Gray scale Medical Image Compression using SPIHT and SVD techniques

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Abstract*: Medical images are *generated by different medical imaging techniques require various compression techniques to reduce the storage space with considerable image quality. This paper presents the performance of two different compression techniques for images i.e. Singular Value Decomposition (SVD) using singular values and wavelet transform based progressive structure of Set Partitioning In Hierarchical Trees (SPIHT) to reduce the size of images for accurate diagnosis. These two techniques are practiced on medical images of MRI,CT images of brain and X-ray of hand, and the results of these techniques are compared. SVD with less singular value provides high Compression Ratio (CR) with less Peak Signal to Noise Ratio (PSNR), whereas wavelet based multi resolution SPIHT technique provides more PSNR with better CR. These two techniques are compared with the quality metrics of PSNR, Mean Squared Error (MSE), CR and Bit Per Pixels (BPP). From the results, Wavelet based progressive SPIHT technique provides high PSNR, low MSE with better CR compared to SVD technique.

Index Terms*: *Singular Value Decomposition, Set Partition in Hierarchical Tree, PSNR, MSE.

I. INTRODUCTION

The techniques of Image compression are used to lessen the size of the graphical files by reducing or removing redundant and irrelevant information without degrading the essence of the image. More images are to be stored in memory space by lessening of data in the files and also reduce the transmission time whenever these images sent through internet. Redundancy is the duplication of significant components of image which increases the memory size. Redundancy is categorized into coding; inter pixel and Psycho visual redundancies based on spatial and temporal techniques. The compression of image is done by decreasing the no. of bits needed to represent an image by eliminating various types of redundancies. Compressions of images divided into two type's i.e. lossy and lossless techniques. Lossy methods reduce bit rate of the data with considerable loss such as photography, printing and etc. Losses less compression techniques reducing the size of the image by decreasing the bit rate without reducing the quality and are used in satellites, military and medical applications[1]. In medical applications, storage of large number of medical images are required for further reference of patients and transmitting these medical images through internet to multiple physicians for better diagnosis. So compression of medical images has a great impact on diagnosis of critical diseases and surgeries[2]. So selections of proficient compression techniques are essential to solve the storage and transmission problem of the medical images. There are different image compression techniques like spatial based and transform based to reduce the size of the image like SVD, wavelet based transform techniques[3], hierarchical based wavelet transform techniques like SPIHT, EZW and etc. In this paper, two well known techniques for compression are of SVD and SPIHT used and their performances are compared with respect to PSNR, MSE, CR and BPP. SVD technique is based on different singular values, whereas SPIHT method uses various wavelet transforms and encoding techniques with different encoding loops.The paper is planned such that Section II explains wavelet Transform based progressive hierarchical SPIHT algorithm, Section III describes the decomposition algorithm of Singular Value Decomposition, the methodology of both techniques for compression and decompression of images are described in Section IV gives, Section V explains the experimented results with MRI, CT images and conclusion gives in Section VI.

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II. WAVELET TRANSFORM BASED PROGRESSIVE SPIHT ALGORITHM

Wavelet transforms are efficient tools with time-frequency localization property and plays vital part of digital signal processing and digital image processing and etc. [4]. Due to its progressive structure for fast encoding, decoding and less memory constraint, the image compression technique of SPIHT with Discrete WT becomes more powerful, efficient and popular. Initially, the image is decomposed using different wavelet transforms like bi-orthogonal, Daubechies, and etc. It is an iterative process until it reaches the final value. Four sub-bands are obtained for each level of decomposition. These sub bands are approximation coefficients and high frequency of horizontal, vertical, diagonal coefficients [5]. In SPIHT algorithm, the coefficients of sub bands are associated with similar characteristics in the structure like pyramid. The spatial relationship of the hierarchical structure of tree is called spatial orientation tree (SOT). The wavelet decomposition structure with 3 levels and the structure of SOT are shown in Fig 1.

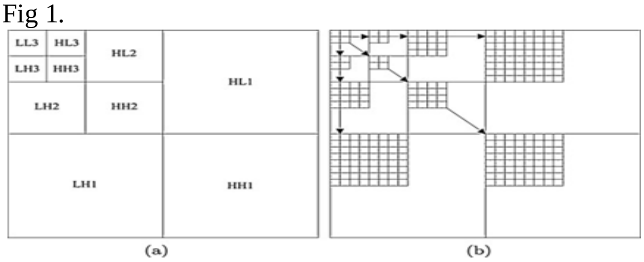

Fig. 1 - (a) Three Level Wavelet Decomposition;
(b) Parent-children relation in SOT.

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There are mainly three steps for the algorithm of SPIHT using wavelet by the magnitude of the coefficients. These are of initialization/sorting, refinement and quantization [6]. The coefficients of transformed image are divided into three lists such as List of Insignificant Set (LIS), List of Insignificant Pixels (LIP) and List of Significant Pixels (LSP). Initially, the maximum value of bits which represents the largest value among all wavelet transformed coefficients is and it is taken by the equation (5).

$$A = [\log_2(\max_{i,j}(|C_{i,j}|))] \qquad (1)$$

Where $C_{i,j}$ is the largest value of pixel in the spatial tree.

LIP, LIS and LSP are distinguished by applying Threshold T to all coefficients in the sorting list. All pixels are taken as insignificant initially. The threshold can be represented as equation (2) given below.

$$Threshold(T) = \begin{cases} 1, \max(|C_{i,j}|) \geq 2^A \\ 0, otherwise \end{cases} \qquad (2)$$

SPIHT algorithm procedure is analyzed IN Fig .2 below.

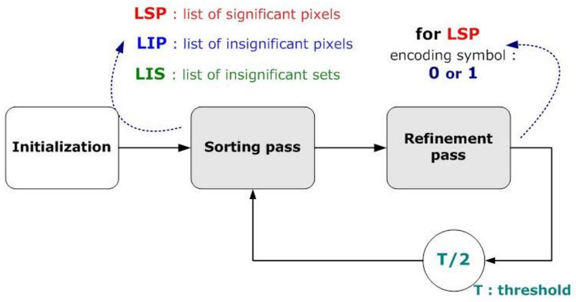

Fig. 2- Implementation of SPIHT Technique

III. SINGULAR VALUE DECOMPOSITION (SVD)

The Singular value decomposition was discovered in 1873 by Beltrami and in 1874 by Jordan for square matrices and it can be enhanced to rectangular matrices in 1930 by Eckart and Young. It is also called as Rank based Reduction technique. The SVD of a rectangular matrix R can be represented by the equation give below [7].

$$R = PDQ^T \qquad (3)$$

P and Q are the rectangular matrices of ortho-normal. The diagonal matrix is D with singular values as diagonal elements. $\sigma_1, \sigma_2, \sigma_3, \ldots\ldots\sigma_N$, are the singular values along main diagonal of D. The rank of the matrix R is the number of non-zero singular values. The equation (1) can be rewritten as

$$R_{MXN} = [P_1 \;\; P_2 \;\; P_3 \ldots\ldots P_N] \begin{bmatrix} \sigma_1 & 0\ldots\ldots\ldots & 0 \\ 0 & \sigma_2\ldots\ldots\ldots & 0 \\ 0 & 0\ldots\ldots\ldots & \sigma_N \end{bmatrix} \begin{bmatrix} Q_1^T \\ Q_2^T \\ \cdots \\ Q_N^T \end{bmatrix} \qquad (4)$$

The square root of Eigen values of RR^T and $R^T R$ are taken as the singular values of matrix R. The Eigen values and SVD are related by the following equations. The Eigen vectors of RR^T and $R^T R$ are the values of A and B respectively. The applications of SVD are image compression, texture classification and etc. [8-9].

IV. METHODOLOGY

The image compression using these two techniques are explained below .

A. Image Compression using Wavelet based progressive SPIHT Algorithm

For the compression of Images using wavelet based progressive SPIHT algorithm is described below. At first, the input image is decomposed using Biorthogonal wavelet 3.7. Depending on level of decomposition, low frequency coefficients are further divided into different components. After discrete wavelet decomposition, the image is compressed in the steps of initialization/sorting, refinement and quantization using SPIHT encoding process. Initially all the coefficients are in LIP [10].In the sorting pass, the magnitudes of wavelet coefficients are compared with the threshold value shown in Eq (6). LIP contains the wavelet coefficients which magnitude is less than threshold (T) and the magnitudes higher than T are in LSP. And also the descendants except the immediate off springs are in the last of LIS. The final output is the Pth MSB of the LSP coefficients in the refinement step of SPIHT encoding. The steps of sorting and refinement are repeated by declining the value of P by ‘1’ .These passes are repeated until the value of P becomes ‘0’ or LIS becomes empty. Final coefficients in LSP are quantized using quantization process. After the SPIHT encoding, the compressed output is transmitted through the channel[11]. At the receiver encoded bit stream is decoded using the process of SPIHT decoding and the output image is decompressed using inverse DWT. The process is explained in Fig .3 below.

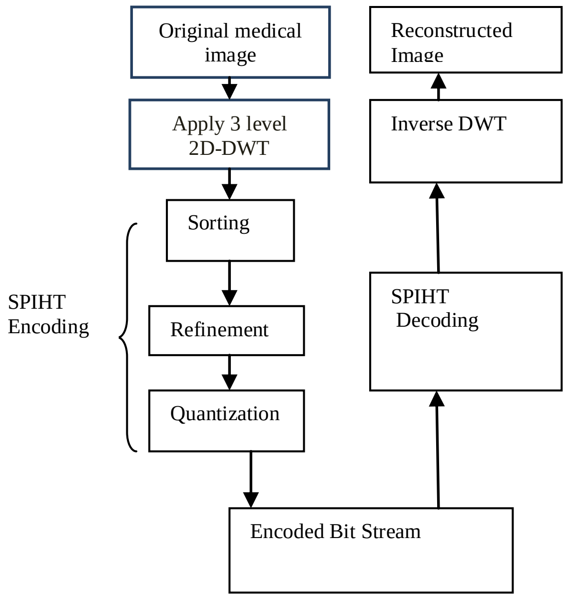

Fig. 3- Image compression using SPIHT Technique.

B. Image Compression using SVD technique

When image is decomposed using SVD, it can be divided into three matrices of ortho-normal and diagonal matrix [12]. With less number of singular values in diagonal matrix, the image can be reconstructed at the receiver with minimum error and more PSNR [13]. Image compression using SVD is shown in Fig.4.

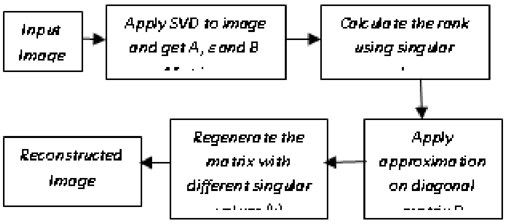

Fig. 4- Image compression using SVD.

C. Performance Metrics

The quality of compression and decompression of the medical images can be obtained by calculating the metrics of PSNR, MSE, CR and BPP. The difference between input and output images gives the excellence of the image is referred to as MSE.

$$MSE = \frac{1}{LM}\sum_{a=0}^{L-1}\sum_{b=0}^{M-1}((x(a,b)-y(a,b))^2) \qquad (5)$$

where *x(a,b)* and *y(a,b)* are input and decompressed images of L×M. The excellence of the image is represented by PSNR.

$$PSNR = 10\log_{10}\left(\frac{255^2}{MSE}\right) \qquad (6)$$

CR is ratio of compressed image bits to original image bits and it is taken as percentage.

V. Results and Conclusions

In this paper, the compression and decompression of medical images have done with two techniques of singular values/ rank based Singular Value Decomposition and progressive SPIHT algorithm. These two techniques have applied on medical images of CT and MRI of brain image and x-ray of hand. The performance metrics of PSNR, MSE and CR are compared for both SVD and SPIHT techniques. Compression ratio is more for less number of singular values but the values of PSNR is less and MSE is more. By increasing the singular values, reconstructed images are obtained with more PSNR and less MSE. But in SPIHT, by increasing the no. of encoding loops up to 13, the value of PSNR increases and MSE value decreases. The metrics of PSNR, MSE, CR of MRI, CT and X-ray images with 2 to 75 singular values Table I, Table II, and Table III respectively. Table IV, V and VI shows PSNR, MSE, CR of MRI, CT, and X-ray images for SPIHT with the encoding loops from 3 to 13 respectively. Fig. 5 and Fig.6 shows the Comparison of PSNR values of CT and MRI of brain image and x-ray of hand for SVD and SPIHT Techniques and Fig. 7shows the original and decompressed images using SVD and SPIHT. From the results of both the techniques, it is found that better reconstructed image is obtained using wavelet based SPIHT technique compared to singular value based SVD with respect to the quality metrics of CR,PSNR and MSE. And also observed that the results of MRI of brain image are better than CT brain image and x-ray of hand image using SPIHT.

Table I - Comparison of PSNR values for different singular values from 2 to 75 of Singular Value Decomposition for MRI and CT image of brain and x-ray of hand.

Singular Values	MRI	X-Ray	CT
2	19.26778	20.99394	17.1981
4	20.92352	22.58913	18.37787
6	22.18069	25.40553	19.41159
8	23.35301	27.47908	20.34838
10	24.57054	28.69543	21.29577
12	25.5234	29.82652	22.08012
14	26.4587	30.73044	22.81105
16	27.36421	31.43489	23.54916
18	28.23838	32.06425	24.26104
20	29.13271	32.65442	24.90867
25	31.03191	34.18097	26.64911
50	39.54582	40.15317	34.48635
75	46.10412	45.37698	41.85691

Table II - Comparison of MSE values for different singular values from 2 to 75 of Singular Value Decomposition for MRI and CT image of brain and x-ray of hand.

Singular Values	MRI	X-Ray	CT
2	769.6658	719.7585	1239.568
4	525.6889	358.2348	944.6981
6	393.5604	187.2955	744.5974
8	300.4546	116.1909	600.126
10	227.0001	87.80868	482.507
12	182.2805	67.67496	402.7806
14	146.9638	54.95867	340.3886
16	119.3052	46.72948	287.1867
18	97.55346	40.42548	243.7677
20	79.39795	35.28891	209.9969
25	51.27312	24.83036	140.6597
50	7.219361	6.277168	23.14436
75	1.594661	1.30864	4.240229

Table III - Comparison of CR values for different singular values from 2 to 75 of Singular Value Decomposition for MRI and CT image of brain and x-ray of hand.

Singular Values	MRI	CT	X-Ray
2	54.26	48	38.5
4	45.68	35.9	22.7
6	40.72	26.4	17.6
8	36.43	21.8	13.2
10	32.28	18.22	9.95
12	29.36	15.25	8.7
14	26.36	13.12	7.3
16	23.31	11.16	4.56
18	21.09	10.24	2.76
20	18.97	8.99	1.67
25	15.2	7.32	0.96
50	5.58	5.76	0.7
75	4.86	4.09	0.3

Encoding loops	MRI	X-Ray	CT
3	20.37	19.72	12.4
4	25.95	22.3	17.17
5	29.83	26.58	20.88
6	33.16	29.97	25.01
7	36.08	31.1	28.49
8	39.24	36.42	31.99
9	42.6	40.49	35.05
10	45.99	44.62	38.48
11	49.14	48.12	41.88
12	51.08	50.26	44.71
13	51.08	50.26	46.09

Table IV - Comparison of PSNR values for encoding loops from 3 to 13 of SPIHT Encoding for MRI ,CT image of brain and X-ray of hand.

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Table V - Comparison of MSE values for encoding loops from 3 to 13 of SPIHT Encoding for MRI ,CT image of brain and X-ray of hand.

Encoding loops	MRI	X-Ray	CT
3	20.37	19.72	12.4
4	25.95	22.3	17.17
5	29.83	26.58	20.88
6	33.16	29.97	25.01
7	36.08	31.1	28.49
8	39.24	36.42	31.99
9	42.6	40.49	35.05
10	45.99	44.62	38.48
11	49.14	48.12	41.88
12	51.08	50.26	44.71
13	51.08	50.26	46.09

Table VI - Comparison of CR values for encoding loops from 3 to 13 of SPIHT Encoding for MRI ,CT image of brain and X-ray of hand.

Encoding loops	MRI	X-Ray	CT
3	597.4	693.4	3742
4	165.3	304.3	1248
5	67.55	143	530.8
6	31.4	65.56	205.2
7	16.4	33.22	91.98
8	7.75	14.84	41.08
9	3.575	5.8	20.31
10	1.638	2.243	9.236
11	0.7923	1.003	4.215
12	0.5071	0.612	2.197
13	0.5071	0.612	1.602

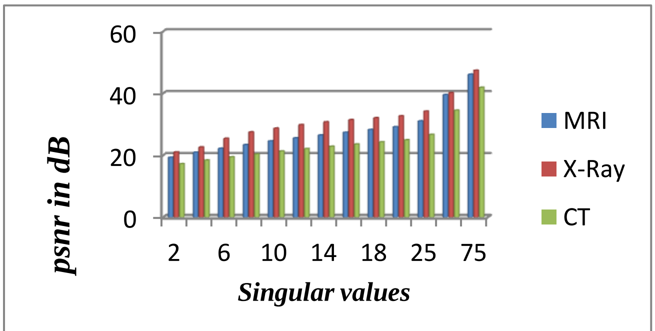

Fig. 5. Comparison of PSNR values of CT and MRI of brain image and x-ray of hand for the singular values from 2 to 75 of SVD Technique

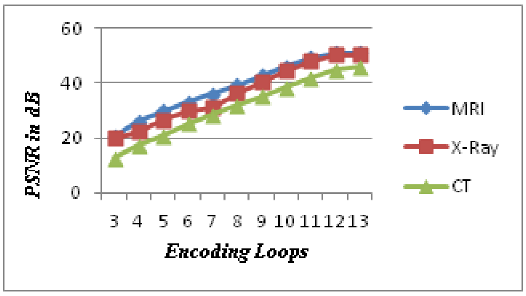

Fig. 6. Comparison of PSNR values of CT and MRI of brain image and x-ray of hand for encoding loops from 3 to 13 of SPIHT Technique.

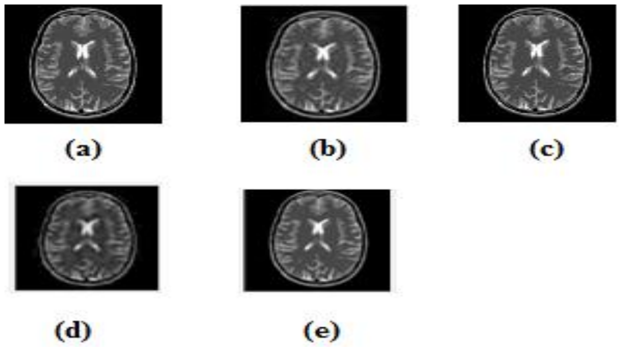

Fig. 7. a) original image; (b), (c) are the decompressed images of SVD Technique with singular values of 20 and 75 and (d), (e) are decompressed images of MRI of brain of SPIHT Technique with encoding loops of 4, 0 and 13 respectively.

VI. CONCLUSION

SVD or Rank reduction technique and wavelet based progressive SPIHT algorithm are described and simulated in this paper . These two techniques are applied to CT and MRI of brain image and x-ray of hand. The performances of these two techniques are compared with quality metrics of PSNR, MSE and CR and BPP. From the results, it is concluded that more PSNR, less MSE and better CR are obtained with SPIHT technique than SVD technique. The values of PSNR, MSE are better for MRI images when compared with CT image in SPIHT technique and X-ray image produces more PSNR and less MSE in SVD. In SVD, as the value of PSNR increases, CR decreases. But in SPIHT, as PSNR increases, CR also increases. Images obtained using SPIHT technique provides better visual quality than SVD. Therefore, SPIHT technique with more encoding loops (13) is better in phrases of PSNR, MSE and CR than SVD technique.

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