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An Improved Method for Colour Medical Image Compression Using Wrapping Based Hybrid Curvelet Transform

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Abstract

Medical images have been acquired from patients in day to day life and are used for surgical and diagnostic purposes. They are stored as colourimages which normally consume high memory space. Hence, the compression of colour medical images is needed for storage and transmission. Due to the requirement of better accuracy in reconstruction and also loss of data is not tolerable, effective lossless compression algorithm is preferred. Colourmedical modalities are compressed using wrapping based curvelet transform hybrid by lifting, coded by Huffmanncoding and decompression using inverse transforms result in better Peak SNR and Compression value. This paper deals with the performance improvement such as improving the PSNR and CR in colourmedical image compression. Colourmedical modalities like Magnetic Resonance Image (MRI),Ultrasound, Computerised Tomography (CT)are compressed having varied image sizes and then result analysis is executed. It also ensures that other parameters like bits per pixel, correlation values, mean square error and difference in average are not getting affected and do not degrade the performance of compression/decompression. Most importantly it outperforms DCT, Haar, Contourlet and ripplet transforms with different coding.

Keywords: *Colourmodalities, Curvelet hybrid Lifting;Huffmann;Reconstruction; Quality metrics*

1. Introduction

Diagnosis based on medical images save the human life by curing diseases. So, utility of medical images with best quality are needed. Consumption of additional bandwidth is the need to store best quality images. Data is exponentially increasing and compression is the wayto adhere. Colourmedical modalities, lossof information will lead to diagnostic issues. Hencebig data gathering is done through improved algorithms.

2. Literature review

From recent literatures,the low frequency coefficients are encoded by DPCM, medium frequency coefficients are coded by SPHIT and high frequency coefficients are removed.[1] Proper reconstruction with encoding has been discussed [13] Rapid evolution in lifting for fingerprint compression give good PSNR using set partitioning in hierarchical trees [2].Ripplet transform provides good compression at varied scales as well as directions. [15]. Both algorithms were not tested on colourimages.Various transforms DWT, 3D IWT,Daubechis wavelet hybrid with lifting are used for compression. [9]. These wavelet transforms produce less compression ratio. The lifting waveletprovides better results. [1]. Lifting with 1D-daubechis delivered a better CR andbpp [3]. Though there is improved compression ratio but diminishing quality of the image [1]. Fine details in the curvy region is not well reproduced [11]. Huffmann coding is best suited for hybrid compression [15]. Fractal image compression and other algorithms are presented here [15].They don't focus much on PSNR, CR and other quality metrics.

The lowest frequency FDCT output coefficients are quantized using Differential Pulse Code Modulation,
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3. Proposed work

In this work, curvelet with hybrid lifting and coding by Huffmann is done compress medical modalities. These are filtered by weiner filter, then curvelet transformation is done. Further splitting into tiles and resizing is done together. It is summed to obtain the resultant modality. Then the lifting transformation is done to the resulted curvelet transformed coefficients which results in low-low image. After the decomposition, hybrid wrapping based curvelet transformation is executed and coded by Huffmann. Then reconstructed through inverse lifting and inverse curvelet transformation that matches with the original. Figure.1 illustrates the entire methodology.

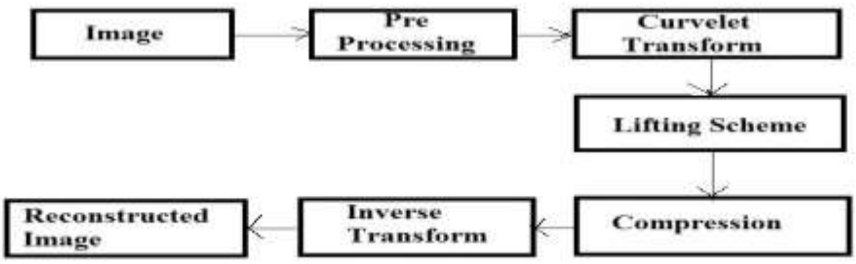

Figure.1.Block diagram of proposed methodology

- Medical Image acquiring and filtering by median as well as wiener filters
- Curvelet transformation for decomposition.
- Lifting to extract the high detailed (Low-Low) image.
- Coding by Huffmann to compress.
- Reconstruction by inverse lifting withinverse curvelet transforms
- Quality metrics are computed by relevant formulae.

3.1 Image acquisition and pre-processing

The image data base is created by acquiring colourmedical images from recognized medical centres and through dicom and filtered by array of filters.

3.2 Curvelet transform

Curvelet transform represent edges and singularities along curves effectively when compared with other transforms usinga very few coefficients with high accuracy in reconstruction [14]. It requires $1/\sqrt{N}$ in curvelets for the representation of edge to squared error whereas there is need of 1/N wavelets for 1/N. It possesses directional parameter and the curvelet pyramid has directional specific elements.[12] [5].Among various methods, the wrapped curvelet transform is rapid and easier for implementation [7]. Curvelet transform forsplittinginto three primarybands (i.e., Red, Green, Blue) and for each band the wrapping algorithm is imposed as follows.

- Compute Fast Fourier transform(FFT) of the modality and division into digital tiles.
- In each tile,
  (a) Transform it to the origin andapply wrapping the parallelogram beside the rectangle near the origin.
  (b) Perform inverse FFT and sum the array of curvelet to its coefficients.

3.3. Lifting wavelet transform

Lifting differsfrom the conventional constructions is the way of dependence on fourierand thiscan be utilized to deploy second generation wavelets. The removal of redundancythrough computation of cross correlation is the good idea.
Data is classified into samples of odd and even in split phase andeven samples predict the neighbouringthe value of odd in predict phase. It then updates even samples with newly computed odd value samples and hence the desired property is retained. Figure.6illustrates the lifting mechanism.The lifted images as are LL,LH,HL,HH.

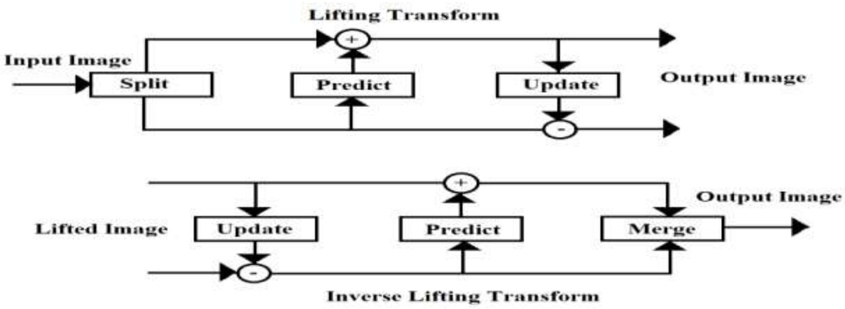

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Figure.2.Lifting methodology

Splitting:$S_i^0 = \Pi_{2i} d_i^{0\,=}\, \Pi_{2i+1}$ (1)

Lifting : $d_i^1 = d_i^0 - (1/2)(S_i^0 + S_{i+1}^0)$ (2)
(predict step)
$(S_i^1 = S_i^0 + (1/4)(d_{i-1}^1 + d_i^1)$ (3)
(update step)
Π – **S**amples of input;S – Even Samples;d – Odd Samples

3.4. Encoding
Encoding is done by regular Huffmann procedure and the coefficients are coded for compression**.**
3.5.Reconstruction
The reconstruction by inverse lifting and inverse curvelet through inverse wrapping algorithm is executed as follows:
For each array of curvelets coefficients
(a) Calculate the array of FFT and unwrap to get the original shape from the rectangular support
(b) Translate it to the original position and store it.
(c) Sum all translated arrays and compute the inverse FFT

4. Quality metrics

4.1. Mean square error
Mean square error is the error in the image and a minimum value of MSE is good.

$$MSE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=i}^{N}(f(i,j) - f'(i,j))^2 \quad (4)$$

4.2 Peak signal to noise ratio

High PSNR indicates reflect in high quality.
PSNR = 20 log 10 (255/√MSE) (5)

4.3. Structural correlation

It shows similarity between the structure and the value should be one.

$$SC = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}[f(i,j)]^2}{\sum_{i=1}^{M}\sum_{j=1}^{N}[f\prime(i,j)]^2} \qquad (6)$$

4.4. Normalised correlation

It denotes the closeness between original and reconstructed modalities. It is complementary to difference measures and the value is expected to be one always.

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$$NK = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}[f(i,j)-f'(i,j)]}{\sum_{i=1}^{M}\sum_{j=1}^{N}[f(i,j)]^2} \qquad (7)$$

4.5.Average difference

It should be zero for the better reconstruction.

$$_{A}D = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=i}^{N}(f(i,j)-f'(i,j)) \quad (8)$$

5. Results and discussions

The medical modalities of 200 numbers with different pixel sizes obtained from various body portions are compressed and sample interpretation is shown below in figure 3.

Figure.3. MRI female body image compression

Table 1 Compression ratio at 1.2 bpp

Images	DCT with SPIHT	Haar with SPIHT	Contourlet with SPIHT	Ripplet with SPIHT	Curvelet with Huffmann
CT-Heart	8.06	9.73	8.81	9.76	9.81
MRI of brain	12.04	10.44	11.34	12.08	18.47
MRI whole body	10.29	12.22	10.4	10.89	14.56

CT nervous	9.56	10.42	9.62	9.73	11.70
MRI lungs	10.23	9.57	9.17	12.27	13.84
CT bone	8.65	9.83	9.10	9.98	9.98

Table.2.Estimation of Quality Metric Parameters

Images	PSNR	MSE	Structural Content	Normalized correlation	Average difference
CT-Heart	73.93	0.290	0.7498	1.0470	0.0068
MRI of brain	66.19	0.173	0.8563	1.0766	0.0163
MRI whole body	64.43	0.251	0.3357	1.3123	0.0819
CT nervous	66.30	0.290	0.1310	1.7896	0.0288
MRI lungs	69.93	0.176	0.8863	1.0524	0.0276
CT bone	69.92	0.150	0.3849	1.1554	0.0153

- From Table.1, in the proposed algorithm, CR is improvedthan the existing methods. It is applicable and works well for colour medical images

- In table.2 ,PSNR is around 70% which is better and MSE mean of 0.2 is acceptable. Structural, Normalized, Average difference are good and indicates good quality

6. Summary and conclusion

Thus, the proposed compression of colour medical modalities by wrapped curvelet transform hybrid of lifting and coded by Huffmann generatesbetter values of CR, PSNR than other combinations. It performs well with variety and different images. It is useful for telemetry and telemedicine.

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