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Medical Image Compression Using Wrapping Based Fast Discrete Curvelet Transform and Arithmetic Coding

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Abstract

Due to the development of CT (Computed Tomography), MRI (Magnetic Resonance Imaging), PET (Positron Emission Tomography), EBCT (Electron Beam Computed Tomography), SMRI (Stereotactic Magnetic Resonance Imaging), etc. has enhanced the distinguishing rate and scanning rate of the imaging equipments. The diagnosis and the process of getting useful information from the image are got by processing the medical images using the wavelet technique. Wavelet transform has increased the compression rate. Increasing the compression performance by minimizing the amount of image data in the medical images is a critical task. Crucial medical information like diagnosing diseases and their treatments is obtained by modern radiology techniques. Medical Imaging (MI) process is used to acquire that information. For lossy and lossless image compression, several techniques were developed. Image edges have limitations in capturing them if we make use of the extension of 1-D wavelet transform. This is because wavelet transform cannot effectively transform straight line discontinuities, as well geographic lines in natural images cannot be reconstructed in a proper manner if 1-D transform is used. Differently oriented image textures are coded well using Curvelet Transform. The Curvelet Transform is suitable for compressing medical images, which has more curvy portions. This paper describes a method for compression of various medical images using Fast Discrete Curvelet Transform based on wrapping technique. After transformation, the coefficients are quantized using vector quantization and coded using arithmetic encoding technique. The proposed method is tested on various medical images and the result demonstrates significant improvement in performance parameters like Peak Signal to Noise Ratio (PSNR) and Compression Ratio (CR).

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Keywords

Medical Image Compression, Discrete Curvelet Transform, Fast Discrete Curvelet Transform, Arithmetic Coding, Peak Signal to Noise Ratio, Compression Ratio

1. Introduction

The foremost important purpose of image compression is to ease spectral and spatial redundancy to save or to communicate information. Another purpose is to maintain the quality of the image even at lower bit rate to represent an image and to reconstruct it without any degrade in its visual quality. In lossless compression scheme, the reconstructed image will be similar to the original image. In lossy compression scheme, the reconstructed image may not be similar to the original image. But, lossy compression scheme gives higher compression ratio than lossless compression scheme. The proposed scheme is a kind of lossless compression. In the proposed scheme, the coefficients are obtained using second generation of Curvelet Transform. In the quantization stage, the coefficients carrying least information are rounded off. The transform based compression spatially distributes the energy into less number of data samples so that no information is lost. The compressed image is reconstructed into spatial domain by the inverse transformation process [1].

Mohammed Hussien Miry [2] had proposed a novel approach for grayscale image compression using a new hybrid transform, namely Improved Ridgelet Transform. This hybrid transform is based on using Slantlet transform instead of wavelet transform. On different images, compression using Ridgelet transform was performed to obtain comparison results. For natural images, a high quality image compression has been achieved. The improved Ridgelet transform is superior and gives faster compression performance when compared to Ridgelet transform approaches. Giridhar Mandyam [3] had proposed a new method for lossless image compression of images using Discrete Cosine Transform. In this method, the high energy coefficients in each block are quantized. The number of coefficients used in this method is based on the performance parameters. A. Vasuki [4] had proposed a novel image compression algorithm using the nonlinear Contourlet Transform. Capturing of directional information in images was performed effectively by Contourlets, by using elongated, directional and flexible set of basis functions. Because of the Contourlet transform is redundant, authors have used a contourlet transform based on wavelet on the image. Contourlet transform based on wavelet applies wavelet transform prior to contourlet transform on the sub band of image. It has been shown that the results are superior to ordinary wavelet transform. K. Prasanthi Jasmine has proposed an efficient hybrid combination of wavelet-Ridgelet techniques for compression of images. The original image in the RGB color space is converted into grayscale image and to avoid degradation of picture quality due to noise, and denoising of this image is done by Gaussian filter. First DWT (Discrete Wavelet Transform) is applied to the image followed by application of FRT (Finite Ridgelet Transform) to obtain the compressed image. Decompression is done using the inverse FRT and inverse DWT in succession [5]. Veenadevi S. V. has proposed a technique for compressing satellite images using Fractals Transform. In this method, the input image is subdivided into various range and domain blocks. Each range block is matched with domain block. Then affine transformation is applied for each domain block. The improvement in performance parameters is based on the range block dimensions [6].

Over the past years, several researchers accepted wavelet transform for researches on image compression. Here artifacts are avoided at high compression ratios, but on images with different contents, wavelet decomposition produces poor compression ratio. A new compression technique called CALIC was developed for the purpose of context formation, quantization, and modeling. It did not gain popularity because of its poor performance and complex operation on binary and continuous modes.

The above-mentioned methods are inefficient because they use many number of co-efficient to reconstruct edges along curves and to characterize edge discontinuities along a curve. So in order to overcome these drawbacks a new multi resolution transform called the Curvelet Transform was introduced [7]. This transform is superior over wavelet transforms in the cases followed:

1) It is optimally sparse representation of objects with edges.
2) It is optimal image reconstruction in severely ill posed issues.
3) it is optimal sparse representation of wave propagators.

In this paper, wrapping based Curvelet Transform is used. The obtained coefficients after transformation are subjected to vector quantization where quantization process happens in a group. Finally, arithmetic encoding is performed to encode stream of characters. The parameters like Compression Ratio and Peak Signal to Noise Ratio (PSNR) are measured.

2. Curvelet Transform

There are several techniques for image compression and observation infers the wavelet may not be the best choice to compress medical image. This is because wavelets have the tendency to ignore edge smoothness. The drawback of wavelet is overcome by the introduction of a technique developed by Candes and Donoho in 1999. This was designed originally to represent edges and curves well than wavelet. The representation of an edge using wavelet is shown in **Figure 1(a)**. Curvelet is an extension of wavelet so there is a relationship between the curvelet and wavelet sub bands [8]. Curvelet Transform elements have location, orientation, and scale, whereas wavelet elements have only location and scale parameters [9] [10]. The representation of an edge using curvelet is shown in **Figure 1(b)**. The basic defect of wavelet is the inability to represent the edges and discontinuities along curve and for compression purpose less number of coefficients are involved but for reconstruction process, many in number are needed [11] [12]. This is mainly because to reconstruct the edge discontinuities it needs large number of coefficients.

2.1. Continuous Curvelet Transform

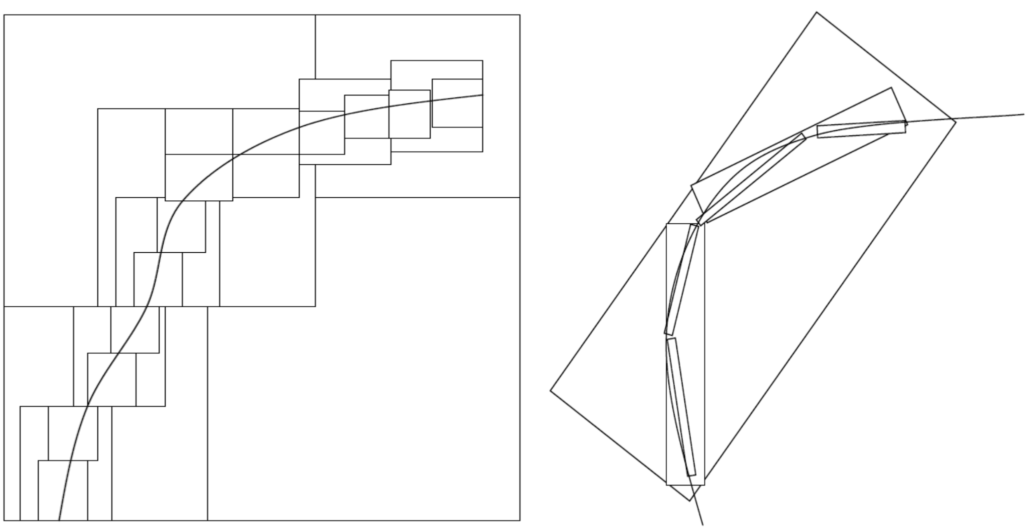
Two generations of Curvelet Transform has been developed. First generations Curvelet Transform (Continuous Curvelet Transform) were obtained from sub band filter theory and Ridgelet theory. The curvelet decomposition takes place in four stages [8]. They are: Sub Band decomposition, Smooth Partitioning, Renormalization and Ridgelet analysis

Ridgelet analysis of radon transform is used in the first generation of Curvelet Transform. Ridgelet transform performance is very slow. Thus, the use of Ridgelet transform was eliminated and a new method to curvelet as tight frame is taken. Using tight frame, an individual curvelet has frequency support in a parabolic wedge area of the frequency domain [13] [14].

In an experimental argument, all curvelet fall into one of these three categories [8].

1) The magnitude of curvelet coefficient will be zero. Whose discontinuities will not intersect with the length wise support (**Figure 2(a)**).

2) A curvelet whose discontinuity intersects with length-wise support, but not at its critical angle. At this point magnitude of the curvelet coefficient is approximately equal to zero (**Figure 2(b)**).



(a) (b)

Figure 1. (a) Edge representation in wavelet; (b) curvelet.

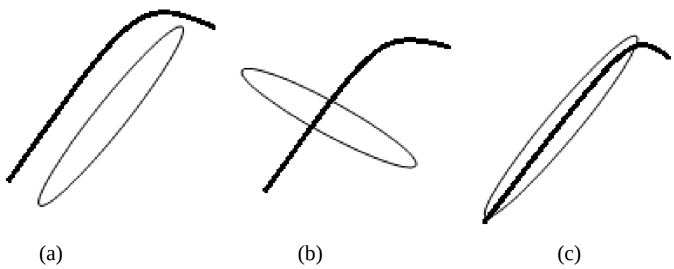


Figure 2. Curvelet types.

3) A curvelet whose length-wise support intersects with a discontinuity, at there the curvelet coefficient magnitude will be greater than zero. (Figure 2(c))

2.2. Fast Discrete Curvelet Transform

Second generation of Curvelet Transform (Fast Discrete Curvelet Transform) have the advantage of FFT (Fast Fourier transform). Using FFT, the image is represented in Fourier domain [13] [15]. In spatial domain, convolution of the Curvelet Transform becomes product in their Fourier domain. Curvelet coefficients are obtained by the application of inverse FFT to the spectral product after the end of entire computation process [16].

All the coefficients of the orientation and scale are in increasing order. The frequency response of the curvelet is a trapezoidal wedge. The digital curvelet tiling of space and frequency is shown in Figure 3. The wrapping of wedge is obtained using rectangular coefficients, which are collected from surrounding parallelograms. The process of wedge wrapping is called "wrapping based Curvelet Transform".

2.3. Wrapping Based Fast Discrete Curvelet Transform

In the Curvelet Transform theory, there are two methods to obtain the curvelet coefficients:

1) USFFT (Unequal Space Fast Fourier Transform) method,

2) Wrapping method.

In USFFT method, the coefficients are obtained by irregularly sampling of the Fourier samples of an image. In wrapping method, the coefficients are determined by a sequence of translation and the wrap around technique. Both these methods give same output, but the wrapping based method has better and faster computation time [13]. In this paper, curvelet based on wrapping technique is used.

The oversampled curvelet coefficients is defined by,

$$c^{D,O}(j,\ell,k)=\frac{1}{n^2}\sum_{n_1,n_2\in R_{j,\ell}}\hat{f}[n_1,n_2]\tilde{U}_{j,\ell}[n_1,n_2]e^{2\pi i\left(k_1n_1/R_{1,j}+k_2n_2/R_{2,j}\right)} \tag{1}$$

where, the superscripts "D" and "O" mention "Digital" and "oversampled".

$R_{j,l}$ is a rectangle of size $R_{1,j}\times R_{2,j}$ and containing the parallelogram $P_{j,l}$. If we assume that $R_{1,j}$ and $R_{2,j}$ divide the image of size n, then the coefficients $C_{D,O}(j,l,k)$ is obtained by the discrete convolution of a curvelet and the signal $f(t_1,t_2)$. Then the coefficients are down sampled regularly in the manner that one selects only one out of each $n/R_{1,j}\times n/R_{2,j}$ pixel. The dimensions $R_{1,j}$ and $R_{2,j}$ of the rectangle are large. In wrapping approach, $R_{1,j}$ and $R_{2,j}$ are replaced by $L_{1,j}$ and $L_{2,j}$, the original dimensions of the parallelogram $P_{j,l}$. By copying the data by wrap-around or periodicity, we can fit $P_{j,l}$ into a rectangle with the same dimensions. This is just like relabeling of the frequency samples of the form,

$$n_1'=n_1+m_1L_{1,j} \tag{2}$$

$$n_2'=n_2+m_2L_{2,j} \tag{3}$$

The two dimensional inverse FFT of the wrapped array is of the form,

$$c^{D}(j,\ell,k)=\frac{1}{n^2}\sum_{n_1=0}^{L_{1,j}-1}\sum_{n_2=0}^{L_{2,j}-1}W\left(\tilde{U}_{j,\ell},\hat{f}\right)[n_1,n_2]e^{2\pi i\left(k_1n_1/L_{1,j}+k_2n_2/L_{2,j}\right)}. \tag{4}$$

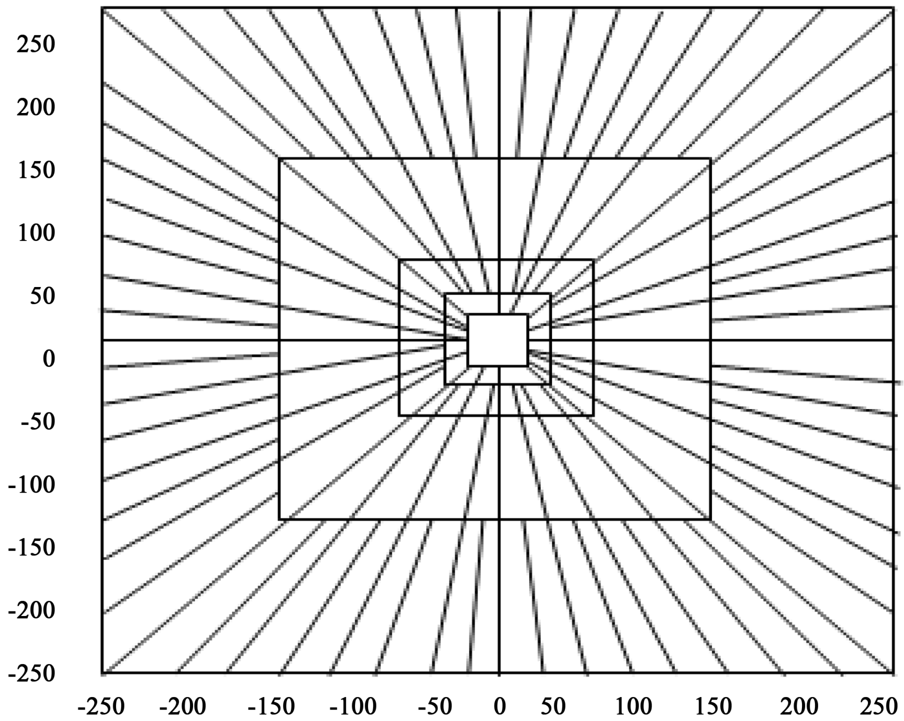


Figure 3. Digital curvelet tiling of space and frequency.

Note that the relabeling of wrapping does not affect the phase factors. Therefore, we can rewrite the above equation as

$$c^D(j,\ell,k)=\sum_{n_1=-n/2}^{n/2-1}\sum_{n_2=-n/2}^{n/2-1}\tilde{U}_{j,\ell}[n_1,n_2]\hat{f}[n_1,n_2]\mathrm{e}^{2\pi i\left(k_1n_1/L_{1,j}+k_2n_2/L_{2,j}\right)}. \tag{5}$$

Let consider the mother curvelet at scale "*j*" and angle "*l*" of the form,

$$\varphi_{j,\ell}^D(x)=\frac{1}{(2\pi)^2}\int \mathrm{e}^{i(x,w)}\tilde{U}_{j,\ell}(\omega)\mathrm{d}\omega. \tag{6}$$

And $\varphi_{j,\ell}^{\#}$ specifies its periodization over the unit square $[0, 1]^2$,

$$\varphi_{j,\ell}^{\#}(x_1,x_2)=\sum_{m_1\in Z}\sum_{m_2\in Z}\varphi_{j,\ell}^D(x_1+m_1,x_2+m_2). \tag{7}$$

The coefficients in the east and west quadrants are given by

$$c^D(j,\ell,k)=\frac{1}{n^2}\sum_{t_1=0}^{n-1}\sum_{t_2=0}^{n-1}f[t_1+t_2]\overline{\varphi}_{j,\ell}^{\#}\left(\frac{t_1}{n}-\frac{k_1}{L_1,j},\frac{t_2}{n}-\frac{k_2}{L_2,j}\right). \tag{8}$$

This is a discrete circular convolution if and only if $L_{1,j}$ and $L_{2,j}$ both divide n.

Steps for curvelet based on wrapping method

Step 1: Fast Fourier transform (FFT) is applied to input image.

Step 2: Curvelet is obtained at given orientation n and scale s.

Step 3: Divide the FFT into digitally small sets.

Step 4: Each set is translated to origin for every set.

Step 5: Wrap the parallelogram.

Step 6: Apply inverse FFT.

Steps for inverse curvelet based on wrapping method

Step 1: Inverse FFT of the array is obtained for each curvelet coefficient array.

Step 2: Inverse process is applied to unwrap the rectangular support to the original orientation shape.
Step 3: Original position is obtained by translating the shape.
Step 4: The whole curvelet array is stored.
Step 5: All the translated and stored curvelet array are added
Step 6: Reconstructed image is obtained by taking Inverse FFT.

3. Algorithmic Approach for Image Compression

Image compression algorithmic flow is given below.
Step 1: Image is read from the user.
Step 2: The three level decomposition is used here, discrete curvelet wrapping technique is used to obtain curvelet coefficients.
Step 3: The curvelet coefficient values are quantized so that the approximate values are obtained from this.
Step 4: After quantization process, thresholding is applied. The thresholding value is initially set. The coefficient value below the threshold is neglected and above is maintained.
Step 5: Curvelet coefficients above the threshold values are calculated.
Step 6: Apply arithmetic encoding technique to encode the coefficients.
Step 7: Inverse Curvelet Transform is achieved by applying Inverse wrapping based algorithm.
Step 8: Reconstructed image is obtained from the Inverse Curvelet Transform.
Step 9: Finally, the performance parameters are calculated.
Flowchart for the algorithmic approach is shown in **Figure 4**.

4. Vector Quantization and Arithmetic Coding

Since 1980, Vector Quantization (VQ) is a popular technique. In VQ, inputs are sampled into set of well-defined vectors by the use of some distortion measures. Multimedia images and many other formats of images are used

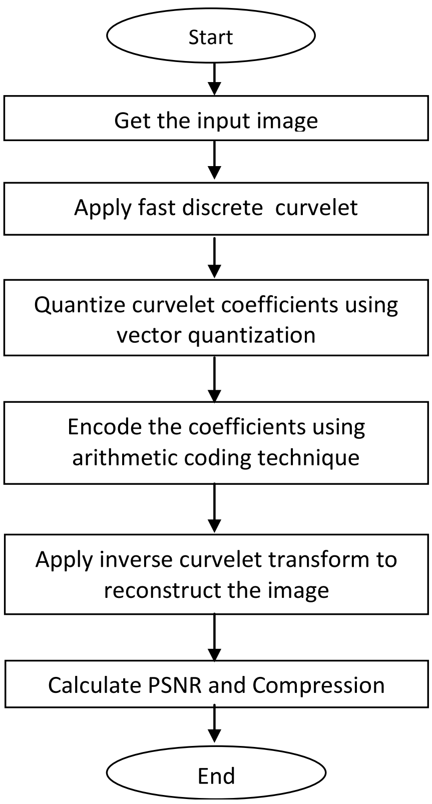


Figure 4. Algorithmic approach for image compression.

in varied applications these days. Storage of multimedia data needs bigger storage. So in order to reduce memory image compression plays a vital role. In quantization large set of inputs are mapped into small set of possible outcomes. Inputs are individual numbers in scalar quantization. Scalar quantization refers to the process of rounding off to the nearest value. The vector input is considered for vector quantization. In VQ, the modeling of probability density functions is done through allocation of prototype vectors. In this method, the large set of vectors is divided into a set which has almost the same number of points [17].

Varieties of techniques are employed for compression having complexities ranging at different degrees. The final step of any compression system is entropy encoding which represents data in a compact manner. This encoding process may complement the outputs for prior stages. Of all entropy encoding techniques, arithmetic coding is the most effective, versatile and an elegant process [18]. The relationship between the actual bits and coded symbols are known in arithmetic coding. Each symbol is assigned to a real-valued number which is coded one at a time [19]. The symbols are then coded in the interval (0,1). Real numbers with fractional digits is the compressed data's sequence with a code value "v" and equal to the sequence symbols. Codes are formed by padding zeros at the beginning of each coded sequence which interpret the result as a integer value with base-D notation. Here D is coded sequence alphabets number.

5. Performance Parameters

Peak Signal to Noise Ratio is a ratio of the highest signal power and the unwanted noise power. The real image is the signal and the error in re-establishment is the noise. The large Peak Signal to Noise Ratio is used for an enhanced compression. The PSNR is inversely proportional to compression ratio. In order to get actual compression, the PSNR and compression ratio should be balanced. The PSNR can be measured using following equation:

$$\text{PSNR}(\text{dB}) = \frac{20 \times \log_{10}(\text{Maximum pixel value})}{\sqrt{\text{MSE}}}. \quad (9)$$

Mean Square Error is the amount of difference among the real image and the compressed image. MSE is the collective square of difference among the compressed image and the real image. The Mean Square Error should be as low as possible in order to get smaller distortion and large output value. MSE can be measured using following equation:

$$\text{MSE} = \frac{\sum_i \sum_j \left(f(i,j) - F(i,j) \right)^2}{\text{MN}} \quad (10)$$

where,

$f(i,j)$ is the pixel in the input image,

$F(i,j)$ is the pixel in the reconstructed image,

$M \times N$ is the size of input image.

Compression ratio means the ratio of amount of bits needed to denote the real image to the amount of bits needed to denote the compressed image. If the compression ratio is high then the quality is negotiated. Compression methods with no loss of information will have smaller compression ratio than the lossy compression methods.

$$\text{CR} = \frac{\text{Original Image Size}}{\text{Compressed Image Size}}. \quad (11)$$

Peak Signal to Noise Ratio and Compression Ratio are the important parameters which are used to determine the quality of any compression algorithm.

Simulation results are shown in **Figures 5(a)-(g)**. We have calculated PSNR and Compression ratio for various medical images using proposed algorithm and it has been compared with wavelet and Discrete Cosine Transform results. PSNR and compression ratio values are calculated by using Equation (9) and Equation (11). Comparison of PSNR values obtained for various medical images by proposed algorithm with wavelet and DCT algorithms is shown in **Figure 6**. Comparison of compression ratio values obtained by proposed algorithm with wavelet and DCT algorithms is shown in **Figure 7**. Simulation result shows that the proposed method gives better performance in both PSNR and Compression Ratio. The comparison of performance parameters is tabulated in **Table 1**.

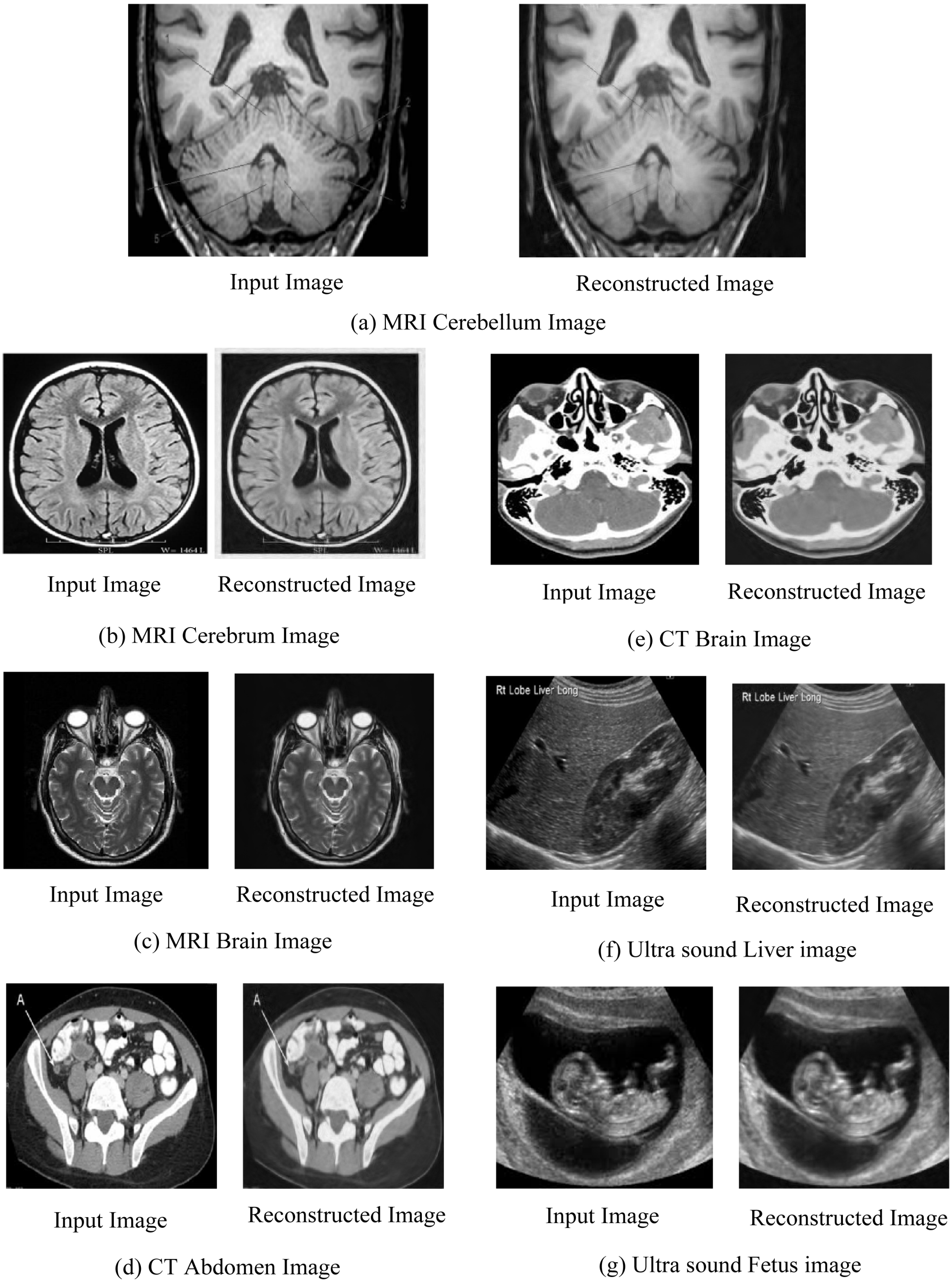


Figure 5. (a)-(g) Simulation results.

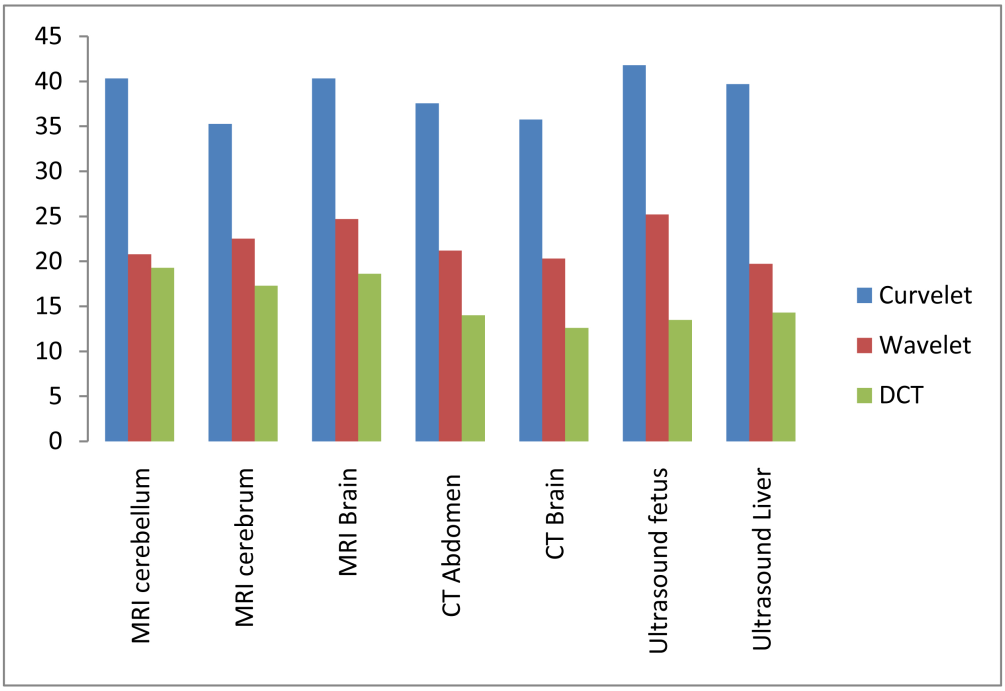


Figure 6. Comparison of PSNR values in dB.

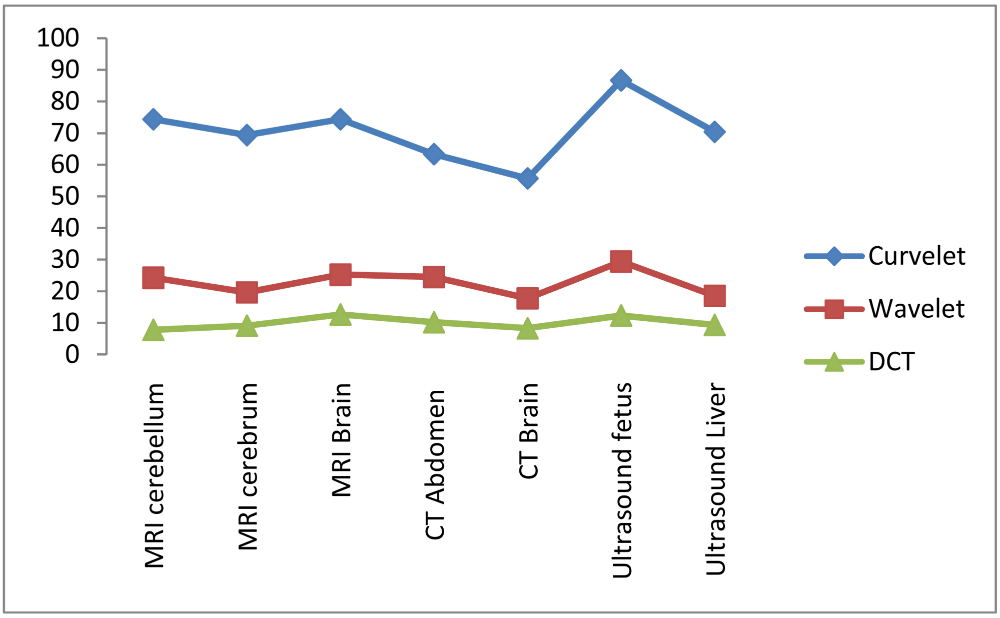


Figure 7. Comparison of compression ratio values.

6. Conclusion

In this paper, we have proposed a new method for image compression depending on wrapping based fast discrete Curvelet Transform. The coefficients are obtained using fast discrete Curvelet Transform. In proposed method, we have used vector quantization to quantize the coefficients. Arithmetic coding technique is used for encoding the quantized coefficients of fast discrete Curvelet Transform. The proposed scheme has been tested on various medical images and the result demonstrates significant improvement in PSNR and compression ratio. Our method can further be enhanced for compressing real time videos with some necessary modifications. This is our future work.

Table 1. Comparison of performance parameters.

Input Image	Technique	PSNR	CR
MRI cerebellum image	Proposed method	40.32	74.3
	DCT	19.28	7.8
	Wavelet	20.8	24.2
MRI cerebrum image	Proposed method	35.27	69.3
	DCT	17.3	9.12
	Wavelet	22.5	19.6
MRI brain image	Proposed method	40.32	74.3
	DCT	18.6	12.65
	Wavelet	24.7	25.2
CT abdomenimage	Proposed method	37.55	63.3
	DCT	14	10.2
	Wavelet	21.2	24.5
CT brain image	Proposed method	35.75	55.61
	DCT	12.6	8.3
	Wavelet	20.3	17.8
Ultrasound image of a fetus	Proposed method	41.80	86.63
	DCT	13.5	12.34
	Wavelet	25.2	29.3
Ultrasound liver image	Proposed method	39.7	70.32
	DCT	14.3	9.36
	Wavelet	19.7	12.34

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