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Using the Wavelet Transform to Minimize Image File Size

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ABSTRACT

Wavelet theory unifies a variety of methods that have been developed separately for use in signal processing by providing a common framework. Multiresolution pixel-level picture compression is possible using wavelet transformations. Some additional areas where this theory has found use include filtering, multi-resolution image fusion, noise suppression, picture restoration, and many more. In this study, we take a look at how multi-resolution picture compression may be achieved using the existing wavelet method and programming. Examining the suitability of various wavelet transform methods for picture analysis and compression is the objective. We run the code for two distinct wavelet algorithms and compare their output levels to see which one performs better.

Keyword: Wavelet transformations, multi-resolution analysis, digital image processing, and image compression...

1. INTRODUCTION TO D.I.P

Digital image processing encompasses a broad range of techniques for digitally processing and analyzing pictures or signals. There are a lot of messages around us in our contemporary society. Many signals are created by humans, while others are natural. Signal conveys data, some of which is desirable and some of which is not. Consequently, making the most of a mix by removing and improving upon irrelevant data of conflicting information is the simplest form of Signal Processing. This technique (of extracting information) is application dependent. The signals we encounter in practice are mostly the analog signals. These signals vary continuously with time, and amplitude, are processed, using electrical networks containing active and passive circuit

elements. This approach is known as analog Signal Processing (ASP).

A major drawback of ASP is its limited scope of performing complex signal processing applications. Some important applications of DSP over ASP are:

1) Systems using the DSP approach can be developed using software running on a general-purpose computer. Therefore, DSP is relatively convenient to develop and test, and the software is portable.
2) DSP operations are based solely on additions and multiplications leading to extremely stable

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processing capability-for example, stability independent of temperature.

3) DSP operations can easily be modified in real time, often by simple programming techniques.
4) Speed of operations in high frequency is the greatest advantage of DSP.

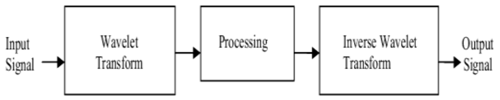

Figure 1 : Digital Image processing using Wavelet transform

The transform of a signal is just another form of representing the signal. It does not change the information content present in the signal. The Wavelet Transform provides a time -frequency representation of the signal. It was developed to overcome the short coming of the **Short Time Fourier Transform (STFT),** which can also be used to analyze non- stationary signals. While STFT gives a constant resolution at all frequencies, the Wavelet Transform uses multi-resolution technique by which **different frequencies are analyzed with different resolutions.** The wavelet analysis is done similar to the STFT analysis. The signal to be analyzed is multiplied with a wavelet function just as it is multiplied with a window function in STFT, and then the transform is computed for each segment generated. However, unlike STFT, in Wavelet Transform, the width of the wavelet function changes with each spectral component.

2. INTRODUCTION TO WAVELET TRANSFORMATION

A wave is an oscillating function of time or space and is periodic. In contrast, wavelets are localized waves.

1. They have their energy concentrated in time or space & are suited to analysis of transient signals. While Fourier Transform and STFT use waves to analyze signals, the Wavelet Transform uses wavelets of finite energy.

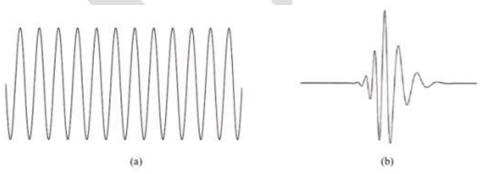

Figure 2 : a) Sinusoidal wave of infinite energy,

b) Wavelet of finite energy

2. Wavelet transform is efficient for continuous and moving signals

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3. The Wavelet Transform, at high frequencies, gives good time resolution and poor frequency resolution, while at low frequencies, the Wavelet Transform give good frequency resolution and poor time resolution.
4. They are feasible if waves are of

   a. Limited duration.

   b. Average value of zero.

   c. Varying frequency.

3. TIME FREQUENCY CONCEPT

In quantum physics, the Heisenberg uncertainty principle states that certain pairs of physical properties, like position and momentum, cannot both be known to arbitrary precision. The same principle holds in signal processing. We cannot locate both time and frequency very precisely. The product of variation in time and variation in frequency can be viewed as a rectangle with constant area and different transform adjusts the widthand height of the rectangle. The three transforms are shown in Figure 3.

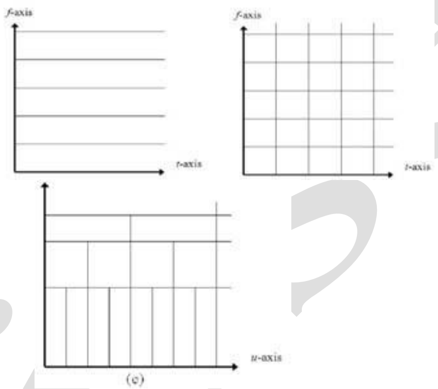

Figure 3: (a) Fourier Transform (b) STFT

(c) Wavelet Transform

Fourier transform: The time information is completely lost. Frequency axis is divided uniformly. Frequency resolution can be very precise if we integrate along the whole time axis.

STFT: Add a window to take the time domain information into consideration. The frequency resolution depends on the time resolution, or the size of the window. We cannot zoom in a particular frequency

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range because the box is uniformly placed.

Wavelet transform: The S- parameter is inversely proportional to the frequency. As we see, if we want to focus on low frequencies, larger S is used while higher frequencies uses small. This flexibility increases the time- frequency analysis.

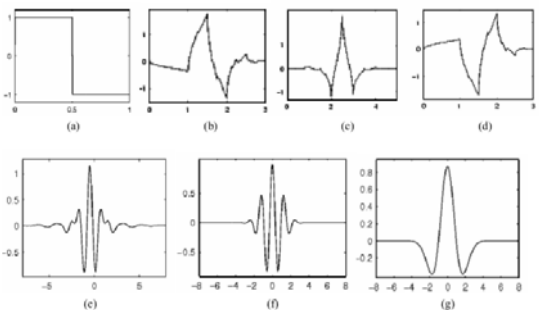


Figure 4: Wavelet families (a) Haar (b) Daubechies (c) Coifletl (d) Symlet2 (e) Meyer (f) Morlet (g) Mexican Hat

Among these, Haar wavelet is one of the oldest and simplest wavelet. Therefore, any discussion of wavelet starts with Haar wavelet. The wavelets are chosen based on their shape and their ability to analyze the signal in a particular application.

4. Wavelet Transformation

The wavelet expansion involves two functions:

1. Scaling functions or Father function, represented as $\varphi(t)$.
2. Wavelet function or Mother function, represented as $\psi(t)$.

The two shapes are translated and scaled to produce wavelets at different locations and on different scales.

φ (t-k) : where "k" is the scaling coefficient/ Low pass coefficient

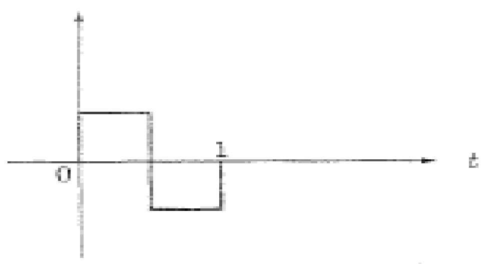
Ψ (2^jt-k) : where "j" is the translation coefficient/ High pass coefficient

The wavelet transform, f (t) is written as linear combination of φ **(t-k)** and **Ψ (2^jt-k) :**

$$f(t) = \sum c_k \varphi(t-k) + \sum\sum d_{jk} \Psi(2^j t-k)$$

The scaling function contract/ expand the wavelet and the translation function changes the position of the wavelet.

5. HAAR Scaling and Wavelet Functions



(b) ψ(t)

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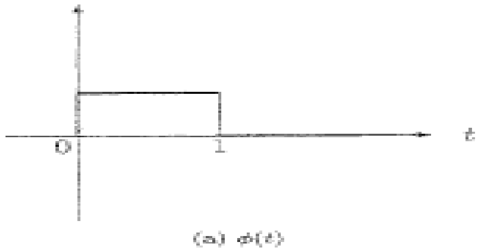

Figure 5: Haar wavelet transformation

$$\psi(x) = \begin{cases} 1 & \text{if } 0 \le x < 1/2 \\ -1 & \text{if } 1/2 \le x < 1 \\ 0 & \textit{otherwise} \end{cases}$$

$$\phi(x) = \begin{cases} 1 & \text{if } 0 \le x < 1 \\ 0 & \textit{otherwise} \end{cases}$$

The scaling function contract/ expand the wavelet and the translation function changes the position of

The scaling coefficient/ Low pass coefficient gives the averaged value, and the High pass coefficient gives the difference between Low pass and high pass frequencies.

In Haar wavelet transformation, the scaling function φ(t) computes average, and the wavelet function ψ(t) computes details.

6. Decomposition Levels

Through wavelet transformation, in order to have perfect (or close) (precise) information content, and in order to achieve the difficult task of feature extraction, the image is decomposed into several levels, based on low pass and high pass divisions. These signals can be decomposed into many levels. It should be taken care that decomposition of signal must not increase the noise levels, and feature extraction is possible.

7. Observations

We ran a MATLAB program to compress images using the HAAR transformation and saw the results at different levels.

1. Firstly, and original image as an input in taken, and programming is done.

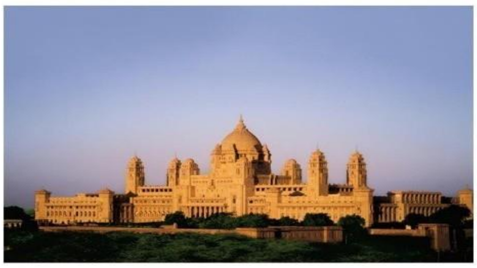

Figure 6: Level 1 Haar

2. The original .jpg image was decomposed into LL, LH, HL & LL sub bands. In this output, we can easily

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extract the average value of information.

Figure 7: Level 1

3. Level 2 decomposition leads to further possibilities of feature extraction from **LH, HL & HH sub-bands** respectively.

4. Level 3 decomposition leads to the output,
i.e compressed image which can be reconstructed at the receiving end.

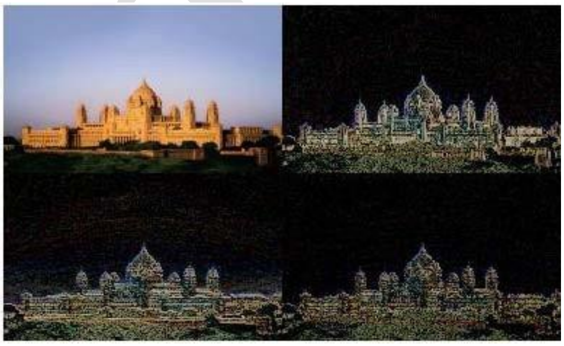

Figure 8: Level 2 Haar

5. The algorithm used in programming was transferred into an FPGA chip, and then to the computers. Further, the scaling and translating coefficient (instead of whole image) were sent to the receiving end. By inverse wavelet transformation, the original image was reconstructed. Consequently this helped in feature extraction and de- noising of image.

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