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RESEARCH ARTICLE

An Efficient Image Compression Method by Using Optimized Discrete Wavelet Transform and Huffman Encoder

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Image compression performs a vital role for image transmission and storage. Image compression signifies diminishing the image size, with no loss in the image quality. For mitigating the storage necessities of image transmission, image compression approach is projected to proffer a compact illustration of an image. Even though the image compression methodology has a salient role for compressing images certain conflicts are still present in these techniques. We introduced a unique image compression methodology by pooling Single Value Decomposition (SVD) and optimized Discrete Wavelet Transform (DWT). In the initial stage, the input image is subjected to decomposition through SVD. The decomposed image thus obtained is restored through inverse SVD. The restored image thus achieved is inputted to the DWT, where the optimization is performed through a renowned optimization technique called genetic algorithm (GA). Consequently the processing speed gets increased. The outcome of the optimized DWT process will be given as input to the Huffman encoding and decoding. Finally, the actual image is regained through Inverse Discrete Wavelet Transform (IDWT) process, for attaining the decompressed image. Our suggested technique of image compression will be applied in MATLAB platform. The operation of our image decomposition methodology will be analyzed by a lot of other images. Moreover the performance will be compared with the prevailing techniques according to Peak Signal Noise Ratio (PSNR), Structural Similarity Index Measurement (SSIM), Mean Square Error (MSE), and Compression Ratio (CR).

Keywords: Single Value Decomposition (SVD), Peak Signal Noise Ratio (PSNR), Structural Similarity Index Measurement (SSIM), Mean Square Error (MSE), Compression Ratio (CR).

1. INTRODUCTION

Image compression has been mitigating the bytes of a graphics file size without corrupting the image quality to an intolerable level. The diminution in file size permits more images for being hoarded in a provided amount of disk or else memory space. And, this reduction permits more images for being hoarded in a provided amount of memory space but the main advantage is the diminution of the time needed for images for being sent by Internet or else downloaded from Web pages.[1] Image compression has been a prominent technology in the improvement of divergent multimedia computer services and also telecommunication applications of teleconferencing; digital broadcast codec and video technology, etc.[2] Image compression algorithms can be divided into two types[3] i.e., lossy[4] where data loss occurs in the procedure of decompression and then lossless[5] where the decompressed data is accurately similar as the initial data. Compression is attained by the eviction of one or else more of the three essential type of data redundancies: 1. Coding Redundancy, 2. Inter-pixel Redundancy, 3. Psycho-visual Redundancy.[6] The benefits of image compression includes: (1) Transferring abridged amount of data through the switched telephone network thereby reducing the cost, as in the switched telephone network the call cost relies upon the period of transferring the data, (2) The storage requirements and the execution time gets reduced, (3) It lessens the chances of transmission errors as few bits are transferred, (4) It yields some kind of

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precautions against illicit monitoring. The delineation of the paper is structured as follows: Section 2 includes the investigation of the reviews of related works regarding the suggested technique. Section 3 includes the motivation for the research. Section 4 reveals a concise idea behind the suggested technique. Section 5 includes the investigation of the experimental outcomes. Lastly Section 4 terminates the paper.

2. RECENT RELATED RESEARCHES: A REVIEW

Mohammed et al.[7] have intended physics-based transform where the image compression is allowed by improving the spatial coherency. In addition they enhanced the expanded modulation distribution, an innovative density function that proffers the instructions for image compression. The investigational result reveals that by utilizing the above technique the performance gets better in the JPEG 2000 format.

Amutha et al.[8] have suggested an innovative approximation band transform algorithm. The minimal bit rate image compression algorithm was employed exclusively for resource-constrained low-power sensors. The operation of the minimal bit rate image compression algorithm was studied according to particular terms like bit rate (bit per pixel), processing time, energy consumption and image quality in an Atmel Atmega 128 processor. It has been revealed that the above algorithm consumes less energy i.e., it uses only 12% of energy essential for the joint photographic experts group (JPEG) [independent JPEG group (IJG)] version. When compared with the JPEG the above algorithm yields enhanced results in low bit rates. Thus the above suggested technique performs a salient role in enhancing the lifespan of low power sensors.

Ranjan et al.[9] have developed an improved LSK (ILSK) algorithm which carry out coding for one zero to many insignificant sub bands. By using that algorithm the output bit string length, decoding and encoding time and the dynamic memory requirement gets reduced considerably. In addition, the ILSK algorithm was pooled with discrete Tchebichef transform (DTT). The HLDTT transform developed in that paper have attractive attributes such as,

(1) Fully embedded for progressive transmission,
(2) Precise rate control for incessant bit rate traffic,
(3) In case of low power applications the complexity gets lowered.

Yangan et al.[10] have proposed an innovative error-based statistical feature extraction technique. Initially, for creating a reconstructed image, decompression of the JPEG file was achieved. After that, an error image was achieved through computing the dissimilarities betwixt the inverse discrete cosines transform coefficients and the values of the pixel in the reconstructed image. Then the fault image was evaluated by two classes of obstacles present in the fault image called as rounding error block and truncation error block. A set of features was introduced so as to illustrate the statistical distinction of the error blocks between single and double JPEG compressions. The support vector machine classifier was applied in the last step for identifying whether the JPEG image was compressed doubly or not.

Sunet et al.[11] have proposed an effective non-predictive image compression system. In the above system the quantization of hard-decision quantization (HDQ) and soft decision quantization (SDQ) and entropy coding were entirely revamped regarding the LPTCM. The whole coding results were tested over standard test images which reveal that the proposed system yields good results just like H.264 or HEVC intra (predictive) coding regarding the rate versus virtual quality.

3. MOTIVATION FOR THE RESEARCH

The diminishing process of the essential storage space through reducing the bits of data is termed as image compression. Lossless image compression methodology has been included in majority of the image compression methodologies. In lossless image compression the compression ratio is low and provides better quality whereas in lossy technique the compression ratio is high and the quality is low. The lossless technique needs more storage space than the lossy technique. The discrete wavelet transform is the commonly used wavelet during image compression process but for processing data this wavelet takes more time. The above mentioned troubles inspired me to put forward for a novel image compression methodology by pooling the lossless and lossy compression methodologies.

4. PROPOSED IMAGE COMPRESSION METHODOLOGY BY COMBINING SINGLE VALUE DECOMPOSITION (SVD) AND OPTIMIZED DISCRETE WAVELET TRANSFORM (DWT)

In the novel image compression methodology, initially decomposition of the input image is done through SVD and it is one of the sorts of lossy compression methodology. In the SVD method of decomposition the singular smaller values are removed it does not alters the image quality while we restore it. Subsequently, for image restoration Inverse SVD is performed. The retrieved image thus achieved is given as input to DWT. Optimization of the DWT is done by genetic algorithm for augmenting the processing speed. The outcome thus attained from the DWT process is subjected to Huffman encoding and decoding. Finally, for deriving the decompressed image the initial image is restored by Inverse Discrete Wavelet Transform (IDWT) process. The block diagram of our suggested technique is presented in Figure 1.

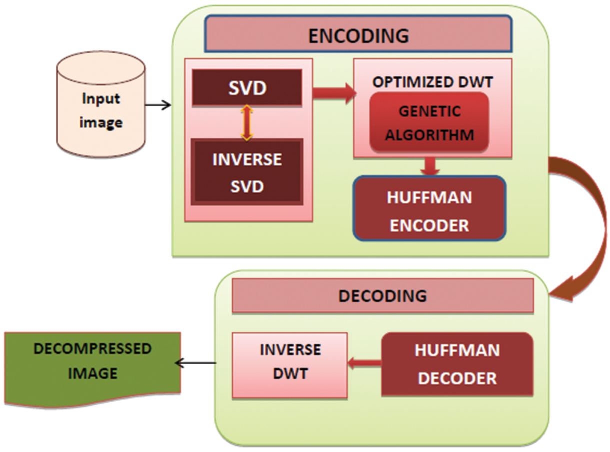

Fig. 1. Architecture of the suggested image compression process.

4.1. Initial Preprocessing

Let us consider the database D_b which comprised of several images in RGB format and the database is represented in the equation below

$$D_b = \{I_{d^1}, I_{d^2}, \ldots, I_{d^i} \mid I \in a \times b\}; \quad i = 1, 2, 3, \ldots, N \tag{1}$$

Where N signifies the complete number of images in the database D_b and I_{d^l} denotes the lth image from the database D_b. Each image has 'a' rows and 'b' columns.

4.1.1. *Conversion to Gray Scale*

The input image I_d which is in RGB format is converted to gray scale image. The pixel in the gray scale image is signified by the changeable intensity value of the range of 0 to 256. Here, the gray scale images are completely based on the gray shades that differs from black (pixel value 0) to white (pixel value 256). Images of grayscale are the outcome of computing the force of light at all pixel in one band of the electromagnetic spectrum. Matching the gray scale image's luminance with the color image's luminance is a recognizable approach for converting a color image into a gray scale image. Generally for converting the color image (RGB) to a gray scale image representation by its luminance 30% of the red value, 59% of the green value, and 11% of the blue value present in the RGB image are added simultaneously. In spite of the scale used in the range of 0.0 to 1.0, 0 to 255 or 0% to 100%, the resultant number obtained is the most preferred linear luminance value which is having necessity of gamma compression to recover to its standard gray scale representation. The resultant gray scale image I'_d thus obtained is then allowed for the subsequent process called SVD decomposition.

4.2. SVD Decomposition

Singular value decomposition is a kind of linear image matrix transformation. Here the image matrix I'_d is decomposed into 3 component matrices M, N and P, which is signified in the equation below

$$I_d = MNP^T \tag{2}$$

Where M denotes the left singular matrix, N signifies the right singular matrix, P represents the diagonal matrix.

The column elements in the M and P matrixes are denoted as m_i, p_i respectively and the diagonal features in the N matrix is represented by n_i termed as single values. The singular vectors form orthonormal basis, and the relation is mentioned below,

$$I_d p_i = n_i m_i \tag{3}$$

Equation (3) illustrates mapping of each right singular vector with the equivalent left singular vector. The single values are ordered on the significant diagonal in the order as illustrated in Eq. (4).

$$\sigma_1 \geq \sigma_2 \geq \sigma_3, \ldots, \sigma_r \sigma_{r+1} = \sigma_p = 0 \tag{4}$$

Where, r denotes the rank of the matrix I_d, and (p) denotes the smaller of the dimensions m or n. In the input matrix, rank is indicated as the number of linearly independent rows and columns. The input image is indicated as a matrix for calculating the image rank. If it possesses low rank then SVD type of decomposition is chosen to get the approximation. This low rank approximation is more suitable than the original image. The Singular Value Decomposition process starts by choosing the matrix I'_d which possesses m rows and n columns. Factorization is performed in the I'_d matrix into three matrices M, N and P^T. Generation of matrix P is done by performing the following procedures:

(1) Pre-multiplying I_d^T on both sides of the component matrix $I_d = MNP^T$

$$I_d^T I_d = (MNP^T)^T (MNP^T) = PN^T M^T MNP^T \tag{5}$$

In Eq. (5), $M^T M$ signifies the identity matrix, $N^T N = N^2$ since N has been a diagonal matrix. By replacing such values in Eq. (5) yields,

$$I_d^T I_d = PN^2 P^T \tag{6}$$

(2) For finding the N and P matrices the Eigen values with Eigen vector of matrix $I_d^T I_d$ are required. The Eigen vectors of a square matrix have been the nonzero vectors which while multiplied through a matrix is in proportional with the original vector. It means the magnitude will change and there is no modification in direction. For each Eigen vector, the equivalent Eigen value has been the factor while multiplied by this matrix there is a modification in Eigen vector. The mathematical

interpretation of this concept is illustrated below:

If I'_d is a square matrix, of size $n \times n$ and λ is an associated Eigen value such that

$$I'_d p_i = \lambda p_i, \quad i = 1, 2, 3, \ldots, n \tag{7}$$

Where p is an Eigen vector of matrix A, associated with Eigen value λ.

The above equation can also be modified as

$$I'_d p_i = \lambda I p_i \tag{8}$$

Where, G indicates the identity matrix of size $n \times n$. The dimension of the identity matrix has to be the same as that of the matrix for computing the Eigen values and Eigen vectors.

$$(I'_d - \lambda G) p_i = 0 \tag{9}$$

The homogenous system mentioned in the above equation possesses non-zero solution when the Eigen values λ of matrix I'_d are real numbers. The Eigen vectors in the matrix A related with λ are the non-zero solutions in the system. When the coefficient matrix is noninvertible then the above equation contains non-zero solution, this is achievable when its determinant is equal to zero.

$$|I'_d - \lambda G| = 0 \tag{10}$$

The Eq. (10) denotes the quality equation of matrix A. The Framework of SVD decomposition includes Eigen values which are the square of the features of S (the single values), and the Eigen vector which includes the columns of matrix V (the right singular vectors).

(3) Post-multiply I_d^T on both the sides of the equation $I_d = MNP^T$ so as to obtain I_d

$$I_d I_d^T = (MNP^T)(MNP^T)^T = MNP^T PN^T M^T \tag{11}$$

Where, $P^T P$ denotes the Identity matrix and $N^T N = N^2$ since N is a diagonal matrix.

On replacing such values in Eq. (11) provides,

$$I_d I_d^T = MN^2 P^T \tag{12}$$

The Eigen vectors for the matrix $I_d I_d^T$ are computed. This represents the columns of M (the left singular vector). The same procedure is repeated for computing Eigen values and Eigen vector in the calculation of matrix I_d.

When M, N and P matrices are achieved, matrix A is formed merely by the product of matrices M, N and P^T.

$$I_d = [M_1, \ldots, M_r, \ldots, M_K] \begin{bmatrix} \sigma & & \\ & \ldots \sigma_r & \\ & & \ldots\ldots 0 \end{bmatrix} \begin{bmatrix} P_1^T \\ . \\ P_r^T \\ . \\ P_l^T \end{bmatrix} \tag{13}$$

Where, M is $k \times k$ matrix and N is $l \times l$ matrix.

4.2.1. *Inverse SVD Decomposition*

The inverse square diagonal matrix is attained by simply inverting every element of the matrix. Through far less entries in the initial matrix the matrix $k \times l$ is estimated.

The redundant information is eliminated if the rank $r < k$ or $r < l$, Here the rank signifies the whole number of non-zero diagonal essentials of the S-matrix which are recognized as single values. These particular values are structured in the decreasing order with the main diagonal. If the values are more than the rank are considered as zero.

$$I_d = \sigma_1 m_1 p_1^T + \sigma_2 m_2 p_2^T \cdots + \sigma_r m_r p_r^T + 0 m_{r+1} p_{r+1}^T + \cdots \tag{14}$$

The quality of the image doesn't gets affected by adding the dependent terms of the single values equal to zero and the single values which are greater than zero. Consequently the terms at the ending in the Eq. (14) is zero which is illustrated in the equation below given,

$$I_d = \sigma_1 m_1 p_1^T + \sigma_2 m_2 p_2^T \cdots + \sigma_r m_r p_r^T \tag{15}$$

In addition approximation of the matrix is done by eliminating more number of singular terms in the matrix I_d thus the reconstructed SVD image was achieved.

4.3. Image Compression Utilizing Optimized DWT

The SVD reconstructed image I_d derived from the step above then undergoes compression through optimized DWT. The vital technique used in compressing the image is wavelet transform. By using wavelet based coding, at high compression ratios there is a salient enhancement in picture quality because of the unique property of enhanced energy compaction in wavelet transforms. Wavelet transform denotes the representation of a common function according to simple, stable building obstacles at variant positions and scales. Through dilation and translation operations, such building obstacles are extracted from the single fixed function termed as mother wavelet. Here, the Wavelet transform is computed for all segments of the time-domain signal at variant frequencies. Consequently, for evicting few amounts of explanations in the signal, decimation is executed in the wavelets' coefficients. Wavelets possess an odd advantage as it can break up the minute details in the signal. Extremely small wavelets can be utilized for separating very minute details in the signal whereas the very large wavelets can divide coarse explanations. There are variant kinds of images few of them are Morlet, Daubechies. All type of wavelet creates different forms of sparse representation so all the sorts of wavelets should be analyzed carefully which type is most appropriate for this type of image compression. A wavelet function $\psi(t)$ possess two main properties.

$$\int_{-\infty}^{0} \psi(t)\, dt = 0 \tag{16}$$

Which means the function is oscillatory or hold wavy appearance.

$$\int_{-\infty}^{0} |\psi(t)|^2 \, dt < \infty \tag{17}$$

Which signifies, approximately every energy in $\psi(t)$ is confined to a finite duration.

The wavelet is created through a scaling function (S) this function explains the scaling properties. But there is certain constraint as this scaling function should be orthogonal to its discrete translations. The wavelet which is attained from the function of scaling is demonstarted below

$$I_d(x) = \sum_{k=-\alpha}^{\alpha} (-1)^k a_{N-1-k} \psi(S-k) \tag{18}$$

Where I_d denotes the input image, $I_d(x)$ denotes the DWT image, N represents an even integer and S represents the scaling factor. The scaling factor S is the set of wavelets which is utilized to orthonormal basis for performing signal decomposition. It is noted that a few coefficients a_k are nonzero which simplifies the computations. Through genetic algorithm, optimization must be performed in the function of scaling S so as to achieve precise results where PSNR is employed as the fitness function.

4.3.1. Optimal Feature Selection Using Genetic Algorithm

In the field of progressive computation, a heuristic search technique known as Genetic Algorithm (GA) plays a dominant role for determining the global maximum/minimum solutions. Chromosomal representation describes the fitness function, application of the GA operators and any type of optimization problem can be represented in GA. In the initial generation GA process includes random gene selection known as population (see Fig. 2). There is an equivalent solution for each individuals in the population known as chromosome which possess finite length strings. The aim of the issue termed as the fitness function is utilized to detect each chromosome quality in the population. Moreover, the good quality chromosomes are regarded as fit and they survive, which create a new population in the generation following. To find the better solution over successive generations, the GA operators called as the selection, mutation and crossover are frequently used to the chromosomes. Figure 2 shows the GA process.

4.3.1.1. Initial Phase. The initial phase includes the haphazard generation of populations of the chromosomes $d(d = \{1, 2, \ldots, N\})$ where d is the scaling factor and N is the dimension of the population. For deriving the optimum scaling factor (O_{sf}), the scaling factor (d) is generated randomly. Each randomly generated scaling factor is substituted in DWT function; subsequently this scaling factor performs compression. By measuring the PSNR value betwixt the input image and also the condensed image the Fitness value is attained.

4.3.1.2. Fitness Function. For all individual in the chromosome the Fitness value (F_d) is calculated. The chromosome which possesses the highest fitness value is chosen as the best chromosome. The PSNR value is employed as

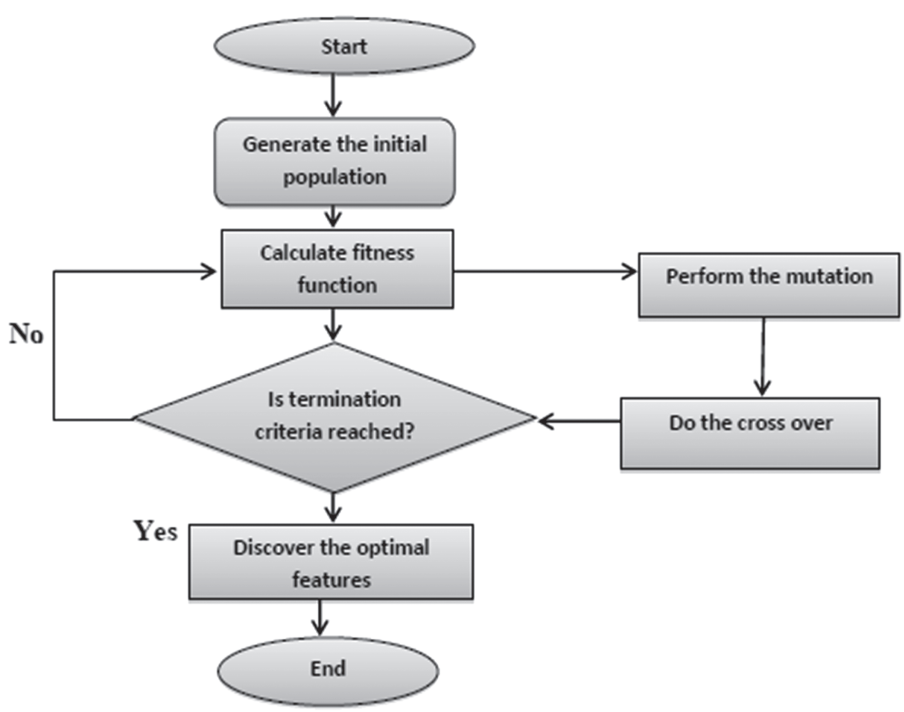

Fig. 2. Process of genetic algorithm.

the fitness function so as to assess the chromosome. The calculation for PSNR is mentioned below:

$$f_d = \text{PSNR} = \log 10[255^2/\text{MSE}]^{10} \tag{19}$$

$$f_n = \max(f_d) \tag{20}$$

For next generation, Genetic operators like crossover plus mutation are carried out on the selected parents for generating new offspring. These offsprings are incorporated in the population so as to form next generation.

- *Mutation*: For undergoing the mutation process the probability should be set low. During mutation the chromosomes' values gets changed in proportion to the probability.
- *Crossover*: Through the roulette wheel choice technique one or more parent chromosomes are preferred so as to attain an innovative solution.
- *Evaluation*: The Fitness for the new solution is computed if the new fitness value is greater than the recent fitness value, then the current fitness value is replaced with the new one. The complete process is repeated for several generations so as to achieve the best solution.

The optimum scaling feature (O_{sf}) thus chosen by Genetic Algorithm is then inputted to the DWT so as to perform image compression.

4.4. Huffman Coding

The outcome of the DWT i.e., image (I''_d), then undergoes Huffman coding. Huffman coding comes under lossless encoding technique. This coding is identified as entropy encoding algorithm. For source symbol the entropy encoding algorithm employs variable-length code table. This variable-length code table is achieved regarding the anticipated probability occurrence of the source symbol. There is a definite coding for preferring the source symbol. The bit string which signifies a distinctive symbol does not prefix any other symbol is termed as prefix code. For smaller strings of bits employed for minimal common source cryptogram this prefix code uttered the most frequent source symbols. Huffman is one of the proficient compression method here the independent source symbols is mapped with distinctive strings of bits for yielding the output of small size. The basic concept is behind this is the data which arises more repeatedly is encoded by employing lower number of bits. In the Huffman code dictionary each data symbol is associated with a codeword, when no codeword is there in the dictionary then it is called to be a prefix for any other codeword in the dictionary. As per Huffman the code tree is the source for coding, here the short code words are assigned for most commonly used symbols and long code words are assigned for uncommon symbols employed for both AC and DC coefficients. From the allocated table of Huffman from the 8×8 blocks image feature the symbols are encoded with variable length code. Each symbol is a leaf and a root where the encoding is done through this Huffman algorithm.

The number of data is computed after and before the encoding process to evaluate the efficiency of Huffman coding is given below:

d_{avg} is the number of data present in the image I''_d of size $a'' \times b''$ with gray levels (g). The equation for calculating d_{avg} is illustrated below

$$d_{\text{avg}} = g(r_0)p(r_0) + g(r_1)p(r_1) + \cdots + g(r_{G-1})p(r_{G-1}) \tag{21}$$

Where, $g(r_k)$ denotes the number of bits utilized for representing gray level and $p(r_k)$ denotes the probability of gray level in the image. The d_{avg} should be low after Huffman encoding.

4.4.1. *The Functioning Steps for Huffman Coding*

Step 1: Interpret the output of optimized DWT image I_d.
Step 2: Classify or prioritize the characters regarding the frequency count of every character in the file.
Step 3: Compute the probability of each symbol.
Step 4: The symbols' probability is kept in order in declining sequence and also the symbols having minimal probabilities are evolved. Repeat these steps till only two possibilities are left and codes are ordered according to highest probable symbol having shorter length code.
Step 5: Perform Huffman encoding i.e., code words are mapped with the equivalent symbols so as to form the compressed data.
Step 6: After performing compression through Huffman encoding, the initial image is restructured by Huffman decoding i.e., decompression is accomplished by matching the code words with code dictionary.

4.5. Decoding Process

- Huffman decoding
- Inverse DWT.

4.5.1. *Huffman Decoding*

Compression is done in encoding whereas decompression is performed during decoding. The Huffman decoding process is the reverse of the Huffman encoding process. The compressed image obtained is decompressed through Huffman decoder.

4.5.2. *Inverse DWT*

For attaining the perfect reconstructed image (synthesis step) inverse DWT is carried out through the same lifting algorithm. This inverse DWT is the reversing of the DWT implemented during encoding process.

Fig. 3. Input images from the database.

Fig. 4. Preprocessed SVD images.

5. RESULTS AND DISCUSSION

Our suggested image compression methodology is employed in the MATLAB (version 14a) platform with machine configuration of Processor: Intel core, i3OS: Windows 7, CPU speed: 3.20 GHz, RAM: 4 GB. According to optimized DWT the intended image compression methodology is evaluated by utilizing images derived from the database (see Fig. 3). The operation of our suggested technique is assessed through performance metrics. In the initial stage, SVD (see Fig. 4) is employed for reducing the data subsequently for compression process and the optimized DWT (see Fig. 5) is performed. In the last step the IDWT is performed for restoring the original images (Fig. 6).

5.1. Performance Analysis

During comparative analysis, the operation of our Huffman encoding is compared through the conventional JPEG encoding and run length encoding method subsequently the operation of the GA-DWT based reconstruction technique is matched through conventional DWT and PSO-DWT.

The parameters such as the Compression Ratio (CR), Peak Signal to Noise Ratio (PSNR) and Average No of Search Points are employed for evaluating the outcome of the suggested Huffman encoding and GA-IDWT technique system. Similarly for analyzing the operation of the compression methodology the value of the Peak Signal to Noise Ratio (PSNR) regarding the Mean Square Error (MSE), Structural Similarity Index Measure (SSIM), and Correlation are calculated as a quality measure and these values are calculated through the equation illustrated below.

PSNR

$$\mathrm{PSNR} = 10\log\left(\frac{(255)^2}{\mathrm{MSE}}\right)\mathrm{dB} \tag{22}$$

SSIM

SSIM is employed for computing the similarity betwixt two images.

$$\mathrm{SSIM} = [l(x,y)]^2 * [c(x,y)]^2 * [s(x,y)]^2 \tag{23}$$

$$l(x,y) = \frac{2\mu_x\mu_y + C_1}{\mu_x^2 + \mu_y^2 + C_1} \tag{24}$$

$$c(x,y) = \frac{2\sigma_x\sigma_y + C_2}{\sigma_x^2 + \sigma_y^2 + C_2} \tag{25}$$

$$s(x,y) = \frac{\sigma_{xy} + C_3}{\sigma_x\sigma_y + C_3} \tag{26}$$

Fig. 5. GA-DWT images.

Fig. 6. Reconstructed image by IDWT.

$\mu_x \cdot \mu_y \rightarrow$ mean, $\sigma_x \cdot \sigma_y \rightarrow$ standard deviation, $\sigma_{xy} \rightarrow$ cross variance.

Compression Ratio

Compression Ratio (CR) is denoted like the ratio betwixt the numbers of bits required to store the image before compression (I) and the number of bits demanded to store the image after compression (O).

$$\mathrm{CR} = I/O \tag{27}$$

Where, I denotes the dimension of the original frame (uncompressed Size) and O (Compressed Size) denotes the dimension of the compressed frame.

MSE

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(\hat{Y}_i - Y_i)^2 \tag{28}$$

Where, n represents the dimension of the image, $\hat{Y}$ denotes the output image and Y_i represents the input image.

Correlation

$$\text{Correlation} = \mathrm{sum}(a \times b) / ((\mathrm{sum}(\mathrm{sum}(a \times b))) * \mathrm{sum}(\mathrm{sum}(b \times b)))^{1/2} \tag{29}$$

Where, a denotes the input image and b denotes the output image.

The results of comparison has proven that high values of PSNR, Correlation, MSE are achieved by using our recommended Huffman encoding method than the conventional JPEG and Run Length technique. The performance evaluation of our comparison techniques has been demonstrated in Table I.

Discussion

Table I illustrates that the operation of our recommended Huffman encoding technique is equated with the traditional methods of Run Length and JPEG methods regarding the parameters like Correlation, MSE and also PSNR. It reveals that our suggested technique has shown higher values for the parameters like Correlation, MSE and also PSNR than the conventional JPEG and Run Length techniques. Therefore it clearly shows that our recommended Huffman encoding method yields higher encoding results than the traditional techniques. Figure 7 elucidates the comparison graph of our recommended Huffman encoding with the conventional encoding procedures based on Table I.

Discussion

The graph in the Figure 7 is derived by measuring the average of Correlation, PSNR and MSE metrics. Figure 7 clearly reveals that our recommended Huffman encoding method is more improved than the traditional JPEG, Run Length techniques regarding Correlation, PSNR, and MSE. By considering the correlation value it shows that our suggested image compression method is 9 times greater than the JPEG and Run Length encoding techniques. Subsequently the MSE value is low in our suggested technique than the conventional techniques. Thus the performance evaluation graph clearly proves that our recommended Huffman encoding methods yields better performance based on certain parameters like Correlation, PSNR, MSE than the traditional JPEG, Run length encoding methods.

Table I. Performance comparison of recommended Huffman encoding procedures with the typical encoding techniques on account of correlation, PSNR, MSE metrics.

	Huffman			JPEG			Runlength		
Images	CORR	PSNR	MSE	CORR	PSNR	MSE	CORR	PSNR	MSE
1	0.98411	50.93773	0.523972	0.279494	35.57762	18.00189	0.266657	35.57759	18.00202
2	0.937193	50.52275	0.576508	0.00436	35.28389	19.26155	−0.00236	35.31445	19.12648
3	0.947567	47.13649	1.257278	0.05585	26.62722	141.3704	−0.04664	26.63137	141.2354
4	0.985129	56.28389	0.153	0.154045	37.15623	12.51576	0.155292	37.17126	12.47252
5	0.956813	44.91902	2.094971	0.095562	24.03214	24.03214	0.101753	24.03407	256.8465

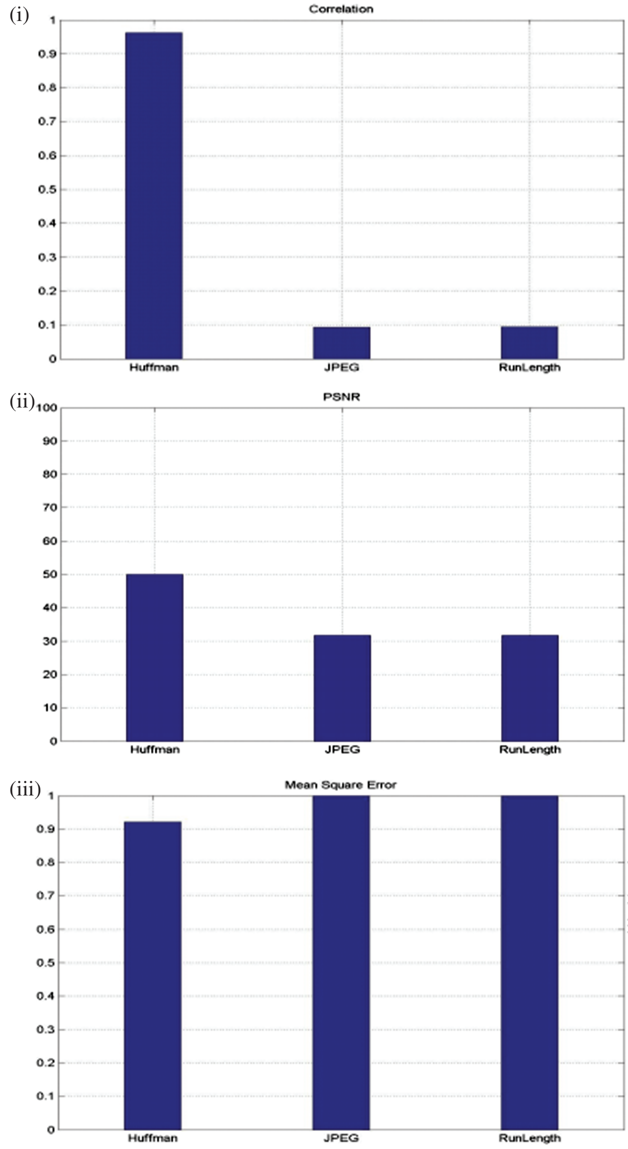

Fig. 7. Performance graph analysis for the recommended Huffman encoding techniques with the conventional encoding procedures on account of (i) correlation, (ii) PSNR, (iii) MSE metrics.

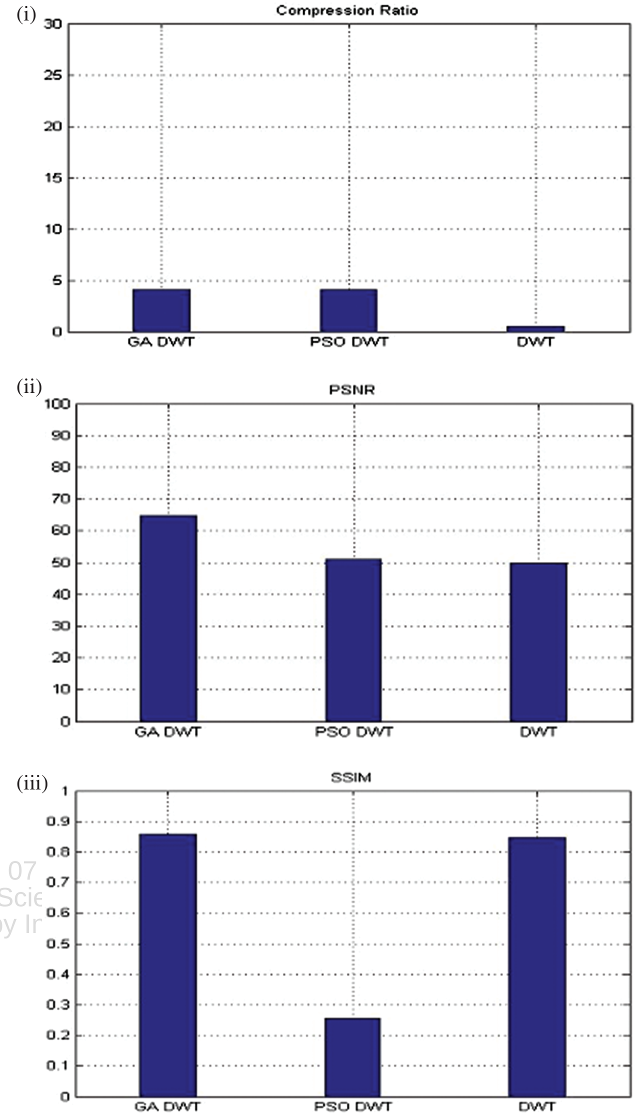

Fig. 8. Performance graph evaluation of the proposed GA-DWT techniques with the traditional DWT techniques on account of (i) compression ratio, (ii) PSNR, (iii) SSIM metrics.

Based upon the evaluation results it is notable that our GA-DWT yields higher Compression Ratio, PSNR, SSIM values than the traditional PSO-DWT and DWT techniques. The performance result of our suggested techniques is elucidated in Table II.

Discussion

Our GA-DWT technique's performance is related with the traditional techniques like DWT and PSO-DWT techniques in Table II. It demonstrates that the values of Compression Ratio, PSNR, SSIM metrics of our suggested

Table II. Performance table of proposed GA-IDWT techniques with the conventional DWT techniques according to compression ratio, PSNR, SSIM metrics.

	DWT			GA-DWT			PSO-DWT		
Images	CR	PSNR	SSIM	CR	PSNR	SSIM	CR	PSNR	SSIM
1	0.39313	50.93773	0.804249	3.870667	**67.45899**	**0.802779**	4.067725	49.74701	0.1986
2	0.414394	50.52275	0.810127	2.091628	54.1684	0.969264	4.067725	53.41401	0.342333
3	0.631736	47.13649	0.801281	7.131977	69.2199	0.872464	6.586719	50.29896	0.280674
4	0.304005	56.28389	0.952677	3.48855	72.2302	0.943238	3.567379	58.61292	0.349708
5	0.885555	44.91902	0.862272	3.69446	59.44267	0.710316	3.919547	42.73142	0.108353

technique is high when compared with the traditional DWT and PSO-DWT techniques. Figure 8 demonstrates the comparison graph of our recommended Huffman encoding with the conventional encoding methods based on Table II.

Discussion

The graph in Figure 8 is signified through the average values of CR, PSNR and SSIM values derived from Table II. It clearly demonstrates that the Correlation values, PSNR, SSIM of our proposed GA-DWT technique is more than the traditional PSO-DWT, DWT techniques. Consequently from the assessment of performance graph, it is definite that our proposed GA-DWT technique yields better performance.

6. CONCLUSION

This paper illustrates the proposal of a novel image compression methodology by pooling SVD and optimized Discrete Wavelet Transform (DWT). The optimization in DWT is done through a Genetic algorithm. For deriving the decomposed image, the DWT process' result will subjected to Huffman encoding and decoding. The experimental outcome reveals that the novel GA-DWT technique yields better performance in image compression when compared with the traditional techniques according to PSNR, CR, and SSIM. Therefore it is recognized that by utilizing GA-DWT technique and also Huffman encoding and decoding technique the novel image compression methodology can reconstruct the images effectively.

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