PERFORMANCE ANALYSIS OF LOSSLESS COMPRESSION TECHNIQUES TO INVESTIGATE THE OPTIMUM IMAGE COMPRESSION TECHNIQUE

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Abstract

The amount of data associated with visual information is so large that its storage require large memory. Image data compression techniques are mainly concerned with reduction of the number of bits required to store the image and to achieve a faster data transmission. It is evident that the aim of compression is to reduce the storage memory size, but in some applications like medical imaging, military and astronomic data analysis, image quality is the main constraint which is to be preserved. There exist various lossy and lossless compression techniques in the literature providing high compression ratio at the cost of image quality. In this paper a new transform technique called Burrow Wheeler Transform (BWT) is proposed. BWT was originally developed for text data compression and in this paper, it is extended to the 2D image data compression and anlysed for various input images.

In this paper, a comparison is made between the compression techniques: DCT, DWT and proposed BWT. The performance analysis of each technique is made by comparing with performance metrics: PSNR (Peak Signal to Noise Ratio), Mean Square Error (MSE), Memory and Compression Ratio (CR). Each technique is analyzed by applying three different input images. From the results it is observed that, BWT provides high PSNR for all the three input images. Using BWT technique the quality of the reconstructed image is very high compared to DCT and DWT. It is observed that BWT not only gives the good image quality, but also reduces the memory space largely similar to that of DWT and DCT. Therefore it can be concluded that, Burrows-Wheeler transform best suits and can yield better results for compression applications where image quality is to preserved with reduced memory.

1. Introduction

In data compression, the main idea is to convert the original data into a new data form, which contains the same information but can use a smaller space for storing the data. This is very important for saving expensive data storage space and for achieving a faster data transmission ratio. Data compression techniques can be divided into lossless and lossy compression techniques.

In lossless image compression methods, when the images have been compressed with some specific methods, the original images can be reconstructed from the compressed images without losing any information, that is

$$f(x, y) = f^{\wedge}(x, y), \quad (1)$$

Where $f(x, y)$ denotes the original image and $f^{\wedge}(x, y)$ is the reconstructed image. Lossless compression methods are also known as reversible because of this lossless feature. The transform techniques comes under lossless compression.

In lossy compression, images cannot be reconstructed exactly to their original form, that is

$$f(x, y) \neq f^{\wedge}(x, y) \quad (2)$$

Lossy image compression methods will always yield some loss of information and thus provides high compression ratio.

There are many different transform methods for image compression; however, in this paper the Discrete Cosine Transform (DCT), Discrete Wavelet Transform (DWT) and Burrow Wheeler Transform (BWT) methods are utilized. Transform based compression techniques use a reversible linear mathematical transform to map the pixel values onto a set of coefficients which are then quantized and encoded.

2. Discrete Cosine Transform (DCT)

Discrete cosine transform (DCT) is one of the most commonly used transformation techniques in image compression. DCT converts the spatial image representation into frequency components. Low frequency components appear at the topmost left corner of the block that contains maximum information of the image.

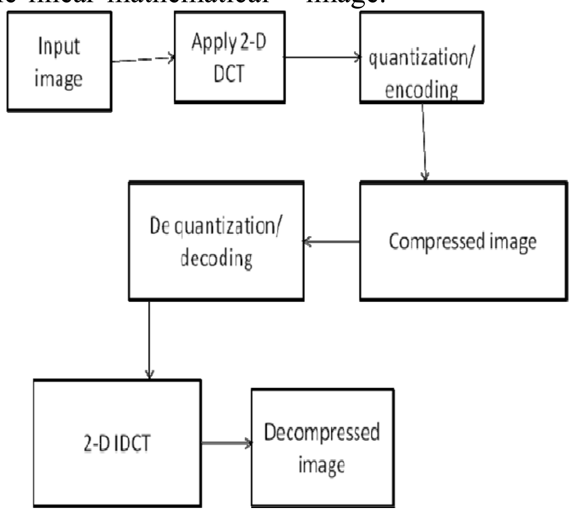

Figure: 1 Architecture of DCT

DCT Compression includes the following steps:

(a) In DCT, the image is divided into blocks of pixels, typically 8□8 blocks.

(b) The forward 2-dimensional DCT is to be applied on 8□8 block image and is given by

$$F(u,v) = \frac{1}{4} C(u)C(v) \sum_{x=0}^{7} \sum_{y=0}^{7} f(x,y) \cos\left(\frac{(2i+1)u\pi}{16}\right) \cos\left(\frac{(2j+1)v\pi}{16}\right) \quad (3)$$

F(u,v) is the transformed DCT coefficient and f(x,y) is the pixel value of original 8□8 pixels block. The forward DCT concentrates the energy on low frequency elements, which are located in the top-left corner of the sub image.

(c) Now the 64 DCT coefficients are ready for quantization. Each of the DCT coefficient $F(u,v)$ are divided by the *JPEG* quantization table $Q(u,v)$, and then rounded to the nearest integer.

$$F_q(u,v) = \frac{F(u,v)}{Q(u,v)} \quad (4)$$

DCT transformation is said to be near-lossless, because Equation 4 is already rounded to the nearest integer.

Equation (5) is inverse discrete cosine transform (IDCT) for decoding the compressed image

$$\hat{f}(x,y) = \frac{1}{4} C(u)C(v) \sum_{u=0}^{7} \sum_{v=0}^{7} F(u,v) \cos\left(\frac{(2i+1)u\pi}{16}\right) \cos\left(\frac{(2j+1)v\pi}{16}\right) \quad (5)$$

where $C(u)C(v) = \begin{cases} \frac{1}{\sqrt{2}} & u,v = 0 \\ 1 & otherwise \end{cases}$

$\hat{f}(x,y)$ is the reconstructed image. The difference of original image and reconstructed image is given by

$$e(x, y) = \hat{f}(x, y) - f(x, y)$$

3. Discrete Wavelet Transform (DWT)

The Wavelet transform provides us with both the time and frequency information of the signal or image. The Discrete Wavelet Transform (DWT) is based on sub band coding. In sub band coding, an image is decomposed into a set of band limited components, called sub bands, which can be reassembled to reconstruct the original image without error. Each subband is generated by band pass filtering the input. Since the bandwidth of the resulting subbands is smaller than that of the original image, the subbands can be down sampled without loss of information. Reconstruction of the original image is accomplished by up sampling, filtering, and summing the individual subbands.

Digital image is represented as a two-dimensional array of coefficients, each coefficient representing the brightness level in that point. Most natural images have smooth color variations, with fine details being represented as sharp edges in between the smooth variation. Technically, the smooth variations in images can be termed as low frequency variations and the sharp variations as high frequency variations. The low frequency components (smooth variation) constitute the base of the image and the high frequency components (the edges which give the details) add upon them to refine the image thereby giving the detailed image. Hence, the smooth variations are more important than the details.

DWT transforms a discrete time signal into a discrete wavelet representation by splitting frequency band of image in difference subbands. In 2- dimensional DWT, it is first necessary to apply 1-dimensional DWT in each row of the image before applying one-dimensional column-wise to produce the final result [6]. Four subband images named as *LL, LH, HL* and *HH,* are created from the original image. LL is the subband containing lowest frequency, which is located in the top left corner of the image and other three are subbands with higher frequencies. In a 2-dimensional image signal in wavelet transform, it is containing one *scaling function*, $\varphi(x, y)$, and three 2-dimensional *wavelet* $\psi h\ (x, y)$, $\psi V\ (x, y)$, $\psi d(x,y)$ are required.

Each is a product of a one-dimensional scaling functionand corresponding wavelet [4]. The definition of scaling function is defined as

$$\varphi(x, y)= \varphi(x)+ \varphi(y) \qquad (6)$$

There are three different basic functions of the wavelet: is for the horizontal, for the vertical and for the diagonal subband. Wavelets are defined as

$$\begin{aligned} \psi h\ (x, y) &= \psi(x)+ \varphi(y) \\ \psi V(x,y) &= \varphi(x)+\psi(y) \\ \psi d(x,y) &= \psi(x)+ \psi(y) \end{aligned} \qquad (7)$$

Figure 2 shows four quarter-size output subimages, which are denoted as , ψh , ψV , ψd , and $W\varphi$

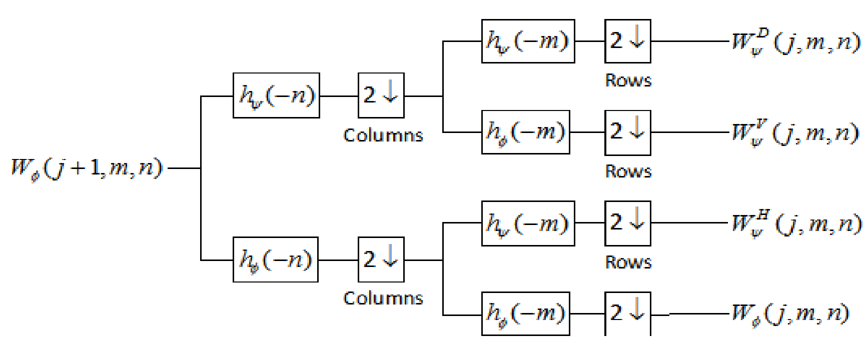

Fig.2 Discrete Wavelet Transform

The top-left corner sub image is almost the same as the original image, due to the energy of an image being usually distributed around the lower band. A top-left corner subimage is called the approximation and others are the details. The 1-level decomposition has four subimages, where the most important sub-image in located at top-left corner of the image. For the 2-level

decomposition, the final image consists of seven sub images. Figure 3 shows the block diagram of DWT
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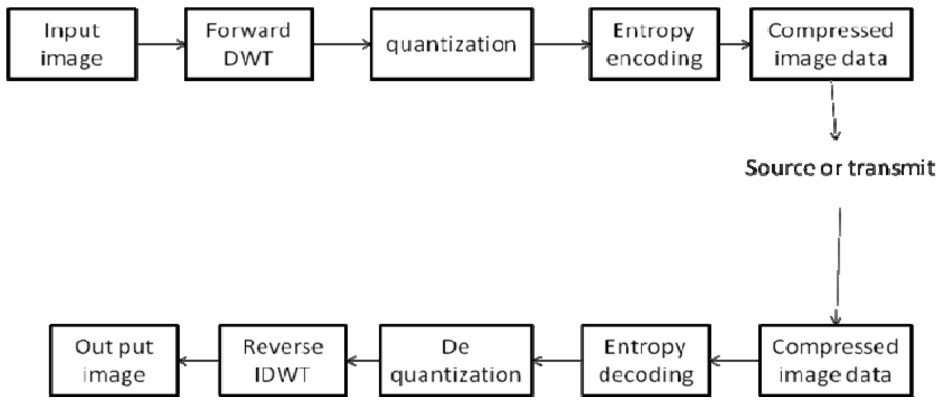


Fig.3 Block diagram of DWT

4. Proposed Burrows - Wheeler Compression Technique

The Burrows-Wheeler transform is based on the block-sorting lossless data compression algorithm. The BWT transforms a block of data into a form, which is easier to compress. One-dimensional sequences of pixels are obtained by path scanning; two-dimensional transformed image is converted into a one-dimensional sequence of pixels by using zigzag, Hilbert path filling or raster scanning methods. The Burrows-Wheeler transformation is then applied for the sequence and transforms it to an easier form for compression.

Sequence of steps in BWT are:

Apply DCT.

Perform the quantization procedure.

Instead of assigning the Huffman codes to each DC value and each pair of zeros' length, assign a number to each of them.

Process the above numbers by the Burrows-Wheeler transform.

Process the output by Move-to-front procedure and Run-length coding.

Finally, compress by Arithmetic coding.

The concept of this technique is performing the DCT and the quantization as they are done in the original JPEG algorithm. Then, we take the run-length scheme of JPEG including the zigzag order, but instead of giving variable length codes as in Huffman coding, we give fixed length codes. These fixed length codes are the input of the Burrow-Wheeler compression. The suggested algorithm is depicted in Figure 4.

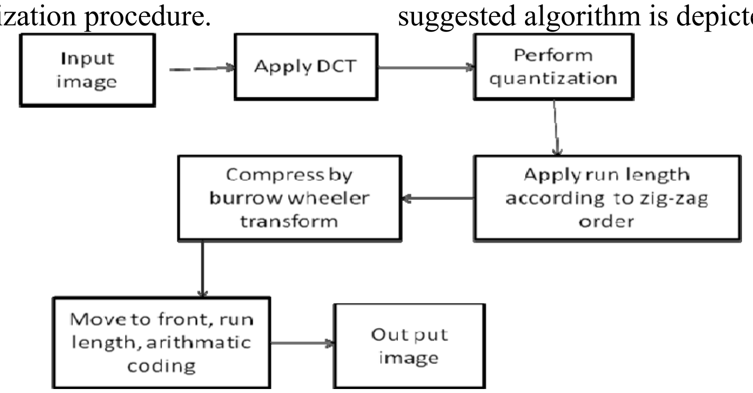
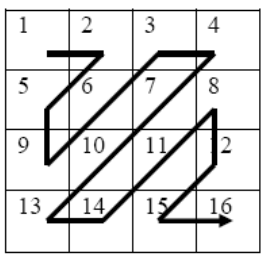


Figure: 4 Block diagram of proposed BWT Compression technique

The Burrows Wheeler Transform is an algorithm that takes a block of data and rearranges it using a sorting algorithm. The resulting output block contains exactly the same data elements that it started with, differing only in their ordering. The transformation is reversible meaning original ordering of the data can be restored with no loss of fidelity. Compression is based upon two quite different transformations, a forward transformation, which permutes the input data into a form which is easily compressed, and a reverse transformation, which recovers original input from the permuted data. The BWT is performed on entire block of data at once.

Zig-Zag scan: Zig-Zag scans the image along the anti-diagonals beginning with the top-most anti-diagonal. Each anti-diagonal is scanned from the left top corner to the right bottom corner [6]. The result of the 2-dimentional image using a zig-zag scan yields a coefficient ordering sequence which is .

ZigZag =(1,2,5,9,6,3,4,7,10,13,14,11,8,12,15,16)



The ***move-to-front transform*** **(MTF)** is an encoding of data designed to improve performance of entropy encoding techniques of compression. The move-to-front is a process that is usually used after Burrows-Wheeler transformation to ranking the symbols according to their relative frequency. After processing MTF, the sequence is as long as the original sequence because it does not compress the original sequence. The main idea is to achieve a better compression performance in entropy coding.

The **run-length encoding (RLE)** is a simple compression technique, which can be used either before or after the BWT to reduce the number of runs in data sequence. RLE is more efficient when the sequence includes much data that is duplicated. The main idea of RLE is to count the runs that are repeated in the input data and replace the pixels with a different number of repetitions.

5. Performance Evaluation Metrics

Digital image compression techniques are examined with various metrics. Among those, the most important one is Peak Signal to Noise Ratio (PSNR) which gives the information about image quality. There is another parameter which expresses the quality, is Mean Square Error (MSE). The other important metric is Compression Ratio (CR), which express the amount of compression embedded in the technique.

(a) Mean Square Error (MSE) = $\frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}\left\| f(i,j) - f^{\wedge}(i,j)\right\|^2$

(b) Peak Signal to Noise Ratio (PSNR) = $10\log_{10}\left(\frac{Max^2}{MSE}\right)$

(c) Compression ratio (CR): $= \frac{Original\ \ image\ \ size}{Compressed\ \ image\ \ size}$

6. Results and Discussion

In this paper, algorithms are developed for the three image compression techniques: Proposed Burrow wheeler transforms (BWT), discrete cosine transforms (DCT), and discrete wavelet transforms (DWT). In this paper we applied different input images to compression techniques. Various parameters are calculated such as Peak Signal to Noise Ratio (PSNR), Mean Square Error (MSE), and compression ratio. The algorithm for each compression technique is implemented using MATLAB. The performance comparison of compression techniques is made with respect to the parameters PSNR, MSE, Compression ratio and size of the output image

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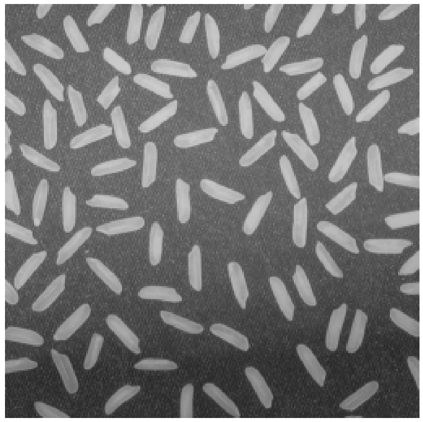

Fig.5

Fig. 5 is the input image ‘rice.jpg’ given as input to the three compression techniques.

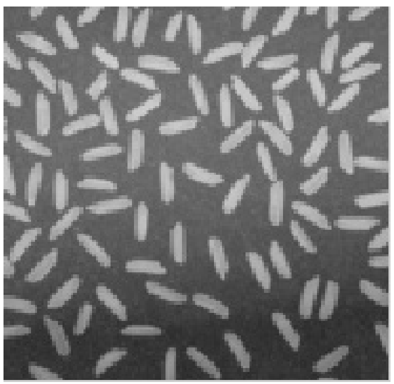

Fig. 5a Reconstructed image using IDCT

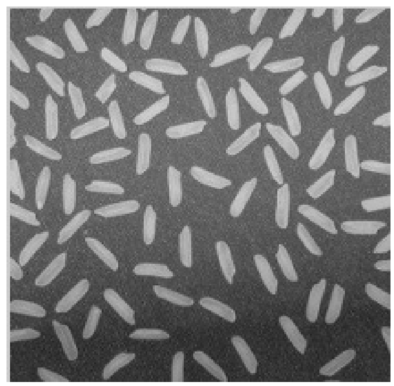

Fig. 5b Reconstructed image using IDWT

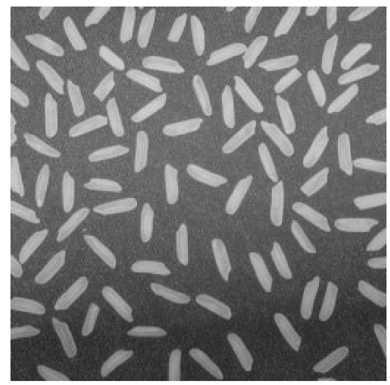

Fig. 5c Reconstructed image using BWT

The three techniques DCT, DWT & BWT are compared with respect to the parameters such as Peak Signal to Noise Ratio (PSNR), Mean Square Error (MSE), Compression ratio (CR). These parameters are calculated and tabulated in table 1

Parameters	DCT	DWT	BWT
PSNR	89.2359	85.0362	92.3554
MSE	0.06	0.04	0.02
Size of reconstructed image	23.6 kb	17.1 kb	16.9 kb
Compression Ratio	1.822	2.068	3.569

Table 1 Comparison of DCT, DWT, and BWT for the input image ‘rice.jpg’

From Table 1 it is observed that the PSNR of BWT is 92.3554 which is high when compared to the other two transform techniques. It is also observed that the size of the reconstructed image using BWT is small among the three techniques

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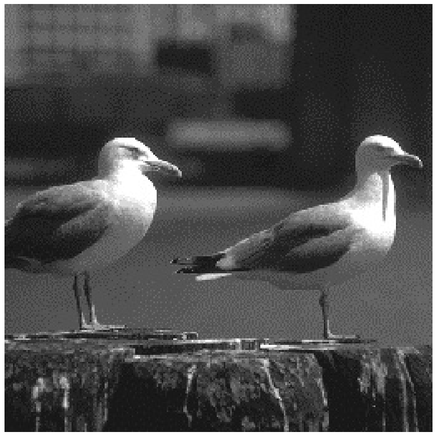

Fig.6

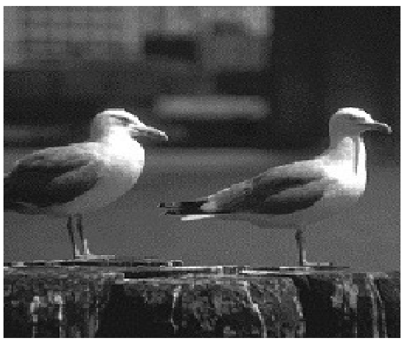

Fig. 6a Reconstructed image using IDCT

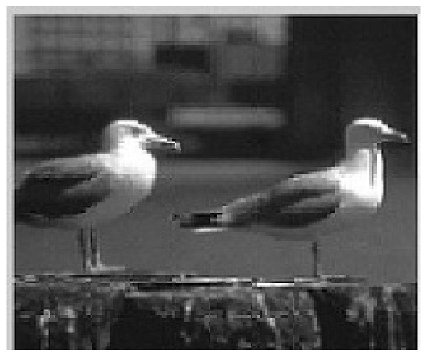

Fig. 6b Reconstructed image using IDWT

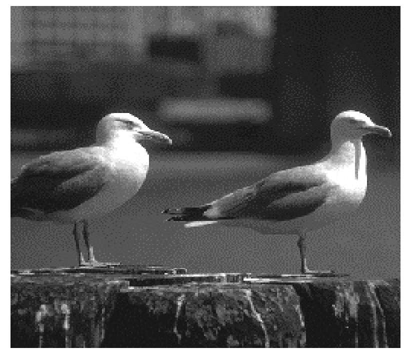

Fig. 6c Reconstructed image using BWT

Fig. 6 is the input image 'birds.jpg' given as input to the three compression techniques. As discussed earlier, the three compression techniques are compared with the parameters PSNR, MSE & compression ratio and are tabulated in table 2

.

Parameters	DCT	DWT	BWT
PSNR	60.813	59.1216	108.030
MSE	0.05	0.0802	0.02
Size of reconstructed image	11.6 kb	13.0 kb	14.6 kb
Compression Ratio	5.0927	4.4911	3.5396

Table 2: Comparisons of DCT, DWT& BWT for the input image 'birds.jpg'

From the Table 2, it is observed that the PSNR of BWT is 108.030 from the table it is observed that the PSNR of BWT is high when compared to the other transform techniques. When compared to the other transform techniques DCT reduces the large memory size. There is no much difference between the memory size of the output images of DCT, DWT and BWT.

Fig.7

The Figure 7 is the 'lena.jpg' giving as an input to the three transform techniques. The above shown figure is taken as input to the different transform techniques.

Fig. 7a Reconstructed image using IDCT

Fig. 7b Reconstructed image using IDWT

Fig. 7c Reconstructed image using BWT

Parameters	DCT	DWT	BWT
PSNR	71.0948	95.0404	109.4811
MSE	0.08	0.06	0.05
Size	12.1 kb	16.4 kb	14.5 kb
Compression Ratio	4.391	3.852	2.689

Table 3: Comparisons of DCT, DWT & BWT for the input image 'lena.jpg'

From the Table 3 it is observed that the PSNR of BWT is 109.4811 from the table it is observed that the BWT of PSNR is high when compared to the other transform technique. When compared to the other transform techniques DCT reduces the large memory size. There is no large difference between the memory size of the output images of DCT, DWT and BWT. High quality images are very important for some implementations such as astronomic data or military data. In such cases BWT considering optimum compression technique can yield better results.

Conclusions

In this paper, a comparison is made between the compression techniques: DCT, DWT and proposed BWT. The performance analysis of each technique is made by applying three different input images. From the results it is observed that, BWT provides high PSNR for all the three input images. Therefore using BWT technique the quality of the reconstructed image is very high compared to DCT and DWT. It is observed that BWT not only gives the good image quality, but also reduces the memory space largely. Though the aim of compression is to reduce the storage memory size, in some applications like medical imaging, military and astronomic data analysis, the quality of the images is the main constraint. Therefore in such applications it can be concluded that Burrows-Wheeler transform is suitable and can yield better results.

References

[1] R. C. Gonzalez and R. E. Woods, Digital Image Processing, 2nd edition., Pearson Education, 2002.

[2] M. Mozammel Hoque Chowdhury and Amina Khatun, " Image Compression Using Discrete Wavelet Transform", IJCSI International Journal of Computer Science, Vol. 9, Issue 4, No 1, July 2012.

[3] S. Bhavani, K. Thanushkodi, "A Survey on Coding Algorithms in Medical Image Compression", International Journal on Computer Science and Engineering, Vol. 02, No. 05, pp. 1429-1434, 2010.

[4] Donald Adjerob, Timothy Bell and Amar Mukherjee, The Burrows-Wheeler Transform: Data Compression, Suffix Arrays, and Pattern matching, *Springer, New York, 2008*.

[5] Dipti Bhatnagar, Sumit Budhiraja, "Image Compression using DCT based Compressive Sensing and Vector Quantization", IJCA, Vol 50 (20), pp.34-38, July 2012.

[6] V.S. Vora, Prof. A.C. Suthar, Y.N.Makwana and S.J.David, "Analysis of Compression Image Quality Assessments", International journal of Advanced Engineering and Applications, January 2010.