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AN EFFICIENT TRAPEZOIDAL COMPRESSION ALGORITHM USING WAVELET TRANSFORMATION FOR MEDICAL IMAGE

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Abstract: Image compression processes moderate the number of bits essential to signify an image, which can improve the performance of systems during storage and transmission without compromising image quality. They are classified into lossy compression and lossless compression. In this work, a new algorithm called trapezoidal algorithm has been proposed for image compression. The encoding part of proposed algorithm is like trapezoid shape so it is named as trapezoidal algorithm. Two transformation techniques DWT, IWT with three wavelets such as Haar, Sym4 and Coif1 have been combined for image compression to confer good characteristics of these methods. In this each pixel coordinates are encoded using the logic from SPECK algorithm. In SPECK, the set S is encoded when the pixel level is reached whereas in proposed algorithm (trapezoidal) the set S is encoded when the size of set S is reached 4x4. The approximation of image is named as set S. set S can be formed into three subset termed as s1, s2, s3. S is grouped into many subsets each set can be defined based on a pattern of proposed algorithm. Magnetic Resonance Imaging (MRI) of brain and Computer Tomography (CT) of lung images are used for analyzing compression. The proposed algorithm gives high PSNR compared to existing algorithms EZW, SPIHT and SPECK. The performance metrics such as Peak signal-to-noise ratio (PSNR), Structural Similarity Index (SSIM), Mean square error (MSE), Bits Per Pixel (BPP), Compression Ratio (CR) and Compression Time (CT) are measured for lung and brain images. The dataset has been collected from various scan centers.

Keywords: compression; SPECK; DWT; IWT; BPP; PSNR; SSIM; MSE; CR; CT.

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1. INTRODUCTION

Compression is the process of coding that will effectively reduce the total number of bits needed to represent certain information. The image compression techniques are classified into lossy compression and lossless compression. In lossy compression techniques reconstructed image contains loss of information. In lossless compression techniques reconstructed image contains no loss of information as exact reconstruction of the original image is possible. In this work, both lossless and lossy compression has been examined with medical image data such as lungs and brain image.

In this work, the compressions of two medical image modalities such as CT and MRI are analyzed. Proposed algorithm Trapezoidal is a wavelet based image compression technique. In this work three wavelets such as Haar, Sym4 and Coif1 are applied in DWT-Trapezoidal and IWT-Trapezoidal for compression of images. DWT is a mathematical tool for decomposing an image. It does not change the information content present in the signal. IWT is used for lossless compression. Coefficients of this transform are represented by finite precision numbers and this allows for lossless coding.

2. RELATED WORK

Compression in medical image becomes an important research area. A lot of work is done to solve the problem of compression in medical images. Following are the some image compression techniques used in medical image processing:

Ming Yang and Nikolaos Bourbakis proposed various lossless image compression techniques and the types of image standards. Lossless compression is necessary for high performance applications such as geophysics, telemetry, nondestructive evaluation, and medical imaging. Lossless image compression can be always modeled as a two-stage procedure one is Decorrelation and other one is entropy coding. Current standards for lossless compression include, Lossless JPEG, JBIG, GIF, Photo CD, PNG, JPEG-LS and JPEG-2000. [1]

Jia ZhiGang, Guo XiaoDong and Li LinSheng proposed the combination of integer lifting wavelet transform with set partitioning in hierarchical trees algorithm for compression. This algorithm takes Human Visual System and modifies SPIHT algorithm is according to the characteristic of weighted wavelet coefficients and analyzing contrast sensitivity function (CSF) through distributing different weights to different sub-bands then improves coding algorithm. PSNR for lena image with three db value. Original: 28.3177 31.4093 34.3746 New : 28.1089 31.2882 33.7661.[2]

Puja Bharti, Dr. Savita Gupta and Ms. Rajkumari Bhatia proposed a framework for ROI based compression of medical images using JPEG2000 and SPIHT compression techniques.JPEG2000 and SPIHT are the wavelet-based image compression technique. The performance is evaluated using image quality metrics like PSNR, SSIM and Correlation**.** Wavelet-based coding provides good quality of image and high compression ratio. [3]

Md. Ahasan Kabir, M. A. Masud Khan, Md. Tajul Islam, Md. Liton Hossain, Abu Farzan Mitul proposed the algorithm for medical image compression based on lifting base wavelet transform coupled with SPIHT (Set Partition in Hierarchical Trees) coding algorithm to improve the drawbacks of conventional wavelet transform. PSNR value of brain axial slice image is 26.83. MSSIM value of brain axial slice image is 0.77. [4]

Miss. Rohini N. Shrikhande and Dr. Vinayak K. Bairagi proposed the performance of various lossless grayscale image compression algorithms using the method called CALIC. It is standard of context-based, adaptive and lossless image code. CALIC is based on paradigm of universal modeling and coding. CALIC operate in two modes binary and continuous modes. Compression ratio achieved by using the method of CALIC is 0.4130. [5]

Amol Baviskar, Shweta Ashtekart and Amruta Chintawar proposed a 3D-Discrete Cosine Transform (DCT) for compressing high resolution of images. Performance evaluation of various algorithms such as JPEG Lossy, Sub-Band replacement DWT and K-Means. Each of the compression algorithms can be evaluated by using the image quality metrics such as PSNR, MSE, CR, Normalized Cross Correlation, and Normalized Absolute Error. [6]

Bhagyashree I. Kochi and B.B.S.Kumar proposed the analysis of EZW, SPIHT and denoising algorithms. X-ray image has been used for implementing EZW, SPIHT and denoising algorithm. The quality of image is measured by PSNR, MSE and CR. Denoising is calculated by adding Speckle noise for both soft and hard threshold. PSNR value of hard thresholding is 47.53 MSE value of hard thresholding is 1.14. [7]

Mr. Chandrashekhar Kamargaonkar and Dr. Monisha Sharma proposed a hybrid medical image compression method using spiht algorithm and haar wavelet transform. In the medical image, the ROI part that is the diseased part extracted by using the thresholding method of segmentation and compress the ROI by the use of wavelet based compression technique called SPIHT and NROI part is compressed by using Haar Wavelet Transform. PSNR = 34.8400 for bpp = 1.00 for SPIHT algorithm. PSNR = 41.8750 for bpp = 1.00 for Haar Wavelet Transform. [8]

Preeti V. Joshi and C.D.Rawat proposed a region based hybrid compression for medical images. In this brain image the ROI part is compressed by using arithmetic coding and NROI part is compressed by using SPIHT. The hybrid method is evaluated by Peak Signal to Noise Ratio (PSNR), Structural Similarity Index (SSIM) and Virtual Information Fidelity (VIF) for MRI brain images. PSNR for SPIHT is 23.90 and SSIM for SPIHT is 0.8398 VIF for SPIHT is 0.3455. [9]

Surabhi N and Sreeleja N Unnithan proposed a review of various image compression algorithm EZW, DWT, SPIHT and also the performance metric (PSNR, MSE, CR) for these algorithm. The main objective of image compression is to decrease the redundancy of the image thereby increasing the capacity of storage and efficient transmission. [10]

Chih-chien Chao and Robert M. Gray proposed Image Compression With A Vector Speck Algorithm. Vector SPECK shows a performance improvement over JPEG 2000 at the cost of added complexity. In this work, variation on SPECK using vector quantization to code the significant coefficients. Different VQ techniques including TSVQ and ECVQ are also proposed. [11]

N.B. Chopade, A. A. Ghatol and M. T. Kolte proposed Efficient Image Compression and Transmission Using SPECK. In this work, describes wavelet based embedded block, image coding algorithm Set Partioning Embedded Block Coder (SPECK). It uses recursive set partitioning procedure to sort subsets of wavelet coefficient by maximum magnitude with respect to threshold. An image block is divided in subblocks of equal size. This algorithm has very fast encoding and decoding which makes it very efficient in multimedia communication. [12]

Gloria Menegaz proposed Trends in Medical Image Compression. This paper presents an overview on the state-of-the-art in the field of medical image coding. A versatile model-based coding scheme for three dimensional medical data is introduced. The potential of the proposed system is in the fact that it copes with many of the requirements characteristic of the medical imaging field without sacrificing compression efficiency.[13]

Sudhakar Radhakrishnan and Jayaraman Subramaniam proposed Novel Image Compression Using Multiwavelets with SPECK Algorithm. This paper is to develop an efficient compression scheme and to obtain better quality and higher compression ratio using Multi-wavelet transform with Set Partitioned Embedded Block Coder algorithm (SPECK). [14]

Shalini Prasad, PrashantAnkur Jain and Satendra Singh, “Lossless medical image compression by IWT”, Medical Image Compression is very important in the present world for efficient archiving and transmission of images. Integer wavelet Transform (IWT) show the effectiveness of the methodology used, different image quality parameters are measured and observed the increased higher PSNR values. The proposed work is to compress the medical data without any loss (i.e. lossless). Medical information is either in multidimensional or multi-resolution form, this creates enormous amount of data. Retrieval, Efficient storage, management and transmission of this voluminous data are highly complex. This technique combines integer transforms and JPEGLS Prediction to enhance the performance of lossless compression.[15]

D. Muthukumar, “HYPERSPECTRAL IMAGE COMPRESSION USING 3D SPIHT, SPECK AND BEZW ALGORITHMS”, A number of wavelet-based compression methods have been successfully used for hyper spectral image data. In many applications, karhunen–loève transform (KLT) is the well-liked approach to decorrelate spectral redundancies. In this paper, an analysis of efficient compression techniques is done, with more emphasis on 3D set partitioning embedded block (SPECK), binary embedded zero tree wavelet (BEZW), and 3D set partitioning in hierarchical trees (SPIHT). In relationship with the techniques discussed, the BEZW technique has better performance, lower computational cost, high effectiveness and simplified coding algorithm.[16]

Mohd Ali Moustafa Yousif Alsayyh,Tanzila Saba, Amjad Rehman and Jarallah S. AlGhamdi,”A Novel Fused Image Compression Technique Using DFT, DWT, and DCT”, Image compression processes moderate the number of bits essential to signify an image, which can improve the performance of systems during storage and transmission without compromising image quality. To test the level of compression, the quantitative measures of the peak signal-to-noise ratio

(PSNR) & mean squared error (MSE) are used to ensure the effectiveness of the suggested system. [17]

Rosa A Asmara, Reza Agustina and Hidayatulloh,"Comparison of Cosine Transforms (DCT), Discrete Fourier Transforms (DFT), and Discrete Wavelet Transforms (DWT) in Digital Image Watermarking", Frequency domain transformation methods used widely in Digital Image Compression and Digital Image Watermarking. Popular transformation method used are Two Dimensional Discrete Cosine Transform (2D DCT), Two Dimensional Discrete Fourier Transforms (2D DFT), and Two Dimensional Discrete Wavelet Transform (2D DWT). This paper will show the comparison result of those three transformation method. [18]

K.V. Sridhar and K.S.R. Krishna Prasad, "PERFORMANCE ANALYSIS OF WAVELET BASED ROI MEDICAL IMAGE COMPRESSION USING OPTIMUM SUBBAND SHIFT CODING", This paper presents an approach for an Enhanced Image Compression Method using Optimal sub-band Shift based SPIHT (Set partitioning in Hierarchal Trees)Algorithm. This is based on the progressive image compression algorithm, SPIHT which is an extension of Shapiro's embedded Zero tree Wavelet Algorithm. The proposed Optimal Sub-band Shift (OSS) Algorithm overcomes the difficulty of Embedded zero Wavelet EZW that loses its efficiency in transmitting lower bit planes. In this paper, we include integer wavelet transformation and region of interest coding to Partial EZW and hence make it more superior to EZW and SPIHT Algorithm and hence proved from the results.[19]

Himanshu M. Parmar, "Comparison of DCT and Wavelet based Image Compression Techniques", Fourier based transforms (e.g. DCT and DFT) are efficient in exploiting the low frequency nature of an image. The high frequency coefficients are coarsely quantized, and hence the reconstructed quality of the image at the edges will have poor quality. Discrete Wavelet Transform (DWT) is applied to an image and the energy compaction performance of both Discrete Cosine Transform (DCT) and DWT is compared. It is observed that both transforms provide comparable energy compaction performance.[20]

3. METHODOLOGY

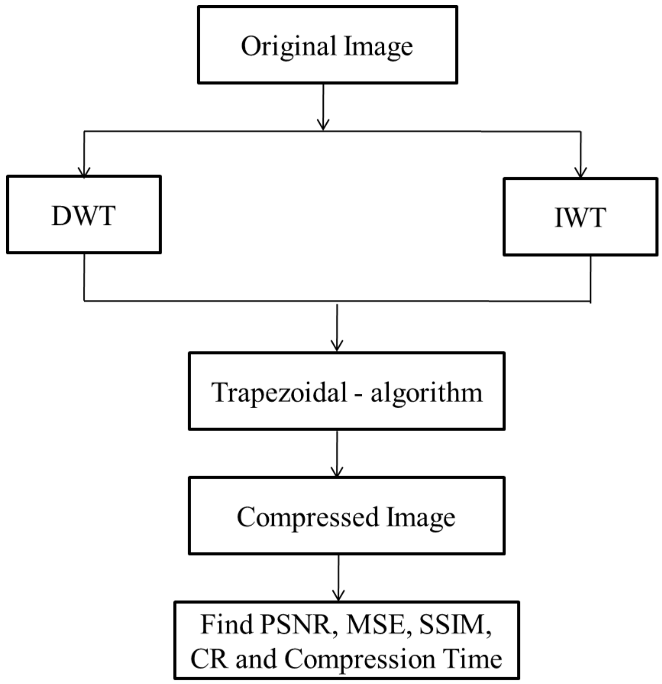

Figure 1: Flowchart of the Proposed Compression algorithm

3.1 TRAPEZOIDAL ALGORITHM

Trapezoidal algorithm has been proposed for image compression. In order to utilize the high energy compaction property of wavelet transform, proposed algorithm starts with DWT and IWT. DWT does not change the information content present in the signal. Wavelet transform provides both frequency and spatial description of an image. IWT map one integer dataset to another dataset. It has no loss of information through forward and inverse transform. This decomposition produces collection of low and high frequency coefficients called sub-bands. Each sub-band represents the components of the original input image at specific resolutions. In SPECK, the set S is encoded when the pixel level is reached whereas in proposed algorithm (trapezoidal) the set S is encoded when the size of set S is reached 4x4. The approximation of image is named as set S. set S can be formed into three subset termed as s1, s2, s3. S is grouped into many subsets each set can be defined based on a pattern of proposed algorithm. Each pixel coordinates is encoded using the logic from SPECK algorithm. SPECK algorithm -If the size of the Set S is greater than 4x4 then it is partitioned into 4 sub sets by quad-tree decomposition (Figure 3). This partition is applied in trapezoidal algorithm with three sets recursively until the size of the sub set is equal to 4x4.

The first step of trapezoidal algorithm is the partition of the transformed image into two sets S and I (Figure 2). The proposed algorithm is applied always to the Set S and Set I when the size of the set is reached 4x4. If the set is significant then test the individual pixel coefficients of set. Proposed algorithm (trapezoidal) uses two lists: LSP and LIS. If the pixel coefficient is significant update the LSP and LIS. The proposed algorithm (trapezoidal) is applied by testing the Set S against the threshold $n = n_{\max}$. This partition is applied in proposed algorithm with three S sets recursively until the size of the sub set is equal to 4x4 and set is empty. (Figure 4). The performance of trapezoidal coder is compared with SPIHT, SPECK and EZW coder.

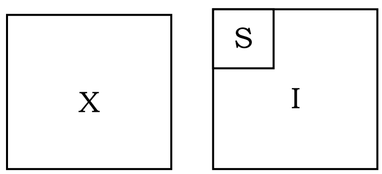

Figure 2: Image partition into sets *S* and *I*.

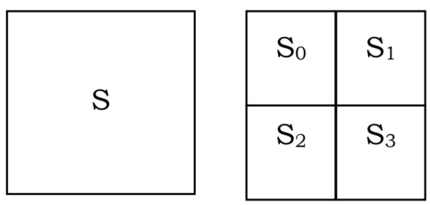

Figure 3: Partitioning of S set

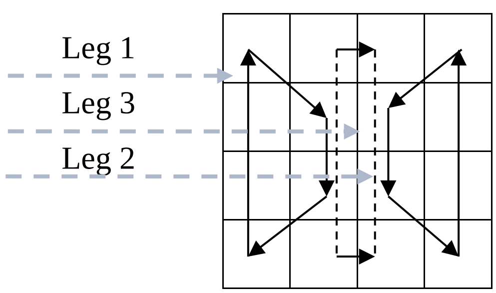

Figure 4: Proposed algorithm pattern

Next, if the set I is significant against the same threshold n, then the same partitioning is applied to set I recursively until the size of the sub set is equal to 4x4 and set is empty. This partition generates three S sets and one reduced I set (Figure 6). This procedure is repeated until the set I is empty.

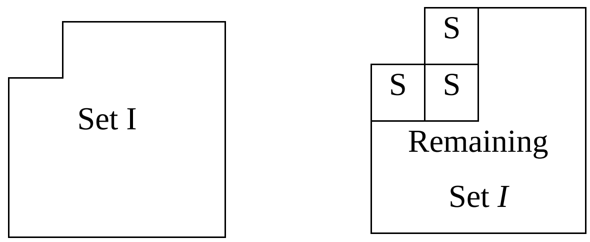

Figure 6: Partitioning of *I* set

Finally, the refinement pass is initiated which refines the quantization of the pixels that are significant during the previous sorting passes. Then the sequence of sorting and refinement passes is repeated for threshold value of $n-1$. For lossless compression, this process is repeated for all thresholds up to $n=0$. The decoding is the reverse process of encoding. The proposed encoding algorithm is reversed for decoding the image.

4. Results and Discussion

In this section, the results of DWT-Trapezoidal and IWT-Trapezoidal for medical image compression are discussed. Table 1 to Table4 shows the lossy performance of IWT compared with the DWT for a set of lung and brain images. Table 1 shows the PSNR value of DWT and IWT for CT lung images and MRI brain images using three wavelets such as Haar, Sym4 and Coif1.Table 2 shows the MSE value of DWT and IWT for CT lung images and MRI brain images using three wavelets such as Haar, Sym4 and Coif1.Table 3 shows the SSIM value of DWT and IWT for CT lung images and MRI brain images using three wavelets such as Haar, Sym4 and Coif1.Table 4 shows the CT (Compression Time) value of DWT and IWT for CT lung images and MRI brain images using three wavelets such as Haar, Sym4 and Coif1. The lossless compression results of IWT are obtained in terms of achieved bit rate. Table 5 shows the lossless compression PSNR value of IWT for lung and brain images using Haar, sym4 and COIF1wavelets. Fig 7 shows the two different original lung and brain images and reconstructed images in four different BPP values. From this analysis the lung image2 and brain image1 gives high PSNR value at 2 BPP using coif1 wavelet.

Table 1: PSNR value of Trapezoidal algorithm for lung and brain images

Images	CR	BPP	Haar		Sym4		COIF1	
			PSNR					
			DWT	IWT	DWT	IWT	DWT	IWT
Lung Image1	32:1	0.25	39.20	33.82	41.76	36.65	45.80	41.20
	16:1	0.50	42.14	38.50	44.16	42.12	46.99	44.06
	8:1	1	46.07	44.95	46.25	44.64	48.20	45.89
	4:1	2	53.12	48.60	50.67	47.27	51.34	48.23
Lung Image2	32:1	0.25	38.33	32.38	37.64	34.26	38.86	35.25
	16:1	0.50	41.25	32.59	42.78	38.68	43.25	39.15
	8:1	1	44.80	34.48	47.43	42.04	49.67	44.80
	4:1	2	50.09	38.45	51.98	47.99	53.88	49.68
Brain Image1	32:1	0.25	43.80	39.20	39.76	34.65	37.20	31.82
	16:1	0.50	44.99	42.06	42.16	40.12	40.14	36.50
	8:1	1	46.20	43.89	44.25	42.64	44.07	42.95
	4:1	2	49.34	46.23	48.67	45.27	51.12	46.60
Brain Image2	32:1	0.25	36.86	33.25	35.64	31.26	36.33	30.38
	16:1	0.50	41.25	37.15	40.78	36.68	39.25	30.59
	8:1	1	47.67	42.80	45.43	40.04	42.80	32.48
	4:1	2	51.88	47.68	49.98	45.99	47.09	36.45

Table 2: MSE value of Trapezoidal algorithm for lung and brain images

Images	CR	BPP	Haar		Sym 4		COIF1	
			MSE					
			DWT	IWT	DWT	IWT	DWT	IWT
Lung Image1	32:1	0.25	3.52	6.54	2.55	5.25	3.26	6.54
	16:1	0.50	2.51	3.81	1.50	3.56	2.25	4.20
	8:1	1	1.60	1.82	1.01	1.70	1.99	3.97
	4:1	2	0.71	1.19	0.52	1.09	0.82	2.53
Lung Image2	32:1	0.25	3.89	7.72	3.53	6.54	3.91	5.66
	16:1	0.50	2.78	6.06	2.40	5.67	2.88	6.98
	8:1	1	1.85	3.84	1.44	2.57	1.57	3.46
	4:1	2	1.13	1.88	0.99	1.02	1.54	2.18
Brain Image1	32:1	0.25	2.69	3.21	8.15	5.79	4.43	7.42
	16:1	0.50	1.51	1.98	8.00	3.68	3.38	3.95
	8:1	1	0.75	1.09	5.46	2.37	1.87	2.72
	4:1	2	0.43	0.57	4.32	1.33	0.89	2.53
Brain Image2	32:1	0.25	3.64	4.25	1.37	8.06	5.24	6.75
	16:1	0.50	2.16	2.77	7.83	6.73	4.13	5.44
	8:1	1	1.11	1.44	6.87	4.91	2.57	3.31
	4:1	2	0.57	0.73	5.47	2.15	1.18	2.62

Table 3: SSIM value of Trapezoidal algorithm for lung and brain images

Images	CR	BPP	Haar		Sym 4		COIF1	
			SSIM					
			DWT	IWT	DWT	IWT	DWT	IWT
Lung Image1	32:1	0.25	0.8847	0.8200	0.9115	0.9211	0.3503	0.8409
	16:1	0.50	0.9267	0.9039	0.9481	0.9574	0.4703	0.8969
	8:1	1	0.9586	0.9559	0.9734	0.9784	0.4784	0.9109
	4:1	2	0.9898	0.9791	0.9867	0.9883	0.5778	0.9303
Lung Image2	32:1	0.25	0.8892	0.6562	0.8892	0.8903	0.3383	0.5766
	16:1	0.50	0.9182	0.7885	0.9225	0.9247	0.3887	0.6782
	8:1	1	0.9459	0.8924	0.9497	0.9527	0.4405	0.8248
	4:1	2	0.9759	0.9494	0.9773	0.9798	0.5107	0.9027
Brain Image1	32:1	0.25	0.9267	0.8827	0.8126	0.4741	0.9448	0.8076
	16:1	0.50	0.9660	0.9333	0.9159	0.5060	0.9980	0.8873
	8:1	1	0.9882	0.9675	0.9430	0.5088	0.9926	0.9375
	4:1	2	0.9953	0.9881	0.9574	0.6110	0.9971	0.9801
Brain Image2	32:1	0.25	0.9016	0.8387	0.8173	0.2825	0.9198	0.7277
	16:1	0.50	0.9522	0.8976	0.8788	0.5103	0.9622	0.8228
	8:1	1	0.9794	0.9514	0.9308	0.5238	0.9883	0.9109
	4:1	2	0.9934	0.9844	0.9482	0.6320	0.9958	0.9648

Table 4: CT value of Trapezoidal algorithm for lung and brain images

Images	CR	BPP	Haar		Sym 4		COIF1	
			CT					
			DWT	IWT	DWT	IWT	DWT	IWT
Lung Image1	32:1	0.25	2.01	2.50	1.13	1.11	1.40	1.05
	16:1	0.50	2.29	3.46	1.83	1.97	2.42	2.09
	8:1	1	1.18	3.05	1.02	1.16	1.52	1.06
	4:1	2	1.45	1.52	1.45	1.45	3.77	1.48
Lung Image2	32:1	0.25	1.76	1.92	1.47	1.18	1.27	1.24
	16:1	0.50	5.09	4.56	2.46	1.86	2.03	2.38
	8:1	1	1.70	1.95	3.56	2.82	1.41	1.15
	4:1	2	4.53	4.05	4.15	3.32	2.35	2.94
Brain Image1	32:1	0.25	1.10	2.15	1.27	1.30	1.91	1.62
	16:1	0.50	2.05	4.04	3.43	3.36	2.88	2.77
	8:1	1	1.13	1.28	1.65	1.86	1.21	1.27
	4:1	2	5.48	4.78	1.59	1.14	3.92	5.48
Brain Image2	32:1	0.25	1.70	1.90	1.15	1.62	1.13	1.14
	16:1	0.50	3.21	2.56	3.12	2.69	2.12	2.20
	8:1	1	1.10	1.29	1.39	4.89	1.06	1.28
	4:1	2	4.15	2.54	1.84	1.57	4.18	5.47

Table 5: Lossless performance of Trapezoidal algorithm for lung and brain images using Haar, sym4 and COIF1 wavelet.

Images	Haar	Sym4	COIF1
	Lossless Compression		
Lung Image1	5.575	5.55	5.986
Lung Image2	6.56	7.55	6.986
Lung Image3	6.525	6.575	7.881
Lung Image4	6.976	5.925	6.916
Brain Image1	6.588	7.765	4.515
Brain Image2	5.678	4.55	6.976
Brain Image3	6.645	3.881	6.788
Brain Image4	6.697	6.525	6.588

5. COMPARATIVE ANALYSIS

In this section, comparison of existing algorithms such as EZW, SPIHT and SPECK are compared with proposed algorithm called Trapezoidal is discussed. Table 6 shows the performance metrics (PSNR, MSE, SSIM, CT) of Lung Image1 with BPP=2 and CR=4 for Haar wavelet. Table 7 shows the performance metrics (PSNR, MSE, SSIM, CT) of Lung Image1 with BPP=2 and CR=4 for Sym4 wavelet. Table 6 shows the performance metrics (PSNR, MSE, SSIM, CT) of Lung Image1 with BPP=2 and CR=4 for Coif1 wavelet. From this analysis, the proposed algorithm Trapezoidal is given high PSNR value using Haar Wavelet and low MSE value using Sym4 wavelet and achieve good SSIM and CT value of an image. From this discussion, the proposed algorithm is better than the existing algorithm.

Table 6: Comparison of existing algorithm and proposed algorithm using Haar Wavelet

Algorithm	DWT	IWT	DWT	IWT	DWT	IWT	DWT	IWT
	PSNR		MSE		SSIM		CT	
EZW	42.01	35.92	2.30	3.57	0.9310	0.8466	5.79	4.15
SPIHT	48.07	39.92	1.30	2.57	0.9710	0.9466	4.79	3.15
SPECK	48.49	44.98	0.96	1.44	0.9812	0.9717	3.88	4.63
Proposed (Trapezoidal)	53.12	48.60	0.71	1.19	0.9898	0.9791	1.45	1.52

Table 7: Comparison of existing algorithm and proposed algorithm using Sym4 Wavelet

Algorithm	DWT	IWT	DWT	IWT	DWT	IWT	DWT	IWT
	PSNR		MSE		SSIM		CT	
EZW	45.96	34.51	2.02	4.57	0.8698	0.8527	4.32	3.94
SPIHT	47.94	39.51	1.02	2.57	0.9798	0.9027	3.32	2.94
SPECK	50.38	39.60	0.77	2.67	0.9883	0.9303	1.45	1.48
Proposed (Trapezoidal)	50.67	47.27	0.52	1.09	0.9867	0.9883	1.45	1.45

Table 8: Comparison of existing algorithm and proposed algorithm using COIF1 Wavelet

Algorithm	DWT	IWT	DWT	IWT	DWT	IWT	DWT	IWT
	PSNR		MSE		SSIM		CT	
EZW	45.47	28.83	2.08	9.23	0.8673	0.5007	5.15	3.35
SPIHT	47.47	29.83	1.08	8.23	0.9773	0.5107	4.15	2.35
SPECK	49.87	30.54	0.82	7.58	0.9867	0.5778	1.45	3.77
Proposed (Trapezoidal)	51.34	48.23	0.82	2.53	0.5778	0.9303	1.42	3.45

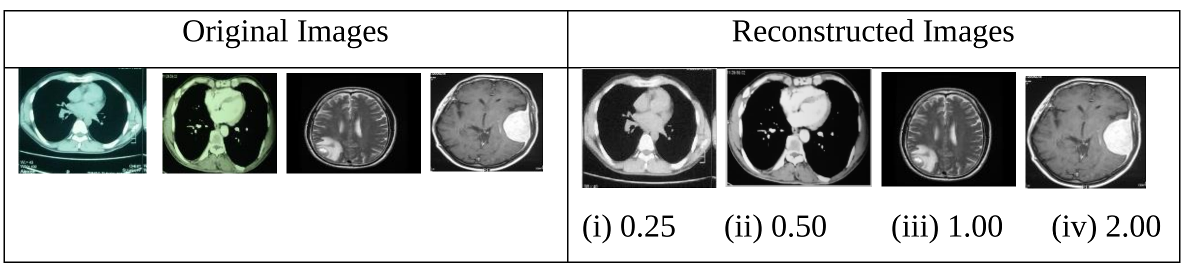

Fig 7: Original Lung, Brain Images and reconstructed images

6. Conclusion

In medical image processing, image compression is very significant because of there is huge amount of memory space is occupied in medical image. The percentage of loss of data provides improper diagnosing the patient. In this work, the lossy and lossless compression performance of the Trapezoidal algorithm is analyzed with DWT and IWT. Also, three wavelets namely as Haar, Sym4, and Coif1 are analyzed on gray scale CT lung images and MRI brain images. This Trapezoidal algorithm will results in reduced MSE, increased PSNR for lung and brain images so it can be used for transmission and storage of images. The higher PSNR value becomes better quality of the compressed or reconstructed image. The reason for choosing three wavelets such as Haar, sym4 and Coif1among more types of wavelet families. These three wavelets only gives better PSNR for lung and brain images. Results are obtained for both lossless and lossy compression showing that the obtained IWT implementations achieve lossless compression at specific bit rate and DWT implementation gives high PSNR, less MSE and less execution time for compression of grayscale images. Experimental results are obtained for PSNR, MSE, SSIM, CR and CT. The results are compared for both CT lung images and MRI brain images. In the future work apply the Trapezoidal coding techniques in the color image compression and in the bio-medical images. The Trapezoidal algorithm for Image Compression may be updated by using hybrid encryption technique during medical image data transmission for the purpose of security.

CONFLICT OF INTERESTS

The authors declare that there is no conflict of interests.

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