Research Journal of Applied Sciences, Engineering and Technology 9(9): 727-735, 2015
DOI:10.19026/rjaset.9.2618
ISSN: 2040-7459; e-ISSN: 2040-7467

Submitted: September 18, 2014 Accepted: October 17, 2014 Published: March 25, 2015

Research Article

Hybrid Continuous Wavelet Based Controulet Transform Method for DICOM Image Compression and Improved SPHIT Coding

[1]C.S. Manikandababu and [2]N.J.R. Muniraj
[1]ECE, Sri Ramakrishna Engineering College,
[2]Tejaa Shakthi Institute of Technology for Women, Coimbatore, India

Abstract: The widely used standard for medical image storage and transmission is named as Digital Imaging and Communication in Medicine (DICOM). In every field of medicine including diagnosis, treatment, and research, medical images that are obtained as the outputs of the techniques such as the Computerized Tomography (CT), magnetic resonance (MR), digital subtraction angiography (DSA) and Ultrasonography (US) are saved as DICOM format. Network sharing of these larger sized radiology images require large bandwidth. Hence before transferring, compression of such larger image files is necessary for easy and faster communication even with lower bandwidth. Huge amount of data either in multidimensional or multiresolution form is been created as a result of medical information. This makes the following steps like retrieval, efficient storage, management, and transmission of these data a complex process. This complexity could be reduced by compressing the medical data without any loss. Many methods have been proposed so far for compression of the large DICOM images, however with some limitations. Thus, specific methods to overcome the limitations like reducing the noise of MSE error signal and improving the PSNR value results in the medical images are to be proposed for the study. One such method is referred as Hybrid Weibull Probability Density Function based Continuous Wavelet based controulet transform (WPDF-CWBCT) that helps for compression of medical images without any data loss and also for improving the PSNR and reducing the MSE of the signal. The directional filter banks are being applied by initializing using the wavelet transform such that the image coding scheme is maintained based on the proposed transform. WPDF-CWBCT also uses a new set partitioning in hierarchical trees by employing a sorting method (SPIHT) algorithm that provided an embedded code. In this method, the diagnostics capabilities are not compromised to ensure the better performance of image compression is also been justified by the combination of wavelet based controulet transform and SPIHT. The performance evaluation of different DICOM and medical images is possible by using parameters like PSNR, MSE and image compression quality measures.

Keywords: Continuous Wavelet Transform (CWT), Controulet Transform (CT), Digital Imaging and Communication in Medicine (DICOM), image compression, Mean Square Error (MSE), medical image processing, Peak Signal to Noise Ratio (PSNR), Set Partitioning In Hierarchical Trees (SPIHT), Wavelet Transform (WT), Weibull Probability Density Function (WPDF)

INTRODUCTION

The growing demand for high speed image transmission, efficient image storage and remote treatment can be met out by introducing an efficient image compression technique. This study reviews about the different image compression techniques to arrive at a systematic approach for improving the performance of medical image compressing. Among many methods preferred by the medical community, JPEG and wavelet compression are the most popular methods.

Most of the electronic medical records constitute medical images as key components. The storing of these medical records along with its medical images requires enormous space. This makes the network sharing difficult as it consumes more time for transferring such medical images. These images comprising large set of data could be managed by DICOM standard as it offers reliable transfer of medical images when sharing patient's record. The integrity, reliability and security of the shared medical images are assured by retaining its archives thus complying with the legal and authentic issues. Thus on the whole the performance of PACS systems in storing the diagnostic images and other DICOM contents is been improved.

The high speed transfer of image file from one place to another even under lower bandwidth requires compression methods thus reducing the complexity in

Corresponding Author: C.S. Manikandababu, ECE, Sri Ramakrishna Engineering College, Coimbatore, India

files communication and sharing. Wavelet compression helps for such sharing of medical images and has been proposed knowing its high scope for compressing medical images. The significant part (ROI) is kept separately from the less significant region to be compressed while diagnosing the medical images and is carried out by Discrete Wavelet Transform. The definition of mathematical functions called wavelets over a definite interval carries zero as an average value that helps for data transformation into various frequency components each of which represents its scale of matching resolution (Mathew and Singh 2009). The superposition of any arbitrary function as a basic set of wavelets or functions forms the basis for the wavelet transformation. A single prototype wavelet is called mother wavelet from which the basic set of functions called baby wavelets are derived by means of dilations and translations (shifts) (Mathew and Singh 2009). For two-dimensional capturing of singularities in images, these wavelets are not suitable. Hence, to efficiently capture edges in natural images, several transforms with inherent directionality and multiresolution is to be proposed for image signaling. Examples for such transforms are steerable pyramid (Simoncelli and Freeman, 1995) and contourlets (Do and Vetterli, 2003). One of the new geometrical image transforms is the contourlet transform as the image containing contours and textures (Do and Vetterli, 2003; Do, 2001) is been represented efficiently.

The accurate performance of image compression reduces the complexity of the problem of DICOM image. Therefore, a novel method of integrated Weibull Probability Density Function Continuous Wavelet based controulet transform (WPDF-CWBCT) method is presented in this work. Here the wavelet coefficient function x(t) are calculated based on the WPDF that possess a construction as like that the contourlet transform. Also, the non-redundant WBCT is used in conjugation with an SPIHT-like algorithm (Kassim and Siong, 2001) for constructing an embedded image coder.

A detailed repositioning algorithm for the CWBCT coefficients is also developed owing to parent-child relationship dissimilarities arising between the CWBCT coefficients and wavelet coefficients so that similar spatial orientation trees (Kassim and Siong, 2001) (the zero-trees introduced in (Shapiro, 1993)) as used for the wavelet coefficients scanning. The contourlet-based scanning in SPIHT is referred here as CSPIHT. The proposed standard is surely competitive to the original SPIHT coder and is observed from the simulation results. Also the PSNR values suggest that it competes and proves superior to SPIHT coder that too for "non-wavelet-friendly" images having significant amount of textures and oscillatory patterns. The speed of the SPIHT algorithm can be improved by using the criteria of smallest mean-square error and thereby performing quick sort algorithm (QSA) in the sorting pass of the SPHIT followed by refinement phase by which the most important wavelet coefficients are encoded to show its better compression performance.

LITERATURE REVIEW

By the method of image compression, the amount of data that are kept in a storage media can be increased due to reduction of file size ultimately increasing the data transmission speed. With the help of specialized software, the data of DICOM images are converted into smaller files by compression and the description of it is detailed further in this work. Lossless and lossy are the two main types of data compression and any of these methods is chosen based in the requirement of the system. When the size of any file is compressed without any information losses is termed as lossless compression. Though it generally limits the compression ratio, total data fidelity is ensured after the reconstruction. Lossy method leads to information loss to some extent with slight observable difference between reconstructed and original images, however providing information more than the compression ratio (Liu *et al*., 2002).

Adaptive threshold-based block classification is a newer medical imaging compression technique proposed (Singh *et al*., 2007) in which a computational algorithm has been introduced for the classification of blocks based on the adaptive threshold value of the variance. As it is suitable for all types of medical imaging, it is used for the performance evaluation of images derived from CT and ultrasound scanning, X-ray so as to compare the obtained results with JPEG in terms of quality indices.

An efficient FPGA implementation of DWT (Discrete Wavelet Transform) and modified SPIHT (set partitioning in hierarchical trees) has been proposed (Jyotheswar and Mahapatra, 2007) for lossless image compression. The correlation between the image pixels is mainly considered for the DWT (Discrete Wavelet Transform) architecture and is based on the lifting process whereas a modified SPIHT (Set Partitioning in Hierarchical Trees) algorithm was helps for encoding the wavelet coefficients. This joint implementation of algorithm promotes both better compression ratio and peak-signal-to-noise ratio (PSNR) for 3D medical images.

The detailed review about the image compression, its necessity and principles, classes and various algorithm is been discussed (Dhawan, 2011) particularly on the grey scale lena and finger print images. Various compression algorithms based upon wavelet, JPEG/DCT, VQ, fractal was also discussed and their results are compared on the basis of PSNR

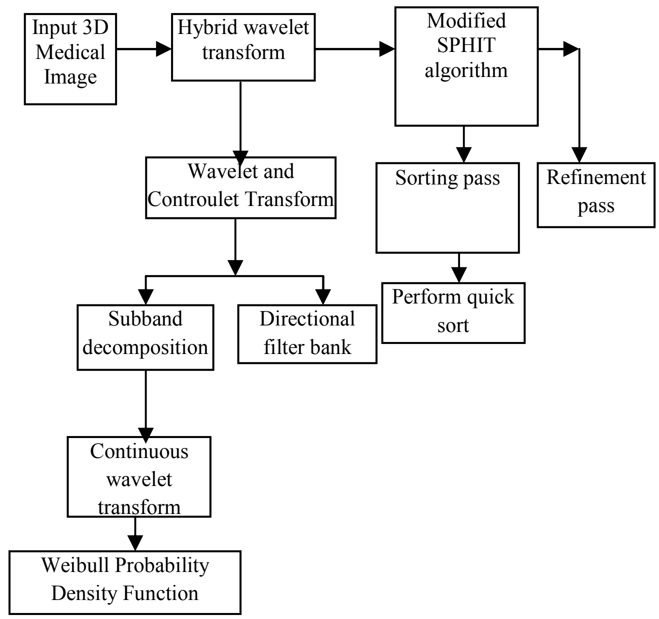


Fig. 1: Structural representation of the proposed work for medical image compression using DICOM images

values and CPU time over encoding and decoding. From these discussions, they arrived at the conclusion of wavelet based compression algorithms highly suitable. An adaptive quantization table must be used by a discrete cosine transform. VQ approach is not suitable for a low bit rate compression however; fractal approach gets suitable by means of its resolution-free decoding property.

Xiong *et al*. (2003) used 3D wavelet transforms for studying a technique called lossy to lossless compression in which the approximation process of a 3-D unitary transformation is done by exhibiting a 3-D integer wavelet packet transform structure and by supporting implicit bit shifting of wavelet coefficients. 3D-SPIHT (set partitioning in hierarchical trees) and 3D included subband coding using optimal truncation process are the 3-D wavelet video coding methods used in their study and found that the results arrived due to lossy and lossless compression of volumetric medical images are quite good.

The selection of wavelets for compression of medical image is performed by a proposed methodology (Bairagi and Sampkal, 2013) which dealt on various wavelets transform methods over several metrics like MSE (Mean Square Error), PSNR (Peak Signal Noise Ratio), Structural contents, Normalized Absolute Error etc. for analyzing DICOM CT images. The quality measure is also been taken into consideration for different wavelet type on DICOM CT images. However, wavelets type used in image compression carries no specification remains as a major limitation.

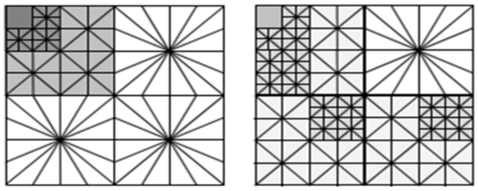
Another one of the most efficient image compression algorithms called Set Partitioning in Hierarchical Trees (SPIHT) has been proposed (Said and Pearlman, 1996). The efficient subset partitioning and the compact significance information together assured the effectiveness of the SPIHT algorithm that outlines spatial orientation trees, sets of coordinates and recursive set partitioning rules (Said and Pearlman, 1996).

PROPOSED METHODOLOGY

Mostly time lossless compression methods are used in medical applications thus preserving the data integrity facilitating an authentic diagnosis yet its inability to reach high compression ratio is a major disadvantage makes it unsuitable for applications involving telemedicine, fast searching and browsing of medical volumetric data. Lossy compression could be proved to be an alternative for such applications in which volumetric medical images of a studied body part constitutes series of sequences of slices. A single slice among many sequences of slices is been encoded to maintain uniform quality and the decoder receives the compressed bit stream followed by the processing of next sequence of slices.

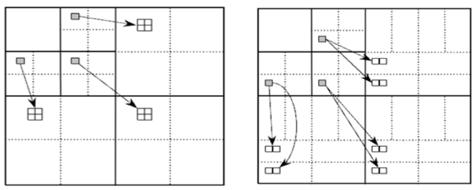
Weibull Probability Density Function based Continuous Wavelet Based Controulet Transform (WPDF-CWBCT) helps for compression of DICOM images which are later encoding through Quick Sort Algorithm (QSA) in the sorting pass by keeping the refinement pass as the same using improved SPIHT algorithm. The complete organization of the proposed medical image compression for method DICOM images is illustrated in Fig. 1.

Hybrid wavelet based controulet transformation for image compression: In contrast to the Laplacian pyramid used in contourlets, two stages of filter bank



(a) (b)

Fig. 2: Wavelet-based contourlet packets



(a) (b)

Fig. 3: Parent-child relationships between bands

are present in WBCT in which the first stage enables for decomposition of the DICOM image into subbands, called wavelet transform in WBCT. Calculation of the wavelet coefficient functions for continuous wavelet transformation function having subbands for each DICOM input images are also performed in this stage. The angular decomposition is provided by a Directional Filter Bank (DFB), a second stage of WBCT. The separable and non-separable filter banks are been implemented in first and second stage respectively. Using improved SPHIT algorithm single band is encoded after which the compressed bit stream is being sent to the decoder in order to maintain uniform quality for all sequences of subbands.

For every DICOM input images, the traditional three high pass bands is obtained corresponding to the LH, HL and HH bands at each level $(j), W(a,b)$ in the continuous wavelet transformation methods. To each band in a given level $(j) = W(a,b)$, DFB with the same number of directions is applied. The number of directions is been decreased while proceeding through the coarser levels $(j < J)$at every other dyadicscale when desired maximum number of directions $N_D = 2^L$ on the finest level of the wavelet transform $J = f(t)$ is been started. Thus, the anisotropy scaling law; stating$width \approx length^2$ could be achieved. The value of $x(t)$ is calculated by directly applying the input data of any distribution type and by randomly defining the Square-integrable function $x(t)$at a scale $a > 0$ in the wavelet transformation domain. In this study, distribution function based methods are used to calculate the values of the $x(t)$ in the scale parameter by additionally considering the shape parameter (slope) in addition to overcome the difficulties of the CWT transformation methods. This additional consideration of slope results in improvement of the wavelet transformation results than normal Continuous Wavelet Transformation (CWT) results by changing the values of the image scale followed by calculation of its decomposition values using:

$$W(a,b) = \frac{1}{\sqrt{a}}\int_{-\infty}^{\infty} x(t)\psi\left(\frac{t-b}{a}\right)dt \tag{1}$$

where, $a > 0$. The considered mother wavelet functions are oscillatory bandpass filters in the time domain. Hence, the basic function is a low frequency function holds a stretched version of the mother wavelet for larger a values and a contracted version called short-duration, high-frequency function for smaller a values.

In Weibull Probability Density Function with continuous wavelet transforms (WPDF-CWT), a translation of the wavelet provides time localization and is defined by a parameter b. The Weibull distribution that works based on the shape parameter value is a versatile most widely lifetime distributions in reliability engineering thus constituting the characteristics of other types of distributions.

The 3-parameter Weibull *pdf* is given by:

$$x(t) = \frac{\beta}{\eta}\left(\frac{t-\gamma}{\eta}\right)^{\beta-1} e^{-\left(\frac{t-\gamma}{\eta}\right)^{\beta}} \tag{2}$$

where, $t \geq 0, \beta > 0, \eta > 0, -\infty < \gamma < +\infty$

η = Scale parameter in wavelet transform

β = Wavelet slope parameter

γ = Location parameter values of wavelet in image

So it is applied into equation in the name of Weibull Probability Density Function with Continuous Wavelet Transform (WPDF-CWT) as it is changed to original wavelet. The transformation becomes irreversible only if it holds the following admissibility condition:

$$c_\psi = \int_0^{\infty}\frac{|\Psi(f)|^2}{|f|}df < \infty \tag{3}$$

The above equation implies that the DC component $\Psi(0)$ must disappear. Thus, to provide good time resolution, $\psi(t)$ is a bandpass signal that must sufficiently decayfast. The Parseval relation for the wavelet transform is:

$$\int_{a=0}^{\infty}\int_{b=-\infty}^{\infty}|W(a,b)|^2\frac{db\,ba}{a^2} \vDash c_\psi\int_{-\infty}^{\infty}|x(t)|^2\ dt \tag{4}$$

The orthonormal wavelet transforms withholds the energy between the different scales that are parameterized by *a* in the way such that:

$$\int_{a=0}^{\infty}|\psi(t)|^2\,dt = \int_{-\infty}^{\infty}\frac{1}{|a|}\ \psi\left|\left(\frac{t-b}{a}\right)\right|^2 dt \tag{5}$$

For the construction of the continuous wavelet transform, the Morlet wavelet becomes a good example of a mother function that is defined by:

$$\psi(t) = [\exp(-2i\pi f_0 t) - \exp(-2\pi^2 f_0^2\sigma^2)]\exp(-\frac{t^2}{2\sigma^2}) \quad (6)$$

Its Fourier transform is:

$$\psi(f) = \sqrt{2\pi\sigma^2}\{\exp[-2\pi^2\sigma^2(f-f_0)^2] - exp(-2\pi^2\sigma^2 f^2)\, exp(-2\pi^2\sigma^2 f_0^2)\} \quad (7)$$

which satisfies the admissibility condition $\Psi(0) = 0$. By choosing this mother function, the continuous wavelet transform upon time discretization $t = n\Delta T$ becomes:

$$W(a,b) = \frac{\Delta T}{\sigma\sqrt{2\pi a}}\sum_{n=-\infty}^{\infty} s(n)\exp\left[-\frac{(n\Delta T-b)^2}{2a^2\sigma^2}\right] \times \exp{-2i\pi f0 n\Delta T - ba} \quad (8)$$

where, ΔT is the sampling time in seconds.

The schematic plot of CWBCT is illustrated by the Fig. 2a using 3 wavelet levels and $L = 3$ directional levels. Logically, partially decomposed DFB's with vertical and horizontal directions on the HL and LH bands has to be used as the DICOM images have vertical directions in the HL image and horizontal directions in the LH. Yet, fully decomposed DFB on each band is completely used as the wavelet filters are imperfect in splitting the frequency space into lowpass and high pass components which means that not all of the directions in the HL image are vertical and in the LH image are horizontal.

Wavelet-based Contourlet Packets is almost similar to the Wavelet Packets and is a major advantage of the CWBCT. It is explained by the fact that the quad-tree decomposition of both lowpass and high pass channels in wavelets are allowed by the anisotropy scaling law and on each subband DFB is applied. The schematic illustration of the wavelet-based contourlet packets is given in Fig. 2b. The proper construction of a quad-tree like angular decomposition which is introduced as Contourlet Packets is possible by ignoring the anisotrophy constraint (Shapiro, 1993). Similar to the procedure followed in Do and Vetterli (2003), for an l −level DFB, 2^l directional subbands with $G_k^{(i)}$, $0 \le k \le 2^l <$ equivalent synthesis filters are given and hence the overall down sampling matrices of $S_k^{(i)}, 0 \le k \le 2^l$ defined as:

$$S_k^{(i)} = \begin{cases} \begin{bmatrix} 2^{l-1} & 0 \\ 0 & 2 \end{bmatrix} if\ 0 \le k \le\le 2^{l-1} \\ \begin{bmatrix} 2 & 0 \\ 0 & 2^{l-1} \end{bmatrix} if\ 2^{l-1} \le k < 2^l \end{cases} \quad (9)$$

Thus, $(g_k^l)[n - S_k^{(l)} m]\}, 0 \le k \le 2^l, m \in \mathbb{Z}^2$ is a directional basis for $l^2(\mathbb{Z}^2)$; in which $g_k^{(l)}$ is the impulse response of the synthesis filter $G_k^{(l)}$. By assuming an orthonormal separable wavelet transforms:

$$V_j^2 = V_j \otimes V_j \text{ and } V_{j-1}^2 = V_j^2 \oplus W_j^2 \quad (10)$$

where, W_j^2 is the detail space and orthogonal component of V_j^2 in V_{j-1}^2. The family $\{\psi_{j,n}^1, \psi_{j,n}^2, \psi_{j,n}^3\}_{n\in\mathbb{Z}^2}$ is an orthonormal basis of W_j^2, l directional levels to detail multi resolution space W_j^2, obtain 2^{l_j} directional of subbands W_j^2:

$$W_j^2 = \bigoplus_{k=0}^{2^{l_j}-1} W_{j,k}^{2,(l_j)} \quad (11)$$

Defining:

$$\eta_{j,k,n}^{i,(l_j)} = \sum_{n\in\mathbb{Z}^2} g_k^{l_j}[m - S_k^{(l_j)} n]\psi_{j,m}^i, i = 1,2..3 \quad (12)$$

The family $\left\{\eta_{j,k,n}^{1,(l_j)}, \eta_{j,k,n}^{2,(l_j)}, \eta_{j,k,n}^{3,(l_j)}\right\}_{n\in\mathbb{Z}^2}$ is a basis for the subspace $W_{j,k}^{2,(l_j)}$.

Improved SPHIT algorithm for wavelet coding: Based on the SPIHT algorithm (Kassim and Siong, 2001) for wavelet coding of images, the similar concept of spatial orientation tree of wavelet coefficients having a parent-child relationship along wavelet scales, parent-child dependencies in other subband systems can also be found. Depending on the number of directional decompositions in the contourlet subbands (Po and Do, 2003), two different parent child relationships can be assumed in case of the contourlet transform.

If the two successive scales have the same number of directional decompositions to the parent and children, then both the parent and children would lie in the corresponding directional subbands whereas if the children lie in the scale having twice as many directional subbands as that of the parent, all the four children will be in two adjacent directional subbands. These two directional subbands correspond to the parental location performing directional decomposition of the directional subband. Thus the similarities between WBCT and contourlet transform for each LH, HL and HH subband made us to assume the below illustrated parent-child relationships as shown in Fig. 3.

Two possible parent-child relationships in the CWBCT are shown in Fig. 3a during which the numbers of directional subbands are the same at the two wavelet scales. However, 4 directions at each wavelet subband as shown in Fig. 3b is followed if the number of directional subbands in the finer wavelet scale (say, 8) is twice as given for coarser wavelet scale (say, 4). The set of coordinates representing the coding method is as follows:

$O(i,j)$ in the tree structures is the set of offspring (direct descendants) of a tree node defined by pixel location (i,j).

In DICOM images, $D(i,j)$ is the set of descendants of node denoted by pixel location (i,j) in which $L(i,j)$is the set defined by $L(i,j) = D(i,j) - O(i,j)$. the set partitioning trees is defined as below except for the highest and lowest pyramid levels:

$$O(i,j) = \{(2i, 2j), (2i, 2j+1), (2i+1, 2j), (2i+1, 2j+1)\}$$

The following are the rules for splitting the set (when identified as significant):

- The initial partition is formed with sets (i,j) and $D(i,j)$, for all $(i,j) \in H$.
- If $D(i,j)$ is significant, then it is partitioned into $L(i,j)$ plus the four single-element sets with $(k,l) \in O(i,j)$.
- If L (i, j) is significant, then it is partitioned into the four sets $D(k,l)$with$(k,l) \in O(i,j)$. In the spatial orientation tree, the significant values of the wavelet coefficients are modeled and stored in three ordered lists namely.
  - List of Insignificant Sets (LIS) containing the set of wavelet coefficients are defined by tree structures and found to have magnitude smaller than a threshold (are insignificant). The coefficient corresponding to the tree or all sub tree roots that are having atleast four elements are being excluded in the sets. The entries in LIS are sets of the type $D(i,j)$ (type A) or type $L(i,j)$ (type B).
  - List of insignificant pixels (LIP) containing the individual coefficients have magnitude smaller than the threshold.
  - List of Significant Pixels (LSP) containing the pixels are found to have magnitude larger than the threshold (are significant).

In the sorting pass, the insignificant LIP pixels that are tested in the previous pass and those emerging significant LIP pixels are moved to the LSP. Then, during the sequential assessment of the sets along the LIS order if asset is found to be significant it is removed from the list and partitioned. Based on their significance, the new sets having more than one element are added back to LSP, while adding the one element sets to the end of LIP or LSP.

The significance function is defined as follows:

$$S_n(T) = \begin{cases} 1 & \max\{c_{i,j}\} \geq 2^n, (i,j) \in T \\ 0 & otherwise \end{cases} \quad (13)$$

Improved SPHIT algorithm:

1) **Initialization:** Output $n = \log_2(\max_{i,j}\{|c_{i,j}|\})$, set the LSP as an empty set and add the coordinates $(i,j) \in H$ to LIP and only those with descendants also the LIS as type of A entries

2) Sorting pass

2.1) for each entry in the LIP do:

2.1.1) Quick sort algorithm - quick sort(LIP, i, k):

2.1.1.1) output $S_n(i,j)$

2.1.2) if $S_n(i,j) = 1$ then move (i,j) to the LSP and output the sign of$c_{i,j}$

2.2.) for each entry (i,j) in this LIS do

2.2.1.) if the entry is of type A then
Output $S_n(D(i,j))$
if $S_n(D(i,j)) = 1$ then
for each $(k,l) \in O(i,j)$ do
output $S_n(k,l)$
if $S_n(k,l) = 1$ then add (k,l) to the LSP and output the sign of $C_{k,l}$
if $S_n(k,l) = 0$ then add (k,l) to the end of LIP
if $L(i,j) \neq 0$ then move (i,j) to the end of the LIS as an entry of type B and go to Step 2.2.2)
otherwise, remove entry (i,j) from the LIS

2.2.2.) if the entry is of type B then
Output $S_n(L(i,j))$
if $S_n(L(i,j)) = 1$then, add each $(k,l) \in O(i,j)$ to the end of the LIS as an entry of type A
Remove (i,j) from the LIS

3) Refinement Pass
For each entry (i,j) in the LSP, expect those included in the last sorting pass (i.e., with same n), output the n^{th} most significant bit of $|C_{i,j}|$

4) Decrement n by 1 and go to Step 2

Quick Sort Algorithm (QSA) for sorting pass in the SPHIT algorithm: When the number of the data becomes more, the difficulty in sorting the data in the dataset is solved by using the sorting algorithm to sort the elements in the data or array. It is known as Quick sort that is similar to the wavelet coefficient values in the wavelet transform for SPHIT coding in LIP. It is presented in this study to overcome the problem of sorting of LIP pixels. This tool first divides a large pixels array of high pixel elements into smaller sub-pixels array called as the low pixel elements. Then the sub-pixels arrays are recursively sorted by following the steps involved in the quick sorting:

- From the LIP list, pick anyone of the LIP values randomly and name as pivot.
- Reorder the LIP list based on the randomly selected pivot elements, which is referred as the partition operation in which LIP list starts with lesser pixel value to greater pixel

Fig. 4: MRI 3D backbone image

Fig. 5: Wavelet image sample

Fig. 6: Wavelet compressed image sample

- Recursively apply the above steps to the sub-LIP Pixels list of elements with lesser values and to the sub LIP of elements separately with greater values.

EXPERIMENTATION RESULTS

In this section measure the performance of the proposed Continuous Wavelet Based Controulet Transformation (CWBCT) and existing image wavelet compression methods for 3D backbone DICOM images are samples is shown in Fig. 4. The image samples are taken from DICOM sample image sets from http://www.osirix-viewer.com/datasets/. These image samples results are measured using the parameters like Peak Signal to Noise Ratio (PSNR), Mean Square Error (MSE), Root Mean Square Error (RMSE).

In Fig. 4 shows the MRI 3D image sample of the backbone, wavelet transformation methods applied samples results is illustrated in Fig. 5, then compressed CWBCT transformation method results is illustrated in Fig. 6.

Root-Mean-Square Error (RMSE): Root mean square value is used to measure the results between the predicted values actually observed values. The predicated values are defined as $\hat{y}_t$ for times *t* and the actual value is mentioned as the parameter y_t for number of the samples n:

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(y_t-\hat{y}_t)^2}{n}} \tag{14}$$

Peak Signal to Noise Ratio (PSNR): Peak signal to noise ratio is used to measure the results of the outcomes and measure the noise value of the image. It is calculated by using following formula:

Table 1: DICOM MRI image results

	MSE (%)		PSNR(dB)		RMSE (%)	
S.No	WT	CW BCT	WT	CW BCT	WT	CW BCT
1	0.76	0.55	58.4	72.1	0.89	0.64
2	0.73	0.51	49.8	75.25	0.87	0.638
3	0.68	0.49	48.99	78.12	0.865	0.635
4	0.78	0.48	52.4	77.18	0.86	0.63
5	0.76	0.52	59.8	81.2	0.855	0.624

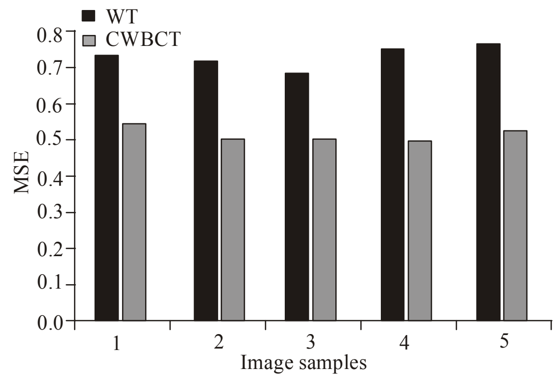


Fig. 7: DICOM Backbone MRI image samples MSE results

$$PSNR = 10\log_{10}(MAX_i^2/MSE) \tag{15}$$

MAX_I is the maximum possible pixel value of the image.

Mean Square Error (MSE): Mean Square Error (MSE) is defined as the difference amongst an estimator results and the actual of the original images results are computed as:

$$MSE = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I(i,j) - K(i,j)]^2 \tag{16}$$

where, $I(i,j)$ denotes the original image and $K(i,j)$ denotes the approximation to the original image which is also called as the decompressed image. M, N is the image dimensions. If the values of the MSE is less it shows the error value of the system is also less, on other hand the PSNR is high. Table 1 shows the values of performance comparison results of the WT, CWBCT compression methods with the parameters like MSE, RMSE and PSNR for DICOM Backbone MRI image samples results.

In Fig. 7 illustrates the MSE results of the DICOM Backbone MRI image sample results for five samples between the Wavelet transformation and the proposed Continuous Wavelet Based Controulet Transformation (CWBCT). It shows that the proposed CWBCT have lesser MSE results than the existing Wavelet Transformation (WT) methods.

In Fig. 8 illustrates the RMSE results of the DICOM Backbone MRI image sample results for five

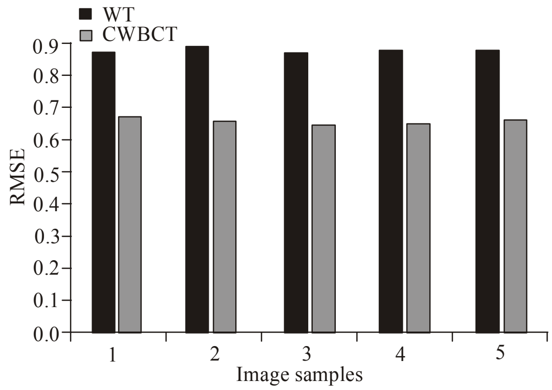


Fig. 8: DICOM Backbone MRI image samples MSE results

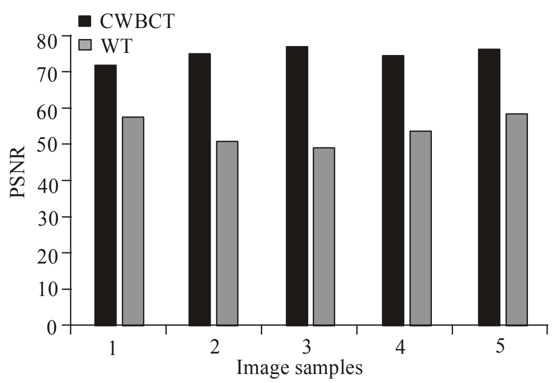


Fig. 9: DICOM MRI image samples PSNR results

image samples between the Wavelet Transformation and the proposed Continuous Wavelet Based Controulet Transformation (CWBCT). It shows that the proposed CWBCT have lesser RMSE results than the existing Wavelet Transformation (WT) methods.

Figure 9 clearly depicts the comparison of both techniques on the basis of PSNR values. The above results quiet familiarize that the values of Continuous Wavelet Based Controulet Transformation (CWBCT) is quiet reliable and optimist as compare to Wavelet Transform (WT).

CONCLUSION

DICOM is one of the standards followed by now days to maintain the different standards of the medical images in the 3D format. Since due the development of the medical technologies it becomes important to maintain the proper standard for the diagnosis of the diseases of the different patients. In this study, presents a novel wavelet compression of DICOM images using Continuous Wavelet Based Controulet Transform (WPDF-CWBCT) and presents novel improved SPHIT coding methods which performs sorting pass based on the Quick Sort Algorithm (QSA). The performance and accuracy comparison of the DICOM Backbone 3D medical images samples results are measured between the proposed CWBCT compression method and existing WT compression methods using the parameters namely PSNR, MSE and RMSE. The results of the proposed and existing system clearly shown, that the proposed methods have high PSNR, less MSE and less RMSE when compare to existing WT compression methods. In order to further improve the speed of the transformation methods in this study by lattice factorization in wavelet transformation methods. This reduces the time complexity of the system and memory reductions.

REFERENCES

Bairagi, V.K. and A.M. Sampkal, 2013. ROI-based DICOM image compression for telemedicine. IEEE, 38: 123-131.

Bojovic, M. and D. Bojic, 2005. Mobile PDR: A mobile medical information system featuring update via internet. IEEE T. Inf. Technol. B., 9(1): 1-3.

Dhawan, S., 2011. A review of image compression and comparison of its algorithms. Int. J. Electron. Commun., 2(1): 22-26.

Do, M.N., 2001. Directional multiresolution image representations. Ph.D. Thesis, EPFL, Lausanne, Switzerland.

Do, M.N. and M. Vetterli, 2003. Contourlets in Beyond Wavelets. Academic Press, New York.

Esakkirajan, S., T. Veerakumar, V. Senthil Murugan and P. Navaneethan, 2008. Image compression using multiwavelet and multi-stage vector quantization. Int. J. Signal Process., 4(4): 246.

Jyotheswar, J. and S. Mahapatra, 2007. Efficient FPGA implementation of DWT and modified SPIHT for lossless image compression. J. Syst. Architect., 53: 369-378.

Kassim, A.A. and L.W. Siong, 2001. Performance of the color set partitioning in hierarchical tree scheme (CSPIHT) in video coding. Circ. Syst. Signal Pr., 20(2): 253-270.

Liu, Z., J. Ha, Z. Xiong, Q. Wu and K. Castleman, 2002. Lossy-to-lossless ROI coding of chromosome Images using modified SPIHT and EBCOT. Proceeding of the IEEE International Symposium on Biomedical Imaging, pp: 317-320.

Mathew, A. and B.R. Singh, 2009. Image compression using lifting based DWT. Int. J. Comput. Inf. Tech. Eng., 2: 27-31.

Po, D.D.Y. and M.N. Do, 2003. Directional multiscale modeling of images using the contourlet transform. Proceeding of the IEEE Workshop on Statistical Signal Processing, pp: 262-265.

Said, A. and W.A. Perlman, 1996. A new, fast and efficient image codec based on set partitioning in hierarchical trees. IEEE T. Circ. Syst. Vid., 6: 243-250.

Shapiro, J.M., 1993. Embedded image coding using zerotrees of wavelet coefficients. IEEE T. Signal Proces., 41: 3445-3462.

Simoncelli, E.P. and W.T. Freeman, 1995. The steerable pyramid: A flexible architecture for multi-scale derivative computation. Proceeding of the International Conference on Image Processing. Washington, DC., 3: 444-337.

Singh, S., V. Kumar and H.K. Verma, 2007. Adaptive threshold-based block classification in medical image compression for teleradiology. Comput. Biol. Med., 37: 811-819.

Xiong, Z., X. Wu, S. Cheng and J. Hua, 2003. Lossy to lossless compression of medical volumetric data using 3D integer wavelet transforms. IEEE T. Med. Imaging, 22: 459-470.