Medical Image Compression using Curvelet Transform

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Abstract

Curvelets provide a new multiresolution representation with several features which set them apart from existing representations such as wavelets, multi-wavelets, steerable pyramids etc. This paper presents a comparative study of an adaptive image-coding algorithm with the existing methods like curvelet-SPIHT and wavelet-SPIHT. The objective results based on PSNR and CR is tested for different images are presented. Experimental results show that the adaptive image-coding algorithm attains high PSNR and significant compression ratio as compared with curvelet and wavelet transforms.

Keywords: *Adaptive image coding, Haar Wavelet Transform, Curvelet transform, Image compression, SPIHT*

1. Introduction

The most important type of information perceived, processed and interpreted by the human brain is visual information. One third of the cortical area of the human brain is dedicated to visual information processing. The major issue that arises in day to day life is the difficulty of transmitting large volume of data with relatively low bandwidth. Medical images are much important in the field of medicine. The trend in medical imaging is increasing toward direct digital image acquisition.

Image compression is a major concern in Internet, mobile communications, multimedia, teleconferencing and medical applications. Image compression aims at reducing the number of bits needed to represent an image by removing the spatial and spectral redundancies as much as possible. In this paper a comparative and experimental study is done on a modified curvelet transform with existing transforms. Here a modified curvelet transform with an SPIHT encoder is used for comparison.

2. Review of literature:

Compression is meant for storage and communication purposes. Even though there are many compression schemes which provide a very high compression rate but there is considerable loss of quality. Medical imaging which has a great impact on the diagnosis of diseases and surgical planning need long-term storage and efficient transmission.

Wavelet transform is able to efficiently represent a function with 1D singularities. Although the discrete wavelet transform (DWT) has established an excellent reputation for mathematical analysis and signal processing, the typical wavelet transform is unable to resolve two dimensional (2D) singularities along arbitrarily shaped curves. The curvelet transform has been very efficient for many different applications in image processing because it can resolve 2D singularities along smooth curves. It uses parabolic scaling law to achieve anisotropic directionality. The first D discrete Curvelet transform preserves the important properties, such as parabolic scaling, tightness and sparse representation for singularities of co-dimension one [1].It is evident that Curve functions are effective in representing functions that have discontinuities along straight lines [2]. Normal Wavelet transforms fail to represent such functions effectively. A multiresolution geometric analysis (MGA), named Curvelet transform [6], was proposed in order to overcome the drawbacks of conventional two-dimensional discrete wavelet transforms.

The introduction of wavelets gave a different dimension to the compression. But there are some limitations of wavelets while handling the line and curve singularities in the image [3]. Wavelet performs the least and is also affected by the blocking artifacts. Curvelet Transform gives the best performance for PSNR [3,4] and the subjective visual inspection shows that the Curvelet is the best for Compression when compared to wavelet [4].Curvelet Transforms are more suitable for the image data to represent the singularities over geometric structures in the image. Curvelet is designed to age data to represent handle the singularities on curves. Curvelet provides stable, efficient, and near-optimal representation of smooth objects having discontinuities along smooth curves [5]. Curvelet, a multiscale directional transform allows an almost optimal non adaptive sparse representation of objects with edges.

We can analyze an image with different block sizes, but with a single transform using curvelet transform [7]. This analyses imposes a relationship between the width and length of the important frame elements so that they are anisotropic and obey approximately the parabolic scaling law width ≈ length^2 [7,8]. Thus Curvelets are a multiscale system [10, 9] in which the elements are highly anisotropic at fine scales, with effective support shaped according to the parabolic scaling principle. An extension to the 2D transform was developed recently known as the 3D curvelet transform. This resulting curvelet frame preserves the important properties, such as parabolic scaling, tightness and sparse representation for singularities [11].

Over the past few years, a variety of sophisticated wavelet-based methods for image compression have been developed and implemented. Haar wavelet transform is a simplest wavelet transforms [12]. Compression with this wavelet transform is scalable as the transform process can be applied to an image as many times as wanted and hence very high compression ratios can be achieved [13]. . It bears various properties like orthogonality, linear phase, compact support, perfect reconstruction, high imperceptibility and Robustness [14,24].

Set partitioning in hierarchical trees (SPIHT), an efficient implementation of EZW [16] provides even better performance [15] than the other extensions of EZW. The main advantage of SPIHT is that it is fully progressive [17]. It provides significantly better quality and compression with spatial scalability [19]. In the recent years a 3D lossless SPIHT encoder was developed which produces up to 30-38% decrease in compressed file sizes compared to the best 2D lossless image compression algorithms [18]. SPIHT provides salient features such as better quality, visually superior and low computational effect when compared with other encoding algorithms such as JPEG, EBCOT, and BISK [20, 21, 22]. Thus SPIHT encoder provides features for simple and effective method for gray-scale image compression [23].

3. Background

3.1 Adaptive image-coding algorithm

3.1.1 Haar Transform :

The Haar transform was proposed in 1910 by a Hungarian mathematician Alfred Haar [**Error! Reference source not found.**. The haar transform (HT) is one of the simplest and basic trans-formations from a space domain are a local frequency domain. This method reduces the calculation work and it is compact, dyadic and orthonormal [26].HT decomposes each signal into two components, one is called average and other is known as difference. The first level of approximation $\boldsymbol{a}^1 = \left(a_1, a_2, \cdots, a_{N/2}\right)$ is defined as

$$a_m = \frac{x_{2m-1}+x_{2m}}{\sqrt{2}} \quad \text{-----(1)}$$

for $m = 1,2,3,\cdots,N/2$, where X is the input signal. The basic vectors of haar matrix bears various properties like orthogonality, linear phase, compact support, perfect reconstruction.

3.1.2 Modified Curvelet Transform:

Curvelet, a multiscale transformation is to represent a curve as a superposition of functions of various lengths and widths obeying the scaling law [7,8] 2 width » length. Curvelet transform works by first decomposing the image into subbands, i.e., separating the object into a series of disjoint scales and each scale is then analysed by means of a local ridgelet transform.

In the modified curvelet transform this decomposing is done with a haar wavelet where the image is decomposed into 2 parts: approximation and detail. These subbands are then analysed by ridgelet transform. Haar transform is the simplest of the wavelet transforms.Decomposing with haar wavelet transform is scalable and hence very high compression ratios can be achieved. The input image is decomposed using a modified curvelet transform which works in four steps: (1) Subband Decomposition using haar-wavelet (2) Smooth Partitioning (3) Renormalization (4) Ridgelet Analysis.

3.1.3 SPIHT Encoding :

Once the decomposition using modified curvelet is over the next phase is to code the coefficients into an efficient result. Even though there are many encoding algorithms for image compression one of the most efficient algorithms that provides salient features such as better quality, visually superior, fast coding and decoding, low computational effect and low-bit rate performance, is SPIHT algorithm .

The coefficients are further encoded using SPIHT algorithm which exploits the dependencies between the location and value of the coefficients across sub-bands. After the curvelet transform is applied to an image, the adaptive image coding works by partitioning the decomposed image into significant and insignificant partitions [25] based on the following function:

$$s_n(T) = \begin{cases} 1, \max |C_{i,j}| \geq 2^n \\ 0, otherwise \end{cases} \text{--------(2)}$$

Where, it is classified into three sets, namely the list of insignificant points (LIP), the list of significant points (LSP), and the list of insignificant sets (LIS) based on the threshold value. Here $S_n(T)$, is the significance of a set of co-ordinates , $C_{i,j}$ represents the combination of curvelet transformed coefficients and the coarsest coefficients at coordinates (i,j) .

The sub-band coefficients are then grouped into sets known as spatial-orientation trees, which efficiently exploit the correlation between the frequency bands. The coefficients in each spatial orientation tree are then progressively coded from the most significant bit-planes (MSB) to the least significant bit-planes (LSB), starting with the coefficients with the highest magnitude and at the lowest pyramid levels. This pyramid structure is commonly known as spatial orientation tree. The SPIHT algorithm sends the top coefficients in the pyramid structure using a progressive transmission scheme. This method allows obtaining a high quality version of the original image from the minimal amount of transmitted data.Fig.1 depicts the block diagram of adaptive image coding algorithm.

Algorithm for the adaptive image coding

Step-1 *Data*: Input image f(m,n) of size 256x256.

Step-2 *Apply curvelet transform*:

Sub-band Decomposition: The object f is decomposed into

$f \mapsto (P_0 f, \Delta_1 f, \Delta_2 f, \ldots)$ sub-bands.

Smooth Partitioning: Each sub-band is smoothly windowed into “squares” of an appropriate scale.

$$\Delta_s f \mapsto (w_Q \Delta_S f)_{Q \in Q_S}$$

Renormalization: Each resulting square is renormalized to unit scale.

$$g_Q = (T_Q)^{-1}(w_Q \Delta_S f), Q \in Q_S$$

Ridgelet Analysis: Each square is analyzed via the DRT.

Step-3 Apply SPIHT coding:

Step-4 Apply inverse SPIHT coding:

Decoding: An additional task done by decoder is to update the reconstructed image. For the value of n when a coordinate is moved to the LSP, it is known that

$$2^n \leq |C_{i,j}| < 2^{n+1}$$

So, the decoder uses that information, plus the sign bit that is input just after the insertion in theLSP, to set

$$C_{i,j} = \pm 1.5 * 2n$$

Similarly, during the refinement pass the decoder adds or subtracts 2n - 1 to $C_{i,j}$ when it inputs the bits of the binary representation of $|C_{i,j}|$.

step-5 Apply inverse curvelet transform :

*Ridgelet Synthesis:*Each ‘square’ is reconstructed from the orthonormal ridgelet system. Summation all the Ridgelet coefficinets with basis:

$$g_Q = \sum_\lambda \alpha_{(Q,\lambda)} \cdot \rho_\lambda$$

Renormalization: Each ’square’ resulting in the previous stage is renormalized to its own proper square.

$$h_Q = T_Q g_Q \quad , \quad Q \in Q_s$$

Smooth Integration: Then reverse the windowing dissection to each of the windows reconstructed in the previous stage of the algorithm.

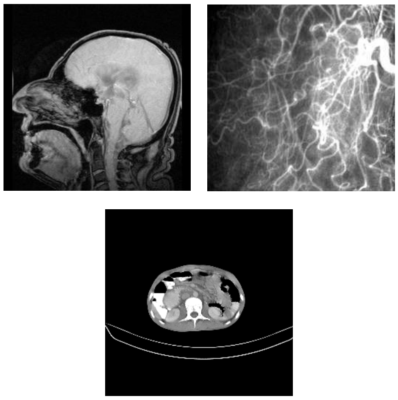
$$\Delta_s f = \sum_{Q \in \mathbf{Q}_s} w_Q \cdot h_Q$$

Subband Recomposition: Then undo the bank of subband filters, using the reproducing formula to summation all the sub-bands.

$$f = P_0(P_0 f) + \sum_s \Delta_s(\Delta_s f)$$

4. Performance evaluation and Results

The performances are evaluated for the different transforms using a set of 3 medical images of size (256X256). The quality of the compressed images has been attained using different metrics and the efficiency of the adaptive image coding is evaluated by comparing it with Curvelet SPIHT method and Haar SPIHT based compression method.



a) Head **b)Cerebral**
c)Pancreas

Fig. 2 Original Images

Peak Signal to Noise Ratio (PSNR), Mean Square Error (MSE), Bits per Pixel (BPP), Compression ratio(CR) and Computational time (CT) are used as different metrics. Table 1and 2 shows the performance comparison of MSE and CR for various techniques used in different images.

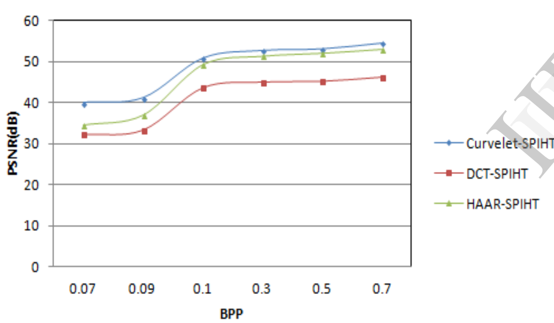


Fig. 3 Rate-PSNR performance of the head image using the adaptive image coding and existing techniques

Table 3- Table 5 shows the comparison results of rate Vs PSNR for different images respectively. Fig 3-5 plots these values respectively for the images. It is clear from the graphs that the PSNR value reaches maximum with high bpp.

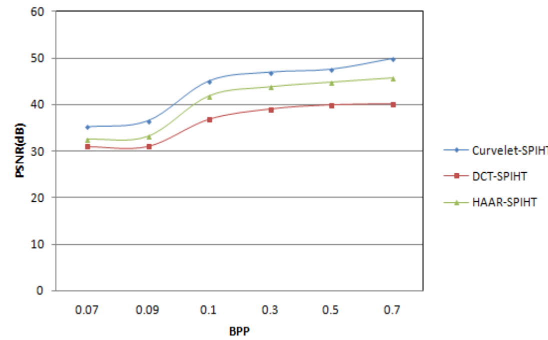


Fig. 4 Rate-PSNR performance of the cerebral image using the adaptive image coding and existing techniques

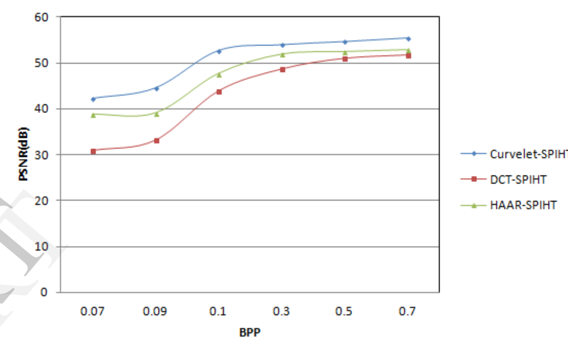


Fig. 5 Rate-PSNR performance of the pancreas image using the adaptive image coding and existing techniques

5 Conclusion

Thus a comparative study of an adaptive image coding with other coding techniques was experimentally analysed. From the experimental results it was clear that the optimal sparse representation of objects with edges was well defined and the resulting image is visually superior. Experimental results show that the adaptive image coding method achieves a significant improvement in high PSNR value and CR compared to other techniques. Since all the properties of the curvelet transform were found in the observed results it was clear that adaptive image coding can be well used in areas which specifies no quality loss and degradation of images.

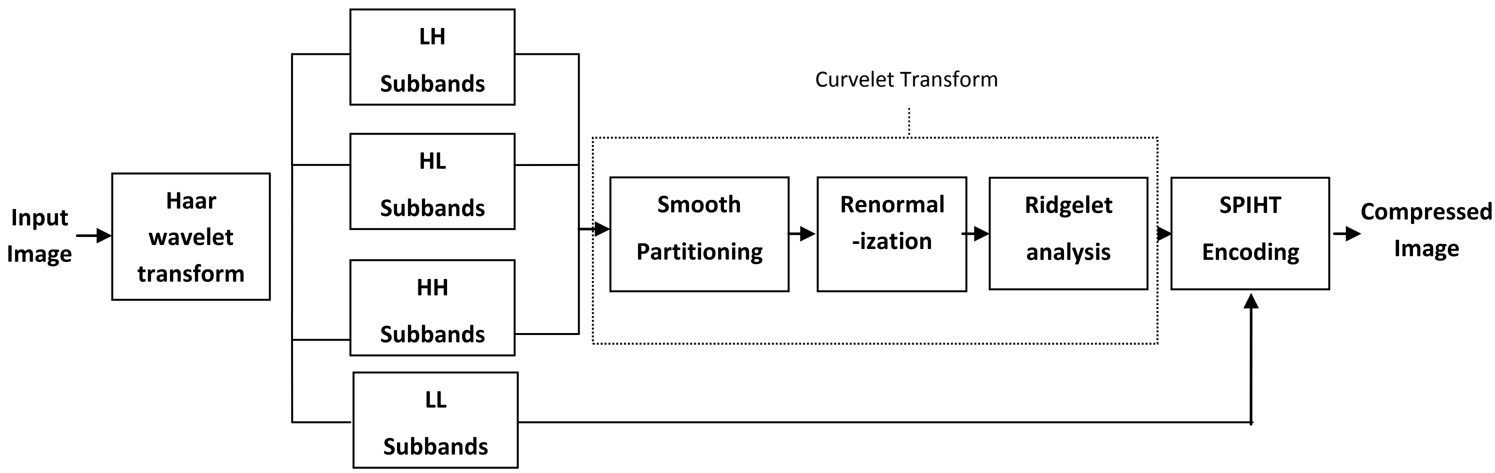


Fig. 1 The block diagram of the Adaptive image-coding algorithm

Table 1 Values of MSE using the adaptive image coding and existing techniques

Compression Methods	Pancreas	Cerebral	Head
Curvelet-SPIHT	2.59	3.5	1.16
Haar-SPIHT	2.37	3.98	1.77
Proposed	2.01	3.1	0.96

Table 1 Values of CR using the adaptive image coding and existing techniques

Compression Methods	Pancreas	Cerebral	Head
Curvelet-SPIHT	11.07	10.56	8.87
Haar-SPIHT	08.71	08.42	7.09
Proposed	13.11	14.82	12.02

Table 3 Values of rate vs PSNR for head image using the adaptive image coding and existing techniques

BPP Values	Curvelet-SPIHT	DCT-SPIHT	HAAR-SPIHT
0.07	39.98	32.11	34.45
0.09	41.14	33.24	36.9
0.1	50.98	43.53	49.26
0.3	52.87	44.9	51.34
0.5	53.27	45.12	52.05
0.7	54.69	46.11	53.01

Table 4 Values of rate vs PSNR for cerebral image using the adaptive image coding and existing techniques

BPP Values	Curvelet-SPIHT	DCT-SPIHT	HAAR-SPIHT
0.07	35.22	31.01	32.59
0.09	36.52	31.05	33.21
0.1	45.06	36.8	41.94
0.3	46.94	38.98	43.89
0.5	47.56	39.89	44.9
0.7	49.84	40.09	45.81

Table 5 Values of rate vs PSNR for pancreas image using the adaptive image coding and existing techniques

BPP Values	Curvelet-SPIHT	DCT-SPIHT	HAAR-SPIHT
0.07	42.17	30.87	38.78
0.09	44.46	33.11	39.08
0.1	52.62	43.84	47.76
0.3	53.88	48.62	52
0.5	54.55	50.96	52.56
0.7	55.34	51.69	52.98

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