# Adaptive Dynamic Image Compression for Transmission

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**Abstract:** Nowadays video communication is still a challenge for multimedia communication. They are mainly three important exigencies that are strongly been demanded in multimedia communication: the efficient compression of the video stream (good resilience) to minimize the memory occupation; the progressiveness, which is requested by the tremendous market of the world wide web, and resolution independence, which is a key requirement for desktop publishing. In this paper, to satisfy these three requirements, a dynamic compression method is proposed. The new approach is based on traditional Discrete Cosine transformation (DCT), fractal, and Wavelet Trellis-Code Quantization (TCQ) method. The high compression and the resolution independency are assured using Hybrid Fractal-Wavelet method, and the TCQ the progressiveness in transmission, by quantize the residual error in the encoding. The efficiency of our method has been proved comparing to the common Fractal-Wavelet method.

**Keywords:** Discrete Cosine Transform (DCT) Fractal, wavelet theory, Trellis-Code Quantization, Video compression.

## 1 Introduction

Let introduce the fundamental approach of wavelet and fractal theory. The idea behind single scalar wavelet image compression theory [1, 2, 3], like other transform compression techniques, is fairly simple. It consists by applying the wavelet transform to an image and then removes some of the coefficient data from the transformed image. The encoding process may be applied to the remaining coefficients. The compressed image is reconstructed by decoding the coefficients.

The motivation for fractal image compression is that images contain not only the spatial redundancy [3, 4] incorporated into the transform coder, but also redundancy in the scale [ 5]. Fractal compression takes advantage of this redundancy in scale by using coarse scale image features to quantize fine-scale features without using the Karhumen-loeve transform . The codebook consists of larger blocks from the image, which are locally averaged and sub-sampled. Which is effective for coding constant regions and straight edges due to the scale invariance of these features. Fractal encoding algorithm entail the construction of a map from the plane top itself of which the unique fixed point is an approximation to the image to be coded. Compressed images are stored by saving the parameters of this map and recovered by iteratively applying the map to find its fixed point. There are fundamental connections between the two approaches. [3, 6, 7] Fractal methods use self-similarity across different scales to reduce stored information. Wavelet methods exploit redundancies in scale to reduce information stored in the wavelet transform domain.

The Discrete Cosine Transform [8] is widely used in image coding because of its near optimum ability to decorrelate signals with Gauss-Markov-1 statistics. Many existing DCT based systems are simply enhancements of the basic JPEG system using more appropriate quantization schemes [ 9,10] or adaptive segmentation strategies.

A fundamental problem for the multi-dimensional wavelet transforms rise the question on how to iterate the decomposition scheme; that is which of the 4 subbands (LL, HL, HH, LH.) should be used as the input for the next level of wavelet decomposition. The traditional approach is to choose the "LL" cases resemble of the original image in a sub-sampled version. This decomposition scheme is called "pyramid decomposition" since it results in sub-bands geometrically decreasing in size, all embedded on the original image.

The problem of fractal-wavelet encoding is the domain-range matching process [4, 7]. Thus, the lack of sufficient encoding fidelity to the upper left corner of the wavelet transform array, and the repartition of the range block coefficients in wavelet domain still stay a big problem for decode process the speed of the compression is slow. We tackle this problem by using an Adaptive Wavelet Transform only on the range who distance error with the match domain block is more then the optimal distance error. To assure an efficient using in Internet application; we substitute to the hybrid Fractal-Wavelet, the Trellis Code Quantization.

## 2. Mathematics of Fractal-Wavelet compression theory

### 2.1. Introduction

In all the paper, the operators we used preserve the subtrees, and the basic steps in fractal coding have simple wavelet analogs. So the wavelet analog of an image block, set of pixels associated with a small region in space, is a wavelet subtree together with its associated scaling function coefficient. Thus, the extraction of a domain block, by the operator, will correspond to the extraction of the subtree by the operator, plus the extraction of the scaling function coefficient. The coefficients are then rearranged into a sub-band structure which outwardly resembles a wavelet transformed image, with the number of sub-bands being related to the size of DCT used. The zerotee coding algorithm is then employed to quantize the coefficients.

To localize the cosine bases, the image is normally partitioned into a number of smaller blocks and the DCT applied individually to these. Where the difference is insignificant, we used the smallest block size in order to reduce ringing effects Results show that the DCT remains a competitive compression technology when used with good quantization strategies, so that full advantage can be taken of the significant investment that has occurred in fast DCT algorithms and hardware.

### 2.2 Contractivity in fractal space Domain

The general procedure in standard fractal coding can be described as follows: An input image I is partitioned into a set of non-overlapping range blocks $\{r_i, i = 1,\dots,n_R\}$ of size M×M, and domain block $\{d_j, j = 1,\dots,n_D\}$ of size 2M×2M. Where $d_k$ , $r_k$ are, respectively the domain block and range block averaged pixels. For a given range block $r_i$ , the best approximation of the tuple $(s_k, o_m, r_j, \tau_p)$ yields a local collage error

$$d(r_i, s_k, o_m, d_j, \tau_p) = \left\| r_i - \left(s_k S^{(n+1)} \tau_p d_j + o_m 1\right)\right\|_2^2 \qquad (1)$$

where $\tau_p, p = 1,\cdots,8$ , is the isometrics; $s_k, k = 1,\cdots,n_R$ ,is the contrast scaling and $o_m, m = 1,\cdots,n_R$ the offset. $S^{(n+1)} : R^{2^{2(n+1)}} \rightarrow R^{2^{2n}}$ is a down-sampling operator, which via pixel averaging shrinks a block to match the range block size. $n_R, n_D$ respectively the number of range and domain block.

To compute $s$ , $o$ , we use the following formulas:

$$s = \frac{\sum_{\substack{1\le i\le n \\ 1\le j\le n}} \left(r_{i,j} - \bar{r}\right)\left(d_{i,j} - \bar{d}\right)}{\sum_{\substack{1\le i\le n \\ 1\le j\le n}} \left(d_{i,j} - \bar{d}\right)^2} \qquad o = \bar{r} - s\,\bar{d}$$

(2)

where $\bar{r} = \sum_{\substack{1\le i\le n \\ 1\le j\le n}} r_{i,j} / n^2$ and $\bar{d} = \sum_{\substack{1\le i\le n \\ 1\le j\le n}} d_{i,j} / n^2$ are the average intensities in r and d respectively.

The result of applying this mapping is an approximation to the $j^{th}$ range block, $\hat{r}_j$ which we write as follows

$$\hat{r}_j = \tau_j(d_k) \approx \alpha_j l_{I(j)}\left(S\left(d_{N(j)}\right)\right) + o_j \qquad (3)$$

Where $N(j)$ is a domain block selection function, which associates the $j^{th}$ range block with a domain block from $\{d_j\}$.

And $I(j)$ is an isometry selection function, which maps the $j^{th}$ range block to one of a set of possible isometry operations. And $l_k(\bullet)$, is the domain block pixels shuffling (isometry), and $S(\bullet)$ the contraction operator. For each range block $r_j$ , it requires a high computational complexity to search the best matching domain block. To reduce the complexity, it is possible to search within a subset $d_j$ of the entire domain pool for locality control and/or classified block matching. Once the range-domain match pair $\hat{r}_j = \tau_j(d_k)$ is determined, fractal decoding can be carried out iteratively. This method fail to the rate-distortion, so the quality of decode image is improved. Exploiting the similarity of the fractal and wavelet, we used the Adaptive Wavelet Transform to some range blocks whose do not fulfill the formula (3).

**2.3. Contractivity in the Wavelet Domain**

The chain of spatial contractive [5, 7, 11] mapping operations, characteristic of fractal theory can be extended to wavelet theory. The averaging and subsampling operation $S(\bullet)$ is equivalent to moving up the domain block by one scale in the wavelet domain. The isometrical transformation $\tau_j$ corresponds to a pixel shuffling operation, which may involve additional sign changes and inter-subband coefficient exchanges. The contrast factor $\alpha_j$ is reduced in half because of the normalization process in the wavelet transform, and the offset $o_j$ is related only to the difference between the dc components of the range [7, 9].

Each subband is split into two other subbands or left intact, depending on the estimated coding gain from each decision. The splitting decision is taken considering the two different directions for applying the decomposition filters (along lines and columns) and the various wavelet filters in consideration.

## 3. Trellis Coded Quantization (TCQ)

A trellis is a state transition diagram; it's only used in the context quantization on digital communication for error correction [8, 9]. The TCQ encoder is a sequence of N input values, $x_i$. The output of the TCQ encoder is an initial state, $s_0$, followed by a sequence of N symbols, $s_i$. These symbols and initial state, after possible entropy coding and decoding, are available as the input to the TCQ decoder. The output of TCQ decoder is a sequence of N quantized values, $q_i$. The average rate and distortion induced by the entire TCQ encoder/decoder.

**3.1 Terminology**

Let introduce the fundamental theory of the TCQ. The Trellis is a mapping T, defined by T: $(A_x B) \to A$, where $A = \{0,\cdots,|A|-1\}$, is the set of states. $B = \{0,\cdots,|B|-1\}$ is the alphabet, and T is the state transition function. Let $a_n \in A$ denote the current state of the trellis and $b_n \in B$ the current symbol. Since the next state is uniquely defined by the current state and symbol, i.e.

$$a_{n+1} = T(a_n, b_n) \qquad (4).$$

This recursion produces all states, $a_n$, given the initial state $a_0$ and the sequence of symbols $b_n$. Associated with the state transition function $T(A,B)$ is the quantizer function denoted by $Q(A,B)$. Just like any other quantizer, this is a mapping $Q: R \to C$, where C is the set of codewords, i.e. it maps any real value to one of the values of C. This is in fact done indirectly through states and symbols: $x_n \to (a_n, b_n) \to q_n$

TCQ works a follow:

- Given the state transition and quantizer functions T and Q,
- Given an input sequence $x_i, i \in 0,\cdots\cdots, N-1$,
- The encoder calculates the initial state $a_0$ and a sequence of symbols $b_i, i \in 0,\cdots\cdots, N-1$.
- The decoder applies the recursion for

$$i = 0,\cdots, N-1,\; q_n = Q(a_n, b_n),\; \mathrm{a}_{n+1} = T(a_n, b_n)$$

(5)

The TCQ calculates the sequence of symbols $b_i, i \in 0,\cdots\cdots, N-1$, together with the initial state $a_0$ that minimizes some error function. In order to provide optimal quantization (in the rate-distortion sense) we use the error function.

$$E = \sum_{i=0}^{N-1} L(b_i \mid a_i) + \lambda \sum_{i=0}^{N-1} (x_i - q_i)^2 \qquad (6)$$

where $\lambda \in [0.+\infty)$ is a Lagrange multiplier that allows for different tradeoffs between bit rate and effective distortion. Clearly, for $\lambda = 0$ one looks for the sequence of symbols that result in the minimum bit rate, regardless of the distortion induced, while for $\lambda \to \infty$, we obtain the sequence that produces the minimum average distortion, regardless of the coding cost (in bits). And $L(\bullet \mid \bullet)$ is the arithmetic coding length function. Thus we can completely characterize a TCQ with a quadruple, $(T, Q, L, \lambda)$.

**3.2 Progressive TCQ**

In order to apply TCQ in a progressive manner, there is need to further quantize the residual error(s) from previous quantization steps. That is, if we denote with $V_0$ the original image to be quantized, then

$$E_0 = V_0 - Q(V_0) \qquad (7)$$

is the error introduced by the first quantization step and, in general, we define the sequence of errors as

$$E_j = V_j - Q(V_j),\; V_j = E_{j-1},\; j = 1,\cdots,\infty \quad (8).$$

## 4. Practical considerations

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Here we use uniform quantization and fixed-length codes for the scaling factors and the offsets. The encoding method is specified by the follow: fractal, and Adaptive wavelet Transform. To evaluate the encoding gain, the rate-distortion model is needed for the wavelet subbands.

The decision to split a given subband carries some cost due to the additional information that the coder needs to transmit to the decoder regarding the decomposition scheme. For example, our TCQ coder relies on the knowledge of the variance of each subband, since the codebooks are normalized to have unit variance; the same is true for scalar quantizers. In this way, even though we only need to transmit one such variance if we choose not to split, we need to transmit two variances (for the two "children" subbands) it we do split. The cost it also logarithmically proportional to the number of choices for the wavelet filters, W. Thus, assuming F bits to efficiently quantize a variance and a choice among W wavelet filters. The coding cost in bits is given by.

$$c = F + \log_2 W + 3 \qquad (9).$$

For the fractal coding process, we used $c$ bits to code each range block match (coding use only fractal match method), $c$ is compute using the following formulas:

$$c = \log_2 n_s + \log_2 n_o + \log_2 N_D + 5 \qquad (10)$$

where $n_s, n_o, N_D$ are respectively the number of bit necessary to code the luminance, the contrast, and the domain block.

## 5. Conclusion and Implementation

In this paper, we have presented a new method for image compression, based on combination of fractal theory, Adaptive Wavelet Transform and Mulistage Trellis-Coded quantization.

The following result of the implementation have been obtain by using the computer who has a following hard resource: the Genuine Intel Pentium II Processor Intel x86 Family 6 Model 8 Stepping 128.0MB RAM.

The following table (1.1) represent the results of our simulation. We can see in the table the difference between the encoding time and the quality of the reconstruction.

The figure (1.1): (a) the original image of Lena. (b) Represent the compress image using the Fractal-Wavelet approach PSNR = 12.5853 and the encode time 155 s). (c) The image compressed using the Fractal-wavelet-DCT with Trellis Code Quantization approach PSNR = 30.9052dB and the encode time 125 s. (d) represent the residual image between the original image and the compressed image using Fractal-Wavelet compression. (e) represent the residual image between the original image and the compressed image using Fractal-Wavelet-DCT with Trellis Code Quantization.

| Image | Hybrid Fractal-Wavelet approach | | Hybrid Fractal-Wavelet-DCT Trellis Code Quantization | |
|---|---|---|---|---|
| | Encode Time in second | PSNR in dB | Encode Time in second | PSNR in dB |
| Lena | 155 | 12.5853 | 125 | 30.9052 |
| Rose | 170 | 12.1192 | 150 | 29.9186 |
| berries | 139 | 13.6052 | 109 | 23.7883 |
| Winter | 146 | 12.2090 | 109 | 24.2073 |

(a )

(b)

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(c)

(d)



(e)

The above result proved that the proposed method surpasses the Fractal-Wavelet in the reconstruction of the image comparing the figures 1.1 and the Peak Signal Noise Ration (PSNR) value on the table 1.1 and the encoding time. The proposal method offered an additional advantage of progressive transmission and universality.

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