Performance Comparison Of Enhanced Region Growing Segmentation Algorithm Based CT Scan Image Compression Using Discrete Wavelet Families.

D. Suganya Deva Malar
Student-M.E(Communication Systems)
Loyola Institute of Technology,Chennai.

Mrs. S. Uma Maheswari
Assistant Professor,
Loyola Institute of Technology,Chennai.

Abstract

In this paper proposes an efficient region of interest (ROI) technique and Discrete wavelet Transform (DWT), which is based on attempting to preserve the important image characteristics and to achieve good compression ratio. In medical images only a small portion of an image is used to diagnose. That spatial region is segregated to the end users by using "Region Of Interest" (ROI). Improvement of compression is achieved by using enhanced "Region Growing" algorithm. DWT is applied to each region on the segmented image. This new method reduces the importance of background coefficients in the ROI block. Extensive experimental results shows that the proposed method gives better quality of CT images when applying Haar wavelet than Daubechies 3, Symlet 2, Biorthogonal 1.5 wavelets. The performance of the system has been evaluated based on bits per pixel (bpp), peak signal to noise ratio (PSNR) and mean square error (MSE).

Index Terms— Image Compression, Segmentation, Region Of Interest, Region Growing, Discrete Wavelet Transform

1. Introduction

Telemedicine is crucial one, where internet is used to transfer or receive medical data by healthcare professional. Today's modern medical equipments are creating huge number of high resolution images continuously at various health care centers and hospitals around the world. The most common images used in medicals are Computed Tomography (CT) and Magnetic Resonance Imaging (MRI). These images are used by medical practitioners during analysis and diagnosis. These images while are revolutionizing the healthcare industry creates the problem of storage and transmission.

Medical imaging has had a great impact on the diagnosis of diseases and surgical planning. However, imaging device continue to generate more data per patient, often 1000 images or ~500 MB. For example, an image of size 512 x 512 pixels created by CT requires about 1/4 MB of storage space. This long-term digital archiving or rapid transmission is prohibitive without the use of image compression to reduce the file sizes. Thus image compression algorithms is necessary for storage and communication purposes.

Image compression is the process of eliminating redundant data in an image that minimizes the storage space requirement while maintaining the quality of the image. Removing redundancy can only give a limited amount of compression. To achieve high ratios, some of the non-redundant information must also be removed. Wavelet transform provides one such approach for image compression.

A number of previous approaches have been suggested to solve above specific problem. ROI is compressed with lossless and lossy techniques [1]. Lifting Wavelets and SPIHT are used to compress the images for Telemedicine application [2]. In lossless context, resolution or rate scalability coding is allowed by interleaved hierarchical interpolation (HINT) [3]. Eficient entropy coding developed for image compression [4].Semi-automatic region of interest identification algorithm using wavelets [5]. Efficient Medical Image Compression Algorithms was implemented with JPEG, Wavelet Transform and SPIHT [6].Recently, medical images compressed by using wavelet transform [7]. JPEG-LS algorithm is used to compression of an image [12].

A new, fast, and efficient image codec was used based on set partitioning in hierarchical trees [13]. Image was Compressed by using Wavelet Transform and Multiresolution Decomposition[14]. Texture classification and segmentation was done by using wavelet frames [15]. Using EBCOT, High performance scalable image compression was evaluated [16]. Near-lossless and scalable compression techniques are used for medical imaging [17]. Various Wavelet filters are applied on ultrasonic image for compression [18]. Wavelet transform was used in medical image processing [19]. DWT Based Context Modelling used for Medical Image Compression [20]. One of the intent of this paper is to investigate the effect of different types of wavelet for compression applying on medical images.

2. Region Of Interest (ROI) Segmentation

In medical imaging we need important region of the image rather than the whole image. That region contains most important information of the patient for the diagnosis purpose. So we separate the required region from the whole image. Spatial regions in images that are most important to the end user are called ROI (Region Of Interest). The general theme is to preserve quality in diagnostically critical regions, while allowing lossily encoding the other regions. A small bit of distortion in ROI may lead to undesirable treatment for patient. For securing medical images, ROI should be preserved and the remaining part of the image called as Region of Non Interest.

3. Proposed Technique

There are numerous segmentation techniques in medical imaging depending on the region of interest. In This Paper Enhanced Region Growing Segmentation technique is used during the initial stage of ROI-based medical image compression.

3.1 Enhanced Region Growing Segmentation

The goal of region growing segmentation algorithm is to group regions having common properties between a pixel and its neighbour. The properties can be intensity values of the original image or unique texture patterns of each region or spectral profiles that provide multidimensional image data.

The algorithm provides multiple merits during segmentation. The borders of regions found by region growing are perfectly thin and well connected. Region growing has shown to be a very useful and efficient segmentation technique in image processing. Region growing in its simplest sense is the process of joining neighboring points into larger regions based on some condition or selection of a threshold value.

The algorithm is very stable with respect to noise. Most importantly, membership in a region can be based on multiple criteria. It is possible to take advantage of several image properties, such as low gradient or gray level intensity value, at once, while using region growing algorithm.

The traditional region growing algorithm has two major issues. The first is the selection of initial seed points. Incorrect selection leads to inaccurate segmentation and therefore an automatic process is always preferred. The second is that even with automated process, the selected seed point may lie on an edge.

The last step in the algorithm consist of two conditions that examine the candidate pixels and makes sure that the selected seed point is highly similar to its neighbour and is not a boundary region. For this purpose, the relative Euclidean distance between the seed point and its neighbours is calculated using Equation 1.

$$d_i = \sqrt{\frac{P - NPi}{\sqrt{P^2}}} \qquad (1)$$

where 'P' denotes the seed point and i denotes its 8 neighbouring pixels.The automated process of initial seed selection is shown in Figure 1. Enhanced region growing algorithm consists of the following steps.

(i) Apply automatic seed selection algorithm to obtain . initial seeds for region Growing
(ii) Calculate distance between seed point and its neighbours.
(iii) Check the neighbouring pixels and add them to the region if they are similar to the seed .
(iv) If there is no more pixels to add means stop the algorithm,otherwise repeat the steps from (i) to (iv).

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 2 Issue 5, May - 2013

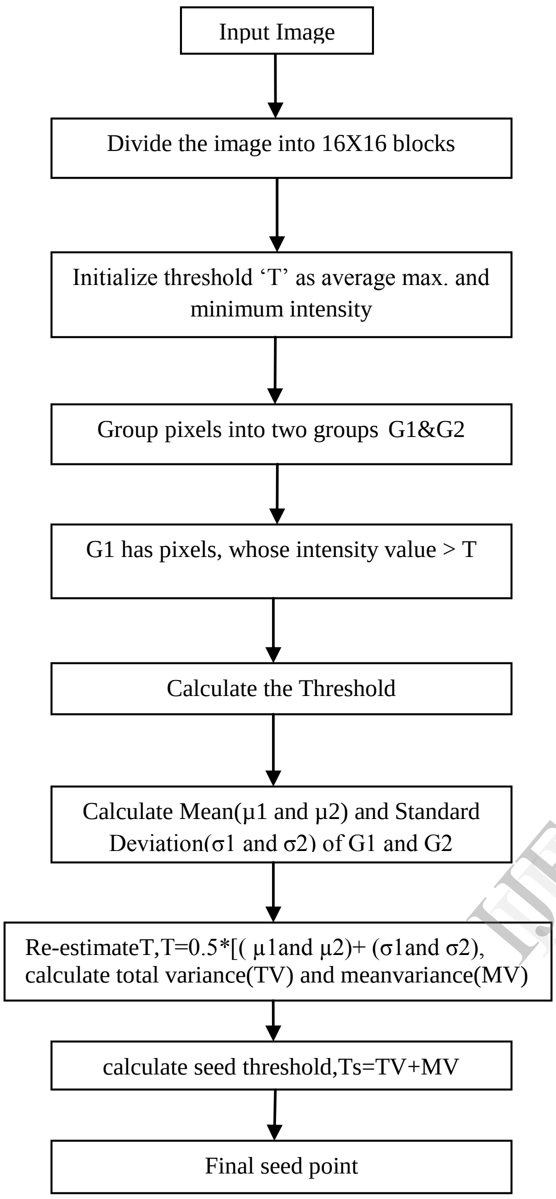


Figure 1. Flow Chart of Automatic Selection of Initial Seeds

4. Image Compression Based On DWT

Image compression is the process of eliminating Redundant data present in an image. The images can be transferred from one domain to another. Applying wavelet transforms over the images converts them from spatial domain to time-scale domain

4.1 2- D Discrete Wavelet Transform

Discrete wavelets transform is the combination of the low pass and high pass filtering in a spectral decomposition of signals along with a very fast implementation. The goal of this paper is to achieve higher compression ratio in images using the two-dimensional DWT more effectively by exploiting image structure characteristics, In the field of image compression and analysis wavelet transforms has widely used. It has very good energy compaction capabilities, robustness under transmission, high compression ratio.

In 2D,a two-dimensional scaling function, $\varphi(x,y)$,and three two-dimensional wavelets, $\psi^H(x,y)$, $\psi^V(x,y)$ and $\psi^D(x,y)$ are required. Seperable scaling function for 2D DWT can be obtained by multiplying two 1-D scaling function is given by,

$$\varphi(x,y) = \varphi(x)\varphi(y) \qquad (2)$$

Three wavelet function that analyses details in Horizontal, Vertical, Diagonal direction.The Separable,"directionally sensitive" wavelets are,

$$\psi^H(x,y) = \psi(x)\varphi(y) \qquad (3)$$

$$\psi^V(x,y) = \varphi(x)\psi(y) \qquad (4)$$

$$\psi^D(x,y) = \psi(x)\,\psi(y) \qquad (5)$$

These wavelets measure fun-intensity variations for images along different directions.The discrete wavelet transform of image f(x,y) of size M X N is then,

$$W_\varphi(j_0,m,n)= \frac{1}{\sqrt{MN}}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1} f(x,y)\varphi_{j_0,m,n}(x,y) \qquad (6)$$

$$W^i_\psi(j,m,n)=\frac{1}{\sqrt{MN}}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1} f(x,y)\psi^i{}_{j_0,m,n}(x,y) \qquad (7)$$

$$i = \{H,V,D\}$$

The decomposition process of high and low frequency components by using DWT is depicted in Fig.2. The implementation of wavelet compression method is very similar to that of subband coding scheme.Wavelet produces one lowpass subband and one highpass subband in each dimension. During a single level of decomposition using a wavelet transform, 2D image data is replaced by four blocks corresponding to the subbands representing either lowpass or highpass filtering in each direction.

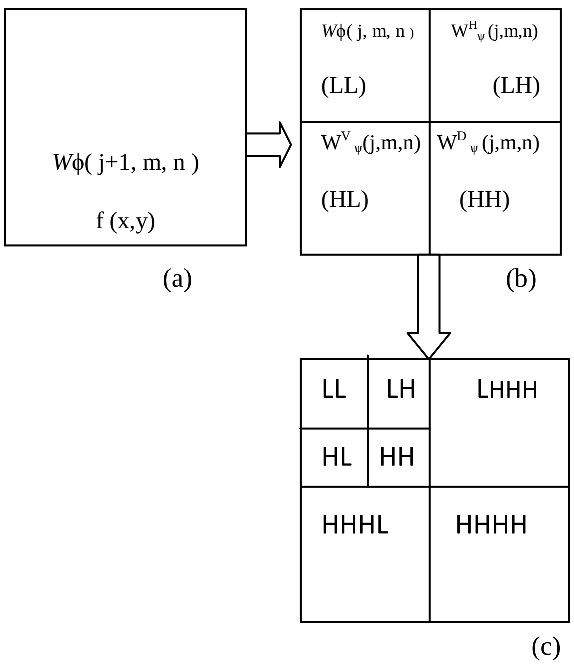


Figure 2. Two level decomposition in 2-D DWT (a) Original Image function level 0 (b) Level one decomposition (c) Two Level Decomposition

We have basically four types of wavelets and various types of wavelets families.

1. Haar wavelet transform
2. Daubechies wavelet transform
3. Symlet wavelet transform
4. Biorthogonal wavelet transform

f (x,y) is obtained by using the inverse discrete wavelet transform.It is given by eqn.8.

$$f(x,y) = \frac{1}{\sqrt{MN}}\sum_m \sum_n W_\varphi\left(j_0,m,n\right)\varphi_{j_{0,m,n}}(x,y) + \frac{1}{\sqrt{MN}}\sum_{i=H,V,D}\sum_{j=j_0}\sum_m\sum_n W^{i}_{\varphi}(j,m,n)\,\psi^{i}_{j,m,n}(x,y) \tag{8}$$

5. Algorithm For Compression

The compression algorithm for medical image compression based on the wavelet transforms is given in following steps.

For Compressing the Medical Image:
1. The goal of the first stage of the proposed methodology is, to segment the image into two regions namely, ROI and Non-ROI.
2. The DWT of the region growing segmented medical image is generated by obtaining wavelet decomposition coefficients for the desired levels. Four types of wavelets are used for decomposition.
3. A threshold for the decomposed image coefficients is selected, below which all the coefficients are made zero. This reduces the band space of the image signal, as large number of coefficients are made zero.
4. The thresholded coefficients are saved instead of the image.

For Decompressing the Medical Image:
1. When the image is to be uncompressed, threshold coefficients are obtained.
2. Image is regenerated from these threshold coefficients by taking inverse discrete wavelet transform (IDWT).

6. Results And Discussion

Results have been obtained by calculating few parameters obtained by the comparing original image and recovered image. They are defined as follows:
(i) Mean Square Error (MSE): Mean square error measures the cumulative square error between the original and the compressed image. The formula for mean square is given as

$$\text{MSE} = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}\|I(i,j) - K(i,j)\|^2 \tag{9}$$

Where m*n is the size of the image. $I(i,j)$ and $K(i,j)$ is the original image and the compressed image at (i,j) pixel. Thus MSE should be as low as possible for effective compression.
(ii) Peak Signal to Noise Ratio (PSNR): Peak signal to reconstructed image measure known as PSNR.

$$PSNR = 10log_{10}\left(\frac{255^2}{MSE}\right)(dB) \tag{10}$$

Here signal is original image and noise is error in reconstructed image. In general, a good reconstructed image is one with low MSE and high PSNR.

(iii) Bits Per Pixel (BPP): It is the number of bits used to encode each pixel value. Thus for the purpose of compression BPP should be less to reduce storage on the memory.

(iv) Compression Ratio: The compression ratio is equal to the size of the original image divided by the size of the compressed image.

$$CR=n1/n2 \qquad (11)$$

where CR is the compression ratio, n1 and n2 is the number of information carrying units in the original and compressed images respectively.CR is express in percentage.This ratio gives how much compression is achieved for a particular image.

(v) Compression Speed: Compression time and decompression time are defined as the amount of time required to compress and decompress a picture, respectively.

6.1 CT Scan Image Result

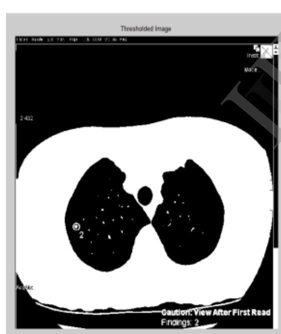
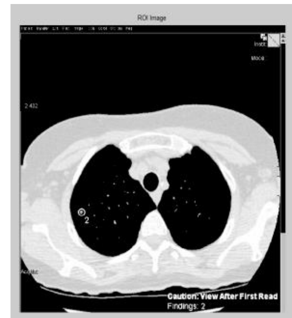


Figure 3. Input CT scan image **Figure 4.** Thresholded Image

Here, CT scan image of Human Lungs is taken as an input image is shown in Figure 3. If an input image is RGB color image, it is transformed into gray scale image. Next image is a thresholded image is shown in Figure 4.



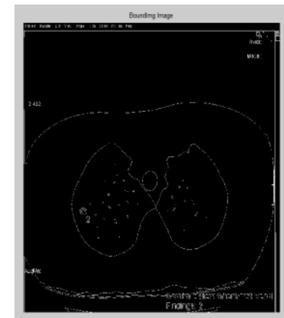


Figure 5. ROI image **Figure 6.** Boundary image

Here, the gray image is segmented into regions where each region corresponds to a seed. That is the pixels are grouped together with similar properties The segmented region is shown in Figure 5. The difference between the two region is called as boundary. The boundary detection on CT human lungs is shown in Figure 6. From the figure it is observed that edge detection methods try to show the edges inside the ROI.

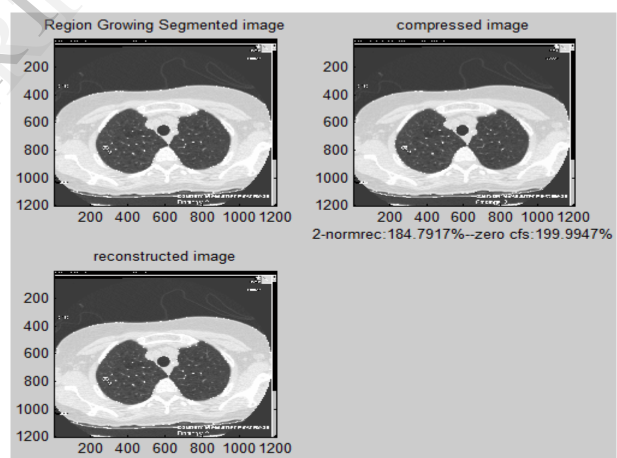


Figure 7. Final Region Growing Segmented Image,Compressed Image And Reconstructed Image Using Haar Wavelet.

Finally, Region growing segmented image is taken as an input for image compression. Wavelet used in an image for decomposition is haar and the desired decomposition level is 2. Reconstructed image is also shown in Fig. 7. The results over the images have been obtained using Haar, Daubechies(db3), Symlet 2,and Biothogonal 1.5 wavelets. Results are analyzed in tabular form, and graphs.

Table-1: Values Of CT Scan Image parameter

No. Of CT Lungs Image	Wavelet Used	MSE	PSNR (dB)	BPP
1	haar	1.2930	47.0147	4.1557
2		0.8128	49.0311	5.2318
3		3.8922	42.2289	4.2284
4		2.3774	44.3699	5.5675
5		9.8927	38.1777	3.9723
1	db3	0.5456	50.7624	4.1557
2		0.1969	55.1889	5.2318
3		1.5903	46.1159	4.2284
4		1.4310	46.5744	5.5675
5		3.2697	42.9857	3.9723
1	Sym2	0.6277	50.1531	4.1557
2		0.1957	55.2152	5.2318
3		1.9328	45.2689	4.2284
4		1.5075	46.3481	5.5675
5		4.6614	41.4457	3.9723
1	bior1.5	1.4936	46.3884	4.1557
2		0.8659	48.7561	5.2318
3		4.4384	41.6585	4.2284
4		2.6545	43.8910	5.5675
5		11.0051	37.7148	3.9723

Table 2: Compression Performance of CT Images

No. of CT Lungs Images	Wavelet Used	CR %	CPU TIME (sec)
1	haar	84.7917	4.076556
2		87.6756 84.5521	5.9017664. 672203
3		84.5116	5.975017
4		84.5417	4.524283
5			
1	db3	84.4728	4.585760
2		87.0855	7.957836
3		84.3902	6.104877
4		84.3942 84.3818	7.162193
5			5.383555
1	sym2	84.6304	3.672950
2		87.3366	7.479830
3		84.4597	5.200603
4		84.4793	6.177136
5		84.4461	4.282267
1	bior1.5	84.3030	7.623928
2		86.5949	9.836402
3		84.2641	7.066517
4		84.2813	8.598316
5		84.2431	5.734608

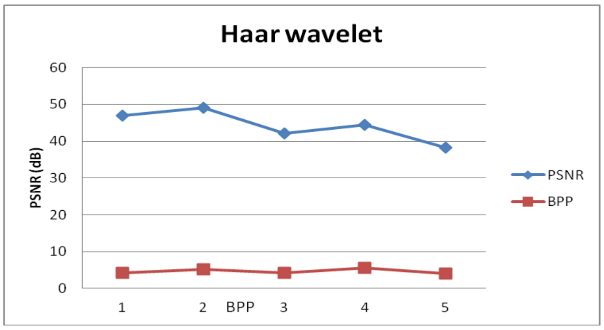


Figure 8. PSNR vs BPP plot of CT image for Haar wavelet.

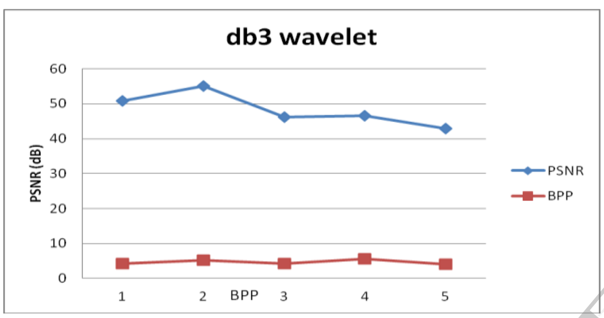


Figure9. PSNR vs BPP plot of CT image for db3 wavelet.

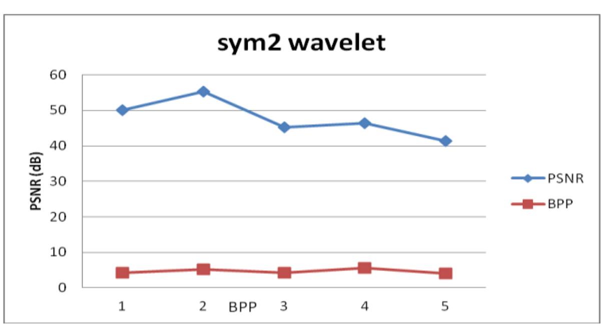


Figure10. PSNR vs BPP plot of CT Image for sym2 wavelet.

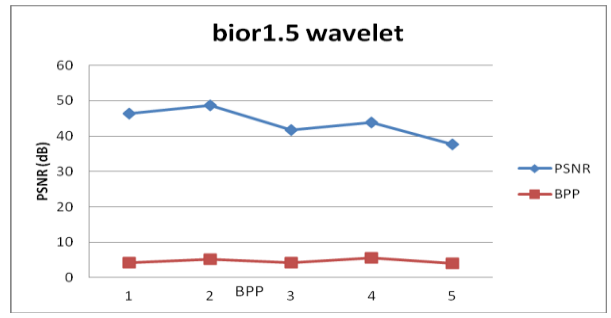


Figure11. PSNR vs BPP plot of CT Image for bior1.5 wavelet.

A graph between PSNR and BPP is plotted for four wavelets applied over the CT image. Biorthogonal 1.5 and Haar wavelet showed a poorer result. Db3 and sym2 have similar characteristic curves of PSNR v/s BPP. The First test image is that of a CT of a human lungs. The best result was obtained with db3 wavelet. The MSE is as low as 0.5456 and PSNR is 50.7624dB at the BPP of 4.1557 is shown in Table 1. The compression ratio at this point is 84.4728% is shown in Table 2.

7. Conclusion

The algorithm works well over the images as shown by the results. At the most optimal compression the original and decompressed from wavelet coefficient is almost the very same. Various wavelets are applied on CT medical images. The performance of the system has been evaluated based on bits per pixel (bpp) , peak signal to noise ratio (PSNR) and mean square error (MSE). Experiment results showed that the proposed method gives better quality of images when applying Haar wavelet.

Acknowledgement

The authors wish to thank D.Suganya Deva Malar and Mrs.S.Uma Maheswari. This work was supported in part by a grant from Mrs.S.Uma Maheswari Asst. Professor.

REFERENCES

[1]. Balpreet Kaur, Deepak Aggarwal, Gurpreet Kaur, Amandeep Kaur, " Efficient Image Compression based on Region of Interest" IJCST Vol. 2, Issue 1, March 2011.

[2]. T. M. P. Rajkumar, Mrityunjaya V Latte, "ROI Based Encoding of Medical Images: An Effective Scheme Using Lifting Wavelets and SPIHT for Telemedicine*", Computer Theory and Engineering*, Vol. 3, No. 3, June 2011.

[3]. A. Abrardo, L. Alparone, and F. Bartolini, "Encoding-interleaved hierarchical interpolation for lossless image compression," *Signal Prcess.*, vol. 56, no. 3, pp. 321–328, Feb. 1997.

[4]. A. Krivoulets, "Efficient entropy coding for image compression", IT Univ. Copenhagen, Copenhagen, Denmark, Tech. Rep. TR-2002-13,Feb. 2002.

[5]. Sedig A. et al., "Semi-automatic region of interest identification algorithm using wavelets", J. of Optical Engineering, Vol-46(3)035003-6, March 2007.

[6]. M.A.Ansari and R.S.Anand, "Implementation of Efficient Medical Image Compression Algorithms with JPEG, Wavelet Transform and SPIHT*", Int. Journal of Computational Intelligence Research and Applications* (IJCIRA), Vol.2, No.1, pp. 43-55, 2008.

[7]. Ruchika, Mooninder Singh, Anant Raj Singh,"Compression of Medical Images Using Wavelet Transforms*", International Journal of Soft Computing and Engineering* (IJSCE), ISSN: 2231-2307, Vol-2, Issue-2, May 2012.

[8]. R.Sumalatha, M.V.Subramanyam,"Medical Image Compression Using Multiwavelets For Telemedicine Applications",*International Journal of Scientific & Engineering Research* (IJSER), ISSN: 2229-5518, Vol-2, Issue-9, Sept-2011.

[9]. Puja D Saraf, Deepti Sisodia, Amit Sinhal and Neetesh Gupta, "Comparisons Of Wavelets Based Image Compression Methods", *World Journal of Science and Technology*, ISSN: 2231 – 2587, April 2012.

[10]. Nikkoo Khalsa, Dr. G. G. Sarate, Prof. D. T. Ingole, "Factors Influencing The Image Compression Of Artificial And Natural Image Using Wavelet Transform", International Journal of Engineering Science and Technology (IJEST), ISSN: 6225-6233 Vol. 2(11), 2010.

[11].Gunpreet Kaur, Mandeep Kaurm"Performance Evaluation of ROI-based Image Compression Techniques", *International Journal of Scientific & Engineering Research* (IJSER), ISSN: 2229-5518, Vol- 2, Issue 10, Oct-2011.

[12]. Weinberger, M.J., Seroussi, G. and Sapiro, G, "The LOCO-I lossless image compression algorithm: principles and standardization into JPEG-LS", *IEEE Transactions on Image Processing*, Vol. 9, Issue 8, Pp.1309-1324,2000.

[13]. A. Said and W. A. Pearlman, "A new, fast, and efficient image codec based on set partitioning in hierarchical trees," *IEEE Trans. Circuits Syst. Video Technol.*, vol. 6, no. 3, pp. 243–250, Jun. 1996.

[14]. Amir Averbuch, "Image Compression Using Wavelet Transform and Multiresolution Decomposition*", IEEE Trans. Image Processing*; vol. 5, no. 1, pp 4-15, January 1996.

[15]. M. Unser, "Texture classification and segmentation using wavelet frames", *IEEE Trans. Image Processing*, Vol-4,no. 11, pp. 1549-1560, Nov. 1995.

[16].D.Taubman,"High performance scalable image compression with EBCOT", *IEEE Trans. Image Process.*, vol. 9, no. 7, pp. 1158–1170,Jul. 2000.

[17]. J. Taquet and C. Labit, "Near-lossless and scalable compression for medical imaging using a new adaptive hierarchical oriented prediction,"in Proc. 17th IEEE ICIP, pp. 481–484, 2010.

[18]. S. Udomhunsakul and K. Hamamoto, "Wavelet filters comparison for ultrasonic image compression," *Conf. IEEE TENCON*, vol. 1, pp. 171-174, Nov. 2004.

[19]. Da-Zeng Tian, Ming-Hu Ha, "Applications of wavelet transform in medical image processing", *IEEE Proc. of Int. Conf. on Machine Learning and Cybernetics*, Vol.3, pp.1816–1821, 26-29 Aug. 2004.

[20]. M.A. Ansari, " DWT Based Context Modeling Of Medical Image Compression", National Systems Conference, Dec 2008.