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Image compression Using Discrete Haar Wavelet Transforms

Monika Rathee, Alka Vij
M-Tech Scholar, PDM college of Engineering, Bahadurgarh
Assistant Professor, Department of ECE, PDM college of Engineering for Women, Bahadurgarh

Abstract: This paper presents discrete haar wavelet transform (DWT) for image compression. We are using Haar discrete wavelet transform (HDWT) to compress the signal. The image compression techniques are broadly classified into two categories depending whether or not an exact replica of the original image could be reconstructed using the compressed image. Different redundancies that are used to compress the image signal are Coding Redundancy, Inter-pixel Redundancy and Perceptual Redundancy. Simulation results are presented for the image compression with Haar wavelet with different level of decomposition. Result also reveals that the level of decomposition increases visual perception of the images goes on decreasing but the level of compression is very high. DWT can be used to reduce the image size without losing much of the resolutions. Experimental results demonstrate the effectiveness of the proposed algorithm.

Index Terms: **Discrete Wavelet Transform (DWT), Haar discrete wavelet transform (HDWT), Coding Redundancy, Inter-pixel Redundancy and Perceptual Redundancy.**

I. INTRODUCTION

From last few decays, the increasing demand of storage and transmission of digital images, image compression is now become an essential application for storage and transmission [1]. Demand for communication of multimedia data through the telecommunications network and accessing the multimedia data through Internet is growing explosively [2]. With the use of digital cameras, requirements for storage, manipulation, and transfer of digital images, has grown explosively. Discrete wavelet transformations (DWT) followed by embedded zero tree encoding is a very efficient technique for image compression. Discrete wavelet transform DWT) [3][4] represents image as a sum of wavelet functions (wavelets) on different resolution levels. Basis for wavelet transform can be composed of any function that satisfies requirements of multiresolution analysis [5]. It means that there exists a large selection of wavelet families depending on the choice of wavelet function. The choice of wavelet family depends on the application. In image compression application this choice depends on image content. Discrete Wavelet Transform (DWT) [5]-[7] can be efficiently used in image coding applications because of their data reduction capabilities. Unlike the case of Discrete Cosine Transform [6] (DCT) which basis is composed of cosine functions, basis of DWT can be composed of any function (wavelet) that satisfies requirements of multiresolution analysis. Different compression algorithms are Shapiro's embedded zero tree wavelet (EZW) algorithm [9], Said and Pearlman's set partitioning in hierarchical trees (SPIHT) algorithm [10], Servetto et al.'s morphological representation of wavelet data (MRWD) algorithm [11], and Taubman's embedded block coding with optimized truncation (EBCOT) algorithm [12], SOM based vector quantisation [14], arithmetic coding [16], Singular Value Decomposition [13]. This paper presents an efficient signal processing technique based on discrete wavelet transform (DWT) for image compression. Discrete wavelet transformations (DWT) [14] followed by embedded zero tree encoding is a very efficient technique for image compression. This method is computationally efficient. We are using Haar discrete wavelet transform (HDWT) [5] to compress the signal. The rest of the paper is organized as follows: In Section II, basic of discrete wavelet transform is explained. In section III, image compression based on discrete wavelet transform (DWT) such as HAAR transforms. Section IV introduces the different steps implemented for the image compression based on discrete wavelet transform (DWT). In Section V, simulation results will be explained with the help of graphical representation and different composition levels. Section VI, conclusions will be put forward.

II. DISCRETE WAVELET TRANSFORM (DWT)

The DWT represents an image as a sum of wavelet functions, known as wavelets, with different location and scale [8]. It represents the data into a set of high pass and low pass coefficients. The input data is passed through set of low pass and high pass filters. The Daubechies filter coefficients [16] are used. The output of high pass and low pass filters are down sampled by 2. The output from low pass filter is an approximate coefficient and the output from the high pass filter is a detail coefficient. Fig. 1 shows the schematics of this (1-D) DWT method.

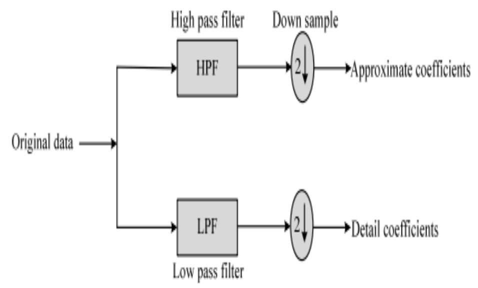

Fig.1 Block diagram of 1-D forward DWT

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In case of 2-D DWT, the input data is passed through set of both low pass and high pass filter in two directions, both rows and columns. The outputs are then down sampled by 2 in each direction as in case of 1-D DWT [6]. As shown in Fig. 2, output is obtained in set of four coefficients LL, HL, LH and HH. The first alphabet represents the transform in row where as the second alphabet represents transform in column. The alphabet L means low pass signal and H means high pass signal. LH signal is a low pass signal in row and a high pass in column. Hence, LH signal contain horizontal elements. Similarly, HL and HH contains vertical and diagonal elements, respectively.

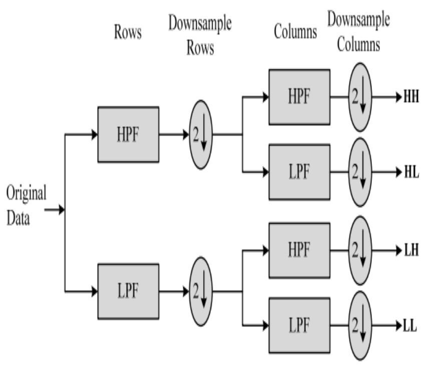

Fig. 2 Block diagram of 2-D forward DWT

In DWT [4][7] reconstruction, input data can be achieved in multiple resolutions by decomposing the LL coefficient further for different levels as shown in Fig. 3. In order to reconstruct the output data, the compressed data is up-sampled by a factor of 2. The signal is further passed through the same set of high pass and low pass filter in both rows and columns. The entire reconstruction procedure is shown in Fig. 4.

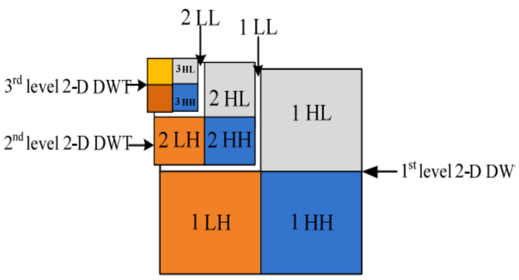

Fig. 3 Illustration of forward DWT

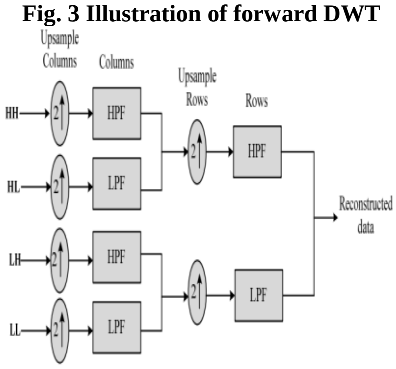

Fig. 4 Block diagram of 2 dimensional inverse DWT

III. IMAGE COMPRESSION USING DWT

A signal is passed through a series of filters to calculate DWT [6] [8]. Procedure starts by passing this signal sequence through a half band digital low pass filter with impulse response h(n). Filtering of a signal is numerically equal to convolution of the tile signal with impulse response of the filter.

$$x[n]*h[n]=\sum_{k=-\infty}^{\infty} x[k].h[n-k] \quad (1)$$

A half band low pass filter removes all frequencies that are above half of the highest frequency in the tile signal. Then the signal is passed through high pass filter. The two filters are related to each other as

$$h[L-1-n]=(-1)^n g(n) \quad (2)$$

Filters satisfying this condition are known as quadrature mirror filters. After filtering half of the samples can be eliminated since the signal now has the highest frequency as half of the original frequency. The signal can therefore be sub sampled by 2, simply by discarding every other sample. This constitutes 1 level of decomposition and can mathematically be expressed as

$$Y1[n]=\sum_{k=-\infty}^{\infty} x[k]h[2n-k] \quad (3)$$

$$Y2[n]=\sum_{k=-\infty}^{\infty} x[k]g[2n+1-k] \quad (4)$$

where y1[n] and y2[n] are the outputs of low pass and high pass filters, respectively after sub sampling by 2.

This decomposition halves the time resolution since only half the number of sample now characterizes the whole signal. Frequency resolution has doubled because each output has half the frequency band of the input. This process is called as sub band coding. It can be repeated further to increase the frequency resolution as shown by the filter bank [8].

IV. COMPRESSION STEPS USING DWT

1. Digitize the source image into a signal s, which is a string of numbers.
2. Decompose the signal into a sequence of wavelet coefficients w.
3. Use threshold to modify the wavelet coefficients from w to w'.
4. Filter Bank 4. Use quantization to convert w' to a sequence q.
5. Entropy encoding is applied to convert q into a sequence e.

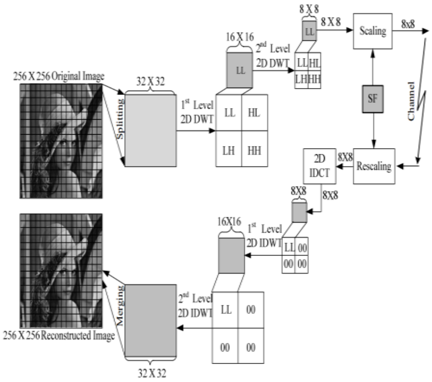

Fig. 5 Block diagram of the DWT decomposition

1. ***Digitation:*** The image is digitized first. The digitized image can be characterized by its intensity levels, or scales of gray which range from 0(black) to 255(white), and its resolution, or how many pixels per square inch.
2. ***Thresholding:*** In certain signals, many of the wavelet coefficients are close or equal to zero. Through threshold these coefficients are modified so that the sequence of wavelet coefficients contains long strings of zeros. In hard threshold, a threshold is selected [6]. Any wavelet whose absolute value falls below the tolerance is set to zero with the goal to introduce many zeros without losing a great amount of detail.
3. ***Quantization:*** Quantization converts a sequence of floating numbers w' to a sequence of integers q. The simplest form is to round to the nearest integer. Another method is to multiply each number in w' by a constant k, and then round to the nearest integer. Quantization is called lossy [5] because it introduces error into the process, since the conversion of w' to q is not one to one function.
4. ***Entropy encoding:*** With this method, a integer sequence q is changed into a shorter sequence with the numbers in e being 8 bit integers. The conversion is made by an entropy encoding table. Strings of zeros are coded by numbers 1 through 100,105 and 106, while the non-zero integers in q are coded by 101 through 104 and 107 through 254.

V. SIMULATION RESULTS

The Haar wavelet's mother wavelet function $\psi(t)$ can be described as

$$\psi(t)=\begin{cases}1 & 0\leq t<1/2,\\ -1 & 1/2\leq t<1,\\ 0 & \text{otherwise.}\end{cases} \quad (5)$$

Its scaling function $\phi(t)$ can be described as

$$\phi(t)=\begin{cases}1 & 0\leq t<1,\\ 0 & \text{otherwise.}\end{cases} \quad (6)$$

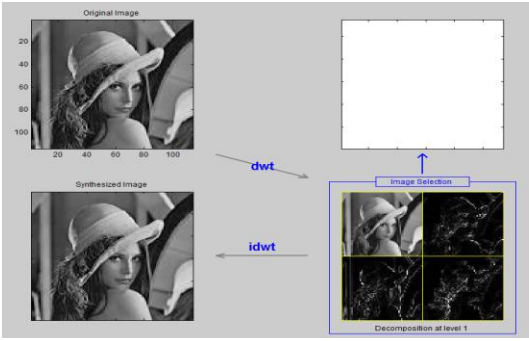

Fig. 6 Synthesis Lena image using Haar wavelet with 1-level decomposition

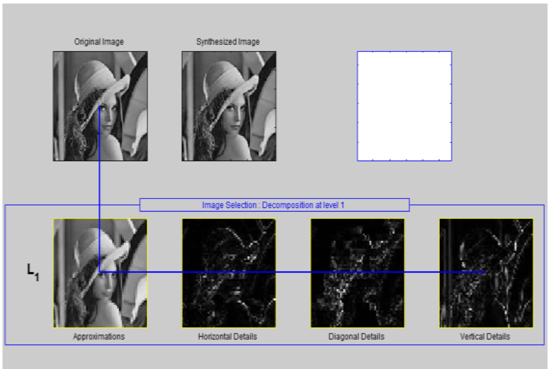

Fig. 7 Synthesis Lena image using Haar wavelet with 1-level decomposition (Tree representation)

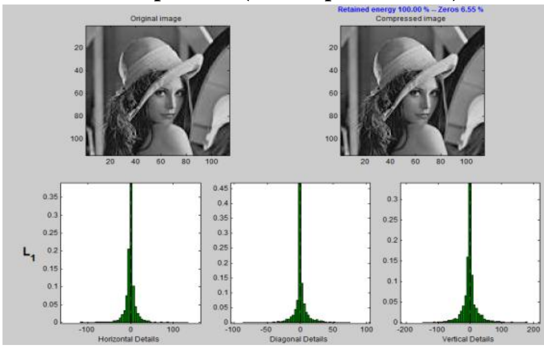

Fig. 8 Compression of Lena image using Haar wavelet with 1-level decomposition as level thresholding

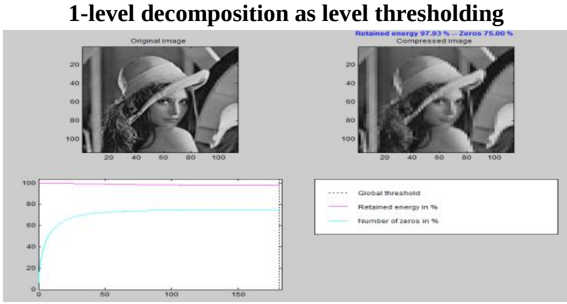

Fig. 9 Compression of Lena image using Haar wavelet with 1-level decomposition as global thresholding

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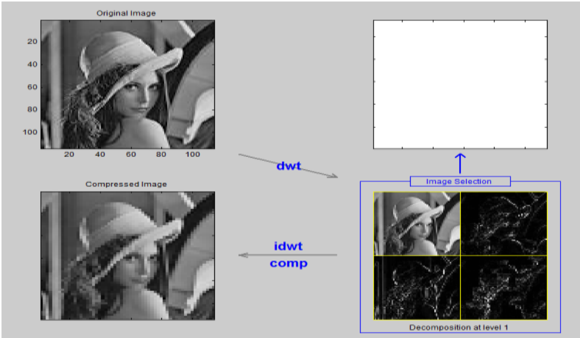

Fig. 10 compressed Lena image using Haar wavelet with 1-level decomposition

Fig. 6 depicts the Synthesis Lena image using Haar wavelet with 1-level decomposition. Fig. 7 demonstrates the Synthesis Lena image using Haar wavelet with 1-level decomposition (Tree representation). Fig. 8 shows the Compression of Lena image using Haar wavelet with 1-level decomposition as level thresholding. Fig. 9 depicts the Compression of Lena image using Haar wavelet with 1-level decomposition as global thresholding. Fig. 10 shows the compressed Lena image using Haar wavelet with 1-level decomposition. Fig. 11 depicts the Synthesis Lena image using Haar wavelet with 2-level decomposition. Fig. 12 demonstrates the Synthesis Lena image using Haar wavelet with 2-level decomposition (Tree representation). Fig. 13 shows the Compression of Lena image using Haar wavelet with 2-level decomposition as level thresholding. Fig. 14 depicts the Compression of Lena image using Haar wavelet with 2-level decomposition as global thresholding. Fig. 15 shows the compressed Lena image using Haar wavelet with 2-level decomposition.

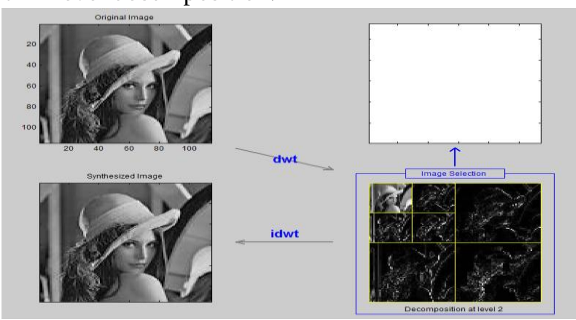

Fig. 11 Synthesis Lena image using Haar wavelet with 2-level decomposition

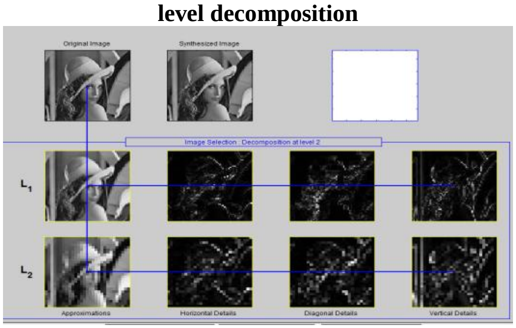

Fig. 12 Synthesis Lena image using Haar wavelet with 2-level decomposition (Tree representation)

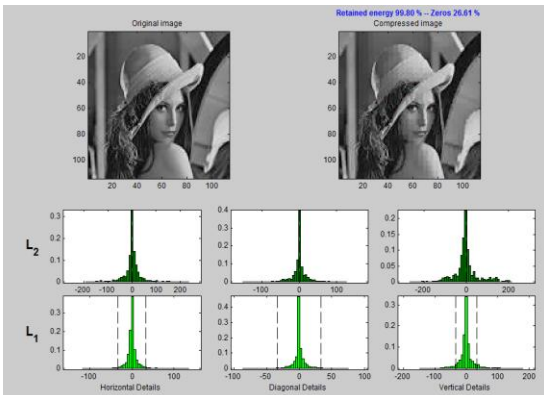

Fig. 13 Compression of Lena image using Haar wavelet with 2-level decomposition as level thresholding

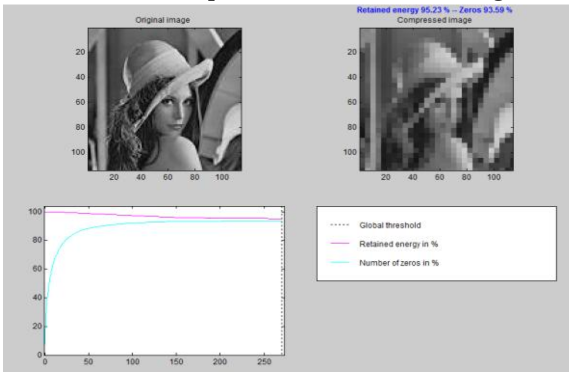

Fig. 14 Compression of Lena image using Haar wavelet with 2-level decomposition as global thresholding

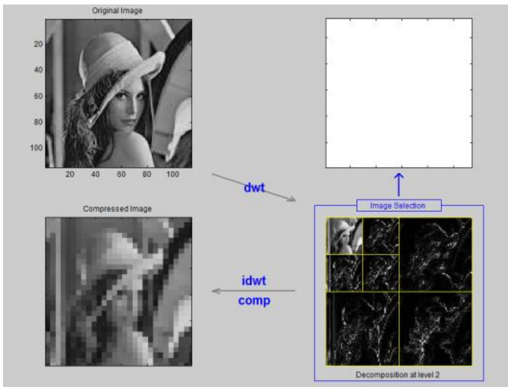

Fig. 15 compressed Lena image using Haar wavelet with 2 level decomposition

VI. CONCLUSIONS

In this paper we have proposed a new way of image compression based on HAAR wavelet transform (HDWT). The proposed compression techniques considerably improve the time performance of the system. Also the proposed Compression technique is simple and computationally less complex. The performance can be further improved when used other wavelet transform such as crude wavelet (Gaussian wavelet), infinity regular wavelet (Meyer wavelet), orthogonal wavelet (Daubechies, symlets and coiflets).

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