Performance Comparison of Wavelet Transforms based Medical Image Compression

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Abstract

Medical image analysis plays a vital role in diagnosis of diseases and the need of the day is to arrive at a simple and efficient compression technique. This paper proposes a comparative analysis of three different wavelet based medical image compression techniques. First algorithm is based on Bi-orthogonal wavelet with Parallel coding (BiWT-PC), second is based on Haar wavelet with block coding (HWT-BC) and third algorithm is based on stationary wavelet transform with Parallel coding (SWT-PC). In this work, 3D medical image is converted into 2D slices and preprocessed using lifting scheme. Wavelet transform is applied to this preprocessed image, which divides the image into multilevel sub-bands. Then, the suitable encoding method is applied to get the compressed image. At the receiver side, the original image is recovered back by applying inverse wavelet transform and proper decoding over the compressed image. Experimentations are carried out over MRI and CT images with four quantitative metrics such as PSNR, CR, DcT and EcT. From the experimental analysis, it is observed that SWT-PC method is quite efficient since it has high PSNR and low CR.

Keywords: Stationary Wavelet Transform; Haar Wavelet Transform; Biorthogonal Wavelet Transform; MRI; CT

1. Introduction

Due to the advancement in medical field, the usage of medical images becomes essential to diagnose the patients. In our day-to-day life, large quantity of images are produced and used every day. For continuous monitoring of the patients, these images have to be stored for further reference. The image acquisition technology is carried out through X-Ray, Ultrasound, MRI/fMRI (functional Magnetic Resonance Image), Nuclear Medicine, PET (Positron Emission

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Tomography), CT (Computerized Tomography) [1]. Due to the necessity of storing volume of data, it is mandatory to do compression before storing or transmitting data through internet. Hence, medical image compression plays a vital role for efficient storage and transmission. The compression method have the ability to process large volume of data with fast interaction and able to search context dependent images quickly [2]. The performance of the compression technique will be good only when it uses minimum bandwidth and storage. Several medical image compression techniques are evolving in day-to-day basis that have the compromise between the storage and quality of the image. These techniques are broadly classified into lossy and lossless compression techniques. The lossy compression compresses the image with loss of data but have high compression ratio. Here, the quality of the image is degraded after compression. In lossless compression method, there is no loss of the data and able to get the compressed image identical to that of the original image. Hence, this lossless method is preferred where the information is more important. I.e. it is widely preferred for the medical image compression [3].

Over the years, number of medical image compression techniques is evolving. The different techniques uses different medical images like computed tomography (CT); Magnetic resonance images (MRI) and X-ray angiograms (XA) etc. The knowledge about all such compression techniques is important for storing, transmitting and viewing of the medical images. Now-a-days wavelet based compression techniques have gained more popular because they provide considerable refinement in picture quality at higher compression ratios. Due to multiresolution property, signal is decomposed into course and detail components that enhance the performance of compression algorithm. Now the world is stepped into 3D images, wavelet encoders are mostly preferred for image compression. This paper proposes a comparative analysis of wavelet based compression for medical images. Section 2 describes the related work in medical image compression. Section 3 covers the proposed methods and Section 4 describes the experimental results. Finally, Section 5 concludes the paper.

2. Related works

Venugopal et.al [4] applied hadamard transform to obtain lossless image compression. In addition, they adopted Huffman coding to minimize the complexity and better compression ratio. Priya et.al [5] used Integer wavelet transform (IWT) and Discrete Gould transform (DGT) to develop a secure and reversible medical image watermarking. Rinisha et.al [6] applied different wavelet based segmentation techniques to identify fracture in human bone. In addition, they used neural network based classification to locate or detect fracture in the bone. They proved that Haar walelet showed maximum correlation between the images. Murat [7] proposed an efficient optimal compression procedure for noisy images. This work is based on the combination of the wavelet-based JPEG2000 compression algorithm and wavelet-based denoising algorithms. They concluded that optimum performance of the compression method depends on the type of image modality used. Juliet et. al. [8] proposed Ripplet transform, which provides a good quality of the images and attains high compression rate. They had represented the images at different scales and directions to achieve higher compression rate. Hye [9] analyzed the data restoring system for X-ray images. They compared the image performance of three standard compression techniques in terms of PSNR. Cyriac et.al [10] proposed a novel methodology, which includes a Visually Lossless Run Length Encoder/Decoder to solve the expansion problem in the traditional Run Length Encoder/Decoder. In this paper, the proposed technique is able to sufficiently compress the image and helps to minimize the hardware implementation. Brahimi et. al. [11] proposed a novel method based on single codec which has the ability to compress the signal and the image simultaneously. By using this, wavelet-decomposed signal is embedded into the decomposed image. Arif et. al. [12] reported very high compression ratio when compared to other conventional techniques. In this work, they used the combination of Run Length and Huffman coding for the compression of the fluoroscopic images. Zhiyong et.al [13] proposed an improved medical image compression technique which is based on region of interest (ROI). Das and Kundu et. al. [14] used seven different modalities for experimentation also proved that the proposed work is simple and provides more security to the database. The presented technique relies over Region of Interest (ROI) and able to find solutions to the multiple problems regarding the medical data distribution.

Jia Li et.al [15] applied the wavelet transform to obtain the interrelated multi-level sub-bands. The sub band wavelet coefficients make the flexible quantization coding strategy of image compression. Lucas et. al. [16] proposed a novel lossless compression technique for volumetric sets of medical images. The concept relies over the mechanism of minimum rate predictors (MRPs). It is proved that the proposed technique is able to achieve minimum error probability and high compression efficiency over the HEVC and other standard for depth medical signals. Spelic and Zalik [17] proposed a novel method for effective compression and transmission of CT images. Initially, the medical image is segmented using Hounsfield scale and then voxel compression algorithm is applied to compresses the 3D CT images. Prototype mechanism is used to evaluate the performance of the proposed technique. Anusuya et. al. [18] proposed a novel lossless compression algorithm using entropy coder to compress the 3D brain images. This work analyzed the

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efficiency of the proposed algorithm with existing algorithms. In addition, computation time is considerably reduced with the help of parallel computing. Xio et. al. [19] discussed Integer Discrete Tchebichef Transform to compress different modalities of medical images without any loss of data. In this work, integer-to-integer mapping for effective lossless compression is introduced. Due to this, the proposed algorithm is able to achieve higher compression ratio than iDCT. Sanchez et al. [20] proposed wavelet based lossless compression for 3D medical image data. This method encodes the coefficients by block based intraband prediction method. Then, the images are compressed by modified version of the embedded block coder.

Seddeq et al. [21] improved the performance of compression by using bi-orthogonal wavelet transform CDF 9/7 combined with SPIHT coding algorithm. It provides better performance when compared to partial EZW and SPIHT. Bouklihacene et al. [22] proposed a compression algorithm for color medical images. This work based on a Biorthogonal wavelet and SPIHT coding. The performance of the proposed algorithm is better when compared to other compression techniques.

3. Proposed Method

The proposed comparative analysis of medical image compression comprises of three different method using wavelet transforms. First algorithm based on Bi-orthogonal wavelet transform then followed by Huffman coding. Second one based on the combinations of Haar wavelet and block coding. Final algorithm comprises of Stationary wavelet transform with parallel coding. Initially the input images are preprocessed using lifting scheme [23]. Then, the preprocessed image is subjected to various algorithms and their performance is compared with suitable parameters. The proposed flow is shown in Fig.1.

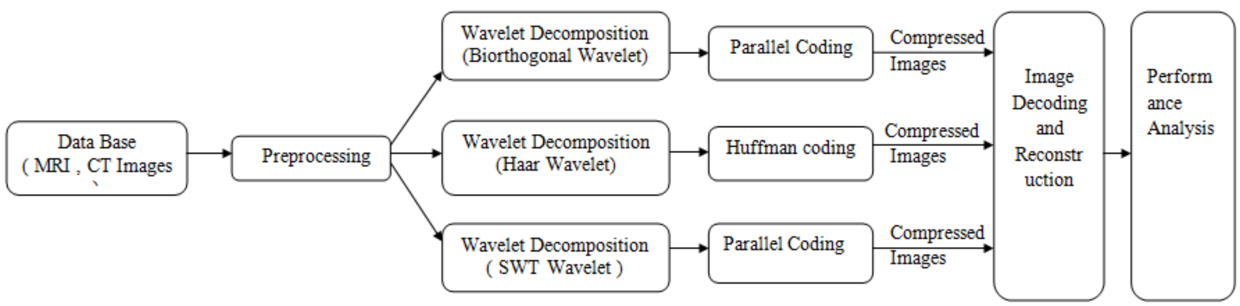

Figure 1. Proposed System

3.1 Bi-orthogonal Wavelet with Parallel Coding (BWT-PC)

The input is a 3D medical image, which is eventually transformed into 2D slices. The slices are preprocessed and subjected to a bi orthogonal Wavelet Transform with dyadic decay. The bi-orthogonal 4.4 wavelet filter is used in this work. The slices are decomposed into 8 frequency sub-groups. High pass components have the detailed information about the image whereas low pass contains a granular version of the image. Then, the coefficients are coded using EZW and Huffman coding. The obtained bit stream is decoded and and reconstructed using inverse DWT. Bi orthogonal wavelet Transform is represented by the Equ. 1 & 2.

$$\psi(t) = 2\sum_{n=-\infty}^{\infty} g(n)\phi(2t-n) \quad (1)$$

$$\tilde{\psi}(t) = 2\sum_{n=-\infty}^{\infty} \tilde{g}(n)\tilde{\phi}(2t-n) \quad (2)$$

3.2 Haar Wavelet Transform with block coding (HWT-BC)

A Haar Wavelet Transform (HWT) with dyadic disintegration is applied to the preprocessed 3-D input medical image. It has optimal invertibility with a minimum of precision. This is necessary for accurate signal reproduction. The bi-symmetrical LeGall 5/3 wavelet given in equ.3 & 4 is used in this work. The image is partitioned into eight frequency sub-groups for further process. The approximation low-pass sub-band represents a coarser adaptation of the original image, whilst the other sub-bands reject the intricacies of the image. On the approximation low-pass sub-groups, the disintegration is iterated. Then, the mean energy of each forum is calculated. Each group of coefficients is encoded

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separately using block coding and that has unique parameters of scalable-layered bit-stream. By using the VOI's geographical coordinates and the mean energy of the gathered coefficients, weights for each grouping of coded wavelet coefficients is calculated by means of a weight assignment model. These weights are used to reorganize the yield bit-stream and able to construct a more adaptive layered bit-stream that is capable of VOI decoding. As a result, the fringe consistency around the VOI is gradually improving. On the decoder side, wavelet coefficients are obtained by using a decoder. The decoder can able to truncate the obtained bit stream to generate an image at any bit rate. Finally, to achieve the reconstructed image, an inverse HWT is used. The Equ represents Haar Wavelet Function. 3 & 4

$$\psi(t) = \begin{cases} 1 & 0 \leq t < 1/2, \\ -1 & 1/2 \leq t < 1, \\ 0 & otherwise \end{cases} \quad (3)$$

Its scaling function

$$\phi(t) = \begin{cases} 1 & 0 \leq t < 1 \\ 0 & otherwise \end{cases} \quad (4)$$

3.3 SWT with Parallel Coding (SWT-PC)

This method is based on an entropy coding. The input is a 3D medical image is converted into 2D slices. Segmentation is applied to the 2D-slice which removes the brain mass (Region of Interest) from the input image. Then, the extricated information is decimated using the 2D-Stationary Wavelet Transform (SWT) given in Equ.5. The embedded bit-stream is compressed in parallel utilizing implanted block coding and Optimized Truncation of the annihilation coefficients. These bit streams are decoded and reconstructed using inverse SWT. Parallel coding is the combination of arithmetic coding and block coding.

$$A_{j,k1,k2}=\sum_{n1}^{n}\sum_{n2}^{n} h_0^{\uparrow 2^j}(n1-2k1)h_0^{\uparrow 2^j}(n2-2k2)A_{j-1,n1,n2}$$

$$D^1_{j,k1,k2}=\sum_{n1}^{n}\sum_{n2} h_0^{\uparrow 2^j}(n1-2k1)g_0^{\uparrow 2^j}(n2-2k2)A_{j-1,n1,n2}$$

$$D^2_{j,k1,k2}=\sum_{n1}\sum_{n2}^{n} g_0^{\uparrow 2^j}(n1-2k1)h_0^{\uparrow 2^j}(n2-2k2)A_{j-1,n1,n2} \quad (5)$$

$$D^3_{j,k1,k2}=\sum_{n1}^{n}\sum_{n2}^{n} g_0^{\uparrow 2^j}(n1-2k1)g_0^{\uparrow 2^j}(n2-2k2)A_{j-1,n1,n2}$$

Where $A_{j,k1,k2}$,$D^1_{j,k1,k2}$,$D^2_{j,k1,k2}$,$and\ D^3_{j,k1,k2}$ represent low frequency components(LL),the horizontal high-frequency component (LH),vertical high-frequency component(HL) and diagonal components(HH) of the stationary wavelet transform respectively. $h_0^{\uparrow 2^j} and\, g_0^n 0 \uparrow 2^j$ are used to denote that $2^j - 1$ zeros are inserted between the two points $h_0\ and\, g_0$.The inverse discrete stationary wavelet transform (IDSWT) is shown in equ.6.

$$A_{j-1,n1,n2} = \frac{1}{4}\sum_{i=0}^{3}\{\sum_{k1}^{n}\sum_{k2}^{n} h_1(n_1-2k_1-i)h_1(n_2-2k_2-i)A_{j,k1,k2} + \sum_{k1}^{n} \mathrm{h1}\,(n_1-2k_1-i)g_1(n_2-2k_2-i)D^1_{j,k1,k2} + \sum_{k1}^{n}\sum_{k2}^{n} g1\,(n_1-2k_1-i)h1(n_2-2k_2-i)D^2_{j,k1,k2} + \sum_{k1}^{n}\sum_{k2}^{n} g1\,(n_1-2k_1-i)g1(n_2-2k_2-i)D^3_{j,k1,k2}\} \quad (6)$$

4. Experimental Results & Discussion

The proposed approaches were tested on real datasets of CT, MRI scans with dimensions of 512×512, 256×256, and all images are in DICOM format. The proposed work is executed in MATLAB 7.8 and can be run on Pentium IV processors with a clock speed of 3.0 GHz and 512 MB of RAM running Microsoft Windows.

4.1 Evaluation of Image Performance

i) Results of BWT-PC Method

The Fig. 2 shows the axial image of brain has the size of 512X512, Bi-orthogonal wavelet based decomposed image and output image of BWT-HC method. The quality of compressed image depends on the number of decompositions used in wavelet transform. Also, it determines the resolution of the lowest level in wavelet domain. Larger numbers of decomposition level will help us to determine significant DWT coefficients. After decomposing the image and representing it with wavelet coefficients, compression can be performed by ignoring all coefficients below some

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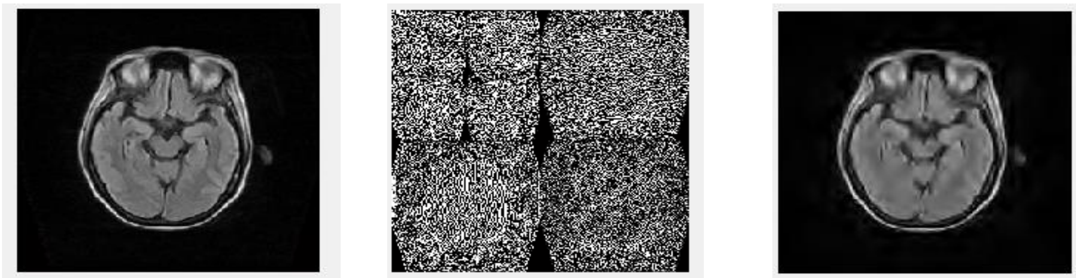
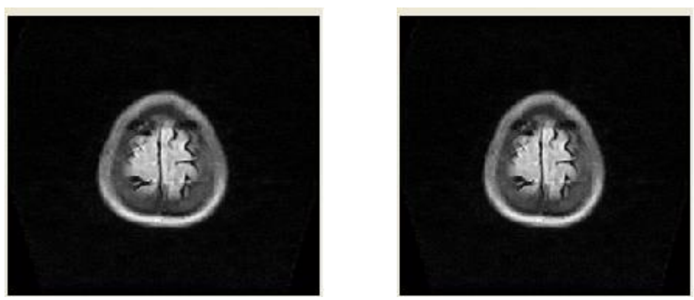
threshold. The number of decompositions determines the quality of compressed image. The decompressed image is shown in fig.3.



(a) (b) (c)

Figure 2. (a) Axial View of MRI Brain image, (b) Decomposed image and (c) output image of BWT-HC method

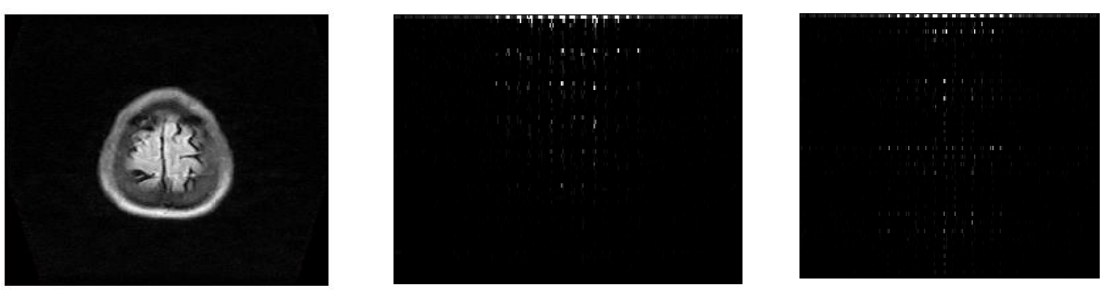


(a) (b)

Figure 3. (a)MRI Brain image and (b) Reconstructed image of BWT-HC method

ii) Results of HWT-BC Method

Fig 4 (a) shows the MRI brain image of size 516X516. DCT of input image is shown in (b). Haar wavelet is applied to input and then block coding is applied to compress the image. The resultant image of HWT-BC method is shown in (c). At the other and reconstruction is performed using inverse Haar wavelet and decoding is performed. The decompressed image is shown in 5.



(a) (b) (c)

Figure 4. (a) MRI brain image, (b) DCT of input image and (c) output image of HWT

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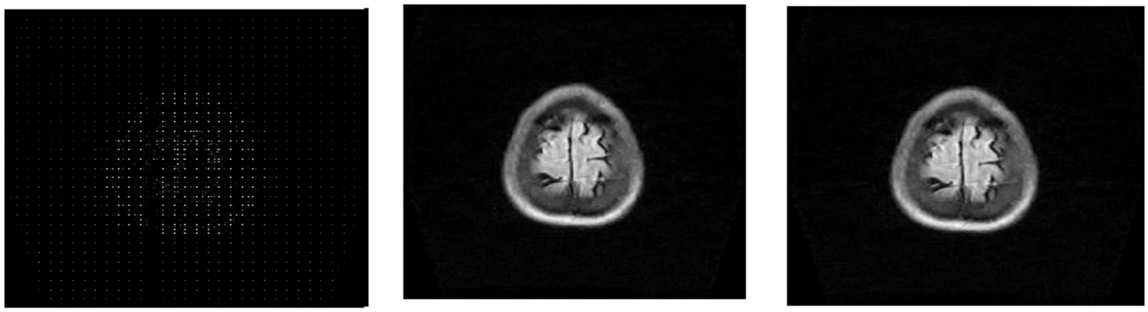
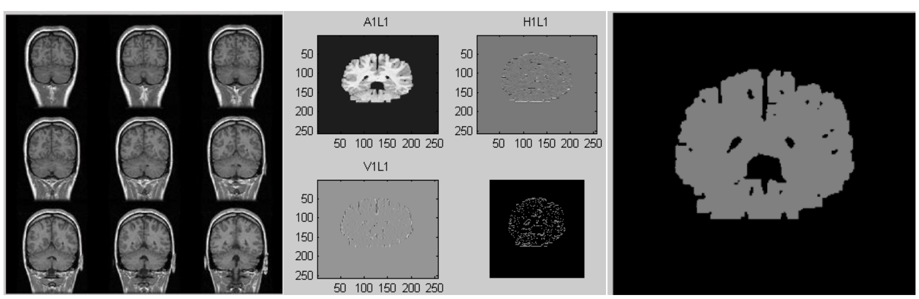


(a) (b) (c)

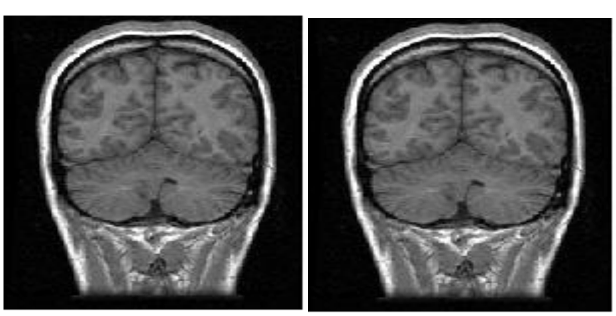
Figure 5. (a) Output image of block -coding (b) Compressed image of HWT-BC (c) Decompressed image of HWT-BC

iii) Results of SWT-PC Method

The proposed SWT with parallel coding (block coding and arithmetic encoding) techniques has been applied over various images of MRI and CT Images and the results are shown in Fig 6. (a) shows the 2d slices obtained from 3D medical images. The SWT is applied to these slices and the results are shown in (b). It shows that the more details are present in LL band. Then, the region of interest is extracted from LL band that is shown in (c). Then, the encoding method is applied to ROI to obtain the compressed image, which is shown in (D). At the decoding side, the image is reconstructed which is shown in (e). When compared to BWT-HC and HWT-BC methods the quality of reconstructed image is better in SWT-PC method.



(a) (b) (c)



(d) (e)

Figure 6. (a) 2D slices, (b) output of SWT, (c) Region of Interest, (d) Encoded image and (e) Reconstructed image of SWT-PC method

Statistical analysis

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The proposed compression algorithm is evaluated over different modalities of medical images such as MRI and CT images of different sizes 512X512 and 256X256. Their performance is examined by using four different parameters such as PSNR, CR, EcT and DcT. The observed values are given in Table.1.

Table 1: Statistical Analysis

Iodality (Slices :Pixel per Slice:bpp)	Methods	Quality Measures			
		PSNR(bits per rate: bits per pixel)	CR(bit rate: bits per pixel)	EcT	DcT
MRI(100:512x512:8)	JPEG 2000	38.01(0.25)	2.88(2.77)	2.53	2.58
	EBCOT	24.44 (0.25)	3.19(2.49)	95.12	5.24
	BWT-HF	15.12(0.52)	3.13(1.00)	76.09	191.16
	HWT-BC	38.69(1.44)	18.05(1.44)	8.86	0.09
	SWT-PC	38.01(0.25)	24.44(0.25)	2.86	3.34
MRI(14:256x256)	JPEG 2000	24.45(0.06)	8.29(2.58)	4.10	3.18
	EBCOT	22.11(0.06)	3.33(4.80)	35.12	18.84
	BWT-HF	20.39(1.00)	3.13(1.00)	43.07	115.24
	HWT-BC	47.05(3.97)	49.57(1.00)	4.98	2.97
	SWT-PC	41.67(1.00)	16.98(0.94)	2. 63	0.07
MRI(14:128x128)	JPEG 2000	21.45(0.06)	11.45(0.07)	4.03	3.28
	EBCOT	22.34(0.06)	3.34(0.07)	30.97	2.13
	BWT-HF	21.09(0.52)	3.24(1.00)	41.46	96.37
	HWT-BC	41.84(1. 00)	16.41(1.00)	4.25	1.12
	SWT-PC	47.75(3.47)	40.14(3.97)	1.09	0.09
CT(100:512X512:32)	JPEG 2000	40.00(0.25)	4.28(3.73)	0.19	0.13
	EBCOT	39.98(0.25)	3.22(4.96)	0.27	0.24
	BWT-HF	15.12(1.26)	3.13	77.21	196.97
	HWT-BC	35.79(4.28)	15.87(1)	10.93	1.21
	SWT-PC	41.30(0.91)	17.82(4.28)	0.17	0.12
CT(60:512X512:32)	JPEG 2000	30.82(0.06)	4.51(3.54)	24.23	17.12
	EBCOT	28.93(0.06)	3.25(4.92)	245.12	21.89
	BWT-HF	15.123(1.26)	3.13(1.00)	76.34	193.32

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	HWT-BC	37.81(2.54)	0.14(3.03)	11.20	11.41
	SWT-PC	41.321(1.00	14.97(1.00)	0.27	0.24
CT(44:512X512:32)	JPEG 2000	30.82(1.00)	4.16(3.84)	24.52	18.10
	EBCOT	30.82(1.00)	3.22(4.90)	235.09	22.18
	BWT-HF	15.12(1.26)	3.13(1.00)	76.35	196.97
	HWT-BC	36.45(3.27)	13.62(3.27)	11.17	11.32
	SWT-PC	40.96(1.00)	16.13(1.00)	0.17	0.1276

CT images of different compression techniques. The Average CR of 100 MRI Images of size 512 x 512 using JPEG 2000 compression techniques is 2.88 and using EBCOT is 3.19. The Average CR of 40 MRI Images of size 256 x 256 using JPEG 2000 compression technique is 8.29 and using EBCOT is 3.33db. The Average CR of 40 MRI Images of size 256 x 256 using JPEG 2000 compression technique is 8.29db and using EBCOT is 3.33db. The average CR of 100CT images of size 512x512 using JPEG2000 is 4.28 and EBCOT is 3.22. The CR ratio of both MRI and CT images of different sizes by using proposed SWT with parallel coding method is high when compared to existing compression techniques such as JPEG2000, EBCOT and Haar Wavelet lifting Scheme with block coding. So the performance of this system improved compared to Haar Wavelet Lifting Scheme with block coding. The Encoding Time and Decoding Time of both MRI and CT images of different sizes by using SWT with block coding with block coding compared to JPEG 2000, Haar Wavelet Lifting Scheme with block coding takes more time to encode and decode an image, it takes less time to decode an image because it gives better reconstructed image. The time of encoding and decoding is less when compared to EBCOT. The SWT with parallel coding compared with Haar Wavelet Lifting Scheme with block coding the CR, PSNR ratio is high and encoding time is improved. In this system encoding time and decoding time is reduced because of parallel computing. The advantages of Haar Wavelet lifting scheme required half number of computation, no auxillary memory needed, and significant advantages of block coding is create a layered bit stream that is scalable by resolution and quality. Fig 7 – 10 shows the performance comparisons of proposed methods for MRI images. Fig.11-13 shows the performance comparisons of proposed methods for CT images.

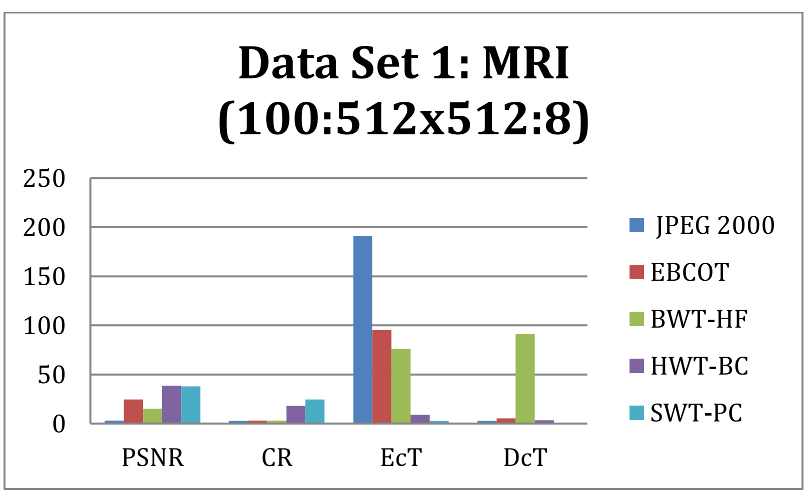

Figure 7. Performance Comparison of proposed methods with existing method of data set1 of MRI images

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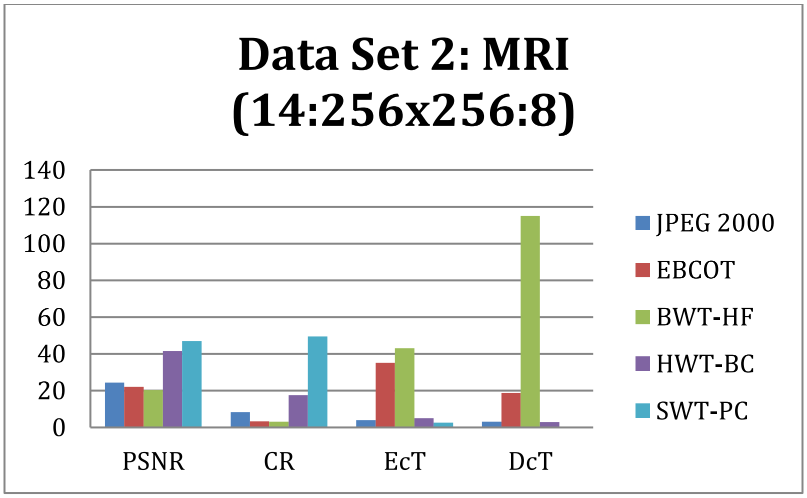

Figure 8. Performance Comparison of proposed methods with existing method of data set 2 of MRI images

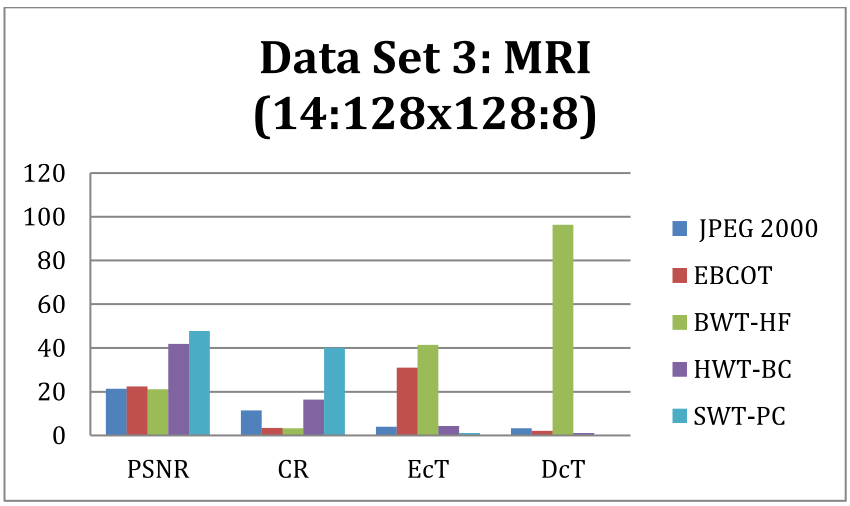

Figure 9. Performance Comparison of proposed methods with existing method of data set 3 of MRI images

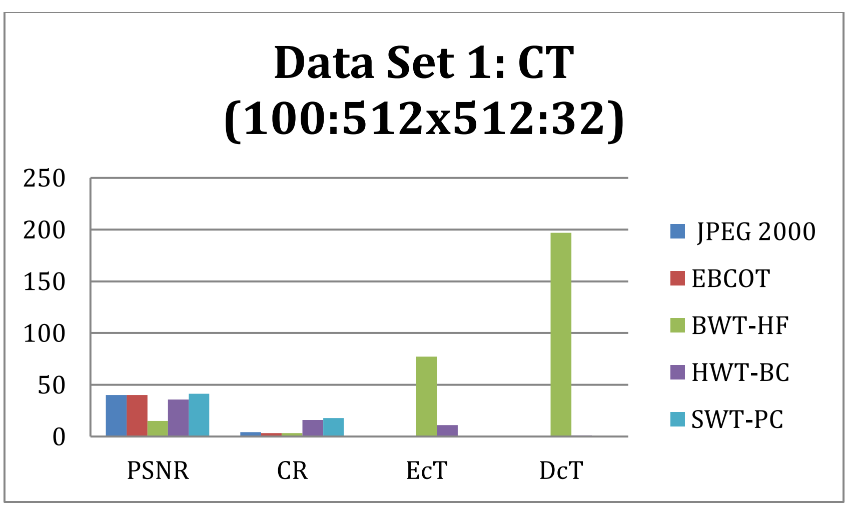

Figure 10. Performance Comparison of proposed methods with existing method of data set 1 of CT images

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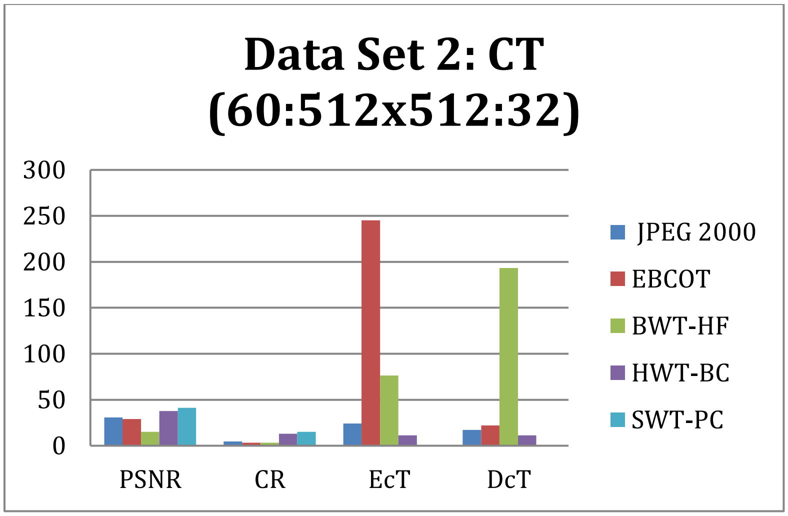

Figure 11. Performance Comparison of proposed methods with existing method of data set 2 of CT images

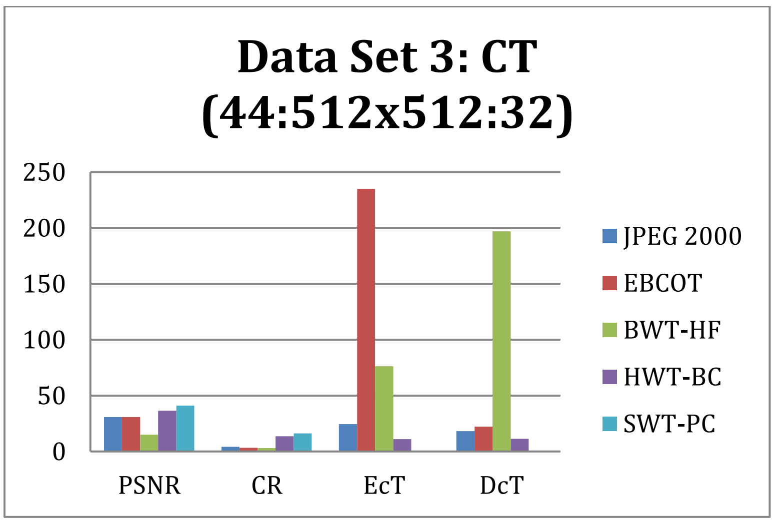

Figure 12. Performance Comparison of proposed methods with existing method of data set 3 of CT images

5. Conclusion

In this paper, comparative analysis of wavelet, based medical image compression is proposed. In medical field, lossless compression is preferred because loss of data can make diagnosis result incorrect. This work has been experimented on real medical images, where lossless compression is needed. From the experimental results, it is proved that stationary wavelet transform with parallel coding performs better when compared to other methods, since it has high PSNR and better visual quality. The results demonstrated that SWT-PC approach yields a higher quality reconstruction of 3D images than the traditional JPEG technique. Our proposed algorithm is general and it will be applied to any kind of high-resolution medical images.

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