

**Modified DWT Based Medical Image Transmission Using Reduced Storage Space**K.A. Mohamed Junaid<sup>1</sup>, Dr.G.Ravindran<sup>2</sup><sup>1</sup> RMK Engineering College, Kavaraipettai-601206, India<sup>2</sup> Centre for Medical Electronics, Anna University, Chennai, India**Article details:**

Received:

15th April 2012

Received in revised form:

27 July 2012

Accepted:

28th July 2012

Available online:

20th Aug 2012

Online ISSN 2249-622X  
<http://www.jbiopharm.com>**ABSTRACT**

With the rapid development in communications technology, various methods of medical image transmission are investigated. A comprehensive system integrating various applications within a common infrastructure is usually necessary for this purpose. This infrastructure includes the physical facilities and equipments which are used to capture, transmit, store, process, and display medical data and images. To effectively reduce the cost of realizing the infrastructure, data compression is usually desired so that the bandwidth and storage requirements for delivering and storing medical data are lowered.

In this research work, initially the images are enhanced using local adaptive filter and the Pixels of Interest (POI) is selected to reduce the size of the medical image to be transferred. The second step is where a modified Discrete Wavelet Transform (MDWT) is applied to compress the image data with minimum storage space, and then the image is transmitted over the Internet. At the receiving side the POI image is reconstructed.

The objectives of this research are to design and implement Modified DWT compression technique using a uniform quantizer and reduced Sub band Coding to split up the frequency band of a image and then to code each sub band using a coder. Dimension reduction technique is used to reduce the storage space. The developed algorithm involves dimension reduction technique by using intermediate co-efficient storage to reduce the storage space in the DWT architecture. Hence, at the receiver the side, retrieval of intermediate co-efficient is obtained by decoding each sub band using decoder for the frequency band of the images. By using the IDWT, the original image is retrieved without any loss of information in the image. To compare the measure of compression MSE, PSNR and SNR values, ROI of the CT images are compressed by using standard JPEG and DWT methods.

Image compression using JPEG, DWT and Modified DWT has been developed to find optimum method for transmitting medical images through the Internet with less storage space and low bandwidth requirements. The present method offered better results and is found to be the optimum method with high PSNR, low MSE and less storage space. As a future work, the effectiveness of Modified DWT will be compared with other emerging Imaging techniques by taking image as a whole. In medical image transmission, instead of still medical images which used imaging techniques, moving images may also be transmitted using modified DWT.

**Keywords:** Image Compression, JPEG, Discrete Wavelet Transform (DWT), IDWT, Medical image transmission

**INTRODUCTION**

With the rapid development in communications technology, various methods of medical image transmission are investigated. A comprehensive system integrating various applications within a common infrastructure is usually necessary for this purpose (11,5). This infrastructure includes the physical facilities and equipments which are used to capture, transmit, store, process, and display medical data and images (8). To effectively reduce the cost of realizing the infrastructure, data compression is usually desired so that the bandwidth and storage requirements for delivering and storing medical data are lowered (4).

Analysis and compression of medical images is an important area of Biomedical Engineering. This may be very useful and can play an important role in the diagnosis of sophisticated and complicated images through consultation (10). As medical images come in large sizes and huge volumes that require ample transmission time which have to be transmitted over networks at large distances, it is necessary that be transmitted in compressed and secure form for reliable, improved and fast diagnosis (3). Image Compression Methods are used to reduce storage space and to increase the speed of transmission of image files. Compression is achieved by reducing number of bits per pixel required to represent an image. The difficulty, however, in several applications lies on the fact that, while high compression rates are desired, the applicability of the reconstructed images depends on whether some significant characteristics of the original images are preserved after the decompression process has been completed.

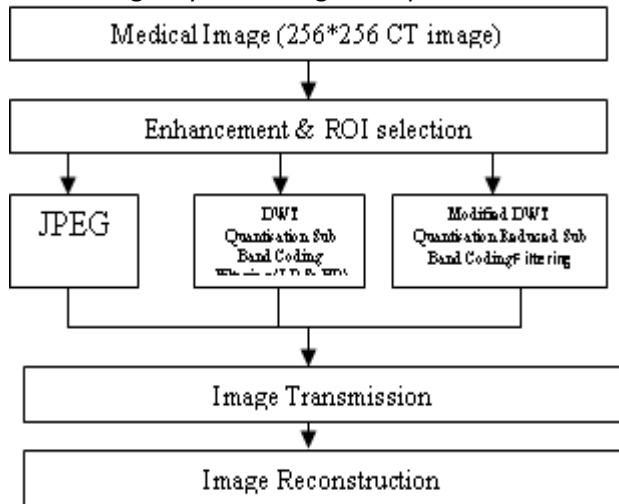
**MATERIALS AND METHODS:**

In this research work, initially the images are enhanced using local adaptive filter and the Pixels of Interest (POI) is selected to reduce the size of the medical image to be transferred. The second step is where a modified Discrete Wavelet Transform (MDWT) is applied to compress the image data with minimum storage space, and then the image is transmitted over the Internet. At the receiving side the POI image is reconstructed. The following block diagram Figure 1 shows the procedural steps followed in this developed work.

**2.1 Block Diagram**

The scanned images from CT scan centers are read and stored in Compact Disc for ease of use. The images are read and the following steps are developed. To eliminate the Background pixels of CT images and to enhance the same, locally adaptive non-linear filter can be used. Threshold based Region of Interest technique is used for the selected region of the image. By eliminating

background pixels, the full binary images with clinical interest area of the image pixels are obtained. All the details of the selected organ (in our case, brain) by eliminating only the back ground pixels are selected as ROI.



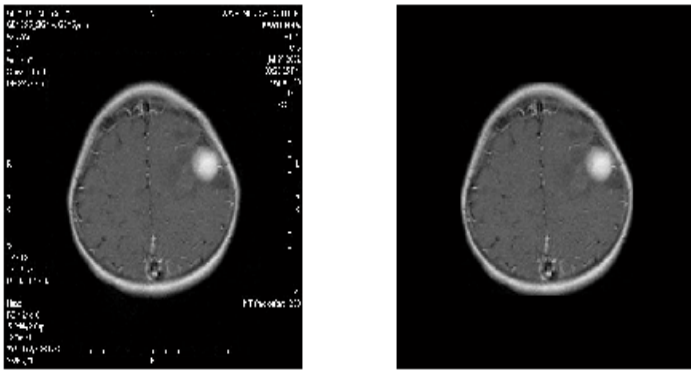
**Figure 1 Block diagram of the present work**

The objectives of this research are to design and implement Modified DWT compression technique using a uniform quantizer and reduced Sub band Coding to split up the frequency band of a image and then to code each subband using a coder. Dimension reduction technique is used to reduce the storage space. The developed algorithm involves ddimension reduction technique by using intermediate co-efficient storage to reduce the storage space in the DWT architecture. Hence, at the receiver the side, retrieval of intermediate co-efficient is obtained by decoding each sub band using decoder for the frequency band of the images. By using the IDWT, the original image is retrieved without any loss of information in the image. To compare the measure of compression MSE, PSNR and SNR values, ROI of the CT images are compressed by using standard JPEG and DWT methods.

**2.2 Preprocessing and Image Enhancement**

Initially the images are preprocessed to remove the unnecessary labels on it or it can be termed as the elimination of background pixels. To achieve this, the intensity images are converted into binary. Then, simple morphological erosion is applied to eliminate the background labels. Thus, a binary image that contains only the Pixels of Interest (POI) alone is obtained. Only these pixels are extracted from the original image and the background pixels are eliminated.

The following Figure2 shows the original and the preprocessed image.



**Figure 2 Original and preprocessed image**

Contrast enhancement techniques are widely used to increase the visual image quality. Local contrast enhancement tries to enhance the visibility of local details in the image. For any medical image, the local details are very much important in the perspective of physicians to diagnose the affected portion of the organs. Hence, Image enhancement is necessary to improve the visibility of the local details in the image.

With the advent of high-speed processors, such as array and image display processors, the increased computational power has shifted emphasis in image processing away from 'global' to 'local' techniques. Local adaptive filtering has been found to provide excellent results for noise reduction and image enhancement of medical images, without losing information of edges, boundary and feature details(13). It is difficult to perform image enhancement, using only one simple filter, for a real world image which may consist of many different regions. Adaptive filters have been implemented by computing the central pixel value using neighborhood centered averaging and subsequently applying the adaptive correction on each pixel using the local variance and overall noise variance estimates.

In locally adaptive non-linear filter, the enhanced image  $y(m,n)$  is obtained from the input image  $x(m,n)$  is given in equation (1)

$$y(m,n) = \mu(m,n) + [1+g(m,n)][x(m,n)-\mu(m,n)] \quad \dots\dots (1)$$

where  $\mu(m,n)$  is the local mean,  $g(m,n)$  is the enhancement gain,  $m$  is the row number, and  $n$  is the column number. Here, a locally adaptive nonlinear filter is employed to find the local mean by averaging two opposite direction non-linear filters and rational gain function is designed to suppress noise visibility in smooth regions.

The local mean  $\mu(m,n)$  at row  $m$  and column  $n$  is the output of the filter, which is the average of two different filter outputs given in equation (2)

$$\mu(m,n) = \frac{\mu_F(m,n) + \mu_B(m,n)}{2} \quad \dots\dots\dots (2)$$

where  $\mu_F(m,n)$  and  $\mu_B(m,n)$  are the outputs of the two opposite direction filters that run horizontally on a single row. The first filter runs from left to right and is referred to as the forward filter with output  $\mu_F(m,n)$ . The second filter runs from right to left and is similarly referred to as the backward filter output  $\mu_B(m,n)$ . The two filters are single pole Infinite Impulse Response (IIR) filters at any given pixel location. The input-output relationship for the forward filter  $\mu_F(m,n)$  is given in equation (3)

$$\mu_F(m,n) = \lambda(m,n) \mu_F(m,n-1) + [1-\lambda(m,n)] x(m,n) \dots\dots\dots (3)$$

where  $\lambda(m,n)$  is the edge adaptive delay coefficient. The relationship for the backward filter  $\mu_B(m,n)$  is similar.

The adaptation of  $\lambda(m,n)$  to the edge information is crucial for preventing the smoothing of edges. Considering that  $\lambda(m,n)$  is the weight of the previous output, stronger  $\lambda(m,n)$  which increases the low-pass characteristic of the filter. Hence, when an edge is encountered,  $\lambda(m,n)$  must be decreased so that the edge will be preserved in the output. The edge signal used in this realization and is given in equations (4) and (5)

$$|\mu_F(m,n-1)-x(m,n)| \text{ for the forward filter, and} \quad (4)$$

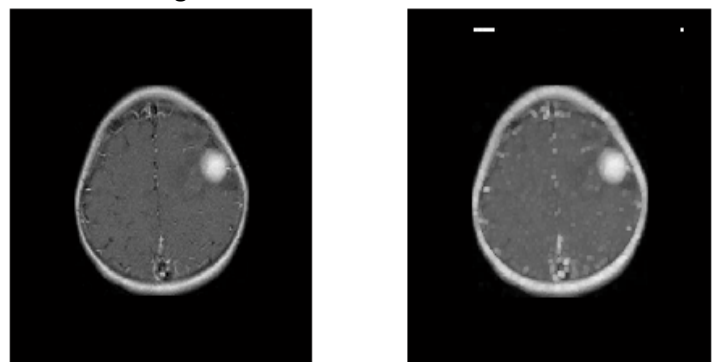
$$|\mu_B(m,n+1)-x(m,n)| \text{ for the backward filter.} \quad (5)$$

Both of the edge signals are the differences between the original pixel value and the previous filter output.

Using these edge signals,  $\lambda(m,n)$  is obtained using equation (6)

$$\lambda(m,n) = \left[1 - \frac{|\mu_F(m,n-1) - x(m,n)|}{255}\right]^\alpha \quad (6)$$

for the forward filter, and similar for the backward filter. Here maximum possible pixel value used is 255. It is observed that the strong edges reduce  $\lambda(m,n)$  more, hence the low-pass characteristic of the signal at that locality is lessened (8). Figure 3 shows the preprocessed image and enhanced image.



**Figure 3 Preprocessed and enhanced image ROI Selection**  
Interest in a medical image often can be confined to a specific region. A different bit-rate can be allocated to different spatial regions according to their 'importance' to

the user. This kind of bit-rate allocation, different from the widely used optimal bit allocation to minimize the total distortion such as the MSE of the image, is a region based bit-rate allocation. A region-based method provides another way in solving the conflict between the high fidelity requirement for medical images and the low bandwidth communication.

In this work, a threshold based ROI is selected. That is, based on the peak value from the histogram of the image, the threshold value is selected. With this threshold, the background of the image is removed and the compression algorithm is applied only for the selected ROI.

The following Figure 4 shows the enhanced image and selected ROI.

Image compression for the selected region where Pixels of Interest is developed by utilizing the JPEG, DWT and modified DWT techniques. Quality of compression Technique is measured in terms of MSE and PSNR to find out the optimum method suitable for medical image transmission.

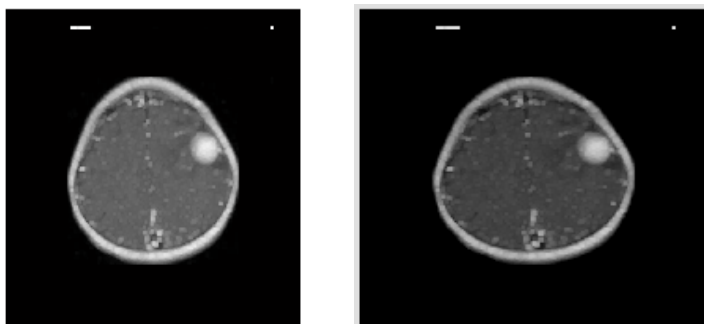


Figure 4 Enhanced image and selected ROI

## 1. DWT BASED IMAGE COMPRESSION

### 3.1 Wavelet Transform

Wavelets are functions defined over a finite interval and have an average value of zero. The basic idea of the wavelet transform is to represent any arbitrary function ( $t$ ) as a superposition of a set of such wavelets or basis functions. These basis functions or baby wavelets are obtained from a single prototype wavelet called the mother wavelet, by dilations or contractions (scaling) and translations (shifts). The Discrete Wavelet Transform of a finite length signal  $x(n)$  having  $N$  components is expressed by an  $N \times N$  matrix (9).

The main concept behind the wavelet transform is to represent the signal as piece-wise linear approximations and the detail functions. The detail function is the information that is lost in going from a finer to a coarser approximation. This can also be viewed as successive low and high pass filtering i.e. first filter the signal into two bands and then filter the low pass region into further two parts. The number of times it is

implemented is termed as the level of decomposition. It is observed that most of the information in the signal is concentrated in the approximation level and some part of it in the initial detail levels. This can be exploited for the purpose of compression since the signal is reconstructed to a fairly good extent even by neglecting the higher detail coefficients (10,11). By optimally allocating bits to the different levels, high compression ratios are achieved by retaining most of the information.

In the case of any real world signal there is always an element of predictability. Using this, the value of the signal at any instant of time depending on its previous values can be predicted. The value can be predicted as the weighted sum of the previous 'p' values. By optimally choosing the weights, best predicted values are obtained. Once the value has been predicted, the differences between the actual and predicted values are retained. Obviously the dynamic range of the difference signal will be much smaller than that of the signal and hence lesser bits will be required to represent it and is exploited in compression algorithm. The optimum weights are determined by minimizing the error between the actual and predicted values of the signal (12).

A significant portion of the information is concentrated in the lower levels. Hence any noise added to the signal will have a stronger effect on the higher wavelet coefficients. In the lower levels the relative noise will be lesser since the signal energy is high. So the higher coefficients are neglected or made as zero which does not affect the signal considerably (13). This will result in reduction in the noise without affecting the signal.

### 3.2 Quantization

Despite all the advantages of JPEG compression schemes based on DCT namely simplicity, satisfactory performance and availability of special purpose hardware for implementation, there are some disadvantages due to blocking artifacts. Since the input image needs to be "blocked," correlation across the block boundaries is not eliminated. This results in noticeable and annoying "blocking artifacts" particularly at low bit rates (14).

In this research work, a 3 level wavelet decomposition of the signal was carried out. The coefficients were then quantized using a uniform quantizer. The step size of the quantizer depends on the number of bits allocated for it, which in turn determines the compression ratio. The number of bits allocated to the different levels also determines the SNR that can be obtained. The optimal numbers were arrived at by trial and error method. For a quantizer of L bits,  $2^L$  quantization levels are taken. For a uniform quantizer these are equispaced. A non-uniform quantizer produces unequal

intervals. However it requires the probability distribution of the signal to be quantized. The quantizer finds the level closest to the signal value and stores/transmits the index of that level. It can be seen that the encoder should also transmit the quantization levels. Higher the L, finer is the quantization. The error between the original and reconstructed signal, which is due to quantization, is known as the 'quantization noise'.

**3.3 Subband Coding (SBC)**

Over the past several years, the wavelet transform has gained widespread acceptance in signal processing. In many applications wavelet-based schemes also referred as subband coding outperform other coding schemes. Since there is no need to block the input image and its basis functions have variable length, wavelet coding schemes at higher compression avoid blocking artifacts. Wavelet-based coding is more robust under transmission and decoding errors, and also facilitates progressive transmission of images (14).

The fundamental concept behind SBC is to split up the frequency band of a image and then to code each subband using a coder and bit rate accurately matched to the statistics of the band. SBC has been used extensively in image coding because of its inherent advantages namely variable bit assignment among the subbands as well as coding error confinement within the subbands.

**3.4 Modified DWT**

An image signal  $X_i$  which is corrupted by Gaussian random noise  $Z_i \sim N(0, \sigma^2)$  is expressed in the following equation (7)

$$Y_i = X_i + Z_i \quad (i = 0, 1, \dots, N - 1) \tag{7}$$

From this noisy signal  $Y_i$ , to find an approximation  $\chi_i$  to the original  $X_i$  that minimizes the mean squared error which is given

equation (8)

$$\|X - \chi\|^2 = 1/N \sum_{i=0}^{N-1} |X_i - \chi_i|^2 \tag{8}$$

where  $X = [x_0 \dots x_{N-1}]^T$  and  $\chi = [\chi_0 \dots \chi_{N-1}]^T$ . In this, W is an orthogonal wavelet transformation. Then equation (5.7) can be written as following equation (9)

$$d_j = c_j + e_j \tag{9}$$

with  $d = Wy$ ,  $c = Wx$  and  $e = Wz$ . Since W is an orthogonal transform,  $e_j$  are also with Gaussian random variables  $e_j \sim N(0, \sigma^2)$ . If  $T(\cdot)$  is a wavelet thresholding function, Then the wavelet thresholding based denoising schemes can be expressed as the following equation (10)

$$\chi = W^{-1} (T(Wy)) \tag{10}$$

The wavelet transformation of the noisy signal is passed through the thresholding function  $T(\cdot)$ . The output is then inverse wavelet transformed to obtain the estimate  $\chi$ .

The most common choices for  $T(\cdot)$  are the hard-thresholding function and the soft-thresholding function (which is also known as the wavelet shrinkage function). The hard-thresholding function chooses all wavelet coefficients that are greater than the given threshold  $\lambda$  and sets the others to zero and is given by the equation (11).

$$fh(x) = [x] \text{ if } |x| >= \lambda; fh(x) = [0] \text{ otherwise} \tag{11}$$

The threshold  $\lambda$  is chosen according to the signal energy and the noise variance  $\sigma^2$ . If a wavelet coefficient is greater than  $\lambda$ , then it is significant and attributes it to the original signal. Otherwise, it is due to the additive noise and discards the value. The soft-thresholding function has a somewhat different rule from the hard-thresholding function (11). It shrinks the wavelet coefficients by  $\lambda$  towards zero and hence it is also called the wavelet shrinkage function and is given by the equation (12).

$$fs(x) = [x - \lambda] \text{ if } x >= \lambda; fs(x) = [0] \text{ if } |x| < \lambda; fs(x) = [x + \lambda] \text{ if } x <= -\lambda \tag{12}$$

From the above results, the hard-thresholding function is discontinuous at  $|x| = \lambda$ . Due to this discontinuity at the threshold, the hardthresholding function yield abrupt artifacts in the denoised signal, especially when the noise level is significant. Hence, in the present work, the method of soft thresholding is used to denoise the signal. This is also compared to hard thresholding and shown to be inferior.

The performance of the method was further improved by using linear prediction on the wavelet coefficients. A fifth order predictor was used for predicting the wavelet coefficients. The error signal obtained was quantized using a uniform quantizer. The optimum predictor is essentially a spectral domain matching predictor. Hence the order of the predictor is a very important parameter as far as proper modeling of the signal is concerned. The optimal order can be chosen against the variation of the prediction gain versus order. The point where the curve saturates is a valid value for the optimal order.

In the present work, transform co-efficients are calculated with the scales from 1 to  $\log_2(\min(I,J))$ , where I and J are the input image dimensions. Directions are selected between 0 and  $\pi$  with  $\pi/4$  increments. The dyadic scaling sequence minimizes the time complexity of the algorithm. The result is an image scale directional space.

**3.5 DWT Realization**

The DWT architecture is realized by adopting the methodology as shown in the figure 5. The image is decomposed row by row and then by column by column. Initially the image is filtered along the row and the

resulting row processed image is stored. Then the row processed image is column filtered and the resulting coefficients are also stored. This completes one complete cycle of filtering.

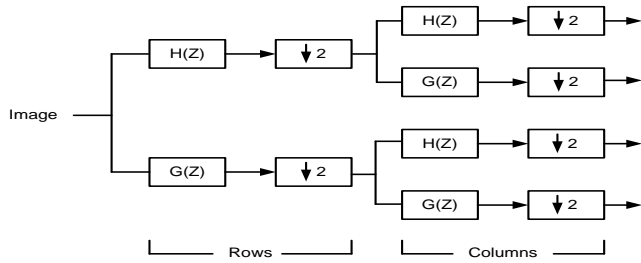


Figure 5 DWT Realization

H(z) = Low pass filter  
G(z) = High pass filter

Figure 6 shows how an image can be converted into detailed and approximation coefficients.

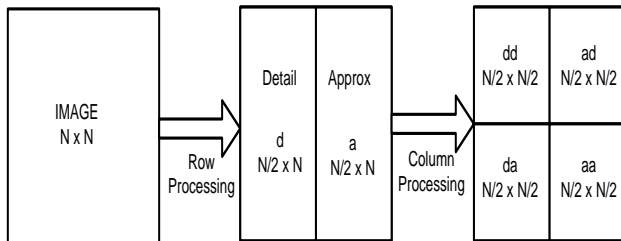


Figure 6: Level -1 DWT filtering of an N x N image

The following Figure 7 to figure 9 show the Image approximation coefficients and detailed coefficients after one complete row and column processing for 3 sample CT images obtained using the modified DWT algorithm.

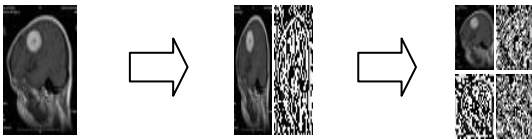


Figure 7: Level -1 DWT filtered 256 x 256 image sample-1

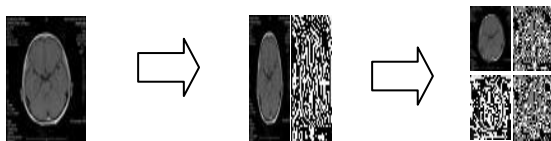


Figure 8: Level -1 DWT filtered 256 x 256 image sample-2

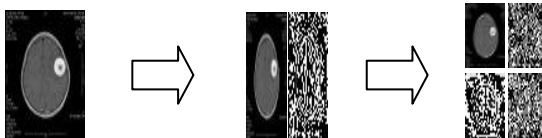


Figure 9: Level -1 DWT filtered 256 x 256 image sample-3

### 3.6 Realization of MDWT

To improve the DWT filtering and to reduce the storage space, a modified DWT technique has been implemented by reducing number of coefficients to be

buffered. The method is applied to row and column processing of the DWT architecture. The coefficients of DWT are L0, H1, L1, H2, and L2. Where, the L0 coefficients are input signals, while H1, L1, H2, and L2 coefficients are intermediate results. H2 and L2 coefficients are scaled by constant value and the output obtained as high-pass, low-pass results, respectively. Conventionally, for performing DWT filtering, L0 coefficients are stored into a buffer assuming two new coefficients are fed at once. However, instead of storing the whole L0 coefficients, storing intermediate results (H1, L1, and H2), the number of coefficients to be buffered is reduced. As shown in Figure 10, only four coefficients (enclosed within the hatched rectangle) are stored to obtain subsequent H2 and L2 coefficients (enclosed within the oval). This filtering method is applied to both row processing and column processing of 2-D DWT architecture to enhance the image.

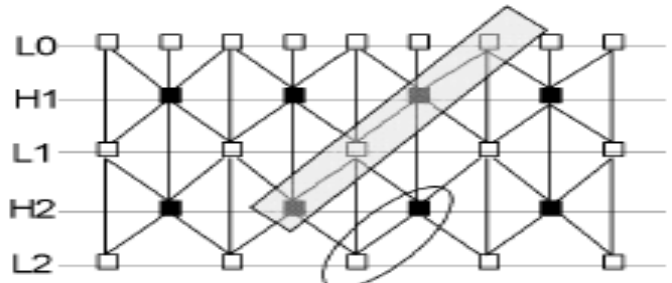


Figure 10 Intermediate co-efficient storage

A dimension reduction is developed, so that only the maximum absolute value from the directional vector is kept for every transform space co-ordinate. It is clear that the co-efficients, which cross the singularities perpendicularly, aggregate higher maximum absolute values in the singularity neighborhoods. This dimension reduction results in an image scale space  $S(\alpha, \tau_1, \tau_2)$ . Gradient calculation by plane approximation is done along  $\tau_1$  and  $\tau_2$  directions in the image space  $S(\alpha, \tau_1, \tau_2)$ . A plane, denoted as a gradient plane is obtained.

Thus the memory space required to store the compressed image is reduced, which is used to accelerate the image transmission. The developed algorithm involves dimension reduction technique by using intermediate co-efficient storage to reduce the storage space in the DWT architecture. Hence, at the receiver the side, retrieval of intermediate co-efficient is obtained by decoding each sub band using decoder for the frequency band of the images. By implementing the IDWT, the original image is retrieved without any loss of information in the image.

It is implemented using MATLAB 7 and the hardware configurations used are: Intel Pentium IV processor, 1.73 GHz, 1 GB RAM. The scanned images from CT scan centers are read and stored in Compact Disc for ease of use. The images are read and the following steps are implemented

- Preprocessing of Images to eliminate background pixels
- Contrast enhancement using locally adaptive non-linear filter
- Threshold based Region of Interest to remove the background of the image and the compression algorithm is applied only for the selected region in which Pixels of Interest (POI).
- Image Compression using
- JPEG standard and to calculate measure of compression in terms of MSE, PSNR
- DWT method - quantization using a uniform quantizer and Subband Coding to split up the frequency band of a image and then to code each subband using a coder and to calculate measure of compression in terms of MSE, PSNR
- Modified DWT-quantization using a uniform quantizer and reduced Subband Coding to split up the frequency band of a image and then to code each subband using a coder. Dimension reduction technique to reduce the storage space and to calculate measure of compression in terms of MSE, PSNR.

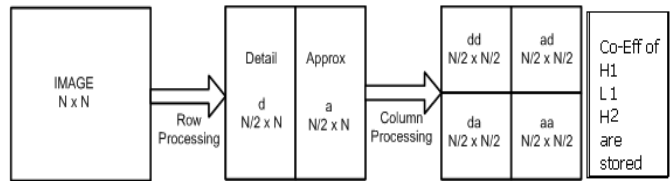


Figure 12 Level -1 Modified DWT filtering of an N x N image

4 RESULTS AND DISCUSSION

Presently, CT images are used for the analysis and to measure the quality of compression, the values of MSE and PSNR are computed for Bit Rates 1, 0.5, 0.2 and 0.125 using JPEG, DWT and compared with the proposed modified DWT Technique and are shown in Figures 13 respectively.

3.7 Architecture of MDWT

The Modified DWT architecture is implemented by adopting the methodology as shown in the figure 11.

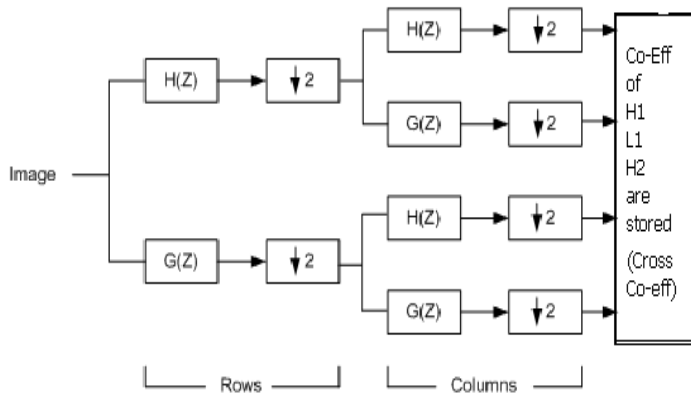


Figure 11: Modified DWT Realization

H(z) = Low pass filter  
G(z) = High pass filter

Figure 12 shows how an image can be converted into detailed and approximation coefficients which can be realized in FPGA.

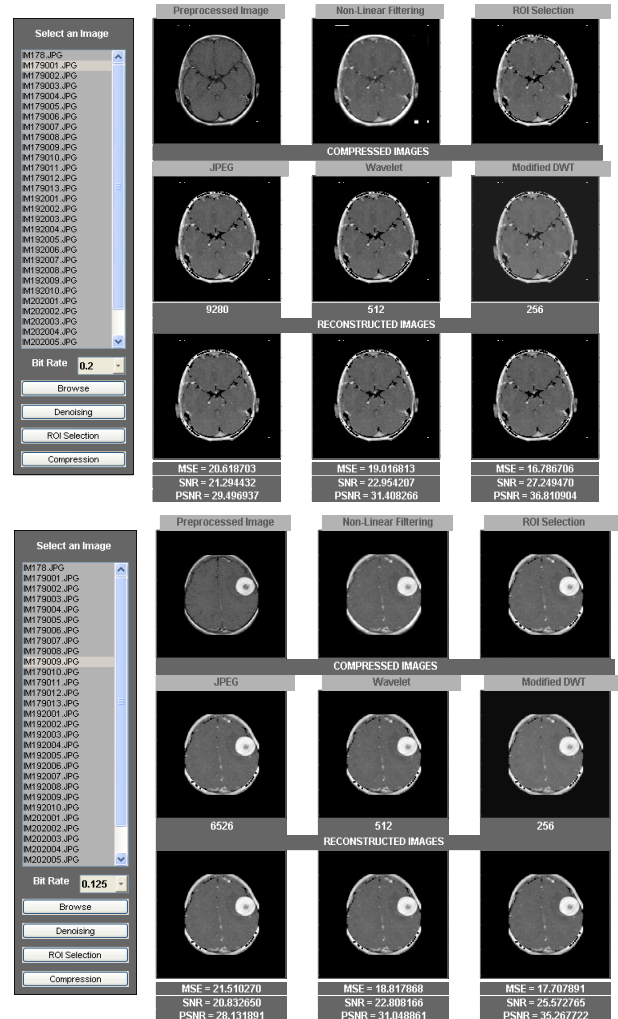


Figure 13 Comparison of PSNR using JPEG, DWT and modified DWT for bit rate = 0.2 and 0.125

From the above results, Modified DWT method outperforms with low MSE and high PSNR with reduced memory space to store the image compared to that of JPEG and DWT methods. 20 CT images were used for the analysis and the values of MSE, SNR and PSNR were

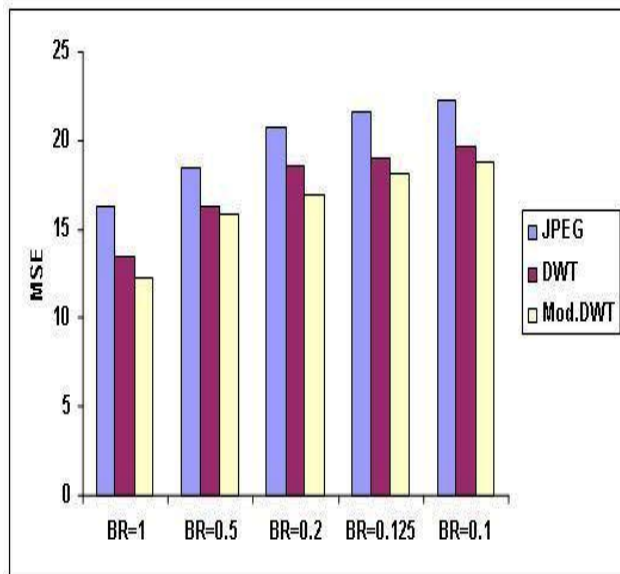
computed. The Following Tables 1 and 2 show the Average MSE and PSNR values for different Bit rates.

BIT RATE	MSE		
	JPEG	WAVELET	MOD DWT
1	16.25	13.34	12.26
0.5	18.46	16.24	15.86
0.2	20.72	18.51	16.93
0.125	21.63	19.00	18.11
0.1	22.26	19.63	18.75

**Table 1** Average MSE values for BR=1, BR=0.5, BR=0.2, BR=0.125 and BR=0.1

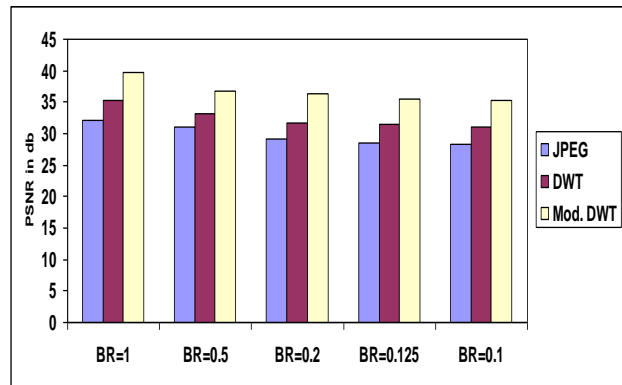
BIT RATE	PSNR in db		
	JPEG	WAVELET	MOD DWT
1	32.04	35.19	39.70
0.5	30.98	33.12	36.76
0.2	29.16	31.71	36.44
0.125	28.58	31.41	35.58
0.1	28.27	31.10	35.27

**Table 2** Average PSNR values for BR=1, BR=0.5, BR=0.2, BR=0.125 and BR=0.1



**Figure 14** Average MSE values for BR=1, BR=0.5, BR=0.2, BR=0.125, and BR=0.1

In the present work, Optimum transformation Technique suitable for Image Transmission through web with less storage space and low band width requirements using modified wavelet transform technique is developed. In this work, initially the images are enhanced using local adaptive filter and the POI in the image is selected to reduce the size of the medical image to be transmitted. For this, a threshold based ROI is selected which is based on the peak value from the histogram of the image and the threshold value is selected. With this threshold, the background of the image is removed and the compression algorithm is applied only for the selected region where the POI of the image is selected. Thus the size of the image is reduced for faster transmission. In the second step, Compression algorithm is developed using JPEG, DWT and Modified DWT using reduce sub band coding to compress the image data with minimum storage space and then the image is transferred over the Internet



**Figure 15** Average PSNR values for BR=1, BR=0.5, BR=0.2, BR=0.125 and BR=0.1

To summarise, Image compression using JPEG, DWT and Modified DWT has been developed to find optimum method for transmitting medical images through the Internet with less storage space and low bandwidth requirements. The present method offered better results and is found to be the optimum method with high PSNR, low MSE and less storage space. As a future work, the effectiveness of Modified DWT will be compared with other emerging Imaging techniques by taking image as a whole. In medical image transmission, instead of still medical images which used imaging techniques, moving images may also be transmitted using modified DWT.



**REFERENCES:**

1. Irini Reljin and Branimir Reljin (2001), 'Telecommunication Requirements in Telemedicine', Annals of the Academy of Students published by Institute of Oncology Sremska Kamenica, Yugoslavia, pp. 53-61.
2. Jiecheng Xie, Dali Zhang, Wenli Xu and Tsinghua (2004), 'Spatially adaptive wavelet denoising using the minimum description length principle', IEEE Transactions on [Image Processing](#), Vol. 13, No. 2, pp. 179-187.
3. Karras D.A., Karkanis S.A. and Maroulis D.E. (2001), 'Efficient Image Compression of Medical Images Using the Wavelet Transform and Fuzzy c-means Clustering on Regions of Interest', IEEE Transactions on Image Processing, Vol. 1, pp. 179-187.
4. Keng Siau (2003), 'Health Care Informatics', IEEE Transactions on Information Technology in Biomedicine, Vol. 7, No. 1, pp.1-7.
5. Kustov V., Srinivasan P., Mitra S., Shishkin S. and Mehrl D. (2000), 'Adaptive Wavelet Technique for Effective Storage and Fast Internet Transmission of Medical Images', IEEE Transactions on Image Processing, Vol. 2, pp. 179-187.
6. Masaomi Takizawa, Shusuke Sone, Kazuhisa Hanamura and Kazuhiro Asakura (2001), 'Telemedicine System using Computed Tomography Van of High Speed Telecommunication Vehicle', IEEE Transactions on Information Technology in Biomedicine, Vol. 5, No. 1, pp. 2-9.
7. Masatsugu Tsuji (2002), 'The Telehomecare / Telehealth System in Japan', Global Health care – Healthcare Field Telemedicine Report Issue, Vol. 3, pp. 72-74.
8. Muhammad Younus Javed and Muhammad Habib Khan (2008), 'Wavelet Based Medical Image Compression through Prediction', IEEE 9<sup>th</sup> Biennial Conference on Digital Image Computing, Glenelg, Australia, pp. 155-159.
9. Saxena N, G L Baheti, D K Tripathi, K C Songara, L R Meghwal & V L Meena, (2008) "Adaptive Filtering For Image Enhancement And Noise Reduction In Computed Tomography Images", Vol.50, Iss.1, pp.22-24.
10. Subhasis Saha (2000), 'Effect of Image Activity on Lossy and Lossless Coding Performance', IEEE Data Compression Conference Proceedings, Snowbird, UT, p. 570.

**Conflict of Interest: None Declared**