Fast algorithm for VQ-based wavelet coding system

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Abstract

The increasing demand of multimedia computing has led to the demand of using digital images. The manipulation, storage and transmission of these images in their raw form is very expensive, it significantly slows the transmission and makes storage costly. In this paper**,** a modified version of (Linde-Buzo-Gray)LBG algorithm using Partial Search Partial Distortion (PSPD) is presented for coding the wavelet coefficients. The proposed scheme can save 70 - 80 % of the Vector Quantization (VQ) encoding time compared to fully search VQ and reduced arithmetic complexity with out sacrificing performance.

Key Words: Image Compression, Wavelets Multiresolution, Vector Quantization.

1 Introduction

Wavelet Transform [10] [11] [12] has emerged as a powerful mathematical tool in many areas of science and engineering specifically for data compression [3]. It has provided a promising vehicle for image processing applications, because of its flexibility in representing images and its ability to take into account Human Visual System characteristic. It is mainly used to decorrelate the image data, so the resulting coefficients can be efficiently coded. It also has good energy compaction capabilities, which results in a high compression ratio. It can be viewed as a special case of multi-rate filter bank with dyadic tree decomposition.

Wavelets were developed independently in the fields of mathematics, physics, electrical engineering and seismicgeology. Interchanges between these fields during the last ten years have led to many wavelet applications, such as image compression, de-noising, human vision, radar, etc. Also, it is being used in many areas of science and engineering such as: signal processing, fractal analysis [19], numerical analysis [2], statistics [4], and astronomy [15]. Recently, wavelets were determined to be the best way to compress a huge library of fingerprints [7].

The advantages of using the Discrete Wavelet Transform (DWT) over the Discrete Cosine Transform (DCT) lies in the fact that the DWT projects high details of image components onto shorter basis function with higher resolution. Where lower details components are projected onto larger basis functions, which corresponds to narrower subbands. It is establishing a trade off between time and frequency. In addition, the wavelet transform compression provides a superior image quality at a low bit rate, since it is free from blocking effects. Also, it has a link with digital filters and can handle non-stationary signals. However, there are still significant amounts of redundancies within the subbands. Since the wavelet basis functions have short support for high frequencies and long support for low frequencies, smooth area of an image may be represented with very few bits. It is known that most of the energy is concentrated in low frequency information, and for the remaining high frequency components of the image, most energy is spatially concentrated around edges. High frequency details are added where they are needed. Indeed, before the introduction of wavelets, a number of closely related coding works have been extensively studied in the image coding community, including pyramid coding [3], where the coarse version is derived from the original image by filtering. From this coarse version, the original image can be predicted and the prediction error can be calculated. If the prediction error is small it can be well compressed. The process can be iterated on the coarse version. A perfect reconstruction can be achieved if the compression of difference signals is lossless by simply predicting the original image and adding back the predicted image and the difference. The compression rate depends on how well the original image can be predicted from the filtered and down sampled image. Also subband coding [19] and transform coding. They split up the input image into frequency bands and then code each subband using coder bit rate method to the statistics of the band.

Initial efforts in using wavelet transform in compression research concentrated on the hope of more efficient compaction of energy into a few numbers of low frequency. This generated some of wavelet based coding algorithms [1] [16] 19] which were designed to exploit the energy compaction properties of the wavelet transform by applying scalar or vector quantizers for the statistical of each frequency band of wavelet coefficients.

2 The Discrete Wavelet Transform

The application of wavelet transform in signal and image compression has attracted a great deal of attention. It is known that it generates a multiresolution representation of an image. There are several subimages or subbands that might be encoded more perfectly than the original image. The wavelet transform technique breaks the image information into various frequency bands and encodes each subband using suitable coding system**.**

Consequently, different coding approaches or different bit rates could be assigned to every subimage. Separate coding of different subbands provides some desirable features. First, by allocating the available bits for encoding among subbands and using an appropriate quantizer for each of them, encoding process can be tailored to the statistics of each subband. Second, spectral shaping of quantisation noise is possible. This feature can be used to take advantage of noise perception of human auditory system for speech or human visual for images. Third, subband decomposition of a signal or image leads naturally to multiresolution decomposition. This is useful for progressive transmission of images in which an increasingly higher resolution and quality image can be reconstructed by decoder. To get high compression ratio, one can not code whole information of an image. Only the significant information of an object that is needed to reconstruct the image with less distortion or degradation.

A more sophisticated wavelet can also provide more energy compaction than Haar wavelet. Daubechies *et al* [5] has shown that a wavelet ability measure is to provide compaction by the number of vanishing moments it possesses. More vanishing moments imply more compaction in smooth regions. Haar wavelet has only one vanishing moment. Therefore, it does not possess very strong compaction ability.

Daubechies has generated a family of wavelets parameterised by the number N of vanishing moments [5]. This family has 2N non-zero coefficients. These wavelets have problems because of the asymmetry that it introduces which result in subjective displeasing distortions when errors are introduced into the decomposition coefficients. She also designed another family of wavelets called the coiflet. It has vanishing moments for both the wavelets and the scale function. These filters are very close to symmetric where this wavelet is increased filters length: for L vanishing moments, the filters have 3L non-zero coefficients. During the appropriate design the following characteristics are desirable:

1. Perfect reconstruction or the ability to exactly obtain the original input.
2. Orthonormal or biorthogonal bases.
3. Reasonable spatial and frequency resolution.

The two-channel filter bank has four filters involved: two are analysis filters and two are synthesis filters. The system is said to be a biorthogonal filterbank if $R(e^{j\omega})E(e^{i\omega}) = I$ for all ω . This implies perfect reconstruction, i.e., $\hat{x}(n) = x(n)$. The coder is orthonormal or paraunitary if $E(e^{j\omega})$ is unitary for all ω . In this case biorthogonality is achieved by setting $R(e^{j\omega}) = E^{+}(e^{j\omega})$.

The DWT can be easily implemented using phase finite impulse response filter banks [1] 16] 17]. Two-dimensional (2-D) of DWT can be obtained by a separable decomposition in the horizontal and vertical directions [12] [18]. A pair of appropriately designed Quadrature Mirror Filters (QMFs) can efficiently implement the forward and inverse wavelet transforms. Therefore, it can be viewed as a form of subband coding. The Quadrature Mirror Filter (QMF) pair consists of a low pass filter $G = G(h(n))$, and $H = H(h(n))$, $n \in Z$, where $h(n)$, $g(n)$ are Daubeche's 6-tap filter. The impulse response H , and G are mirror images, and related by:

$$g_n = (-1)^{1-n} h_{1-n}$$

The impulse response of the forward and inverse transform QMFs - denoted $(H^{\wedge}, G^{\wedge})$ and (H, G) respectively are related by:

$$g_n = \hat{g}_{-n}$$
$$h_n = \hat{h}_{-n}$$

Each pair consists of a lowpass filter (H) and a highpass filter (G) which divide or split the input signal/image into two components.

The choice of filter bank in wavelet compression is an important issue that affects image quality as well as system design. Figure (1) illustrates a single 2-D forward wavelet transform of an image, which is implemented by two separate 1-D transforms. The image $f(x, y)$ is first filtered along the x-dimension, then down sampled by 2 with out loss of any information, then filtered along y-dimension and down sampled by 2, resulting in four subimage $f_{1-1}(x, y)$, $f_{1-2}(x, y)$, $f_{1-3}(x, y)$ and $f_{1-4}(x, y)$. The resulting are the main signal $f_{1-1}(x, y)$ which is the low frequencies band and three detail signals. The process is repeated on the low band to generate the next level of the decomposition. It can note the energy compaction is concentrated in LL subband as the natural images as shown in table 1.

3 Wavelets features for Image Compression

This is a summary of some features of image compression using Wavelets.

1. Wavelet transform has a good energy compact, it is preserved across the transform, i.e. the sum of squares of the wavelet coefficients is equal the sum of squares of the original image.
2. Wavelets can provide a good compression [1] [3], it can perform better than JPEG2000, both in terms of SNR and image quality. Thus show no blocking effect unlike JPEG2000.
3. The entire image is transformed and compressed as a single data object using wavelet transforms, rather than block by block. This allows for uniform distribution of compression error across the entire image and at all scales.
4. The wavelet transform methods have been shown to provide integrity at higher compression rates than other methods where integrity of data is important e.g., medical images and fingerprints, etc.
5. Multiresolution properties allow for progressive transmission and zooming, without extra storage.
6. It is a fast operation performance, in addition to symmetry: both the forward and inverse transform have the same complexity, in both compression and decompression phases.
7. Many image operations such as noise reduction and image scaling can be performed on wavelet transformed images.

Resultant wavelet multiresolutions are scaled subbands. Coarse approximation scaled from the original image and the others are detail coefficients where there are a statistical dependence across scale in these coefficients. Efficient encoding is to exploit such dependence. This is how the art wavelet transforms compression is achieved.

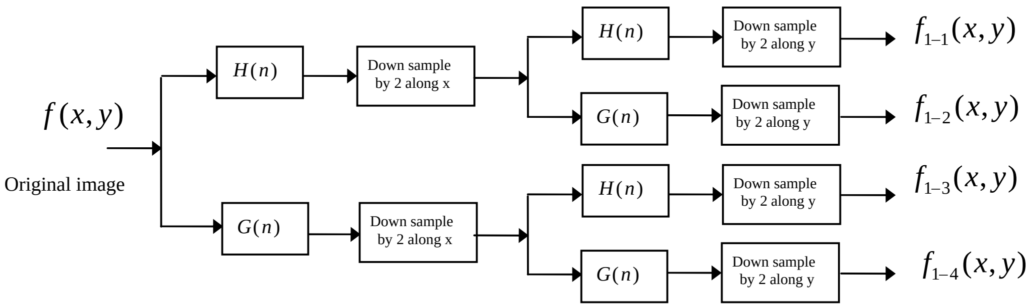

Figure 1: Block diagram of 2-D forward Wavelet Transform

Table 1 Energy weight for the four subbands of a number of still test images after first-level wavelet decomposition.

Subband	Natural images				Medical Images	
	Lena	Boat	Camera	Goldhill	Chest(CT)	Head (MR)
LL	94.03 %	94.27%	92.92%	91.40%	99.22%	91.82%
LH	2.58 %	2.50 %	3.11 %	3.12 %	0.31 %	3.92 %
HL	1.95 %	2.23 %	2.52 %	3.50 %	0.32 %	3.28 %
HH	1.44 %	1.00 %	1.45 %	1.98 %	0.15 %	0.98 %

4 Modified LBG Algorithm using Partial Search Partial Distortion

In basic VQ, a full search technique is used, where the Euclidean distance measure is calculated for the entire code vector in the codebook. It results in complexity in computing and time consummation. These are the most serious problems facing VQ. In this paper, the LBG algorithm is modified to make it more efficient in speed up of codebook generation and in case of encoding phase. The improvement is based on the fact that two equal-sized image blocks cannot be closely matched unless their local means and variance are closely matched.

In the proposed modification a significant feature, the combination of variance σ^2 and mean m is used to reject a large number of code vectors from the search consideration without calculating their distortion distance from the training vectors. Then, the partial search is used to find the closed or best match code vectors from the remaining possible match of the codebook.

The algorithm is described as follows:

Step (1). Initialization.

Let n =length of training vectors, N =Codebook size, k =Vector dimension, C_0 =Initial codebook, D_{-1} =Initial average distortion.

Step (2). Compute the variance σ^2 and mean m values of each code vector in the codebook to find $h = \frac{\sigma^2}{m}$, and sort the codebook in ascending order according to the increase of h.

Step (3). Calculate the minimum distortion partition. All training vectors are grouped into clusters S_i using the minimum distortion rules as follows:

(a). Compute h_x for the input vector x (e.g. $h_x = \frac{\sigma_x{}^2}{m_x}$).

(b). Find the best match of h_x from the sorted codebook in step (2).

(c). Define the partial codebook, the upper and lower bound from the sorted codebook with a window size $\pm T$ from the best match vector.

(d). Find the best match code vector of the input vector from the partial codebook by calculating the distortion of each codevector by select the minimum distortion.

(e). Repeat (a) to (d) for all training vector.

Step (4). Calculate the average distortion $D_{iteration}$ for this iteration as follows:

$$D_{iteration} = \frac{1}{n} \sum_{i=0}^{n-1} \min_{y \in C_{iteration}} d(x_i, y)$$

Step (5). If $(D_{iteration-1} - D_{iteration}) / D_{iteration} \leq \zeta$, stop with codebook, otherwise go to *step (6).*

Step (6). Compute the centroid of each cluster and then go to *step (1)* for next iteration.

The previous description of the proposed Modification of LBG for codebook generation, but some of the steps can also be used in case of encoding.

5 Simulation Results

Experiments are performed on standard 256x256 greyscale Lena, Cameraman, Boat and Goldhill images to test the proposed algorithms at several bit rates. The Daubechies filters are used in the experiments with 4-level wavelet decomposition. The lowest band is coded separately from the remaining bands. The results of this algorithm on the above test images are presented. All the images have a mixture of large smooth regions and long oscillatory patterns. In order to evaluate the performance of the algorithm, it is compared to the standard JPEG2000. The performance of the algorithm is reported in figure 2, 3. Figure 2 shows the PSNR versus compression ratio for the test images using this algorithm. Figure 3 shows reconstructed 'Lena' test image with different compression ratios and PSNR in decibel. As it may be seen, no blocking effect can be noticed and the image quality is acceptable. The images out side the training has less PSNR approximately by 1-1.5 dB.

6 Comparison with Other Coders

The measure criterion for comparison was PSNR, which can be calculated directly from the original and reconstructed data. Figure 4 show a comparison of JPEG2000 and the proposed wavelet codec for the test image Lena and with a size 256x256. In terms of statistical error, wavelet codec gives higher signal to noise ratio in two of the examples, Lena and Cameraman. Although all images contained noise introduced by the digitisation process, the wavelet codec effectively removed this noise whilst JPEG2000 spent valuable bits sending this data. As a conclusion, it provides a very efficient implementation in terms of execution time, quality and compression ratio. To summarise, the proposed wavelet codec performed well when compared with the industrial standard JPEG2000 algorithm and much better than vector quantisation technique. These results show that the algorithm provides a highly competitive solution to the problem of image data compression.

7 Conclusions

The quality of reconstructed images within the training set are yielded a compression ratio of 60 - 50 and the PSNR2000 was 39 - 32 dB, with greatly reduced computation and execution time needed for codebook design and encoding phase. It reduces the computation complexity to *O(kf)* arithmetic operations instead of *O(kN)* in full search, where N is the number of codevectors, k is the vector dimension, and f is the window width, (where *f* << *N*). The proposed scheme can save 70 - 80% of the VQ encoding time compared to full search VQ. To increase the efficiency, fast algorithm for wavelet transform has to be incorporated. Developing Fast hardware architecture for wavelet transforms and vector quantization are an area to be investigated

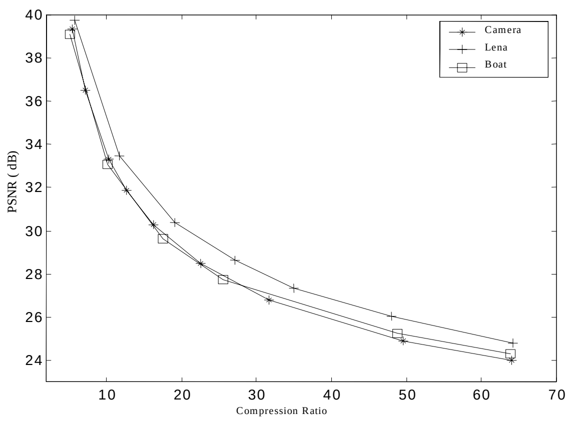

Figure 2: Compression ratios vs. PSNR of the proposed algorithm upon some of the test images

Figure 3: Simulation results using wavelet transform.(a) Original test image (top left). (b) Compression ratio 16:1, PSNR=32.50 (top right). (c) Compression ratio 35:1, PSNR=27.34 (bottom left). (d) Compression ratio 64:1, PSNR=24.77 (bottom right).

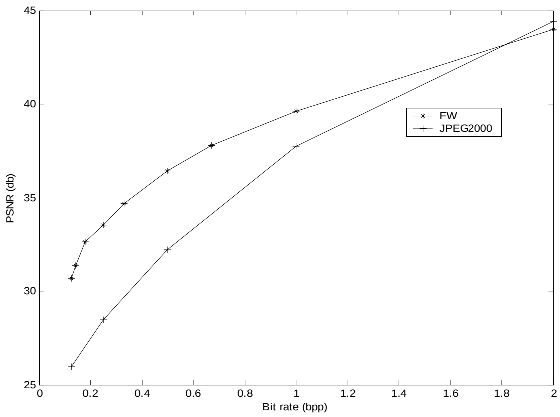

Figure 4: PSNR Comparison between JPEG2000 and proposed wavelet technique for Lena test image

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