International Journal of Electrical, Electronics and Mechanical Controls
A Scientific and Scholarly Resource for Publication of Research Manuscripts

http://www.ijeemc.com

Volume 1 Issue 1 November 2012

IMAGE COMPRESSION: AN OVERVIEW

K. Ranjeet[a] *and B.R.C. Reddy*[b]

PDPM Indian Institute of Information Technology, Design and Manufacturing Jabalpur

Jabalpur (M.P.), India-482005

ranjeet281@gmail.com[a]   brcreddy.mtech@gmail.com[b]

ABSTRACT

A marked progress has been made in the field of image compression and its application in various branches of engineering. Image compression is associated with removing redundant information of image data. It is a solution which associated with storage and data transmission problem of huge amounts of data for digital image. Image transmission application includes broadcast television, remote sensing via satellite and other long distance communication systems. Image storage is required for several purposes like document, medical images, magnetic resonance imaging (MRI) and radiology, motion pictures etc. All such applications are based on image compression. In this paper, therefore presents a research overview of image compression, its techniques with its future scenario.

Keywords: Compression, Image processing, Encoding, Transform *etc*.

1. INTRODUCTION

Image compression is an application of data compression on digital image. In early stage of research data compression involves in 1838 for use in telegraphy, it is 'Morse code' a first approach for data compression [1]. Modern work of data compression was started in the late 1940 with the development of information theory. In this field, the first systematic way for assigning codeword based on probability of data block was presented by Shannon and Fano in 1949. Later on, Huffman has developed an optimal method for assigning codeword in 1951 [1]. Originally image compression was started at 1970; basically it is obtained by mathematical transformations and quantization with encoding techniques. In the 1980 several compression schemes were developed, further these schemes are splitted according two different properties: lossless compression and lossy compression. In lossless compression, the reconstructed image after compression is numerically identical to the original image. While in case of lossy compression, the reconstructed image is not numerically identical to the original image. . There are several techniques where are used in image compression such as: Karhuen-loeve Transform (KLT), Hadmard Transform (HT), Fourier Transform (FT), Discrete Linear Transform (DLT), Block Truncation Coding (BTC) algorithm, Arithmetic coding, Non-uniform sampling, Adaptive vector quantization, Least mean square (LMS) adaptive algorithm, Discrete Cosine Transform (DCT), variable block size segmentation, spatial prediction, optimal prediction, adaptive lifting, Discrete Wavelet Transform (DWT). In last two decade, there is compression standards are introduced such as: Joint Picture Experts Group (JPEG) and Joint Picture Experts Group-2000 (JPEG-2000), which are extremely used for image compression.

The earlier techniques when are based on transformation and encoding techniques gave better performance in term of good compression and minimum rms error for compressed data [2]. Bit rate reduction was further improved in block truncation coding. This technique uses one bit nonparametric quantizer over local region of image [3,4]. In the earlier time analog signals are more common, here using sampling approach possible to convert analog to digital signal. A digital encoded data is suitable to further encoding schemes such as run length encoding (RLE) or entropy coding [5]. Image compression basically started with quantization (scalar and vector), which has rejected spatial redundancy of digital image data [6,7]. Further introduces several algorithms based on prediction encoding, block segmentation of image for data compression. Here, prediction encoding schemes adopt different method such as LMS algorithms, which are uses adaptive prediction filter for image source encoding [8]. There are spatial and optimal prediction compression schemes are used, when apply predictive compression on image data there is implicit assumption that the image is scanned in particular order of image blocks [9,10,11]. Where block size segmentation provide high quality variable-rate image is achieved by segmenting an image into different block size, this is perform as a lossless compression [12, 13,14]. Recently in area of image data compression DCT and DWT based compression area more popular, both are gave good compression using different encoding schemes [15].

2. BASICS OF IMAGE DATA COMPRESSION TECHNIQUE

Image data compression is classified into two different ways according to properties: lossless and lossy data compression.

2.1. LOSSLESS DATA COMPRESSION

Lossless data compression methods are: Run-length coding, Entropy encoding; Block truncation coding, Arithmetic coding.

2.1.1. Run-length coding

Run length coding is a simple form of data compression in which runs of data are stored as a single data value and count, rather than as the original run [16,17]. In binary images or Black-and-White images pixel value is 0 or 1. Here 0 values for black pixel and 1 values for white pixel. Let us a code of image: WWWWWBBBWWWWWWWWBBWWWWWWWWBBBWWBBWBWWWBBBB
After applying Run-length coding, coded image is 5W3B8W2B8W3B2W2B1W1B3W4B.
The run-length code represents the original 42 characters in only 24. Hence compressed value of particular image code stream can be achieved with help of RLE.

2.1.3. Entropy Encoding

Entropy encoding is a lossless data compression scheme; it is created and assigns a prefix code to each unique symbol that occurs in the input. These entropy encoders then compress data by replacing each fixed-length input symbol by the corresponding variable-length codeword. The length of each codeword is approximately proportional to the negative logarithm of the probability. Therefore, the most common symbols use the shortest codes [18]. According to Shannon's source coding theorem, the optimal code length for a symbol is $-log_bP$ where *b* is the number of symbols used to make output codes and *P* is the probability of the input symbol. Two of the most common entropy encoding techniques is Huffman coding and arithmetic coding.

2.1.4. Block Truncation Coding

In case of image compression, consider a data sequence of *m* nonnegative real numbers x_1, $x_{2.,}$ $_{..}x_m$, for the positive integer n^{th} sample moment by X^n , i.e. X^2, Let the output levels of the moment preserving quantizer be denoted by a_n and b_n, and suppose q_n samples are quantized to b_n.

Then the first and second sample moments and the sample variance are, respectively

$$X^n = \frac{1}{m}\sum_{i=1}^{m} x_i \tag{1}$$

$$X^2 = \frac{1}{m}\sum_{i=1}^{m} x_i^2 \tag{2}$$

$$\sigma^2 = X^2 - (X)^2 \tag{3}$$

As with the design of any one bit quantizer, we find a threshold, X_{th}, and two output levels, *a* and *b* such that

If $X_i \geq X_{th}$ output = *b*

If $X_i < X_{th}$ output = *a,* For *i*= 1,2,….,m.

For our first quintizer, we set $X_{th} = X$, this reasonable assumption will be modified to improve performance. The output levels *a* and *b* is found by solving the following equation:

Let *q* = number of X_i 's greater than $X_{th}(=X)$. Then to preserve X and X^2

$$mX = (m-q)a + qb \tag{4}$$

and $$mX^2 = (m-q)a^2 + qb^2 \tag{5}$$

where, $a = X - \sigma[q/(m-q)]^{1/2}$ and $b = X + \sigma[(m-q)/q]^{1/2}$ (6)

Each block is then described y the values of X, σ and $n \times n$ bit plane consisting of 1's and 0's indicating whether pixels are above or below X_{th}. Assigning 8 bit each to X and σ results in a data rate of 2 bit/pixel. The receiver reconstructs the image block by calculating *a* and *b* and assigning these values to pixels in accordance with the code in bit plane. The most noticeable improvement of the reconstructed picture is a little raggedness of sharp edge. Because the calculations are relatively simple and the storage of data small, BTC is fairly easy to implement [3,4].

2.1.5. Arithmetic Coding

Arithmetic coding was introduced by Rissanen, where the last symbol encoded and decoded first [20]. The number of operation required to encode each symbol with a fixed precision arithmetic unit is the same independent of the length of the string. Thus, the numbers of operations to encode a string grow linearly with its length.

2.2. LOSSY DATA COPMRESSION

Lossy image data compression scheme are give great amount of compression. Here compressed image may be differing to original image due to some data loss. Lossy compression obtained by transformation methods and quantization of image signal. There are following scheme for lossy compression:

2.2.1. Transform coding

Transform coding scheme in image data compression is lossy compression scheme. Here mathematical transform apply on the image signal, it's divided a signal into sub-spaces and discarded some redundant data. The remaining information can be compressed via a variety of method. When the output is decoded, the result may not be identical to the original input that's we called this scheme of data compression is lossy scheme. There are following transformation scheme in image compression:

(a) Karhunen Loeve Transform

The KL transform becomes the optimal transform where it is based on the statistical properties of the image. It is possible to select a matrix T, for a given vector *X* such that the output *Y* has pair-wise uncorrelated components i.e. $Y = TX$. This transformation matrix is called the KL transform or the Hotteling transform [2,20].

Let $R_x = E\left[XX^t\right]$ denotes the autocorrelation matrix of the input (column) vector *X* with eigenvectors U_i and λ_i, *i* = 1,2,3, . . . , k, the corresponding eigenvalues. Since any autocorrelation matrix is symmetric and nonnegative definite, there are k orthogonal eigenvectors and the corresponding eigenvalues are real and nonnegative. It is assumed for convenience in notation that the eigenvalues have been arranged in descending order.

So that, $\lambda_1 \geq \lambda_2 \geq ..... \geq \lambda_k \geq 0$.

The KLT transformation matrix is defined as: where *U* is a K-dimensional vector and the superscript [t] denotes vector transpose. Then, the autocorrelation matrix of *Y* will be given by:

$$R_y = E\left[YY^t\right] = U' R_x U = \begin{pmatrix} \lambda_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \lambda_k \end{pmatrix} \tag{7}$$

We can reconstruct *X* from only the M eigenvectors corresponding to the largest M eigenvalues of R_x then, we get $\hat{X}$ as an approximation of *X*, i.e.

$$\hat{X} = T'_m Y$$

(8)

The MSE between *X* and $\hat{X}$ would be:

$$MSE = \sum_{i=1}^{k} \lambda_i - \sum_{j=1}^{m} \lambda_j = \sum_{j=m+1}^{k} \lambda_j \tag{9}$$

(b) Discrete Cosine Transform

DCT is the most recent know transform in the image compression field because of its excellent properties of energy compaction [20,21]. The image to be transformed is divided into square blocks each block consist of $n \times n$ pixels, and each block is transformed into $n \times n$ DCT coefficient.

Discrete cosine transform is:

$$F(u) = \frac{2c(u)}{n} \sum_{j=0}^{n-1} f(j) \cos \frac{(2j+1)u\pi}{2 \times n} \tag{10}$$

Where, u= 0, 1,…., n-1.

For the inverse transformation the following one dimensional IDCT is applied two times.

$$f(j) = \sum_{u=0}^{n-1} c(u) F(u) \cos \frac{(2j+1)u\pi}{2 \times n} \tag{11}$$

where j= *0, 1, …., n.*

After apply DCT on the image we get DCT coefficients for image, non-integer DCT coefficients are quantized to integers. Generally the values of most DCT coefficients are zero or nearly zero. That means there are some information loss, it occurs only in the process of coefficient quantization [22,23]. In the last decade JPEG image compression standard introduced based on DCT [24,25].

(c) Discrete wavelet Transform

JPEG/DCT based compression has the drawbacks of blockiness and aliasing distortion in the reconstructed image at low bit rates [26]. Wavelet transform has become popular in image and video applications since the basis function match the human visual characteristics [27]. Wavelet coding techniques result in subjectively pleasing image due to the absence of blocking effect and aliasing distortion, its introduce a new standard for image compression JPEG2000 [28.29.30].

International Journal of Electrical, Electronics and Mechanical Controls
A Scientific and Scholarly Resource for Publication of Research Manuscripts

http://www.ijeemc.com

Volume 1 Issue 1 November 2012

In wavelet-based image coding, the choice of wavelets is crucial and determines the coding performance and reconstructed image quality [31,32,33]. Any decomposition of an image into wavelets involves a pair of waveform: one to represent the high frequencies corresponding to the detailed part of an image (wavelet function ψ) and one for the low frequencies or smooth parts of an image (scaling function ϕ) [34,35].

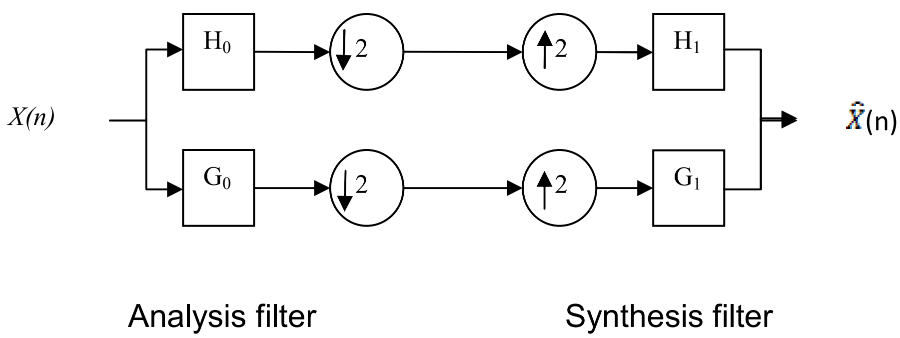

Fig. 1 2-band wavelet analysis and synthesis filter.

Where, *X(n):* input image and $\hat{X}(n)$: reconstructed image.

H_0 and H_1 is Detail coefficients of image;

G_0 and G_1 is approximation coefficients of image.

The DWT of a signal *x* is calculated by passing it through a series of filter [35,36]. First time sample are passed through a Low-pass filter with impulse response *g* resulting in a convolution of two:

$$y(n) = (x * g)[n] = \sum_{k=-\infty}^{\infty} x[k]\,g[n-k] \tag{12}$$

The signal is also decomposed simultaneously using a High-pass filter *h.* The output gives the Detail coefficients (from the high-pass filter) and approximation coefficients (from the low-pass filter). Therefore:

$$y_{low}[n] = \sum_{k=-\infty}^{\infty} x[k]\,g[2n-k] \tag{13}$$

International Journal of Electrical, Electronics and Mechanical Controls

A Scientific and Scholarly Resource for Publication of Research Manuscripts

http://www.ijeemc.com

Volume 1 Issue 1 November 2012

And $$y_{high}[n] = \sum_{k=-\infty}^{\infty} x[k]h[2n+1-k] \quad . \tag{14}$$

Where, LL (low-pass filter): approximation coefficients and HL,LH,HH (high-pass filter): vertical detail, diagonal detail, horizontal detail coefficients of image in decomposition structure.

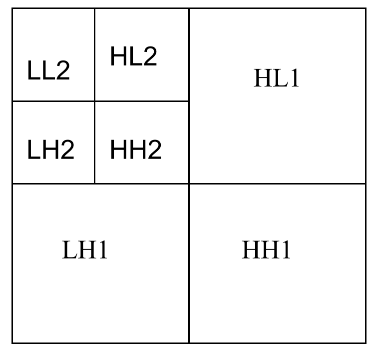

Fig.2 Structure of wavelet decomposition.

2.2.1.1. Steps of Transformation for Image compression

For image compression, input image is transformed and then set the threshold and coded by Entropy coder. Let *f(x,y)* be a $N \times N$ matrix representing the gray levels of an image.

(a) The image *f(x,y)* is subdivided into non-overlapping $M \times M$ blocks.

(b) The Transformed is applied to each block of image (for DWT the image is treated as one block).

(c) The transformation coefficients values less than a given threshold are set to zero. The threshold takes a percentage of the minimum and maximum coefficient values throughout the whole block coefficients.

(d) Apply an entropy coding technique.

(e) The reconstructed image *F(x,y)* is compared to the original image to get the compressed image.

International Journal of Electrical, Electronics and Mechanical Controls

A Scientific and Scholarly Resource for Publication of Research Manuscripts

http://www.ijeemc.com

Volume 1 Issue 1 November 2012

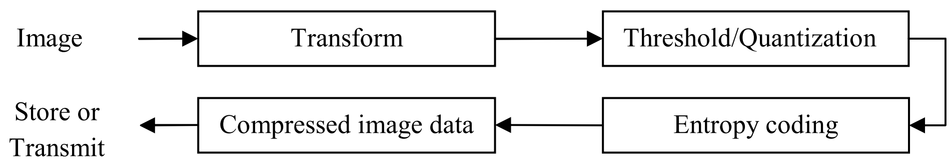

Fig.3 Block diagram for image compression

The peak signal to noise ratio [PSNR] and the compression ratio [CR] are calculated. Peak signal-to-noise ratio (***PSNR***) is define as,

PSNR [dB] = $10\log\left(\frac{x_{\max}^{2}}{MSE}\right)$, X_{max} = 255 for gray scale image

and, MSE= $\frac{1}{N\times N}\sum_{x=0}^{N-1}\sum_{y=0}^{N-1}\left[f(x,y)-F(x,y)\right]^{2}$

The compression ratio (***CR***) is defined as,

CR = $\frac{\text{Original image size}}{\text{Compressedd image size}}$

2.2.2. Fractal Compression Technique

Fractal technique is used for encoding/decoding images, it is based on the collage theorem and fixed point theorem [22,37] for a local iterated function system consisting of a set of contraction affine transformation. A fractal compression algorithm first partitions an image into non-overlapping $n\times n$ blocks, called range block and form a domain pool containing all of possibly overlapped $n\times n$ blocks, associated with 8 isometries from reflections and rotation, called domain block. For each range block, it exhaustively searches, in a domain pool, for a best matched domain block with the minimum square error after a contractive affine transform is applied to the domain block. A fractal compressed code for a range block consists of quantized contractivity coefficients in the affine transform, an offset which is the mean of pixel gray levels in the range block, the position of the best matched domain block and its type of isometry. The decoding is to find the fixed point, the decoded image, by starting with any initial image. The procedure

International Journal of Electrical, Electronics and Mechanical Controls

A Scientific and Scholarly Resource for Publication of Research Manuscripts

http://www.ijeemc.com

Volume 1 Issue 1 November 2012

applies a compressed local affine transform on the domain block corresponding to the position of a range block until all of the decoded range blocks are obtained.

2.2.3. Vector Quantization Compression

The basic idea of VQ for image compression is to establish a code consisting of code-vectors such

that each codevector can represent a group of image blocks of size $m \times m$, (m=4 is always used)[7,37]. An image or a set of image is first partitioned into $m \times m$ non-overlapping block which are represented as m^2-tipple vectors, called training vectors. The size of training vectors can be very large. The goal of codebook design is to establish a few representative vectors, called codevector size, from a set of training vectors. The encoding procedure is to look for a closest codevector in the codebook for each non-overlapped $m \times m$ block of an image to be encoded.

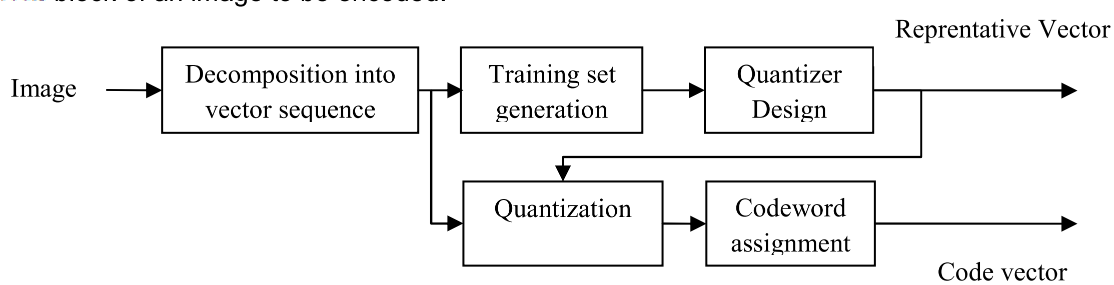

Fig.4 Vector Quantization coding process.

3. COMPARISION OF IMAGE DATA COMPRESSION TECHNIQUE

Image compression is area of data compression which is associated with remove redundant data. Data compression is spitted over on its properties: lossless and lossy. These technique deals with data compression as a two stage process in that an efficient coding machine can be realized only through accurate modeling of the input data [38]. Early information theory approaches to these problems resulted in the use of variable length codes based on a symbol probability table such as in Huffman coding and

Shannon-Fano coding techniques. These techniques find their greatest utility in the signal processing areas of digitized image and audio data**.** JPEG, JPEG2000, FRACTAL etc are several lossy data compression standards [39,40,41,42,43]. Compared feature of data compression standards are following:

(i). Data compression rate of lossless compression are generally small ranging from 1:1 for uncompressed data to 1:3.

(ii). Lossy compression rate ranging from 1:5 to 1:30 using standard techniques (e.g. JPEG) and up to 1:300 using new technique/standards (e.g. JPEG2000/DWT, Fractal compression). Lossy compression technique is based on two-dimensional transform, followed by quantization and encoding stage. The loss of information is introduced by the quantization stage which intentionally rejects less relevant part of the image information.

(iii). Some Adapted techniques which achieve high compression rate exist for artificial images. These technique are based on run length coding, something followed by an entropy coder.

(iv). JPEG image compression are based on DCT, JPEG2000 image compression are based on DWT. Both are lossy compression technique, but in case of JPEG2000 it's lossless also, her we use for lossless compression Daub 5/3 transform and for lossy its Daub 9/7.

(v). Wavelet-based coding provides substantial improvement in image compression in term of Quality at higher compression ratio over DCT –based compression.

(vi). All compression technique are more effective on artificial images as compare to natural image, gives the high compression ratio.

3. PRESENT & FUTURE TREND OF IMAGE COMPRESSION

Image compression is comes from information theory, where we rejected the redundant data. Today image compression is centered in lossy and lossless both of compression techniques according to its application. For Medical image, remote sensing imaging or other important image we use generally lossless technique. At present time in image compression stream wavelet-based 2-D image compression technique are popular. DWT is used with different algorithm, Quantization technique and encoding techniques (e.g. SHIHT, EZW algorithms; linear, uniform quantization; Huffman, Shannon-fano encoding etc.).

Future of image compression is progressive for 2-D image and its goes on 3-D image compression [44,45] also. For 3-D image compression as well as video compression used Three-dimensional mathematical Transforms [45] with encoding techniques. In future image compression centered high compression ratio with quality improvement.

4. CONCLUSION

Image data compression in previous two decade achieves substantial progress. It's done using different quantization methods, Entropy coding and mathematical transformation. In overview study, every new approach gives better performance compare to previous methods. There are two standards introduced in image data compression: JPEG and JPEG2000, where both perform as lossless or lossy image compression respect to different algorithms. Image compression used at different images like medical images, natural image, artificial images and satellite image etc. basically data compression most applicable when we need to transmit or store a huge amount of data. At present time image compression around at different transformation and coding techniques, we discussed already compression techniques. In future Data compression more emphasis on feature preserve as well as compression rate. Image compression now around to two-dimensional images but in future comes to tree-dimensional image also. New approaches are being proposed for progressive work in term of feature preserve with compression rate for image data compression.

5. REFERENCES

1. Stephen Wolfram, *A New Kind of Science* (Wolfram Media, 2002), page 1069.
2. Robert M. Harlick and K.Shanmugam, "Comparative Study of a Discrete Linear Basis for Image Data Compression" IEEE Transactions on Systems, Man and Cybernetics; Vol. SMC-4, No.1, January 1974.
3. Edward J. Delp and O.R.Mitchell, "Image Compression Using Truncation Coding" IEEE Transactions on Communication, Vol.COM-27, No.9, September 1979.
4. D. R. Halverson, N.C. Griswold and G.L. Wise, "A Generalized Block Truncation Coding Algorithm for Image Compression" IEEE Transaction on Acoustics, Speech and Signal Processing, Vol. ASSP-32, No.3, June 1984.

International Journal of Electrical, Electronics and Mechanical Controls

A Scientific and Scholarly Resource for Publication of Research Manuscripts

http://www.ijeemc.com

Volume 1 Issue 1 November 2012

5. Jon W. Mark and Terence D. Todd, “A Nonuniform Sampling Approach to Data Compression” IEEE Transaction on Communication, Vol. COM-29, No.1, January 1981.
6. P. Boucher and M. Goldberg, “Color Image Compression by Adaptive Vector Quantization” IEEE Transaction, 1984.
7. M. Goldberg, Paul R. Boucher and S. Shlien, “Image Compression Using Adaptive Vector Quantization” IEEE Transaction on Communications, Vol.COM-34, No.2, June 1986.
8. S.T. Alexander and A. Rajala, “Image compression Results the LMS Adaptive Algorithm” IEEE Transaction on Acoustics, Speech and Signal Processing, Vol. ASSP-33, No.3, June 1985.
9. E. Feig and H. Peterson, V. Ratnakar, “Image Compression Using Spatial Prediction”, IEEE transactions 1995.
10. N. D. Memon, K. Sayood and S. S. Magliveras, “Lossless Image Compression with a Codebook of Block Scans”, IEEE Journal on selected areas in Communication, Vol.13, No.1, January 1995.
11. N. V. Boulgouris, D. Tzovaras and M. G. Strintzis, “Lossless Image Compression Based on Optimal Prediction, Adaptive Lifting, and Conditional Arithmetic Coding”, IEEE Transactions on Image Processing, Vol.10, No.1, January 2001.
12. N. Ranganathan, S.G. Romaniuk and K.R. Namuduri, “A Lossless Image Compression Algorithm Using Variable Block Size Segmentation”, IEEE Transaction, 1994.
13. N. Ranganathan, S. G. Romainiuk and K. R. Namuduri, “A Lossless Image Compression Algorithm Using Variable Block Size Segmentation”, IEEE Transactions on Image Processing, Vol.4, No.10, October 1995.
14. J. Vaisey and A. Gersho, “Image Compression with Variable Block Size Segmentation”, IEEE Transactions on Signal Processing, Vol.40, No.8, August 1992.
15. Z. Xiong, K. Ramchandran, M. T. Orchard, and Ya-Qin Zhang; “A Comperative Study of DCT-and Wavelet-Based Image Coding”, IEEE Transactions on Circuits and System for Video Technology, Vol.9, No.5, August 1999.
16. W. Berghorn, T. Boskamp, M. Lang and Heinz-Otto Peitgen, “Fast Variable Run-Length Coding for Embedded Progressive Wavelet-Based Image Compression”, IEEE Transactions on Image Processing, Vol.10, No.12, December 2001.
17. S. Arazaki, M. Saigusa, S. Hashiguchi, M. Ohki, M. Uchiyama and Fumiyoshi Itoh, “Image Data Compression by DCT with Adaptive Run-Length Coding” IEEE Transaction on consumer electronics, Vol.37, No.4, November 1991.
18. Myung-Sin Song “Entropy Encoding in Wavelet Image Compression”, Department of Mathematics and Statistics, Southern Illinois University Edwardsville.
19. Glen G. Langdon member IEEE and J. Rissanen, “Compression of Black-White Images with Arithmetic coding” IEEE Transactions on Communication, Vol.COM-29, No.6, June 1981.

20. A.S. Ragab, Abdalla S.A. Mohmed, M.S. Hamid, “Efficiency of Analytical Transforms for Image Compression” 15th National Radio Science Conference, Feb.24-26, 1998, Cairo- Egypt.
21. Norman B. Nill, “A Visual Model Weighted Cosine Transform for Image Compression and Quality Assessment” IEEE Transaction on Communications, Vol.COM-33, No.6, June 1985.
22. Y. Zhao and B.Yuan, “Image Compression using Fractals and Discrete Cosine Transform”, Vol.30, No.6, Electronics Letters 17th March 1994.
23. K. A.Birney and T. R. Fischer, “On the Modeling of DCT and Subband Image for Data Compression”, IEEE Transactions on Image Processing, Vol.4, No.2, February 1995.
24. G. Langdon, A. Gulati and Ed Seiler, “On the JPEG Model for Lossless Image Compression”, IEEE Transactions, 1992.
25. G. Wallace. “Overview of the JPEG (ISO/CCITT) still image compression standard”, Proc. SPIE (Image Processing Algorithms and Techniques), 1244:220-233, 1990.
26. Z. Xiong, K. Ramchandran, M. T. Orchard, and Ya-Qin Zhang; “A Comperative Study of DCT-and Wavelet-Based Image Coding”, IEEE Transactions on Circuits and System for Video Technology, Vol.9, No.5, August 1999.
27. S. G. Mallat, “A Theory for Multiresolution Signal Decomposition: The Wavelet Representation” IEEE Transaction on Pattern Analysis and Machine Intelligence, Vol.11, No.7, July 1989.
28. A. Skodras, Ch. Christopoulos, and T. Ebrahimi, “The JPEG-2000 Still Image Compression Standard”, IEEE Signal Processing Magazine, September 2001.
29. S. Lawson and J. Zhu, “Image compression using wavelets and JPEG2000: a tutorial, “IEEE Electronics & Communication Engineering Journal, June 2002.
30. M. Rabbani and R. Joshi, “An overview of the JPEG2000 still image compression standard”, Signal Processing: Image Communication 17 (2002) 3–48, Elsevier.
31. P. P. Gandhi, “On Wavelet-Based Multiresolution Image Compression”, IEEE Transaction, 1994.
32. S. Grgic, K. Kers and M Grgic, “Image Compression Using Wavelet”, IEEE Transactions, ISIE’99- Bled, Slovenia.
33. R.H.G. Tan, J.F. Zhang, R. Morgan and A. Greenwood, “Still Image Compression Based on 2-D Discrete Wavelet Transform”, IEEE Electronics letters, Vol.35 No.22, 28 October 1999.
34. A.S. Lewis and G.Knowles, “Image Compression using the 2-D Wavelet Transform”, IEEE Transaction on Image Processing, Vol.1, No.2. April 1992.
35. Z. Ye, Z. Guotian and Yu Hengchun, “Wavelet Transform and its Application in Image Compression”, IEEE Tencon’93/Beijing, 1993.
36. M.K. Mandal, S. Panchanathan and T.Aboulnasar, “Wavelet for Image Compression” IEEE Transactions, 1994.

37. Chaur-Chin Chen, "On the Selection of Image Compression Algorithms", Department of Computer Science, National Tsing Hua University, Hsinchu 300, Taiwan.
38. D. J. Jackson and S. J. Hannah, "Comparative Analysis of Image Compression Techniques", IEEE Transaction, 1993.
39. S. Grgic, M. Grgic and B. Zovko-Cihlar, "Perfomance Analysis of Image Compression Using Wavelets", IEEE Transaction on Industrial Electronics, Vol.48, No.3, Jun 2001.
40. H. G. Lalgudi, A. Bilgin, Michael W. Marcellin, and Mariappan S. Nadar, "Compression of Multidimensinal Image Using JPEG200", IEEE Signal Processing Letters, vol.15, 2008.
41. M.G. Albanesi and S.Bertoluzza, "Human Vision Model and Wavelet for High-Quality Image Compression", IEEE Transactions Image Processing and its application, 4-6 July 1995.
42. A. Averbuch, D. Lazer and M. Israeli, "Image Compression Using Wavelet Transform and Multiresolution Decomposition", IEEE Transaction on Image Processing, Vol.5, No.1 January 1996.
43. Shih-Chung B. Lo, H. Li and M. T. Freedman, "Optimization of Wavelet Decomposition for Image Compression and Feature Preservation", IEEE Transactions on Medical Imaging, Vol.22, No.9, September 2003.
44. V. Sanchez, R. Abugharbieh and P. Nasiopoulos, "Symmetry-Based Scalable Lossless Compression of 3-D Medical Image Data", IEEE Transactions on Medical Imaging, Vol.28.No.7, July 2009.
45. A. Das, A. Hazra and S. Banerjee, "A Efficient Architecture for 3-D Discrete Wavelet Transform", IEEE Transactions on Circuits and Systems for Video Technology, Vol.20, No.2, February 2010.