Volume 1, No. 4, November 2010
Journal of Global Research in Computer Science
ISSN-2229-371X
RESEARCH PAPER
Available Online at www.jgrcs.info

PERFORMANCE ANALYSIS OF LOSSY COMPRESSION ALGORITHMS FOR MEDICAL IMAGES

Dr. V. Radha*[1] and Pushpalakshmi[2]

*[1]Professor, Department of Computer Science
Avinashilingam Deemed University for Women, Coimbatore, India.
radharesearch@yahoo.com
[2]Research Scholar
Avinashilingam Deemed University for Women, Coimbatore, India.
mppuspalakshmi@gmail.com

Abstract: Image compression addresses the problem of reducing the amount of data required to present a digital image with acceptable image quality. The underlying basis of the reduction process is the removal of redundant data. Medical image compression plays a key role as healthcare industry move towards filmless imaging and goes completely digital. The problem of medical image compression is a continuing research field and most of the researches being proposed concentrate either on developing a new technique or enhance the existing techniques. The medical community has been reluctant to adopt lossless methods for image compression. The main goal has been to produce an exact replica of the original image, suffering high file size. Only recently, attention to use lossy image compression, which maximizes compression while maintaining clinical relevance data, has been probed. Four solutions to answer the above problem statement have been selected, namely, Block Truncation Coding (BTC), Discrete Cosine Transformation (DCT), Discrete Wavelet Transformation (DWT) and Singular Value Decomposition (SVD) were selected because of their predominant place in general image processing field. Various experiments were conducted to analyze the performance of the four image compression models on medical image compression.

Keywords*:* Medical Image Compression, Block Truncation code, Discrete Cosine Transformation, Discrete Wavelet Transformation Singular Value Decomposition, Lossy Compression.

INTRODUCTION

The development of modern equipments and communication devices in healthcare industry has made it possible to take specialty healthcare to the rural and remote population of a country. The future of healthcare industry is shaped by teleradiology and technologies such as telemedicine [1]. Patient information, which may include patient details, treatment history, images of previous tests, etc., plays an important role in these technologies. In particular, image data acquired from various medical equipments like X-Ray, CT, MRI, etc. is increasingly transmitted through World Wide Web, telephone, mobile, WANs, etc. All these systems face two common problems, high storage requirement and image quality.

A solution proposed in such situation is 'image compression', which is defined as a technique that involves methods to reduce the size of the image data files while retaining necessary important information [2]. It is an area which has found use in several applications like the Internet, photography and medical industry. Many works have been proposed in the area of photographic image compression, compound image compression, graphics, etc., but when it comes to medical images, a compression requirement varies and therefore the amount of work proposed reduces significantly.

In general, the medical community uses lossless compression techniques, where the image quality is an exact replica of the original image. These techniques produce good image quality but suffer from huge file size. Only recently, attention to use lossy image compression to maximizes compression while maintaining clinical relevance data has been probed. In this paper, four solutions are compared on their applicability to medical images and the technique that best suits medical image compression is identified. The techniques selected are Block Truncation Coding (BTC), Discrete Cosine Transformation (DCT), Discrete Wavelet Transformation (DWT) and Singular Value Decomposition (SVD). These techniques were selected because of their predominant place in general image processing field.

The paper is organized as below: Section 1 provided a brief introduction to the topic. Section 2 gives an overview of the related reviews in this area. Section 3 discusses the methodology behind each technique, while Section 4 presents the result of various experiments conducted. Section 5 concludes and summarizes the work with future research directions.

REVIEW OF LITRATURE

This section reviews work related to medical image compression.

Lossy compression approach for medical images started to gain popularity in medical domain only after 2000. The classical examples of popular lossy compression algorithms are Joint Photographic Expert Group (JPEG) [3] and a more recent standard JPEG2000 [4]. These algorithms are based on Discrete Cosine Transformation (DCT) for JPEG and Discrete Wavelet Transform (DWT) [5] for JPEG2000. Lossy predictive coding is also used for the near-lossless compression when the degree of imposed degradation is limited. Lossy predictive coding assumes that the prediction error is not encoded precisely but quantized, thereby causing minor errors when the image sample is reconstructed. This technique is used in JPEG-LS near-lossless mode, for example.

Another approach for lossy compression is, instead of transforming the whole image, to separately apply the same transformation to the regions of interest in which the image could be divided according to a predetermined characteristic.

One important such characteristic of medical images is texture. More specifically, texture analysis of these images can lead to very significant results concerning real tissue motion and thus, can result in improved diagnosis [6]. The goal of such a lossy compression methodology that aims at maximization of the overall compression ratio is to compress each region separately with its own compression ratio, depending on its textural significance, so as to preserve textural characteristics.

With regard to clinically relevant region encoding, not much has been published. In 1994, [7] made use of regions of interest using subband analysis and synthesis orvolumetric datasets using wavelets. They followed up this work in [8] by using structure preserving adaptive quantisation methods as a means of improving quality for compression rates in the regions of interest. But all of their effort was on lossy approaches. Storm and Cosman [9] developed a region based coding approach. They discussed two approaches: one uses different compression methods in each region such as 'contour-texture' coding and subband decomposition coding, and the other uses the same compression method in each region such as the discrete cosine transform but with varying compression quality in each region such as by using different quantisation tables. They used two multiresolution coding schemes: wavelet zerotree coding and the S-transform, and considered only 8 bit images. In their implementation, the regions of interest were selected manually.

COMPRESSION TECHNIQUES

Four techniques are selected for testing its applicability in medical image compression domain. They are (i) Block Truncation Coding (BTC) (ii) Discrete Cosine Transformation (DCT) (iii) Discrete Wavelet Transformation (DWT) and (iv) Singular Value Decomposition (SVD). The working is explained in the following sections.

A. BTC

Block Truncation Coding (BTC) is a lossy moment preserving quantization method for compressing digital gray-level images. Its advantages are simplicity, fault tolerance, the relatively high compression efficiency and good image quality of the decoded image. The BTC algorithm is a lossy fixed length compression method that uses a Q level quantizer to quantize a local region of the image. The quantizer levels are chosen such that a number of the moments of a local region in the image are preserved in the quantized output. In its simplest form, the objective of BTC is to preserve the sample mean and sample standard deviation of a grayscale image. Additional constraints can be added to preserve higher order moments. For this reason BTC is called as a block adaptive moment preserving quantizer. The principle used by the block truncation coding (BTC) method and its variants is to quantize pixels in an image while preserving the first two or three statistical moments. The algorithm begins by dividing an image into blocks (4×4 or 8×8 pixels). Assuming that a block contains n pixels with intensities p_1 through p_n, the first two moments are the mean and variance, can be calculated using Equations (1) and (2), from which the standard deviation of the block can be calculated (Equation 3).

$$\bar{p} = \frac{1}{n}\sum_{i=1}^{n} p_i \quad (1)$$

$$\overline{p^2} = \frac{1}{n}\sum_{i=1}^{n} p_i^2 \quad (2)$$

$$\sigma = \sqrt{\overline{p^2} - \bar{p}} \quad (3)$$

The principle of the quantization is to select three values, a threshold p_{thr}, a high value p^+, and a low value p^-. Each pixel is replaced by either p^+ or p^-, such that the first two moments of the new pixels (i.e., their mean and variance) will be identical to the original moments of the pixel block. The rule of quantization is that a pixel p_i is quantized to p^+ if it is greater than the threshold, and is quantized to p^- if it is less than the threshold (if p_i equals the threshold, it can be quantized to either value). Thus,

$$p_i \leftarrow \begin{cases} p^+ & \text{if } p_i \geq p_{thr} \\ p^- & \text{if } p_i > p_{thr} \end{cases} \quad (4)$$

Intuitively, it is clear that the mean $\bar{p}$ is a good choice for the threshold. The high and low values can be determined by writing equations that preserve the first two moments, and solving them. The number of pixels in the current block that are greater than or equal to the threshold is denoted by n+. Similarly, n^- stands for the number of pixels that are smaller than the threshold. The sum $n^+ + n^-$ equal the number of pixels n in the block. Once the mean $\bar{p}$ has been computed, both n^+ and n^- are easy to calculate. Preserving the first two moments is expressed by the two equations

$$n\bar{p} = n^- p^- - n^+ p^+, n\overline{p^2} = n^-(p^-)^2 - n^+(p^+)^2 \ldots\ldots \quad (5)$$

And the solutions are

$$p^- = \bar{p} - \sigma\sqrt{\frac{n^+}{n^-}}, \quad p^+ = \bar{p} + \sigma\sqrt{\frac{n^-}{n^+}} \quad (6)$$

As these solutions are generally real numbers, they are rounded to the nearest integer, which implies that the mean and variance of the quantized block may be somewhat different from those of the original block. The solutions located on the two sides of the mean $\bar{p}$ at distances are proportional to the standard deviation σ of the pixel block.

B. DCT

The Discrete Cosine Transform (DCT) is a mathematical transformation technique that is used to convert a spatial representation of data into a frequency representation. A data in the frequency domain contains the same information as that in the spatial domain. The order of values obtained by applying the DCT is coincidentally from lowest to highest frequency. This feature and the psychological observation that the human eye and ear are less sensitive to recognizing the higher-order frequencies leads to the possibility of compressing a spatial signal by transforming it to the frequency domain and dropping high-order values and keeping low-order ones. When reconstructing the data and transforming it back to the spatial domain, the results are remarkably similar to the original signal. The DCT method can be used to compress both color and gray scale images. DCT is a method is most frequently used in several areas including WWW, industries, etc. and this popularity has made the author choose DCT as a format to be analyzed and compared.

The block diagram of the DCT image compressor is shown in Figure 1 and the step by step procedure is given below.

1. The image is divided into 8 x 8 blocks of pixels.
2. Working from left to right, top to bottom, apply DCT to each block.
3. Compress each block through a process called quantization
4. The resulting array of blocks that constitute the image is highly compressed and occupy very small amount of space.
5. When desired, the image can be reconstructed through Inverse Discrete Cosine Transform (IDCT), which is a reverse process of compression.

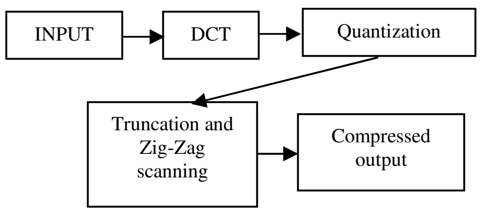

Figure 1. Block Diagram of DCT Compression

C. *DWT*

The wide spread attention on digital image compression has attracted the attention of several researchers and academicians, leading to the standardization of various digital image compression algorithms for different types of images and applications. Existing techniques, despite having the advantages like simplicity and satisfactory performance, are not without shortcomings. The major disadvantage is the "blocking artifacts" produced due to the fixed block size limitation (Thakur and Kakde, 2007). This disadvantage can be overcome by using a concept called wavelets, introduced 20 years ago, which yields a multiscale decomposition and can be efficiently coded (Welland, 2003). Over the past several years, the wavelet transform has gained widespread acceptance in signal processing in general and in image compression research on particular.

In general, there are three essential stages in a wavelet transform-based image compression system: transformation, quantization, and lossless entropy coding. Figure 2 depicts the encoding and decoding processes. The only different part in the decoding process is that the de-quantization takes place and it is followed by an inverse transform in order to approximate the original image. The purpose of transformation stage is to convert the image into a transformed domain in which correlation and entropy can be lower and the energy can be concentrated in a small part of the transformed image.

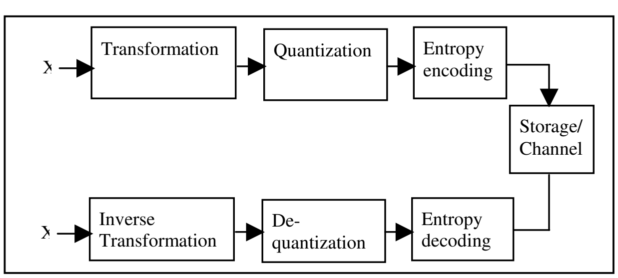

Figure 2. Block diagram of DWT based Compression Scheme

Quantization stage results in loss of data because it reduces the number of bits of the transform coefficients. Coefficients that do not make significant contributions to the total energy or visual appearance of the image are represented with a small number of bits or discarded while the coefficients in the opposite case are quantized in a finer fashion (Kofidisi *et al*., 1999; Schomer *et al*., 1998). Such operations reduce the visual redundancies of the input image (Gonzalez and Woods, 1992). The entropy coding takes place at the end of the whole encoding process. It assigns the fewest bit code words to the most frequently occurring output values and most bit code words to the unlikely outputs. This reduces the coding redundancy and thus reduces the size of the resulting bit-stream.

D. *SVD*

Singular Value Decomposition (SVD) is considered to be one of the significant topics in linear algebra by many renowned mathematicians. SVD has many practical and theoretical values, other than image compression. One special feature of SVD is that it can be performed on any real (m,n) matrix. It factors A into three matrices U, S, V, such that, A = USV T . Where U and V are orthogonal matrices and S is a diagonal matrix. In this research work, the values of SVD are used to perform medical image compression and the process is explained in this section.

The main purpose of (SVD) is to factor a image matrix A into USV^T. The matrix U contains the left singular vectors, the matrix V contains the right singular vectors, and the diagonal matrix S contains the singular values. The singular values to attain this goal are arranged on the main diagonal as given in Equation (7)

$$\sigma_1 \geq \sigma_2 \geq \ldots.\sigma_r > \sigma_{r+1} = \sigma_p = 0 \qquad (7)$$

where r is the rank of matrix A, and where p is the smallest of the dimensions m or n. There are many properties and attributes of SVD, some of the properties used with medical image compression are listed below.

1. The singular value $\sigma_1, \sigma_2, _{\ldots} \sigma_n$, are unique, however, the matrices U and V are not unique;
2. Since $A^TA = VS^T SV^T$ and V diagonalizes A^TA , it follows that the v_js are the eigenvector of A^TA .
3. Since $AA^T = USS^T U^T$, so it follows that U diagonalizes AA^T and that the u_i's are the eigenvectors of AA^T .
4. If A has rank of r then v_j and v_j, …, v_r form an orthonormal basis for range space of A^T , $R(A^T)$, and u_j and u_j, …, u_r form an orthonormal basis for .range space A, R(A).
5. The rank of matrix A is equal to the number of its nonzero singular values.

According to the property 5 of SVD in section 6.2, "the rank of matrix A is equal to the number of its nonzero singular values". In many applications, the singular values of a matrix decrease quickly with increasing rank. This propriety allows to reduce the noise or compresses the matrix data by eliminating the small singular values or the higher ranks.

When an image is SVD transformed, it is not compressed, but the data take a form in which the first singular value has a great amount of the image information. With this, it is possible to use only a few singular values to represent the image with little differences from the original. To illustrate the SVD image compression process, the following detail procedures are given below.

$$A - USV^T = \sum_{i=1}^{r} \sigma_i u_i v_i^T \qquad (8)$$

That is A can be represented by the outer product expansion:

$$A = \sigma_1 u_1 v_1^T + \sigma_2 u_2 v_2^T + \ldots + \sigma_r u_r v_r^T \qquad (9)$$

When compressing the image, the sum is not performed to the very last SVs and the SVs with small enough values are dropped, as they are ordered on the diagonal fashion. The closet matrix of rank k is obtained by truncating those sums after the first k terms:

$$A_k = \sigma_1 u_1 v_1^T + \sigma_2 u_2 v_2^T + \ldots + \sigma_k u_k v_k^T \qquad (10)$$

The total storage for k A will be k(m + n + 1) . The integer k can be chosen confidently less then n and the digital image corresponding to kA will still be very close the original image. However, the selection of different k values will produce different corresponding image and with different memory usage. For typical choices of the k, the storage required for kA will be less the 20 percentage.

EXPERIMENTAL RESUTLS

The proposed system was vigorously tested with test images to analyze its performance on compressing medical images. The results obtained are discussed in this chapter. The images used for this research were 512x512, 8 bits per pixel (bpp) images (Figure 3). All the experiments were conducted using Pentium IV machine with 512MB RAM. The system is evaluated using the performance parameters, like, Compression Ratio, Peak Signal to Noise Ratio (PSNR), Compression Time and Decompression Time.

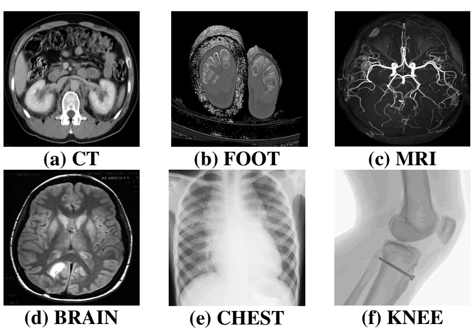

Figure 3. Test Images

- **Compression Ratio**

The degree of data reduction obtained as a result of the compression process is known as the compression ratio. This ratio measures the quantity of the compressed data in comparison to the quantity of the original data.

Compression ratio = original size/ compressed size (11)

From the above equation, it is obvious that as the compression ratio increases the compression technique employed is more effective.

- **Compression and Decompression Time**

Compression and decompression time are the basic measurements used to evaluate an image compression system. Compression and decompression time denotes the time taken for the algorithm to perform the encoding and decoding algorithm respectively.

- **Peak Signal to Noise Ratio (PSNR)**

Peak Signal to Noise Ratio ratio is often used as a quality measurement between the original and a compressed image. The higher the PSNR, the better the quality of the compressed, or reconstructed image. To compute the PSNR, the block first calculates the mean-squared error using the following equation:

$$MSE = \frac{\sum_{M,N} [I_1(m,n) - I_2(m,n)]^2}{M \times N} \qquad (12)$$

In the previous equation, M and N are the number of rows and columns in the input images, respectively. Then the block computes the PSNR using the following equation:

$$PSNR = 10 \log_{10}\left(\frac{R^2}{MSE}\right) \qquad (13)$$

In the previous equation, R is the maximum fluctuation in the input image data type. For example, if the input image has a double-precision floating-point data type, then R is 1. If it has an 8-bit unsigned integer data type, R is 255, etc.

For color images with three RGB values per pixel, the definition of PSNR is the same except the MSE, which will be the sum over all squared value differences divided by image size and by three. Typical values for the PSNR in lossy image and video compression are between 30 and 50 dB, where higher is better. The PSNR for color images with color components, R, G and B is given as below:

$$PSNR = 10 \log_{10}\left[\frac{255^2}{\frac{MSE(R) + MSE(G) + MSE(B)}{3}}\right] \qquad (14)$$

In the previous equation, *R* (=255) is the maximum fluctuation in the input image data type.

E. Compression Ratio

The result obtained while analyzing the compression ratio of the four models is given in Figure 4.

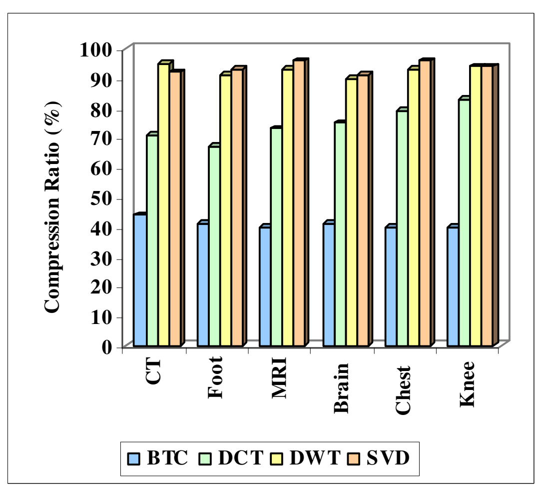

Figure 4. Compression Ratio

From the compression results, it could be noted both DWT and SVD perform well on medical images. While comparing DWT and SVD, SVD ranks first with efficiency gain of more than 1.1%. BTC's performance is very poor in comparison.

F. PSNR

Figure 5 shows the PSNR values obtained for the different techniques selected on the test images.

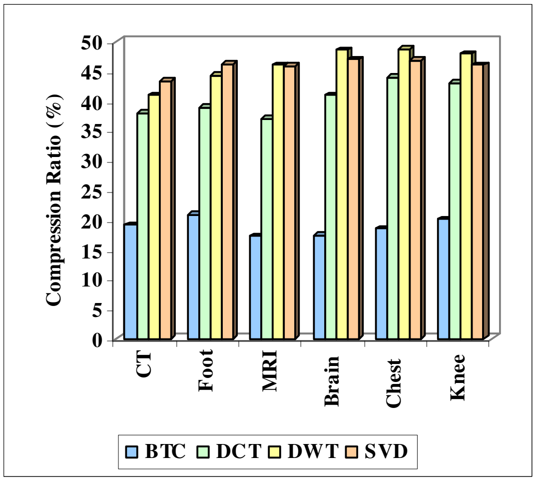

Figure 5. PSNR

Again from the results, it could be seen that both DWT and SVD's ability of producing quality decompressed image is more when compared to BTC and DCR. However, on average, the performance of wavelet with respect to decompressed image quality is better than SVD.

G. Compression and Decompression Time

The compression and decompression time taken by the four selected algorithms is shown in Table I.

TABLE I. COMPRESSION AND DECOMPRESSION TIME

Image	CT	DT	CT	DT	CT	DT	CT	DT
CT	0.22	0.14	0.24	0.13	0.13	0.16	0.21	0.12
Foot	0.26	0.11	0.31	0.15	0.23	0.15	0.22	0.11
MRI	0.29	0.19	0.32	0.17	0.26	0.09	0.23	0.13
Brain	0.3	0.16	0.3	0.14	0.24	0.16	0.2	0.15
Chest	0.33	0.18	0.34	0.15	0.16	0.14	0.19	0.09
Knee	0.28	0.13	0.26	0.11	0.12	0.19	0.18	0.08

Again from the results, it could be seen that the performance of DWT and SVD are on par with each other. On average, SVD is quicker than DWT. BTC seems to be the slowest of all the four algorithms.

CONCLUSION

This paper analyzed the applicability of four lossy image compression techniques, namely, BTC, DCT, DWT and SVD. From the results, it could be concluded that both DWT and SVD can be applied safely to compress medical images. DWT, achieves better compression ratio, but falls behind SVD in terms of PSNR and time. Since, image quality is given more importance in medical domain, from the present study, it could be concluded to select SVD as the right choice for medical image compression followed by DWT. BTC and DCT may be adopted by medical applications like teleconferencing, where the quality is not given much importance. In future, hybrid techniques which combine DWT and SVD could be designed and tested.

REFERENCES

[1] Norcen, R., Podesser, M., Pommer, A., Schmidt, H.P. and Uhl, A. (2003) Confidential storage and transmission of medical image data, Computers in Biology and Medicine, Vol. 33, Pp.277–292.

[2] Loussert, A., Alfalou, A., El Sawda, R. and Alkholidi, A. (2008) Enhanced System for image's compression and encryption by addition of biometric characteristics, International Journal of Software Engineering and its Applications, Vol. 2, No. 2, Pp. 111-118.

[3] Pennebaker, W.B. and Mitchell, J.L. (1993) JPEG: Still Image Data Compression Standard, New York: Van Nostrand Reinhold, New York, NY.

[4] Taubman, D. and Marcellin, M. (2002) JPEG2000: Image Compression Fundamentals, Practice and Standards, Kluwer Academic Publishers.

[5] Mallat, S. (1999) A Wavelet Tour of Signal Processing, 2nd Edition, Academic Press, San Diego.

[6] Karras, D.A. (2009) Compression of MRI images using the discrete wavelet transform and improved parameter free Bayesian restoration techniques, IEEE International Workshop on Imaging Systems and Techniques, 2009. IST '09, Pp. 173-176.

[7] Chen, C.W., Zhang, Y.Q. and Parker, K.J. (1994) Subband analysis and synthesis of columetric medical images using wavelet, Visual Communication and Image Processing '94, Vol. 2306, No. 3, Pp.1544–1555.

[8] Chen, C.W., Zhang, Y.Q., Luo, J. and Parker, K.J. (1995) Medical image compression with structure-preserving adaptive quantization, Visual Communication and Image Processing '95, Vol. 2501, No. 2, Pp.983–994.

[9] Storm, J. and Cosman, P.C. (1997) Medical image compression with lossless regions of interest, Signal Processing, Vol. 59, No. 2, Pp.155–171.