Image Compression by Embedded Zerotrees Wavelet Coding

Mau Reen, Khathy Khaing
University of Computer Studies, Mandalay
maureen192@gmail.com

Abstract

Image compression is very important in many applications, especially for progressive transmission, image browsing, multimedia applications. Image contains large amounts of information that requires much storage space, large transmission bandwidths and long transmission times. Therefore, it is large advantages to compress the image by storing only the essential information needed to reconstruct the image. Image Compression reduces the number of bits needed to represent an image while maintaining a desirable quality. Wavelet image transform is a form of lossy image compression method. It has the ability to divide the original image into un-overlapped blocks depending on the threshold values. This system present image compression and decompression using embedded zerotrees wavelet (EZW) algorithm. And then tests discrete wavelet transforms and compare of their compression ratio (CR) and peak signal to noise ratio (PSNR) with different wavelet families.

1. Introduction

With the rapid of expansion of computer technology, digital image processing places a great demand on efficient data storage. This explanation including what is wavelet transform, embedded zerotree wavelet (EZW) compression that is selected as a compression algorithm for this paper.

In many applications, the efficiency of algorithms for wavelet image compression is Embedded Zerotree Wavelet (EZW). Most of the research work for image compression state that the EZW encoding is powerful scheme and is also provide better performance for high compression ratios than other image coders in the literature. EZW is a lossy image compression will have different pixel values in reconstructed image from original image. EZW is able to encode large portions insignificant regions of an image with a minimal number of bits. EZW is fairly general and performs well with most types of images.

Image compression has four steps: (a) digitize the source image into signals (a string of numbers), (b) decompose the signals into a sequence of coefficients, (c) use thresholds to modify the coefficients and (d) apply entropy coding to compress the coefficients. Embedded Zerotrees Wavelet (EZW) algorithm is the most suitable for wavelet image compression and less compression times than other methods.

2. Image Compression Techniques

There are two types of image compression: lossy and lossless. With lossless compression, the original image is recovered exactly after decompression. A lossy compression method is one where compression data and then decompression it retrieves data that is different from the original. Lossy compression is most commonly used to compress multimedia data (audio, video, still images). There are a number of image compression methods as Fractal, JPEG, JPEG 2000, VQ, Wavelet compressions, etc. EZW algorithm is a lossy.

3. Methods used in Wavelet Image Compression

The general method of the system is:
(1)Wavelet Transform
 (1.1) Discrete Wavelet transform
 (1.2) Wavelet Families
 (1.3) Thresholding
(2) Filter Banks
(3) Embedded Zerotrees Wavelet Transform
 (3.1) Compression of Significance Maps Using Zerotrees of Wavelet Coefficients

3.1. Wavelet Transform

Wavelets are a class of functions that satisfy certain mathematical requirements and are used in representing data or other functions. Wavelets are an extension of Fourier analysis. The goal of wavelet analysis is to turn the information of a signal into numbers-coefficients-that manipulated, stored, transmitted, analyzed, or used to reconstruct the original signal.

The wavelet transform formula is as below in Equation 1:

$$X(s,r) = \int_{-\infty}^{\infty} x(t)\left[\frac{1}{\sqrt{s}}h\left(\frac{t-\tau}{s}\right)dt, s>0\right]$$

Equation 1. Wavelet Transform Formula

For reconstruction formula is as below in Equation 2:

$$x(t)=\frac{1}{C_{\psi}}\int_{0}^{\infty}\int_{-\infty}^{\infty}X(s,\tau)\left[\frac{1}{\sqrt{s}}h\left(\frac{t-\tau}{s}\right)\right]\frac{dsd\tau}{s^{2}}$$

Equation 2. Wavelet Reconstruction Formula

3.1.1. Discrete Wavelet Transform (DWT)

This system used DWT while compiling MATLAB program. DWT, a time-scale representation of the digital signal is defined by a square matrix of coefficients. If correctly constructed, the matrix is orthogonal, and not only the transform but also its inverse are implemented. It is identical to a hierarchical sub-band system, where the sub-bands are represented octave-band decomposition.

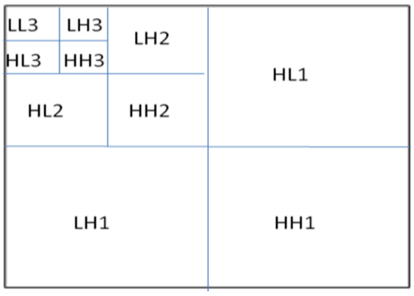

Figure 1.Example of wavelet decomposition

3.1.2 Wavelet Families

There are different types of wavelet families whose qualities vary according to several criteria. The main criteria are: The support of ψ , $\hat{\psi}$ (and $\phi,\hat{\phi}$): the speed of convergence to 0 of these functions($\psi(t)$ or $\hat{\psi}$ (W)) when the time t or the frequency w goes to infinity, which quantifies both time and frequency localizations.

1. The symmetry, which is useful in avoiding de-phasing in image processing.
2. The number of vanishing moments for ψ or for ϕ (if it exists), which is useful for compression purposes.
3. The regularity, which is useful for getting nice features, like smoothness of the reconstructed signal or image and for the estimated function in nonlinear regression analysis. Where ϕ and ψ are wave functions. Several wavelets have their time definitions, others by their frequency definitions and still others by their filters. The wavelet families are as shown in table:

Table 1.Wavelet Families

Wavelet Family Short Name	Wavelet Family Name
1.haar	Haar wavelet
2.db	Daubechies wavelets
3.sym	Symlets
4.coif	Coiflets
5.bior	Biorthogonal wavelets
6.rbio	Reverse biorthogonal wavelet
7.dmey	Discrete approximation of Meyer wavelet

3.1.3 Thresholding

Thresholding is the simplest method of image segmentation. During the thresholding process, individual pixels in an image are marked threshold value (assuming an object to be brighter than the background) and as background pixels otherwise. This convention is known as threshold above and opposite is threshold below.

Thresholding is called adaptive thresholding when a different threshold is used for different regions in the image. This is called local or dynamic thresholding. Color images were thresholded. One is to designate a separate threshold for each of the RGB components of the image and combine them with an AND operation. The image density estimation is (1) Global threshold and (2) By level threshold 1, By level threshold 2, By level threshold 3, etc. The latest includes a sparsity parameter a (a<1); the default is 0.6. More about the thresholding strategies are scare high, medium, and low. These strategies are based on
(1) the level of the decomposition
(2) a positive constant
(3) a sparsity parameter (a>1).

3.2. Filter banks

Filters are one of the most widely used signal processing functions. Wavelets are realized by iteration of filters with rescaling. The resolution of the signal, which is a measure of the signal and scale is determined by sampling and down-sampling operations. The signal is computed by successive low-pass and high-pass filtering of the discrete time-domain signal.

3.3. Embedded Zerotrees Wavelet (EZW) Transform

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The EZW algorithm recognized that a significant fraction of the total bits needed to code an image were required significance maps. A significance map is determines whether each code position information, which EZW called significant maps. A significance map is determines whether each coefficient is significant or not significant. If a coefficient is not significant, it is assumed to quantize to zero.

3.3.1. Compression of Significance Maps Using Zerotrees of Wavelet Coefficients

The improvement of the compression of significance maps of wavelet coefficients, a data structure called zerotree. A zerotree is a quad-tree of which all nodes are equal to or smaller than the root. EZW algorithm uses a series of decreasing thresholds and compares the wavelet coefficients with those thresholds. The EZW uses four symbols to represent a tree node: POS (positive significant), NEG (negative significant), IZ (isolated zero node) and ZTR (zerotree) instead of o and 1.

In scanning order of the sub-bands for encoding a significance map, parents were scanned before the children and all positions in a given sub-band are scammed before the scan moves to the next sub-band. Scanning order has two manners. They are Zigzag scanning order and Morton scanning order. The system used Morton scan order because that scan is more accurate and produces standard result. Morton scan order is as shown in below.

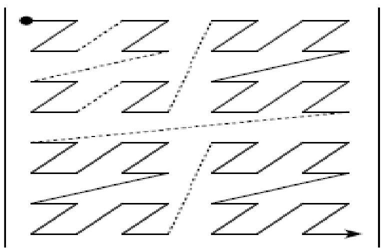

Figure 2. Morton Scanning order

4. Compression Performance

Two qualitative measures giving equivalent information are commonly used as a performance indicator for the compression:

1. The compression ratio CR, which means that the compressed image is stored using only CR% of the initial storage size.
2. Peak signal to noise ratio PSNR, which means that presents a measure of the peak error and is expressed in decibels.

For Compression ratio,

CR = (Compressed size/Raw size)

Compression ratio percentage = (1-(Compressed size/Raw size)) * 100

For peak signal to noise ratio,

$$PSNR=10.\log_{10}\left(\frac{255^2}{(MSE(R)+MSE(G)+MSE(B))/3}\right)$$

Where, f and g between two images is defined by

$$MSE=\frac{1}{N}\sum_{j-k}(f[j,k]-g[j,k])^2$$

In which, j and k are the sum over all pixels in the images. N is the number of pixels in each image.

1. The lower the value of MSE, the lower the error.
2. The higher the PSNR, the better the quality of the compressed or reconstructed image.

5. System Architecture

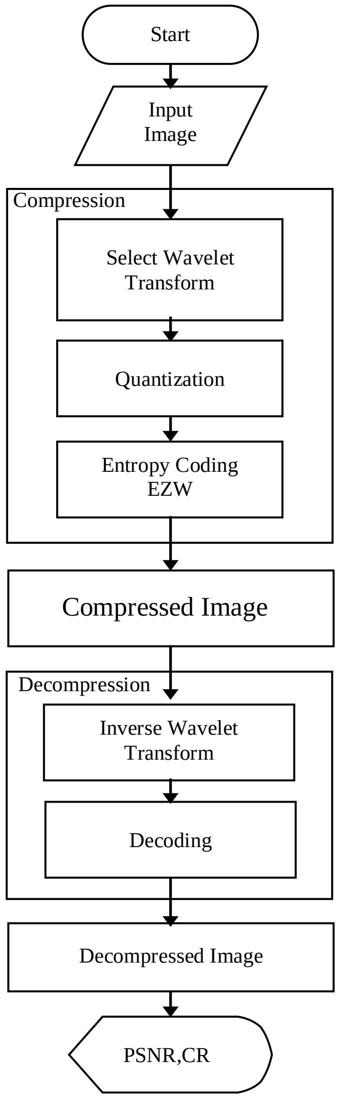

Figure 4. System design for image compression

6. Experimental Result

In this section, the effectiveness of the system is described in detail. This system is implemented on MATLAB Software, version 7.0.4.

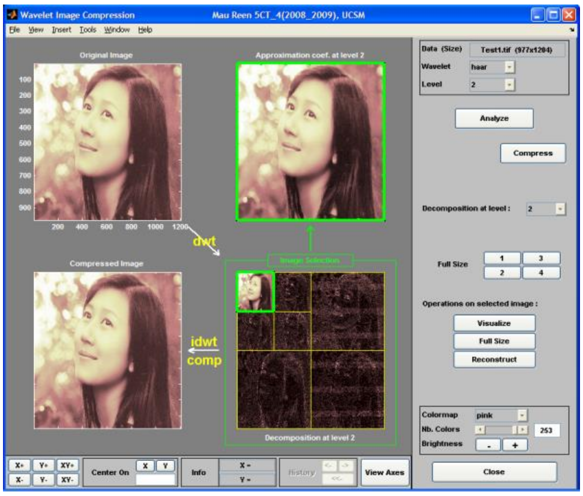

Figure 5. Original Test1.tif image, Decomposition at level 2, Approximation of coefficients and Compressed image

Table 2. Experimental Result of Compression and Decompression

Image	size	PSNR	CR	RE	NZ
Test1.tif	977* 1204	27.51 dB	14.1:1	100%	42.37%
Test2.jpg	256* 384	31.32 dB	8.6:1	99.99%	45.75%
Test3.tif	340* 454	36.47 dB	5.2:1	100%	45.78%
Test4.bmp	208* 246	39.65 dB	2.3:1	100%	44.81%
Test5.jpg	768* 1024	42.93 dB	1.6:1	99.90%	44.76%

For quality evaluation of the images, this system used five images namely Test1.tif, Test2.jpg, Test3.tif, Test4.bmp and Test5.jpg for experimental studies.

In order to measure the effect of wavelet compression in the reconstructed image qualities following method have been used:

- Compression ratio=original image size/compressed-size

- Peak signal to noise ratio=20*log10(255sqrt(MSE))
- Retained energy= $\frac{100*(Vn(CCD,2))^2}{(Vn(originalSignal))^2}$
- NZ= $\frac{100(ZCD)}{No.ofcoefficients}$

Where, Vn is the vector norm, CCD is the coefficients of the current decomposition and the NZ is the number of zeros of the current decomposition.

7. Conclusion

Embedded Zerotree Wavelet (EZW) algorithm is effective and important compression algorithm. The encoding encodes the image by Discrete Wavelet Transform (DWT) with five levels decomposition. The decoding algorithm used inverse discrete wavelet transform to get the reconstructed image. This algorithm compressed different sized images and different formats. The advantages of this algorithm are that it a fully embedded bit stream, providing competitive compression performance, gets clearer picture by changing thresholding values. RE and NZ are determined for noiseless and noisy images for compression. A small threshold yields a result close to the input. But RE and NZ is depends on decomposition level, type of image, threshold and also type of transform used. For maximum threshold value and greater level of decomposition, more energy are lost because at higher levels of decomposition. There is higher proportion of the coefficients in the detail sub-signals.

8. References

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