STUDY OF EFFECT OF FILTERS AND DECOMPOSITION LEVEL IN WAVELET IMAGE COMPRESSION

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ABSTRACT

In this paper, we introduce a compression algorithm using wavelet transform. The principle of wavelet transform is to decompose hierarchically the input image into a series of successively lower resolution reference images and detail images which contain the information needed to be reconstructed back to the next higher resolution level .

The histogram of image sub-bands provides us with information on the distribution of the coefficient values in this sub-image. The sub-band images resulting from wavelet transform are not of equal significance. Some sub-bands contain more information than others. The total number of available bits describing an image is however inevitably limited. Therefore, it is desirable to allocate more bits to those sub-bands images which can be coded more accurately than others. The objective of a such bit allocation method is to optimize the overall coder performance and minimize the quantization error. In determining which wavelet filter is to be used for image compression, some of the properties considered are vanishing moments. The phase non-linearity of the filter can cause severe degradation in the subjective quality of an image. It is related to the symmetry of the filter coefficients. The wavelet transform is implemented using a linear-phase Biorthogonal filter with four levels of decomposition.

For this study, we use a scalar quantization with uniform threshold quantizers. The quantization method is PCM (pulse coded modulation) for the coefficients in all high-pass sub-bands. The coefficients of low-pass sub-bands are DPCM (Differential PCM) quantized per region.

Key-words : Image compression, Daubechies fillters, Biorthogonal wavelet, Bit allocation algorithm, Quantization .

1. INTRODUCTION

The advantage of numerous transforms for information compression applications is that they project the signal into a basis of orthogonal functions, i.e they distribute the signals energy over a set of decorrelated components. There are a variety of orthogonal transforms, each with specific properties.

The discrete Fourier transform (DFT), the discrete cosine and sine transforms (DCT, DST), the karhunen-loeve (KLT) transform and the Haar Hadamard transforms are the most well known and widely used.

The karhunen-loeve transform is an optimal transform in that it diagonalizes the covariance matrix. The lack of rapid algorithm, however, makes the DCT more attractive in many cases, this latter yields comparable results. The drawback of the DCT is that it does not have a rigorous convolution property, and therefore the DFT in its FFT version is often preferred. These transforms are well suited in localizing the energy in frequency domain, but not in the time domain since they do not admit non-stationary properties.

The Gabor functions, which are well localized in both space and frequency domains, do not have associated digital filters (unless the continuous functions are sampled).

The wavelet transform defined par Y. Meyer and J. Lemarie admits non-stationary signals and offers good localization in both space and frequency domains and can be implemented in a fast algorithm.

These properties, due to the fact that they are particularly suitable to image signals and takes human vision mechanisms into account, make the wavelet transform an ideal candidate for image signal processing.

2. PRINCIPLE OF THE METHOD

The Image compression and transmission system used in this paper is shown in fig1. A more detailed description of each block in the image compression is given below.

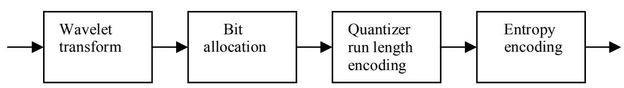

Figure 1 : Building blocks for Image coder in this study

2.1 Wavelet transform

The principle of the discrete wavelet transform is to decompose hierarchically the input signals into a series of successively lower resolution reference signals and their associated detail signals.

At each level, the reference signals and detail signals that contain the information are needed to be reconstructed back to the next higher resolution level (fig.2, fig.3 and fig.4).

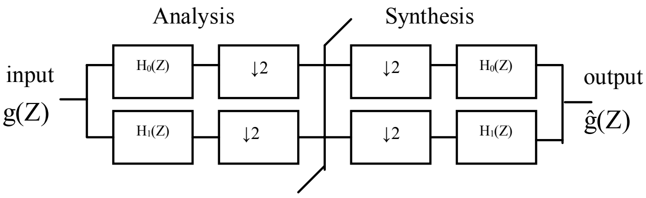

Figure 2 : One-Dimensional DWT

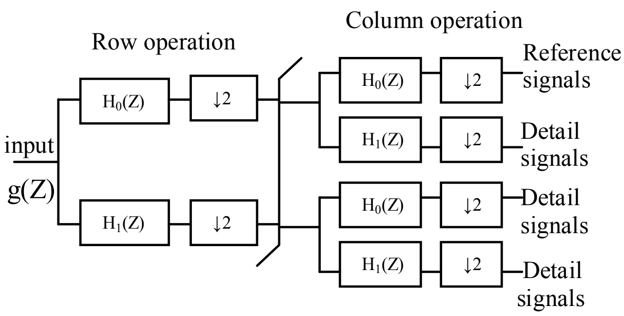

Figure 3 : Analysis of 2D DWT

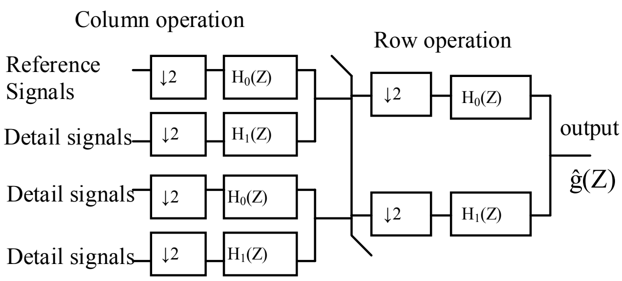

Figure 4 : Synthesis of 2D DWT

In determining which wavelet filter is to be used for image compression, some of the properties considered are

1- vanishing moment,
2- phase non-linearity,
3- step response.

Vanishing moment are the degrees of the polynomials representing a linear combination of the smoothing function and its translation. It determines the convergence rate of wavelet approximation.

The phase non-linearity of the filter can cause severe degradation in the subjective quality of an image. It is related to the symmetry of the filter coefficients. In general, the symmetric errors are more tolerable than the non-symmetrical ones for the human system.

Step response measures how well a wavelet filter approximates edges in an image is important since it can provide good visual fidelity.

For this study, the (16,4) filter Biorthogonal symmetric wavelet filter is used (this choice is provided for a comparative study between Daubechies filters and Biorthogonaol filters. fig.5 and fig.6 show that the filter (16,4) is the best in all filters used (Daubechies filters (5,6,8) and Biorthogonal filters (16,4), (11,4), (9,7)).

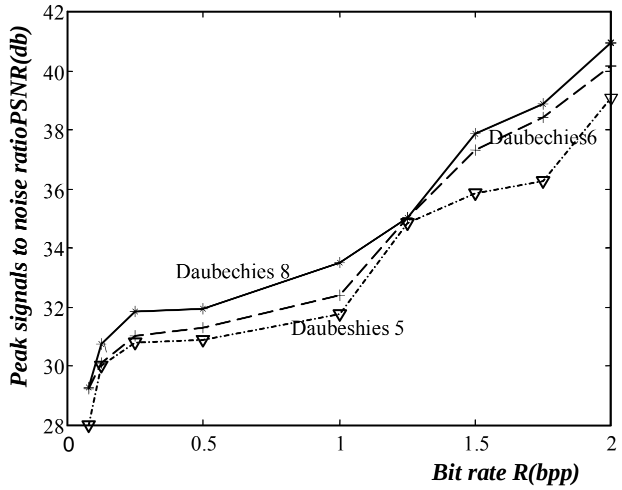

Figure 5: Quality of compression varying Daubechies filters(5,6,8)

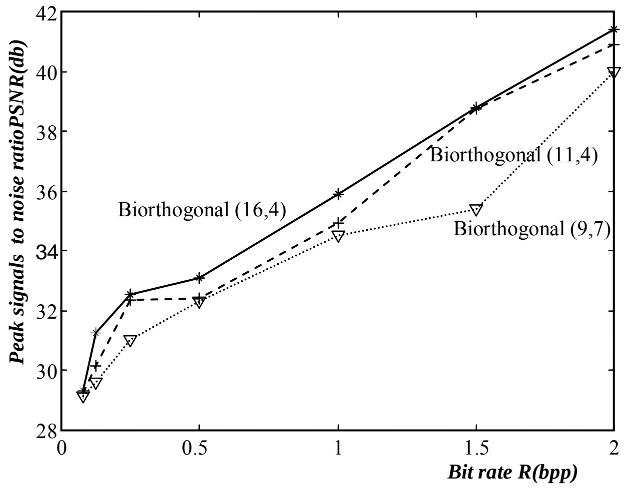

Figure 6: Quality of compression varying Biorthogonal filters((16,4),(11,4),(9,7))

2.2 Bit allocation

The type of the quantizer to be used as well as its image coding performances can be determined from statistical analysis of sub-images obtained after wavelet transform.

The normalized histogram of a sub-images provides us with information on the distribution of the coefficient values in the sub-image (fig.7).

The sub-images resulting from wavelet transform are not of equal significance. Some sub-bands contain more information than others. The total number of available bits to describe an image is, however, inevitably limited. Therefore, it is desirable to allocate more accurately than others.

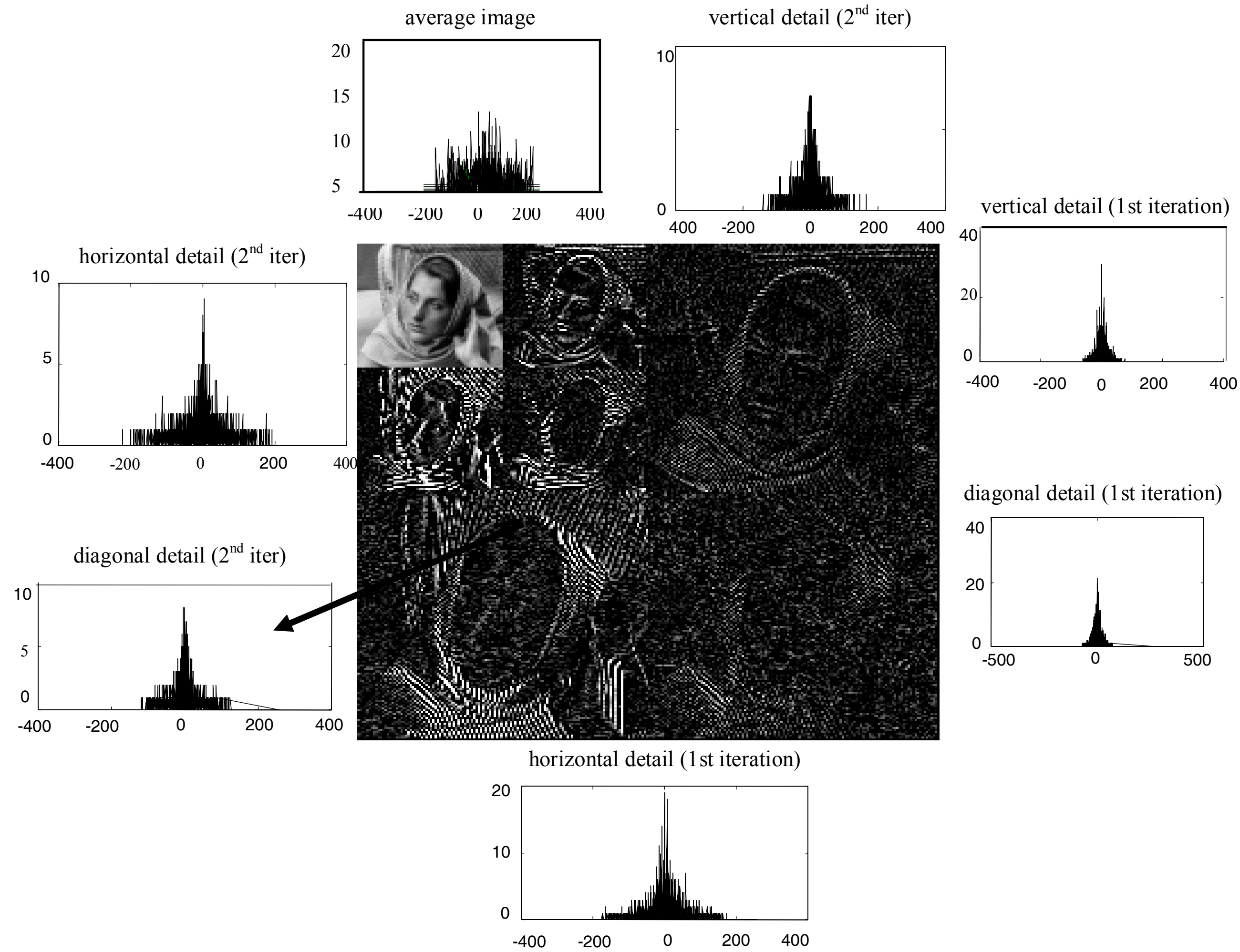

Figure 7 : Histograms of sub-images of Barbara image with two levels of decomposition using Haar filter.

The objective of such a bit allocation method is to optimize the overall coder performance and minimize the quantization error.

For this study, the bit allocation algorithm used is taken from [3].

The algorithm is given below:

$$b_k = \frac{R_c}{\sum_{k=0}^{M-1} \alpha_k} + \log_2 \left[\frac{\sigma_k}{(\prod_{k=0}^{M-1} \sigma_k^{\alpha_k}) \sum_{k=0}^{M-1} \alpha_k} \right] \quad (1)$$

$$b_k = R_c + \log_2 \left[\frac{\sigma_k}{(\prod_{k=0}^{M-1} \sigma_k^{\alpha_k})} \right] \quad (2)$$

where b_k is the number of bits allocated to the k^{th} sub-band, R_c is the desired bit rate, M is the total number of sub-bands, σ_k is the standard deviation of the k^{th} sub-band and α_k is the relative size of the k^{th} sub-band .

Two conditions associated with the above equations may need to be imposed. First, the equa- tions are not constrained to positive bit values. For the case of low bit rates, assign negative bit values to several sub-bands which are indesirable. Second, an upper limit value b_{max}, may be used to set at the maximum allowable number of bits.

To incorporate these two conditions into the bit allocation algorithm. The procedure for using the equations is modified as fellows.

1. For initialization, calculate b_k using (2) for all sub-bands k.
2. Exclude all sub-bands l with $b_l \leq 0$ from the calculation and set b_l=0
3. Exclude all sub-bands m with $b_m \geq b_{max}$ from the calculation and set b_m=b_{max}.
4. If there are no sub-bands that are assigned to a negative number of bits. and no sub-bands that are assigned a number of bits greater than b_{max}. No further iterations are necessary. Otherwise, subtract from the desired bit rate *R*c. The part that is produced by the sub-bands already allocated with a number of bits and continue with step 5.
5. Recalculate the bit allocation scheme for the remaining sub-bands by using (1). The sum over α_k is smaller than1) go to step 2.

The number of bits allocated to each sub-band is then rounded off to obtain the integer number of bits.

2.3 Quantization

For this study, we used a scalar quantization with uniform threshold quantizers. The quantization method is PCM (Pulse Code Modulation) for the coefficients in all high-pass sub-bands. The coefficients of low-pass sub-bands are DPCM (Differential PCM) quantized per region.

2.4 Run length encoding

After bit allocation and quantization, we have sub-images with discrete levels represented by integer coefficients where a string of consecutive zeros can be encoded.

2.5 Entropy coding

The fixed-length symbols resulting from quantization and run-length encoding step further compressed by the Huffman coding technique. The Huffman coding is an invertible and loss-less coding technique that, on average, uses shorter length code words to represent the fixed–length symbols.

3. PERFORMANCE CRITERIA

Suitable criteria are needed to evaluate rigorously the performance of a compression scheme. In case of images, the search for simple and suitable criteria is hindered by the fact that the results obtained by statistical performance criteria may not agree with the subjective evaluation of the human eye. Since the objective is data compression, the compression ratio at optimal distortion is obviously an important performance measure. The reconstructed image quality can be evaluated by mean-squared error (MSE) and peak signal to noise ratio (PSNR).

$$MSE = \frac{1}{N^2}\sum_{i=0}^{N-1}\sum_{j=0}^{N-1}\left[f(i,j) - \hat{f}(i,j)\right]$$

The bit per pixel (bpp) value and compression ratio (CR) are calculated as follows :

$$PSNR = 10\log_{10}\left(\frac{1}{MSE}\right)$$

Bpp = nbr of bits required to represent the Image/nbr the pixels in the image

CR = bpp of original image/bpp of compressed image

4. RESULTS

The results obtained after using this algorithm of compression (PSNR) are presented in fig.8 and fig.9.

Fig8 presents the effect of the level of decomposition in image compression quality (PSNR). Fig 9 presents the effect of bit rate in image compression quality. Fig.10 shows the comparison between wavelet algorithm compression and JPEG (zonale1, zonale2).

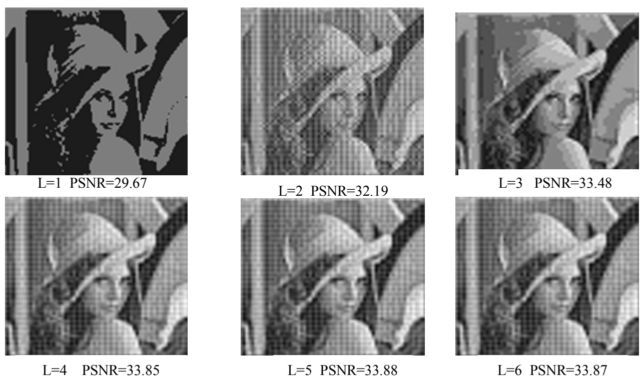

Figure 8 : Effect of decomposition level on compression quality

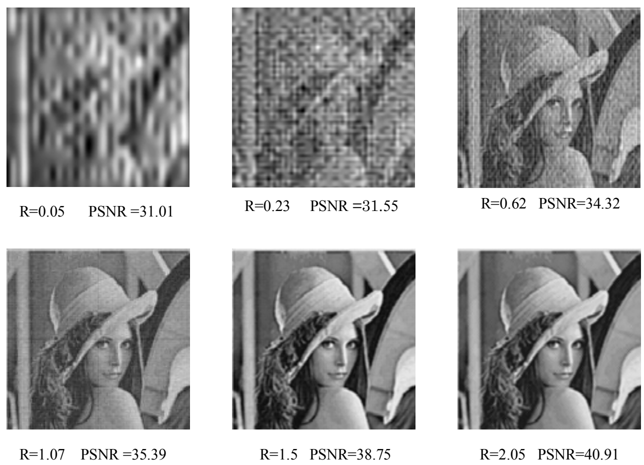

Figure 9 : Effect of bit rate on compression quality

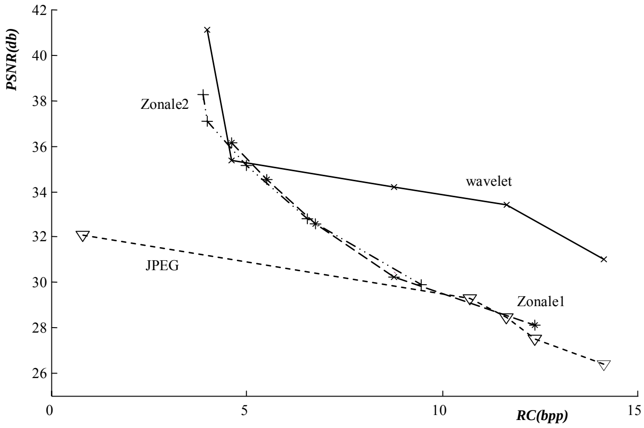

Figure 10 : Comparaison between JPEG (zonale1, Zonale2) and wavelet

CONCLUSION

We can subdivide the image in one or more sub-images; if we increase the level of decomposition, the compression quality (PSNR) will improve.

From this study, we can conclude that the PSNR is very similar when the level of decomposition is greater than 4 (i.e L=4, L=5, L=6). The Biorthogonal filters provide us good results in image compression.

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