients are rescaled and padded with zeros, and passed through the wavelet filters. We have used the Daubechies filter coefficient [11] in this work.

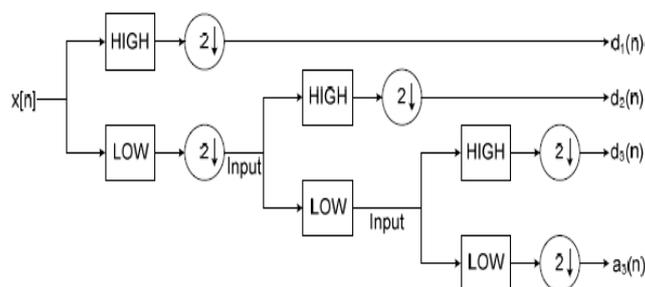


Fig. 2 Block diagram of the 2-level DWT scheme

IV. PROPOSED HYBRID DWT- DCT ALGORITHM

The main objective of the presented hybrid DWT-DCT algorithm is to exploit the properties of both the DWT and the DCT. Giving consideration of the type of application, original image/frame of size 256×256 (or any resolution, provided divisible by 32) is first divided into blocks of $N \times N$. Each block is then decomposed using the 2-D DWT. (9) Low-frequency coefficients (LL) are passed to the next stage where the high frequency coefficients (HL, LH, and HH) are discarded.

The passed LL components are further decomposed using another 2-D DWT. The 8-point DCT is applied to these DWT coefficients. By discarding the majority of the high coefficients, we can achieve a high compression. To achieve further compression, a JPEG-like quantization is performed. In this stage, many of the higher frequency components are rounded to zero. The quantized coefficients are further scaled using scalar quantity known as scaling factor (SF). Finally, the image is reconstructed following the inverse procedure. During the inverse DWT, zero values are padded in place of the detail coefficients (10). The entire procedure is summarized below and illustrated in Fig. 3 (for $N=32$). The sub-sampling schemes used in this work are shown in Fig. 4

A. Hybrid algorithm

The hybrid is briefly presented below:

SF = Scaling Factor

SFold = Starting Scaling Factor

MSF = increment of SF

CRdesired = Maximum CR desired

M = Input data of dimension ($N \times N$)

Wcoeff = wavelet filter coefficient

Wwv = 2D DWT coefficient

Wiwv = 2D IDWT coefficient

Zdct = 2D DCT coefficient

Zidct = 2D IDCT coefficient

Q = Q table

ZQN = Quantized DCT coefficients

ZDQN = De-quantized DCT coefficients

ZSF = Scaled DCT coefficients

ZRSF = Rescaled DCT coefficients

A.1 Compression Procedure

1. Compute 2-level 2D DWT coefficients of the input samples ($N \times N$):

$$(N \times N): W_{w,v} = W_{coeff} \times M \times W'_{coeff}$$

2. Perform 2D DCT on the four $W_{w/4,v/4}$ coefficients of $N/4 \times N/4$:

$$Z_{dct}(i, j) = \frac{1}{\sqrt{2N}} B(i) B(j) \sum \sum W_{w/4,v/4}(x, y) \\ \times \cos \left[\frac{2x+1}{2N} i\pi \right] \times \cos \left[\frac{2y+1}{2N} j\pi \right]$$

$$\text{for } i, j = 0, \dots, \frac{N}{4} - 1, \quad B(u) = \begin{cases} \frac{1}{\sqrt{2}} & \text{if } u = 0 \\ 1 & \text{if } u > 0 \end{cases}$$

3. Quantize the four DCT coefficient matrices ($N/4 \times N/4$) using four different Q tables:

$$Z_{qn}(i, j) = \text{round} \left(\frac{Z_{dct}(i, j)}{Q(i, j)} \right) \text{ for } i, j = 0, \dots, \frac{N}{4} - 1$$

4. Calculate Compression ratio (CR):

If $CR = CR_{desired}$

Go to step 8 (End)

Else

Continue to step 5

5. Perform Scaling on the quantized coefficients $Z_{qn}(i, j)$:

$$Z_{sf}(i, j) = \text{round} \left(\frac{Z_{qn}(i, j)}{SF_{old}} \right) \text{ for } i, j = 0, \dots, \frac{N}{4} - 1$$

$$SF_{old} = SF_{old} + \Delta SF$$

$$SF = SF_{old}$$

6. Sub-sample the three higher order coefficient matrices, LH, HL, and HH (if needed)

7. Go to step 4

8. End

A.2 Reconstruction Procedure

1. Interpolate the three higher order coefficient matrices (zeropadding)

2. Perform Rescaling

3. Perform De-Quantization

4. Compute 2D IDCT of the $N/4 \times N/4$ samples

5. Compute 2-level 2D IDWT to get back the $N \times N$

Reconstructed matrix

6. Calculate PSNR

7. Calculate SSIM

8. End

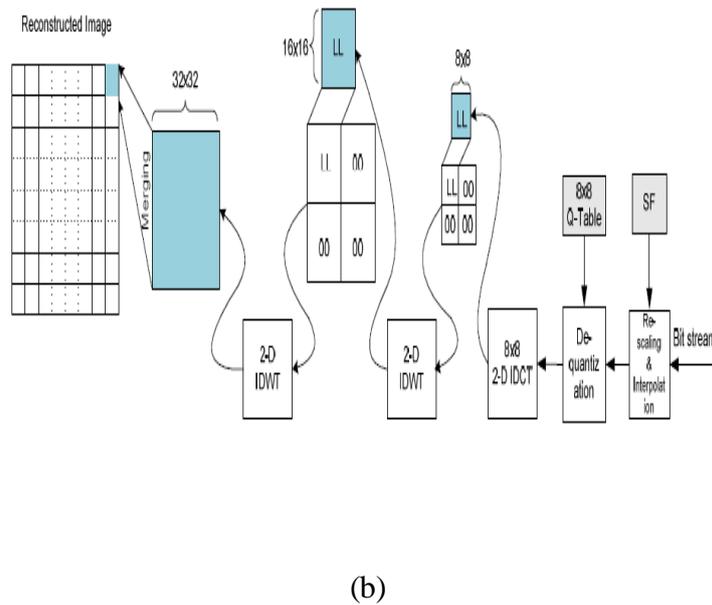
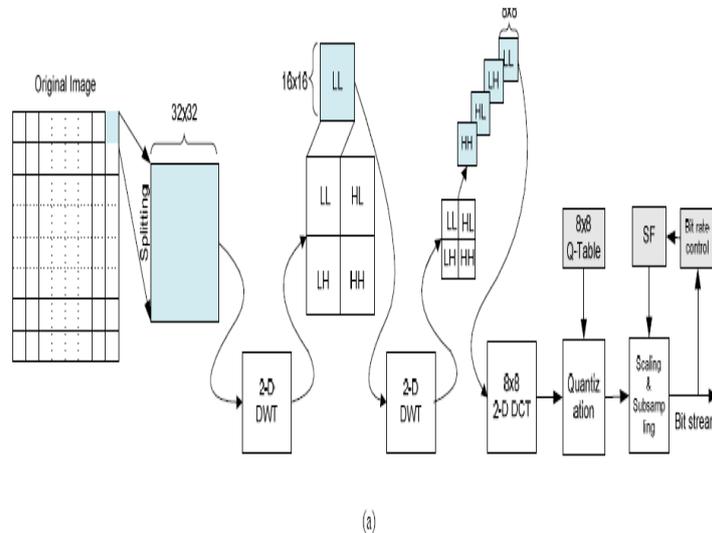


Fig. 3. Block diagram of the proposed hybrid DWT-DCT scheme for $N=32$: (a) compression algorithm; (b) decompression algorithm

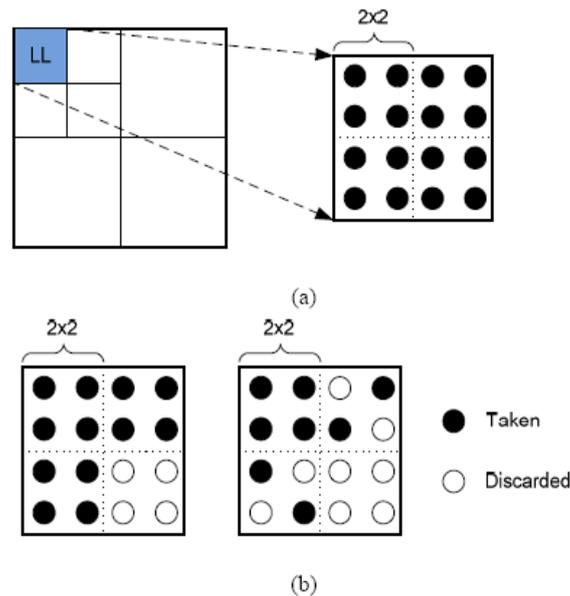


Fig. 4. Sub-sampling of the DWT coefficients: (a) fully sampled for LL; (b) quarterly sampled and half sampled for LH, HL, and HH

V. EVALUATION CRITERION

In this section, the performance of the algorithms using two popular measures: compression ratio (CR) and peak signal to noise ratio (PSNR) has been analyzed. Mean Square error(MSE) Image having same PSNR value may have different perceptual quality. The Structural Similarity Metric (SSIM) index is another measurement technique that is proven to be well matched to perceived visual quality of the image. By adjusting the parameters, trade-off can be achieved for compressed image against reconstructed image quality over wide a range.

1. Mean Square Error (MSE):

Mean square error is a criterion for an estimator: the choice is the one that minimizes the sum of squared errors due to bias and due to variance. The average of the square of the difference between the desired response and the actual system output. As a loss function, MSE is called squared error loss. MSE measures the average of the square of the "error". The MSE is the second moment (about the origin) of the error, and thus incorporates both the variance of the estimator and its bias. For an unbiased estimator, the MSE is the variance. (10) In an analogy to standard deviation, taking the square root of MSE yields the root mean squared error or RMSE. Which has the same units as the quantity being estimated. for an unbiased estimator, the RMSE is the square root of the variance, known as the standard error.

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

2. Peak Signal-to-Noise Ratio(PSNR):

It is the the ratio between the maximum possible power of a signal and the power of corrupting noise .Because many signals have a very wide dynamic range, PSNR is usually expressed in terms of the logarithmic decibel scale. The PSNR is most commonly used as a measure of quality of reconstruction in image compression etc. It is most easily defined via the mean squared error (MSE) which for two $m \times n$ monochrome images I and K where one of the images is considered noisy.

$$PSNR = 10 \cdot \log_{10} \left(\frac{MAX_I^2}{MSE} \right) = 20 \cdot \log_{10} \left(\frac{MAX_I}{\sqrt{MSE}} \right) \quad --(4)$$

3. Compression ratio (CR)

The compression ratio is defined as follows:

$$CR = \frac{\text{Discarded data}}{\text{Original data}}$$

The resulting CR can be varied according to the imagequality and the level of compression depends on the QT and the SF.

4. . SSIM index

The SSIM index is the objective image quality measure and can be defined as below:

$$SSIM(A, B) = \frac{(2\mu_A\mu_B + C_1)(2\sigma_{AB} + C_2)}{(\mu_A^2 + \mu_B^2 + C_1)(\sigma_A^2 + \sigma_B^2 + C_2)}$$

Where, μ_A, μ_B = mean intensities of original data A and reconstructed data B; σ_A, σ_B =standard deviation of original data A and reconstructed data B; $C(1), C(2)$ = constant.

$$\sigma_{AB} = \frac{1}{N-1} \sum_{i=1}^N (A_i - \mu_A)(B_i - \mu_B)$$

If the reconstructed data is retrieved exactly similar tooriginal data then the best SSIM index of value 1 can beachieved.

VI. CONCLUSION

In this paper, we present a new hybrid scheme combining the DWT and the DCT algorithms under high compression ratio constraint. The algorithm performs the DCT on the lowest level DWT coefficient. It is tested on several types of images, such as, natural, medical, endoscopic, etc., as well as several endoscopic videos. The results of this exhaustive simulation show consistent improved performance for the hybrid scheme compared to the JPEG-based DCT, the Daubechies-based DWT(12), and the FWHT schemes. The new scheme performs better in a noisy environment and reduces the false contouring effects and blocking artifacts significantly. The analysis shows that for a fixed level of distortion, the number of bits required to transmit the hybrid coefficients would be less than those required for other schemes. The proposed scheme has medium computational complexity and is intended to be used as the image/video compressor engine in imaging and video applications.

REFERENCES

1. R. K. Rao and P. Yip, Discrete Cosine Transform: Algorithms, Advantages and Applications. NY: Academic, 1990.
2. G. Joy and Z. Xiang, "Reducing false contours in quantized color images," Computer and Graphics, Elsevier, vol. 20, no. 2, pp. 231–242, 1996.
3. A. K. Jain, Fundamentals of Digital Image Processing. Prentice Hall Inc., 1989.
4. U. S. Mohammed and W. M. Abd-elhafiez, "Image coding scheme based on object extraction and hybrid transformation technique," Int. J. of Engineering Science and Technology, vol. 2, no. 5, pp. 1375–1383, 2010.
5. T.-H. Yu and S. K. Mitra, "Wavelet based hybrid image coding scheme," in Proc. IEEE Int Circuits and Systems Symp, vol. 1, 1997, pp. 377–380.
6. S. Singh, V. Kumar, and H. K. Verma, "DWT-DCT hybrid scheme for medical image compression." J Med Eng Technol, vol. 31, no. 2, pp. 109–122, 2007.
7. J. D. Kornblum, "Using JPEG quantization tables to identify imagery processed by software," Digital Forensic Workshop, Elsevier, pp. 21–25, 2008.
8. Suchitra Shrestha and Khan Wahid, "Hybrid DWT-DCT Algorithm for Biomedical Image and Video Compression Applications", Proc. of the 10th IEEE International Conference on Information Sciences, Signal Processing and their Applications, pp. 280-283, 2010.
9. U. S. Mohammed, "Highly scalable hybrid image coding scheme," Digital Signal Processing, Science Direct, vol. 18, pp. 364–374, 2008.

10. R. Singh, V. Kumar, and H. K. Verma, "DWT-DCT hybrid scheme for medical image compression," *Medical Engineering and Technology*, vol. 31, pp. 109–122, 2007.
11. K. A. Wahid, M. A. Islam, S. S. Shimu, M. H. Lee, and S. Ko, "Hybrid architecture and VLSI implementation of the Cosine-Fourier-Haar transforms," *Circuits, Systems, and Signal Processing*, vol. 29, no.6, pp. 1193–1205, 2010.
12. I. Daubechies, *Ten Lectures on Wavelets*. SIAM, 1992.