

COMPARATIVE ANALYSIS OF WAVELET TRANSFORM WITH INBUILT WAVELET FUNCTION AND WAVELET TRANSFORM WITHOUT INBUILT WAVELET FUNCTION FOR IMAGE COMPRESSION

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ABSTRACT

Image compression is a technique that is concerned with number of bits are reduced to store the images in less amount of space, it is easy to transmit and reconstructed the images without any loss of information. Through various wavelet transforms techniques are used in image compression. In this research paper, Daubechies wavelets have been implemented and comparative results of wavelet transform methods without inbuilt function and wavelet transform methods with inbuilt function using the wavelet has been performed and compared to the Discrete Wavelet Transform technique. Image quality metrics is measured objectively, using mean to square error (MSE), peak signal-to-noise ratio (PSNR) and Normalized Absolute Error (NAE) for DWT techniques. We are performed an experiment on 256 x 256 Barbara jpeg 2000 format.

Keywords: DWT, MSE, PSNR, NAE.

I. INTRODUCTION

Image compression is the art of science of reducing the amount of data are required to represent an image. It is one of most useful and commercially successful technologies in the field of digital image processing. The basic purpose of compression is to remove the redundancy and irrelevancy present in the image in the source data or image. The compressed image is represented by less number of bits compared to original. Hence, the required storage size will be reduced, consequently maximum images can be stored and it can transferred in faster way to save the time, transmission bandwidth [1].

When an image is taken from digital camera or other electronic gadgets, graphics are scanned from a digital image, it require a more space to save a file. Also, it is time consuming to transmit it from one place to another because larger size of images. Therefore, the amount of data in the image file can be reduced into smaller size. This process is called "image compression". There are several methods of image compression available today. Basically image compression fall into two types: - lossless and lossy [2,3]. A lossless compression, every single bit of data that was

originally in the file remains after file is uncompressed. On the other hand, lossy compression reduces a file by permanently eliminating certain information especially redundant information.

The basic idea behind any image compression is to represent data take less space and reducing the size of data ,it take less time to transfer data from one place to another via communication channels. Image compression is the process of representing information in a compact form. Today, image compression is employed in modern multimedia applications. Therefore, image compression is a necessary and essential method for creating image files with manageable and transmittable sizes.

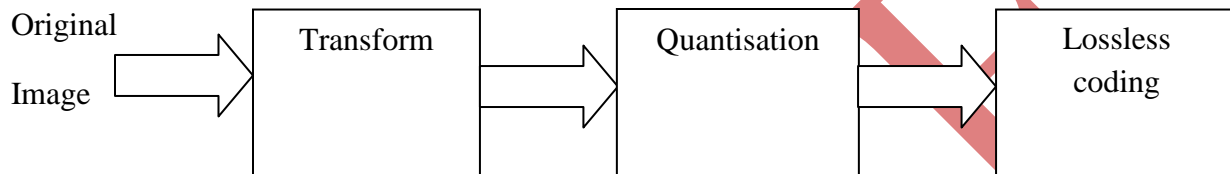


Fig.1 Image Compression Models

II. DISCRETE WAVELET TRANSFORM

Wavelet transform (WT) represents an image as a sum of wavelet functions (wavelets) with different locations and scales [4]. Any decomposition of an image into wavelets involves a pair of waveforms: one to represent the high frequencies corresponding to the detailed parts of an image (wavelet function Ψ) and one for the low frequencies or smooth parts of an image (scaling function Φ). DWT is a multi-resolution decomposition scheme for input signals. The original signals are first decomposed into two subspaces, low-frequency (low-pass) sub band and high-frequency (high-pass) sub band. For the classical DWT, the forward decomposition of a signal is implemented by a low-pass digital filter H and a high-pass digital filter G. Both digital filters are derived using the scaling function $\Phi(t)$ and the corresponding wavelets $\Psi(t)$. In a wavelet representation, we represent our signal in terms of functions that are localized both in time and frequency. Wavelets have become very popular in image processing. Wavelets are mathematical functions that can be used to transform one function representation into another. Wavelet transform performs multi-resolution image analysis. Multi-resolution means simultaneous representation of image on different resolution levels. For a two dimensional images, the approach of the 2D implementation of the discrete wavelet transform (DWT) is to perform the one dimensional DWT in row direction and it is followed by a one dimensional DWT in column direction

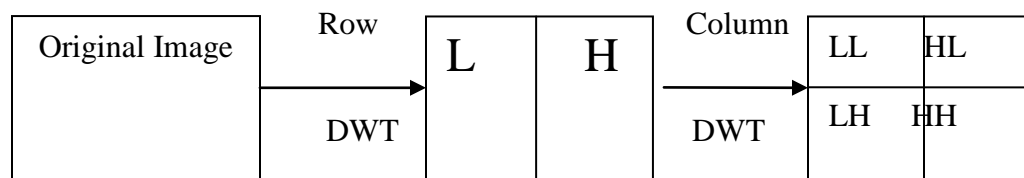


Fig.2 the 2D Row and Column Computation of DWT

LL is a coarser version of the original image and it contains the approximation information which is low frequency
LH, HL, and HH are the high frequency sub-band containing the detail information.

2.1 Daub Wavelet Transformation without Inbuilt Function

The Daubechies wavelets are a family of orthogonal wavelets defining a discrete wavelet transform and characterized by a maximal number of vanishing moments for some given support. Scaling functions and wavelets can be constructed with desired degree of smoothness.

Daub2:-Daub2 wavelet have two scaling function (α) and two wavelet functions (β).

$$\alpha_1 = 7.071067811865475E-01 \quad \alpha_2 = 7.071067811865475E-01$$

$$\beta_1 = \alpha_2 \quad \beta_2 = -\alpha_1$$

Daub4:- Daub4 wavelet have four scaling function (α) and four wavelet functions (β).

$$\alpha_1 = \frac{3+\sqrt{3}}{4\sqrt{2}} \quad \alpha_2 = \frac{3+\sqrt{3}}{4\sqrt{2}} \quad \alpha_3 = \frac{3-\sqrt{3}}{4\sqrt{2}} \quad \alpha_4 = \frac{1-\sqrt{3}}{4\sqrt{2}}$$

$$\beta_1 = \frac{1-\sqrt{3}}{4\sqrt{2}} \quad \beta_2 = \frac{\sqrt{3}-3}{4\sqrt{2}} \quad \beta_3 = \frac{3+\sqrt{3}}{4\sqrt{2}} \quad \beta_4 = \frac{-1-\sqrt{3}}{4\sqrt{2}}$$

If a signal f is linear over the support of a Daub4 wavelet, then the corresponding fluctuation value is zero. True for functions that have a continuous 2nd derivative.

$$f''(x) \approx \text{const} \rightarrow f'(x) \approx (\text{const}) x$$

Daub6:-Daub6 wavelet have six scaling function (α) and six wavelet functions (β).

$$\alpha_1 = 0.332670552950083, \alpha_2 = 0.806891509311092, \alpha_3 = 0.459877502118491,$$

$$\alpha_4 = -0.135011020010255, \alpha_5 = -0.00854412738820267, \alpha_6 = 0.0035226291887095$$

$$\beta_1 = \alpha_6, \beta_2 = -\alpha_5, \beta_3 = \alpha_4, \beta_4 = -\alpha_3, \beta_5 = \alpha_2, \beta_6 = -\alpha_1$$

If a signal f is quadratic over the support of a Daub6 wavelet, then the corresponding fluctuation value is zero.

2.2 Procedure for daub wavelet without inbuilt function

1. Read the original Image.
2. Convert color image into gray scale image.
3. Apply DWT (Daub wavelet) for compression on original image.
4. Obtained the compressed image.
5. Apply inverse DWT (Daub wavelet) on compressed image.

6. Obtained the reconstructed image.
7. Displaying the resulting image and analysis the performance of the reconstructed image.
8. Display and compare the various results based on MSE, NAE and PSNR quality metrics.
9. The same process is repeated for other test images

2.3 Daub wavelet transform with inbuilt function

Ingrid Daubechies, one of the brightest stars in the world of wavelet research, invented what are called compactly supported orthonormal wavelets. The names of the Daubechies family wavelets are written dbN , where N is the order, and db the “surname” of the wavelet.

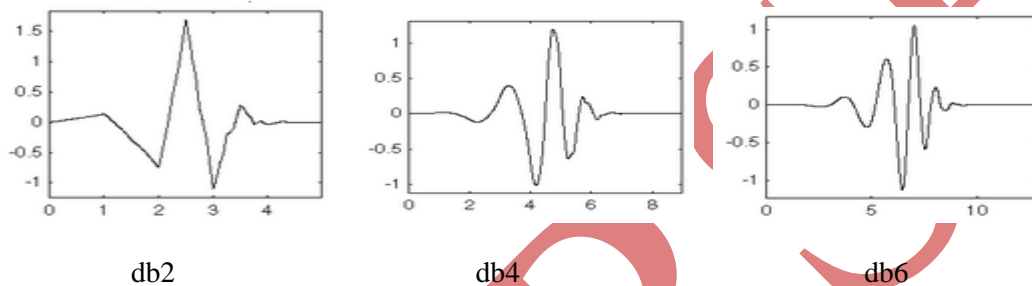


Fig.3 db2, db4 and db6 of DWT.

2.4 Procedure for daub wavelet without inbuilt function

1. Read the original Image.
2. Convert color image into gray scale image.
3. Apply 2 Dimensional DWT using Daubechies transform for compressing anImage.
4. Threshold Detail Coefficients: For each level, a threshold is selected and hard thresholding is applied to the detail coefficients.
5. Image is compressed using Daubechies wavelet.
6. Inverse Transformation/ Reconstruction: Reconstruct an estimate of the original image by applying the inverse transform.
7. Displaying the resulting image and analysis the performance of the reconstructed image.
8. Display and compare the various results based on MSE, NAE and PSNR quality metrics.
9. The same process is repeated for other test images.

III. QUALITY METRICS

Digital image compression techniques are normally analyzed with objective fidelity measuring metrics like Mean Square Error (MSE) and Normalized Absolute Error (NAE), Peak Signal to Noise Ratio (PSNR) is defined as

$$MSE = \frac{1}{MN} \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} |x(m, n) - \hat{x}(m, n)|^2$$

Where $M * N$ is the size of the original image.

3.1 Normalized Absolute Error (NAE)

The larger value of Normalized Absolute Error (NAE) means that image is poor quality. NAE is defined as follow

$$NAE = \frac{\sum_{m=1}^M \sum_{n=1}^N |x(m, n) - \hat{x}(m, n)|}{\sum_{m=1}^M \sum_{n=1}^N x(m, n)}$$

3.2 Peak Signal to Noise Ratio (PSNR)

PSNR is the evaluation standard of the reconstructed image quality, and is an important measure of image compression. The objective performance is measured by **peak signal-to-noise-ratio (PSNR)** of the reconstructed image \hat{x} . PSNR measured in decibels (dB) is given by:

$$PSNR = 10 \log_{10} \left(\frac{255^2}{MSE} \right)$$

Where the value of 255 is the maximum possible value that can be attained by the image signal Higher the PSNR value is, the better the reconstructed image is.

IV. RESULTS AND ANALYSIS

The coding of this paper is done in MATLAB R2010a. In this paper, we compared and analyzed Daubechies wavelet of Discrete wavelet transform (DWT) with and without inbuilt functions. The quality of a compression method could be measured by the quality metrics such as Peak Signal to Noise Ratio (PSNR) and Normalized Absolute Error (NAE). We compared the performance of Daubechies wavelet transform using image compression on "Barbara (256 x 256) JPEG 2000".

Table-1

Wavelet name	MSE	PSNR	NAE
Duab2	1.1330e+003	17.5886	0.2627
Duab4	6.4004e+003	10.0687	0.6613
Duab6	4.4423e+003	11.6547	0.5393

Table-1 shows the MSE, PSNR and NAE of Daub wavelet transform without inbuilt functions.

Table-2

Wavelet name	MSE	PSNR	NAE
Duab2	0.5407	50.8014	0.0041
Duab4	0.5017	51.1260	0.0039
Duab6	0.5529	50.7042	0.0042

Table-2 shows the MSE, PSNR and NAE of Daub wavelet transform with inbuilt functions.

V. CONCLUSION

Image compression is the important field of Digital image processing. In this work, we are compared duab2, duab4 and daub6 wavelet transform filter using inbuilt function and duab2, duab4 and daub6 wavelet transform filter without inbuilt function on true color image of Barbara (256 x 256). In this paper, comparison and analyzed the Daubechies wavelet transform based on image compression is described. The Daub wavelet transform with inbuilt functions shows its better results in terms of MSE, PSNR and NAE than Daub wavelet transform without inbuilt functions. PSNR is used as a measure the performance accuracy.

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