International Journal of Applied Engineering Research ISSN 0973-4562 Volume 12, Number 24 (2017) pp. 14114-14121

Multi Spectral Efficient Image Coding Approach for Medical Image Compression

S.Jagadeesh
Assoc. Prof., HOD, Dept., of Electronics and Communication Engineering,
Sri SaiJyothi Engineering College, Vattinagulapally, Gandipet, Hyderabad, Telangana, India.

Orcid: 0000-0002-3992-3043

Dr. E. Nagabhooshanam
Professor, Dept., of Electronics and Communication Engineering,
CMR Engineering College, Medchal Road, Hyderabad, Telangana, India.

Abstract

Image compression is a primal need in all image coding applications. Images are processed in spatial domain or spectral domain, where finer resolution of the image content is processed in multiple spectral bands for finer resolution. In the compression approach, images are decomposed using multi spectral wavelet coding, and finer resolution bands are processed for compression. The decomposition process, gives a finer detail of the image content however the recurrent pixel values in decomposed band leads to processing overhead. To overcome, this issue a new compression model based on band selection and entropy optimization is selected. The compression model is a optimal solution approach to image compression, where the accuracy of compression is achieved at lower processing overhead and overall processing delay.

Keywords: Image compression, spectral coding, band redundancy, entropy compression optimization.

INTRODUCTION

Image compression has been a need for image coding from its evolution. Digital images has an enormous impact on industrial, scientific and computer applications. It is no surprise that image coding has been a subject of great commercial interest in today's world. Uncompressed digital images require considerable storage capacity and transmission bandwidth. Efficient image compression solutions are becoming more critical with the recent growth of data intensive, multimedia-based web applications. In different image compression model, the accuracy of coding depends on the selection of the coefficient and the compression approach. The problem for image compression is more important in many applications, particularly for progressive transmission, image browsing [2], multimedia applications, and compatible Transcoding in a digital hierarchy of multiple bit rates. The tree wavelet coding for image processing [1] uses universal coding for its implementation. Various works shows the implementation of various algorithms for the compression of transformed image data. A technique that is closer in spirit to the zero trees in the end-of-block (EOB) symbol used in JPEG [7], which is also a terminating symbol indicating that all remaining DCT coefficients in the block are quantized to zero. Targeting toward JPEG 2000 [8], [9] Standard the Embedded Zero-Tree wavelet coding [1], [8] uses the wavelet [5], [6] coefficient for encoding. Wavelets use the multi resolution analysis [6] for decomposing the image into sub-band [4] as detail and approximate coefficients. In Subband coding systems [4], the coefficients from a given subband are usually grouped together for the purposes of designing Quantizer and coders. The past developments that very few works on generation of an accurate bit stream that claims higher PSNR performance at rates between 0.25 and 1 bit/pixel were made. Z. Xiong, K. Ramchandran and M. Orchad [3] uses a tree coding where the said value is zero if its energy is less than perceptually based threshold. An approach to the low bit rate image transform coding is presented by S.Mallat and F.Falzon [2]. The overview to lossy wavelet image compression for JPEG 2000 [9] and Wavelet transformation with Embedded zero-tree coding were presented by Bryan E. Usevitch [8]. ColmMulcahy presented the application of embedded coding on an isolated tile image for image compression [10] using Haar wavelet. These coding were also defined for natural images, however the issue of medical image compression is two fold. Where the medical image compression demands for higher accuracy it also need a faster processing to obtain the information at a faster refreshment rate. To obtain the processing efficiency in medical image various research were with the focus of achieving higher level compression. The conventional coding approaches developed for medical image coding are limited to multi stream bit coding at multi bit stream coding. In the case of multi bit rate [11] applications, the conventional multi bit-stream approaches are constrained and inefficient to the heterogeneity issue. At various resolutions and at various quality levels the multi bit stream coding allows partial decoding. In earlier, various scalable coding algorithms have been proposed at various international standards, but these earlier coding methods are applicable only for limited applications and also having limited decoding properties. The main problem of conventional multi bit stream approaches, inefficient and impractical due to the issue of wide varying requirements of user resources. The scalable codec's developed based on bit-level for this system allow optimal reconstruction of a medical image from an arbitrary truncation point within a single bit-stream. Recently, in the field of medical image compression, the wavelet transform has been developed as a cutting edge technology. Wavelet-based coding [12], [13], [14], [15] methods provide an improved picture quality at high compression ratios. To achieve the better compression performance, the wavelet filters should have the property of symmetry, orthogonality, higher approximation order and short support. Due to the constraints in the implementation, scalar wavelets can't satisfy all these enhanced properties. Compared with scalar wavelets, Multiwavelets [16], [17], [18] have several advantages and are generated by only a finite set of functions. One of the main advantage with multiwavelet, it can possess symmetry and orthogonality simultaneously [19] whereas the scalar DWT can't possess these two properties simultaneously. Wherein efforts are made in improving compression performance, the dual objective of computation overhead and processing speed is needed to be overcome. To achieve this objective, this paper defines a new compression model based on the spectral correlation logic and entropy redundancy coding for image compression based on bands, coefficients and bit pattern matching. To present the objective this paper is outlined in 6 sections, where the system model for the compression approach is outlined in section 2. Section 3 outlines the compression approach and section 4 defines the experimental results for the developed approach. The conclusion is presented in section 5.

SYSTEM MODELING

In order to be useful, a compression algorithm has a corresponding decompression algorithm that, given the compressed file, reproduces the original file. There have been many types of compression algorithms developed. These algorithms fall into two broad types, loss less algorithms and lossy algorithms. A lossless algorithm reproduces the original exactly. A lossy algorithm, as its name implies, loses some data. Data loss may be unacceptable in many applications. For example, text compression must be lossless because a very small difference can result in statements with totally different meanings. There are also many situations where loss may be eitherUnnoticeable or acceptable. In image compression, for example, the exact reconstructed value of each sample of the image is not necessary. Depending on the quality required of the reconstructed image, varying amounts of loss of information can be accepted. Various research works were carried out on both lossy and non-lossy image compression. The JPEG committee released a new image-coding standard, JPEG 2000 that serves the enhancement to the existing JPEG system. The JPEG 2000 implements a new way of compressing images based on the wavelet transforms in contrast to the transformations used in JPEG standard. A majority of today's Internet bandwidth is estimated to be used for images and video transmission. Recent multimedia applications for handheld and portable devices place a limit on the available wireless bandwidth. The bandwidth is limited even with new connection standards. JPEG image compression that is in widespread use today took several years for it to be perfected. Wavelet based techniques such as JPEG2000 for image compression has a lot more to offer than conventional methods in terms of compression ratio. Currently wavelet implementations are still under development lifecycle and are being perfected. The wavelet based coding are further improved by means of multi wavelet coding where, higher sub spectral band decomposition is carried out for each finer band to obtain finest degree of resolution. The approach of a compression model for image compression applied for medical image compression is shown in figure 1.

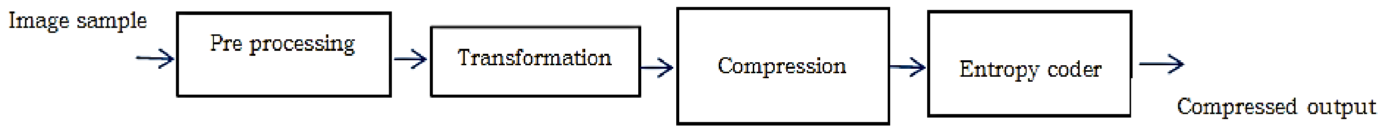


Figure 1: Image compression model in reference to JPEG-2000 image coding [9].

The compression model reads the original image and pre-process for a uniform dimensional coding and planar transformation for each color plane. The processed image data is then coded for transformation using wavelet transformation. The spectral bands derived are then coded using block based coder such as EZW, EZBC, SPHIT, EBCOT etc., to eliminate the redundant non-significant pixels from the coefficient bands. These selected coefficients are then coded for bit compression using entropy coder using Huffman coding scheme. The compressed data is processed and passed over the channel to the receiver unit. The decoder unit performs a reverse process, where the compressed bits are decoded back and mapped to the resolution band to recover the original image back. A decoding architecture is illustrated in figure 2.

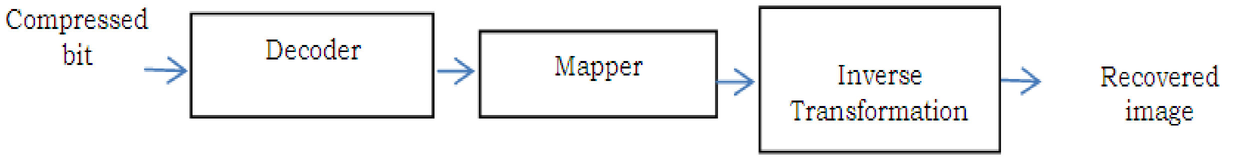


Figure 2: Decoding approach to the compression model

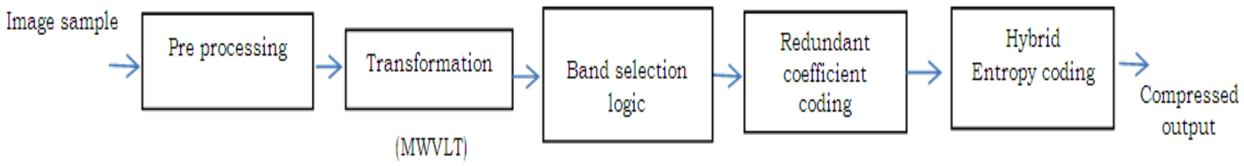


Figure 3: compression model of the proposed approach

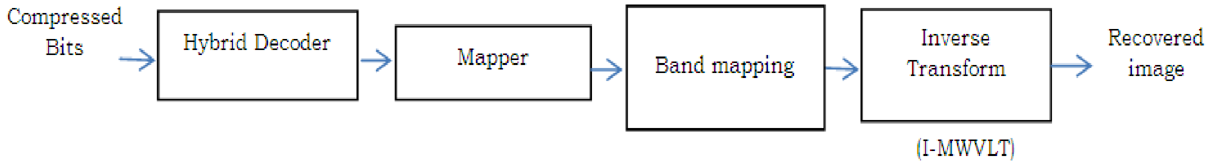


Figure 4: Decoding approach of the proposed model

The implementation of the decoder is a revere Huffman logic, based on the lookup table of code book. The decoded data are mapped onto bands based on the positional coding and inverse transformed using Inverse wavelet transform (IWT). Here the transformation is based on the wavelet transform where, the image is decomposed to fundamental bands using hierarchical decomposition. The Band retrieved from this decomposition is a 1 resolution finer band. To achieve finer details, multi-wavelet decomposition is used. The modified approach of compression and decoding model is shown in figure 3 and 4 respectively.

The unmarked region is the modified approach for the proposed system. The proposed approach minimizes the redundancy factors in terms of bands, coefficients and bits to achieve compression in image compression model. The compression algorithm developed this proposed approach is presented in next section.

Compression Coding

In the compression of medical image data, finer details are to be preserved, to achieve this multi wavelet are optimal. In this approach multiwavelet are considered for decomposition. However as the band decomposition increases, the probability of redundancy among different bands increases. This redundancy of information increases the processing overhead, and intern makes the system slower. Hence it is required to have an adaptive band selection process for extracting the actual informative band from the processed bands. In this approach the image sample is partitioned into N subbands by the analysis filters $H_0(z)$, … Hn-1(z). The resulting subband signals are then critically decimated to a lower sampling rate relative to their demanded bandwidth. The images bands are selected based on inter-correlative error defined by,

$$e_{i,D}(k) = d_{i,D}(k) - y_{i,D}(k) = d_{i,D}(k) - u_i(k)w(k)$$

Where $d_{i,D}(k) = d_i(kN)$ are the successive band coefficients. For error minimization, the error are optimized with a recursive weight optimization defined by,

$$w(k+1) = w(k) + \mu \sum_{i=0}^{N-1} \frac{u_i^T(k)}{\|u_i(k)\|^2} e_{i,D}(k)$$

Where μ is the step size.

This weight is used to optimize the band selection process. Using this weight vector and taking the expectation a MSD is computed which satisfies the absolute expectation 'E'. The difference of MSDs between two successive bands. With bands having minimum MSD is then chosen to have a selective band for processing rather to all decomposed bands. This band selection process reduces the processing coefficient with minimum deviation due to the selecting criterion of minimum MSD value. To this selected band then a modified encoding process is used to achieve higher level of compression. To this selected bands the redundant coefficient are been eliminated using coefficient redundant spectral coding. To compute the spectral magnitude of the band coefficient a power spectral densities (PSD) is computed. PSD is defined as a density operator which defines the variation of power over different content frequencies, in a given signal x(t).

The Power spectral density (PSD) for the given matrix 'x' varying with 't' is defined as,

$$P = \lim_{T\to\infty} \frac{1}{2T}\int_{-T}^{T} B(t)^2 \, dt$$

Where $B(t)$is the band obtained through the multiwavelet decomposition and P is the power spectral density over a time period t. Taking the selected band 'B_{Ni}' as reference, a PSD for each coefficient, 'PB_i' is computed. The PSD coefficients for the normalized band matrix of dimension m x n is defined by,

$PB_{i,j}$ = PSD ($B_{Ni,j}$), for i = 1 to m and j = 1 to n

The PSD per coefficient is defined as,

$$PB_{i,j} = \lim_{T\to\infty} \frac{1}{2T}\int_{-T}^{T} B_{Ni,j}(t)^2 \, dt$$

Where, i,j are the corresponding row and column, which are read over a time period of 't'. 't' is the time taken to read the whole set of 'B_{Ni}' matrix.

For the obtained power spectral densities of all bands, a correlation factor is measured successively. The correlation is measured for all bands with respect to all bands i.e., intra bands and inter bands (multi wavelet bands from LL band and the remaining LH, HL and HH bands). The sub bands which having less correlation is selected for further encoding. The bands which have minimum correlation can reduce the redundant information more precisely and also ensures less computational complexity. The band selection procedure based on the correlation is evaluated in the following step by step procedure.

Step 1: Perform Multiwavelet decomposition on the original image, the obtained sub bands can be represented as $B_{LL}^n, B_{LH}^n, B_{HL}^n$and B_{HH}^n.

Step 2: Measure the power spectral densities of all bands

Step 3: Evaluate correlation between all bands obtained as

For k={LL,LH,HL,HH} // types of bands

For b=1:N // number of band for each type

For i=1:m

For j=1:n

$$cor_b^k(i,j) = correlation(B_b^k(i,j), B_{b\pm1}^k(i,j))$$

End

End

End

End

$$[mc\ b] = \min(cor)$$

Here, the parameter $cor_b^k(i,j)$ represents the correlation between the band (b) obtained by further decomposing k type band. $mc$is the minimum correlation and b is the bands having minimum correlation.

Step 4: Like this the correlation is evaluated for all bands and forms the obtained values, the bands with minimum correlation was selected.

Further, the selected bands were processed for further encoding through hierarchical image coding.

The selected coefficients are then coded for compression based on the entropy coding using a hybrid compression model of variable and fixed length coding. The compression model, integrate the variable and fixed coding structure, where the first 3 highest probability blocks are given variable codes and other are coded with a fixed code of '1' prefixed to the original bits. The coded pattern is as shown in table 1.

Table 1: Code bit pattern for the proposed entropy encoder

Code blocks	Code bits
Highest 3 probable's block	Variable length bits
Other block codes (O)	'1' (O)

EXPERIMENTAL RESULTS

For the suggested system approach a compression model is realized over Matlab tool and simulated for differed medical samples. The observations obtained are presented below.

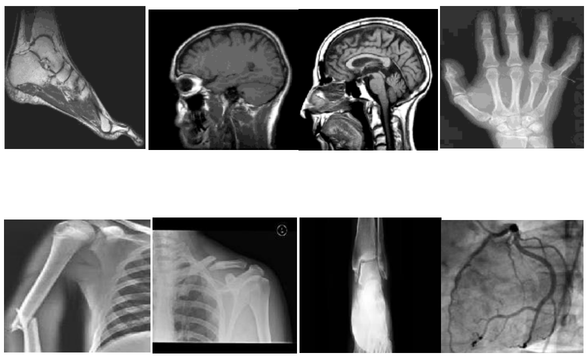
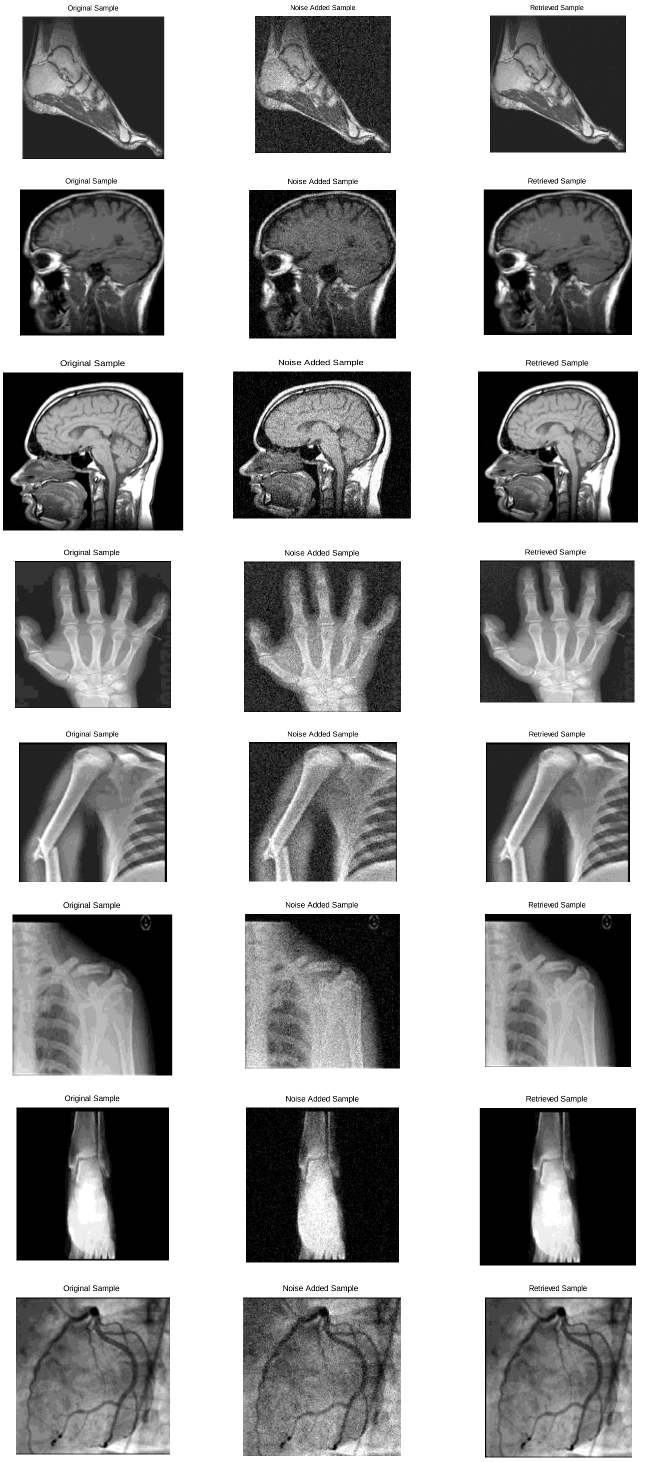


Figure 4: test samples

Table 2: Observed results for the test samples under noise variance

Original sample Noise Added Sample Retrieved Sample



For the suggested approach various case studies were carried out and the observations are compared to the existing benchmarking algorithms. For the evaluation of the suggested approach various Qualitative parameters were evaluated. A Mean square error (MSE) is computed which is one of the representation to quantify the amount by which an estimator differs from the true value of the quantity being estimated. As a loss function, MSE is called squared error loss. MSE measures the average of the square of the "error". The error is the amount by which the estimator differs from the quantity to be estimated.

$$MSE = \frac{1}{MXN}\sum(f-\hat{f})^2$$

Here M,N are the size of the row and column dimension of the image and $\hat{f}$ is the estimated image sample and f is the original sample. A Peak signal-to-noise ratio (PSNR), defines the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. Because many signals have a very wide dynamic range, PSNR is usually expressed in terms of the logarithmic decibel scale. The PSNR is most commonly used as a measure of quality of reconstructed image.

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

Where *Ipeak is* the peak values of the input signal (usually 255 the maximum value of luminance level). Another important metric for evaluating the proposed algorithm is the measurement of the amount of time required to encode, and decode the image. In this approach, actual time in CPU cycles is used as a measure of execution time.

The compression ratio for the developed approach based on proposed coding is also computed to evaluate the coding efficiency for various medical samples. the Compression ratio is given by,

CR = ((Or–Cd) /Or) * 100

Where,

Or = Original dimension

Cd = coded data dimension

The observations obtained for the system developed is as presented below,

Along with these metrics the performance of Proposed compression model is measured through some more performance evaluation parameters such Compression Rate (CR), Encoding Time (ET), Decoding Time (DT) and Total Time (TT). The obtained performance metrics under different cases of noise variances are shown in the table.2.

Table 3: Performance Metricsunder various noise variances

Sample	Noise variance = 0.01					Noise variance = 0.03				
	CR	ET	DT	TT	PSNR	CR	ET	DT	TT	PSNR
S1	2.8854	6.8845	2.5466	9.4391	56.2341	2.5471	6.7412	2.4485	9.1897	54.1432
S2	2.7451	6.2358	2.8563	9.0921	57.2145	2.3369	6.3325	2.6685	9.0011	55.5421
S3	2.3678	7.1258	3.4178	10.2736	58.1234	2.1242	7.0028	3.1472	10.1523	56.4235
S4	3.2214	7.2235	3.3387	10.5622	56.0014	2.9987	7.1247	3.2014	10.3261	53.3385
S5	2.9965	6.3385	2.8741	9.2126	58.8742	2.5574	6.2358	2.5813	8.8171	56.8752
S6	3.0028	6.8564	2.5671	9.4235	57.0067	2.8541	6.8654	2.4478	9.3132	55.3145
S7	2.8512	5.3874	2.0035	7.3909	55.8954	2.6635	5.7438	2.1038	7.8476	53.6632
S8	3.1458	6.2285	2.8562	9.0847	56.3217	3.0008	6.2547	2.7968	9.0515	52.8547

Table 4: Performance Metrics under various Bit Rates (Bit Per Pixels (BPP))

Sample	BPP = 0.2					BPP = 0.5				
	CR	ET	DT	TT	PSNR	CR	ET	DT	TT	PSNR
S1	3.2254	6.3312	3.0245	9.3557	58.2278	3.5568	6.7845	3.2254	10.009	59.3314
S2	3.4578	6.8745	3.1247	9.9992	59.6978	3.8741	6.9986	3.3369	10.335	59.8975
S3	3.2689	6.3598	3.6985	10.058	58.4478	3.5328	6.6632	3.8654	10.528	59.1278
S4	3.4589	7.0021	3.2457	10.247	57.4586	3.8657	7.3247	3.4475	10.772	58.9687
S5	3.0058	6.4589	3.8852	10.344	56.3242	3.4412	6.5879	3.9687	10.556	58.2201
S6	3.2568	7.2231	3.4752	10.698	56.3324	3.4568	7.3320	3.7542	11.086	58.1453
S7	3.7742	5.9986	3.5471	9.5457	58.2475	3.9964	6.3254	3.7145	10.039	59.2274
S8	3.6539	5.9863	3.1287	9.1152	57.3328	3.7249	6.2289	3.2278	9.9538	59.0028

Table 5: comparitive analysis between the proposed and standard JPEG compression

Metric	S1		S2		S3		S4	
	JPEG	Proposed	JPEG	Proposed	JPEG	Proposed	JPEG	Proposed
CR	2.0156	2.9956	1.2031	1.9985	1.6719	2.5685	2.3358	3.0417
ET	5.2188	6.3245	4.6406	6.4523	5.2520	6.8885	6.8957	7.1458
DT	9.4063	4.2250	7.2188	4.8795	9.7656	7.2147	9.8886	4.8874
TT	14.625	10.5465	11.8594	11.3498	15.0153	14.1302	16.7843	12.0332
PSNR	39.8869	45.8635	42.5901	48.5278	39.5556	44.7898	39.7456	46.3289

From the table.4, it can be observed that the all performance metrics for the proposed copression model is optimal compared with standard JPEG, expect encoding time. Since the proposed approach accomplishes the multiwavelet transform for feature extraction, the time taken for encoding is high. The proposed approach is based on the multiwavelet transform whereas as the JPEG is based on the Discrete wavelet transform. The proposed approach selects the bands followed by feature form the selected bands in an iterative fashion.

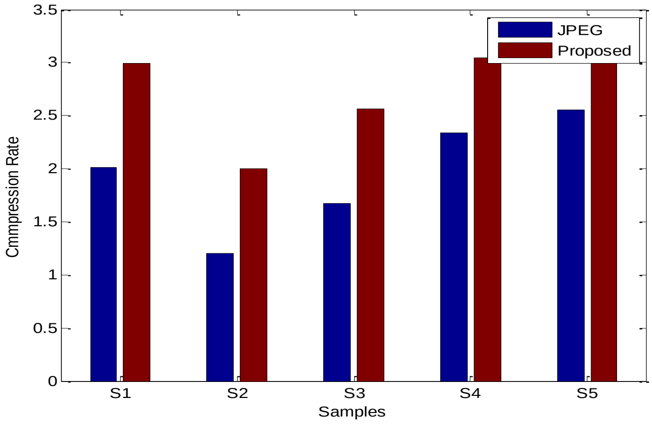


Figure 5: Compression rate comparision

This phase consumes more time. Thus the encoding time for the proposed approahc is obsreved as high compared to JPEG. Except encoding the remaining paramatere such as compression ratio, docidng time, total time and PSNR of proposed approach is observed as optimal compared with JPEG. The repestive compraision plots for compression ratio, total time and PSNR are represneted in figure.5, figure.6 and figure.7 respectively.

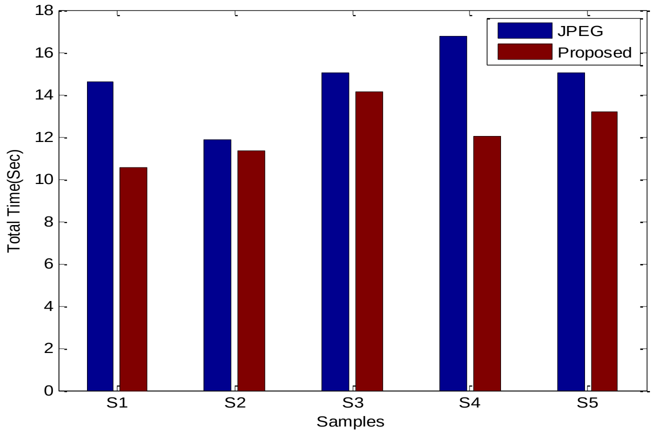


Figure 6: Total time taken in seconds comparision

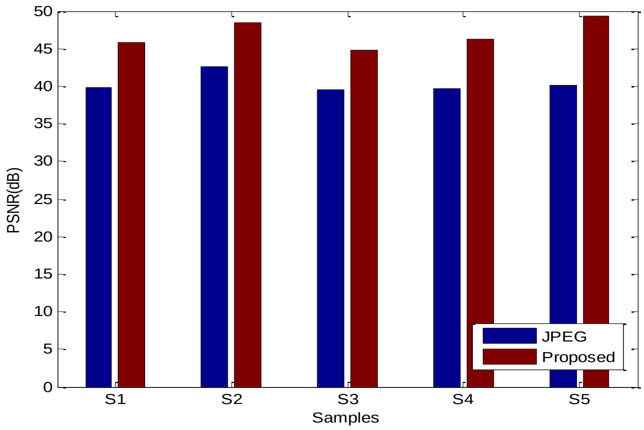


Figure 7: PSNR comparision

From the above figures, it can be observed that the proposed approach has high compression ratio, lower total time and higher PSNR. It can also be observed that the proposed approach works effectively even under noise contamination. Thus the proposed compression model achieves an optimal performance for medical image compression.

CONCLUSION

This paper presented a novel approach of image compression based on the redundancy coding in image compression. The objective of image compression using the multi spectral approach is achieved by the incorporation of multi wavelet decomposition and image compression model using band selection and coefficient selection modeling. The approach of weight optimization and spectral selection logic defines the approach of code selection. The hybrid coding model for entropy based coder result in finer compression and achieving high compression ratio. The approach results in higher PSNR with lower computation time.

REFERENCES

[1] J.Shapiro, "Embedded image coding using zerotrees of wavelet coefficients," IEEE Trans. Signal Processing, vol. 41, pp.3445-3462, Dec 1993.

[2] S.Mallat and F. Falzon, "Analysis of low bit rate image transform coding," IEEE Trans. Signal Processing, vol. 46, pp. 1027-1042, Apr. 1998.

[3] Z. Xiong, K . Ramchandran, and M. Orchad, "Space-frequency quantization for wavelet image coding," IEEE Trans. Signal Processing, vol. 6, pp. 677-693, May 1997.

[4] E. H. Adelson, E. Simoncelli, and R. Hingorani, "Orthogonal pyramid transforms for image coding," Proc. SPIE, vol. 845, Cambridge, MA, Oct. 1987, pp. 50-58.

[5] R. A. DeVore, B. Jawerth, and B. J. Lucier, "Image compression through wavelet transform coding," IEEE Trans. Informat. Theory, vol. 38, pp. 719-746, Mar. 1992.

[6] S. Mallat, "A theory for multiresolution signal decomposition: The wavelet representation," IEEE Trans. Pattern Anal. Mach. Intell., vol. 37, pp.2091-2110, Dec.1990.

[7] G. K. Wallace, " The JPEG Still Picture Compression Standard," Commun. ACM, vol. 34, pp. 30-44, Apr. 1991.

[8] Bryan E. Usevitch, "A Tutorial on "Modern Lossy Wavelet Image Compression: Foundations of JPEG 2000", IEEE signal processing magzine, 1053-5888,sep-2001.

[9] AthanassiosSkodras, CharilaosChristopoulos, and TouradjEbrahimi, “The JPEG 2000 Still Image Compression Standard” IEEE signal processing magzine, 1053-5888,sep-2001.

[10] ColmMulcahy “Image Compression using the Haar wavelet transform”, spelman science and Math Journal.

[11] Lalitha Y. S, “Image Compression of MRI Image using Planar Coding”, (IJACSA) International Journal of Advanced Computer Science and Applications, Vol. 2, No. 7, 2011.

[12] B.Nassiri, R.Latif, “Study of Wavelet Based Medical Image Compression Techniques”, International Journal of Engineering Science and Innovative Technology (IJESIT) Volume 3, Issue 3, May 2014.

[13] S. M. Ramesh, Dr. A. Shanmugam, “Medical Image Compression using Wavelet Decomposition for Prediction Method”, International Journal of Computer Science and Information Security, Vol. 7, No. 1, 2010.

[14] Anuja P Parameshwaran, ManishaGaonkar, “DCT and DWT in Medical Image Compression”, International Journal on Advanced Computer Theory and Engineering, Volume-2, Issue-3, 2013.

[15] Neha S. Korde1, A. A. Gurjar, “Wavelet Based Medical Image Compression for Telemedicine Application”, American Journal of Engineering Research (AJER), Volume-03, Issue-01, 2012.

[16] E. Praveen Kumar, M.G.Sumithra, “Medical Image Compression Using Integer Multi Wavelets Transform For Telemedicine Applications”, International Journal Of Engineering And Computer Science, Volume 2 Issue 5 May, 2013.

[17] N.Thilagavathi, K.Subramani, “Medical Image Compression Using Multiwavelet Transform”, IOSR Journal of Electronics and Communication Engineering (IOSRJECE), Volume 1, Issue 1 May-June 2012.

[18] Strela V., Heller P., Strang G., Topiwala P., and Heil Ch., “The Application of Multiwavelet Filter Banks to Image Processing,” IEEE Transactions on Image Processing, Georgia Institute of Technology, Atlanta, 2002.

[19] Yang Shouzhi, “A Fast Algorithm for Constructing Orthogonal Multiwavelets”, Australian Mathematical Society 2004.