Analysis of Efficient Wavelet for Compression of Medical images using SPIHT Technique

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Abstract— Image compression is a technique to minimize the size of a graphics file without degrading the quality of the image to an unacceptable level. So due to this unique property, Image compression is widely used in many applications, especially in telemedicine to reduce the cost of storage and increase the transmission speed at available bandwidth of medical data and images. Various compression techniques are developed for data and image compression. The most popular SPIHT compression technique has been successfully used in many areas. In this paper, the Rbio2.4, Bior 3.3 and Haar wavelets are used in SPIHT technique. The objective of this paper is to analyze the effect of different wavelets for image compression of natural images like Boat, Lena and some medical images with different PSNR and bpp values.

Keywords— Telemedicine, SPIHT, PSNR, bpp.

I. INTRODUCTION

Medical field is a vast domain which is significantly dependent on science and technologies. Combination of medical service with telecommunication technology gives the idea of Telemedicine. Telemedicine is a developing area in engineering and medical science. Telemedicine plays significant role in medical diagnosis, treatment, and patient care for rural area which are far from the hospital or places where medical help is not reachable. There are two modes in telemedicine, one is Real-time mode and other is store-and-forward mode. In store- and-forward mode data is stored then send according to the requirements of the base medical station.

The medical data could be in the form of graphics, audio, video and image. If there is lack of storage capacity then there is need to compress the medical data. So during transmission medical data is to be compressed for efficient running of telemedicine. Hence to reduce the cost of storage and increase the transmission speed at available bandwidth, compression is required. Thus image compression is a process to minimize the size in bytes of a graphics file without corrupting the quality of the image. Compression of an image is minimizing the size in bytes of a graphics file without degrading the quality of the image to an unacceptable level. The reduction in file size allows more images to be stored in a given amount of disk or memory space. It also reduces the time required for images to be sent over the Internet or downloaded from Web pages. Some images contain the information which is not useful or important like pixels which have redundant information (having same intensity as its neighboring pixels) and irrelevancy. So image compression is a technique which is performed to remove repeated information resulting reducing duplicity. Redundancy reduction targets only at removing similar information from the signal source (image/video).

Various methods have been used for still image compression. Every method follows some basic steps: transformation, quantization and encoding. Fig.1. shows the basic steps of wavelet image compression.
Wavelet based image compression is based on Discrete Wavelet Transform (DWT) (Marecllin.et.al, 2002). For wavelet based image compression many coders (Joshi et.al.,1995;Joshi et.al.,1993;Shapiro, 1993; Said and Pearlman ,1996; Herley et.al.,1995; Sriram and Marcellin, 1993) are used. There were some wavelet based algorithms which were used in earlier Davis and Nosratinia(1998) and Mallat(1998).

The wavelet based image compression technique based on set partitioning in hierarchical trees (SPIHT) Said and Pearlman(1993) and Shapiro(1993) is proposed which is a powerful, efficient and yet computationally simple image compression algorithm. It provides a better performance when compared to the Embedded Zerotree wavelet (Joshi et.al., 1993) transform.

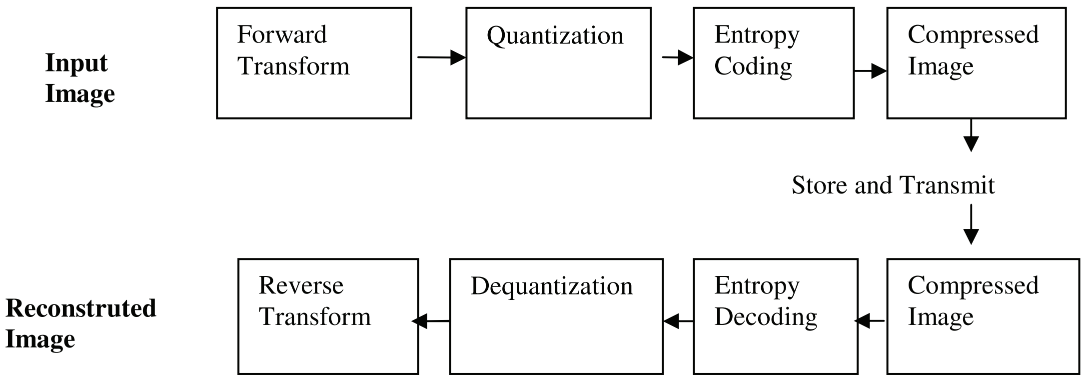


Figure 1.Flow diagram of Image Compression using DWT

The objective of this paper is divided into some sections. In section II the discrete wavelet transforms is explained and demonstrated the single level and two level decomposition of natural and medical image. SPIHT algorithm is briefly discussed in Section III. Experimental results are discussed in Section IV. In Section V, the performance evaluation is discussed. Finally, conclusion is discussed in Section VI.

II. DISCRETE WAVELET TRANSFORM

Wavelet transform has become an important method for image compression. There is significant improvement in picture quality due to wavelet based coding. This enhancement is due to better energy compaction property of wavelet transforms. At present there is significant improvement in multimedia technology and image compression is a major property of any multimedia so it requires higher performance as well as new features.

Wavelet is a mathematical function which divides the data into different frequency components, then fits each component with a resolution suitable for its scale Rao and Bopadikar(2002). Wavelets are functions generated from a single function by dilations and translations (Stollnits et.al.,1996).

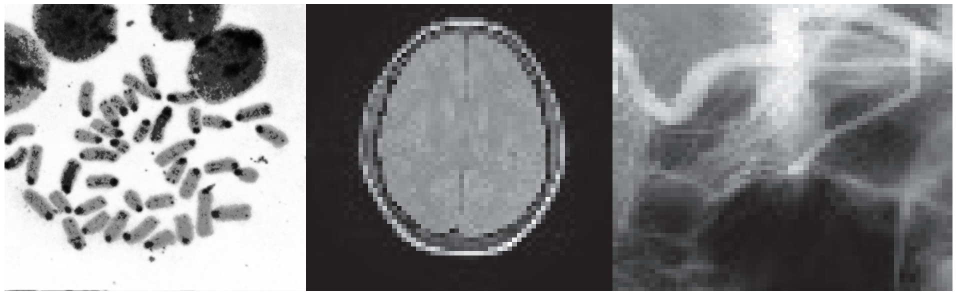
From the scaling equation of this function a wavelet equations of the first (known as mother wavelet) can be formed as follows.

$$\Psi_{(a,b)}(t) = |a|^{-1/2}\,\Psi\left(\frac{t-b}{a}\right) \qquad (1)$$

$\Psi_{(a,b)}(\cdot)$ is obtained by scaling the wavelet at time b and scale a, where $\psi(x)$ represents the wavelet. Wavelet transform has the main properties in still image compression that the occurrence of minimum distortion in the reconstructed image even when exercising removal transform coefficients are near zero. In the wavelet transform process for 2-dimensional image, there are two ways to decompose the pixel values, the standard decomposition and nonstandard decomposition (Stollnits et.al.,1996).

Fig.2 is demonstrating original natural images and medical images which are used in the present paper.

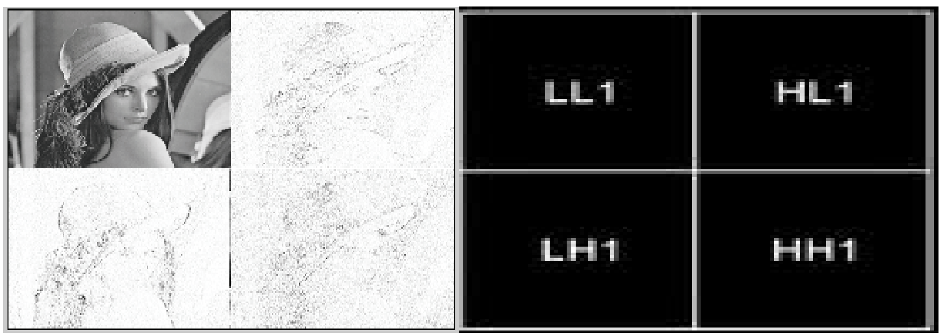
(a) (b)



(c) (d) (e)

Figure 2. Original natural and Medical Images. (a) Lena (b) Boat (c) Chromos (d) Brain (e) BrainMRI

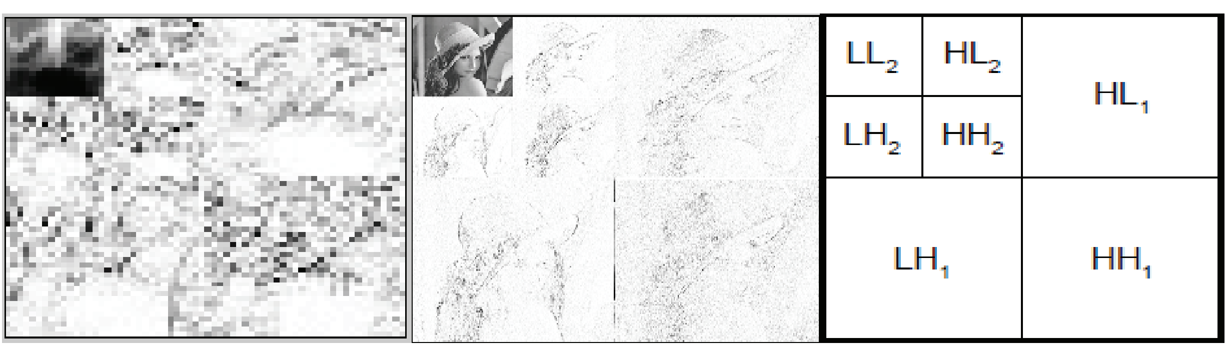
Fig.3 explains the single level DWT decomposition of Lena and its frequency components. Image will be divided into 4 sub bands in the decomposition level 1. The 4 sub bands are HH, HL, LH, and LL.



(a) (b)

Figure 3.(a) Lena image, Fig.5. (b) Single level DWT decomposition of Lena image

Fig.4 explains frequency components of 2 level decomposition. First Brain MRI and Lena will be divided into 4 sub bands in the decomposition process. The 4 sub bands are HH, HL, LH, and LL. In these sub bands HH sub band image gives details on the diagonal, HL sub band image means the horizontal direction, the LH sub band provides detailed images in the vertical direction. Here LL sub band is a low-resolution residue which has low frequency components and named average image. After this LL sub band is again divided to obtain second level decomposition level.



(a) (b)

Figure 4.Decomposition of image and its frequency components, (a) 2 Level decomposition of Lena. (b) Frequency components

III. SPIHT ALGORITHM

There are different algorithms which are based on wavelet based image compression. In the present paper SPIHT algorithm is used. The set partitioning in hierarchical trees (SPIHT) algorithm was introduced by Said and Pearlman (1993).This technique is a very efficient and simple image compression algorithm. By applying this compression technique, the better PSNR values for given compression ratios for images can be obtained. SPIHT was designed for two important parameters -optimal progressive transmission and compression.

In a progressive transmission method, the decoder starts by setting the reconstruction image to zero. The main aim in progressive transmission is to transmit the most important image information first.

The transformed image is sent to the SPIHT encoder in such a sequence that will make the decoder to decode the most important details (ROIs) first and followed by the less important details. Most significant bits of significant coefficients that contain the significant information for reconstructing the image are sent first by the process.

The SPIHT technique is one of the most superior methods available that surpasses even the modern JPEG 2000 under certain circumstances.

IV. EXPERIMENTS

Natural images like Boat, Lena and Medical images like brain, brain MRI, chromos are used for the experiments. In the experiment SPIHT compression technique is used by applying Bior 3.3, Rbio2.4 and Haar wavelets. For each wavelet PSNR value is calculated for compressed natural and medical images at different bpp. After getting PSNR values, a comparative study is done for each wavelet. The experiment is performed on Core i3 HP laptop with 4 GB Ram. The software Matlab 7.10(R2010a) is used for the experiment. The results of experiments are used to find the PSNR (Peak Signal to Noise Ratio) values at different bpp for the reconstructed images using different wavelets. Haar, Bior3.3, Rbio2.4 and Haar wavelets are used for objective evaluation.

V. PERFORMANCE ANALYSIS

The Table 1 and Table 2 explain the performance of different wavelet by calculating PSNR at BPP1 and BPP 0.5. The PSNR value is calculated by using the following formula.

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

Table I PSNR for Natural and Medical images at BPP 1

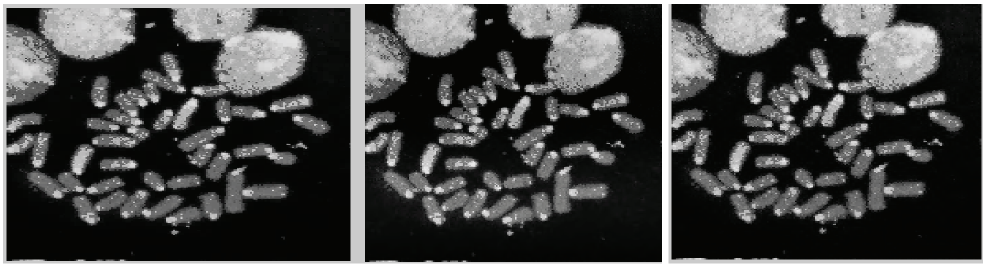
WAVELET	LENA	BOAT	CHROMOS	BRAIN	BRAIN MRI
BIOR3.3	38.12	36.66	25.54	27.66	20.18
RBIO2.4	37.95	36.18	32.24	29.06	29.22
HAAR	37.49	36.10	33.54	31.27	29.49

Table II PSNR for Natural and Medical images at BPP 0.5

WAVELET	LENA	BOAT	CHROMOS	BRAIN	BRAIN MRI
BIOR3.3	35.09	32.05	20.34	23.43	19.58
RBIO2.4	34.53	31.62	29.74	24.64	25.33
HAAR	33.56	31.60	30.52	25.81	26.06

From the table 1 and table 2, it is well stated that PSNR value of Haar wavelet is greater than Bior 3.3 and Rbio 2.4 for medical images while Bior3.3 gives better PSNR value for natural images.

Fig.5 and Fig.6 show the compressed medical images using different wavelets. The PSNR value is tabulated in table 1and 2 for BPP at 1.



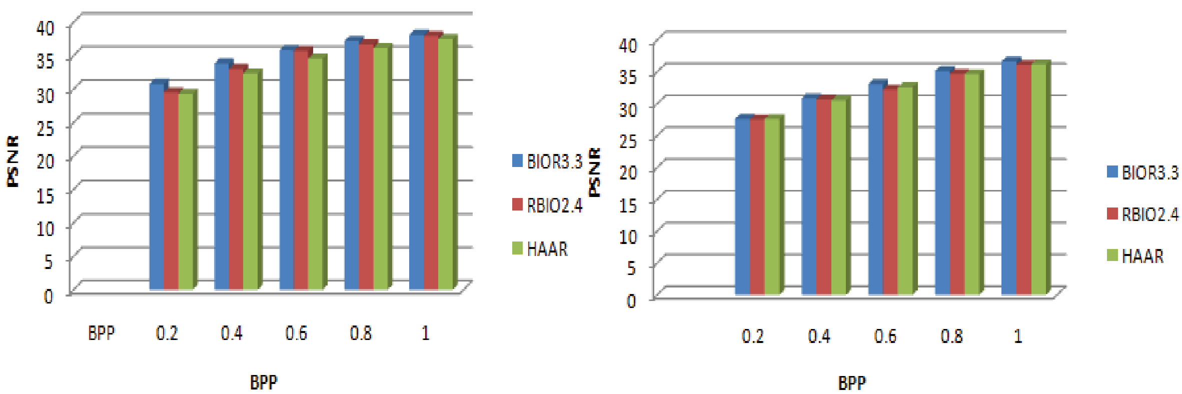
(a) (b) (c)

Figure 5. SPIHT Compression of Chromos at bpp=1, (a)HAAR wavelet.(b) BIOR3.3wavelet.(c)RBIO 2.4 wavelet

(a) (b) (c)

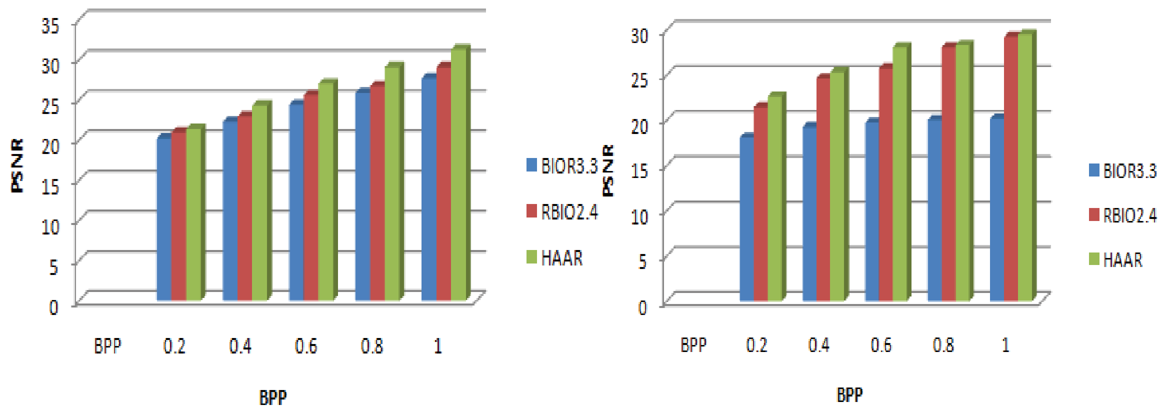
Figure 6. SPIHT Compression of Brain at bpp=1, (a) HAAR wavelet.(b) BIOR3.3wavelet.(c)RBIO 2.4 wavelet

After objective evaluation of PSNR vs BPP for medical images (Chromos and Brain) and natural images(Lena and Boat), it can be easily interpreted from Fig. 7 and Fig 8 that Haar wavelet give better PSNR value for medical images as compare to natural images.



(a) **(b)**

Figure 7. Objective Evalution, PSNR vs BPP of Natural Images (a) Lena (b) Boat



(a) **(b)**

Figure 8. Objective Evalution, PSNR vs BPP of Medical Images (a) Chromos (b) Brain

VI. CONCLUSION

In this paper, the results of image compression technique using different wavelets are compared. The PSNR values on different bpp are examined for natural and medical images are examined. The Rbio2.4, Bior 3.3 and Haar wavelets are compared by using parameter PSNR value from the reconstructed images at different bpp. The results are successfully tested on natural and medical images. It is observed that HAAR wavelet provides a better PSNR values as compare to BIOR3.3 and Rbio2.4 for medical images while results are reversed for natural images like Lena and Boat.

VII. ACKNOWLEDGEMENT

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