Wavelet based Image Compression using Self Organizing Feature Maps

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Abstract

Despite rapid progress in mass storage density, processor speeds and digital communication system performance demand for data storage capacity and data transmission bandwidth continues to outstrip the capabilities of available technologies. Various image compression techniques have been developed to reduce the transmission rates and increase the storage capacity for still images without sacrificing much of the image quality. Image compression has thus become a hub of contemporary research activity. In this paper, a new scheme for image compression combining Discrete Wavelet Transform with Vector Quantization has been proposed. This method is based on Kohonen's Self Organizing Feature Maps (SOFM) which takes into account the neighborhood property of an image and designs the codebook. Arithmetic Coding is then used to remove redundancies between the indexes of vectors corresponding to the neighboring blocks in the original image, which then leads to further compression. The simulation results demonstrate the improved coding efficiency of the proposed method, when compared with JPEG. The proposed scheme allows achieving a compression ratio upto approximately 40:1 with reasonable image quality. Further the simulations results demonstrate that an additional bit-rate reduction of approximately 30-50% can be achieved using Arithmetic Coding, without any further any degradation of the image quality.

Keywords : Wavelet, Self Organizing Feature Maps, JPEG

1. Introduction

In contemporary communication systems, compression of an image is of great concern due to requirement of storing capacities and constraints in the transmission rate. Images are known to constitute of large data bits requiring huge memory space for storage and large transmission times. Thus image compression techniques are popularly used to reduce the image size before their storage and transmission. Images are compressed by techniques which exploit the redundancy so that the number of bits required to represent the image can be reduced with acceptable degradation of the decoded image [1]. Although many image compression standards have been developed and are available in literature [2], but there is a need to design more efficient coding algorithms. The two fundamental image compression techniques frequently used are Transform Coding [1, 2] and Vector Quantization [3].

In transform coding, correlation between pixels in an image is reduced. Image data is first transformed into transform coefficients. Therefore the compression can be achieved by packing as much information as possible into a smaller number of transform coefficients. Only few of the transformed coefficients having significantly higher energy are then transmitted after quantization and entropy

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coding. The most commonly used transform is the Discrete Cosine Transform, which is also used in JPEG standard.

Another relatively recent and computationally efficient technique of transform coding for compression of image data is the Discrete Wavelet Transform (DWT). The image compression based on the wavelet transform shows no block artifacts and the quality of the restored image degrades slowly as the compression increases [4]. Much of the research has been focused on image coding based on DWT, which has become a standard tool in image compression applications because of their efficient image compression capability [5]. An overview of the wavelets that cut up data into different frequency components and then study each component with the resolution matched to its scale is discussed in [6 & 7]. In [8] various important features of wavelet transform in compression of still images are discussed, including the extent to which the quality of image is degraded by compressing and de-compressing image using wavelet transform.

In the recent past, neural network approach is being exploited in many applications including the image compression, due to its fast speed and parallel processing structure. A Back-propagation Neural Network for image compression has been reported [9] with fixed number of hidden layer neurons (lesser than that of input and output neurons). The network is trained for a sufficient number of epochs and the final weights are transmitted. The compression ratio in this case is lower than that of standard JPEG (around 8:1). The basic Back-propagation Neural Network is further extended to construct a hierarchical Neural Network by adding two more Hidden layers into existing network as proposed in [10]. An application of Neural Networks to implement vector quantization has now become well established. Kohonen's algorithm is a reliable and efficient way to achieve vector quantization and has been proved to be faster than other algorithms. The Kohonen's Self Organizing Feature Maps (SOFMs) are also used to avoid the problem of dead units that arise e.g. in the LBG algorithm. Since the consecutive blocks of an image along the horizontal and vertical directions are similar in most cases, so as per the Self organizing property of SOFM, two consecutive and similar blocks will be coded into similar code words. The variable length coding of the indexes of these code words will thus improve the compression ratio [11, 12].

In this paper we present a compression scheme where the input image data is applied to the Discrete Wavelet Transform to yield various transform coefficients. These approximation and detail coefficients are then split into 4x4 non-overlapping blocks and each block serves as an input to the Kohonen's Neural Network. The Kohonen's Self Organizing Feature Map (SOFM), learns to categorize these inputs into various classes. The SOFM while learning also learns both the topology and the distribution of these inputs. The centroids of these clusters are finally Arithmetic coded resulting in an output bit stream which is transmitted. The simulation results using the above scheme have been provided for compression with and without Arithmetic Coding. The results are also compared with the JPEG technique of image compression.

Rest of the paper is organized as follows: In Section 2, below, we present the proposed compression scheme based on the Discrete Wavelet Transform of the original image, Vector Quantization by Kohonen's Self Organizing Feature Map and the Entropy Coding of the indexes obtained after SOFM algorithm. Section 3 summarizes individual components of the proposed image compression technique. Two Dimensional Discrete Wavelet Transform, Self Organizing Feature Maps and Entropy Coding have been discussed in this Section. The Experimental results are presented in Section 4 to illustrate the performance of the proposed scheme. Comparison of the proposed scheme with that of the JPEG is presented in Section 5. Finally the conclusion and brief discussion of the results have been presented in Section 6.

2. Proposed Image Compression Technique

The proposed Image Compression technique is shown in Fig. 1. The input image data is applied to the Discrete Wavelet Transform Block in order to decorrelate the data, so that the resulting coefficients can be efficiently coded. Wavelet transform represents the image as a sum of wavelet functions with different locations and scales. These wavelet transformed coefficients are decomposed into 4x4 non-overlapping blocks and each block is transformed into vectors of 16 elements. These vectors serve as inputs to the Kohonen layer in the SOFM algorithm. Then a supervised algorithm LVQ is used to modify the codebook in a labeled training data. Since the consecutive blocks of an image are often similar, the topology preserving SOFM based LVQ will then quantize to some nearest codeword, hence removes redundancy. Arithmetic Coding is then used to code the indexes of the codeword. The use of Arithmetic Coding is done in order to exploit the occurrence of similar codebook indexes corresponding to neighboring blocks, which then leads to further compression .The decompression scheme performs the inverse operation to regenerate the original image.

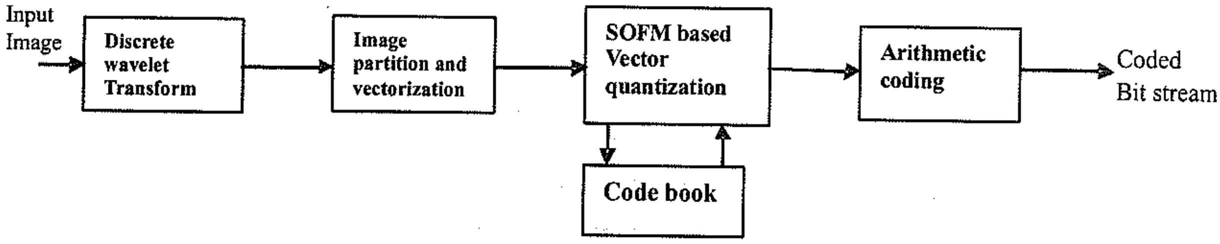


Figure 1: Block Diagram of Proposed Image Encoder

3. Discrete Wavelet Transform

The Discrete Wavelet Transform maps an image into a set of coefficients that constitute a multiscale representation of the image. An image is represented as a two dimensional (2D) array of coefficients, each coefficient representing the brightness level in that point. Technically, the smooth variations in color can be termed as low frequency components and the sharp variations as high frequency components. The low frequency components (smooth variations) constitute the base of an image, and the high frequency components (the edges which give the detail) add upon them to refine the image, thereby giving a detailed image. Hence, the averages/ smooth variations are demanding more importance than the details [13]. In wavelet analysis, a signal can be separated into approximations or averages and detail or coefficients. Averages are the high-scale, low frequency components of the signal. The details are the lowscale, high frequency components. If we perform forward transform on a real digital signal, we wind up with twice as much data as we started with. That's why after filtering downsampling has to be done. During the inverse process at the receiver the average and detail components can be assembled back into the original signal without loss of information. This process is called reconstruction or synthesis. The mathematical manipulation that affects synthesis is called the Inverse Discrete Wavelet Transform. The original signal is reconstructed from the wavelet coefficients. Where wavelet analysis involves filtering and downsampling, the wavelet reconstruction process consists of up sampling and filtering. The DWT algorithm consisting of Forward Discrete Wavelet Transform (FDWT) and Inverse Discrete Wavelet Transform (IDWT) are shown in Figs 2 and 3 respectively where CA_{j+1} are the approximation coefficients and CD_{j+1} are the detail coefficients obtained. The FDWT can be performed on a signal using different types of filters such as db7, db4 or Haar. The Forward transform can be done in two ways, such as matrix multiply method and linear equations. In the FDWT, each step calculates a set of wavelet averages (approximation or smooth values) and a set of details. If a data set s0, s1, ... sN-1 contains N elements, there will be N/2 averages and N/2 detail values. The averages are stored in the upper half and the details are stored in the lower half of the N element array.

4. Self Organizing Feature Maps (SOFM)

Self Organizing Feature Maps has formed a basis for a great deal of research into applying network models to the problem of codebook design in Vector Quantization [14]. The SOFM introduced by Kohonen is an unsupervised learning method which has both clustering and visualization properties and creates a correspondence between the input space of stimuli and the output space constituted of the codebook elements (the code words or neurons). The learning algorithm ensures that the most highly activated node as well as its neighbors move towards a sample presented to the network. The networks are self organizing in that nodes tend to attain weight vectors that capture characteristics of the input vector

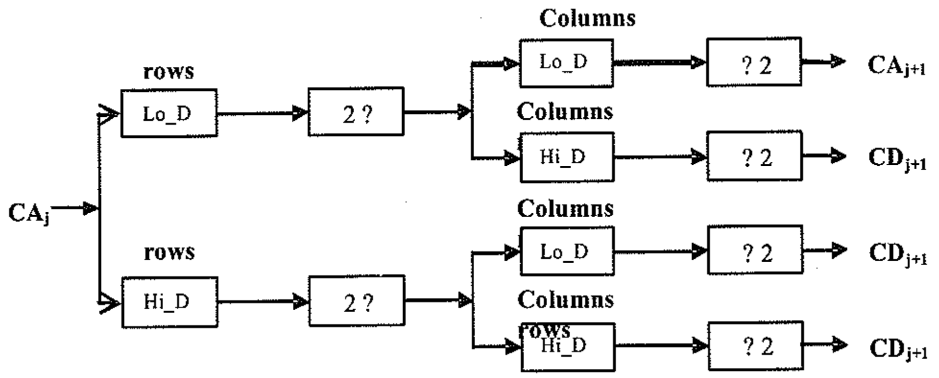


Figure 2 : Block Diagram of FDWT

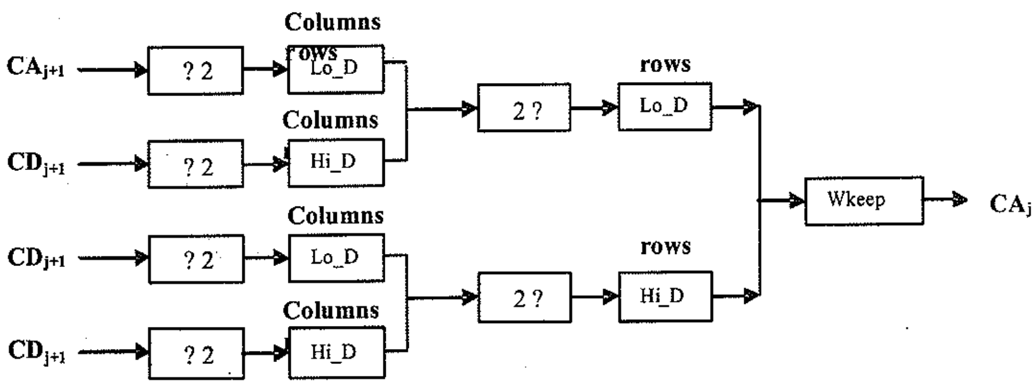


Figure 3 : Block Diagram of IDWT

space, with the neighborhood relation translating into proximity in Euclidean space, even if the initial values of weight vectors are arbitrary. In clustering, the weight vectors associated with nodes in these vectors are interpreted as cluster centriods. In vector quantization, each weight vector is a codebook vector to which input vectors may be mapped based on the minimum Euclidean distance method. In approximating probability distributions, the number of nodes with weight vectors in a given vector space is approximately proportional to the number of input vectors in that region. In the SOFM algorithm, the vector X is used to update not only the winning class but also its neighboring classes according to the following rule:

For each vector X in the training set

1. Classify X according to

$$X \in C_i \quad if \quad |X - W_i| = \min|X - W_j| \qquad \dots (1)$$

2. Update weights W_j according to:

$$W_j(t+1) = \begin{cases} W_j(t) + lr(X - W_j(t))^2 & if \quad C_j \in N(C_i, t) \\ W_j(t) & if \quad C_j \notin N(C_i, t) \end{cases} \qquad \dots (2)$$

Where W is the feature vector, *lr* is the learning parameter in the range of 0-1 and N (C_i, t) is the set of classes, which are in the neighborhood of the winning class C_i at time t. The subscript 'j' represents the index of all vectors in the neighborhood of the i^{th} feature vector. Typically the learning rate parameter is initialized to some value and then decreases monotonically with each iteration to ensure a good convergence of the algorithm. After a suitable number of iterations, the codebook converges and training is terminated.

When an input pattern is presented, the SOFM learning Algorithm updates the winner node and also nodes in its topological vicinity. As a result of application of SOFM algorithm, nodes eventually become ordered and neighboring nodes in the topology become associated with weight vectors that are near each other in the input space. Initially the output nodes are also randomly distributed in the input space, but the nodes are expected to align themselves at the end of the training process.

4.1 Binary Arithmetic Coding

In Arithmetic coding (AC) Scheme, a one to one correspondence between source symbols and codewords does not exist; instead, an entire sequence of source symbols (or message) is assigned a single arithmetic codeword. As the number of symbols in the message increases, the interval used to represent it becomes smaller and the number of information bits required to represent the interval becomes larger [15]. Each symbol of the message reduces the size of the interval in accordance with its probability of occurrence. The Binary Arithmetic Coder is used for encoding any set of events, whatever the original form, by breaking the events down for encoding into a succession of binary events and delivers successive bits of the code string.

5. Simulation Results

The proposed algorithm based on 2D DWT, SOFM and Arithmetic Coding has been implemented using MATLAB-7.02 and the proposed algorithm has been simulated on various grayscale images of size 256x256 with 8 bits per pixel over a PC with Intel Dual-Core, 2.9 GHz and 512 MB RAM under Windows-XP operating system. The 'Lena' and 'Woman' images are used for training the initial set and codebook design. The performance of the proposed technique is tested for images 'Einstein' and 'Couple', which are outside the training sequence, as well as for image 'Lena' and 'Woman'. The performance is measured for various codebook sizes of 2^n where n is the integer varying from 5 to 8, and then compression efficiency is measured in terms of Compression Ratio (CR) which is defined as :

$$CR = \frac{\left(\left(no.\ of\ pixels\ in\ a\ 4\times 4\ block\right)\times\left(No.\ of\ bits\ per\ pixel\ in\ the\ original\ image\right)\right)}{bits\ required\ representing\ each\ codebook\ index} \quad ....(3)$$

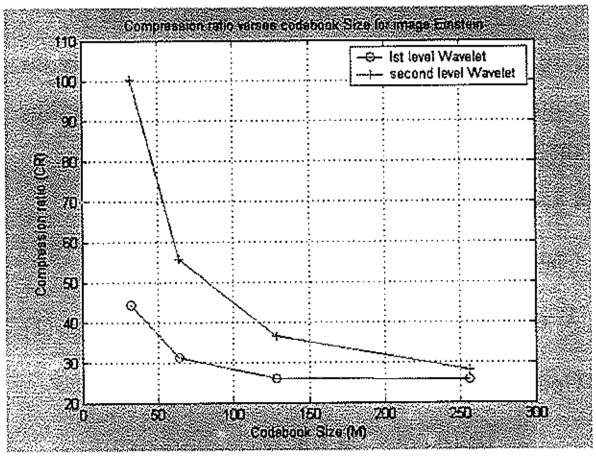
$$CR = \frac{16\times 8}{n} \quad ..(4)$$

Where n=log2k and k is the codebook size. The quality of the decoded image is measured in terms of Peak-Signal-to-Noise-Ratio (PSNR) which is defined as:

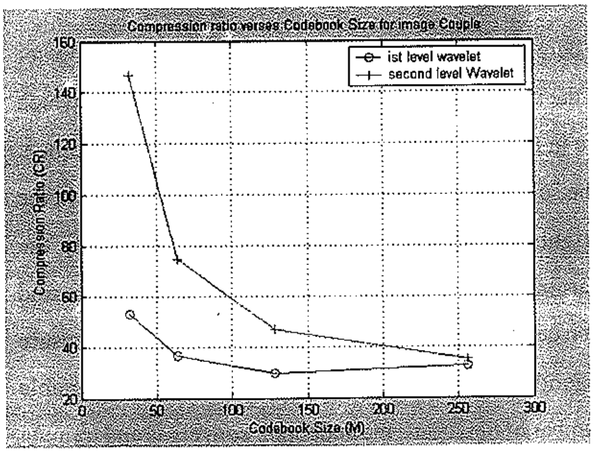
$$PSNR = 10\log_{10}\left\{\frac{255^2}{\frac{1}{MN}\sum_{j=0}^{M-1}\sum_{i=0}^{N-1}\left(f_1(i,j)-f_2(i,j)\right)^2}\right\} \quad ..(5)$$

Where NxM is the image size, $f_1\ (i, j)$ is the random field of the original field intensities and $f_2\ (i, j)$ denotes the random field of the reconstructed image intensities.

Fig. 4 shows the variation of compression ratio (CR) with codebook size 'M' for 'Einstein' and 'Couple' images for first and second level DWT. It has been observed from Fig. 4(b) that for 'Couple' image (which is one of the test images in the present investigation) the compression ratio varies from 32.4 to 52.99 for first level DWT and 34.97 to 146.69 for second level DWT at various codebook sizes. The high compression ratio for this image can be explained by observing its histogram, shown in Fig.5 (b). It is clear that there are lesser number of grey levels and larger number of black pixels in the image. This can also be ascribed from the fact that the mean and the variance of image 'Couple' (0.1505 and 38.38 respectively) are less than the mean and variance of Einstein (Fig. 5), thus resulting in an increased Compression ratio. The variation of Peak Signal to Noise Ratio with the Codebook size for first and second level DWT is shown in Fig. 6 for all test images under consideration. It can be observed that as the codebook size increases, the objective quality of images increases, however, the compression ratio decreases. It has also been observed that PSNR value is the highest for the 'Couple' image. Further, it is seen that the efficiency of compression increases as we go to the higher level decomposition. The variation of PSNR verses Compression Ratio for all the three images is shown in Fig. 7. Moreover, the subjective qualities of the representative reconstructed images are shown in Figs. 8 and 9.



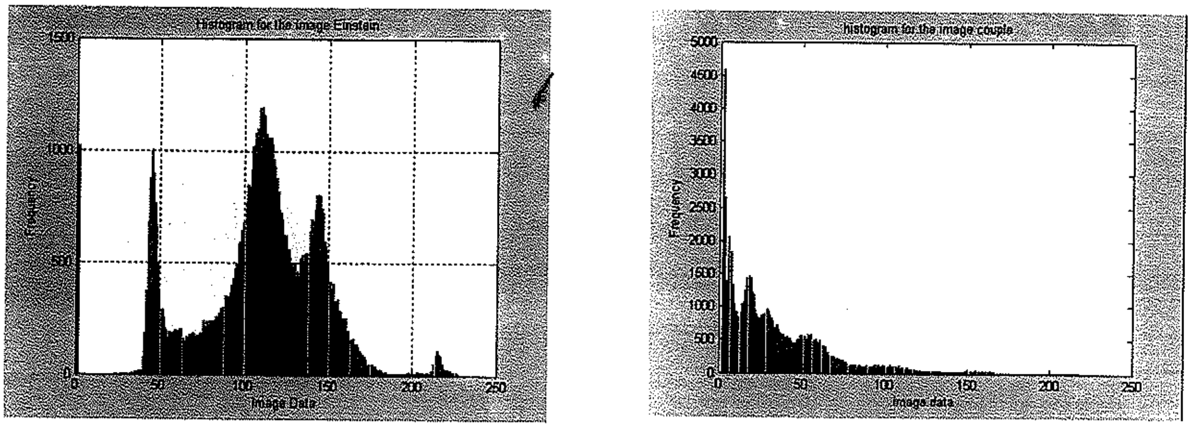
(a)



(b)

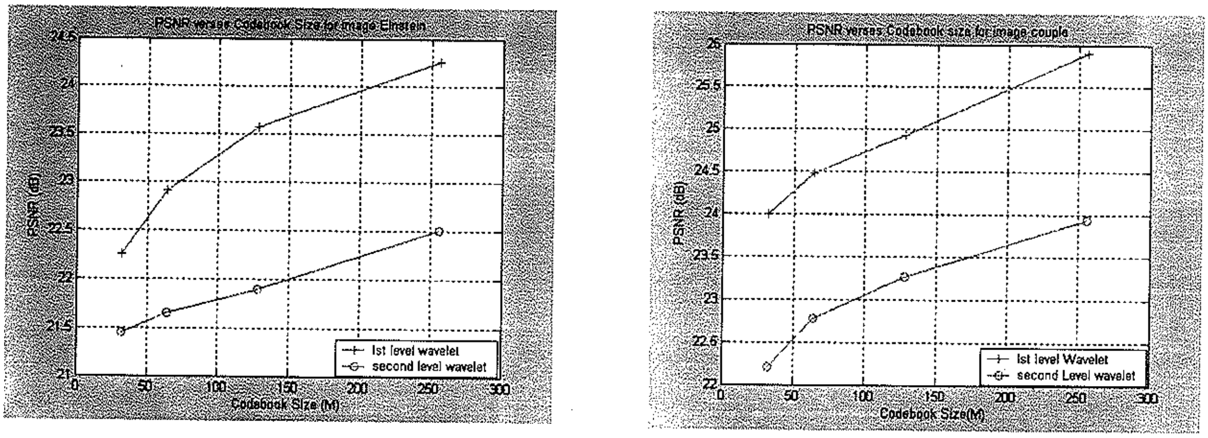
Figure 4 : Variation Of The Compression Ratio With Respect To Codebook Size For First And Second Level 2D DWT for (a) Einstein and (b) Couple

Mean=0.45	Mean = 0.150
Variance=115.89	Variance=38.38



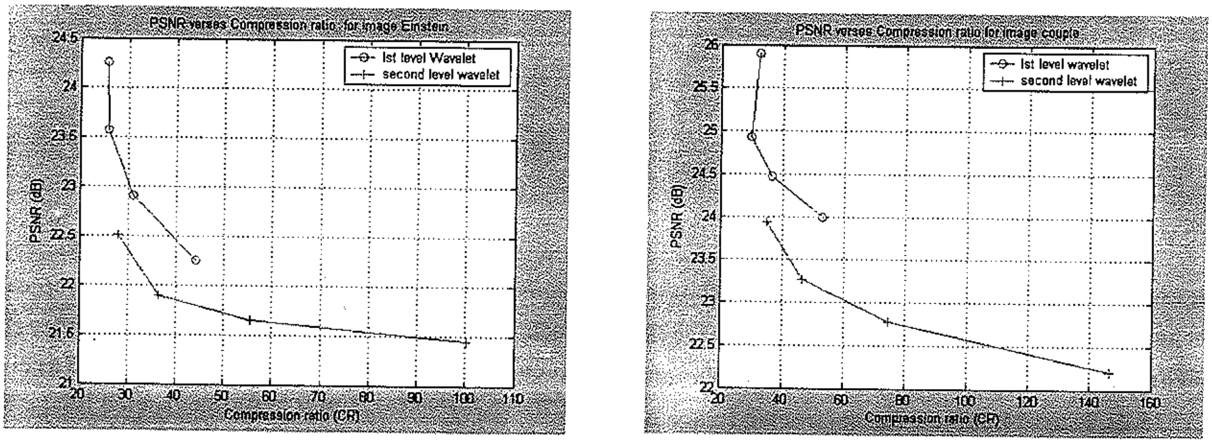
(a) (b)

Figure 5: Histograms of Images used (A) Einstein and (B) Couple



(a) (b)

Figure 6 ; Variation of PSNR with respect to Codebook Size (M) for (a) Einstein and (b) Couple

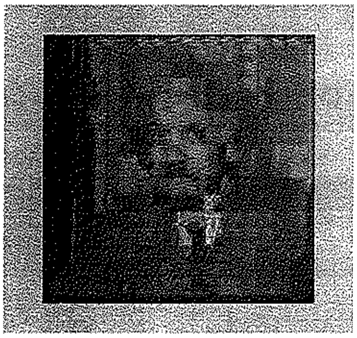


(a) (b)

Figure 7 : Variation of PSNR with respect to Compression Ratio for first and second level DWT For Images (a) Einstein And (d) Couple

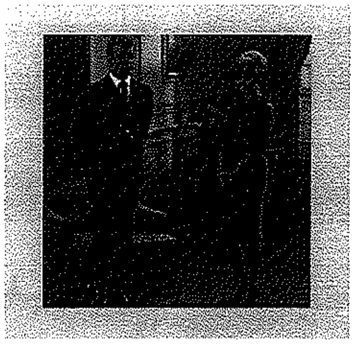
(A)

(B)

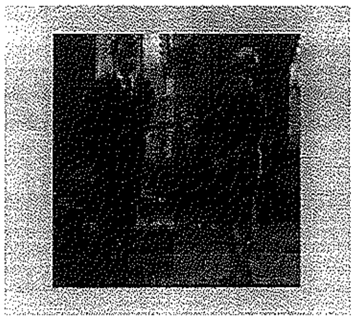


(C)

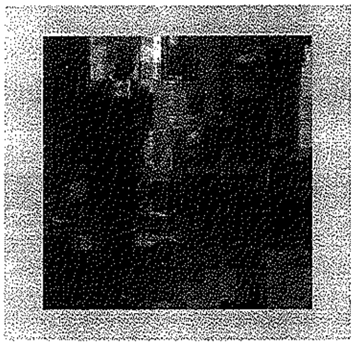
Figure 8 : Image Reconstruction Using The Proposed Technique For Image Einstein (A) Original Image (B) Reconstructed Image By First Level Wavelet (Cr=25.73, Psnr=24.26) (C) Reconstructed Image By Second Level Wavelet (Cr=27.99, Psnr=22.51)



(a)



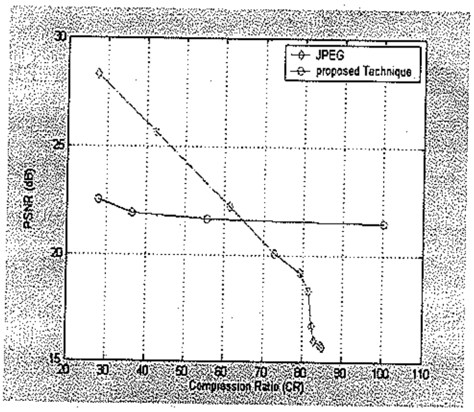
(b)



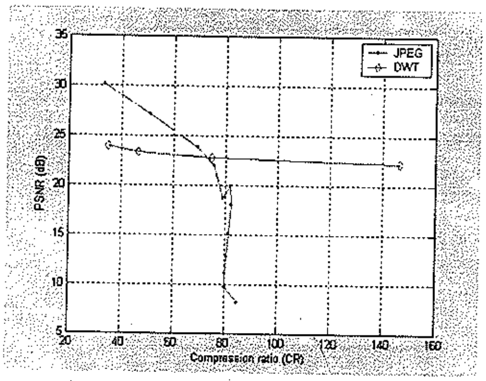
(c)

Figure 9: Image Reconstruction Using The Proposed Technique For Image Couple (A) Original Image (B) Reconstructed Image By First Level Wavelet (CR=32.4, PSNR=25.9) (C) Reconstructed Image By Second Level Wavelet (CR=34.97, PSNR=23.94)

The performance of the proposed technique of image compression is compared with the performance by using JPEG standard as shown in Fig. 12. For the JPEG compression 8x8 default quantization matrix is used. It is observed from the figure that there is degradation in the PSNR at higher Compression Ratio by using the proposed image compression technique. The degradation is however ascribed to using two lossy techniques in the proposed image compression scheme. The proposed scheme will thus be preferred for image compression applications where a high Compression Ratio is of prime importance and a consequent degradation in image quality is acceptable.



(a) Einstein



(b) Couple

Figure 10 : Performance Comparison Of Proposed Image Compression Technique (Using First Level DWT) With That Of The JPEG For Images (A) Einstein And (B) Couple

6. Conclusion

The proposed Image Compression technique has been tested for various grayscale images. The performance of the proposed scheme has been investigated using the first and second level wavelet. Subjective quality of the reconstructed images and the value of PSNR as obtained for various standard images using the proposed scheme for image compression have been found to yield satisfactory results. The performance of the proposed scheme has also been compared with that of the JPEG standard. It has been observed that the proposed technique outperforms the JPEG for lower PSNR at higher Compression ratios (of around 65) is ascribing to using two lossy techniques in the proposed image compression scheme. The proposed technique will thus be preferred for image compression applications where a high Compression Ratio is of prime importance and a consequent degradation in the image quality is acceptable.

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