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HYBRID DCT-DWT BASED ROI MEDICAL IMAGE COMPRESSION FOR TELEMEDICINE APPLICATION

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Abstract
Medical imaging greatly affects medication, particularly in the fields of diagnosis analysis and careful surgical planning. In any case, medical imaging gadgets continue delivering a great deal of data information for each patient. Medical image examination and data compression is a significant region of research which targets delivering calculations that diminish record size and simultaneously keep up important symptomatic data. Medical image compression applications are quality-driven applications which request high caliber for specific areas that have demonstrative significance for diagnosis, where even little quality decrease presented by lossy coding may modify resulting finding, which may cause serious lawful outcomes. The fundamental focal point of this paper is to investigate procedures and discover a compression algorithm that can eliminate irrelevant medical data and reconstruct medical image rapidly while keeping up a decent degree of visual quality for certain regions of medication where it is adequate to keep up high image quality just for indicatively noteworthy regions, for instance, tumor segment of the cerebrum MRI. Wavelet multi-resolution decomposition of images has indicated its proficiency in many image processing areas and explicitly in compression. Because of this, The Discrete Wavelet Transform (DWT) is used to code Region of Interest and Discrete Cosine Transformation (DCT) is utilized to code background region. A couple of examinations were led to break down the calculations dependent on compression proportion, decompressed image quality and execution speed.

Keywords:
Medical Imaging, ROI, DWT, DCT, Lossy and Lossless Compression

1. INTRODUCTION

The World Health Organization has embraced the accompanying portrayal for telemedicine: "The delivery of health care services, where distance is a critical factor, by all health care professionals using information and communication technologies for the exchange of valid information for diagnosis, treatment and prevention of disease and injuries, research and evaluation, and for the continuing education of health care providers, all in the interests of advancing the health of individuals and their communities" In basic terms, Telemedicine, which signifies "Remote delivery of healthcare services, such as health assessments or consultations, over the telecommunications infrastructure", means the utilization of ICT to improve persistent results by expanding access to clinical data. It is accomplished by the exchange of electronic patient records, for example, past assessments result, lab test results, and clinical pictures to remote clinical place for diagnosing [1]. Because of its immense size, it requires bunches of memory space in its original state and rapid web to transmit it at far area over system and network and transmission time as well as cost. Consequently there is a need of clinical information to be compressed before transmission. To satisfy the necessity of quick transmission of clinical information in viable image storage and remote counsel, the ROI coding is imperative to affirm nature of administration. In fact all image information is packed into two gatherings as reversible (lossless) and irreversible (lossy) [2] [3].

With lossy image compression, superfluous pixel information are disposed of during the compression procedure so the encoded image is just a approximation of the primary image. Frequently altering the compression parameters can fluctuate the level of misfortune permitting the image producer to exchange off document size against image quality. It gives higher compression proportion however a few applications like satellite image processing and medication imaging can't manage the cost of any misfortunes in their data. Lossless image compression is favoring for application, for example, clinical imaging where encoded image quality can't be compromised as meager modification in image quality may bring about mistaken analysis. Lossless compression techniques, where compression proportion is low and outwardly quality is indistinguishable from the first image and might be shown as a precise advanced imitation of the first [4] [5]. Just the factual repetition is abused to accomplish compression. When all is said in done, lossless strategies give far lower compression proportions than lossy systems with the reward of protecting all image content.

The adequate parts of compression schemes for clinical information, considered among the variations are as follows [6];

1. The capacity to indicate which parts of the image are crucial for visual trustworthiness and contain the most data, and in this way, should be safeguarded with next to no or no misfortune.
2. The capacity to accomplish as high compression proportions as possible for different segments of the image, prompting huge reserve funds in transmission and capacity necessities.
3. The need to control the misrepresentation acquired by the high compression approach in (2) to inside client determined levels.
4. The capacity to adjust to changes in the information stream.
5. The capacity to play out the compression and decompression as quick as could be allowed, for use continuously applications.

To advance the above necessity for example the high compression proportions and the preservance of the significant data, the ROI based compression is a standout amongst other decision to accomplish the ideal compression proportions with no loss of helpful data which is essentially done by choosing diverse significant regions of an image alongside the background and afterward compression strategy is applied on these areas independently and not in general. Low compression level is applied on the helpful regions while the high compression is applied on the un-significant areas and the background. Subsequently, high CRs are accomplished by this approach with no obvious loss of data and lucidity of the image [7] [8].

2. RELATED WORK

JPEG was created in 1992, utilizing the DCT is basic and it is the generally utilized procedure for compression, yet brings about blocking ancient rarities, ringing impacts and bogus forming obviously for high compression proportion [9] - [11]. Wavelet transform gives various alluring properties, for example, multi-resolution portrayal; adaptability and dynamic transmission which are helpful to image compression applications as there is a need to deal with tons of clinical images in the medical clinics. Discrete Wavelet Transform (DWT) based coding, is another proficient method utilized for image compression. The capacity to show image at various resolutions level like low frequencies and high frequencies at the same time makes it a superior technique contrasted with others [12]. To accomplish alluring degree of compression we need to pick the ROI based plan where ROI is coded by DWT and NON-ROI part is coded by lossy DCT based compression. This paper proposes a way to deal with improve the presentation of clinical image compression while fulfilling clinical group who need to utilize it.

2.1 DISCRETE COSINE TRANSFORM

A DCT speaks to the information focuses as entirety of cosine works that are wavering at various frequencies and extents. There are basically two kinds of DCT: one dimensional DCT and two dimensional DCT. The 2D DCT for N×N input sequence can be characterized as follows [13].

$$D_{DCT}(i,j) = \frac{1}{\sqrt{2n}} B(i) B(j)$$

$$\sum_{x=0}^{N\text{-}1}\sum_{y=0}^{N\text{-}1} M(x,y).\cos\left[\frac{2x+1}{2N} i\pi\right]\cos\left[\frac{2y+1}{2N} j\pi\right]$$

$$B(u) = \begin{cases} \frac{1}{\sqrt{2}} & if\ u = 0\, and\, 1 \\ 1 & if\ u > 0 \end{cases} \tag{1}$$

$M(x,y)$ is the information of size $x \times y$. The information image is first isolated into 8×8 squares; at that point the 8-point 2-D DCT is performed. The DCT coefficients are then quantized utilizing a 8×8 quantization table. The quantization is accomplished by partitioning every component of the changed unique information matrix by comparing component in the quantization matrix Q and adjusting to the closest whole number an incentive as appeared in condition.

$$D_{quant}(i,j) = round\left\{\frac{D_{DCT}(i,j)}{Q(i,j)}\right\} \tag{2}$$

After this, compression is accomplished by applying proper scaling factor. At that point so as to reproduce the information, rescaling and de-quantization is performed. The de-quantized matrix is then changed back utilizing the backwards – DCT [13]. The entire technique is appeared in Fig.1.

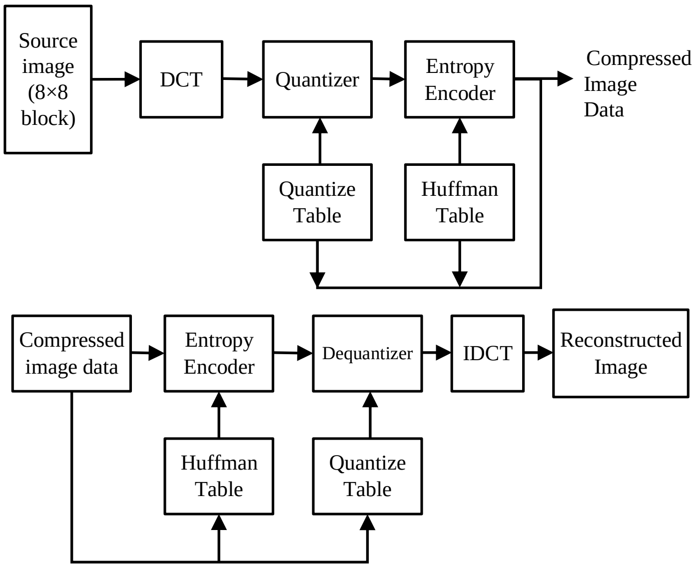


Fig.1. DCT based Image Compression

2.2 DISCRETE WAVELET TRANSFORM

In DWT, an image is represented to by whole of wavelet capacities, which are known as wavelets, having distinctive area and scale.

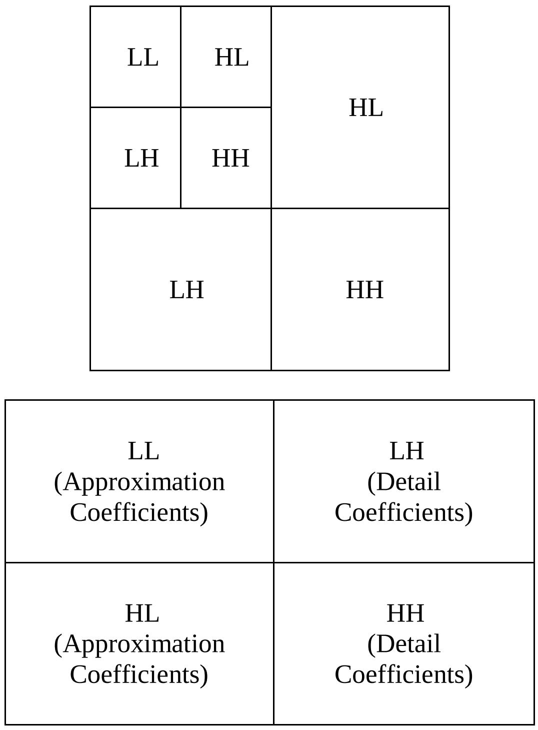


Fig.2. 2-Level DWT transformation

Discrete wavelet change represents to the information into a lot of high pass (detail) and low passes (inexact) coefficients. Image is first separated into squares of 32×32. At that point each square is gone through two filters: In the first level, decay is performed to disintegrate the information into an estimate and detail coefficients [14] [15]. Subsequent to acquiring the changed matrix, the detail and approximate coefficients are isolated as LL, HL, LH and HH coefficients. At that point all the coefficients are disposed of, with the exception of the LL coefficients that are changed into the subsequent level. These coefficients are then gone through a consistent scaling component to accomplish the ideal compression proportion [16]. The Fig.2 is a representation of DWT. here, $x[n]$ is the information signal, $d[n]$ is the high recurrence part, and $a[n]$ is the low recurrence segment. For information recreation, the coefficients are rescaled and cushioned with zeros, and went through the wavelet filters.

3. PROPOSED COMPRESSION SCHEME

New hybrid ROI based medical image compression technique algorithm steps are mentioned as below.

Step 1: Load Medical Image and pre-processing of data.

Step 2: Segmentation of Medical image in two parts: ROI and NON-ROI

Step 3: ROI part is compressed with Hybrid DCT-DWT based algorithm

a. Perform two level wavelet transform that decompose image into approximation and detail sub bands (LL2, LH2, HL2 and HH2). The top-left corner of the transformed image “LL2” is the original image, low-frequency coefficients and the top-right corner “HL2” consists of residual vertical frequencies (i.e. the vertical component of the difference between the “LL2” image and the original image). The bottom-left comer “LH2” contains residual horizontal frequencies, whilst the bottom-right corner “HH2” contains residual diagonal frequencies.

b. Apply two dimensional DCT on approximation image LL2 from iteration 2 according to matrix optimization and sequential search algorithm

c. The detail image LH2, HL2 and HH2 data is compressed using arithmetic coding.

d. LH1, HL1 and HH1 details are very small (threshold) so they can be set to zero without significantly changing the image.

Step 4: NON ROI part is compressed with DCT based algorithm

a. The pixels of an image are organized in groups of 8×8 pixels called data units, and each data unit is compressed separately. If the number of image rows or columns is not a multiple of 8, the bottom row and the rightmost column are padded with zeros as many times as necessary.

b. The discrete cosine transform (DCT) is then applied on the each group of 8×8 pixels to create an 8×8 map of frequency domain. The frequency domain consists of DC coefficient at the first location in 8×8 frequency component, which is represents average pixels value. The components are called AC, which is representing high-frequency coefficients.

c. Each of the 64 frequency components in an 8×8 map are divided by a separate numbers it is called Quantization Coefficient (QC), and then rounded to an integer. This is where information is irretrievably lost. A simple quantization table Q is computed, based on one parameter R specified by the user. A simple expression such as $Q_{ij}=1+(i+j)\times R$ guarantees that QCs start small at the upper-left corner and get bigger toward the lower-right corner.

d. Each 8×8 map frequency component scanned by using zigzag scan, to create a one dimensional array contains 64 quantized frequency coefficients. The one-dimensional array encoded using a combination of Run-Length-Encoding (RLE) and Huffman coding.

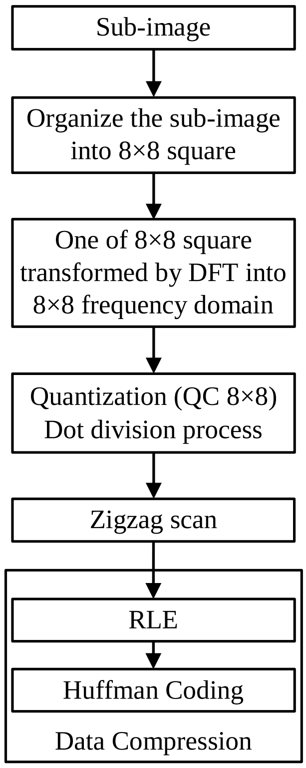


Fig.3. DCT based compression of Non-ROI part

Step 5: Quality Evaluation of ROI Compressed image (Calculation of CR, MSE, PSNR and SSIM)

3.1 MEAN SQUARE ERROR (MSE)

The MSE is used in measuring the difference in the predicted outcome with that of expected outcome. If the MSE value increases, then the image degradation increases. When MSE value reaches zero then pixel by pixel matching of images becomes perfect.

$$MSE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}\left(x(i,j)-y(i,j)\right)^2 \tag{3}$$

where M is the number of pixels in horizontal direction, N is the number of pixels in vertical direction, $x(i,j)$ is the original image at i and j co-ordinates and $y(i,j)$ is the compressed image at i and j co-ordinates.

3.2 PEAK SIGNAL TO NOISE RATIO (PSNR)

When comparing the two images, PSNR is calculated by taking the Mean Squared Error (MSE) between the pixel intensities and taking the ratio of the maximum possible intensity to the result of the calculation. The standard value of PSNR is 35 to 40 db. In general, a higher PSNR value corresponds to a better quality image. The PSNR standard value is subjected to correlative analysis and is depends on MSE. MSE is indirectly proportional to the PSNR. The histogram represents the frequency of differences in intensity between the two compared images. The histogram values spread from 30 to 40dB shows more signal.

However, the PSNR result is unbounded. PSNR can be computed by using the following relation:

$$PSNR = 10\log_{10}\frac{Max^2}{MSE} \tag{4}$$

where n is the maximum pixel value of the image.

3.3 STRUCTURAL SIMILARITY INDEX MATRIX (SSIM)

SSIM is defined as a function of luminance comparison, contrast and structural comparison term. The value lies from 0 to 1. SSIM is a perception-based model that considers the image degradation as perceived change in structural information where, structural information is the idea that the pixels have strong interdependencies especially when they are spatially close. The linear dependence factor is computed using the correlation coefficient in SSIM index. Blurring operation on an image causes fading of the sharp edges of an image. SSIM has a high significance on blurred images with high consistency. In real time, this metric can be widely used in bio-medical applications especially in mammographic diagnosis and cancer detection fields. It is the universal metric where we can apply this metric to assess the quality of any images. Since this metric is operating on luminance, contrast and structural information in images. With N as the total number of pixels in the image, SSIM is given as in Eq.(3).

$$SSIM = \left[l(x,y)\right]^{\alpha}\cdot\left[c(x,y)\right]^{\beta}\cdot\left[s(x,y)\right]^{\gamma} \tag{3}$$

$$l(x,y) = \frac{2\mu_x\mu_y + c_1}{\mu_x^2 + \mu_y^2 + c_1}$$

$$c(x,y) = \frac{2\sigma_x\sigma_y + c_2}{\sigma_x^2 + \sigma_y^2 + c_2}$$

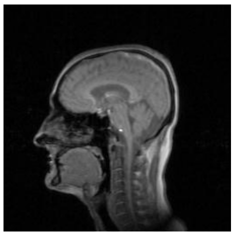
$$x(x,y) = \frac{\sigma_{xy} + c_3}{\sigma_x\sigma_y + c_3}$$

where μ_x, μ_y, σ_x, σ_y, and σ_{xy} are the local means, standard deviations, and cross-covariance for images x, y. c_1, c_2 and c_3 are constants.

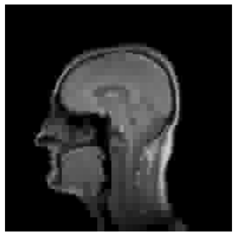
Applying human visual system to image quality assessment is more appealing to human eyes. The luminance of an object's surface observed from human eyes is the product of the illumination and the reflectance, but the structures of an object are independent of the illumination. For the above reason, defines the image structure information is independent of the average luminance and contrast calculating from the local luminance and contrast. The structural similarity measurement system divides the measurement into three mutually independent components: luminance, contrast and structure.

4. SIMULATION RESULTS ANALYSIS

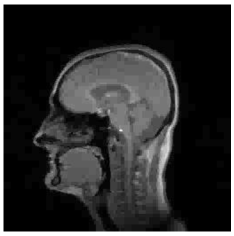
By analyzing results of IQA matrix, MSE and PSNR of some distorted images is irrespective of its quality, but the appearance or distortion level of each of the distorted image is quite related with SSIM. Another set of test image results are shown below with its IQA results.



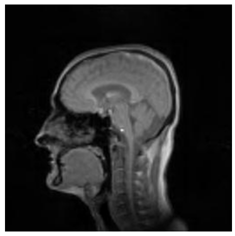
(a) Original Head MR Image



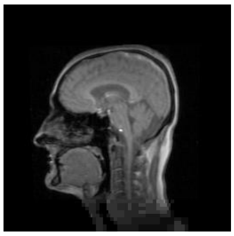
(b) DCT Compressed Image



(c) DWT Compressed Image



(d) Modified SPIHT compressed Image

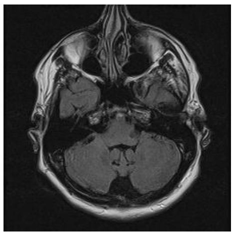


(e) ROI based Compressed Image

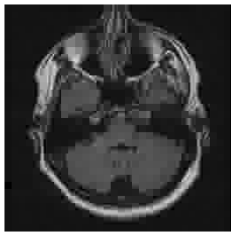
Fig.1. Compression of Head MR Image

Table.1. IQA for Head MR Image

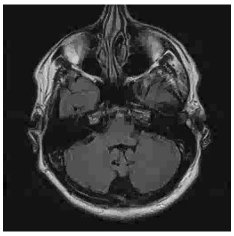
Image	CR	MSE	PSNR	SSIM
DCT Compressed Image	0.956	197.69	25.17	0.2685
DWT Compressed Image	0.851	80.73	29.60	0.4151
Modified SPIHT Image	0.916	85.32	28.82	0.4590
ROI based Compressed Image	0.889	50.29	31.11	0.5455



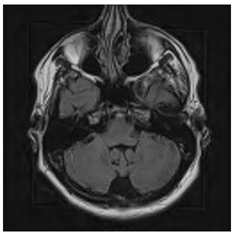
(a) Original Head MR Image



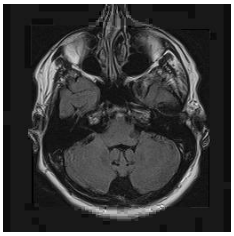
(b) DCT Compressed Image



(c) DWT Compressed Image



(d) Modified SPIHT Compressed Image



(e) ROI based Compressed Image

Fig.2. Compression of Head MR Image

Table.2. IQA for Heart MR Image

Image	CR	MSE	PSNR	SSIM
DCT Compressed Image	0.968	70.92	29.62	0.2135
DWT Compressed Image	0.916	35.21	32.66	0.3114
Modified SPIHT Image	0.916	14.71	36.45	0.4262
ROI based Compressed Image	0.889	12.87	37.03	0.4641

After simulation and analysis of results for more than 50 medical images following results are found.

- DCT is a method for image compression which performs effectively at medium bit rates. Burden of DCT is that only spatial connection of the pixels is thought of and the relationship from the pixels of the neighboring blocks is dismissed. Utilizing DCT blocks can't be de-connected at their limits.
- DWT gives high compression quality at low bit rates. The utilization of bigger DWT functions or wavelet filters produce obscuring close to edges in the images.
- DWT performs better than DCT in that it abstains from blocking artifacts which debase the reproduced image. Anyway DWT gives lower compression ration than DCT.
- There are a number of reasons why MSE or PSNR may not correlate well with the human perception of quality.
- Digital pixel values, on which the MSE is typically computed, may not exactly represent the light stimulus entering the eye.
- Simple error summation, like the one implemented in the MSE formulation, may be markedly different from the way the HVS and the brain arrives at an assessment of the perceived distortion.
- Two distorted image signals with the same amount of error energy may have very different structure of errors, and hence different perceptual quality.

Simulation results shows that SSIM and UIQI based IQA is much better than pixel inaccuracy based matrix MSE and PSNR.

5. CONCLUSION

In this paper we use hybrid concept of DCT-DWT to accomplish higher compression ratio by coding Non ROI part with DCT and keep up quality of ROI by coding it with DWT based algorithm. Our results illustrate that, DCT based compression presents better visual image than wavelet transform for a lower compression ratio. With reasonable bits per pixel, DCT based JPEG compression algorithm works well and compressed images have acceptable visual quality. Although, Image quality significantly degrades at higher compression ration because of "blocking artifacts". On another hand, wavelet based compression algorithm gives better visual quality at low bit rates because of its multi resolution and superior data compaction properties. We also observed that medical images compressed with proposed technique have lower MSE, higher PSNR and nearly great estimation of similarity. With this plan we need to haggle with lower value of Compression ratio to accomplish desirable quality of ROI part.

In this paper, we use manual segmentation of region of interest part of medical image. We can expand research so that segmentation can be automatically performed to identify ROI part. Thus we may reduce the human efforts and increase the speed of data processing.

REFERENCES

[1] A.M. Sapkal and V.K. Bairagi, "Telemedicine in India: Challenges and Role of Image Compression", *American Scientific Publishers: Journal of Medical Imaging and Health Informatics*, Vol. 1, No 4, pp 300-306, 2011.

[2] K.D. Sonal, "Study of Various Image Compression Techniques", *Proceedings of COIT, RIMT Institute of Engineering and Technology*, pp. 799-803, 2000.

[3] Y. Shen and J. Ma, "An Efficient Medical Image Compression", Proceedings of International Conference on Engineering in Medicine and Biology, pp. 1-4, 2005.

[4] A. Said and W. A. Pearlman, "An Image Multiresolution Representation for Lossless and Lossy Compression", *IEEE Transactions on Image Processing*, Vol. 5, No. 9, pp. 1303-1310, 1996.

[5] V.J. Rehna and M.K. Jeya Kumar, "Hybrid Approach to Image Coding: A Review", *International Journal of Advanced Computer Science and Applications*, Vol. 2, No. 7, pp. 1-14, 2011.

[6] Marykutty Cyriac and C. Chellamuthu, "A Novel Visually Lossless Spatial Domain Approach for Medical Image Compression", *European Journal of Scientific Research*, Vol.71, No. 3, pp. 347-351, 2012.

[7] Rick A. Vander Kam, Ping Wah Wong and Robert M. Gray, "JPEG-Compliant Perceptual Coding for a Grayscale Image Printing Pipeline", *IEEE Transactions on Image Processing*, Vol. 8, No. 1, pp. 1-14, 1999.

[8] P.G. Tohoces, J.R. Varela, M.J. Lado and M. Souto, "Image Compression: Maxshift ROI Encoding Options in

JPEG2000", *Computer Vision and Image Understanding*, Vol. 109, No. 2, pp. 139-145, 2008.

[9] C.N. Zhang and X. Wu, "A Hybrid Approach of Wavelet Packet and Directional Decomposition for Image Compression", *Proceedings of IEEE Canadian Conference on Electrical and Computer Engineering*, pp. 755-780, 1999.

[10] Shaou Gang Miaou,, Fu Sheng Ke and Shu Ching Chen, "A Lossless Compression Method for Medical Image Sequences using JPEG-LS and Interframe Coding", *IEEE Transactions on Information Technology in Biomedicine*, Vol. 13, No. 5, pp. 1-18, 2009.

[11] M. Ferni Ukrit, A. Umamageswari and G.R. Suresh, "A Survey on Lossless Compression for Medical Images", *International Journal of Computer Applications*, Vol. 31, No. 8, pp. 1-12, 2011.

[12] V.S. Shingate and T.R. Sontakke, "Still Image Compression Using Embedded Zero Tree Wavelet Encoding", *International Journal of Computer Applications*, Vol. 29, No. 7, pp. 34-45, 2010.

[13] K. Saraswathy, D. Vaithiyanathan and R. Seshasayanan, "A DCT Approximation with Low Complexity for Image Compression", *Proceedings of International Conference on Communications and Signal Processing*, pp. 1145-1156, 2013.

[14] D.V. Babu and D.N. Alamelu, "Wavelet Based Medical Image Compression using ROI EZW", *International Journal of Recent Trends in Engineering*, Vol. 1, No. 3, pp. 56-64, 2009.

[15] R. Janaki and S. Tamilarasi, "A Still Image Compression by Combining EZW Encoding with Huffman Encoder", *International Journal of Computer Applications*, Vol. 32, No. 7, pp. 78-84, 2011.

[16] B. Ramakrishnan and N. Sriraam, "Compression of DICOM Images Based on Wavelets and SPIHT for Telemedicine Applications", *Proceedings of International Conference on Communications and Signal Processing*, pp. 1-5, 2005.

[17] A. Pasumpon Pandian and S.N. Sivanandam, "Hybrid Algorithm for Lossless Image Compression using Simple Selective Scan order with Bit Plane Slicing", *Journal of Computer Science*, Vol. 8, No. 8, pp. 1338-1345, 2012.

[18] G. Kharate, V. Patill and N. Bhale, "Selection of Mother Wavelet for Image Compression on Basis of Nature of Image", *Journal of Multimedia*, Vol. 2, No. 3, pp. 1-18, 2007.

[19] S. Grgic, G. Mislav and Z.C. Branka, "Performance Analysis of Image Compression using Wavelets", *IEEE Transactions on Industrial Electronics*, Vol. 48, No. 3, pp. 682-695, 2001.

[20] Harjeetpal Singh and Sakhi Sharma, "Hybrid Image Compression using DWT, DCT and Huffman Encoding Techniques", *International Journal of Emerging Technology and Advanced Engineering*, Vol. 2, No. 10, pp. 231-237, 2012.