ISSN 2229-5518

2D image compression technique-A survey

Anitha S

Abstract— Advanced imaging requires storage of large quantities of digitized data. Due to the constrained bandwidth and storage capacity, images must be compressed before transmission and storage. However the compression will reduce the image fidelity, especially when the images are compressed at lower bitrates. The reconstructed images suffer from blocking artifacts and the image quality will be severely degraded under the circumstance of high compression ratios. Medical imaging poses the great challenge of having compression algorithms that reduce the loss of fidelity as much as possible so as not to contribute to diagnostic errors and yet have high compression rates for reduced storage and transmission time. To meet this challenge several hybrid compression schemes have been developed in the field of image processing. This paper presents overview of various compression techniques based on DCT, DWT, ROI and Neural Networks for two dimensional (2D) images.

Index Terms— DCT, DWT, Image compression, JPEG ,N N, ROI.

1. Introduction

Increasingly images are acquired and stored digitally or various film digitizers are used to convert traditional raw images into digital format. These images are very large in size and number, and compression offers a means to reduce the cost of storage and increase the speed of transmission. Although the cost of storage is falling precipitously as the capacity per device increases, the cost of transmission bandwidth is also falling; there remains the strong demand for image compression. Since the speed of computing is increasing, the need for sophistication and complexity of compression schemes is also increasing. For transfer over networks with high bandwidth or for storage on electromechanical devices (disk or tape), considerable time can be spent on compression before it becomes a factor in the total transfer time.

Much of the recent research in compression has focussed on lossy compression. Lossy compression involves deliberately discarding information that is not perceptually important. Greater compression can be achieved if some visible loss is acceptable for various application. In most cases scientists may not afford any deficiency in the field of medicine. An approach that briengs a high compression rate with good quality in the ROI is thus necessary. However there is still controversy over the role of lossy compression for particular applications.

Imaging devices produce 2D still medical images, 3D or volumetric medical images and video sequences. This paper reviews only compression techniques for 2D still medical images. In section 2, various image compression schemes based on DCT, DWT, ROI and neural networks techniques are discussed in section 3.

- *Anitha S is currently pursuing PhD in Electonics and Instrumentation in Dr.MGR University, Chennai.*
  E-mail:anithasd@yahoo.com

2 Image compressionTechniques

The following sections discuss many compression techniques that are exclusively used 2D images exploiting the unique characteristics.

2.1 Discrete Cosine Transform Based Compression

Transform coding became popular mainly due to the introduction of the Discrete Cosine transform-an efficient transform with high computational efficiency and compression performance that is close to the performance of optimal Karhunen Loeve Transform [3]. This fact has made the DCT favourable for still image and video coding. The widest used commercial product that is used for the still image coding scheme is the JPEG baseline system, which has the advantage of simple computation, but suffers from blocking artifacts due to course quantization quantization of coefficients at high compression ratios. The DCT is the kernel of the JPEG. Basic 2D – DCT function and its inverse functions are shown in (1) and (2).

$$c(u)=\propto(u)\sum_{x=0}^{N-1} f(x)\cos\frac{(2x+1)u\pi}{2N}\cos\frac{(2y+1)v\pi}{2N} \quad (1)$$

$$f(x)=\sum_{u=0}^{N-1}\propto(u)c(u)\cos\frac{(2x+1)u\pi}{2N}\cos\frac{(2y+1)v\pi}{2N} \quad (2)$$

for x=0,1,2,……N-1 & u=0,1,2……..N-1

$$c(u,v)=\propto(u)\propto(v)\sum_{x=0}^{N-1}\sum_{y=0}^{N-1} f(x,y)\cos\frac{(2x+1)u\pi}{2N}\cos\frac{(2y+1)v\pi}{2N} \quad (3)$$

for u,v=0,1,2,……………………………N-1 and

$$f(x,y)=\sum_{u=0}^{N-1}\sum_{v=0}^{N-1}\propto(u)\propto(v)c(x,y)\cos\frac{(2x+1)u\pi}{2N}\cos\frac{(2y+1)v\pi}{2N} \quad (4)$$

where, $\propto(u)=\sqrt{1/N}$ for u=0 and $\propto(u)=\sqrt{2/N}$ for u=1,2 …N-1

Usually the whole image is divided into non-overlapped subimages (8*8) and DCT is computed for individual blocks rather than computing the transform for the entire image, which is computationally complex.DCT is applied on the captured image and quantized as in fig2. The data

ISSN 2229-5518

is zig-zag scanned, adaptive sampled, Huffman coded and stored for further applicaton. The reverse process is applied for decompression.

2.2 Discrete wavelet transform based compression

Wavelet coding is proving to be very effective technique for medical image compression giving significantly better results than the JPEG standard algorithm which is based on DCT, with comparable computational efficiency[13] [14]. The standard steps in such compression are to perform the Discrete Wavelet Transform (DWT), quantize the resulting wavelet coefficients and losslessly encode the quantized coefficients. These coefficients are usually encoded in raster-scan order, although common variations ar to encode each sub-block in a raster-scan order separately or to perform vector quantization within the various sub0blocks. An alternative scheme for encoding wavelet coefficients, termed embedded zerotreee coding (EZW) , was described by shaprio[15]. Some of the ideas underlying EZW have been significantly modified and enhanced [16].

Wavelet Transform has become an important method for image compression. Wavelet based coding provides substantial improvement in picture quality at high compression ratios mainly due to better energy compaction property of wavelet transforms.

Wavelet transform partitions a signal into a set of functions called wavelets. Wavelets are obtained from a single prototype wavelet called mother wavelet by dilations and shifting. The wavelet transform is computed separately for different segments of the time-domain signal at different frequencies.

Subband coding:

A signal is passed through a series of filters to calculate DWT. Procedure starts by passing this signal sequence through a half band digital low pass filter with impulse response h(n).Filtering of a signal is numerically equal to convolution of the tile signal with impulse response of the filter.

$$x[n]*h[n]= \sum_{k=-\infty}^{\infty} x[k].h[n-k] \quad (5)$$

A half band low pass filter removes all frequencies that are above half of the highest frequency in the tile signal. Then the signal is passed through high pass filter.The two filters are related to each other as

$h[L-1-n]=(-1)^n g(n)$

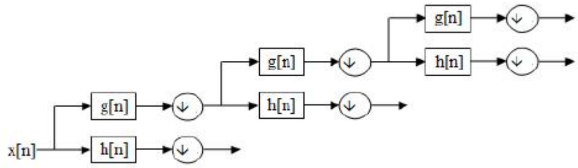
Filters satisfying this condition are known as quadrature mirror filters. After filtering half of the samples can be eliminated since the signal now has the highest frequency as half of the original frequency. The signal can therefore be subsampled by 2,simply by discarding every other sample. This constitutes 1 level of decomposition and can mathematically be expressed as

$$Y1[n]= x[k]h[2n-k]\ k \quad (6)$$

$$Y2[n]= x[k]g[2n+1-k]\ k \quad (7)$$

where y1[n] and y2[n] are the outputs of low pass and high pass filters, respectively after subsampling by 2.

This decomposition halves the time resolution since only half the number of sample now characterizes the whole signal. Frequency resolution has doubled because each output has half the frequency band of the input. This process is called as sub band coding. It can be repeated further to increase the frequency resolution as shown by the filter bank.



Filter Bank

Fig(1)

Compression steps:

1. Digitize the source image into a signal s, which is a string of numbers.
2. Decompose the signal into a sequence of wavelet coefficients w.
3. Use threshold to modify the wavelet coefficients from w to w'.
4. Use quantization to convert w' to a sequence q.
5. Entropy encoding is applied to convert q into a sequence e.

Digitization

The image is digitized first. The digitized image can be characterized by its intensity levels, or scales of gray which range from 0(black) to 255(white), and its resolution, or how many pixels per square inch.

Thresholding

In certain signals, many of the wavelet coefficients are close or equal to zero. Through threshold these coefficients are modified so that the sequence of wavelet coefficients contains long strings of zeros.

In hard threshold, a threshold is selected. Any wavelet whose absolute value falls below the tolerance is set to zero with the goal to introduce many zeros without losing a great amount of detail.

Quantization

Quantization converts a sequence of floating numbers w' to a sequence of integers q. The simplest form is to round to the nearest integer. Another method is to multiply each number in w' by a constant k, and then round to the near-

ISSN 2229-5518

est integer. Quantization is called lossy because it introduces error into the process, since the conversion of w' to q is not one to one function.

Entropy encoding

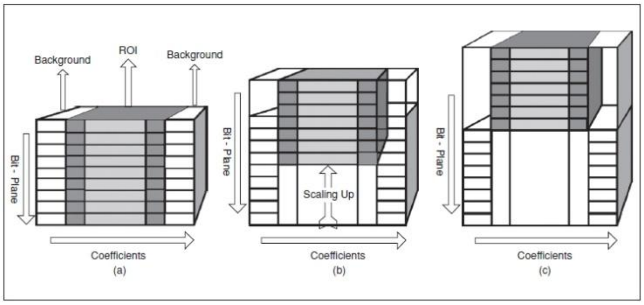
With this method, a integer sequence q is changed into a shorter sequence, with the numbers in e being 8 bit integers. The conversion is made by an entropy encoding table. Strings of zeros are coded by numbers 1 through 100,105 and 106, while the non-zero integers in q are coded by 101 through 104 and 107 through 254.

2.3 Region of Interest Based Compression

Useful information is mostly gathered and occupied in small area in the image. This feature can be utilized to compress an image. The useful areas(which is called as Region of inters tie ROI, low compression is applied to make high density compression the compressed image is kept with useful information as well as small size. This section provides ROI coding techniques applied to still 2-D images.

The principle of the general scaling method is to scale transform coefficients so that the bits associated whit the ROI are placed in higher bit planes than the bits associated with the background. Then, during the embedded coding process, the most significant ROI bit planes are placed in the bit stream before any background bit planes of the image. Depending on the scaling value, some bits of the ROI coefficients might be encoded together with non-ROI coefficients. Thus, the ROI will be decoded, or refined, before the rest of the image. Regardless of the scaling,, a full decoding of the bit stream results in a reconstruction of the whole image with the highest fidelity available. If the bit stream is truncated, or the encoding process is terminated before the whole image is fully encoded, the ROI will be of higher quality than the rest of the image.

According to Maxshift method[22], the scaling value is computed in such a way that arbitrarily shaped ROIs are generated without the need for transmitting shape information to the decoder, which means that the decoder does not have to perform ROI mask generation either. The encoder scans the quantized transform coefficients and chooses a scaling value 's' such that the minimum coefficient of the background. As illustrated in the fig (c), all of the wavelet coefficients that are not part of the ROI are scaled down by (s+D), where D is a small constant. As a result, all the wavelet coefficients corresponding to the background have a magnitude<1. The decoder, after receiving that have a magnitude<1, therefore, no extra information about the shape of the ROI is required , fig(2)



Fig(2)

The JPEG2000 standard ROI coding schemes provide better image quality in diagnostically critical areas. However, lossy-to-lossless compression of ROI is not supported, unless the ROI consists of the whole image. In [24] a lossy-to-lossless ROI compression scheme is proposed, the schme is based on set partitioning in hierarchial trees and embedded block coding with optimized truncation[25]. The input images are segmented into the foreground and background, respectively and a chain code-based shape coding scheme is used to code the ROIs shape information.

ROI segmentation algorithms suffered complexity and large execution time, so methods based on neural networks were introduced[36,37]. The method presented in[37] was a semi-automatic method of ROI segmentation because the centre of ROI was determined manually. Later an automatic segmentaion of ROI though an Artificial Neural Network and an introduced difference fuzzy model(IDFM) was presented. Here the non-ROI is coded with fast and reduced bit embedded zerotree wavelet algorithm(FEZW)[40] and ROI is coded with the same algorithm but with higher refinement level.

This algorithm reduces complexity when compared to others that used both lossy and lossless coding within the same MI, storage space, saves time and had the advantage over previous works that it is fully automatic.

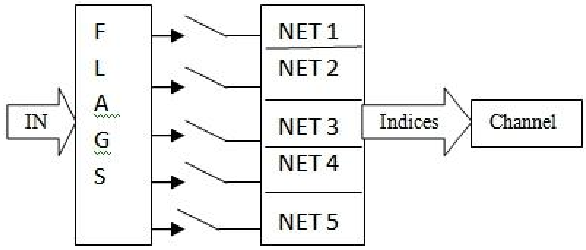
In [41] a multi-ROIs image compression algorithm with edge feature preserving is proposed. Here, useful information is extracted using canny operator and then ROIs are selected by hand and encoded using lossless JPEG2000 algorithm. To non-ROIS, high compression ratio algorithm SPIGHT us used. Then all bit streams are merged to get the result data. This algorithm solves the conflict between high compression ratio and high quality very well. Which makes the algorithm quite practical. The experimental result by the proposed algorithm is better than that of traditional SPHIT algorithm and PSNR is higher than algorithms based on JPEG2000.

2.4 Neural Network Based Compression

Image compression using Artificial Neural Networks is a topic where research is being carried out in various directions towards achieving a generalized and economical network. The algorithms discussed above are based on fixed transforms where as neural network compression use adaptive techniques. Advantages of Neural Networks (NN) include robustness under noisy conditions or incomplete data the performance of Back propagation Neural Network algorithm includes the mode of learning, information content, activation function, target values, input normalization, learning rate and momentum factors. [42*], [43*]. Images contain a number of distinct gray levels with narrow difference with their neighborhood pixels. This makes back propagation algorithm to slow down in converging. The compression achieved is also not high.

To overcome these draw backs a new approach using cumulative distribution function is proposed in [44]. Computational complexity is involved in compression of raw pixels of an image in spatial domain or the mathematically transformed coefficients in frequency domain using Artificial Neural Networks. If the gray levels of the pixels in an image and their neighbors are mapped in such a way that the difference in the gray levels of the neighbor with the pixel is minimum, then compression ratio as well as the convergence of the network can be improved, to achieve this, the cumulative distribution function [45] is estimated fort the image and it is used to map the image pixels. When the mapped image pixels (preprocessed) are used as input, the Back propagation Neural Network algorithm yields high compression ratio as well as it converges quickly . There will not be any loss in data in the preprocessing and hence the finer details in the image are preserved in the reconstructed image. The convergence time, PSNR and compression ratio for BPNN has been improved by this approach.

There exist hundreds of modalities of medical images and each modality has hundreds of subclasses for different organs and and different sizes, in such a situation it is difficult to generalize a neural network for all modalities. To tackle this problem and having a prior knowledge about similar nature and size of acquisition for a single type of medical image, a flag byte was proposed in [46] which is automatically set b the size and some features. The number of modalities determines the number of bits in the flag. This flag byte is then used to select a particular compression architecture configuration. For codebook design, Kohonen's self organizing feature map[47]method is applied , which provides good VQ codebooks leading to better quality reconstructed images as compared to LBG(Linde-Buzo-Gray) algorithm[48]. Once trained and code book is ready it is transmitted to the receiver and then afterwards for any subsequent use it is assumed that receiver know the code book. The only overhead is the flag byte which depends on how many types of medical images are to be treated, prior knowledge. The algorithm is defined clearly in fig(3)



Fig(3)

When an image becomes the input, flag bits are set using size of the image and these act as selector switch. Each image has unique resolution and size and compressed by different networks (containing different no of neurons) and various codebook sizes. On the decoder side flags are used just to identify which code book is to be used for decoding. Decoding process is only a lookup table. Decoder simplicity is vital in images for diagnosis where there is only once encoding and decoding may times and discussions, that is why VQ is chosen as a compressor in which decoder is the simplest. The results of this method have shown that compression ratios are better than JPEG for same PSNR.

3 Discussions

In the previous sections, two dimensional still image compression techniques based upon DCT, DWT, Region of Interest and Neural Networks were discussed. Here , general features of these approaches are summarized using table 1.

Compression techniques based on	Features
DCT	*high computational efficiency *achieves compact representation for highly correlated signals i.e., closed to the performance of optimal KLT *no full frame processing *good compression performance *transform based approach *suffers from blocking artifacts *Used in many coding systems such as JPEG, MPEG and H.26X due to high energy compaction property in the freqency domain.
DWT	*high compression ratio compared to DCT approach *no blurring of images *improves visual quality *no full frame processing *transform based approach *high computational complexity *used in JPEG 2000 scheme
ROI	*can be transform based or non-transform based *preserves image quality in perceptual importat critical regions. *high compression ratio with good quality in ROI *high compression ratio with quality in ROI *part of JPEG 2000
Neural nets	*superior over traditional methods when dealing with noisty or incomplete data *quality of reconstruction image is highly dependent on training data *non transformed approach *simple decoding

3 Conclusions

In this paper, a review of various coding techniques for 2D images has been done. The techniques are classified into four categories and their basic features are discussed. Though there are many techniques propoed with unique characteristics proposed with unique characteristics, research has to be done to develop techniques that will produce high quality reconstructed images with high CR and enable their use in portable and mobile devices, which have limited computing power.

4 References

[1] R. C. Gonzalez and R.. E.. Woods, "Digital Image Processing", Reading, MA: Addison-Welsley,1992

[2] A . Ramaswamy and W. B. Mikhael, "A mixed transform approach for efficient compression of medical images", IEEE Trans. Imag., vol. 12, no 4, pp. 803-811, 1996.

[3] A. K. Jain, "A sinusoidal family of uitary transforms", IEEE trans. Pattern Anal. Machine Intell., vol. PAMI-1,pp.356-365, oct.1979.

[4] G. Strang and T.Nguyen, "wavelets and filter banks", Cambridge, 1996

[5] Shen-Chuan Tai, Yung-Gi Wu and Chang Wie Lin, "An adaptive 3D Discrete Cosine Transform Codr for Medical lage Comression", IEEE trans. on imformation tech. , vol 4, no 3,sep2000

[6] Yung-Gi Wu and S. C..Tai,"medical image compression using 2*2 discrete cosine transform", opt. Eng., vol.37, no.5, pp.1539-546, May 1998

[7] Yung-Gi Wu and S. C..Tai,"medical image compression using 2*2 discrete cosine transform", opt. Eng., vol.37, no.5, pp.1539-546, May 2001

[8] J. Wang and H.K. Huang, "image compression by using Three Dimensional Wavelet Transformation",IEEE Trans. Medical Imaging, Vol.15,no 4, pp.547-554, Aug 1999

[9] Yung-Gi Wu,"medical image compression by sampling DCT Coefficients", IEEE Trans. in biomedicine, Vol.6,no 1, pp.86-94, March 2002

[10] M. Nelson and J. L Gaily , The data compression book, 2nd ed. New York: M&T books, 1996

[11] Y. L. Chan and W. C Siu,"variable temporal- 3D Discrete Cosinr Transform Coding", IEEE Transactions on image Processing, Vol. 6, No.% pp. 758-763, May 1997.

[12] Yen-Yu Chen and Shen-Chuan Tai,"Embedded medical image compression using DCT based subband decomposition ., in proc. 4th IEEE sym. Bioinformatics and bioengineering.

[13] Manduca A, "Medical Image compressin with wavelet/ subband coding", IEEE Eng in Medicine and Biology, vol.14, No. 5, pp.639-646, 1995

[14] Saipetch P, Ho BK, Panwar R, Ma M, Wei J, "Applying wavelet transforms with arithmetic coding to radiological image compression", IEEE Eng in Medicine and Biology,14(5),587-593, 1995he data compression book, 2nd ed. New York: M&T books, 1996

[15] Saipetch P, Ho BK, Panwar R, Ma M, Wei J, "Applying wavelet transforms with arithmetic coding to radiological image compression", IEEE Eng in Medicine and Biology,14(5),587-593, 1995he data compression book, 2nd ed. New York: M&T books, 1996

[16] Said A, Pearlman WA, "image compression using the spatial-orientation tree", IEEE Intl. Symp. On circuits and Systems, May 1993, pp.279-282, 1993

[17] A. Said and W. A. Pearlman,"Anew, fast and efficient image Codec based on SPHIT", IEEE Trans. Circuits syst. Video Technol. Vol. 6, pp.243-250, Jun.1996

[18] Armando Manducal and Amir Said,"wavelet compression of medical images with Set partitioning in H T", in Proc. IEEE int conf. Engg in medicine and Biology.1997

[19] Gulay Tohumoglu, "wavelts and their usage on the medica image compression with a new algorithm", in Proc. IEEE EURASIP workshop on nonlinear signal and image processing, Turkey,pp.229-233, Jun.1999

[20] Xiaojun Qi, John M. Tyler and Oleg S. Pianykh, "diagnostically lossless medical image compression using wavelets", in Oroc. Of SPIE ion Wavelet Application VII, Orlando, vol. 4506, Apr.2000

ISSN 2229-5518

[21] Wen-Jyi Hwang, Ching-Fung Chine and Kup Jung Li, “scalable data compression an transmission using wavelets”, IEEE Trans. information technology in biomedicine, vol.7, no.1, pp54-63, Mar.2003

[22] IS) / IEC JTC 1 / SC 29 / WG 1 (ITI-T SG8), JPEG 2000 part I final committee draft version 1.0.Mar 2000

[23] A. Bradley and F. Stienford,”JPEG2000 and region of interest coding”, inn proc. Int. conf.DICTA2002, Melbourne, Australia, Jan2002

[24] Z. Liu, J. Ha , Z. Xiong”lossy-to-lossless ROI coding od SPHIT”, IEEE int. sym., July 2002

[25] Taubman,”high performance scalable image compression with EBCOT”,IEEE Trans. Image Processing, vol.9,pp1158-1170, Jul 2000

[26] Z. Liu, J. Ha , Z. Xiong,”cascaded differential and wavelet compression of chromosome images,”IEEE Trans. Biomed. Eng., vol.49, pp.323-383

[27] G. Minami Z. Xiong”3-D wavelet coding of video with arbitray regionns of support”, IEEE Trans.Circiuts Syst.vol11,pp.1063-1068,sept.2001

[28] S. Tasdoken and A. Cuhadar,”ROI coding with integer wavelet transforms and unbalanced spatial orientation trees”, inProc. 25th Ann. Int. con. IEEE, Mexico, Sept. 2003

[29] S. Dewitte and J. Cornelis,”lossless integer wavelet transform”, IEEE signal processing letter, vol.4, pp.158-160, Jun.1997

[30] M. Peenedo, W. A. Pearlman, P. G. Tahoces, M. Souto and J.J. Vidal,”Region-based wavelet coding methods for digital mammography”, IEEE Trans. Med. Imag., vol. 22, pp.1288-1296, Oct.2003