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Comparison of Wavelet Transform Filters Using Image Compression

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Abstract

The wavelet transform has become a useful computational tool for a variety of signal and image processing applications.

The aim of this paper is to present the comparative study of various wavelet filters. Eleven different wavelet filters (Haar, Mallat, Symlets, Integer, Conflict, Daubechi 1, Daubechi 2, Daubechi 4, Daubechi 7, Daubechi 12 and Daubechi 20) are used to compress seven true color images of 256x256 as a samples. Image quality, parameters such as peak signal-to-noise ratio (PSNR), normalized mean square error have been used to evaluate the performance of wavelet filters.

In our work PSNR is used as a measure of accuracy performance.
We use two values of compression factors (4.3 and 5.1) to test the wavelet filters [1].

The experimental shows different results but in general the Daubechi Family specialy Daubechi 4, Daubechi 7, Daubechi 12 and Daubechi 20 give better performance in term of PSNR. Matlab 9.0 is used to implement the experiments.
Keywords- Haar, Daubechies , Image Compression, Wavelet transform.

Introduction

Data compression is the process of converting an input data stream into another data stream that has smaller size. The basic principle of compression is to remove the redundancy in the source data. Compression basically is of two types –lossless and lossy.
Computer graphics is used in many areas in everyday life to convert many types of complex information to images. Thus, images are important, but they tend to be big! Since modern hardware can display many colors, it is common to have a pixel represented internally as a 24-bit number, where the percentages of red, green, and blue occupy 8 bits each. Such a 24-bit pixel can specify one of 224 ≈ 16.78 million colors. As a result, an image at a resolution of 512*512 that consists of such pixels occupies 786,432 bytes. At a resolution of 1024*1024 it becomes four times as big, requiring 3,145,728 bytes. Movies are also commonly used in computers, making for even bigger images. This is why image compression is so important. An important feature of image compression is that it can be lossy. An image, after all, exists for people to look at, so, when it is compressed, it is acceptable to lose image features to which the eye is not sensitive. This is one of the main ideas behind the many lossy image compression methods [2].

The basic idea behind any compression is to find a way to represent data that takes up less space, and reducing the time for data transfer via communication channels.

Data compression technology is necessary in today multimedia society. By using this technology, information can be transmitted in shorter amount of time and the storage space can be made smaller. Since data compression in broad terms "expressing" things concisely" it is applied to many fields, such as learning and inference, and so on [3].

Lossy/lossless compression: Certain compression methods are lossy. They achieve better compression by losing some information. When the compressed stream is decompressed, the result is not identical to the original data stream. Such a method makes sense especially in compressing images, movies, or sounds. If the loss of data is small, we may not be able to tell the difference.

Lossless compression consists of those techniques guaranteed to generate an exact duplicate of the input data stream after a compress/ expand cycle. Lossless compression techniques provide for exact reconstruction of the original signal.

Lossless compression works by removing redundancies within the data then coding the resulting signal with an efficient coding scheme. Lossless compression algorithm can provide a limited compression ratio. Instead, it is often applied in conjunction with a lossy compression scheme to provide additional compression [2].

The wavelet transform has become a useful computational tool for a variety of signal and image processing applications. For example, the wavelet transform is useful for the compression of digital image _les; smaller _les are important for storing images using less memory and for transmitting images faster and more reliably [4].

Wavelet Transform

A wavelet is a waveform of effectively limited duration that has an average value of zero. Wavelet analysis is the breaking up of a signal into shifted versions of the original (*or mother*) wavelet. Wavelets are mathematical functions that cut up the data into different frequency components, and then study each component with resolution matched to scale [5].

A wavelet is usually defined as an oscillating function of time or space, such as a sinusoid. Fourier analysis is wave analysis. It expands signals or functions in terms of sinusoids or equivalently complex exponential, which have been proven to be extremely valuable in image compression, mathematics, science, and engineering, especially for periodic, time-invariant, or stationary phenomena. A wavelet is a "small wave", which has its energy concentrated in time to give a tool for the analysis of transient, non-stationary, or time-varying phenomena.

It still has the oscillating wave like characteristic but also has the ability to allow simultaneous time and frequency analysis with a flexible mathematical foundation.

Many classes of the function can be represented by wavelets in a more compact way. For example functions with discontinuities and functions with sharp spikes usually take substantially fewer wavelets bases than sine-cosine bases to achieve a comparable approximation. This sparse coding makes excellent tools in data compression.

However, in wavelet analysis, the scale that can be used to look at a data plays a special role. Wavelet algorithm processes data at different scales or resolutions by looking at the signal with large window, it can notice gross features. Similarly by looking at the signal with small window, it can notice small features [6,7].

Calculating wavelet coefficients at every possible scale is a fair amount of work, it turns out, that if we choose scales and positions based on powers of two – so – called *dyadic* scales and positions – then our analysis will be more efficient and just such an analysis form the *discrete wavelet transform* (DWT).

An efficient way to implement this scheme using filters was developed in 1988 by Mallat. This is a practical filtering algorithm yields a *fast wavelet transform* [8].

For many signals, the low frequency content is the most important part. It is what gives the signal its identity. For example, consider the human voice. If you remove the high frequency components, the voice sounds different, but you can still tell what's
being said. However, if you remove enough of the low – frequency components, you hear gibberish.

It is for this reason that, in wavelet analysis, we often speak of *approximations and details* [9].

The approximations are the high – scale, low – frequency components of the signal.
The details are the low – scale, high – frequency components of the signal.
The decomposition process can be made by filtering the signal by LPF (Low Pass Filter) and HPF (High Pass Filter), then the signal is down sampled by two [10].

The reconstruction process can be made by up sampling f and d in equations (1) and (2), and filtering them with g(n) and h(n).

$$d^{(j-1)}(n) = \sum_k f^{(j)}(k)\, h(k-2n) \qquad (1)$$

$$f^{(j-1)}(n) = \sum_k f^{(j)}(k)\, g(k-2n) \qquad (2)$$

Where
$f^{(j)}$ = the signal.
$f^{(j-1)}$ = the approximation.
$d^{(j-1)}$ = the details.
g(n), h(n) = the LPF,HPF filters impulse responses, respectively.

The aim of the DWT is to decompose the discrete time signal into basis functions, called the wavelets, to give us a good analytic view of the analyzed signal. The decomposition process is divided into stages, called levels or depths. At each depth, different time and frequency resolution is taken (*high frequency resolution means lower time resolution and vise versa*). This variable resolution is done using building blocks, or wavelets, which are derived from an original wavelet, called the *mother wavelet.* The signal is decomposed using dilated and shifted versions of the mother wavelet [11].

Key parameters used in image compression:

Although a lot of key parameters are utilized in the literature for performance evaluation of the various filters type methods, this work will utilize three key parameters.

1- Compression Factor (CF)

This parameter is used to calculate how much the size of the tested image files is compressed; the compression ratio is defined as:

$$\text{Compression Factor (CF)} = \frac{\text{(size of input stream) original}}{\text{(size of output stream) compressed}}$$

CF > 1 means positive compression.
CF < 1 means the output stream (negative compression).
Whenever this factor is big it indicates that the compression is better, otherwise the compression is weak.

2- The Mean Squared Error (MSE)

This parameter is a fidelity parameter which is used to measure the error level caused by the compression system; mean square error can be defined as:

$$MSE = \frac{1}{M.N}\sum_{M=0}^{M-1}\sum_{N=0}^{N-1}\left[X(M.N) - \bar{X}(M.N)\right]^2$$

X[.] is the original image with dimensions M×N, and $\bar{X}$ [.] is the reconstructed image.

$MSE = 1/k \sum_{i=1}^{k} (Pi - Qi)^2$, Root Mean Square Error

$RMSE = \sqrt{MSE}$, *Where, Pi* – Original Image data, *Qi* - Reconstructed image data, *K* is size of image.

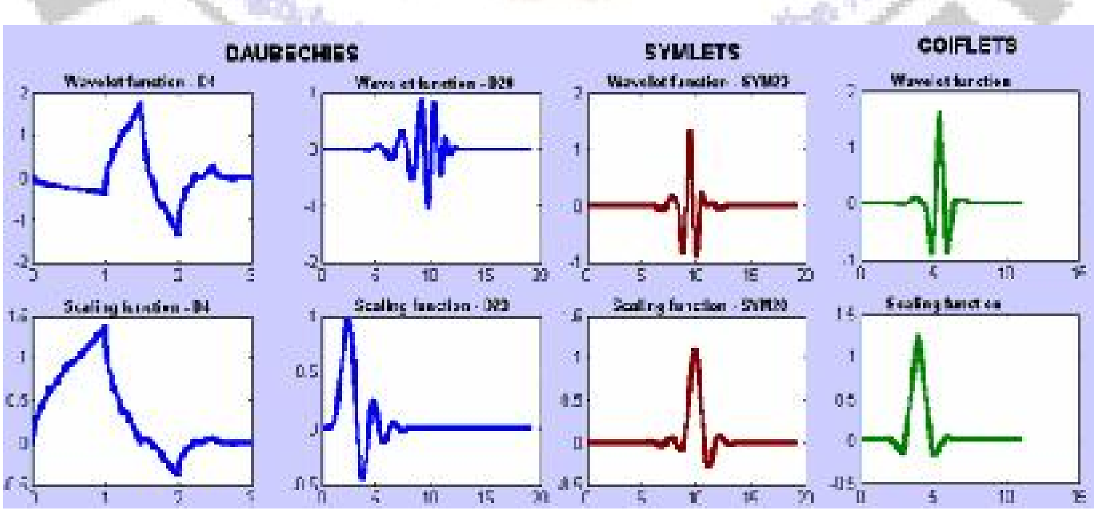
3- Peak Signal to Noise Ratio (PSNR)

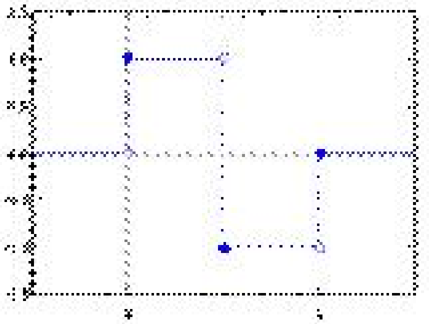
It is also a fidelity parameter used to measure the distortion level caused by the compression system. Peak signal to noise ratio (PSNR) can be defined as:

$$PSNR = 10 \log 10\left(\frac{Max_i \mid P_i \mid}{RMSE}\right)$$ where Max is the greater pixel value.

In this case the large results mean that there is a small noise in the compression system image quality of the reconstructed and image is better. When the value of this parameter is small it means that the compression performance is weak.

The small result of MSE means that there is small overall error in the reconstructed version of image caused by the compression system, this indicates that the objective quality of the reconstructed data is acceptable, when the value of MSE is high it will indicate that the compression system has caused a significant error [12].





The Haar wavelet

a- wavelet families

Type	Symmetry	Orthogonality
Haar	Symmetric	Orthogonal
Daubechies	Asymmetric	Orthogonal
Symlets	Near Symmetric	Orthogonal
Coiflets	Near Symmetric	Orthogonal

b- Wavelet properties

Wavelet families and properties [13].

Evaluation Performance Results:

In this paper, eleven different wavelet filters (Haar, Mallat, Symlets, Integer, Conflict, Daubechi 1, Daubechi 2, Daubechi 4, Daubechi 7, Daubechi 12 and Daubechi 20) are used to compress seven true color images of 256x256 as samples as shown in figure (1). PSNR is used as a measure of accuracy performance. We use two values of compression factors (4.3 and 5.1) to test the above filters.

The results of PSNR for compression factor 4.3 and 5.1 are shown bellow.

Conclusions

In this work we compared among different eleven wavelet filters using seven different true color images of 256x256. These Filters are (Haar, Mallat, Symlets, Integer, Conflict, Daubechi 1, Daubechi 2, Daubechi 4, Daubechi 7, Daubechi 12 and Daubechi 20). The selected images have different color features to illustrate the effects of wavelet filters. PSNR is used as a measure of accuracy performance. The experimental show different results but in general Daubechi Family specialy Daubechi 4, Daubechi 7, Daubechi 12 and Daubechi 20 give better performance in term of PSNR at a compression factor (4.3 and 5.1).

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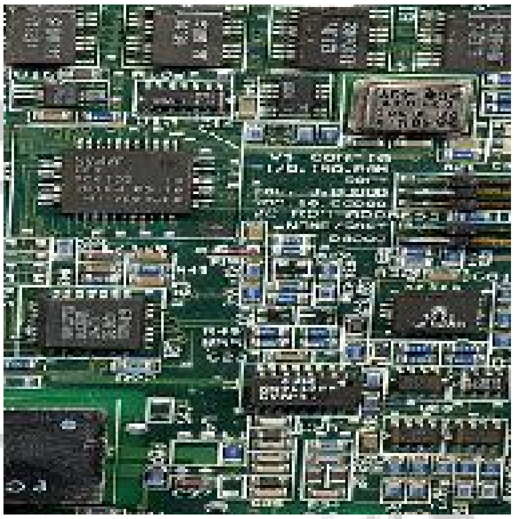
Autumn



Board

Green

Kids


Peppers


Saturn


West

Fig. (1):Different 7 Color Images (256 x 256)

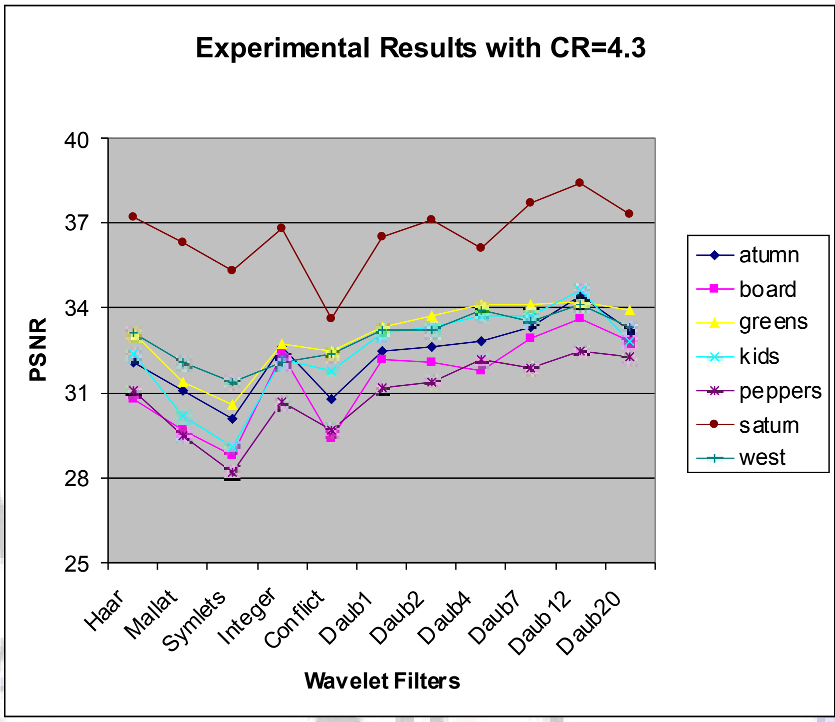


Fig. (2): Illustrates the comparative results of PSNR for Different 7 Color Images Using Different 11 wavelet filters when CF=4.3.

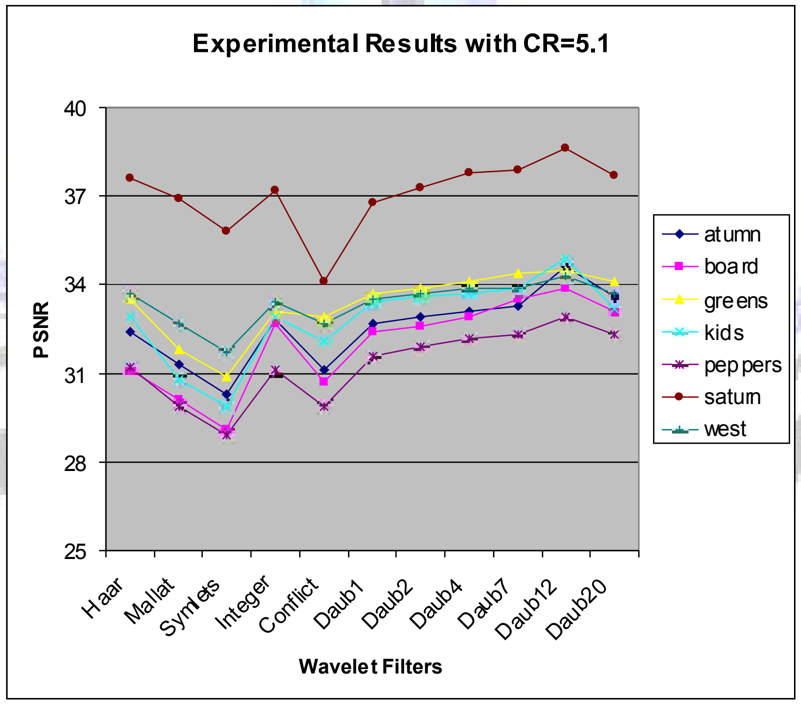


Fig. (3): Illustrates the comparative results of PSNR for Different 7 Color Images Using Different 11 wavelet filters when CF=5.1.

PSNR results for compression factor 4.3

Image Name	PSNR										
	Daubechies Family										
	Haar	Mallat	Symlets	Integer	Conflict	Daub1	Daub2	Daub4	Daub7	Daub12	Daub20
Atum	32.1	31.1	30.1	32.6	30.8	32.5	32.6	32.8	33.3	34.4	33.2
Board	30.8	29.7	28.8	32.4	29.4	32.2	32.1	31.8	32.9	33.6	32.8
Greens	33.1	31.4	30.6	32.7	32.5	33.3	33.7	34.1	34.1	34.2	33.9
Kids	32.4	30.2	29.1	32.2	31.8	33.1	33.3	33.7	33.7	34.6	32.8
Peppers	31.1	29.5	28.2	30.7	29.7	31.2	31.4	32.2	31.9	32.5	32.3
Saturn	37.2	36.3	35.3	36.8	33.6	36.5	37.1	36.12	37.7	38.4	37.3
West	33.1	32.1	31.4	32.1	32.4	33.2	33.2	33.9	33.5	34.1	33.3
AVERAGE	32.828	31.471	30.5	32.786	31.457	33.143	33.343	33.517	33.871	34.543	33.657

PSNR results for compression factor 5.1

Image Name	PSNR										
						Daubechies Family					
	Haar	Mallat	Symlets	Integer	Conflict	Daub1	Daub2	Daub4	Daub7	Daub12	Daub20
Atumn	32.4	31.3	30.3	32.8	31.1	32.7	32.9	33.1	33.3	34.6	33.6
Board	31.1	30.1	29.1	32.7	30.7	32.4	32.6	32.9	33.5	33.9	33.1
Greens	33.5	31.8	30.9	33.1	32.9	33.7	33.9	34.1	34.4	34.5	34.1
Kids	32.9	30.8	29.9	32.9	32.1	33.4	33.6	33.7	33.9	34.9	33.2
Peppers	31.2	29.9	28.9	31.1	29.9	31.6	31.9	32.2	32.3	32.9	32.3
Saturn	37.6	36.9	35.8	37.2	34.1	36.8	37.3	37.8	37.9	38.6	37.7
West	33.7	32.7	31.7	33.4	32.7	33.5	33.7	33.9	33.9	34.3	33.7
AVERAGE	33.2	31.929	30.943	33.314	31.929	33.443	33.7	33.957	34.171	34.814	33.957

مقارنة بين مرشحات التحويل المويجي باستعمال ضغط الصور الملونة

هند خضير عباس

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الخلاصة

التحويل المويجي اصبح أداة حاسوبيه لمختلف الاشارات وتطبيقات معالجة الصور.
الهدف من هذا البحث تقديم دراسة مقارنة لمرشحات التحويل المويجي، اعتمد احد عشر مرشحا" (Haar, Symlets, Mallat, Conflict, Integer, Daubechi 1 Daubechi 2, Daubechi 4, ، Daubechi 7, Daubechi 12, Daubechi 20) لضغط سبعة نماذج لصور ملونه 256x256.
من معاملات جودة الصورة نسبة الاشارة الى الضوضاء (PSNR) و معاير متوسط مربع الخطأ، تستخدم لتقييم أداء مرشحات التحويل المويجيي.
اعتمد PSNR كمقياس لدقة الجودة اعتمادا على معاملي ضغط مختلفين (4.3 و 5.1) لاختبار مرشحات التحويل المويجي. التجارب العملية اظهرت نتائج كان افضلها نسبيا المرشحات (Daubechi 4, Daubechi 7, Daubechi 12 and Daubechi 20)
استعمل برنامج الماتلاب 9.0 لتطبيق تجارب البحث.

الكلمات المفتاحية: الهار، الدوباتشي، ضغط الصور، التحويل المويجي.