International Journal of Recent Trends and Technology in Electronics and Communication Engineering, Vol. (2), Issue (1), 2020

"COMPREHENSIVE MEDICAL IMAGE COMPRESSION USING ENTROPY ENCODING ALGORITHM"

Hemant Choubey [1], Tulsi Kushwaha [2]

Email: Hemantchoubey271986@gmail.com, tulsi.ec 2005@gmail.com
[1]M. Tech. Scholar, Department of Electronics and Communication Engineering,Technocrats institute of Technology(Science),Bhopal,India
[2]Assistant Professor, Department of Electronics and Communication Engineering,Technocrats institute of Technology,Bhopal,India

ABSTRACT:

Medical images produces large amount of data, appropriate compression method for efficient storage and transmission is required. Fractal is a lossy compression technique, used to compress images that contain affine redundancy. Fractal compression can be used to create very small files that decompose very quickly but it is computation intensive and time consuming as it involves pixel-to-pixel comparison between the image blocks. The use of wavelet transform with fractal compression results in a much less compression time compare to the normal fractal compression method. Wavelet based image compression introduces no blocky artifacts in the decompressed image. Pure-fractal and Wavelet-fractal techniques have been applied on the medical images in different configurations and their resultant images have been evaluated in terms of compression ratio, PSNR value and time of computation. The proposed method improves compression ratio, image quality and the computation time is reduced using speed up technique.

KEYWORDS: *Wavelet, Fractal, PSNR, Compression ratio,MRE, MRI, US.*

1. INTRODUCTION

Medical images such as MRI (Magnet Resonance Imaging), US (Ultra Sound), MRE (Magnetic Resonance Elastography), etc. are rich in radiological information. A huge number of these medical images are produced in hospitals and health care center. In case of tele-communication, transmitting those images from one place to another is a tedious task. There are many systems such as RIS (Radiology Information System), HIS (Hospital Information System), and PACS (Patient Archival and Communication Systems) that handle medical images. These systems are rich in diagnostic information and only high bit rate compression is possible to preserve these data for storage and transmission. Lossy compression is good in removing the redundant information that the human visual system cannot observe. But any loss of information also may lead to wrong diagnosis. Hence, lossless compression techniques are most commonly used for medical images processing [1],[2],[3].

Their main objective is to make the decompressed image visually and diagnostically lossless. There are several image compression techniques such as fractal-based, transform based, machine learning –based, contextual-based, and other hybrid images compression methods. Transform-based compression transforms an image from spatial domain representation to other domain (such as frequency domain) using different transforms and codes the transformed coefficients to achieve compression. They are computationally complex but compression achieved is higher compared to other methods. There are different transforms available such as Discrete Cosine Transform (DCT), Discrete Wavelet Transform (DWT), Ripplet transform, Radon Transform, Contourlet transform etc. Image compression using Wavelet Transforms is a powerful method that produces compressed images at higher compression ratios with higher PSNR values [4]. It is a popular transform used for some of the image compression standards in lossy compression methods. Unlike the discrete cosine transform, the wavelet transform is not Fourier-based and therefore wavelets do a better job of handling discontinuities in data. Wavelet supports multi-resolution analysis which produces good visual quality images with high Compression Ratio. Several standards such as JPEG2000, MPEG-2/4 recommend use of Discrete Wavelet Transforms (DWT) for image transformation which leads to compressionwhen encoded. Wavelets are a mathematical tool for hierarchically decomposing functions in multiple hierarchical sub bands with time scale resolutions. The Discrete Wavelet Transform (DWT), has gained wide popularity due to its excellent decorrelation property, many modern image and video compression systems embody Dv b WT as the intermediate transform stage. After DWT was introduced, several codec algorithms such as EZW (Embedded Zerotrees Wavelet Transforms), WDR (Wavelet Difference Reduction), SPIHT (Set Partitioning in Hierarchical Trees), STW (Spatial Orientation Tree Wavelet, TWT (Tree Structured Wavelet) [5],[6],[7] were proposed to compress the transform coefficients as much as possible. Achieving much higher compression ratio is simply not possible without discarding some perceptible information, but a compromise must be maintained between the higher compression ratio and a good perceptual quality of image. The most powerful progressive method, Embedded Zerotree Wavelet (EZW) coding algorithm introduced by Shapiro [8] combines stepwise thresholding and progressive quantization, focusing on the more efficient way to encode the image coefficients in order to minimize the compression ratio. Spatial-Orientation Tree Wavelet (STW) and Set Partitioning in Hierarchical Trees (SPIHT) [8],[9],[10] are found to be more advantageous because of their different approach of encoding the wavelet transform. These wavelet based image/video compression algorithms (SPIHT and STW) are considered as refined versions of the seminal EZW algorithm The 3D-Set Partitioning in hierarchical trees (3D-SPIHT) technique which is proposed by Kim and Pearlman [11],[12]is the extended form of SPIHT coding algorithm, in which the relationship among coefficients lying in different frequency bands is based on octal tree structure rather than quad-tree structure. The most enhanced image compression algorithm is the Adaptively Scanned Wavelet Difference Reduction (ASWDR) algorithm proposed by Walker [13], ASWDR technique adjusts the scanning order used by Wavelet Difference Reduction (WDR) algorithm [14],[15],[16] so as to predict locations of new significant values. The WDR method employs a fixed ordering of the positions of wavelet coefficients. Thus, ASWDR technique achieves high compression than WDR while retaining all of the important features of WDR such as low complexity, region of interest (ROI) capability and progressive SNR capability [17],[18],[19],[20]. The rate of compression achieved is largely determined by the encoding technique and the number of encoding loops used[21]. Thus in this paper the most powerful wavelet based compression technique is identified by presenting a comparative study of the various approaches

2. WAVELET CODING

Wavelet based image compression introduces no blocky artifacts in the decompressed image.Much higher compression ratios much regardless of the amount of compression can be achieved using wavelet transform. Another interesting feature of wavelet is that, the quality of the image can be improved by adding detail information. This feature is attractive for what is known as progressive transmission of images. The complexity and time consumption of the fractal compression can be overcome by implementing wavelet transform[22],[23],

.

SYSTEM DESIGN

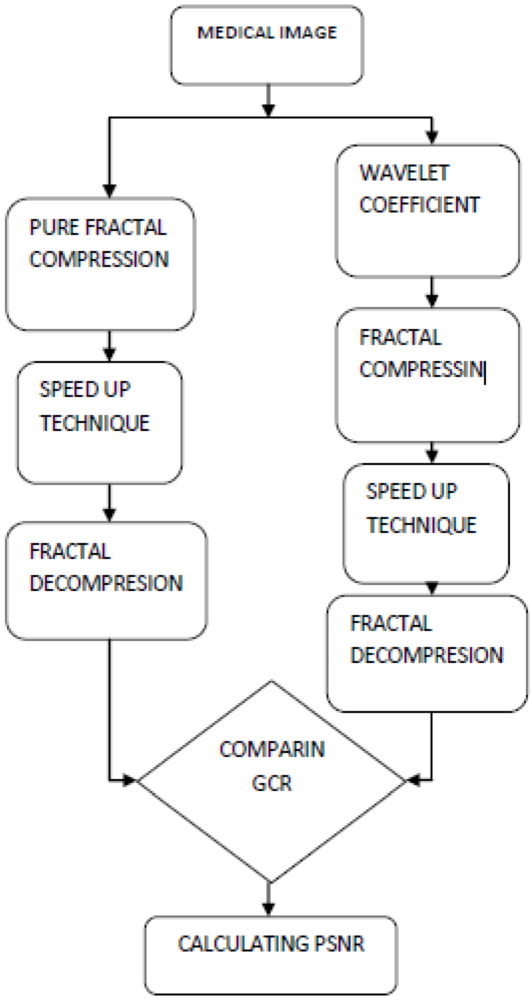

Fig.1 Pure Fractal Image Compression

3. TYPES OF ALGORITHMS

1 EZW -Embedded Zerotree Wavelet
2 SPIHT- Set Partitioning In Hierarchical Trees
3 STW- Spatial-orientation Tree Wavelet
4 WDR- Wavelet Difference Reduction
5 ASWDR- Adaptively Scanned Wavelet Difference Reduction
6 3D_SPIHT -Set Partitioning In Hierarchical Trees 3D for true color images

Step 1: A wavelet transform is performed on the discrete image/frame *f* [j,k], producing the transformed image/frame $\hat{f}$ [j,k].

Step 2: A scanning order for the transformed image is chosen, $\hat{f}$ [j,k] = a(m). The transform values are scanned via a linear ordering, m = 1,2,3…..X where X is the number of pixels. Row-based scanning is used in the horizontal subbands and column-based scanning is used in the vertical subbands with the zigzag scanning order through subbands from higher scale to lower scale.

Step 3: (Significance pass). The positions for new significant values are recorded as depicted in. These new significant indices are then decoded using difference reduction.

Step 4: (Significance pass). The positions for new significant values are recorded as depicted in. These new significant indices are then decoded using difference reduction.

Step 5: (Refinement pass). Record the refinement bits the next significant bits, for the old significant transform values. This generation of refinement bits is also known as standard bit plane encoding which is utilized by all embedded codes

Step 6: (New scanning order). For the level containing the all-lowpass subband, the indices of the remaining insignificant values are used as the scan order at that level. The scan order at level k is used to create the new scan order at level k - 1as follows: Run through the significant values (i.e. the parent values) at level k in the wavelet transform the child values induced by these insignificant parent values. This new scanning order for level k - 1 is further used to create the new scanning order for level k – 2, until all levels are exhausted

The WDR method has two principal advantages. First, it produces an embedded bit stream thereby facilitating progressive transmission over small bandwidth channels and/or enabling multi-resolution searching and processing algorithms

Step 7: Spatial Orientation Tree Wavelet (STW) employs a diverse approach in coding the information of zerotree. A zerotree have insignificant wavelet transform values at each of its locations for a given threshold T. Zerotree is a tree of locations in the wavelet transform with a root say [j, k], and its descendants (children) located at [2j, 2k], [2j+1, 2k], [2j, 2k+1], and [2j+1, 2k+1], and each of their children, and so on. STW is more vigilant in its organization of coding outputs

Step 8 : Embedded Zerotree Wavelet (EZW) [12] and SPIHT algorithm . In EZW, the root location is marked by coding only one symbol for the output R or I as described in . Consequently in EZW, the zerotrees provide narrow descriptions of the locations of insignificant values. The different approach used in STW is the use of a state transition model. The locations of transform values undertake state transitions from one threshold to the next.

The number of bits required for encoding is thus reduced in STW with this representation of state transitions. The state transition model uses states IR, IV, SR and SV as represented in to mark the locations instead of code for the outputs R and I used in . The states involved are defined after knowing the significance .

4. COMPRESSION RATIO

The compression ratio CR, which means that the compressed image is stored using only CR% of the initial storage size. Compression, as the name implies, deals with techniques for reducing the storage required saving an image, or the bandwidth required to transmit it. Although storage technology has improved significantly over the past decade, the same cannot be said for transmission capacity[24] In image compression systems, the truly definitive measure of image quality is perceptual quality. The distortion is specified by mean opinion score (MOS) or by picture quality scale (PQS). MOS is perception based subjective evaluation where as PQS is perception based objective evaluation. PQS methodology uses some of the properties of HVS relevant to global image impairments, such as random errors, and emphasizes the perceptual importance of structured and localized errors[25],[26]... PQS is constructed by regressions with MOS, which is 5-level grading scale developed for subjective evaluation. (5-imperceptible, 4 – perceptible, but not annoying, 3 – slightly annoying, 2 – annoying, 1 – very annoying). The compression efficiency is defined by the parameter compression ratio CR and is given by,

$$\mathrm{CR} = \frac{\text{ORIGINAL DATA}}{\text{COMPRESSED DATA}}. \qquad \text{.... ....[1]}$$

$$\mathrm{CR} = \frac{\text{ACTUAL BPP}}{\text{REDUCED BPP}} \qquad \textbf{...............[2]}$$

For example, if actual bpp = 8 and reduced bpp = 0.5 then CR = 16:1. If original data = 512 x 512 x 8 = 1.497152 Bits and compressed data = 1.497152 Bits then CR = 1000:1.

4.1 BITS PER PIXELS

The Bit-Per Pixel ratio BPP, which gives the number of bits required to store one pixel of the image.

5. RESULT

The simulation results of image compression by applying the embedded zero tree Wavelet (EZW), Set Partitioning In Hierarchical Trees (SPIHT), Wavelet Difference Reduction (WDR), Spatial-orientated Tree Wavelet (STW), Partitioning and Adaptively Scanned Wavelet Difference Reduction (ASWDR) algorithms various comparisons are obtained on the basis of PSNR and MSE and compression ratio (CR) values for the particular bit-per-pixel (BPP) ratio. For this purpose, we use the picture of pers. The original medical image is shown in Fig. and the compressed black and white images are shown in Figs.

Fig. 1 Original black and white image

Fig.2 Original image

Fig.3 E ZW

Fig.4 SPIHT

Fig.5 STW

Fig. 6 WDR

Fig.7 ASWR

Fig.8 SPIHT

Table 1 and 2 show the values of PSNR and MSE for the different algorithms considered in this paper when CR and BP is approximately black and white image consider 1.3 and 0.3 respectively for TABLE 1 and for TABLE1 color image CR and BPP is 2.5 and 0.6 respectively.

Table 1. Pure-fractal image compression

Exp #	Dpmain block size	PSNR	CR	Time(s)
1	2*2	52.2	6.33	256
2	4*4	41.10	26.11	58
3	8*8	34.12	130	13
4	16*16	30.22	692	1.99

Table 2. Numerical results of Wavelet-fractal image compression algroithm

Exp #	PSNR(db)	CR	Time (s)
5	29.82	333	105
6	36.66	24.22	726
7	31.88	101.21	78.66
8	32.55	65	12.21
9	37.15	17.2	156.33

Table 3. Overall results of implemented fractal methods

TECHNIQUE	PSNR	CR
Semi lossless pure Fractal	52	6.11
Lpssy Quality pure Fractal	30.23	690
Wavelet fractal tree	36	16.99
Wavelet fractal	31	333

Table 4. Compression eye image

Algorithm	MSE(%)	PSNR(db)
EZW	18.1991	35.5303
SPIHT	11.9975	37.3399
STW	18.0313	35.5705
WDR	18.1991	35.5303
ASWR	19.1991	35.5303
SPIHT_3D	11.9983	37.3396

Table 5. Original image

Algorithm	MSE(%)	PSNR(db)
EZW	10.1915	38.0484
SPIHT	6.2820	40.1498
STW	9.9473	38.1537
WDR	10.1915	38.0484
ASWR	10.1915	38.0484
SPIHT_3D	6.2820	40.1498

In this paper, we have implemented and compared techniques for image compression. These algorithms are Embedded Zerotree Wavelet (EZW), Set Partitioning In Hierarchical Trees (SPIHT), Wavelet Difference Reduction (WDR), Spatial-orientated Tree Wavelet (STW), 3D-Set Partitioning In Hierarchical Trees (3D-SPIHT) and Adaptively Scanned Wavelet Difference Reduction (ASWDR). With the help of these algorithms each image is compressed and then decompressed. For the purpose to compare image quality, we consider MSE and PSNR as quality parameters. MAXLOOP is selected for compression algorithms on the basis of CR and BPP. We select MAXLOOP by keeping two things in mind that we require a low compression ratio and a better.

6. CONCULUSION

In this report, the results of four different wavelet-based medical image compression techniques are compared. The effects of different values like PSNR, MSE, BPP & CR are examined. The results of the different wavelet like EZW, WDR, SPIHT & STW are compared by using four parameters such as PSNR, MSE, BPP & CR values from the reconstructed image. These compression algorithms provide a better performance in picture quality at low bit rates. These techniques are successfully tested in many images. WDR technique provides high PSNR and low MSE values when compared to the EZW, STW & SPIHT technique.

REFERENCES

(1) mr.jons lee Image Compression with Different Types of image using Wavelets technicsIEEE Transactions on Communication, Control and Computing Technologies,

[2] S.P.Raja & Dr. A. Suruliandi, “Performance Evaluation on EZW & WDR Image Compression Techniques,” IEEE Transactions on Communication, Control and Computing Technologies, vol.5, no.1, pp. 661-664, 2010.

[3] K.Nagamani & AG Ananth , “Study of ezw compression techniques for high and low resolution satellite imageries,” IEEE Transactions on Computing, Communication and Networking Technologies, vol.1, pp.1-7, July.2010.

[4] S.P.Raja & Dr. A.Suruliandi, “Analysis of Efficient Wavelet based Image Compression Techniques,” IEEE Transactions on Computing, Communication and Networking Technologies, pp.1-6, 2010.

[5] Zhenghua-Shu, Guodong-Liu, Lixin-Gan, Lin Zhang, “An Image Coding Combines H.264 Standard and Contourlet Transform,” IEEE Transactions onComm. Systems, Networks and Applications, pp.240-243, 2010.

[6] Li Huifang, Li Moa, “New Method Of Image Compression Based On Quantum Neural Network,” IEEE Transactions on Information Science & Management Engineering, pp.567-570, 2010.

[7] Mohsen Nasri, Abdelhamid Helali, Halim Sghaier & Hassen Maaref, “Adaptive Image Transfer For Wireless Sensor Networks,” IEEE Transactions on Design & technology of Integrated systems in nonoscale era, pp.1-7, 2010.

[8] G.Sadasshivappa, Mahesh Jayakar, “Analysis of Spiht Algorithm Using Tiling Operations,” IEEE Transactions on Signal Acquisition and Proc., pp.332-336, 2010.

[9] Omid Ghahabi, Mohammad H.Savoji, “Modified EZW and SPIHT Algorithms for Perceptually Audio and High Quality Speech Coding,” IEEE Transactions onSignal and Image Processing Applications, pp.530-535, 2009.

[10]Navneet Agrawal, K.Venugopala, “SAR Image Compression Using Wavelet Packets,” IEEE Transactions on Signal Processing Systems, pp.343-347, 2009.

[11] Ashish Tanwer, Rattandeep Singh, Parminder Singh Reel, “Real Time Low Level Parallel Image Processing For Active Vision Systems,” IEEE Transactions on Advance Computing Conference,pp.1347-1352, 2009.

[12] PAN Wei, ZOU Yf, AO Lu, “A Compression Algorithm of Hyper spectral Remote Sensing Image Based on 3-D Wavelet Transform and Fractal,” IEEE Trans. on Intelligent System and Knowledge Engineering, pp.1237-1241, 2008.

[13] Rafael C. Gonzalez, Richared E. Woods, Steven L. Eddins, "Digital Image Processing Using MATLAB," Pearson Education, vol.2, 2008.

[14] G.K. Kharate1, A.A. Ghatol and P.P. Rege, "Selection of Mother Wavelet for Image Compression on Basis of Image," IEEE Transactions on Signal Processing, Communications and Networking, pp.281-285, Feb.2007.

[15] Yuehua Wan, Shiming Ji, Qiaoling Yuan, Yi Xie, "Multivariate Statistical Modeling For Medical Image Compression Using Wavelet Transforms," IEEE Transactions onCognitive Informatics, pp.214-217, 2006.

[16] Cung Nguyen, G. Robert, "Fault Tolerance Design in JPEG 2000 Image Comp. Sys.," IEEE Trans. on Dependable & Secure Computing, pp.57-75, 2005.

[17] Karen Lees, "Image Compression using wavelets," May-2002.

[18] Sonja Grgic, Mislav Grgic and Branka Zovko-Cihlar, "Performance Analysis of Image Compression Using Wavelets," IEEE Transactions onIndustrial electronics, vol.48, no.3, pp.682-695, June.2001.

[19] J. Tian, R.O. Wells, Jr., "Embedded image coding using wdr wavelet Image and Video Compression," Kluwer Academic Publicatios, pp.289-301, 1998.

[20] J. Tian, R.O. Wells, Jr. "A lossy image codec based on index coding," IEEE Transactions on Data Compression, pp.456, 1996.

[21] J. Tian, R.O. Wells, Jr., "Image data processing in the compressed wavelet domain," IEEE Conference on Signal Processing, pp.978- 981, 1996.

[22] Stollnitz, E.J, Derose, "Wavelets for computer graphics: Theory and applications," IEEE Transactions Morgan Kaufman Publisher, USA, 1996.

[23] Amir. Said and W.A.Pearlman, "A new fast and efficient image codec based on set partitioning in hierarchical trees," IEEE Transactions Circuits and Systems for video Tech., vol.6, no.3, pp.243-250, June.1996.

[24] Hubbard, "The World According to Wavelets," A.K Peters Ltd, 2nd ed., 1995.

[25] Amir. Said, W.A. Pearlman, "Image compression using the spatial-orientation tree," IEEE Int. Symp. on Circuits and Sys., Chicago, IL, pp.279-282, 1993.

[26] J.M. Shapiro, "Embedded image coding using zero trees of wavelet coefficients," IEEE Trans. on Signal Proc., vol.41, no.12, pp.,1999