Effectiveness of Contourlet vs Wavelet Transform on Medical Image Compression: a Comparative Study

Negar Riazifar, and Mehran Yazdi

***Abstract*—**Discrete Wavelet Transform (DWT) has demonstrated far superior to previous Discrete Cosine Transform (DCT) and standard JPEG in natural as well as medical image compression. Due to its localization properties both in special and transform domain, the quantization error introduced in DWT does not propagate globally as in DCT. Moreover, DWT is a global approach that avoids block artifacts as in the JPEG. However, recent reports on natural image compression have shown the superior performance of contourlet transform, a new extension to the wavelet transform in two dimensions using nonseparable and directional filter banks, compared to DWT. It is mostly due to the optimality of contourlet in representing the edges when they are smooth curves. In this work, we investigate this fact for medical images, especially for CT images, which has not been reported yet. To do that, we propose a compression scheme in transform domain and compare the performance of both DWT and contourlet transform in PSNR for different compression ratios (CR) using this scheme. The results obtained using different type of computed tomography images show that the DWT has still good performance at lower CR but contourlet transform performs better at higher CR.

***Keywords*—**Computed Tomography (CT), DWT, Discrete Contourlet Transform, Image Compression.

I. Introduction

IMAGE compression is essential for medical picture archiving and communication systems (PACS) as the need for efficient storage and transfer of medical data is dramatically increasing [1]. The aim of compression is to reduce bit rates for communication and to achieve lower data archiving while having an acceptable image quality. Different compression methods have been proposed for medical images earlier based on JPEG [2] and DCT [3]. However, the most successful achieving higher compression ratios have been obtained using DWT [4]. The 2-D discrete wavelet transform is a separable transform that is optimal at isolating the discontinuities at horizontal and vertical edges [5].

In two-dimensional DWT, a signal passes through low pass and high pass analysis filter banks followed by a decimation operation, along x-dimension and y-dimension separately. Finally, the image has been broken into four bands named LL,HL,LH and HH. This procedure can be continued and called payramidal decomposition of image (see Fig. 1).

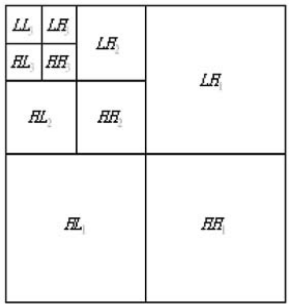


Fig. 1 Frequency bands after three-level DWT decomposition

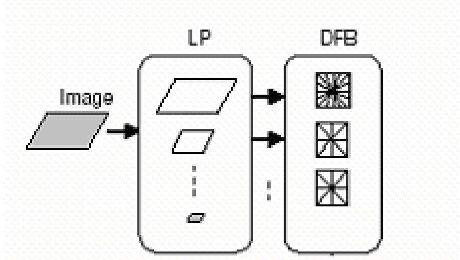


Fig. 2 A flow graph of the Contourlet Transform

Although the wavelet transform is powerful in representing images containing smooth areas separated with edges, it cannot perform well when the edges are smooth curves. New developments in directional transforms, known as contourlets in two dimensions, which have the property of capturing contours and fine details in images can address this issue [6].

The contourlet transform is one of the new geometrical image transforms, which represents images containing contours and textures. The contourlet transform has been introduced by Do and Vetterli [7], and has good approximation property for smooth 2D functions and finds a direct discrete-space construction and is therefore computationally efficient. It is a multiresolution and directional decomposition of a signal using a combination of Laplacian Pyramid (LP) and a Directional Filter Bank (DFB). The LP decomposes images into subbands and DFB analyzes each detail image. (see Fig. 2).

Manuscript received May 1, 2008.
N. Riazifar and M. Yazdi are with the Department of Electrical Engineering, School of Engineering, Shiraz University, Shiraz, Iran (e-mail: yazdi@shirazu.ac.ir).

II. Proposed Scheme

The proposed algorithm is summarized below.

a) Two-dimensional transform (either wavelet or contourlet) is applied to the test images in order to decorrelate the relationship between the pixels.
b) The coefficients of the transform are then quantized using different quantization levels for each subband. Namely, more levels are assigned to important subbands and scales.
c) The indices obtained by variable quantizer are then encoded using Huffman coding.

For the wavelet transform, we use two scale Daubechies 6-TAP wavelet filter. Daubechies is one of the families of wavelets which are called compactly supported orthonormal wavelets. Hereby, the important subbands are considered as a) LL2, b) LH2-HL2-HH2 and c) LH1-HL1-HH1 respectively. So three different quantization levels are used. For the quantizer, a simple uniform quantization is used.

For the contourlet transform, first a standard multi-scale decomposition into different bands is computed, where the lowpass channel is subsampled while highpass is not. Then, a directional decomposition with a DFB is applied to each highpass channel. The DFB is a critically sampled filter bank that can decompose images into any power of two's number of directions. So, one can decompose each scale into any arbitrary power of two's number of directions. Here, we use only two-scale decompositions where each image is decomposed into a lowpass subband and four bandpass directional subbands. For both pyramidal filter and directional filter the "pkva" filter was used. Hereby, two different quantization levels is used for subbands, namely, more levels for lowpass band and less levels for other subbands.

III. Experimental Results

In this study we used 9, 512x512x8 bit, tomography images of 3 patients extracted from their CT exam scanned using a Somatom Siemens spiral CT scanner. The test images were chosen from different parts of body such as head, abdomen and thorax. PSNR of image and PSNR of edges are used as two quality comparison criteria defined as:

$$\mathrm{PSNR} = 10\log\left(\frac{\mathrm{Max}^2}{\mathrm{MSE}}\right) \tag{1}$$

where,

$$\mathrm{MSE} = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}\left\| I(i,j) - I_q(i,j)\right\|^2 \tag{2}$$

Max is the maximum possible pixel value of the image. *I* is the *mxn* original image and I_q is the reconstructed image. To obtain the reconstructed image, first the encoded quantized coefficients are decoded using Huffman decoding. Then, corresponding inverse two-dimensional transform (either wavelet or contourlet) is applied.

Same equation has been used for PSNR of edges after applying an edge detector algorithm on images. Edge detection is performed using Canny algorithm to compare the quality of edges. The Canny method finds strong and weak edges by looking for the local maxima of the gradient of the input image. PSNR of edges is a good criterion in order to measure how well the edges are preserved after applying a compression method.

In order to compare the performance of wavelet and contourlet transform in our proposed compression scheme, we compute the compression ratios (CR) for various quantization levels. CR is defined as the ratio between the uncompressed size and the compressed size of an image. To compute the CR in fairly way, the original image is encoded using Huffman coding and resulting number of bites is saved. The number of bits for coded quantized coefficients is computed and saved. Moreover since we use different quantization levels for each subband, we add the number of bits needed for the generated codebooks in the Huffman table.

By varying the quantization levels in each subband, we can obtain different compression ratios and consequently different PSNRs. However, it is difficult to adjust the quantization levels to have exactly the same compression ratios for wavelet as well as contourlet. Transform. So we tied to compare two transforms for close compression ratios. Tables 1 to 9 gives the results of PSNR and PSNRedges for different compression ratios when using wavelet and contourlet transform for proposed compression scheme and the corresponding plots of only PSNR are shown in Fig. 3 to Fig. 11 respectively. It can be seen that the PSNR obtained by wavelet transform at lower compression ratios is nearly the same(sometimes better) as(than) that of contourlet transform. However at higher compression ratios, the performance of contourlet transform is superior than that of wavelet transform. Hence, a better image reconstruction is possible with less number of bits by using contourlet transform. The same conclusion can be extracted by comparing the PSNR of edges (we did not show the plots for the sake of space limitation).

It is important to note that although the contourlet transform produces more data related to original data, which is not the case for wavelet transform, the entropy of subbands in contourlet transform is much less than that of wavelet transform. Besides, the contourlet preserves better the edges than wavelet causing better PSNR. So, these two facts cause that the overall performance of contourlet transform is better for the compression of CT images. However, at lower compression ratios, effect of producing more data in contourlet transform is dominant which causes that wavelet and contourlet transform produce nearly the same results.

IV. Conclusion

In this paper, compression of CT images using wavelet and contourlet transform has been presented. We propose a compression scheme in transform domain to compare the performance of these two transforms. The results reveal the superior overall performance of contourlet against wavelet transform at higher compression ratios. However at lower compression ratios wavelet transform is still suitable approach.

TABLE I
PSNR AND PSNREDGES VALUES FOR TEST IMAGE 1

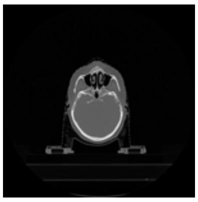
	Wavelet			Contourlet		
	Compression ratio	PSNR	PSNR of edges	Compression ratio	PSNR	PSNR of edges
	6.1243	32.6261	75.2235	4.3065	37.2811	72.5143
	13.0189	21.4238	72.3462	8.9096	27.8781	73.4626
	22.0213	16.2880	69.2164	18.9258	25.1716	74.0541
	48.5156	6.7201	67.0691	39.0566	13.3303	67.9587

TABLE II
PSNR AND PSNREDGES VALUES FOR TEST IMAGE 2

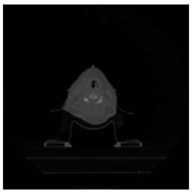
	Wavelet			Contourlet		
	Compression ratio	PSNR	PSNR of edges	Compression ratio	PSNR	PSNR of edges
	5.8363	36.7935	Inf.	4.3512	39.9681	Inf.
	10.75	27.3025	72.9009	9.2678	31.3417	75.2235
	19.3003	22.1477	75.2235	16.9017	24.9843	71.0438
	46.7840	13.3231	68.3975	36.7799	17.9739	67.0287

TABLE III
PSNR AND PSNREDGES VALUES FOR TEST IMAGE 3

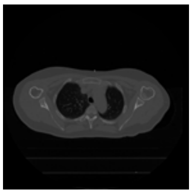
	Wavelet			Contourlet		
	Compression ratio	PSNR	PSNR of edges	Compression ratio	PSNR	PSNR of edge
	7.2288	35.4633	Inf.	4.4618	40.1195	Inf.
	12.5941	27.3690	74.0541	10.2211	32.5423	Inf.
	24.3428	17.9873	71.3006	18.9258	25.1716	74.0541
	58.3814	11.6139	68.8794	43.3270	21.1624	69.3653

TABLE IV
PSNR AND PSNREDGES VALUES FOR TEST IMAGE 4

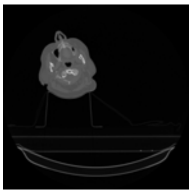
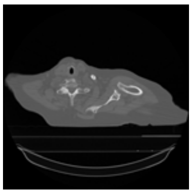
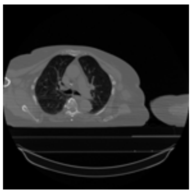
	Wavelet			Cntourlet		
	Compression ratio	PSNR	PSNR of edges	Compression ratio	PSNR	PSNR of edges
	6.4725	35.2435	71.8963	4.5630	39.0815	71.6427
	12.7725	26.6991	73.4626	9.4154	30.2058	73.1190
	21.6424	18.1411	72.9009	17.9625	24.6968	69.8906
	51.9417	13.2398	69.2680	38.7143	15.6743	69.5304

TABLE V
PSNR AND PSNREDGES VALUES FOR TEST IMAGE 5



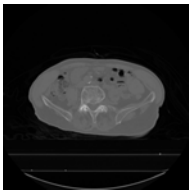
Wavelet			Contourlet		
Compression ratio	PSNR	PSNR of edges	Compression ratio	PSNR	PSNR of edges
5.8718	37.1589	75.2235	4.4076	38.6376	Inf.
12.5704	23.9359	75.2235	9.9202	31.1952	72.2132
26.4791	17.4705	72.2132	18.4233	24.4977	68.1220
59.0169	12.0160	66.6802	46.1192	19.67	68.1120

TABLE VI
PSNR AND PSNREDGES VALUES FOR TEST IMAGE 6



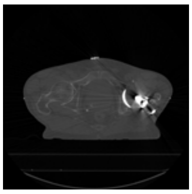
Wavelet			Contourlet		
Compression ratio	PSNR	PSNR of edges	Compression ratio	PSNR	PSNR of edges
3.6909	35.7264	Inf.	4.22	40.2382	75.2235
10.8523	25.2126	75.2235	10.6171	31.5717	72.3462
23.6238	20.1683	70.1646	22.8168	25.9903	75.2235
62.7949	15.3390	69.8207	50.6690	19.6027	68.1277

TABLE VII
PSNR AND PSNREDGES VALUES FOR TEST IMAGE 7



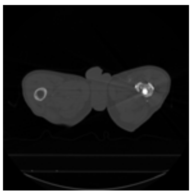
Wavelet			Contourlet		
Compression ratio	PSNR	PSNR of edges	Compression ratio	PSNR	PSNR of edges
7.5070	37.5287	75.2235	4.7263	40.0704	Inf.
14.4903	26.9520	75.2235	10.4427	33.0017	78.2338
26.2351	18.6392	73.4626	20.3179	26.4751	72.3462
63.3644	15.3893	70.2473	49.8467	20.9397	68.9448

TABLE VIII
PSNR AND PSNREDGES VALUES FOR TEST IMAGE 8



Wavelet			Contourlet		
Compression ratio	PSNR	PSNR of edges	Compression ratio	PSNR	PSNR of edges
7.9101	32.6483	72.2132	6.1362	33.7546	75.2235
16.2018	23.9714	73.4626	13.4083	27.0124	72.2132
27.8772	15.3591	70.4523	24.2230	20.2126	69.8003
59.1040	9.7909	66.6293	49.9189	15.2443	68.0398

TABLE IX
PSNR AND PSNREDGES VALUES FOR TEST IMAGE 9



Wavelet			Contourlet		
Compression ratio	PSNR	PSNR of edges	Compression ratio	PSNR	PSNR of edge
7.6111	34.2428	Inf.	5.4134	36.8087	75.2235
16.0450	27.5746	72.2132	11.8339	29.0453	Inf.
26.6816	17.7341	74.0541	20.4126	21.6535	75.2235
61.9478	8.3996	72.9009	48.7945	16.9596	71.6427

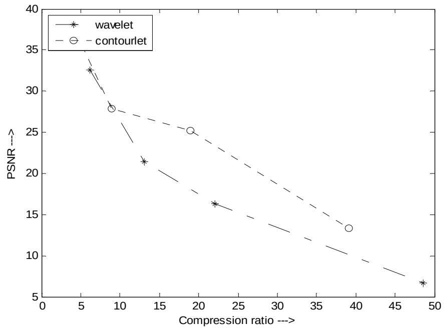


Fig. 3 Comparison of CR vs. PSNR between Wavelet and Contourlet transform for test image 1

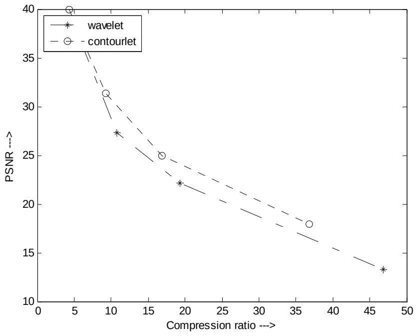


Fig. 4 Comparison of CR vs. PSNR between Wavelet and Contourlet transform for test image 2

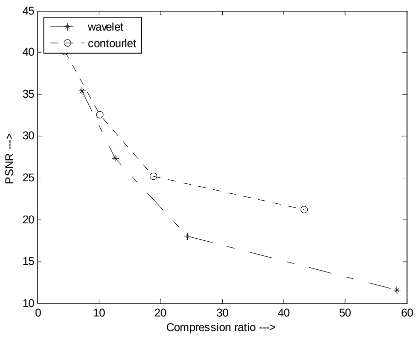


Fig. 5 Comparison of CR vs. PSNR between Wavelet and Contourlet transform for test image 3

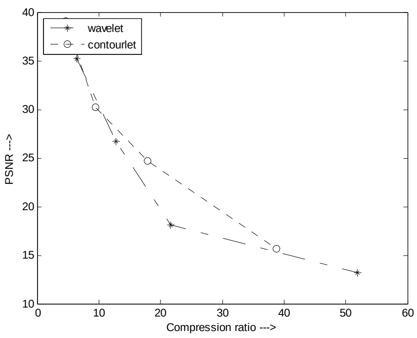


Fig. 6 Comparison of CR vs. PSNR between Wavelet and Contourlet transform for test image 4

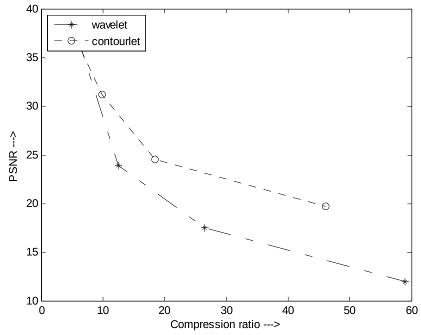


Fig. 7 Comparison of CR vs. PSNR between Wavelet and Contourlet transform for test image 5

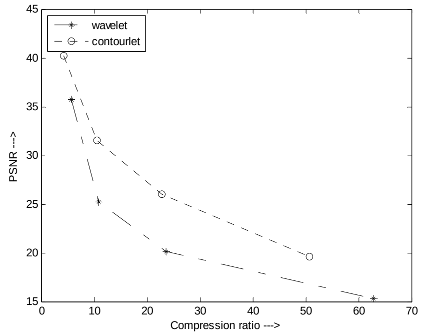


Fig. 8 Comparison of CR vs. PSNR between Wavelet and Contourlet transform for test image 6

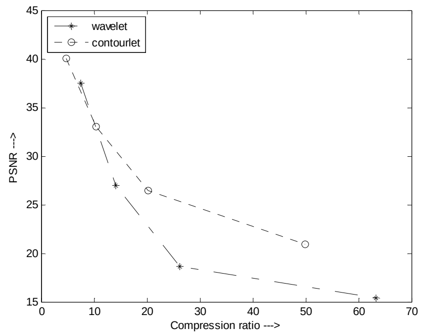


Fig. 9 Comparison of CR vs. PSNR between Wavelet and Contourlet transform for test image 7

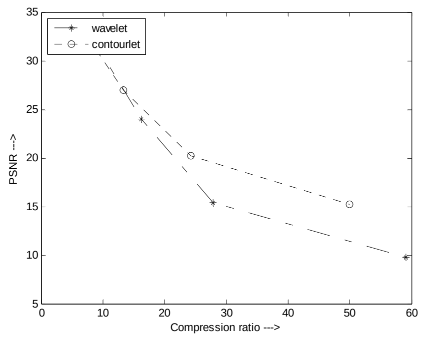


Fig. 10 Comparison of CR vs. PSNR between Wavelet and Contourlet transform for test image 8

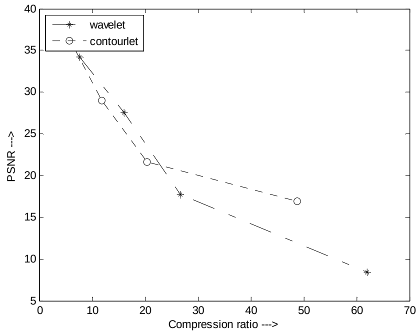


Fig. 11 Comparison of CR vs. PSNR between Wavelet and Contourlet transform for test image 9

REFERENCES

[1] A. Bruckmann, "Selective medical image compression techniques for telemedical and archiving applications", *Computers in Biology and Medicine*, Vol. 30, No. 3, pp. 153 – 169, 2003.

[2] Kim, Christopher Y., "Reevaluation of JPEG image compression to digitalized gastrointestinal endoscopic color images: a pilot study", *Proc. SPIE Medical Imaging*, Vol. 3658, pp. 420-426, 1999.

[3] Yung-Gi Wu, **"**Medical image compression by sampling DCT coefficients**",** *IEEE Transactions on Information Technology in Biomedicine* , Vol. 6, No. 1, pp. 86 – 94, 2002.

[4] Subhasis Saha, "Image Compression - from DCT to Wavelets: A Review" *Crossroads archive*, Vol. 6 , No. 3, pp. 12-21, 2000.

[5] V. Velisavljevic, P. L. Dragotti, M. Vetterli, "Directional Wavelet Transforms and Frames**",** *Proceedings of IEEE International Conference on Image Processing (ICIP2002)*, vol. 3, pp. 589-592, Rochester, USA, September 2002.

[6] S. Esakkirajan, T. Veerakumar, V.Senthil Murugan, R. Sudhakar, "Image compression using contourlet transform and multistage vector quantization", *GVIP Journal*, volume 6, Issue 1,pp.19-28, July 2006.

[7] M. N. Do, M. Vetterli, "The contourlet transform: An efficient directional multiresolution image representation", *IEEE Transactions on Image Processing*, no. 12, pp. 2091-2106, 2005.