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A HYBRID COMPRESSION TECHNIQUE FOR CARDIAC IMAGE ANALYSIS IN TELECARDIOLOGY SYSTEM

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ABSTRACT
Nowadays, remote health care monitoring (RHCM) becomes an intense research area. In which medical signals and images needed to be transmit from patient to doctor and vice versa. In such a scenario image processing plays a vital role. Medical image in its raw form requires a lot of memory for storage. To cope up this in a remote health care monitoring system to develop image compression techniques to preserve image quality while transmission. There are various methods are used for this data compression like Discrete Cosine Transform (DCT) and Discrete Wavelet Transform (DWT). Among these DWT is for multi-resolution transformation and DCT for high energy compaction with less energy resources. In this paper we proposes a new algorithm for compressing cardiac image suitable for health care monitoring based on Minimized Matrix Size Algorithm and arithmetic encoder, decoder performs the better performance than slandered standalone JPEG based DCT and DWT algorithms in terms of compression ratio and peak signal to noise ratio (PSNR). At the receiving end the decompressing is performed based on limited sequential search algorithm. The proposed techniques are compared with Huffman encoder based algorithms. Experimental results confirm that performance of the proposed techniques is better than the conventional techniques.

Keywords: cardiac image, compression, decompression, medical image processing, remote health care monitoring.

INTRODUCTION
Cardiovascular disease (CVD) refers to a large number of medical conditions relating to the heart functionality. World Health Organization (WHO) in its 2015 annual report states that approximately 50% of all non-communicable disease (NCD) deaths are due to CVDs [Health in 2015, 2015]. Among these, most of the deaths are outside the hospital, due to the reason that patient is not treated timely. Also American Heart Association reported that greater than 1 in 3 have greater than one types of CVD [Heart Disease and Stroke Statistics., 2015], CVDs are the number 1 cause of death globally. In such a scenario WHO planned to reduce the deaths due to NCDs globally by 25% by 2025[World Health Organization Fact Sheets on Cardiovascular Diseases., 2015]. Hence research on cardiovascular health care technology becomes an intense area.

In such a scenario, remote health care monitoring plays a vital role to assist patients timely, especially when the patient is in a remote location. Hence, the development of less expensive and high quality cardiac image conditioning systems are required. In a typical remote health care monitoring image conditioning system three processing techniques are needed. They are medical image compression and decompression, denoising at the doctors end, segmentation to identify any abnormalities present in the image. In this paper we propose an efficient cardiac image compression and decompression technique suitable for RHCM cardiac system.

One of the familiar techniques used for medical image compression is wavelet transformation. It provides multi-resolution representation, scalability, numerous desirable properties and embedded coding with progressive transmission which helps to image compression [Antonini *et al.*, 1992]. Particularly wavelet based multi resolution process matches the human visual system, specifically lower detailed information is represented by high resolution and higher detailed information is represented by higher spatial information [Strang *et al.*, 1996]. Such a hybrid approach for wavelet compression is presented in [JPEG 2000 Image Coding System., 1999]. Some hybrid techniques are proposed by H. Hsin *et al.* that is embedded block coding for low frequency and high frequency wavelet coefficients. In the process the low frequency intermediate coding results facilitates the coding operation of high frequency coefficients [Hsi-Chin Hsin *et al.*, 2007]-[Vandana Roy et *al.*, 2013]. Shapiro *et al.*, has introduced an embedded zero tree wavelet coefficient coding [Christopoulos *et al.*, 2000]. But more scales are required in this algorithm for high resolution which in turn increases the complexity of the algorithm. Hence another coding technique Set Partitioning in Hierarchical coding Techniques (SPHIT) is introduced, which out performs the less complexity and high speed then EZW technique [Sana *et al.*, 2009]. However this technique is inferior to JPEG 2000 compression technique. Later set partitioning embedded block coder (SPECK) and it's variants were introduced, but this suffer with more complexity [Shu-Mei *et al.*, 2014].A fractal image compression technique is presented in [Veenadevi *et al.*, 2012], it is based on decomposing the original grey level image in to un-overlapped block depending a threshold. Recently, [Siddeq *et al.*, 2014] discussed a new frame work based on a compression and de-compression strategy. In order to get the better compression ratio with increase PSNR we introduce a new hybrid coding technique. The concept of combining the two transform techniques is popular in recent years that have put effort to develop the efficient coding techniques. In this paper we propose a hybrid algorithm for cardiac medical MRI image compression using DWT, DCT, arithmetic encoding and matrix minimized method. This technique is a hybrid combination of [Veenadevi *et al.*, 2012] and [Siddeq *et al.*, 2014]. The proposed treatment employs fractal sub-band for three sub-bands and quantization, minimize matrix size for fourth sub-band. We test the performance of the proposed algorithm on real cardiac images obtained from cardiac atlas [http://atlas.scmr.org/]. Simulation results confirm that the proposed algorithm is better than the conventional compression techniques. Hence it is suitable for 2D compression, transmitting over a biotelemetry network, remotely decompressing at the doctors end with same resolution as the transmitted image.

BACKGROUND THEORY

The two basic transform techniques used in compression process are classified as,

Discrete Wavelet Transform

In medical image processing spatial and transform are two working domains. In transform domain we directly deal with frequency and in spatial domain we deal with pixels. There are many transforms like Discrete Wavelet Transform (DWT), Discrete Cosine Transform (DCT), Discrete Fourier Transform (DFT) and Fast Fourier Transform (FFT). Among all these techniques DWT is the better transform because it captures the location, frequency and multi-resolution property. Wavelet domain compression is new promising method comparatively others.

When DWT applied to image then the image is divided in to four detailed components.

a) approximate image component (LL)

b) Horizontal detail component (HL)

c) Vertical detail component (LH)

d) Diagonal detail component (HH)

This decomposition process is extended to multilevel decomposition levels.

<table>
<tr><td>LL3</td><td>HL3</td><td rowspan="2">HL2</td><td rowspan="3">HL1</td></tr>
<tr><td>LH3</td><td>HH3</td></tr>
<tr><td colspan="2">LH2</td><td>HH2</td></tr>
<tr><td colspan="3">LH1</td><td>HH1</td></tr>
</table>

Figure-1. Level 3 decomposition of image.

The most signal energy concentrated in approximation sub band. With this it provides the high Compression Ratio (CR) [Christopoulos *et al.*, 2000] with degraded image quality. Edges and texture of images are concentrated in LH, HL and HH sub bands which compressed in to fewer bytes [Sana et al., 2009]. In the process of reconstructing the data Inverse Discrete Wavelet Transform (IDWT) is used to recover the information about the image using all the detailed sub bands.

Discrete Cosine Transform (DCT)

In this method the information regarding the image data is in the form of sum of cosine functions that are oscillating at different magnitude and frequencies. Two dimensional DCT is considered for making the operations on image. Basically DCT coefficients are de-correlated that means many of the coefficients are discarded without affecting the image quality. A compact matrix of de-correlated coefficients can be compressed much more efficiently than a matrix of highly correlated image pixels the fallowing equations are represent the two dimensional DCT and Inverse DCT functions [Grigorios *et al.*, 2008] and [Rao *et al.*, 1990].

$$C(u,v) = p(u)p(v)\sum_{i=0}^{n-1}\sum_{j=0}^{n-1} f(i,j)cos\left(\frac{(2i+1)u\pi}{2N}\right)\times\ cos\left(\frac{(2j+1)v\pi}{2N}\right) \quad (1)$$

Where $p(u) = \sqrt{\frac{1}{N}} \quad for\ u = 0$

$$p(u) = \sqrt{\frac{2}{N}} \quad for\ u \neq 0$$

$$f(i,j) = \sum_{u=0}^{N-1}\sum_{v=0}^{N-1} p(u)p(v)C(u,v)cos\left(\frac{(2i+1)u\pi}{2N}\right)\times\ cos\left(\frac{(2j+1)v\pi}{2N}\right) \quad (2)$$

DCT can be applied on the image as a block or a large rectangular region of the image. It increases the complexity while calculate the DCT using a large rectangular blocks. For this reason it prefers to use 4 X 4 pixel block. The quantizing factor divides the LL band in to 4 X 4 coefficients using matrix dot inversion. This process is called quantization which removes the insignificant coefficients and increasing the zeros in the LL band and the quality value should be greater than 0.01.

Various compressions - Decompression methods

The basic idea of implementation of these methods are coefficient thresholding (global or by level) and encoding by quantization. Huffman encoding and fixed encoding are used for the quantization that depends on type of method [Sayood *et al.*, 2000]. These methods are summarized as follows,

Sub-band thresholding and Huffman encoding (SBT_HE)

This method performs the quantization of sub-band signal samples include less resolution than original signal and entropy encoder by means of Huffman encoder. As a result SBT performs better than conventional thresholding.

Global thresholding of coefficients and fixed encoding (GBT_FE)

In the series of data compression wavelet plays a vital role. In real time compression it is necessary to use the operations like quantization and coding which related to DWT and IDWT, this again combined with fixed Huffman encoding. Fixed length encoding is a process of encoding similar to ASCII. It is very convenient because the boundaries between the letters is easily determined and assign the fixed pattern. For example 'a' is the fixed notation for 97. The standard ASCII character requires 8 bits to store each character. Generally common characters use normally used 8 bits of storage but it faces trouble in case of special characters like*ü*.In an English text document, it might be the case that only 90 or so distinct characters are used at all that means 166 characters in the ASCII never even appear and within those 90 characters there are likely to be significant differences in the character counts. Fixed length encoding uses the same number of bits for each symbol and k-bit code supports 2k different symbols.

Global thresholding of coefficients and Huffman encoding (GBL_HE)

When individual samples are needed to be compress the data Huffman encoding is the optimum data compression algorithm. Huffman coding is the one of the entropy coding used for losses less data compression. This refers to the use of variable length table for encoding a source symbol. Variable length table is derived from the estimation of the probability of occurrence of each possible value of source symbol. The Huffman encoding process takes the advantage of uses the less storage for frequently occurring character at the expense of having to use more storage for more rare characters. Huff man coding is one of the example of variable length coding. Such that some of the characters require 2 to 3 bits and other characters may require 8, 10 and 12 bits. The saving of storage by not use of full 8 bits for more common characters that makes up to use more than 8 bits for rare characters. Huffman coding uses the different number of bits to encode different characters. The original symbols from a compressed file are replaced with bit strings and the more frequently a given symbol appears in the compressed file and the shorter bit string for representing the symbol. The encoded symbols and their corresponding bit strings are represented as a Huffman tree and are used for both compressing and decompressing.

Quatree Decomposition (QTD)

In QTD method, the medical image that has to be processed is divided into four equal sized square blocks. These blocks are compared for some specific criterion of similarity. If a particular block is found as the similarity is present, it is not divided further. For remaining blocks are further divided. The process is repeated until each block meets the specific criteria.

Fractal Quatree Decomposition (FQD)

In this method, the image under test is decomposed into blocks using QTD. Then fractal coding information is recorded using Huffman coding and to reconstruct the image Huffman decoding is used [Veenadevi *et al.*, 2012], [Riccardo *et al.*, 2006]. Several image compression techniques are presented and analyzed in [Ansari *et al.*, 2007]-[Janet *et al.*, 2005].

PROPOSED CARDIAC COMPRESSION ALGORITHM

The proposed cardiac image compression algorithm depends upon single level DWT, which decomposes the image in to approximate coefficients (LL) and high frequency coefficients (LH, HL and HH). This technique is based on the frame work presented in [Siddeq et al., 2014]. The LL matrix is coded by matrix-minimized-algorithm and all the remaining sub bands are encoded with fractal encoding technique. This encoded data is compressed using Arithmetic coding procedure and the compressed data is stored in the file for transmission. The flow diagram of the proposed cardiac compression algorithm is shown in Figure-2.

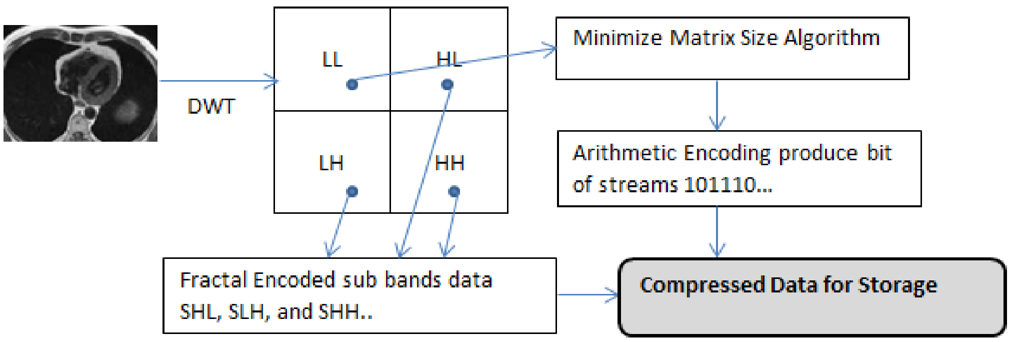

Figure-2. Flow diagram for proposed cardiac compression algorithm.

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Compression by Minimize Matrix Size Algorithm

This algorithm is used to reduce the matrix size of the approximate size coefficients depends on the random -weight -values to store the values in new array. Each of the 4×4 coefficients from the LL band aredivided by quantized factor Q using matrix-dot-diversion. This is called Quantization which increases the zeros by removing the insignificant coefficients. The factor of Q can be formulate as

$$L = Qulity\ factor \times Max(LL) \tag{3}$$

$$Q(p,q) = \begin{cases} 10 & p,q = 1 \\ L + p + q & p > 1 \end{cases} \tag{4}$$

Where p, q=1, 2, 3, 4

The parameter value of the L can be computed from the quality factor which is ≥ 0.01 and the maximum value from the LL band matrix. Here the Quality factor for the maximum ratio value. If this ratio value increases that leads to force the large number of coefficients become zeros, which gives the lower image quality. At first 4×4 block of matrix from LL band quantized by the Eq.(3) and coded by Matrix-Minimized-Algorithm. Before applying the Matrix-Minimized-Algorithm to the data, itis encrypted with help of key generator. This encrypted data is after processed by Matrix-Minimized-Algorithm. The flow steps for this algorithm are as follows:

Let P=3
W=Generate Random Weights (j) %% generate the random weights
Let K=1
For i=1 to column size
For j= 1 to row size
Intermediatevalue[k]=Matrix[i,j] %%row by row scanning
K++
End
End
Let j=1;n=1
While(j<row size*column size)
Array=read_P_cofficients(Intermediatevalue[j])

$$M(p) = \sum_{i=1}^{p} w(i) * Array(i)$$

J=j+n
n++
End

From the above algorithm the weight values are generated randomly multiplied with *Array(i) to* produce minimized array M(n). This algorithm is applied to LL band that has compress independently. Figure-3 shows the Matrix Minimized algorithm applied to medical image data matrix. Remaining high frequency bands are compressed with fractal compression technique in order to minimize the data size. The final step in this compression is Arithmetic coding which converts data stream in to binary data value bounds between ones and zeros. Arithmetic coding needs to compute all the probability of data and assign a range of each, the ranges are limited to low and high values. Figure-4 shows the phenomenon of arithmetic coding of a 5 x 5 matrix.

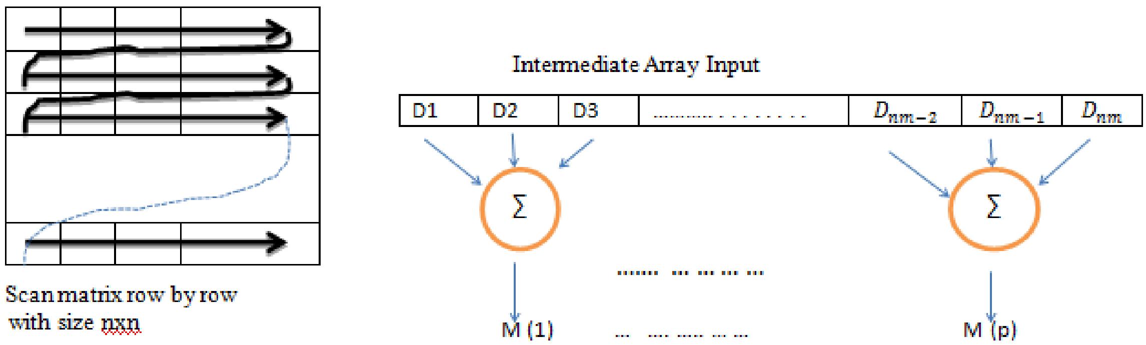

Figure-3. Conversion of nxm size matrix into M size array.

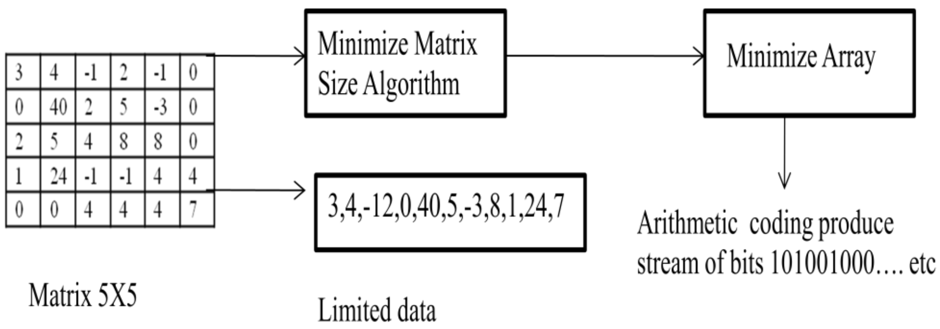

Figure-4. Phenomenon of arithmetic coding for a 5x5 data matrix.

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Decompression algorithm

Decompression process is reverse of the compression algorithm. In the first stage all the fractal compressed sub-bands are recovered with fractal decompressed method and the minimized array is decoded by arithmetic decoder with limited sequential search algorithm (LSS algorithm). The LSS algorithm depends on limited data array. If the limited array data is missed, the image may be degraded or destroyed. Figure-5 shows the decompression methodology in sequence wise. LSS algorithm is basically for finding the original data in the limited data set by reference of three pointers. These pointers refer the positions in limited data matrix. Here three pointers are called S1, S2 and S3 and are incremented by one in a cogwheel fashion. The initial step in decompression is assign the S1=S2=S3=1 the compute the result using fallowing equation

$$Est = W(1)\ X\ Limited(S1) + W(2)X\ Limited(S2) + W(3)X\ Limited(S3) \quad (5)$$

where, W is the generated weights from the Limited Data Matrix.

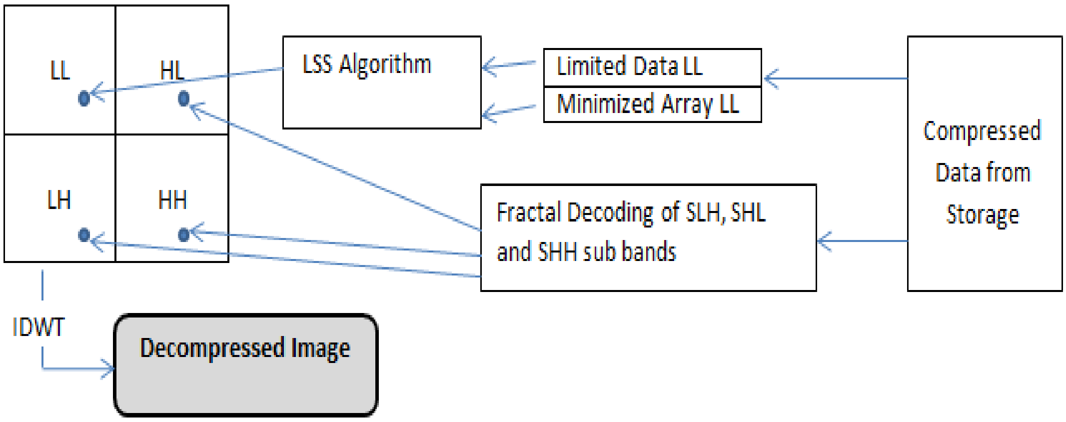

Figure-5. Decompression algorithm for reconstruct the entire sub bands of received cardiac image.

Here LSS algorithms computes *Est*at each iteration and compared with M (i). If the value is zero the estimated values are found at locations = {S1, S2 and S3} according to limited data. If it fails, the algorithm continues to find its original values. This process will continue up to the end of the Minimized Matrix. The following steps describes LSS algorithm for cardiac image decompression.

Let *Limited [1….m]%%represents the limited data*
Let *M [1…..p]%% Minimized array with size p*
For i=1 to p
S1=1;S2=1;S3=1;%% initial condition
Iterations =1
$Est = W(1)\ X\ Limited(S1) + W(2)X\ Limited(S2) + W(3)X\ Limited(S3)$
While ((M(i)-Est)=!0)%% check whether the error is zero or not
S3++;%% increment the pointer
If(S3>m) S2++;S3=1 end;
If(S2>m) S1++;S2=1 end;
If(S1>m) S1=1 end;%%compute Est after increment
$Est = W(1)\ X\ Limited(S1) + W(2)X\ Limited(S2) + W(3)X\ Limited(S3)$
Iterations++%%compute number of iterations
End %% end of while
End

Figure-6. (a) Matrix before applying addition between two values and (b) after applying addition between two values.

After the LL band is decoded by LSS algorithm this will applies to addition between two values (ABV) on the decoded LL band for recover original values. ABV is the just inverse of difference between two values (DBV). ABV applies to all the columns individually which takes the last value at position *m* and add it to previous value. The total value again adds to the next previous value so on. The following equation represents the ABV decoder

$$D(i-1) = D(i-1) + D(i) \quad (6)$$

Where *i=m, (m-1), (m-1) …… 2*

Then the inverse DWT applied to this recovered LL and all the fractal decompressed LH, HL and HH band to reconstruct the required image.

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SIMULATION RESULTS

The rapid development in telecardiology enables transmission of physiological signals and cardiac images from patient end to doctor's end. In such a scenario for fast communication, the cardiac image that has to be sent is needed to be compressed. At the receiving end decompression has to be performed to facilitate the doctor with cardiac image. To prove the ability of the proposed techniques for cardiac image processing techniques suitable for a RHCM system we performed compression and decompression techniques on typical cardiac images. For our experiments we used real cardiac images obtained from cardiac atlas data base [http://atlas.scmr.org/]. These images are taken as input images for compression and decompression phenomenon. Figure-8 and Figure-9 shows the compression techniques for various algorithms include proposed algorithm and the Table-1 shows the analyzing parameters of the reconstructed image quality parameters Peak Signal to Noise Ratio (PSNR), Mean Square Error (MSE) and Structured Similarity Index Module (SSIM) with compression performance evaluated parameters Compression Ratio (CR) and Bits Per Pixels (BPP). These metrics are calculated as follows, Mean Square Error (MSE): It represents the mean square error between decompressed image and original image and is given as,

$$MSE = \frac{1}{MN} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} |X(i,j) - X(i,j)_r|^2$$

The lower the MSE value, lower the error.

Peak Signal to Noise Ratio (PSNR): It represents the measure of the peak error and expressed in decibels.

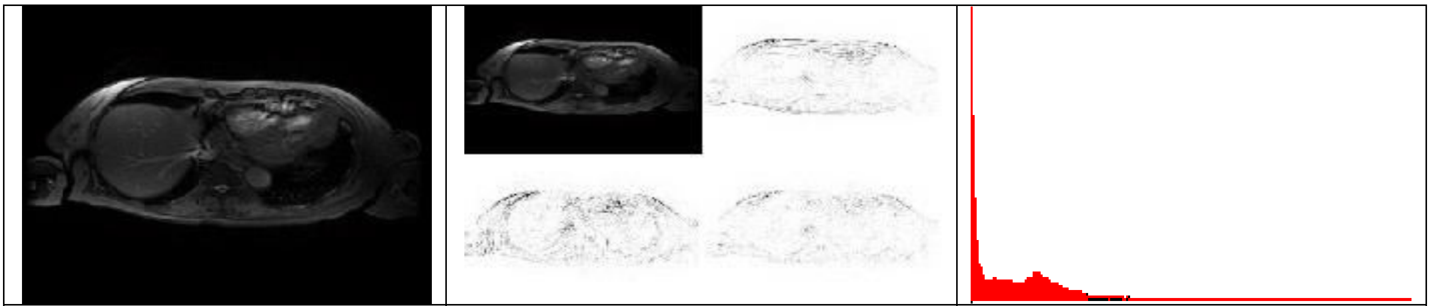
$$PSNR = 10log\left[\frac{255^2}{MSE}\right]$$

Higher the value of PSNR betters the quality of reconstructed image.

Compression Ratio (CR): The compression ratio indicates that the compressed image is stored using only portion of the initial storage size.

$$CR = \frac{Compressed\ Data\ Size}{Original\ Data\ Size}$$

Bits per Pixel (BPP): BPP gives the number of bits required to store one pixel of the image.

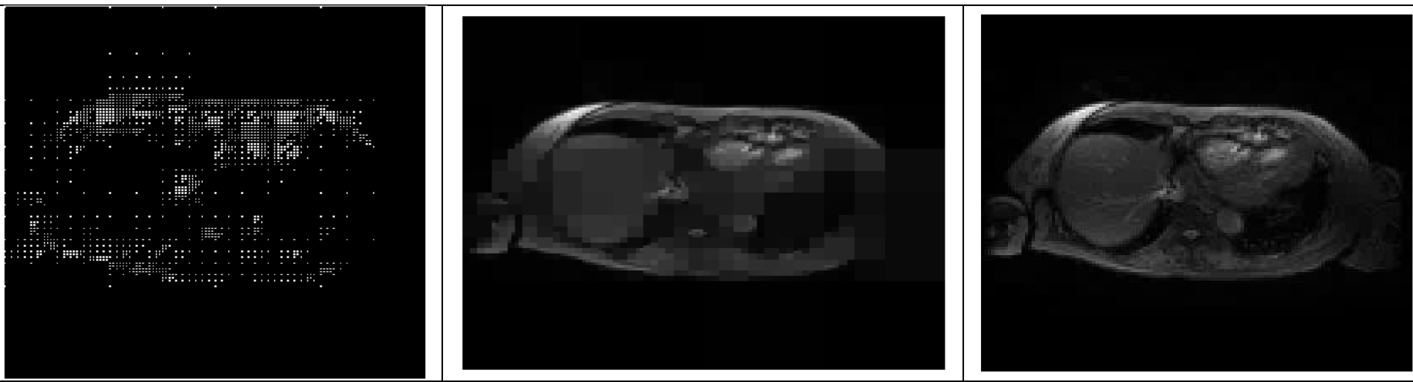


(a). Original Cardiac Image	(b). Level 1 decomposed Image	(c). Normalized histogram of input image

Figure-7. Wavelet level 1 decomposition of cardiac image.

(a). Using SBT_HE method	(b). Using GBT_FE method	(c). Using GBL_HE method

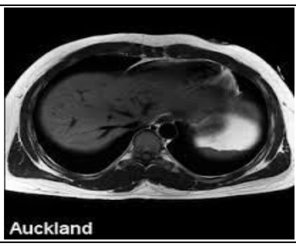
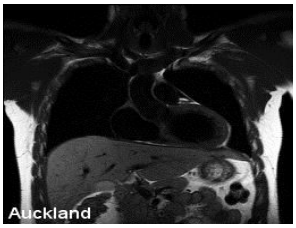
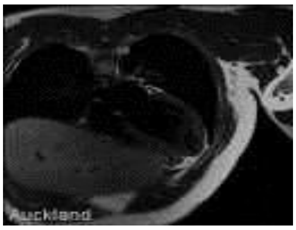
Figure-8. Decompressed images for various coefficients threshold methods.



(a). Using QTD method	(b). Using FQD method	(c). Using proposed hybrid method

Figure-9. Proposed Decompressed image result with fractal Quad tree reconstruction method.

Table-1. Parameter evolution of compression and decompression methods.

Image description	Image	Method	PSNR	MSE	CR	BPP	SSIM
Axial Transverse		SBT_HE	34.87	32.71	5.31	0.42	0.4916
		GBT_FE	25.74	34.02	4.46	0.35	0.4901
		GBT_HE	26.88	33.83	4.30	0.34	0.4903
		FQD	31.36	33.16	8.04	0.64	0.8137
		Proposed method	37.08	32.43	3.92	0.31	0.9055
Caronal		SBT_HE	22.47	34.61	5.96	0.47	0.3120
		GBT_FE	18.25	35.51	4.86	0.38	0.3012
		GBT_HE	18.25	35.51	4.70	0.37	0.3012
		FQD	25.79	34.01	4.82	0.38	0.7595
		Proposed method	29.36	33.45	3.99	0.31	0.896
Long12		SBT_HE	25.46	34.07	7.9	0.34	0.4635
		GBT_FE	16.01	36.08	3.67	0.29	0.3010
		GBT_HE	16.01	36.08	3.47	0.27	0.3010
		FQD	30.51	33.28	7.07	0.56	0.8925
		Proposed method	32.94	33.04	3.12	0.24	0.9223

Our proposed approach is compared with several methods like, SBT_HE, GBT_FE, GBT_HE and FQD. Figure-7 shows the original image; level 1 wavelet decomposed and normalized histogram of the input image. Figure-8 illustrates decompressed images using various coefficients threshold methods. Figure-9 illustrates decompressed images using various Quadtree decomposition methods. In Quadtree decomposition method used huffman coding for the compression of the decomposed data. Figure-9(c) represents the proposed reconstructed image from compressed data. It achieves a better visual quality compared to other methods. The performance of the proposed technique is analyzed by the performance measures like PSNR, MSE, CR, BPP and SSIM. These performance measures are compared with various other techniques and are tabulated in Table-1. Our proposed method gives the better Compression Ratio with more PSNR and optimum BPP compared to other compression algorithms. Hence, these are well suited for real time implementations.

CONCLUSIONS

In this paper proposed and demonstrated a new compression technique for cardiac images suitable for remote health care monitoring applications. This technique is based on the DWT transformations and minimize matrix size method. For evaluation purpose compression techniques based on coefficient threshold methods and Quatree decomposition are implemented and performance analysis is carried. Simulation outputs confirms that the proposed implementation achieve higher compression ratio than the other methods. As we have used two transformations, the compression technique consists high frequency coefficients and results higher compression ratio. Therefore, our experiments confirm that the proposed implementations are well suited for practical implementations.

REFERENCES

2015. Health in 2015: from Millennium Development Goals to Sustainable Development Goals. World Health Organization.

2015. Heart Disease and Stroke Statistics. American Heart Association.

World Health Organization Fact Sheets on Cardiovascular Diseases. World Health Organization, Fact sheet N317, January, 2015.

M. Antonini, M. Barlaud, P. Mathieu, and I. Daubechies. 1992. Image Coding Using Wavelet Transform. IEEE Trans. on Image Processing. 1: 205-220.

G. Strang and T. Nguyen. 1996. Wavelets and Filter Banks. Wellesley-Cambridge Press.

JPEG 2000. Image Coding System. ISO/IEC CD15444-1.

Hsi-Chin Hsin, Jenn-Jier Lien, and Tze-Yun Sung. 2007. A Hybrid SPIHT-EBC Image Coder. IAENG International Journal of Computer Science. 34(1).

Vandana Roy,ShailjaShukla. 2013. Spatial and Transform Domain Filtering Method for Image De-noising: A Review. International Journal of Modern Education and Computer Science (IJMECS). 5(7): 41.

Christopoulos C., Askelof J. and Larsson M. 2000. Efficient methods for encoding regions of interest in the upcoming JPEG 2000 still image coding standard. IEEE Signal Processing Letters. 7(9): 247-249.

Sana K., Kaı¨s O. and Noureddine E. 2009. A novel compression algorithm for electrocardiogram signals based on wavelet transform and SPIHT.WASET International Journal of Signal Processing, 5(4), 11.

Shu-Mei Yun-Wei Lee, Chih-Yuan Hsu and Shy-Jen Guo. 2014. Performance Improvement of Set Partitioning Embedded Block Algorithm for Still Image Compression. Modern Advances in Applied Intelligence, Volume 8482 of the Springer Lecture Notes in Computer Science. pp. 270-278.

Veenadevi. S.V. and A.G. Ananth. 2012. Fractal image compression using quadtree decomposition and Huffman coding. Signal and Image Processing: An international journal. 3(2): 207-212.

M. M. Siddeq M. A. Rodrigues. 2014. A Novel Image Compression Algorithm for High Resolution 3D Reconstruction. pp. 3-17.

The Cardiac Atlas, Auckland MRI Research Group, National Heart Foundation of New Zealand. http://atlas.scmr.org/.

Grigorios D., Zervas N. D., Sklavos, N. and Goutis C. E. 2008. Design techniques and implementation of low power high-throughput discrete wavelet transform tilters for jpeg 2000 standard. WASET International Journal of Signal Processing. 4(1): 36-43.

Rao K. R. and Yip P. 1990. Discrete cosine transform: Algorithms, advantages, applications. San Diego: Academic Press. 1990.

Sayood K. 2000. Introduction to data compression (2nd Ed.). Morgan Kaufman Publishers: Academic Press.

Riccardo Distasi, Michele Nappi and Daniel Riccio. 2006. A Range/Domain Approximation Error Based Approach for Fractal Image Compression. IEEE Trans on Image Processing. 15(1): 89-97.

Ansari. M.A, Anand. R.S. 2007. Performance Analysis of Medical Image Compression Techniques with respect to quality of compression, Proceedings of ICTES 2007, Chennai, India, December. pp. 743-750, ISSN: 0537-9989.

David .A. Huffman. 1952. A method of construction of minimum redundancy codes, Proceedings of I.R.E.

Divya Mohandass, J. Janet. 2010. An Improved Three Pattern Huffman Compression Algorithm for Medical Images in Telemedicine. Proceedings of the International Conference on Business Administration and Information Processing (BAIP'2010), pp. 263-268, ISBN: 978-3-642-12213-2.

Janet. J, Natesan T.R. 2005. Effective image compression technique for medical images in Telemedicine, Asian Journal of Information Technology. 4(12): 1180-1186, ISSN Print: 1682-3915.