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Colour Medical Image Compression Using Ripplet Transform And Huffman Coding

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***Abstract* – Besides newly emerging technologies in data processing, storage and management, data transmission has become a challenging task today. To perform efficient transmission of images for applications like telemedicine and to minimize the storage space, compression is mandatory. This paper aims at achieving better compression ratio, provides freedom in parameter setting which can be optimized for specific problems and helps in easy feature extraction. In this paper, we propose ripplet transform based compression which is the most advantageous approach that processes colour medical images. Also the reconstruction is done by the inverse transforms. Experimental results suggest that in terms of Structural Similarity Index Measure (SSIM), Peak Signal-to-Noise Ratio (PSNR), Compression ratio (CR) and Bits per pixel (BPP), the proposed method outperforms other conventional transforms.**

Keywords—Ripplet transform, Huffman encoding- Reconstruction-Telemedicine

I.INTRODUCTION

Image compression is an important field in digital image processing for reducing the storage cost and bandwidth requirements for transmitting an image [1]. Lossless compression is preferred for medical images as they contain details relevant for medical diagnosis. Feature extraction is better when colour medical images are taken when compared to gray scale images. Also colour medical images are used for identifying different entities in an image and its implementation is easy in any image processing techniques.

Apart from preserving vital information, high compression ratio is a major concern in medical image compression [2].In the proposed method, much interest has been focused on resolving 2D singularities and to reduce the computational complexity during the encoding process. This method employs Ripplet transform as an alternative to other conventional transforms [3] and Huffman encoding to ensure security during transmission of the image over the network.

Over the past decades much interest has been given for wavelet based compression. Wavelet transform is able to resolve 1D singularities [4] but it is unable to resolve 2D singularities like curve discontinuities because such discontinuities affect the high frequency components which in turn affects the wavelet coefficients and its directionality is also poor.

To overcome the limitations of wavelet transform, several MGA (Multiscale Geometric Analysis) transforms such as ridgelet, contourlet, curvelet, surfacelet and bandelet has been proposed. Ridgelet transform proposed by Candes and Donoho is optimal for representing straight line singularities and can resolve 1D singularities [5]. But it cannot resolve 2D singularities. The multiscale ridgelet transform named as curvelet transform proposed by Starck et al [6]represents two dimensional functions with smooth curve discontinuities at an optimal rate. But the discretization of curvelet transform is challenging and its resulting algorithm is highly complicated.

Contourlet transform proposed by Do and Vetterli [7] can effectively deal with piecewise smooth signals and this transform is directly constructed in discrete domain. But it has less directional features which leads to artifacts in image compression. Surfacelets proposed by Lu and Do [8]can represent surface like singularities but they are not able to represent images at different scales and directions.The proposed Ripplet transform provides hierarchial representation of images .They have compact support in frequency domain and decay very fast in spatial domain. Hence they have good localization in both spatial and frequency domain. Ripplet transform localizes the singularity more accurately and is highly directional to capture the orientations of singularities.

An adaptive predictive coding method based on wavelet transform proposed by Chen and Tseng [9] can reduce relevance of pixels in time and space domain. Even though compression is increased , computational complexity is higher. The variable block based encoding achieves high compression ratio but it is at the expense of complexity.Ansari [10] and Kim [11] evaluated the JPEG compression of medical images . The introduction of blocking artifacts can be neglected for higher compression ratio.Biorthogonal wavelet transform coupled with SPHIT coding proposed by Beladgham et al [12] overcame the drawbacks of wavelet transform by applied lifting structure .Although compression of image is good, it lacks providing multiresolution. The Embedded Block Coding with Optimized Truncation (EBCOT) proposed by Taubman [13] processes the code block by bit plane by bit plane but it is more complicated and time consuming. Simard et al [14] proposed tarp coding approach which uses a nonadaptive arithmetic coder coupled with probability estimate of the significance map. But it lacks context coding and cross scale aggregation of symbols .Pan et al [15] proposed progressive binary wavelet tree encoder which uses wavelet transform to convert image into binary format and an entropy encoder to encode the wavelet transformed coefficients. But the rate distortion approach is not so efficient. SPHIT encoding has salient features such as SNR scalability, progressive capability but it cannot remove space redundancy of image pixels. Although several encoding schemes are there for image compression, Huffman encoding is efficient for lossless compression of image. The algorithm achieves its goal by allowing the symbols to vary in length and the computational complexity is also less.

II.PROPOSED METHOD

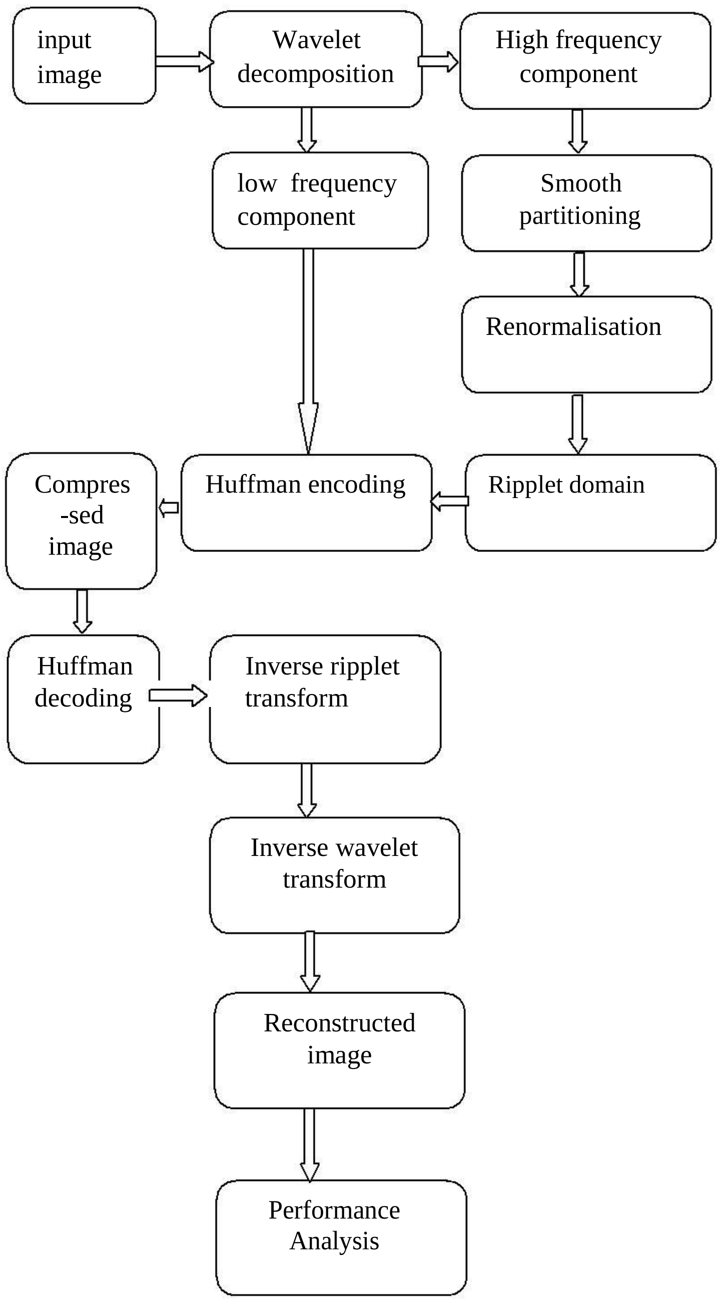
In this paper, we propose a Huffman coding method based on Ripplet transform for compression of colour medical images.The Ripplet transform breaks the inherent limitations of wavelet transform . It represents the image in different scales and directions in order to provide high quality compressed images.At first when Wavelet transform is applied to input medical image *f(x.y)* of size 256x256 , the input image is decomposed into set of subbands. The decomposed wavelet subbands are partially reconstructed to ripplet subbands.The low frequency subbands are directly encoded using Huffman encoding algorithm. The high frequency subbands are dissected into small partitions and the resulting dyadic squares are then renormalized. The effective region is analyzed in the ripplet system and thus finally the resulting ripplet coefficients are further encoded using Huffman encoder. The compressed image is obtained and the compression ratio is calculated .

Then huffman decoding and inverse ripplet transform are taken in order to reconstruct the original image. The performance metrics like PSNR,MSE,BPP and compression ratio are measured.

A. Decomposition of image into subbands

Colour medical image of size 256x256 is taken as input .The colour image is split into three bands(R,G,B) .The wavelet transform is applied separately for each band.Thus, the imput image is decomposed into multiresolution subbands.The low frequency subbands are directly encoded. But for the high frequency subbands, ripplet transform is taken and then encoded.The decomposed image is given as

$$f(x,y) \rightarrow (P_o f(x,y), \Delta_1 f(x,y), \Delta_2 f(x,y), \ldots) \quad (1)$$



B.Ripplet transform

i) Smooth partitioning

The high frequency subbands $\Delta_s f(x,y)$ are dissected into small partitions by multiplying it with the smooth window function .Thus it produces a smooth dissection of the function into squares.The windowing function and filtering are Δ_s are constructed in order to ensure that they result in perfect reconstruction. The squares which do not intersect the edge or ripplet fragment have no energy and hence they can be ignored.

ii)Renormalization

Renormalization is centering each dyadic square to the unit square which results in the aspect ratio of width ≈length^2. Thus each square is renormalized as

$$g_Q = T^{-1}_Q h_Q \qquad (2)$$

iii)Representation in ripplet domain

Each pixels in the renormalized square is analyzed in ripplet domain.The major axis denotes the effective length and minor axis denotes the effective width which is orthogonal to the major axis represents the effective region. This effective region satisfies the property width≈c x length^d where c denotes the support of ripplets and d determines the degree of ripplets. Through this property the ripplets are capable of capturing singularities along the curves.

Algorithm for Ripplet transform:-

Step1:-Input the colour medical image (i.e) f(x,y) of grid size 256 ×256.
Step2:-Decompose the input into frequency subbands of high and low frequency components.

$$f(x,y) \Longrightarrow (P_0 f(x,y), \Delta_1 f(x,y), \Delta_2 f(x,y), \ldots)$$

Step3:-Dissect the higher frequency band further into smaller Partitions by describing the dyadic squares .

$$Q_{(s,k_1,k_2)} = \left[\frac{k_1}{2^s}, \frac{k_1+1}{2^s}\right] \times \left[\frac{k_2}{2^s}, \frac{k_2+1}{2^s}\right] \in Q_s$$

This partition is accomplished by multiplying high frequency component with windowing function to provide smooth dissection of functions into squares of sides $2^{-s} \times 2^{-s}$.

Step4:- Renormalise each resulting dyadic square into unit square by centering each square. For each *Q*, the operator

T_Q

is defined as,

$$(T_Q f(x,y))(x_1, x_2) = 2^s f(2^s x_1 - k_1, 2^s x_2 - k_2)$$

Then,each square will get renormalized into

$$g_Q = T_Q^{-1} h_Q$$

Step5:-Analyse the renormalized square in ripplet domain using

$$R_{(Q,ab\theta)} = \langle g_Q, \rho_{ab\theta} \rangle = \int g_Q(x) \overline{\rho_{ab\theta}(x)}\, dx$$

Where

are ripplet coefficients and

is the ripplet function that gets generated as

$$\rho_{ab\theta}(x) = \rho_{a00}(R_\theta(x - b))$$

Where R is the rotation matrix given as follows:

=

The discrete ripplet transform is given as

$$R_{j,k,l} = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x,y) \times \overline{\rho_{j,k,l}(x,y)}$$

Finally,the ripplet coefficients will be obtained in discrete form that gets coded using huffman technique.

Algorithm for Huffman coding technique:-

Step1:-Read the colour image (RGB) over workspace of the matlab software.
Step2:-Call a function which will find the set of non-repeated pixel values.
Step3:-Call a function which will calculate the probability of each such non-repeated pixel values.
Step4:-Probability of such pixels which is known as symbol are arranged in decreasing order and lower probabilities are merged and this step is continued until only two probabilities are left and codes are assigned based on the concept that lower probability symbol will have shortest length code and higher probability symbol will have largest length code.
Step5:-This way continues the coding process iteratively resulting in compressed image.

Here, colour image in ripplet domain is applied as input to the Huffman encoder.

Similarly,Huffman decoding procedure is as follows:-

- Matching with the codeword of all leaf nodes.
- Getting the codeword symbol from the subtable of the selected leaf node using the bits that match all the leafnode codewords within the table.
- Symbol to be decoded should have number of bits equal to the codelength thereby progressing the input bit stream.

Inverse ripplet transform is applied over the decoded ripplet coefficients that causes fusing of the high and low frequency coefficients together.These fused coefficients are further correlated by performing inverse wavelet transform.

Finally,Reconstructed image is obtained whose performance metrics are compared with original image and with ripplet transformed image.

III.PERFORMANCE EVALUATION

The parameters useful in detecting and measuring the image quality are PSNR, MSE, BPP, SSIM and CR. These values also helps in comparing the features of original image with that of the reconstructed image.

A. ***MEAN SQUARE ERROR***:-It is the most common measure of deviation between the original and the coded image which is expressed as:-

$$MSE = \frac{1}{M \times N} \times \left[\sum_{x=0}^{M-1} \sum_{y=0}^{N-1} \left(f(x,y) - F(x,y) \right)^2 \right]$$

B. ***PEAK SIGNAL TO NOISE RATIO***:-The advantage of this measure is ease of computation and it usually neglects global and composite errors.
This metric is calculated as follows:-

$$PSNR = 10 \times \log_{10} (255^2 / MSE)$$

C. ***BITS PER PIXEL***:-It evaluates the number of pixels in an image.

D. ***COMPRESSION RATIO***:-
It is the ratio of total number of pixels in original image to the total number of pixels in compressed image.

IV.RESULTS AND DISCUSSIONS

The proposed method is applied on colour images which are shown in fig 1,2,3 & 4. They are decomposed by wavelets and the resultant Low-low, Low-high, high-low and High-high images are shown in fig. 5 for lungs CT image.

Fig.1.Lungs CT scan

Fig.2. Angio (Ribcage,heart) CT Scan

Fig.3.Vascular pulmonary CT Scan

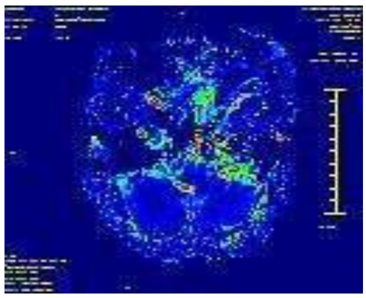


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Fig.4.Brain MRI

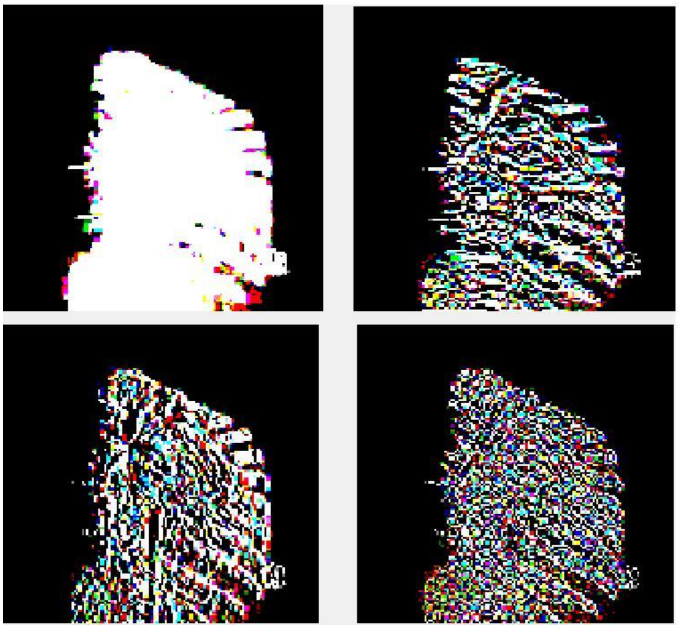

Fig.5. Lungs CT Decomposed Images LL,LH,HL and HH

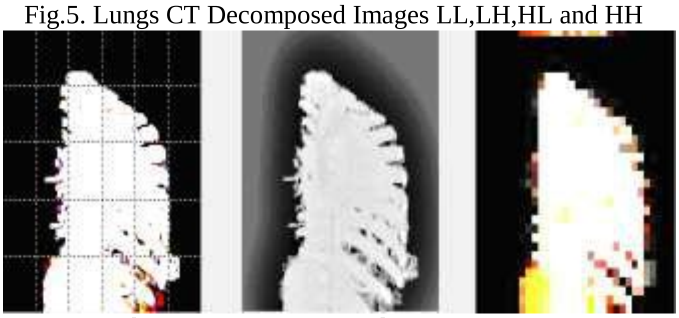

Fig.6.Smooth partitioning,Renormalization, Ripplet Domain

Figure 6 shows the stages of ripplet tansforms applied over lungs CT. The following figure 7 interprets the compressed image and the reconstructed image is shown in figure 8.

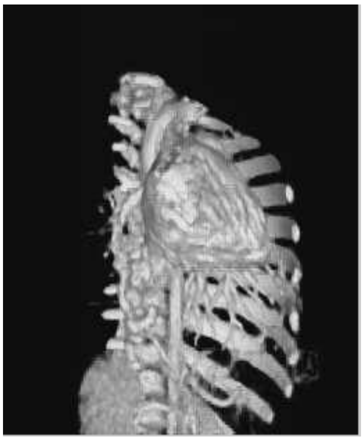

Fig.7. Compressed image

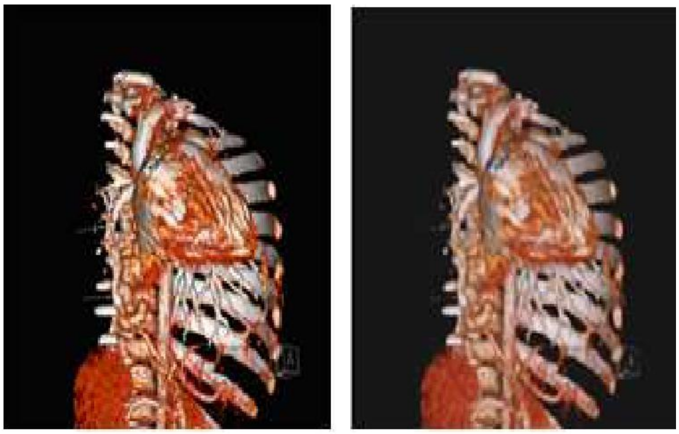

Fig.8. Input image reconstructed image

The simulation results for images of different sizes are tabulated in table 1. The values of Mean square Error, Peak signal to noise ratio, bits per pixel and compression ratio are measured.The PSNR is optimum with reduced MSE values. The compression ratio for colour images is better and bits per pixel is less.

Table 1. Performance metrics

Parameters	Lung CT	Angio CT	Vascular pulmonary CT	Brain MRI
Size	968 ×968	968 ×968	512× 512	256× 256
MSE	0.453	0.264	0.998	1.142
PSNR	42.32	43.44	47.59	46.63
BPP	0.122	0.163	0.184	0.492
CR	12.53	16.49	27.94	9.04

V.CONCLUSION

Since there is a great demand for Telemedicine applications,storage and bandwidth increases in an wide range.In that case,Compression plays an important role in effective transmission..As compression is mainly determined by the elimination of redundant bits,Huffman coding based Ripplet transform which is the proposed work helps in achieving high compression ratio.Also,effective values of other performance metrics are obtained by deploying this proposed work. Future work may be focussed towards reducing latency in transmission.

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