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Article

An Improved Image Compression Algorithm Using 2D DWT and PCA with Canonical Huffman Encoding

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Abstract: Image compression is a top priority today due to the need for faster encoding and decoding. To achieve this, the present study has proposed the use of Canonical Huffman Coding (CHC) as an entropy coder, which has a lower decoding time complexity than binary Huffman codes. For image compression, combining of the Discrete Wavelet Transform (DWT) and CHC with Principal Component Analysis (PCA) has been recommended. The lossy method has been introduced by using PCA, followed by DWT and CHC to enhance compression efficiency. By using DWT and CHC instead of PCA alone, the reconstructed image has been found to have a better peak signal-to-noise ratio (PSNR) value. This study has developed a hybrid compression model combining the advantages of DWT, CHC and PCA. With the increasing use of image data, better image compression techniques are necessary for efficient use of storage space. The proposed technique has achieved up to 60% compression while maintaining high visual quality. This method has also outperformed the currently available techniques in terms of both PSNR (in dB) and bit-per-pixel (bpp) scores. This approach has been tested on various color images, including Peppers 512×512 and Couple 256×256, showing improvement by 17 dB and 22 dB, respectively, while reducing bpp by 0.56 and 0.10, respectively. For grayscale images, i.e., Lena 512×512 and Boat 256×256, the proposed method has shown an improvement by 5 dB and 8 dB, respectively, with a decrease of 0.02 bpp in both cases.

Keywords: Canonical Huffman Coding (CHC); 2D Discrete Wavelet Transform (2D DWT); hard thresholding; Lossy Image Compression

1. Introduction

With phenomenal rise in the use of digital images in the Internet era, researchers are concentrating on image-processing applications [1,2]. The need for image compression has been growing, due to the pressing need to minimize data size for transmission as a result of the constrained capacity of the Internet. The primary objectives of image compression are to store large amounts of data in a small memory space and transfer data quickly [2].

There are primarily two types of image compression methods: lossless and lossy. Lossless compression guarantees that the original and reconstructed images are exactly the same. On the other hand, Lossy compression, although used in many domains, can result in data loss to a certain extent for greater redundancy reduction. Here, the original image is first transformed using the forward transform before quantizing the final image. The compressed image is then produced using entropy encoding. This process is shown in Figure 1.

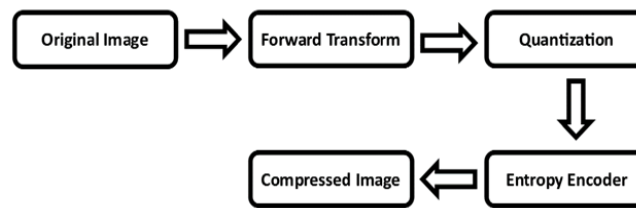


Figure 1. Lossy Image Compression Block Diagram in General.

The lossy compression can additionally be classified into two primary methods [3,4]:

Firstly, the direct image compression method, which works on sampling the image in a spatial domain. This method comprises techniques, such as, block truncation (Block Truncation Coding (BTC) [5], Absolute Moment Block Truncation (AMBTC) [6], Modified Block Truncation Coding (MBTC) [7], Improved Block Truncation Coding using K-means Quad Clustering (IBTC-KQ) [8], Adaptive Block Truncation Coding using edge-based quantization approach (ABTC-EQ) [9]) and vector quantization [10].

Secondly, the Image transformation method that comprises Singular Value Decomposition (SVD) [11], Principal Component Analysis (PCA) [12], Discrete Cosine Transform (DCT) [13] and Discrete Wavelet Transform (DWT) [14]. Through this method image samples are transformed from the spatial domain to the frequency domain to concentrate the energy of the image into a small number of coefficients.

Presently, researchers are emphasizing the DWT transformation tool due to its pyramidal or dyadic wavelet decomposition properties [15], facilitating high compression and superior-quality reconstructed images. The present study has also demonstrated the benefits of the DWT-based strategy using Canonical Huffman coding, which was explained as the entropy encoder in the preliminary work by the same authors [16]. A comparison of Canonical Huffman coding with the basic Huffman coding reveals that Canonical Huffman coding has a smaller code-book size and requires less processing time.

In the present study, the issue of enhancing the compression ratio has been resolved by improving quality of the reconstructed image and by thoroughly analyzing the necessary parameters, such as, PSNR, SSIM, CR and BPP, for standard test images. PCA, DWT, normalization, thresholding and Canonical Huffman coding methods have been employed to achieve high compression with excellent image quality. In course of the present study, Canonical Huffman coding has proved to be superior to both Huffman and arithmetic coding, as explained in Section III D.

The present authors have developed a lossy compression technique during the study using the PCA [12] which is marginally superior to the SVD method [23] and DWT [16] algorithms for both grayscale and color images. Canonical Huffman coding [16] has been used to compress the reconstructed image to a great extent. The authors have also compared the parameters, obtained in their proposed method with those provided in the block truncation [24] and the DCT-based approaches [25].

In the process of the study, the authors have also examined several frequently cited images in the available literature. Slice resolutions of 512x512 and 256x256 have been used, which are considered to be the minimum standards in the industry [26]. Also, the present authors have calculated the compression ratio and the PSNR values of their methods and have compared them to other research findings [5–9,16,19].

The present paper is based on the following structure. A Literature Review is presented in Section II. Section III discusses the approach adopted in the present study, which also covers the necessary concepts. Section IV details the proposed algorithm. The parameters for performance evaluation are discussed in Section V. Section VI presents the experiment findings while Section VII marks the conclusion.

2. Literature Review

An overview of several published works on this subject highlights various other methods, studied by many other researchers. One approach that has gained considerable attention among the research communities in recent years is a hybrid algorithm that combines DWT with other transformation tools [10]. S M Ahmed et al. [17] detailed their method of compressing ECG signals using a combination of SVD and DWT. Jayamol M. et al. [8] presented an improved method for block truncation coding of grayscale images, known as IBTC-KQ. This technique uses K-means quad clustering to achieve better results. Aldzjia et al. [18] presented a method for compressing color images using the DWT and Genetic Algorithm (GA). Messaoudi et al. [19] proposed a technique called DCT-DLUT, which involves using the discrete cosine transform and a lookup table, known as, DLUT to demarcate the difference between the indices. It is a quick and effective way to compress lossy color images.

Paul et al. [10] proposed a technique, called, DWT-VQ (Discrete Wavelet Transform-Vector Quantization) for generating an YCbCr image from an RGB image. This technique compresses images while maintaining their perceptual quality at levels that are acceptable in a clinical setting. A K Pandey et al. [20] presented a compression technique that uses the Haar wavelet transform to compress medical images. A method for compressing images using the Discrete Laguerre Wavelet Transform (DLWT) was introduced by J A Eleiwy [21]. However, this method concentrates only on approximate coefficients from four sub-bands of DLWT post-decomposition. As a result, this approach may affect the quality of the reconstructed images. In other words, maintaining a good image quality while achieving a high compression rate can prove to be a considerable challenge in image compression. Additionally, the author did not apply the Peak Signal-to-Noise Ratio (PSNR) or the Structural Similarity Index Measure (SSIM) index to evaluate the quality of the reconstructed image.

M. Alosta et al. [22] examined the arithmetic coding for data compression, where they measured the compression ratio and bit rate to determine the extent of the image compression. However, their study did not assess the quality of the compressed images, specifically the PSNR or SSIM values, which correspond to the compression rate (CR) or bits per pixel (BPP) values.

3. Fundamental Concepts

Various phases of the suggested strategy for the present study have been outlined in this section. These include Canonical Huffman coding, DWT and PCA. A transformation is a mathematical process through which a function, taken as an input, is mapped into itself. Transformation can extract hidden or valuable data from the original image. Moreover, in comparison with the original data, the transformed data may be more amenable to mathematical operations. Therefore, transformation tools are a significant means for image compression.

The most widely used transformation methods include the Karhunen-Loeve transform (KLT) [27], Walsh Hadamard transforms (WHT) [28], SVD [11], PCA [12], DCT [13], DWT [14] and Integer Wavelet Transform (IWT) [29].

The DCT method is commonly used for compressing images. However, it may result in image artifacts when compressed with JPEG. Moreover, DCT does not have the multi-resolution transform property. In all these respects, DWT is an improvement [30]. With DWT, one obtains the resulting filtered image after going through various levels of discrete wavelet decomposition. One can also collect statistics on the frequency domain for the following procedure via multi-level wavelet decomposition. By combining noise reduction and through information augmentation, better image reconstruction can be ensured following compression [2].

Accordingly, the preferred method of choice for image compression during the present study has been DWT [14]. Because of its high energy compaction property and lossy nature, the image compression technique can remove unnecessary data from an image to achieve the desired compression level. It produces wavelet coefficients iteratively by dividing an image into its low-pass and high-pass components. These wavelet coefficients de-correlate pixels and Canonical Huffman coding eliminates redundant data.

3.1. Principal Component

The principal components are a small number of uncorrelated variables, derived from many correlated variables by means of the PCA [12] transformation technique. The PCA technique explores the finer points in the data to highlight their similarities and differences. Once the patterns are found, datasets can be compressed by reducing their dimensions without losing the basic information. Therefore, the PCA technique is suitable for image compression with minimal data loss.

The idea of the PCA technique is to take only the values of the principal components and use them to generate other components.

In short:

- ❖ PCA is a standard method for reducing the number of dimensions.
- ❖ The variables are changed into a fresh set of data, known as primary components. These principal components are combinations of initial variables in linear form and they are orthogonal.
- ❖ The first principal component accounts for the majority of the potential variation in the original data.
- ❖ The second principal component addresses the data variance.

Mathematical Concepts of PCA

The PCA Algorithm: The following steps make the PCA Algorithm:

Step-01: Obtaining data.

Step-02: Determining the mean vector (μ).

Step-03: Subtracting the mean value from the data.

Step-04: Doing a covariance matrix calculation.

Step-05: Determining the covariance matrix's Eigenvalues and Eigenvectors.

Step-06: Assembling elements to create a feature vector.

Step-07: Creating a novel data set.

Mathematical Example

Two-dimensional patterns have to be taken into account, i.e., (2, 1), (3, 5), (4, 3), (5, 6), (6, 7), and (7, 8). It has to be followed by the principal component calculation.

Step-01:

Data is obtained. $x_1 = (2, 1)$, $x_2 = (3, 5)$, $x_3 = (4, 3)$, $x_4 = (5, 6)$, $x_5 = (6, 7)$ & $x_6 = (7, 8)$.

The vectors provided are— $\begin{bmatrix} 2 \\ 1 \end{bmatrix} \begin{bmatrix} 3 \\ 5 \end{bmatrix} \begin{bmatrix} 4 \\ 3 \end{bmatrix} \begin{bmatrix} 5 \\ 6 \end{bmatrix} \begin{bmatrix} 6 \\ 7 \end{bmatrix} \begin{bmatrix} 7 \\ 8 \end{bmatrix}$.

Step-02:

The mean vector (μ) is identified.

Mean vector (μ) = $((2 + 3 + 4 + 5 + 6 + 7) / 6, (1 + 5 + 3 + 6 + 7 + 8) / 6) = (4.5, 5)$

$$\text{Mean vector } (\mu) = \begin{bmatrix} 4.5 \\ 5 \end{bmatrix}$$

Step-03:

The mean vector (μ) is subtracted from the data.

$$x_1 - \mu = (2 - 4.5, 1 - 5) = (-2.5, -4)$$

Similarly other feature vectors are obtained.

After removing the mean vector (μ), the following feature vectors (x_i) are obtained:

$$\begin{bmatrix} -2.5 \\ -4 \end{bmatrix} \begin{bmatrix} -1.5 \\ 0 \end{bmatrix} \begin{bmatrix} -0.5 \\ -2 \end{bmatrix} \begin{bmatrix} 0.5 \\ 1 \end{bmatrix} \begin{bmatrix} 1.5 \\ 2 \end{bmatrix} \begin{bmatrix} 2.5 \\ 3 \end{bmatrix}$$

Step-04:

A covariance matrix calculation is done.

The covariance matrices are provided by— $\text{Cov Mat} = \frac{\sum (x_i - \mu)(x_i - \mu)^t}{n}$

Now, $m_1 = (x_1 - \mu)(x_1 - \mu)^t = \begin{bmatrix} -2.5 \\ -4 \end{bmatrix} \begin{bmatrix} -2.5 & -4 \end{bmatrix} = \begin{bmatrix} 6.25 & 10 \\ 10 & 16 \end{bmatrix}$

Similarly the value of $m_2 \dots m_6$ is calculated.

Covariance matrix is now equal to $(m_1 + m_2 + m_3 + m_4 + m_5 + m_6) / 6$.

The matrices above are added and divided by 6:

$$Cov\ Mat = \begin{bmatrix} 2.92 & 3.67 \\ 3.67 & 5.67 \end{bmatrix}$$

Step-05:

The Eigenvalues and Eigenvectors of covariance matrix are determined.

A value is considered to be an eigenvalue (λ) for a matrix M if it solves the defining equation $|M - \lambda I| = 0$.

Hence, one gets: $\begin{vmatrix} 2.92 - \lambda & 3.67 \\ 3.67 & 5.67 - \lambda \end{vmatrix} = 0$,

By resolving this quadratic problem = 8.22, 0.38 is obtained.

Hence, eigenvalues λ_1 and λ_2 are 8.22 and 0.38, respectively.

It is obvious that the second eigenvalue is much smaller than the first eigenvalue.

Hence, it is possible to exclude the second eigenvector. The primary component is the eigenvector that corresponds to the highest eigenvalue in the given data set. As a result, the eigenvector is located matching eigenvalue λ_1 . To find the eigenvector, the equation is formulated.

$$MX = \lambda X$$

X = Eigenvector, M = Covariance Matrix, and λ = Eigenvalue

By changing the values in the aforementioned equation, $X_2 = 1$ and $X_1 = 0.69$ are obtained. Then these numbers are divided by the square root of the sum of their squares. The eigenvector V is $\begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} 0.566 \\ 0.821 \end{bmatrix}$.

Hence, the principal component of the presented data set is $\begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} 0.566 \\ 0.821 \end{bmatrix}$.

3.2. Discrete Wavelet Transform: The Operational Principle of DWT

The data matrix of the image is split into four sub-bands, which are LL (low pass vertical and horizontal filter), LH (low pass vertical and high pass horizontal filter), HL (high pass vertical and low pass horizontal filter) and HH (high pass vertical and horizontal filter). These sub-bands are used to apply wavelet transform in computing (DWT [14] and Wavelet [HAAR] [25]). The concept behind the decomposition of the image into the four sub-bands is explained in Figure 2.

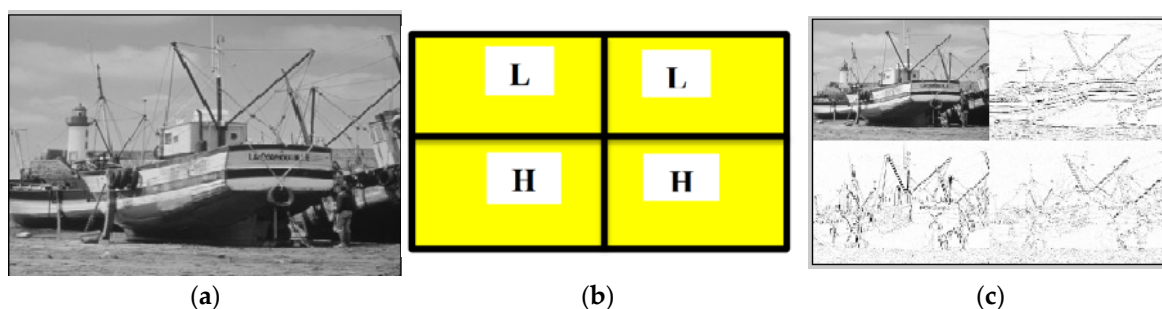


Figure 2. Decomposition of discrete wavelets Transform: (a) Input Image, (b) Image Sub-bands, and (c) 1-Level DWT Decomposition.

The process involves dividing the image into rows and columns after convolution. The Wavelet decomposition and reconstruction phases make the DWT. The image input undergoes a process of convolution that includes both low and high pass reconstruction phases. Figure 3a describes a one-level DWT decomposition. In Figure 3b, the up arrow denotes the up-sampling procedure. The wavelet reconstruction is the opposite of the wavelet decomposition.

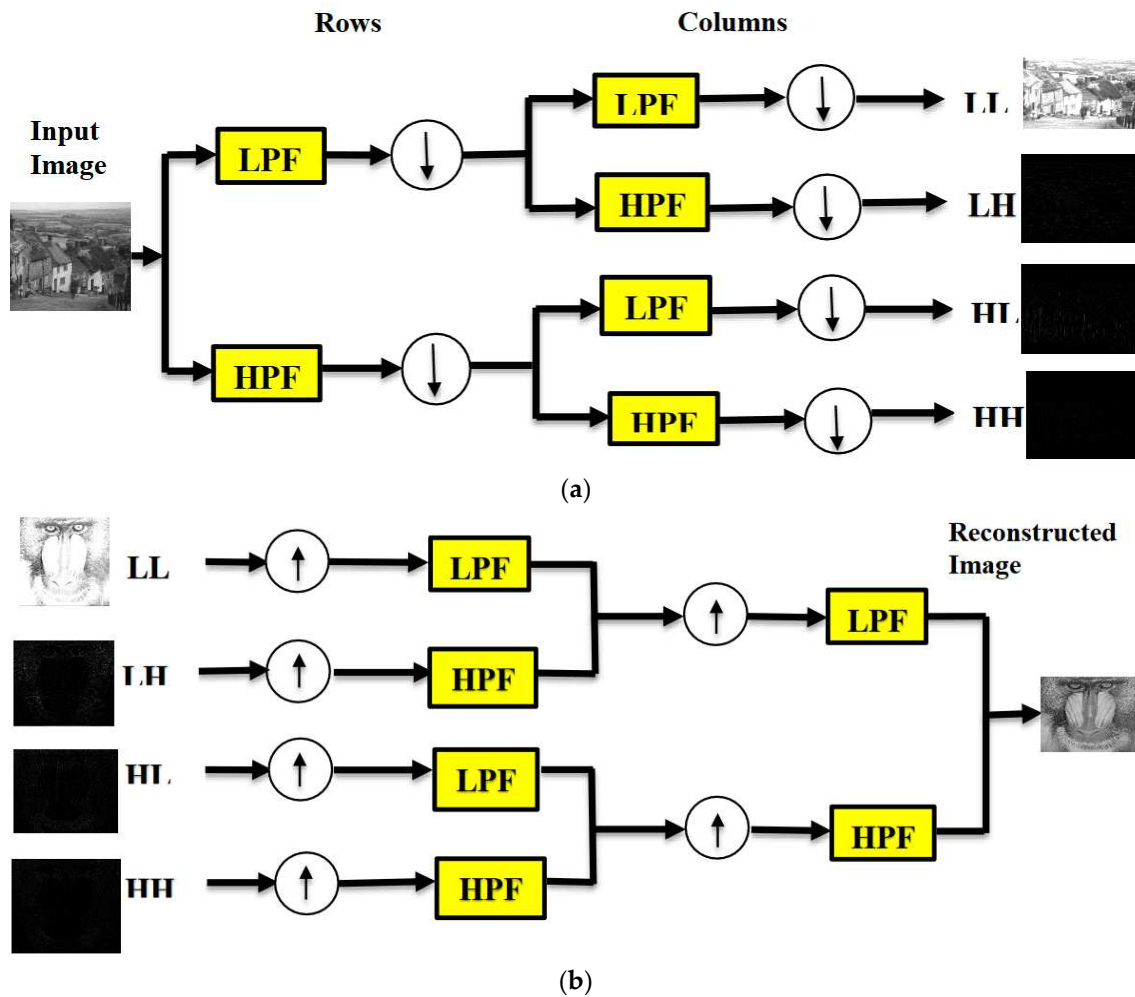


Figure 3. (a) Decomposition and (b) Reconstruction of a One Level Discrete Wavelet Transform.

In the data processing, various wavelet families are commonly used such as Haar ('haar'), Daubechies ('db'), Coiflets ('coif'), Symlets ('sym'), Biorthogonal ('bior') and Meyer ('meyer') [20]. During the present study, the Haar wavelet transform was applied due to its comparatively modest computational needs [25].

3.3. Thresholding: Hard Thresholding

The hard-thresholding method is used frequently in image compression. The hard-threshold function works by $\varphi_T(x) = x \cdot \mathbf{1}\{|x| > T\}$ keeping the input value if it is greater than the set threshold T . If the input value is less than or equal to the threshold, it is set at zero [31].

3.4. Entropy Encoder: Canonical Huffman coding

Canonical Huffman coding [16,32], is a significant subset of regular Huffman coding and has several advantages over other coding schemes (Huffman, Arithmetic). Advantages include faster computation times, superior compression and higher reconstruction quality. Many researchers are working with this coding because of these benefits. The information required for decoding is compactly stored since the codes are in lexicographic order.

For instance, if the Huffman code for 5 bits is "00010," only five will be used for canonical Huffman coding, equaling the entire number of bits available in the Huffman code [33].

4. Proposed Method

In course of the present study, various approaches for compressing images have been examined, including, transforming RGB color images into YC_bC_r color images [34], PCA transformation,

wavelet transformation and extra processing by using thresholding, normalization and Canonical Huffman coding.

4.1. Basic Procedure

To compress the image, the PCA approach has been applied first. Next the output of PCA has been decomposed using DWT. Finally, the image has been further decomposed using Canonical Huffman encoding. In order to breakdown 8-bit/24-bit key images with 256 x 256 and 512 x 512 pixel sizes, a 1-level Haar wavelet transform has been used.

4.2. PCA Based Compression

The PCA procedure involves mapping from an n-dimensional space to a k-dimensional space using orthogonal transformations ($k < n$). The principal components, which are unique orthogonal features in this case, are the k-dimensional features that include the majority of the characteristics of the original data set. Because of this, it is used in image compression.

PCA is a reliable image compression technique that ensures nominal information loss. Compared to the SVD approach, the PCA method produces better results.

PCA_Algorithm

Encoding

$$\text{Input: The image } F(x, y), F(x, y) = \begin{bmatrix} f(0,0) & \cdots & f(m-1) \\ \vdots & \ddots & \vdots \\ f(n-1,0) & \cdots & f(n-1,m-1) \end{bmatrix}$$

Here, the values x and y represent the coordinates of individual pixels in an image. Depending on the type, the value $f(x, y)$ corresponds to the color or gray level.

Step 1: Image normalization has to be done.

The normalization is carried out on the image data set $F(x, y)$.

$$F_{\text{normalized}}(x, y) = \begin{bmatrix} f(0,0) & \cdots & f(m-1) \\ \vdots & \ddots & \vdots \\ f(n-1,0) & \cdots & f(n-1,m-1) \end{bmatrix} - [\bar{f}(0,0) \dots \bar{f}(0,m-1)]$$

Here, $[\bar{f}(0,0) \dots \bar{f}(0,m-1)]$ is the column vector containing the mean value for y_1 to y_m .

Step 2: Compute covariance matrix of $F_{\text{normalized}}(x, y)$

$$\text{cov}(x, y) = \frac{F_{\text{normalized}}(x, y) \times F_{\text{normalized}}(x, y)^T}{m-1}$$

Here, m is the number of element y.

Step 3: Compute Eigenvectors and Eigenvalues of $\text{cov}(x, y)$

Using SVD equation $A^T = \text{cov}(x, y) = U D^2 U^T$, eigenvectors and eigenvalues are calculated.

Here, "U" represents the eigenvectors of " AA^T ", while the squared singular values in "D" are the eigenvalues of " AA^T ". Eigenvector matrix denotes the principal feature of image data i.e. principal component.

Output: Image data with reduced dimension

$$F_{\text{transformed}}(x, y) = U^T F_{\text{normalized}}(x, y)$$

Here, U^T is the transpose of the eigenvectors matrix and $F_{\text{normalized}}(x, y)$ is the adjusted original image datasets.

It can also be expressed as:

$$Y_{m \times k} = U_{n \times k}^T X_{m \times n}$$

Here, 'm' and 'n' represent the matrix's rows and columns, while 'k' represents the number of principal components with $k < m|n$.

Decoding

By reconstructing the image data, one gets

$$\hat{X}_{m \times n} = U_{n \times k} Y_{m \times k}$$

In PCA, the compression ratio (ρ) is calculated as:

$$\rho = \frac{n \times n}{m \times k + n \times k + n}$$

4.3. DWT-CHC Based Compression

The DWT details show zero mean and a slight variation. The more significant DWT coefficients are used and the less significant ones are discarded by using a Canonical Huffman coding. The algorithm based on DWT is presented below.

Algorithm:

Input: An image in grayscale $G(A \times B)$ of size $A \times B$

Output: A reconstruction of a grayscale image $R(A \times B)$ of size $A \times B$

Encoding of Image

Step 1: The DWT is applied to separate the grayscale image $G(A \times B)$ into lower and higher sub bands.

Step 2: The equation $a_n = \frac{(a_d - a_{\min})}{(a_{\max} - a_{\min})}$, is applied to normalize the lower and upper sub bands in the range of (0, 1), where a is $G(A \times B)$ coefficient matrix of the image, a_d is the data to be normalized, and a_{\max} and a_{\min} are the maximum and minimum intensity values, respectively.

Step 3: Hard thresholding on the higher sub-band is used to save the important bits and throw away the unimportant ones.

Step 4: To acquire the lower and higher sub band coefficients, the lower sub band coefficient to the range of 0 to 127 and the higher sub band coefficient to the range of 0 to 63 are assigned.

Step 5: The canonical Huffman coding is applied to each band.

Step 6: Compressed bit streams are obtained.

Decoding of Image

Step 1: Bit streams are compressed.

Step 2: The reverse canonical Huffman coding process is applied to retrieve the reconstructed lower and higher sub band coefficient from the compressed bit streams of approximate and detail coefficients.

Step 3: To get the normalized coefficients for the lower and higher sub bands, their respective coefficients are divided by 127 and 63.

Step 4: The equation is applied to do inverse normalization on the normalized lower and higher sub band.

$$a_d = a_n \times (a_{\max} - a_{\min}) + a_{\min}$$

Step 5: Inverse DWT is applied to obtain an image $R(A \times B)$ that has been rebuilt.

4.4. PCA-DWT-CHC Based Image Compression

The method involves first compressing the image through the PCA, followed by decomposing of the gray scale/color image by using a 1-level Haar wavelet transform. One gets approximate and detailed images by applying this method. To produce a digital data sequence, the approximation coefficients have to be normalized and encoded with Canonical Huffman coding. Moreover, while normalizing the detail coefficients, any insignificant coefficients are removed through hard thresholding. Finally, binary data is also obtained by using the Canonical Huffman coding.

The final compressed bit stream is created by combining all the binary data. This stream is then divided into approximate and detailed coefficient binary data to reconstruct the image. The qualitative loss is apparent only after a certain point by eliminating some principal components. This entire procedure is termed as the DWT-CHC method. During the present study, the proposed strategy has been found to work better when the PCA-based compression technique under the lossy method, was used with DWT-CHC. The DWT outperforms PCA in terms of compression ratios while the PCA outperforms the DWT in terms of the PSNR values. Evaluation of the necessary number of bits yields the CR value for the PCA algorithm.

During the present experimentation, initially, the image was compressed by using the PCA. The approximate image was then further compressed by using DWT-CHC. Accordingly, the image was initially decomposed using PCA, then a few principal components were removed. The reconstructed image was then computed. After that, the reconstructed image was used as the input image for the DWT-CHC segment of the proposed method.

When several primary components were dropped from the PCA segment of the proposed method, the compression ratio was found to be higher. The overall CR value was obtained by multiplying the CR values of the PCA and the DWT-CHC.

To analyze an image, it is first decomposed, applying a Haar wavelet to its approximation, horizontal, vertical and diagonal detail coefficients. Next, the approximation and the detail coefficients are coded with the DWT-CHC. Encoding is the compression process and decoding is the simple process of reversing the encoding stages from which the reconstructed image is derived. After quantization, the image is rebuilt using the inverse DWT-CHC of the quantized block.

This approach combines the PCA and the DWT-CHC to reach its full potential. It uses PCA, DWT and Canonical Huffman coding to achieve a high compression ratio while maintaining an excellent image quality. The structural layout of the proposed image compression approach is shown in Figure 4.

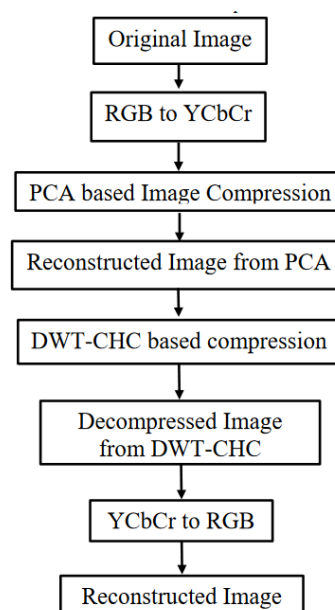


Figure 4. The suggested method's encoder and decoder flowchart.

The steps in the suggested method are as follows:

Encoding:

Step 1:

- (i) For a $C(x, y)$ grayscale image with an $x \times y$ pixel size, by using the PCA method, is decomposed first in order to obtain the Principal Component.
- (ii) If the image is in color, the color transform is used to change the RGB data into YC_rC_b using the formula.

$$\begin{bmatrix} Y \\ C_r \\ C_b \end{bmatrix} = \begin{bmatrix} 0.299 & 0.587 & 0.114 \\ -0.169 & -0.331 & 0.500 \\ 0.500 & -0.419 & -0.081 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix}$$

To determine the Principal Component from the YC_rC_b image, PCA decomposition is carried out.

Step 2: The image is reconstructed just by utilizing these principal components while taking into account only the principal component for compression.

Step 3: Compression ratio is obtained.

Step 4: The decomposition level is set at 1.

Step 5: By utilizing the HAAR wavelet, DWT generates four output matrices: LL (known as the approximate coefficients), LH, HL and HH (known as the detail coefficients). These matrices consist of three components: vertical, horizontal and diagonal details.

Step 6: To obtain bit streams, the DWT-CHC algorithm is applied to these coefficients (Compressed image).

Step 7: The compression ratio is calculated.

Step 8: To determine the final compression ratio of an image, the output from Steps 3 and 7 is multiplied.

Decoding:

Step 1: The DWT-CHC approach is applied in reverse to obtain the approximate and detailed coefficients.

Step 2: A reconstructed image is obtained.

Step 3: The PSNR value is determined.

The flowchart that follows further explains this idea:

5. Performance Assessment

A few of the parameters listed below can be used to gauge the efficacy of the lossy compression strategy.

Compression Ratio (CR): CR [35] is a parameter that measures compressibility.

Mathematically,

$$CR = \frac{S_{original}}{S_{compressed}}$$

where $S_{original}$ = the dimension of the original image data, $S_{compressed}$ = A measure of the compressed image data's size (in bits).

Bitrate (BPP): BPP equals $24/CR$ for color images and $8/CR$ for grayscale images.

Peak Signal to Noise Ratio (PSNR): It is a common metric for calculating the compressed image's quality. Typically, the PSNR for 8-bit images is presented as [36]:

$$PSNR(dB) = 10 \log_{10} \left(\frac{255^2}{MSE} \right) \quad (1)$$

where 255 is the highest value that the image signal is capable of achieving. The term "MSE" in equation (1) refers to the image's mean squared error, written as

$$MSE = \frac{1}{m} \sum_x \sum_y (f(x, y) - F(x, y))^2$$

Here, the variable "m" represents the total number of pixels in the image. $F(x, y)$ refers to the value of each pixel in the compressed image, while $f(x, y)$ represents the value of each pixel in the original image.

Structural Similarity Index (SSIM): It is a process for determining how similar two images can be [37].

$$\text{Luminance change, } l(x, y) = \frac{2\mu_x\mu_y + c_1}{\mu_x^2 + \mu_y^2 + c_1}$$

$$\text{Contrast change, } c(x, y) = \frac{2\sigma_x\sigma_y + c_2}{\sigma_x^2 + \sigma_y^2 + c_2}$$

$$\text{Structural change, } s(x, y) = \frac{\sigma_{xy} + c_3}{\sigma_x\sigma_y + c_3}$$

Here, SSIM can be evaluated as:

$$SSIM(x, y) = l(x, y) \cdot c(x, y) \cdot s(x, y)$$

y displays the image that was recreated, and x displays the original image.

μ_x = average of x, μ_y = average of y

σ_x = Variance of x, σ_y = Variance of y

Two variables, c_1 and c_2 , are used to stabilise a division with a weak denominator.

$$c_1 = (k_1 L)^2, \quad c_2 = (k_2 L)^2, \quad c_3 = \frac{c_2}{2}$$

$$k_1 = 0.001, \quad k_2 = 0.002 \text{ as a rule}$$

In this case, the pixel values range from 0 to 255 and are represented by L. The SSIM index that is generated as a consequence ranges from -1 to 1.

6. Experiment Result

The outcomes of experiment for image compression, utilizing the PCA-DWT-CHC hybrid approach, are shown in this section. Additionally, a comparison between the suggested approach and other available methods (BTC [5], AMBTC [6], MBTC [7], IBTC-KQ [8], ABTC-EQ [9], DWT [16] and DCT-DLUT [19]) has been made in this part. All experiments were conducted using the 512 x 512 and 256 x 256 input images (8-bit grayscale images, which are Lena, Barbara, Baboon, Goldhill, Peppers, Cameraman, Boat and 24-bit color images, i.e., Aeroplane, Peppers, Lena, Couple, House, and Zelda), as presented in Figures 5 and 6.

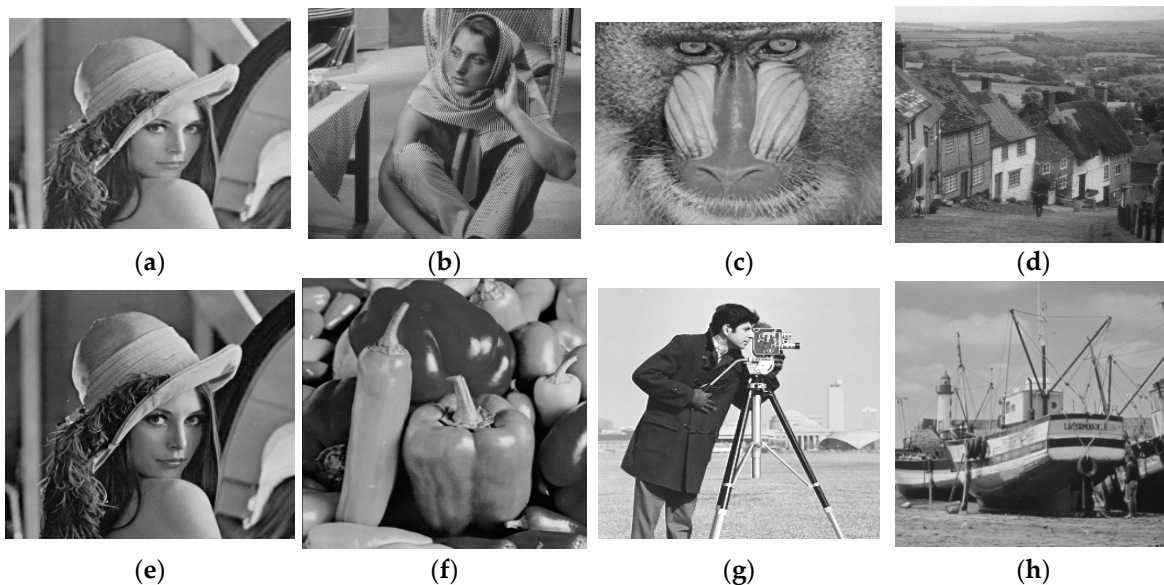


Figure 5. Test images in grayscale for size 512x512 (a-d) & 256x256 (e-h).

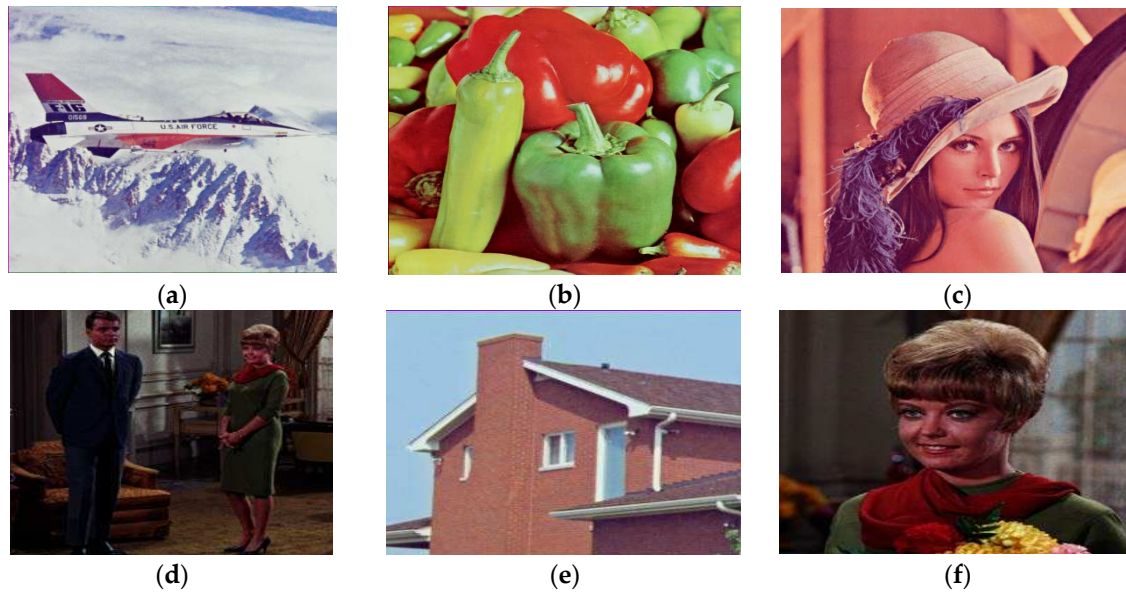


Figure 6. 512x512 (a–c) and 256x256 (d–f) (color test images) in size.

All experiments were run in the interim on the MATLAB software platform using the hardware configurations of an Intel Core i3-4005U processor running at 1.70 GHz, 4.00 GB of RAM and Windows 8.1 Pro 64-bit as the operating system.

The compression performance of images for various approaches is shown in the next part which is based on visual quality evaluation and objective image quality indexes, i.e., PSNR, SSIM, CR and BPP.

Two measurements, namely, CR and BPP, reflect common aspects of image compression. The PSNR and SSIM are used to assess the quality of the compressed image. Greater PSNR and SSIM values indicate better image reconstruction whereas higher compression ratios and lower bitrates indicate enhanced image compression.

The predictive approach was used to determine the threshold values, which were $TH=0.10$. For both color ($256 \times 256 \times 3$ & $512 \times 512 \times 3$) and grayscale (256×256 & 512×512) images, the principal component values of 25, 25, 200 and 400 were taken, respectively, to reconstruct the image.

6.1. Visual Performance Evaluation of Proposed PCA-DWT-CHC Method

Based on the quality of the reconstructed images, the proposed hybrid PCA-DWT-CHC image compression method was compared to the existing approaches. The reconstructed images for visual quality comparison on the PSNR values, 34.78 dB, 33.31 dB, 33.43 dB and 37.99 dB with CR = 4.41, 4.04, 5.15 and 4.45 for the input grayscale images, i.e., 'lena.bmp' and 'barbara.bmp' of size 512×512 and 'cameraman.bmp' and 'boat.bmp' of size 256×256 are shown in Figures 7b,d and 8b,d. Figures 9a,b and 10a,b display the reconstructed image for visual quality comparison on the PSNR values 47.57 dB, 47.99 dB, 54.60 dB, and 53.47 dB with compression factors (in BPP) 0.27, 0.32, 0.69 and 0.70, respectively, for the input color images 'airplane.bmp,' and 'peppers.bmp' of size 512×512 and 'couple.bmp' and 'house.bmp' of size 256×256 .



Figure 7. Results of compression for the 512×512 grayscale images of Lena and Barbara. (a) Lena image reconstruction using DWT with PSNR=29.90 dB and CR=2.43; (b) Lena image reconstruction using the proposed method with PSNR=34.78 dB and CR=4.41 (c) Barbara image reconstruction using DWT with PSNR=27.75 dB and CR=2.11 (d) Barbara image reconstruction using the proposed method with PSNR=33.31 dB and CR=4.04.

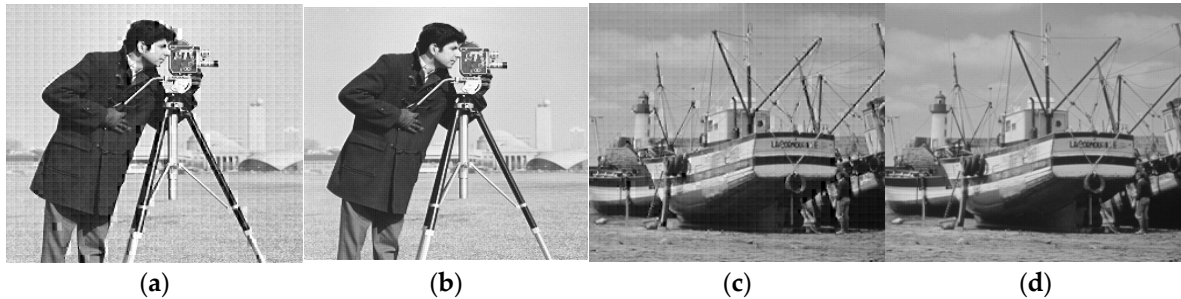


Figure 8. Compression outcomes for the grayscale images Cameraman & Boat of size 256×256 (a) Reconstructed Cameraman image by DWT with PSNR=26.43 dB, CR=2.86, (b) Reconstructed Cameraman image by Proposed Method with PSNR=33.43 dB, CR= 5.15 (c) Reconstructed Boat image by DWT with PSNR=29.65 dB, CR=2.35 (d) Reconstructed Boat image by Proposed Method with PSNR=37.99 dB, CR=4.45.

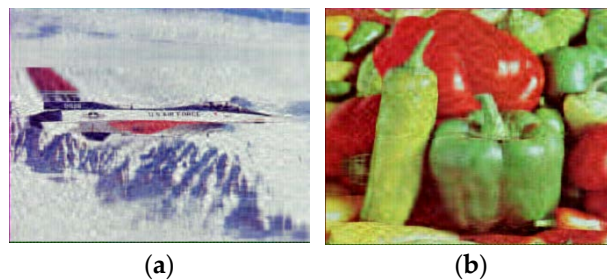


Figure 9. Results of compression for the 512×512 color images Airplane & Peppers. (a) Reconstructed image of an airplane using the proposed method, PSNR = 47.57 dB, and bpp = 0.27 (b) Peppers image reconstruction using the proposed method, PSNR = 47.99 dB, and bpp = 0.32.

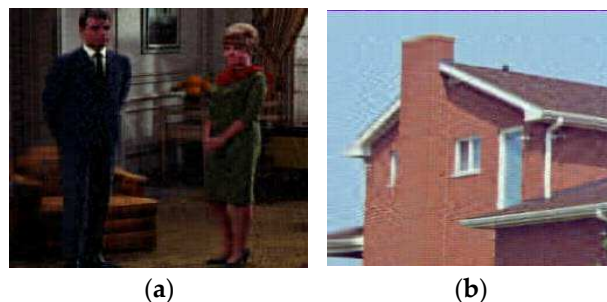


Figure 10. Results of the color images' compression Couple & house with 256×256-sized (a) Reconstructed image of a couple with PSNR of 54.60 dB and bpp of 0.69; (b) Reconstructed image of a house with PSNR of 53.47 dB and bpp of 0.70.

The results in Figures 7–10 demonstrate that the proposed hybrid PCA-DWT-CHC method yielded superior quality image reconstruction as compared to other image compression methods for all input images. Based on the visual quality assessment of various standard test images, it has been demonstrated that the proposed hybrid PCA-DWT-CHC method is more efficient in reconstructing images as compared to the other available methods.

6.2. Objective Performance Evaluation of Proposed PCA-DWT-CHC Method

According to the experiment results, the suggested PCA, followed by the DWT-CHC approach, proved to be better in terms of PSNR, SSIM, BPP and CR values when compared to the other methods, as shown in Tables 1 and 2.

Table 1. Comparative performance of BTC [5], AMBTC [6], MBTC [7], IBTC-KQ [8], ABTC-EQ [9], DWT [16] and proposed method for Gray Scale Images.

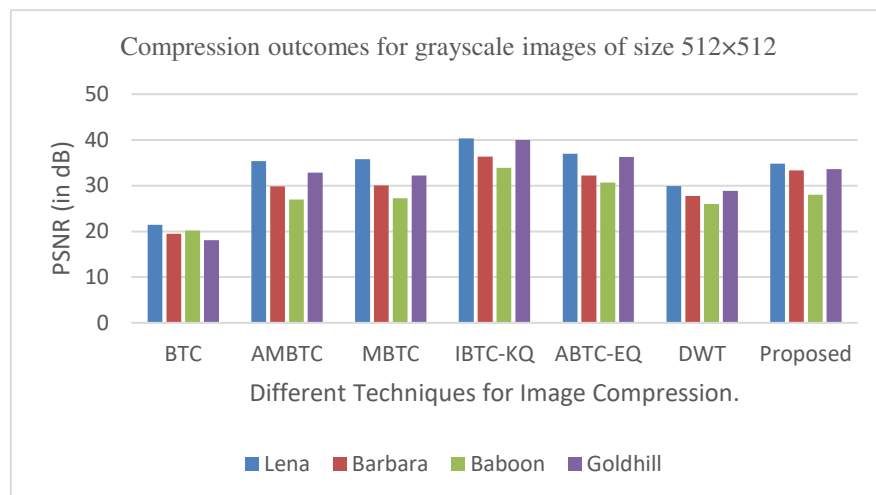
Tested Image	Method	Block Size (4×4) Pixels				Block Size (8×8) Pixels			
		PSNR	SSIM	BPP	CR	PSNR	SSIM	BPP	CR
Lena (512×512)	BTC	21.4520	0.7088	2	4	21.4520	0.7088	1.2500	6.4000
	AMBTC	35.3706	0.9905	2	4	32.0885	0.9639	1.2500	6.4000
	MBTC	35.8137	0.9904	2	4	32.6268	0.9662	1.2500	6.4000
	IBTC-KQ	40.3478	0.9874	4	2	36.4511	0.9664	2.5000	3.2000
	ABTC-EQ	36.9919	0.9632	2.5734	3.1087	33.8401	0.9305	1.8267	4.3794
	DWT	29.9001	0.8943	3.2855	2.4349	29.9001	0.8943	3.2855	2.4349
	Proposed	34.7809	0.9985	1.8158	4.4058	34.7809	0.9985	1.8158	4.4058
Lena (256×256)	DWT	27.0772	0.8326	3.2713	2.4455	27.0772	0.8326	3.2713	2.4455
	Proposed	36.9556	0.9447	1.7831	4.4865	36.9556	0.9447	1.7831	4.4865
Barbara (512×512)	BTC	19.4506	0.6894	2	4	19.4506	0.6894	1.2500	6.4000
	AMBTC	29.8672	0.9747	2	4	27.8428	0.9429	1.2500	6.4000
	MBTC	30.0710	0.9757	2	4	28.1069	0.9451	1.2500	6.4000
	IBTC-KQ	36.3729	0.9847	4	2	33.5212	0.9632	2.5000	3.2000
	ABTC-EQ	32.1986	0.9551	2.6966	2.9667	30.5587	0.9244	1.9487	4.1053
	DWT	27.7496	0.9242	3.7896	2.1111	27.7496	0.9242	3.7896	2.1111
	Proposed	33.3092	0.9986	1.9806	4.0392	33.3092	0.9986	1.9806	4.0392
Baboon (512×512)	BTC	20.1671	0.7288	2	4	20.1671	0.7288	1.2500	6.4000
	AMBTC	26.9827	0.9639	2	4	25.1842	0.9181	1.2500	6.4000
	MBTC	27.2264	0.9653	2	4	25.4677	0.9216	1.2500	6.4000
	IBTC-KQ	33.8605	0.9777	4	2	31.2925	0.9550	2.5000	3.2
	ABTC-EQ	30.6787	0.9400	3.0363	2.6348	28.7947	0.9089	2.1571	3.7086
	DWT	25.9806	0.9479	4.2012	1.9042	25.9806	0.9479	4.2012	1.9042
	Proposed	28.0266	0.9984	2.0917	3.8247	28.0266	0.9984	2.0917	3.8247
Goldhill (512×512)	BTC	18.0719	0.6252	2	4	18.0719	0.6252	1.2500	6.4000
	AMBTC	32.8608	0.9825	2	4	29.9257	0.9438	1.2500	6.4000
	MBTC	32.2422	0.9828	2	4	30.3195	0.9472	1.2500	6.4000
	IBTC-KQ	39.9867	0.9840	4	2	36.1776	0.9599	2.5000	3.2000
	ABTC-EQ	36.3085	0.9536	2.7986	2.8586	33.6061	0.9210	2.0778	3.8502
	DWT	28.8597	0.9255	3.6259	2.2064	28.8597	0.9255	3.6259	2.2064
	Proposed	33.6289	0.9986	1.9020	4.2061	33.6289	0.9986	1.9020	4.2061
Peppers (256×256)	BTC	19.4540	0.6306	2	4	19.4540	0.6306	1.2500	6.4000
	AMBTC	30.5655	0.9409	2	4	26.7127	0.8547	1.2500	6.4000
	MBTC	31.1372	0.9444	2	4	27.4445	0.8596	1.2500	6.4000
	IBTC-KQ	-----	-----	-----	-----	-----	-----	-----	-----
	ABTC-EQ	32.0306	0.9551	2.6966	2.9667	28.9805	0.8985	2.6966	4.0499
	DWT	27.3524	0.8212	3.1735	2.5209	27.3524	0.8212	3.1735	2.5209
	Proposed	37.1723	0.9431	1.7422	4.5918	37.1723	0.9431	1.7422	4.5918
Cameraman (256×256)	BTC	20.7083	0.7214	2	4	20.7083	0.7214	1.2500	6.4000
	AMBTC	28.2699	0.9322	2	4	25.8654	0.8831	1.2500	6.4000
	MBTC	29.0746	0.9392	2	4	26.9365	0.8934	1.2500	6.4000
	IBTC-KQ	36.7714	0.9890	4	2	33.6339	0.9754	2.5000	3.2
	ABTC-EQ	33.9790	0.9725	2.6418	3.0282	31.2452	0.9531	1.8325	4.3656
	DWT	26.4333	0.7483	2.7925	2.8648	26.4333	0.7483	2.7925	2.8648
	Proposed	33.4238	0.8578	1.5536	5.1492	33.4238	0.8578	1.5536	5.1492
Boat (256×256)	DWT	29.6486	0.8758	3.4099	2.3461	29.6486	0.8758	3.4099	2.3461
	Proposed	37.9922	0.9575	1.7985	4.4482	37.9922	0.9575	1.7985	4.4482

Table 2. Comparative Performance of Proposed Method and DCT-DLUT [19] for Color Images.

Image	Proposed method		DCT-DLUT	
	PSNR	Bpp	PSNR	Bpp
Airplane (512×512)	47.57	0.27	31.16	0.48
Peppers (512×512)	47.99	0.32	31.19	0.88
Lena (512×512)	48.95	0.37	32.65	0.74
Couple (256×256)	54.60	0.69	32.62	0.79
House (256×256)	53.47	0.70	23.27	0.79
Zelda (256×256)	53.74	0.71	32.01	0.82
Average	59.71	0.51	35.81	0.75

In other words, from Tables 1 and 2, one could conclude that the proposed method is superior to the BTC [5], AMBTC [6], MBTC [7], IBTC-KQ [8], ABTC-EQ [9] & DWT-CHC [16] and DCT-DLUT [19] for working on the grayscale and color images. This could be explained by the fact that among all the different compression methods, the PSNR and SSIM values in the proposed method are higher than the other available methods. Similarly, the CR value is higher than that of all other methods. Again, the bitrate values of the proposed method are noted to be less than all the other methods for color images.

The graphs in Figure 11–18 show the PSNR, SSIM, CR and the Compression factor (in bpp) results for eight grayscale images. Figures 19–22, on the other hand, present graphs for the PSNR and Compression factor (in bpp) for six other color images. While comparing data from these graphs with the results of various other available techniques, the former demonstrated that the proposed method works better than the presently available ones.

**Figure 11.** Comparison of various compression techniques used on the different test grayscale images (Lena, Barbara, Baboon and Goldhill).

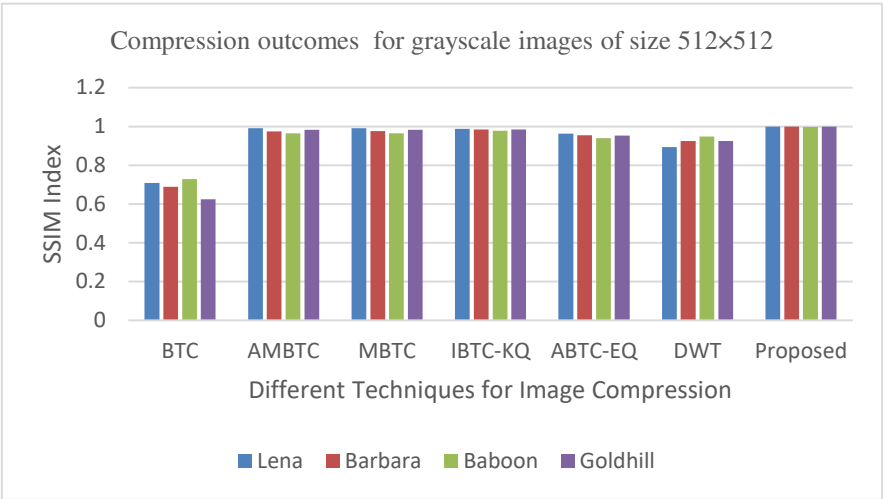


Figure 12. Comparison of various compression techniques used on the different test grayscale images (Lena, Barbara, Baboon and Goldhill).

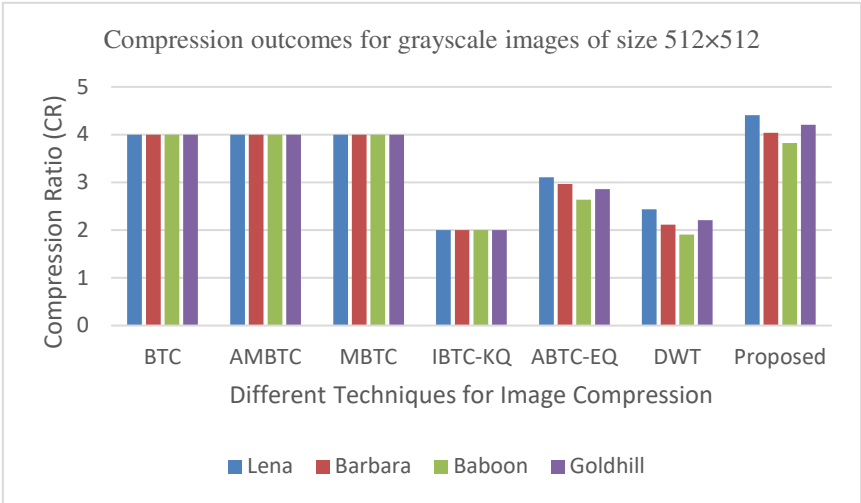


Figure 13. Comparison of various compression techniques used on the different test grayscale images (Lena, Barbara, Baboon and Goldhill).

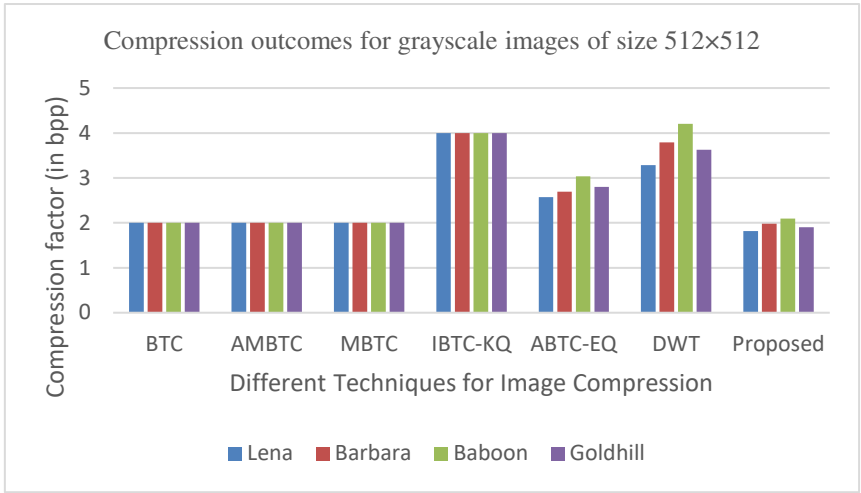


Figure 14. Comparison of various compression techniques used on the different test grayscale images (Lena, Barbara, Baboon and Goldhill).

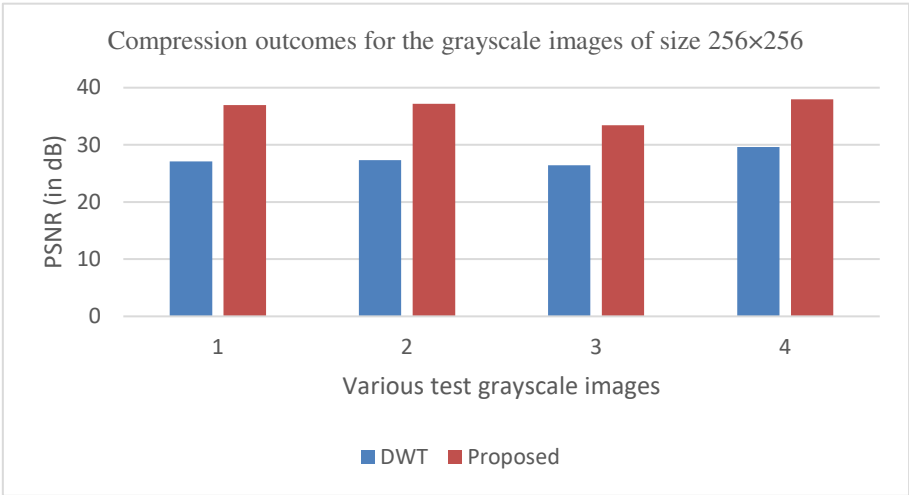


Figure 15. Comparison of various compression techniques used on the different test grayscale images: 1- Lena, 2-Peppers, 3-Cameraman, and 4-Boat.

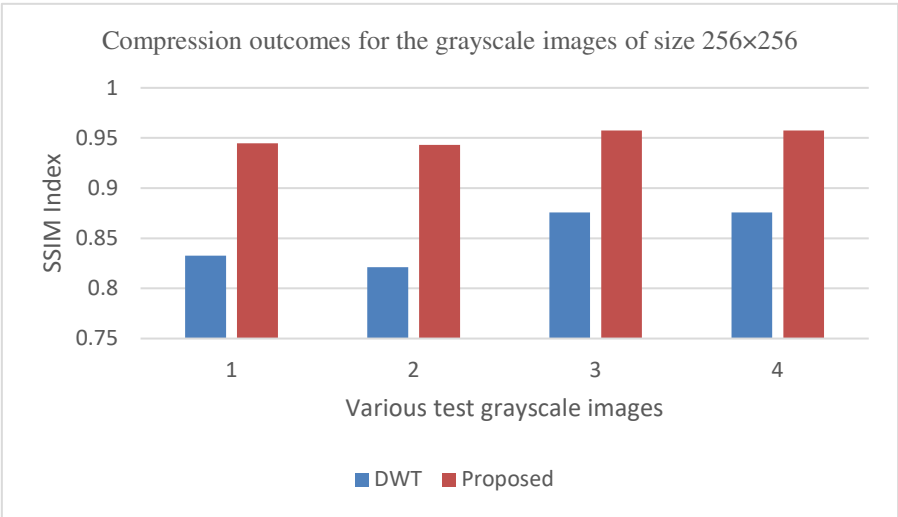


Figure 16. Comparison of various compression techniques used on the different test grayscale images: 1- Lena, 2-Peppers, 3-Cameraman, and 4-Boat.

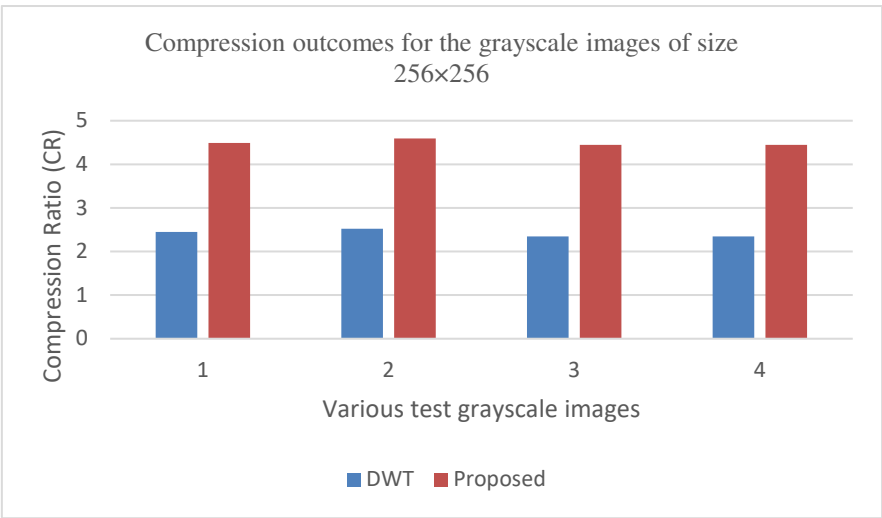


Figure 17. Comparison of various compression techniques used on the different test grayscale images: 1- Lena, 2-Peppers, 3-Cameraman, and 4-Boat.

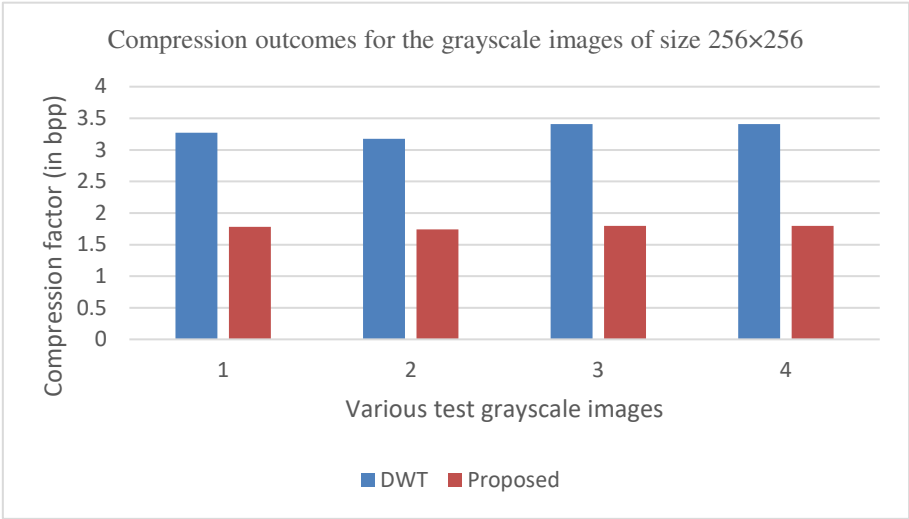


Figure 18. Comparison of various compression techniques used on the different test grayscale images: 1- Lena, 2-Peppers, 3-Cameraman, and 4-Boat.

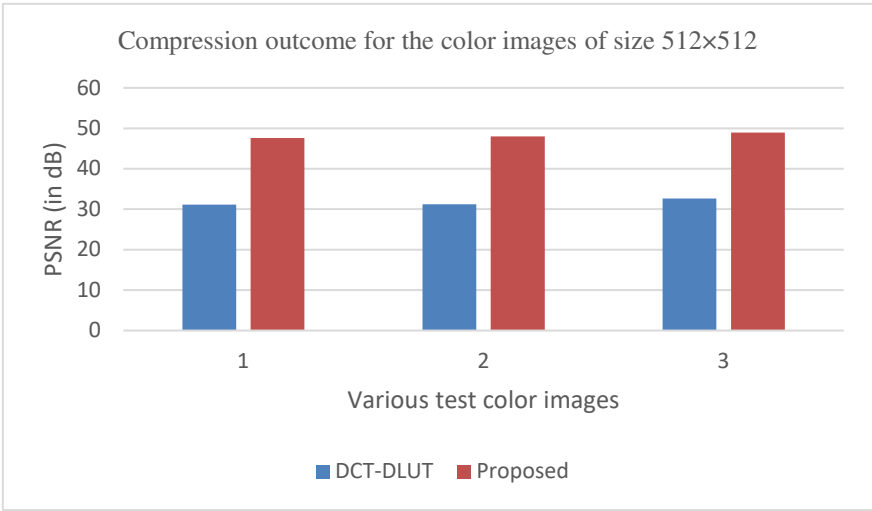


Figure 19. Comparison of various compression techniques used on the different color test images: 1- airplane, 2-pepper, and 3-Lena.



Figure 20. Comparison of various compression techniques used on the different color test images: 1- airplane, 2-pepper, and 3-Lena.



Figure 21. Comparison of various compression techniques used on the different color test images: 1- Couple, 2-House, and 3-Zelda.

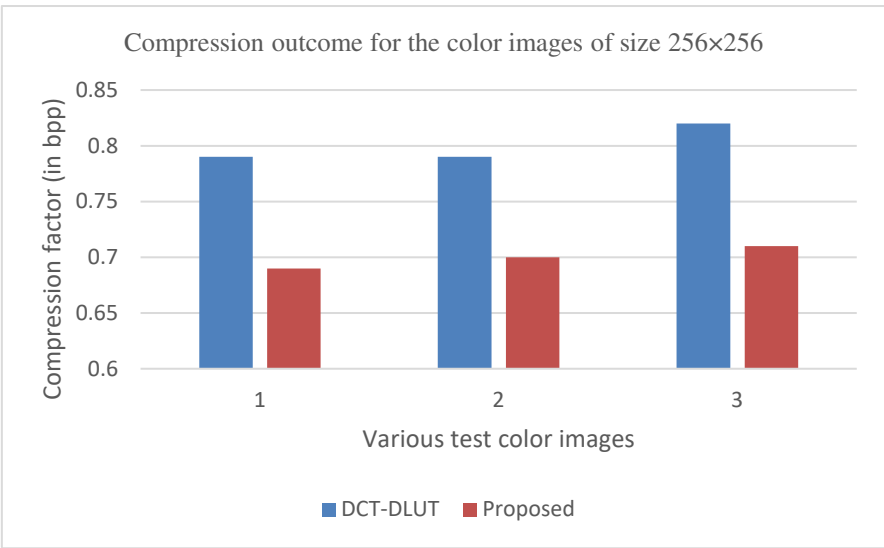


Figure 22. Comparison of various compression techniques used on the different color test images: 1- Couple, 2-House, and 3-Zelda.

Figures 11, 14, 19 and 21 display the PSNR characteristics, while Figures 12 and 16 show the SSIM index. The CR values are found in Figures 13 and 17 and the compression factor (in bpp) can be seen in Figures 14, 18, 20 and 22. It is evident from the four PSNR plots that the proposed hybrid PCA-DWT-CHC method performs better than the DWT and other existing approaches in terms of PSNR values. The hybrid PCA-DWT-CHC method displays significant improvements. When tested on the Lena image, it resulted in a gain of approximately 6 dB, -2 dB, -6 dB, -1 dB, -1 dB and 13 dB in PSNR. The CR values, on the other hand, showed a gain of 2, 1, 2.40, 0.4058, 0.4058 and 0.4058. The values for other standard test images can be obtained from Table 1 and Figures 11, 14, 19, 21, 13 and 17.

The proposed method aims to enhance the image compression without compromising the image quality. In comparison to other methods, such as, DWT, ABTC-EQ, IBTC-KQ, MBTC, AMBTC and BTC, this process has proved to maintain or even improve the original image quality. The proposed

hybrid PCA-DWT-CHC method for color images has revealed a significant increase in the PSNR values for Airplane, Peppers, Lena, Couple, House and Zelda images with gains of 16.41 dB, 16.80 dB, 16.30 dB, 21.98 dB, 30.20 dB and 21.73 dB. Additionally, this method has been found to reduce the compression factor (in bpp) by 0.21, 0.56, 0.37, 0.10, 0.09, 0.11 and 0.24. The parameters concerning the PSNR values are presented in Figures 19 and 21 and concerning the compression factor (in bpp) are presented in Figures 20 and 22.

The proposed method has also improved the SSIM index by 0.3734, 0.0161, 0.0058, 0.0146, 0.0450 and 0.0731 for the Goldhill grayscale image.

In other words, the suggested hybrid method has established with data that it could yield better-quality image reconstruction as compared to the other methods.

It has also shown improvement in image compression, as indicated by its higher CR values and lower compression factor (in bpp). Figures 12 and 16 demonstrate that the SSIM characteristics, showing that the proposed hybrid PCA-DWT-CHC method ensure the highest SSIM values for all the test images. In other words, the proposed method is able to reconstruct all the images with greater similarity to the original ones as compared to the other available methods.

6.3. Time Complexity Analysis OF Proposed PCA-DWT-CHC Method

The speed of an entropy coder's encoding and decoding process is essential for real-time compression. In order to give a clear idea of whether entropy coders can be used in real-time applications, their time complexity needs to be explained. During the present study, the total time needed for an entropy coder to encode and decode data to ensure proper evaluation of its time complexity was assessed. The average time requirements were calculated and compared for analysis purposes. Table 3 presents the average time requirements of two entropy coders for encoding and decoding processes (ATTREDP). According to Table 3, the Canonical Huffman coding entropy coder is quicker than other entropy coders. Compared to the Huffman coding, the process of encoding and decoding of the four test images respectively takes 404.37, 388.05, 276.00 and 336.15 less time. The proposed hybrid PCA-DWT-CHC transform proves to be faster than other hybrid transform methods which use Huffman coding [16] as an entropy coder. Therefore, one could claim the proposed method to be effective for applications that require real-time image compression

Table 3. Time Complexity Comparison of Entropy Coders.

Image (256×256)	Canonical Huffman Coding Compression time (s)	Huffman Coding Compression time (s)
Boat	95.33	509.70
Cameraman	70.06	458.11
Goldhill	86.90	362.90
Lena	74.45	410.60

7. Conclusion

The present study envisaged to develop a method that will improve the image quality and compression. By combining PCA, DWT and Canonical Huffman Coding, a new approach has been developed for compressing images. Accordingly, the proposed method has been able to outperform the existing methods, such as, BTC, AMBTC, MBTC, IBTC-KQ, ABTC-EQ, DWT and DCT-DLUT. Lower bit rates and better PSNR, CR and SSIM values indicate improved image quality. A comparison of the PSNR, SSIM, CR and BPP values, resulting from the proposed technique with that of the other available approaches confirms the superiority of the proposed method.

The findings from the objective and subjective tests indicate that the newly developed approach offers a more efficient image compression technique as compared to the existing techniques. For example, when working with grayscale images of 256×256 and 512×512 resolutions, improved results in metrics, such as, PSNR, SSIM, BPP and CR have been established. Again, in the case of color images of 256×256×3 and 512×512×3 resolutions, improved PSNR and lower BPP results have been noted.

Hence, one could conclude that the proposed technique performs better than BTC, AMBTC, MBTC, IBTC-KQ, ABTC-EQ and DWT for grayscale images. Moreover, it is more useful with regard to the color images as compared to the 'DCT-DLUT'. Therefore, this present research has the potential to greatly improve the storage and transmission of image data across the digital networks

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