# A Fast Fractal-Curvelet Image Coder

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## ABSTRACT
The good image quality and compression ratio of a Fractal image is degraded due to prolonging encoding time. This proposed paper presents a fast and efficient image coder used that Curvelet Transform to the image quality of the fractal compression. For achieving the fast fractal encoding using Partitioned Iterations Functions (PIFs) is applied to the coarse scale (low pass subband) of Curvelet transformed image and a modified set partitioning in hierarchical trees (SPIHT) coding, on the remaining part of coefficients. The image details and Curvelet progressive transmission characteristics are maintained and the common encoding fidelity problem in fractal-Curvelet hybrid coders is solved. In this proposed scheme encoding and decoding time reduction is about 90%. The simulations compare with the results to the SPIHT wavelet coding.

## General Terms
Fractal compression, Compression ratio, Mean square error, Peak signal to noise ratio

## Keywords
Encoding/decoding time, fractals, wrapping FDCT (Fast Discrete curvelet Transform), Wavelet transforms.

## 1. INTRODUCTION
The main objective of image compression is reduction of image size for transmission or storage, while maintaining the quality in reconstruction image. Among all the technical aspects transform coding is the efficient at low bit rate.

The image redundancies can be explored effectively by the way FIC on the basis of self affine transformations. In 1985 fractal image compression was introduced by Barnsley Demko [1] and Jacquin [2, 3] experimented successfully the scheme at 1992. Due to the exhaustive search strategy the encoding speed is very low is a commendable work.

The image blocks constructed according to the variance and intensity by Fisher's in 72 classes of image blocks is called fishers classification method [4, 5]. Since the search space is divided into 72 smaller classes and the encoding speed can be improved. The speedup ratio improved from 1.6 to 5 by Wang et al. [6], four types of range blocks were defined based on the edge property of the image. Truong et al [7] Discrete Cosine Transform (DCT) inner product based algorithm, which is reduced the calculation time so the speed is improved. Davis [8], [9], [10] has presented an approach of both fractal and wavelet image compression.

Li and Kuo [11] use the fractal contractive mapping to predict interscales wavelet coefficients and then encode the prediction residue with a bit plane wavelet coder

There is a SPIHT coding is applied due to the drawback of fine scale coefficients (high pass) has not enough information. The proposed SPIHT is enhancing the quality of image [12].

In this paper, we present a Fractal-Curvelet image coder that applies the speed of the Curvelet transform to the image quality of the fractal compression [13]. In some region of image traditional fractal encoder does not work, unable to achieve sufficient encoding time for the critical information in the low pass region of Curvelet coefficients.

In the wavelet transform there is an inability to represent edge discontinuities along the curves. Due to the large or several coefficients are used to reconstruct edges properly along the curves. For this reason, it needs a transform to handle the two dimensional singularities along the sparsely curve. This is the reason behind the birth of Curvelet transform. Here the Curvlet basis elements have wavelet basis [14].The edge discontinuities and other singularities well than wavelet transform.

In order to solve the problem of without losing the visual quality of the image with expensive fractal encoding time, this work involves as a hybrid coder. This paper present fast, and efficient image coder that applies the speed of the Curvelet transform to the image quality of the fractal compression.

The outline of rest of the paper is organized as follows. Section II discuss the theory of Curvelet Transform section III discuss the SPIHT coding Section IV discuss the proposed fractal image compression and section V discus the result analysis and comparisons with wavelet coder.

## 2. CURVELET TRANSFORM
One of the multiscale geometric transforms and a special member is Curvelet transform. It is a transform with multiscale pyramid with many directions at each length scale is called the decomposition of Curvelet transform. Curvelets will be superior over wavelets in following cases:

1. This transform is optimally sparse representation of objects with edges

2. This transform is optimal image reconstruction in severely ill-posed problems

3. This transform is optimal sparse representation of wave propagators.

In this paper 3k level decomposition taken by the way of frequency wrapping Fast Discrete Curvelet Transform (FDCT) for the image to provides at different levels or scales for their respective coefficients. In specified decomposition level contains simple array of coefficients and this levels gives the information about wedges. After this only concentrate on significant information and removes the insignificant (high level details) by the way of scale or level thresholding. The first and last level of thresholding levels of information not having in wedges.

For simplifying the work of thersholding and quantization steps at these levels. These procedural steps as follows

***Subband Decomposition:*** IT divide image *Im* into several resolution layers and each layer contains details oIm diImferent frequencies

$$Im \rightarrow (P0\, Im, \Delta 1\, Im, \Delta 2\, Im, \ldots) \quad (1)$$

from the above equation (1) $\Delta s$ and $P0$ (where $s \geq 0$) are high pass and low pass filters respectively and the wavelet base is smooth and efficiently represented as *P0 Im* is the smooth low-pass layer. The high pass layer discontinuity represented by $\Delta s\, Im$. Finally, $\Delta s\, Im$ layer having high frequency with fine details

***Square(or) Smooth Partitioning:*** It represent $\Delta s\, Im$ high-pass layers, split the layers into small partitions by defining by the dyadic square like smooth windows *WsQ(x1, x2)* localized.

This will gives nonnegative smooth function and creates ridges of width = $2^{-2s}$ and length $=2^{-s}$. Multiplication of $\Delta s\, Im$ with *WsQ* produces a smooth dissection into squares (*hQ*). The mathematical equation (2) form is as follows:

$$h_{Q} = Ws_{Q} \,.\, \Delta_{s} Im S \quad (2)$$

***Squares Renormalization:*** All the squares renormalized from the previous squares.

***Square Ridgelet Analysis*:** The curvelet transform coefficient can be finding from the normalized square analyse by the way of Ridgelet Transform

## 2.1 SPIHT (Set Partitioning in Hierarchical Trees)

A modified version of traditional embedded zerotree wavelet (EZW) coder was presented by Said and Pearlman [15],. SPIHT as probably used curvelet-based algorithm for image compression, providing a standard of comparison algorithms because of SPIHT and wavlet based compression already used well in image processing.

In this tree partitioning that maintains the insignificant wavelet coefficientsof four larger subsets grouped as (lists to be processed) list of insignificant pixels(LIP), list of insignificant sets (LIS), and list of significant pixels (LSP).

The SPIHT algorithm sends the binary representation of the integer value of Curvelet coefficients (bit-plane coder) . Rao and Yip [16] also present simulations that show the superiority of SPIHT coding over the traditional JPEG

During step of initialization, initial value for threshold is determined and initializes with a set containing all the coefficients in lowest subband (LIP). Moreover, initially empty list set in LSP and LIS contains the coordinates of roots of all trees that are of ¾ of lowest subband. In this paper SPIHT is modified with LIP initialization to be inserted in the hybrid coder. The LSP and LIS lists have not been modified, LSP is originally empty due to the approximation subband and offspring of LIS.

The approximation subband coefficients values have been not included in order to achieve a better detail subband encoding.

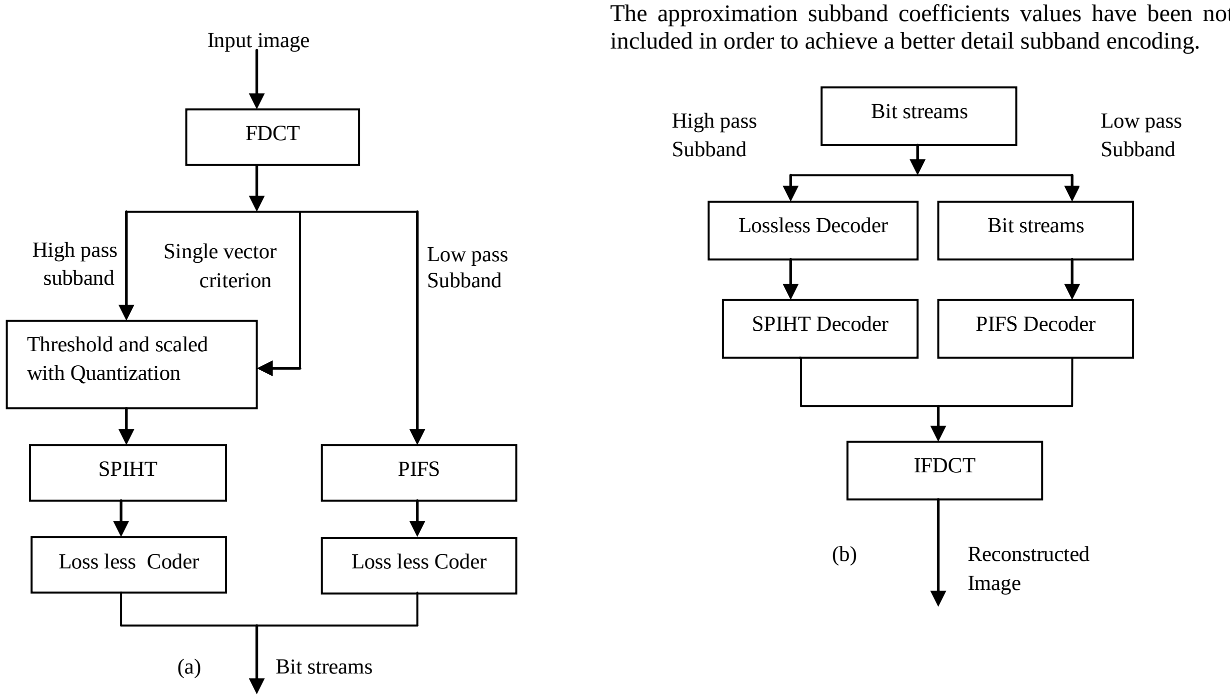



**Fig 1: (a). Fractal-curvelet encoder**
**(b) Fractal-curvelet decoder**

## 3. PROPOPSED FRACTAL IMAGE CODER

In the proposed hybrid coder, fast fractal encoding (QPIFS) using Fisher's accelerator is applied in the approximation subband, and the detail subbands using modified SPIHT coding is applied to curvelet transformed image.

In this proposed method of block diagram represents the fractal curvelet encoder and decoder is in fig 1. In this Fig 1(a) and Fig 1(b) are represented as Frcatal-Curvelet encoder and decoder respectively Finaly, The coding is used as a compression scheme at various bit rate by the application of SPIHT using and it exploits multiresoultion-scaling of curvelet transform as with wavelet transform.it uses maximum bit to be assigned for low-level detail and vice versa, to get high PSNR.

## 4. EXPERIMENTAL RESULTS

The grayscale standard test images (i.e. Boat, CT-MONO2-8-abdoman, Barbara, Hill and Peppers) of size 512 x 512 have been taken from World Wide Web for experiments. Here the MATLAB 7.0 has been used for the implementation of proposed approach and resultshave been conductedon Pentium-IV, 3.20 GHz processor with a memory of 512 MB.

Different quality metrics i.e. Compression Ratio (CR), bitrates and Peak Signal to Noise Ratio (PSNR) are evaluated to compile compression results. For example purpose in this paper Boat and CT-MONO2-8-abdoman image had produce

The fractal-curvelet coder results have been compared to fractal wavelet coder traditional techniques mentioned in the previous sections. The first one, the pure full search fractal coding used PIFs, the second one, the pure SPIHT with curvelet coding, will be referred as "SPIHT".

**Table 1 . Comparision for wavelet anc curvelet encoding and decoing time with the PSNR of CT-MONO-8-abdomen, boat and Lena images**

| Image | Transform Method | Bit rate | Compression Ratio | Time (s) | | PSNR(db) |
|---|---|---|---|---|---|---|
| | | | | Encoding | Decoding | |
| CT-MONO2-8-abdo | Wavelet | 0.25 | 35.01 | 9.966671 | 5.211113 | 21.72 |
| | Curvelet | | 29.80 | 7.627111 | 9.133342 | 28.25 |
| | Wavelet | 0.50 | 15. 31 | 24.99916 | 13.12351 | 31.43 |
| | Curvelet | | 13.85 | 19.06665 | 21.55521 | 32.58 |
| | Wavelet | 0.80 | 11. 31 | 44.99916 | 26.94432 | 34.43 |
| | Curvelet | | 10.85 | 36.22344 | 40.99453 | 36.23 |
| Boat | Wavelet | 0.25 | 35.01 | 10.34452 | 7.443435 | 27.69 |
| | Curvelet | | 29.80 | 8.003342 | 9.999931 | 30.12 |
| | Wavelet | 0.50 | 15. 31 | 24.88536 | 17.45376 | 31.45 |
| | Curvelet | | 13.85 | 19.42325 | 23.29845 | 36.00 |
| | Wavelet | 0.80 | 11. 31 | 44.79814 | 27.17284 | 36.45 |
| | Curvelet | | 10.85 | 34.56211 | 37.77823 | 41.54 |
| Lena | Wavelet | 0.25 | 35.01 | 9.334421 | 6.543335 | 30.51 |
| | Curvelet | | 29.80 | 7.073352 | 8.989898 | 32.45 |
| | Wavelet | 0.50 | 15. 31 | 23.83533 | 16.46366 | 36.76 |
| | Curvelet | | 13.85 | 18.42885 | 22.22825 | 39.66 |
| | Wavelet | 0.80 | 11. 31 | 43.39313 | 26.67686 | 41.45 |
| | Curvelet | | 10.85 | 33.36313 | 36.67626 | 45.76 |

This section presents the comparisons between these methods in terms of coding time, subjective quality, PSNR, and bitrate for Boat as Fig 2, CT-MONO2-8-abdoman as Fig 3 image and Lena as Fig 5.

The SPIHT simulations were performed on a 3 K level decomposition using the wrapping FDCT. For FIC the scaling (*p*) and offset (*q*) parameters are quantized at 5 and 7 bits respectively and so on.

Fig. 2, Fig 3 and Fig 5 shows the original Boat, CT-MONO2-8-abdoman and Lena images are 512 x 512 at 8 bpp, with the decoded Boat, Lena and CT-MONO2-8-abdoman image for full search FIC, SPIHT are applied at 0.25,0.5 and 0.80 bit rates.

The proposed Fractal-Curvelet coder exhibits in Table I shows the comparisons of above methods using the parameters encoding time and PSNR at different compression ratios are shown. The graphical representation of Fractal-Curvelet with

Fractal–Wavelet is shown in fig 4 and shows the Fractal-Curvelet is better than fractal wavelet at lower bitrates

Original image Boat

Reconstructed image
with wavelet

PSNR for bit rate
is = 27.69

Reconstructed image
with curvelet

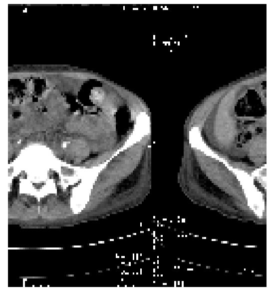
PSNR for bit rate 0.50
is = 36.00

Reconstructed image
with curvelet

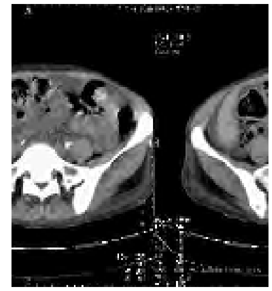
PSNR for bit rate 0.80
is = 41.54

**Fig 2 Fractal -Wavelet & Fractal -Curvelet Transfomed Boat image for various bit rate**

Original image
CT-MONO2-8-abdo

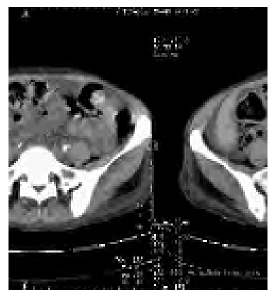


Reconstructed image
with wavelet



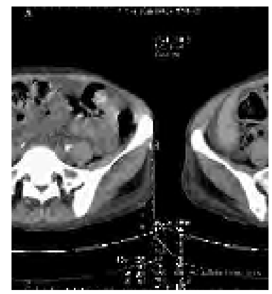
PSNR for bit rate 0.25
is = 21.72

Reconstructed image with
curvelet



PSNR for bit rate 0.50
is = 28.23

Reconstructed image with
curvelet



PSNR for bit rate 0.80
is = 32.58

**Fig 3: Fractal -Wavelet & Fractal -Curvelet Transfomed CT-MONO2-8-abdoman image for various bit rate**

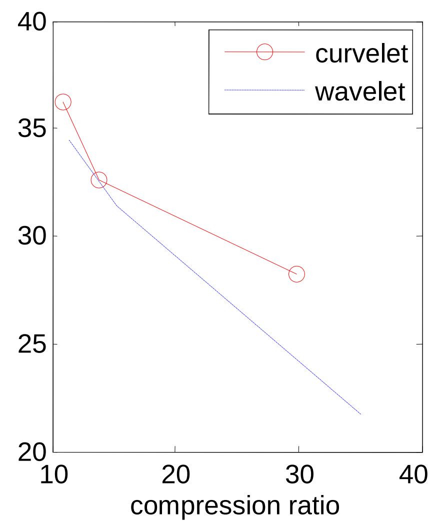



**Fig 4: Comparision of wavelet and proposed algorithms Compression ratio with PSNR**


**Fig 5: Fractal -Wavelet & fractal -Curvelet Transfomed Lena image for various bit rate**

## 5. CONCLUSION

In case of Fractal-Wavelet the most significant subband is retained, but its performance is poor and has annoying blocking artifacts when the numbers of retained coefficients is low. This shows that the Curvelet Transforms is more suitable for the image data to represent the singularities over geometric structures in the image, than the Wavelet counterpart.

From the comparision result the better performance for PSNR is obtained from the Fractal-Curvelet coder as compared with the Fractal –Wavelet coder. It is about 10% to 20% improvement in PSNR had arrived from the above algorithm.

This can again further improved with other compression coding techniques.

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