TELKOMNIKA Indonesian Journal of Electrical Engineering
Vol.12, No.3, March 2014, pp. 1895 ~ 1905
DOI: http://dx.doi.org/10.11591/telkomnika.v12i3.4437

Comparisons of Threshold EZW and SPIHT Wavelets Based Image Compression Methods

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Abstract

Images require substantial storage and transmission resources, thus image compression is advantageous to reduce these requirements. The objective of this paper is to implement the concept of wavelet based image compression to gray scale images using different wavelet techniques. The techniques involved in the comparison process are threshold method, EZW (embedded zerotree wavelet) and SPIHT (set partitioning in hierarchical trees). These techniques are more efficient and provide a better quality in the image. Matlab is used to be carried out the simu1ation where different wavelet and different methods for image compression are applied. The techniques are compared by using the performance parameters CR (Compression Ratio), PSNR (Peak Signal to Noise Ratio), MSE (Mean Square Error), and BPP (Bits per Pixel). Images obtained with those techniques yield very good results. The results showed that the compression effect of wavelet threshold compression is not good. Wavelet decomposition level and wavelet function impacted on the compression effect. Wavelet based image compression based on EZW and SPIHT are more efficient.

***Keywords**: wavelet transform, image compression, zerotree, threshold*

1. Introduction

In modern day, many applications need large number of images for solving problems. Digital image can be store on disk. This storing space of image is also important. Because of less memory space means less time of required to processing for image. Here the concept of image compression comes. The compression offers a means to reduce the cost of storage and increase the speed of transmission. Image compression is used to minimize the size in bytes of a graphics file without degrading the quality of the image.

Wavelet transform praised as “mathematical microscope” has been rapidly developed for its fine frequency property over the few past years [1-3]. It possesses the properties of the low entropy, the de-relativity and the agility of choosing the base. In recent years, many studies have been made on wavelets. An excellent overview of what wavelets have brought to the fields as diverse as biomedical applications, wireless communications, computer graphics or turbulence [4-5]. Image compression is one of the most visible applications of wavelets. The rapid increase in the range and use of electronic imaging justifies attention for systematic design of an image compression system and for providing the image quality needed in different applications.

Recently image compression, especially at low bit rate, has assumed a major role in applications such as storage on low memory devices, narrow-band channel transmitting, wireless transmitting and streaming data on the internet. Wavelet-based coding provides substantial improvements in picture quality at higher compression ratios [6]. A variety of powerful and sophisticated wavelet-based image compression schemes, such as the embedded zero tree wavelet (EZW) coding scheme [7], set partitioning in hierarchical trees (SPIHT) algorithm [8], have been developed.

This paper introduces the theory of wavelet and principle of image compression based on wavelet. Different wavelet based image compression techniques are simulated. The results of simulation are shown and different quality parameters are compared.

Received August 19, 2013; Revised September 26, 2013; Accepted October 15, 2013

2. Theory of Image Compression

Image compression is the application of data compression on digital images. A common characteristic of most images is that the neighboring pixels are correlated and therefore contain redundant information. The foremost task then is to find less correlated representation of the image. Two fundamental components of compression are redundancy and irrelevancy reduction. Redundancy reduction aims at removing duplication from the signal source (image/video). Irrelevancy reduction omits parts of the signal that will not be noticed by the signal receiver, namely the Human Visual System (HVS).

Compression can be categorized in two broad ways:

1) Lossless Compression: Data is compressed and can be reconstituted (uncompressed) without loss of detail or information. These are referred to as bit-preserving or reversible compression systems also lossless compression frequently involves some form of entropy encoding and are based in information theoretic techniques.

2) Lossy Compression: The aim is to obtain the best possible fidelity for a given bit-rate or minimizing the bit-rate to achieve a given fidelity measure. Video and audio compression techniques are most suited to this form of compression. If an image is compressed it clearly needs to uncompressed (decoded) before it can viewed/listened to. Some processing of data may be possible in encoded form however. Lossy compression use source encoding techniques that may involve transform encoding, differential encoding or vector quantisation.

The advantage of lossy methods over lossless methods is that in some cases a lossy method can produce a much smaller compressed file than any known lossless method, while still meeting the requirements of the application. Lossy methods are most often used for compressing sound, images or videos. The compression ratio (that is, the size of the compressed file compared to that of the uncompressed file) of lossy video codes are nearly always far superior to those of the audio and still-image equivalents. Audio can often be compressed at 10:1 with imperceptible loss of quality, video can be compressed immensely (e.g. 300:1) with little visible quality loss. Lossly compressed still images are often compressed to 1/10th their original size, as with audio, but the quality loss is more noticeable, especially on closer inspection.

In general terms, one can describe an image compression system as a cascade of one or more of the following stages:

1) Transformation. A suitable transformation is applied to the image with the aim of converting it into a different domain where the compression will be easier. Another way of viewing this is via a change in the basis images composing the original. In the transform domain, correlation and entropy can be lower, and the energy can be concentrated in a small portion of the transformed image.

2) Quantization. This is the stage that is mostly responsible for the 'lossy' character of the system. It entails a reduction in the number of bits used to represent the pixels of the transformed image (also called transform coefficients). Coefficients of low contribution to the total energy or the visual appearance of the image are coarsely quantized (represented with a small number of bits) or even discarded, whereas more significant coefficients are subjected to a finer quantization. Usually, the quantized values are represented via some indices to a set of quantizer levels (codebook).

3) Entropy coding (lossless). Further compression is achieved with the aid of some entropy coding scheme where the nonuniform distribution of the symbols in the quantization result is exploited so as to assign fewer bits to the most likely symbols and more bits to unlikely ones. This results in a size reduction of the resulting bit-stream on the average. The conversion that takes place at this stage is lossless, that is, it can be perfectly cancelled.

The above process is followed in the encoding (compression) part of the coder/decoder (codec) system. In the decoding (expansion/decompression) part, the same steps are taken in reverse. That is, the compressed bit-stream is entropy decoded yielding the quantized transform coefficients, then 'de-quantized' (i.e., substituting the quantized values for the corresponding indices) and finally inverse transformed to arrive at an approximation of the original image. The whole process is shown schematically in Figure 1.

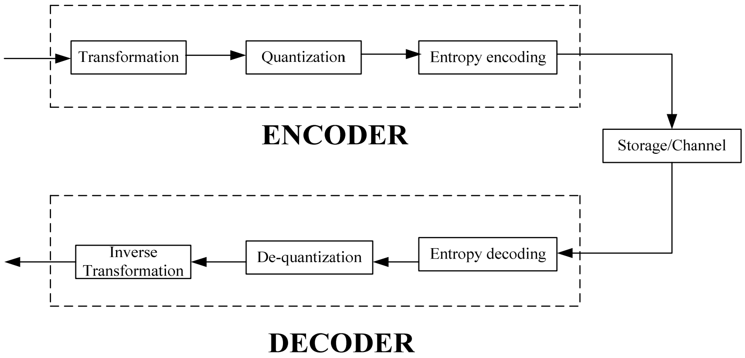

Figure 1. Block Representation of a General Transform Coding System

The phrase Mean Square Error, often abbreviated MSE (also called PSNR, Peak Signal to Noise Ratio) is an engineering term for the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. Because many signals have a very wide dynamic range, MSE is usually expressed in terms of the logarithmic decibel scale.

The MSE/PSNR is most commonly used as a measure of quality of reconstruction of lossy compression codes (e.g., for image compression). The signal in this case is the original data, and the noise is the error introduced by compression. When comparing compression codes it is used as an approximation to human perception of reconstruction quality, therefore in some cases one reconstruction may appear to be closer to the original than another, even though it has a lower PSNR (a higher PSNR would normally indicate that the reconstruction is of higher quality). One has to be extremely careful with the range of validity of this metric; it is only conclusively valid when it is used to compare results from the same codec (or codec type) and same content.

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

The PSNR is defined as:

$$PSNR = 10\cdot\log_{10}(\frac{MAX_I 2}{MSE}) = 20\log_{10}(\frac{MAX_I}{\sqrt{MSE}}) \quad (2)$$

Here, MAX_I is the maximum possible pixel value of the image. When the pixels are represented using 8 bits per sample, this is 255. More generally, when samples are represented using linear PCM with B bits per sample, MAX_I is 2B−1. For color images with three RGB values per pixel, the definition of PSNR is the same except the MSE is the sum over all squared value differences divided by image size and by three.

3. Wavelet Theory and the Wavelet Image Coding

Wavelets mean localized waves. These waves drop to zero instead of oscillating forever. In the transform domain, the wavelets are basis functions for details. Scaling functions are basis functions for approximations. Applying the wavelet transform is decomposing a signal into these approximation and detail domains. Contrary to the “frequency” of the Fourier transform, the wavelet transform uses “scale” and “location” to represent a signal. Iterative decompositions from an approximation domain indicate the number of scales or levels in the wavelet domain. The wavelet transform of a signal yields coefficients as a representation of a signal in the wavelet domain. These coefficients are obtained by separate filter channels. The filters built for the wavelet transform can be considered as quadrature mirror filter banks with perfect reconstruction. The main difference that differentiates the wavelet transform from the filter bank is the iterative filtering structure that gives the scales.

And it is a local time-frequency analysis method that the window size fixed but its shape can be changed, the time and frequency window all can be changed. Partition of time-frequency plane of wavelet transform is shown in Figure 2. Here, its scaling analyzing function can vary its width depending on the frequency information to be analyzed. The scaling analyzing function has a large width in the temporal domain for low frequency components and a small width for the high frequency components. It is very normal for detecting transient signal entrainment anomaly and demonstrates the signal's components. Therefore, it is called a mathematical microscope for analyzing signals. Just because of this characteristic, wavelet transform has the adaptability of the signal.

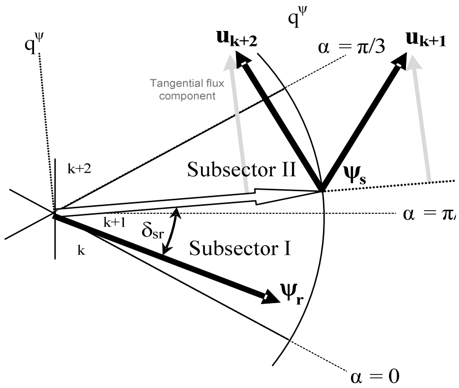

Figure 2. Partition of Time-frequency Plane of Wavelet Transform

In recent years, wavelet theory has been developing extensively and quickly, which applied widely to achieve better effect in many fields because of good frequency domain characteristic. The features of wavelet transforms are described as follows.

(i) Low entropy: It makes the entropy of transformed image decreased that sparse distribution feature of wavelet coefficients;
(ii) Multiresolution: Using the multiresolution method, non-stationary characteristics of the image signal just like edge, aiguilles, and break, etc, can be expressed clearly.
(iii) Relativity eliminated: In respect that relativity of signals can be eliminated by wavelet transform, and moreover, the noises tend to be whiten after transforming processing, so it is easier for wavelet to denoising;
(iv) Flexibility in choosing basis: Due to flexibility in choosing basis for wavelet transform, different wavelet mother function can be chosen to gain the perfect effect for different application fields and research objects.

Wavelet expansion uses a set of basis functions for image decomposition. In a two dimensional case, a scaling function $\varphi(x,y)$ and three wavelet functions $\psi^H(x,y)$, $\psi^V(x,y)$ and $\psi^D(x,y)$ are selected. Each scaling function or wavelet function is the product or the basis functions. Four products produce the scaling function (3) and separable directional sensitive wavelet functions (4)-(6), resulting in a structure of quaternary tree.

$$\varphi(x,y)=\varphi(x)\varphi(y) \tag{3}$$

$$\psi^H(x,y)=\varphi(y)\psi(x) \tag{4}$$

$$\psi^V(x,y)=\varphi(x)\psi(y) \tag{5}$$

$$\psi^D(x,y)=\psi(x)\psi(y) \tag{6}$$

These wavelets measure the variations for images along three directions, where $\psi^H(x,y)$ measures variations along columns (horizontal), $\psi^V(x,y)$ measures variations along rows (vertical), and $\psi^D(x,y)$ measures variations along diagonals (diagonal). The scaled and translated basis functions are defined by:

$$\Phi_{j,m,n}(x,y)=2^{j/2}\varphi(2^{j}x-m,\ 2^{j}y-n) \quad (7)$$

$$\psi^{i}_{j,m,n}\ (x,y)=\ 2^{j/2}\psi\ (2^{j}x-m,\ 2^{j}y-n)|,i=\{H,V,D\} \quad (8)$$

Where index i identifies the directional wavelets of H,V, and D. The discrete wavelet transform of function f(x,y) of size M by N is formulated as:

$$w_{\varphi}(j_0,m,n)=\frac{1}{\sqrt{MN}}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1}f(x,y)\varphi_{j_0,m,n}(x,y) \quad (9)$$

$$w_{\psi}{}^{i}(j,m,n)=\frac{1}{\sqrt{MN}}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1}f(x,y)\psi^{i}_{j,m,n}(x,y) \quad (10)$$

Where i={H,V,D}, j0 is the starting scale, the $w_{\varphi}(j_0,m,n)$ coefficients define the horizontal, vertical and diagonal details for scales j>=j0. Here j_0=0 and select N+M=2^J so that j=0,1,2,…,J-1 and m,n=0,1,2,…,2^j=1. Then the f(x,y) is obtained via the inverse discrete wavelet transform.

The wavelet function acts as a bandpass filter whose bandwidth is reduced to half after each scaling. Filters are one of the most widely used signal processing functions. Wavelets can be realized by iteration of filters with rescaling. The resolution of the signal, which is a measure of the amount of detail that is found in the signal and the scale is determined by upsampling and downsampling operations. The DWT is computed by successive low pass and high pass filtering of the discrete time domain signal as shown in the figure below in Figure 4.

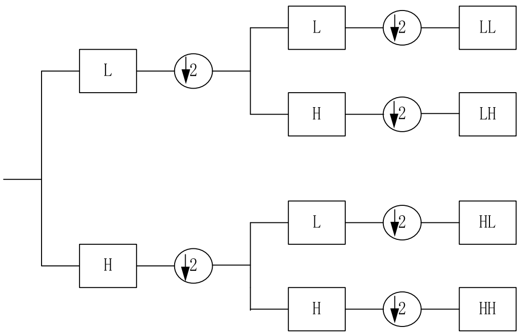

Figure 3. Two-Scale Wavelet Decomposition

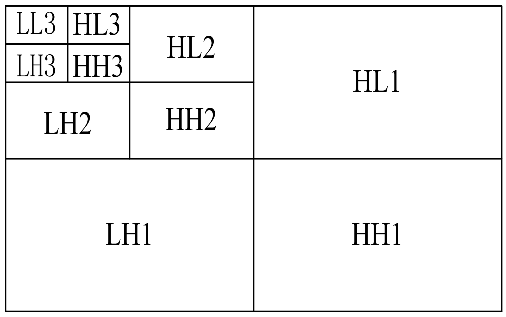

Figure 4. Structure of Wavelet Decomposition

The 2D discrete wavelet transform is implemented as a multiple level transformation. The output at each level always includes: the approximation (LL), horizontal detail (HL), vertical detail (LH) and diagonal detail (HH). Thus, a typical 2D DWT, used in image compression, generates the hierarchical structure shown in Figure 4. As a result, each of them is a quarter size of its original image followed by downsampling with a factor of two. In orthogonal discrete wavelet transform, the information lost between two successive approximations is captured as detail coefficient. Then the next step is about splitting the approximation but the successive details are never reanalyzed.

4. Wavelet Image Compression Technique

Despite all the advantages of JPEG compression schemes based on DCT (discrete cosine transform) namely simplicity, satisfactory performance, and availability of special purpose hardware for implementation, these are not without their shortcomings. Since the input image needs to be ``blocked'', correlation across the block boundaries is not eliminated. This results in noticeable and annoying ``blocking artifacts'' particularly at low bit rates [9]. Over the past several years, the wavelet transform has gained widespread acceptance in signal processing in general, and in image compression research in particular. In many applications wavelet-based schemes (also referred as sub- band coding) out perform other coding schemes like the one based on DCT. A wavelet transform-based image compression algorithm consists of a 2D wavelet transform of the image, followed by quantization and coding of the wavelet coefficients. The wavelet transform achieves a high compression ratio without intolerable degradation by relying on the redundancy within the image and because of some of its similarity with the characteristics of the human visual system.

Most modern image compression algorithms use the hierarchical wavelet decomposition suggested by Mallat in which a set of high-pass (H) and low-pass (L) filters are applied to the original image in both horizontal and vertical directions, and the resulting coefficients are subsampled by a factor to two, thus producing four subbands, namely, LL, LH, HL and HH. The process is then repeated on low pass subband, that is LL, to produce next level of decomposition and so on. The wavelet decomposition is very efficient in removing linear correlations in an image, so the different subbands can be coded independently of each other.

The whole process of wavelet image compression is performed as follows: An input image is taken by the computer, forward wavelet transform is performed on the digital image, threshold is done on the digital image, entropy coding is done on the image where necessary, thus the compression of image is done on the computer. Then with the compressed image, reconstruction of wavelet transformed image is done, then inverse wavelet transform is performed on the image, thus image is reconstructed.

Firstly, forward wavelet transformation is performed on the image. Various wavelet can be used in this step. Once DWT is performed on the image, the next task is threshold, which is neglecting certain wavelet coefficients. For doing this one has to decide the value of a threshold and how to apply the same, which is an important step which affects the quality of the compressed image. The basic idea is to truncate the insignificant coefficients, since the amount of information contained in them is negligible.

$$t = \sigma\sqrt{2\ln N} \tag{11}$$

Here, σ is standard deviation of the N wavelet coefficients.

The value of t should be calculated for each level of decomposition and only for the high pass coefficients. The low pass coefficients are usually kept untouched so as to facilitate further decomposition.

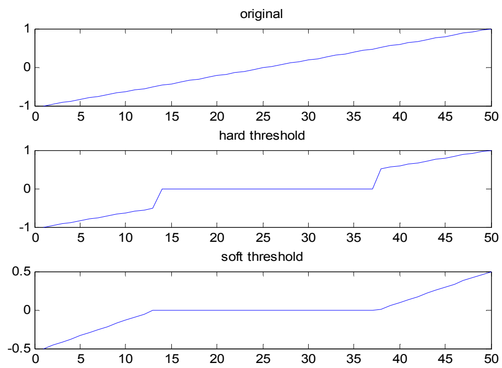

Figure 5. Hard Threshold and Soft Threshold

There are two ways in which threshold can be applied. The principle of the two threshold methods is shown in Figure 5.

a) Hard threshold: If x is the set of wavelet coefficients, then threshold value t is given by, i.e. all the values of x which are less than threshold t are equated to zero.

$$\hat{x} = \begin{cases} x, |x| \geq t \\ 0, |x| \leq t \end{cases} \tag{12}$$

b) Soft threshold: In this case, all the coefficients x lesser than threshold t are mapped to zero. Then t is subtracted from all x ¸ t. This condition is depicted by the following equation:

$$\hat{x} = \begin{cases} sign(x)(|x| - t), |x| \geq t \\ 0, |x| \leq t \end{cases} \tag{13}$$

Entropy defined as:

$$H(S) = -\sum_{i=1}^{q} p(si)\log_2(p(si)) \tag{14}$$

Where s_i are codewords and S is the message. Entropy coding uses codewords with varying lengths, here codewords with short length are used for values that have to be encoded more often, and the longer codewords are assigned for less encoded values. H(S) measures the amount of information in the message, ie. The minimal number of bits needed to encode one word of the message. Unfortunately, the entropy encoding was not implemented on the codes for the color image compression using wavelets. However, Shannon entropy which is defined below used in the code for the image compression with wavelet packets.

Shapiro introduced EZW coding which allowed complete embedded bit representation. Shapiro's EZW marked the beginning of "modern wavelet coders". Since then, different wavelet based coding algorithms have been proposed, which use the fundamental idea of EZW algorithm. One of the most notable is SPIHT algorithm, which achieves better performance than EZW algorithm without the need for arithmetic coding [10].

EZW is a lossy image compression algorithm. At low bit rates (i.e. high compression ratios) most of the coefficients produced by a subband transform (such as the wavelet transform) will be zero, or very close to zero. This occurs because "real world" images tend to contain mostly low frequency information (highly correlated). However where high frequency information does occur (such as edges in the image) this is particularly important in terms of human perception of the image quality, and thus must be represented accurately in any high quality coding scheme.

By considering the transformed coefficients as a tree (or trees) with the lowest frequency coefficients at the root node and with the children of each tree node being the spatially related coefficients in the next higher frequency subband, there is a high probability that one or more subtrees will consist entirely of coefficients which are zero or nearly zero, such subtrees are called zerotrees. Due to this, we use the terms node and coefficient interchangeably, and when we refer to the children of a coefficient, we mean the child coefficients of the node in the tree where that coefficient is located. We use children to refer to directly connected nodes lower in the tree and descendants to refer to all nodes which are below a particular node in the tree, even if not directly connected.

SPIHT algorithm is the improvement of EZW. It uses an effective spatial orientation tree structure and bit-plane coding method, and can achieve embedded code stream of high compression efficiency, and it has higher signal to noise ratio and better image restoration quality. Compared with the EZW, SPIHT algorithm constructs two different types of spatial zero-tree, take better advantage of the attenuation law of wavelet coefficients amplitude [11]. The Drawback is adopting the more complex set partitioning strategy to reduce the coding rate; and store the zero-tree structure of image wavelet coefficients and important factor information by using three set list and reduce memory space utilization.

5. Simulation Results and Analysis

In order to compare the compression effect of threshold methods, the experiments were conducted on boat image of size 512x512. The 'bior4.4' wavelet was used with 3 levels of decomposition. Figure 3 shows the compressed boat images with threshold methods. Hard threshold function is not continuous, so the reconstructed image will have oscillation. The soft threshold function is continuous, and it can overcome the disadvantage caused by the discontinuity of hard threshold function. But the soft threshold function also has its own disadvantages, namely there is always a constant deviation during the processing of coefficients with larger absolute value. This directly affects the approximation degree between reconstructed image and the original image. The edge of the reconstructed image will be blurry. In practical applications, the reconstructed image using soft threshold compression is relatively smooth, but there is a large distortion, and the outline of the image is not clear. The hard threshold compression effect is not ideal.

(a) (b)

Figure 6. Compressed Boat Images with Threshold Methods (a) hard threshold, (b) soft threshold

The quality of compressed image depends on the number of decompositions. Here wavelet bases functions of 'bior4.4' was used with soft-threshold method. The influence of wavelet decomposition level on PSNR was studied. It can be seen from the Figure 7, with the increasing of wavelet decomposition level, PSNR is decreased. Therefore, adaptive decomposition is required to achieve balance between image quality and complexity of computations.

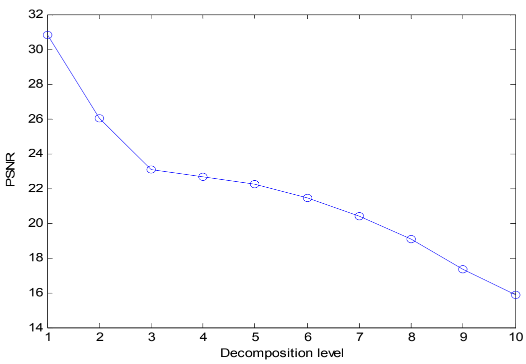

Figure 7. Influence of Wavelet Decomposition Level on PSNR

There are two common thresholding selection methods for sub-picture transform, namely the global thresholding and the subband thresholding. The compression experiments were made on boat image with subband thresholding of coefficients and global thresholding of coefficients. The 'bior4.4' wavelet was used with different levels of decomposition. Table 1 is the compression performances of subband thresholding and global thresholding methods compared with the global thresholding method, in the case of that there are not significant energy losses, the subband threshold compression method can obtain a higher compression ratio.

Table 1. Compression Performances of Subband Thresholding and Global Thresholding Methods

Thresholding selection method	signal energy percentage after compression	percentage of zero elements after compression
subband thresholding	99.2375%	94.8803%
global thresholding	99.8201%	52.8656%

Choice of wavelet function is crucial for coding performance in image compression. This choice should be adjusted to image content. Important properties of wavelet functions in image compression applications are compact support (lead to efficient implementation), symmetry (useful in avoiding dephasing in image processing), orthogonality (allow fast algorithm), order or length of wavelet filter) regularity and degree of smoothness (related to filter. In our experiment five types of wavelet families are examined: Haar Wavelet, Wavelet, Coiflet Wavelet, Biorsplines Wavelet and Biorthogonal Wavelet. The experiments were conducted on boat image of size 512x512. The coefficients thresholding method with subband thresholding of coeeficients and Huffman encoding was used. The decomposition level was 3. Here, the compression result using different daubechies wavelets is shown in Table 2. The compression effect is evaluated by four evaluation functions. CR is the compression ratio and BPP is the bit-per-pixel ratio (BPP). It can be seen that different wavelets can generate different compression effect. Bior3.1 is superior to the other wavelets for the compression of boat image of size 512x512.

Table 2. Evaluation Results by Using Different Wavelets

Wavelet	PSNR	MSE	CR	BPP
harr	25.3728	188.7113	2.3762	0.1901
db4	27.0257	128.9776	3.0449	0.2436
db8	27.0426	128.4742	3.2177	0.2574
db10	27.0415	128.5073	3.3360	0.2669
sym4	27.1461	125.4497	2.6905	0.2152
sym5	27.2205	123.3197	2.6546	0.2124
sym8	27.3637	119.3178	2.7603	0.2208
coif1	26.5427	144.1473	2.6001	0.2080
coif3	27.3246	120.3974	3.6766	0.2941
coif5	27.4198	117.7884	2.7134	0.2171
bior3.1	28.3039	96.0925	5.6503	0.4520
bior4.4	27.3785	118.9121	2.6508	0.2121
bior6.8	27.7135	110.0848	2.8816	0.2305

Wavelet threshold compression method is simple in principle. But it can not control the compression ratio and image errors. Over the past few years, a variety of powerful and sophisticated wavelet-based image compression schemes, such as EZW coding scheme, SPIHT algorithm. Figure 8(a) shows the original image and Figure 8(b) shows the compressed image by EZW. Similarly Figure 9(a) shows original image and Figure 9(b) shows the compressed image by SPIHT image compression algorithms. Table 3 shows the results of CR, BPP, MSE & PSNR by using EZW algorithm. Table 4 shows the values for SPIHT Algorithms. The EZW compression method includes compact multiresolution representation of images by discrete wavelet transformation, zerotree coding of the significant wavelet coefficients providing compact binary maps, successive approximation quantization of the wavelet coefficients, adaptive multilevel arithmetic coding, and capability of meeting an exact target bit rate with corresponding rate distortion function. The SPIHT method provides highest image quality, progressive image transmission, fully embedded coded file, Simple quantization algorithm, fast coding/decoding, completely adaptive, lossless compression.


(a)


(b)

Figure 8. Compression with EZW Method (a) Original Image 3, (b) Compressed Image by EZW


(a)


(b)

Figure 9. Compression with SPIHT Method (a) Original Image 3, (b) Compressed Image by SPIHT

Table 3. Evaluation Results by Using Different Wavelets for EZW Algorithm

Wavelet	PSNR	MSE	CR	BPP
harr	29.7979	68.1229	7.3166	0.5853
db4	30.4395	58.7659	6.4781	0.5182
db8	30.3575	59.8868	6.6891	0.5351
db10	30.3320	60.2390	6.6998	0.5360
sym4	30.5289	57.5687	6.3114	0.5049
sym5	30.5557	57.2144	6.3423	0.5074
sym8	30.5692	57.0377	6.2836	0.5027
coif1	30.2811	60.9491	6.6471	0.5318
coif3	30.4988	57.9699	6.3328	0.5066
coif5	30.5841	56.8426	6.3877	0.5110
bior3.1	26.7984	135.9066	5.6347	0.4508
bior4.4	30.3462	60.0426	5.7373	0.4590
bior6.8	30.6441	56.0624	6.3564	0.5085

Table 4. Evaluation Results by Using Different Wavelets for SPIHT Algorithm

Wavelet	PSNR	MSE	CR	BPP
harr	29.1768	78.5966	5.1430	0.4114
db4	29.7892	68.2596	4.3217	0.3457
db8	29.6948	69.7598	4.4044	0.3524
db10	29.6642	70.2515	4.4487	0.3559
sym4	29.8831	66.7996	4.3106	0.3448
sym5	29.9147	66.3149	4.2618	0.3409
sym8	29.9227	66.1932	4.2198	0.3376
coif1	29.6556	70.3909	4.5193	0.3615
coif3	29.8708	66.9890	4.2587	0.3407
coif5	29.9478	65.8107	4.2904	0.3432
bior3.1	26.4701	146.5774	3.6400	0.2912
bior4.4	29.6881	69.8660	3.9570	0.3166
bior6.8	29.9992	65.0368	4.2011	0.3361

6. Conclusion

Wavelet method using for compression is an important aspect of wavelet analysis applied to the actual. This article described several commonly used principles of wavelet compression method, and achieved wavelet compression method based on threshold in the Matlab. The results are as follows: Discrete wavelet transform has ability to solve the blocking effect introduced by DCT and its suitability in multi-resolution analysis; Wavelet threshold compression method has more of the defects, the compression effect is not good; Wavelet decomposition level and wavelet function are all important factors which impact the compression effect; EZW and SPIHT are powerful and sophisticated wavelet-based image compression schemes; Compared to EZW method, wavelet based image compression based on SPIHT is a powerful efficient and yet computationally simple image compression algorithm.

Acknowledgements

Project supported by the National Natural Science Foundation of China (Grant Nos 61376076, 61274026, and 61377024); supported by the Science and Technology Plan Foundation of Hunan Province (Grant Nos 2013FJ2011 and 2013FJ4232); supported by the Scientific Research Fund of Hunan Provincial Education Department (12C0108 and13C321).

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