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Research Article

A Novel Image Compression Algorithm using Modified Filter Bank

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Abstract

A digital Image is a numeric representation of a two-dimensional signal. Since digital images and video data are inherently voluminous, efficient Image compression techniques are crucial for their archival and transmission. This research paper suggests a novel Image Compression Algorithm employing Modified Wavelet Filter-bank using Kaiser Window. The effectiveness of the new algorithm is justified over various test images. The novel algorithm gives far better results in the terms of Performances Indicators such as Mean Square Error, Peak Signal to Noise Ratio and Compression Ratio. The trade-off between Compression Ratio and PSNR has been reduced by the implementation of this proposed method.

Keywords: *Image Compression; Wavelet; Modified Wavelet Filter Bank; PSNR; Compression Ratio, MSE.*

1. Introduction

Need of compression

The amount of data associated with visual information is so large that its storage would require enormous storage capacity. Although the capacities of several storage media are substantial, their access speeds are usually inversely proportional to their capacity. Typical television images generate data rates exceeding 10 million bytes per second. There are other image sources that generate even higher data rates. Storage and transmission of such data require large capacity and bandwidth, which could be very costly. Image data compression techniques are concerned with the reduction of the number of bits required to store or transmit images without any appreciable loss of information. Image transmission applications are in airing television; remote sensing through satellite, aircraft, radar or sonar; teleconferencing; computer communications; and facsimile transmission. Image storage is required most commonly for educational and business documents, medical images used in patient monitoring systems, and the like. Because of their wide applications, Image compression is of great importance in digital image processing.

Image compression is curtailing the size in bytes of a photograph file without degrading the quality of the image to an objectionable level. For this purpose many compression techniques, i.e. scalar/vector quantization, differential encoding, predictive image coding, transform coding have been introduced. Among all these, transform coding is most efficient especially at low bit rate (R. C. Gonzalez, *et al*, 2004). Transform coding relies on the principle that pixels in an image show a certain amount of correlation with their neighboring pixels. Consequently, these correlations can be exploited to predict the value of a pixel from its respective neighbors. Transform coding relies on the principle that pixels in an image show a certain level of correlation with their neighboring pixels. A transformation is defined as to map this spatial (correlated) data into transformed (uncorrelated) coefficients. Another interesting aspect of using a frequency domain representation of an image stems from the fact that it is much more efficient to de-correlate an image in the frequency domain than in the spatial domain (Muhammad Azhar Iqbal, *et al*, (2007).

It is seen that Fourier or frequency domain is not the only alternative domain to represent images. In fact, any orthogonal coordinates will be suitable to represent an image. The type of domain to choose depends on the intended application. Moreover, the transformation that we choose must be linear and invertible so that we can recover the image from the transform domain. It should also be orthogonal so that one can manipulate the transformed image independently along the different dimensions.

In lossless compression, the reconstructed image after compression is mathematically identical to the original image. In the lossy compression scheme, the reconstructed image comprises degradation relative to the original. Lossy technique causes image quality degradation in each compression or decompression

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step. Lossy techniques provide for greater compression ratios than lossless techniques, i.e. Lossless compression gives good quality of compressed images, but produces only less compression whereas the lossy compression techniques (K.S. Thyagarajan, 2011). Our purpose here in using an orthogonal transform to represent an image in the new domain is to be able to achieve a high degree of data compression without sacrificing visual quality.

This paper is divided as follows: Section 2 explains the classification of Compression techniques; Section 3 describes the Discrete Wavelet Transform (DWT) algorithm; Implementation of Wavelet Filter bank algorithm explained in Section 4; Section 5 explains about the performance indicators, Section 6 gives comparative analysis and result in tabular form and the last Section is the conclusions.

2. Compression Technique

2.1 Lossless v/s lossy compression

The first categorization is centered on the information content of the reassembled image. They are "lossless compression" and "lossy compression" scheme. In lossless compression, the reconstructed image is arithmetically equal to the original image on a pixel by pixel basis after compression. However, only a little amount of compression is attainable in this technique. In lossy compression, on the other hand, the reconstructed image contains deterioration relative to the original, because redundant information is thrown away during compression. As a result, much higher compression of images is attainable and under normal viewing conditions no visible loss is noticed (visually lossless). In this paper, the main focus is on Lossy Image compression.

If any pixel value is changed from a digital image and then the energy will be lost and this technique is called 'lossy' compression. The amount of information retained by an image after compression and decompression is known as 'lossless' compression (M. Ghanbari, 2003).

2.2 Predictive v/s Transform coding

The second categorization of various coding schemes is centered on the domain where the compression method is applied. These are predictive coding and transform coding. In predictive coding, as the name implies information already sent is used to predict future values and the differences are coded. Subsequently, this is completed in the image or spatial domain, it is relatively modest to implement and is enthusiastically adapted to local Image Processing. Differential Pulse Code Modulation (DPCM) is one specific example of predictive coding. Transform coding, on the other hand, first the image is transformed from its spatial domain coefficient to a different type of domain coefficient using some well-known transforms (FFT, DCT, DWT etc.), and codes the transform values (coefficient). The primary advantage is that it provides greater data compression as compared to the predictive method, although at the expense of greater computation. Our main concern is on Transform coding in this paper.

3. Discrete Wavelet Transform

A Wavelet is a mathematical function used to divide a given function or continuous-time signal into different wave signals. It can assign a frequency range for each wave signal. All wave signals that match its scale can be analyzed with a resolution. It is the delegation of a function by wavelets.

$$\psi_{a,b}(x) = |a|^{-\frac{1}{2}} \; \psi\left(\frac{x-b}{a}\right)$$

Where "ψ" is a function called wavelet, a, is another function which measure the degree of compression or scale, and b, is a translation function which measures the time location of the wavelet (Paul S. Addison, 2002).

When the two-dimensional (2D) DWT is separable, we can implement the 2D DWT in a row–column fashion. Even though one can implement the true 2D DWT to exploit the 2D correlation in an image, it is more proficient to implement the 2D DWT using 1D DWT because (a) a whole lot of 1D wavelet design ingredients exist in the literature and (b) fast implementation of 1D DWT is also accessible. Thus, we'll focus our consideration on the implementation of 2D DWT of an image using 1D DWT in a row–column fashion. Starting with the given image of size $N \times N$ pixels, we first filter it row by row by the filter $h0\,[-n]$ and $h1\,[-n]$, and retain every other sample at the filter outputs. This gives a set of two DWT coefficients each of size $N \times N/2$. Next, the DWT coefficients of the filter $h0\,[-n]$ are filtered again along each column by the same two filters and subsampled by 2 to yield two other sets of DWT coefficients of each size $N/2 \times N/2$. Finally, the DWT coefficients due to $h1\,[-n]$ are filtered along the columns by the same two filters and subsampled to give two other sets of DWT coefficients of each size $N/2 \times N/2$ (N. Ahmed*, et al*, 1974). We thus have one level of DWT of the image in question. Figure 1.a depicts a one-level 2D DWT of an image of size $N \times N$ pixels. The four different DWT coefficients are labeled.

$$y_{LL1}\,[m,n], y_{HL1}[m,n], y_{LH1}[m,n] \; and \; y_{HH1}[m,n]$$

The suffix LL stands for the output of the $h0\,[-n]$ filters in both dimensions, HL for the output of $h1\,[-n]$ along the rows first and then of $h0\,[-n]$ along the column, LH for the output of $h0\,[-n]$ first and then of $h1\,[-n]$, and finally HH stands for the outputs of $h1\,[-n]$ along both dimensions. The suffix 1 refers to the level number. The inverse 2D DWT of the DWT coefficients to reconstruct the image is shown in block diagram form in Figure 1b.

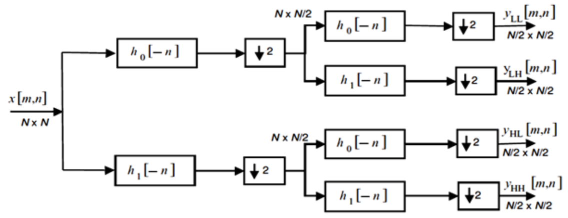


Fig.1 Analysis Filter Bank and Synthesis Filter Bank

4. New proposed Algorithm for Image Compression.

This paper presents a new approach for image compression using the coefficients of Near Perfect Reconstruction filter bank using Kaiser Window. Perfect reconstruction is a process by which an image is completely recovered after being detached into its low frequencies and high frequencies. A block diagram of a perfect reconstruction practice which uses ideal filters is shown below. The perfect reconstruction process requires four filters, two low-pass filters ($H0$ *and* $G0$) and two high-pass filters ($H1$ *and* $G1$). In addition, it requires a down-sampler and up-sampler between the two low-pass and between the two high-pass filters. It should be noted that the output filters need to have a gain of two to compensate for the preceding up-sampler.

The half band low pass filter is designed using Kaiser Window Technique, The **Kaiser window**, also known as the **Kaiser-Bessel window**, was developed by James Kaiser at Bell Laboratories. It is a one-parameter family of window functions used for digital signal processing, and is defined by the formula (J.F. Harris, 1978).

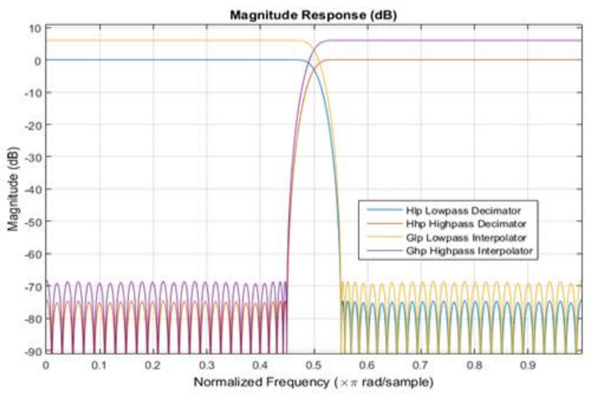


Fig 2: Magnitude Response of Analysis & Synthesis filter

The Kaiser window is very useful in practice. Zero^th order modified Bessel function of the first kind.

$$w[n] = \begin{Bmatrix} I_0\left[\beta^2\sqrt{\left[(1-\left[\frac{n-\alpha}{\alpha}\right]^2\right]}\right], 0 \le n \le M \\ 0, \qquad\qquad else \end{Bmatrix}$$

Where, $\alpha = M/2$, $I_0(\cdot)$ is Bessel function, β is a parameter that determines to some extent the "shape" of the filter. M and β trade off side lobe amplitude and main lobe width. β controls both width and tapering off (i.e., as β increases, width gets large, but side lobe amplitudes get smaller.)

Kaiser empirically found formula going from $\delta, \omega s, \omega p$ to M *and* β.

$$\Delta\omega = \omega s - \omega p$$

$$A = -20log10\ \delta$$

$$\beta = \begin{matrix} 0.1102(A-8.7), & A > 50 \\ 0.5842(A-21)0.4 + 0.07886(A-21), & 21 \le A \le 50 \\ 0.0, & A < 21 \end{matrix}$$

and, $M = \frac{A-8}{2.285\Delta\omega}$

This makes it very easy to do filter design very quickly. M does not change ripple error this is determined by the side lobe amplitude (determined by β) (Kaiser, 1980).

5. Proposed Algorithm

- Design the Low pass half band filter using Kaiser Window using the specified pass band frequency, stop band frequency, pass band ripple and stop band attenuation and sampling frequency.
- Evaluate δ, β as per as the given formula.
- Calculate the low pass filter coefficient and its transformed High pass filter coefficient.
- Read an image file to be compressed.
- Select the decomposition level.
- These filter coefficients are used as the Analysis Filter Bank for the image decomposition using wavelet transform.
- The decomposed image is now reconstructed by the Synthesis Filter Bank
- Calculate the MSE, PSNR and Compression Ratio.
- Finally, compare the results of all techniques.

6. Performance indicators

Lossy compression techniques leave the reconstructed image with some distortions, as the reconstructed image is only the approximation to the original image. In order to measure and quantify the performance of compression technique, some performance indicators are used as follows.

6.1 Compression Ratio

Compression ratio defines the ratio of number of bits required to represent original image to the number of bits required to represent compressed image. As the compression ratio increases, the quality is compromised. Lossy compression techniques have higher compression ratio than the lossless compression techniques.

$$CR = \frac{n_1}{n_2}$$

6.2 Mean Square Error (MSE)

MSE is the measure of error between the original image and the compressed image. Mean Square Error is the cumulative squared error between the compressed image and the original image. For the lesser distortion and high output quality, the MSE must be as low as possible. Mean Square Error may be calculated using the following expression:

$$MSE = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1} ||\, I(i,j) - K(i,j)||^2$$

6.3 Peak Signal to Noise Ratio (PSNR)

PSNR is the ratio of maximum power of the signal and the power of unnecessary distorting noise. Here the original image is the signal and the noise is the MSE in reconstruction. For a better compression the PSNR must be high. The increase in the peak signal to noise ratio results in the decrease in compression ratio. Therefore a balance must be obtained between the compression ratio and peak signal to noise ratio for the effective compression. The peak signal to noise ratio may be calculated as:

$$PSNR = 10\ log_{10}\left(\frac{MAXi^2}{MSE}\right)$$

Table 1: Result Analysis: Proposed Modified DWT

Image	Performance Parameter			
	MSE	PSNR(dB)	CR (%)	Elapsed time(sec)
Lena.bmp	2.86	43.55	9.57	0.171
Cameraman.bmp	7.49	39.38	9.19	0.263
Barbara.bmp	6.95	39.70	5.85	0.872
Lake.bmp	4.10	41.99	3.4	0.422

Figure 3 Lena

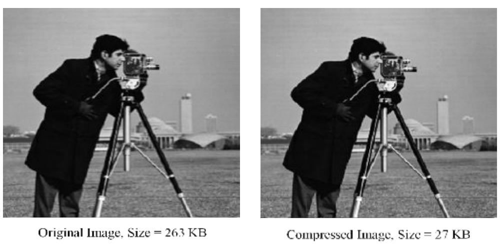


Figure 4 Cameraman

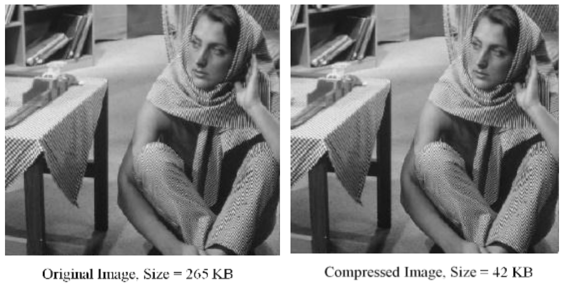


Figure 5 Barbara

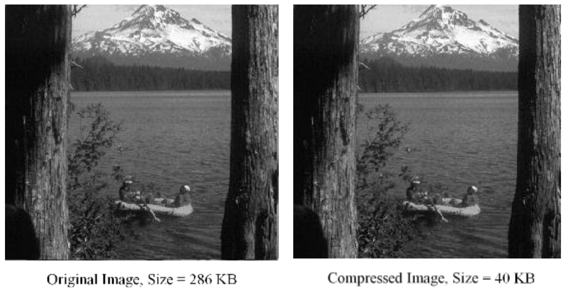
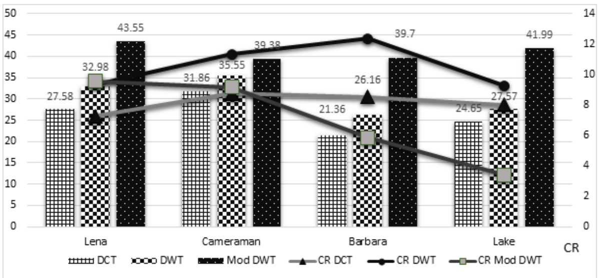


Figure 6 Lake



Comparison of PSNR & CR of DCT, DWT & MOD DWT

Conclusion

A new image compression technique based on discrete wavelet transform using modified Filter Bank is proposed in this research which provides sufficient high compression ratios with no appreciable degradation visual quality of the image. The effectiveness and robustness of this approach have been vindicated using a set of Standard Test images. To demonstrate the performance of the proposed technique, a comparison between the proposed technique and other common compression techniques has been revealed. From the experimental results it is manifest that, the proposed compression technique gives better performance compared to other traditional techniques.

The program is written in MATLAB 2013b, and the laptop is configured with Intel Core i3 Processor, 3 GB of RAM, Windows 10 64 bit OS.

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