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Comparative Analysis of Various Digital Image Compression Techniques Using Wavelets

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Abstract- Image compression is the application of Data compression on digital images. Data compression is the technique to reduce the redundancies in data representation in order to decrease data storage requirements and hence communication costs. Reducing the storage requirement is equivalent to increasing the capacity of the storage medium and hence communication bandwidth. Thus the development of efficient compression techniques will continue to be a design challenge for future communication systems and advanced multimedia applications. This paper entails the study of various image compression techniques and algorithms. Different techniques for digital image compression have been reviewed and presented that includes DFT, FFT, DCT and DWT. Wavelets , however has an advantage over older techniques that it doesn't have any blocking artifacts as in DCT. It is easy to implement and reduces the computation time and resources required. The discrete wavelet transform uses filter banks for the construction of the multiresolutional time-frequency plane. The Discrete Wavelet Transform analyzes the signal at different frequency bands with different resolutions by decomposing the signal into an approximation and detail information. The decomposition of the signal into different frequency bands obtained by successive high pass g[n] and low pass h[n] filtering of the time domain signal. Also, a new algorithm for image compression using Fast Wavelet Transform has been proposed as FWT reduces the problems of border distortions in Image Compression.

Keywords: Discrete Cosine Transform, Fast Wavelet Transform, Approximation and Detail Coefficients, Border Distortion, Redundancy

I. Introduction

Image compression is the application of Data compression on digital images. The objective of image compression is to reduce redundancy of the image data in order to be able to store or transmit data in an efficient form. Image compression can be lossy or lossless.[1] Lossless compression is sometimes preferred for artificial images such as technical drawings, icons or comics. This is because lossy compression methods, especially when used at low bit rates, introduce compression artifacts.[2] Lossless compression methods may also be preferred for high value content, such as medical imagery or image scans made for archival purposes. Lossy methods are especially suitable for natural images such as photos in applications where minor loss of fidelity is acceptable to achieve a substantial reduction in bit rate. The lossy compression that produces imperceptible differences can be called visually lossless. Run-length encoding and entropy encoding are the methods for lossless image compression. Transform coding, where a Fourier-related transform such as DCT or the wavelet transform are applied, followed by quantization and entropy coding can be cited as a method for lossy image compression. A general compression model is shown in figure 3.1. It shows that encoder and decoder consist of two relatively independent functions or sub blocks [1]. The encoder is made up of source encoder, which removes input redundancies, and a channel encoder, which increases the noise immunity of the source encoder's output. Similarly, the decoder includes a channel decoder followed by a source decoder. If the channel between the encoder and decoder is noise free, the channel encoder and decoder are omitted, and the general encoder and decoder is noise free, the channel encoder and decoder are omitted, and the general encoder and decoder become the source encoder and decoder, respectively.

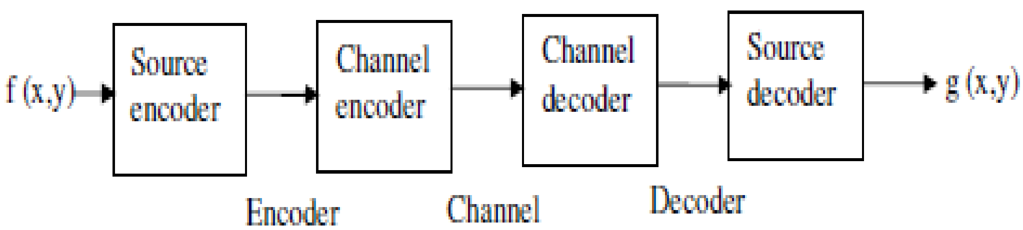
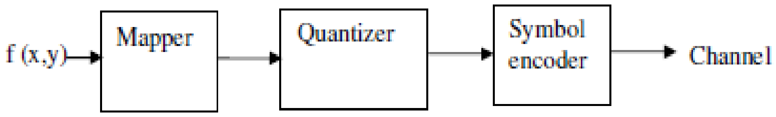
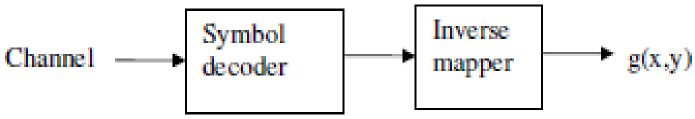


Figure 1: General Compression Model

The source encoder is responsible for reducing or eliminating any coding, interpixel, or psychovisual redundancies in the input image. The specific application dictates the best encoding approach. Normally, the approach can be modeled by a series of three independent operations.



Figures 2(a): Source encoder



Figures 2(b): Source decoder

In the first stage of the source encoding process, the mapper transforms the input data into a (usually non-visual) format designed to reduce interpixel redundancies in the input image. [3] This operation generally is reversible and may or may not reduce directly the amount of data required to represent the image. The second stage or quantizer block reduces the accuracy of the mapper's output in accordance with some pre-established fidelity criterion. This stage reduces the Psychovisual redundancies of the input image. This operation is irreversible. Thus, it must be omitted when error-free compression is desired. [4]In the third and final stage of source encoding processes, the symbol coder creates a fixed or variable-length code to represent the quantizer output and maps the output in accordance with the code. The term symbol coder distinguishes this coding operation from the overall source encoding processes. In most cases, a variable length code is used to represent the mapped and quantized data set. It assigns the shortest code words to the most, frequently occurring output values and thus reduces coding redundancy. The operation is completely reversible. Upon completion of symbol coding step, the input image has been processed to remove each of the three redundancies discussed earlier. It is shown that the source encoding processes consist three successive operations, but all three operations are not necessarily included in every compression. [6] For example, the quantizer must be omitted when error free compression is desired. In addition, some compression techniques normally are modelled by merging blocks that are physically separate in figure 2 (a). The source decoder shown in figure contains only two components: a symbol decoder and an inverse mapper. These blocks perform, in reverse order, the inverse operations of the source encoder's symbol encoder and mapper blocks. Because quantization results in irreversible information loss, an inverse quantizer block is not included in the general source decoder model shown in the figure 2(b).

Channel Encoder and Decoder

The channel encoder and decoder play an important role in the overall encoding-decoding process when the channel of above figure 1 is noisy or prone to error. [7] They are designed to reduce the impact of channel noise by inserting a controlled form of redundancy into the source-encoded data. As the output of the source encoder contains little redundancy, it would be highly sensitive to transmission noise without the addition of this "controlled redundancy".

II. Lossy And Lossless Image Compression

A. LOSSLESS IMAGE COMPRESSION

A loss of information is, however, totally avoided in lossless compression, where image data are reduced while image information is totally preserved. It uses the predictive encoding which uses the gray level of each pixel to predict the gray value of its right neighbour. [10] Only the small deviation from this prediction is stored. This is a first step of lossless data reduction. Its effect is to change the statistics of the image signal drastically. Statistical encoding is another important approach to lossless data reduction.[3] Statistical encoding can be especially successful if the gray level statistics of the images has already been changed by predictive coding. The overall result is redundancy reduction, that is reduction of the reiteration of the same bit patterns in the data. Of course, when reading the reduced image data, these processes can be performed in reverse order without any error and thus the original image is recovered. [3] Lossless compression is therefore also called reversible compression.

When hearing that image data are reduced, one could expect that automatically also the image quality will be reduced. A loss of information is, however, totally avoided in lossless compression, where image data are reduced while image information is totally preserved.

B.LOSSY IMAGE COMPRESSON

Lossy data compression has of course a strong negative connotation and sometimes it is doubted quite emotionally that it is at all applicable in medical imaging. [5] In transform encoding one performs for each image run a mathematical transformation that is similar to the Fourier transform thus separating image information on gradual spatial variation of brightness (regions of essentially constant brightness) from information with faster variation of brightness at edges of the image (compare: the grouping by the editor of news according to the classes of contents). In the next step, the information on slower changes is transmitted essentially lossless (compare: careful reading of highly relevant pages in the newspaper), but information on faster local changes is communicated with lower accuracy (compare: looking only at the large headings on the less relevant pages). In image data reduction, this second step is called quantization. Since this quantization step cannot be reversed when decompressing the data, the overall compression is 'lossy' or 'irreversible'.

1) RELATED WORK, ISSUES AND POSSIBLE SOLUTIONS

[1] shows a discrete wavelet technique to compress the images using wavelet theory in VHDL, Verilog. [2] shows FFT approach for data compression.that its histogram has a desired shape. [3] shows the lossless image compression algorithm using FPGA technology. [4] has shown an image compression algorithm using verilog with area, time and power constraints. [5] has shown a simple DCT technique to for converting signals into elementary frequency components using *mathematica* toolbox. [6] shows comparative analysis of various compression methods for medical images depicting lossless and lossy image compression. [7] shows Fourier analysis and Image processing technique. [8] shows Image compression Implementation using Fast Fourier Transform. [9] Examines a set of wavelet functions (wavelets) for implementation in a still image compression system and to highlight the benefit of this transform relating to today's methods. The paper discusses important features of wavelet transform in compression of still images, including the extent to which the quality of image is degraded by the process of wavelet compression and decompression. Image quality is measured objectively, using peak signal-to-noise ratio or picture quality scale, and subjectively, using perceived image quality. The effects of different wavelet functions, image contents and compression ratios are assessed. A comparison with a discrete-cosine- transform-based compression system is given. [10] Presents a high speed and area efficient DWT processor based design for Image Compression applications. In this proposed design, pipelined partially serial architecture has been used to enhance the speed along with optimal utilization and resources available on target FPGA. The proposed model has been designed and simulated using Simulink and System Generator blocks, synthesized with Xilinx Synthesis tool (XST) and implemented on Spartan 2 and 3 based XC2S100-5tq144 and XC3S500E-4fg320 target device. The results show that proposed design can operate at maximum frequency 231 MHz in case of Spartan 3 by consuming power of 117mW at 28 degree/c junction temperature. The result comparison has shown an improvement of 15% in speed. [11] has presented a quality constrained compression algorithm based on Discrete Wavelet Transform (DWT) is proposed.

2) NEED FOR COMPRESSION

Compression is necessary in modern data transfer and processing whether it is performed on data or an image/video file as transmission and storage of uncompressed video would be extremely costly and impractical. [11] Framensm with 352 x 288 contains 202,752 bytes of information. Recording of uncompressed version of this video at 15 frames per second would require 3 MB. As 180 MB of data storage would be required for 1 minute and hence one 24 hours day would be utilized to store 262 GB of database. Using Compression, at 15 frames per seconds, it takes 24 hrs. would take only 1.4GB and hence 187 days of video could be stored using the same disk space that uncompressed video would use in one day. Hence, Compression while maintaining the image quality is must for digital data, image or video file transfer in fast way and lesser amount of time.

III. Various Techniques For Image Compression

A. DFT: Discrete Fourier Transform

The Fourier Transform is an important image processing tool which is used to decompose an image into its sine and cosine components. The output of the transformation represents the image in the *Fourier* or frequency domain, while the input image is the spatial domain equivalent. In the Fourier domain image, each point represents a particular frequency contained in the spatial domain image. The [3] Fourier Transform is used in a wide range of applications, such as image analysis, image filtering, image reconstruction and image compression. [13] The DFT is the sampled Fourier Transform and therefore does not contain all frequencies forming an image, but only a set of samples which is large enough to fully describe the spatial domain image. [15] The number of frequencies corresponds to the number of pixels in the spatial domain image, *i.e.* the image in the spatial and Fourier domain are of the same size. For a square image of size N×N, the two-dimensional DFT is given by:

$$F(k,l) = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} f(i,j)\; e^{-\iota 2\pi\left(\frac{ki}{N}+\frac{lj}{N}\right)}$$

where *f(a,b)* is the image in the spatial domain and the exponential term is the basis function corresponding to each point *F(k,l)* in the Fourier space. The equation can be interpreted as: the value of each point *F(k,l)* is obtained by multiplying the spatial image with the corresponding base function and summing the result. In a similar way, the Fourier image can be re-transformed to the spatial domain. The inverse Fourier transform is given by:

$$f(a,b) = \frac{1}{N^2} \sum_{k=0}^{N-1} \sum_{l=0}^{N-1} F(k,l)\; e^{\iota 2\pi\left(\frac{ka}{N}+\frac{lb}{N}\right)}$$

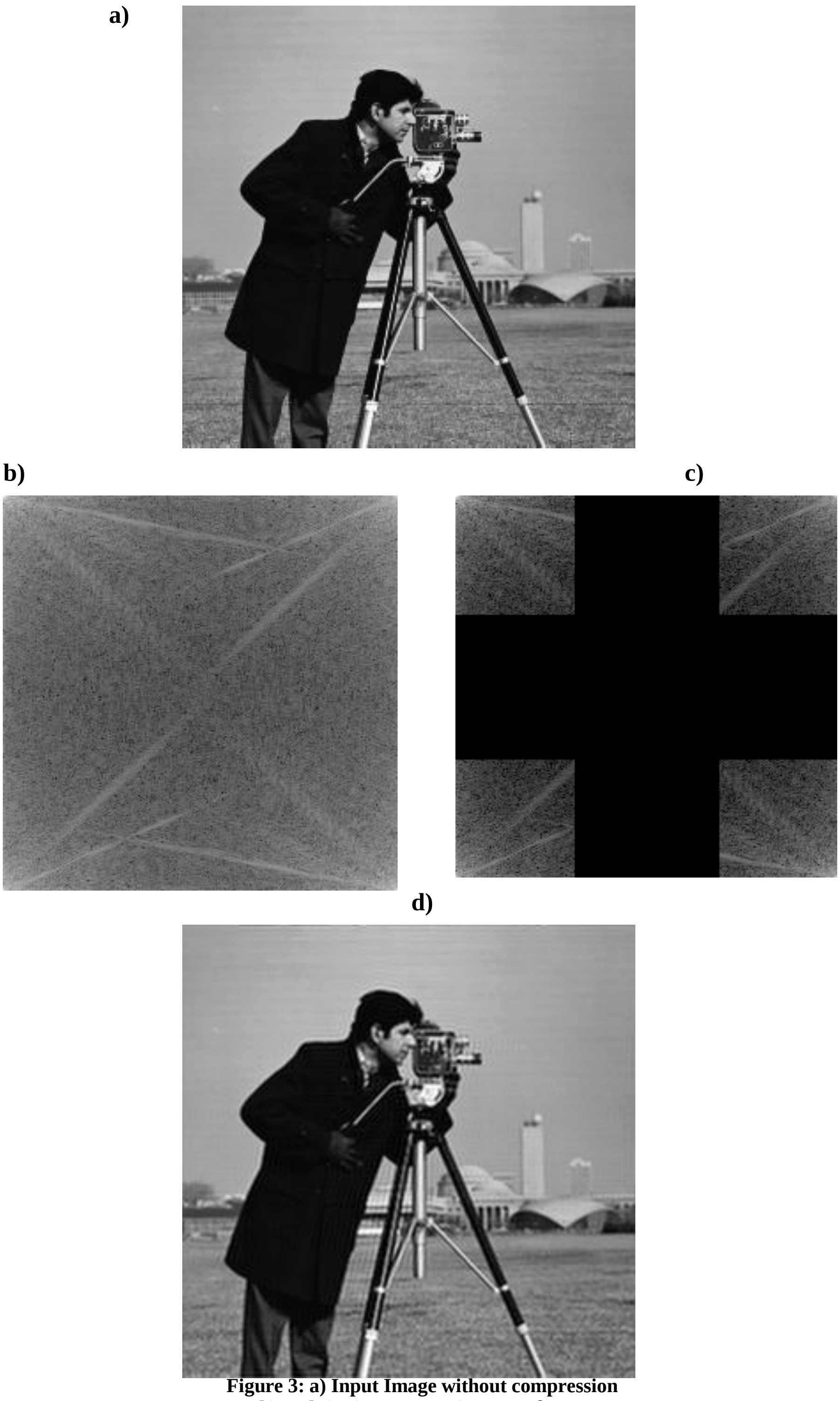
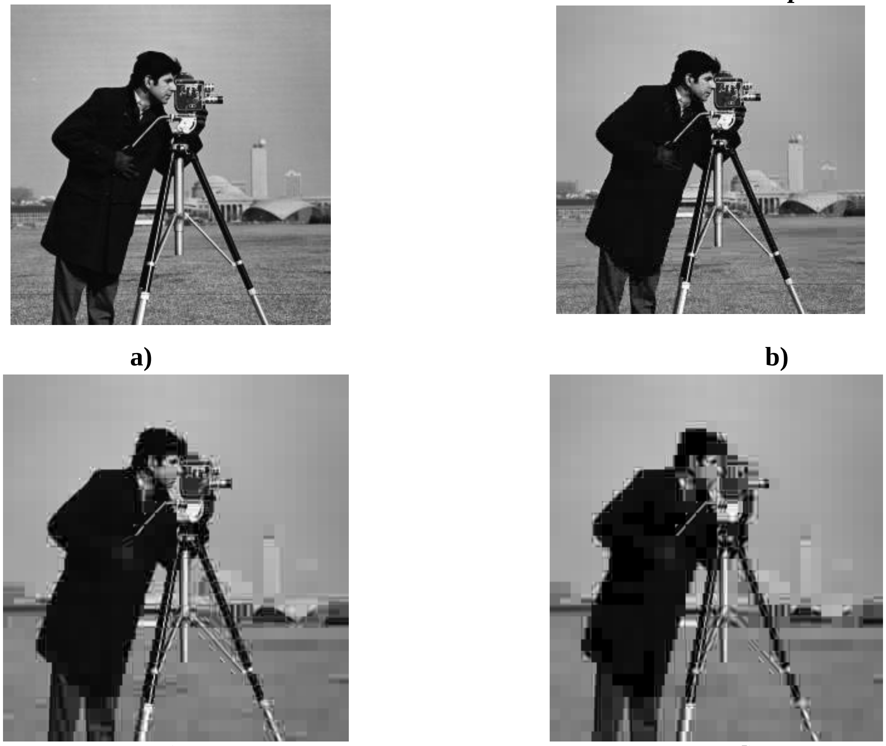


Figure 3: a) Input Image without compression
b) and c) Discrete Fourier Transforms
d) Output Image with Inverse transform that has been reconstructed

B. FFT

A fast Fourier transform (FFT) is an efficient algorithm to compute the discrete Fourier transform (DFT) and its inverse. [15] " There are many distinct FFT algorithms involving a wide range of mathematics, from simple arithmetic to group theory and number theory. A DFT decomposes a sequence of values into components of different frequencies. This operation is useful in many fields but computing it directly from the definition is often too slow to be practical.[3] An FFT is a way to compute the same result more quickly: computing a DFT of N points in the naive way, using the definition, takes $O(N^2)$ arithmetical operations, while an FFT can compute the same result in only $O(N \log N)$ operations. The difference in speed can be substantial, especially for long data sets where N may be in the thousands or millions—in practice, the computation time can be reduced by several orders of magnitude in such cases, and the improvement is roughly proportional to $N / \log (N)$. This huge improvement made many DFT-based algorithms practical; FFTs are of great importance to a wide variety of applications, from digital and solving partial differential equations to algorithms for quick multiplication of large integers.



a) **b)**

c) **d)**

Figure 4: a) The Original Cameraman Image
b) Cameraman Image after decompression (cut off=20, MSE=36.82) using FFT
c) Cameraman Image after decompression (cut off=40, MSE=102.43) using FFT
d) Cameraman Image after decompression (cut off=60, MSE=164.16) using FFT
e)

C. DISCRETE COSINE TRANSFORM

The 1D DCT is defined as

$$\mathbf{D}_X\{f\}(\omega) = a(\omega)\sum_{x=0}^{N-1} f(x)\cos\left(\frac{(2x+1)\omega\pi}{2N}\right) \; ; \; a(\omega) = \begin{cases} \sqrt{\frac{1}{N}} & \omega = 0 \\ \sqrt{\frac{2}{N}} & else \end{cases}$$

which is similar to the DFT

$$F(\omega) = \frac{1}{N}\sum_{x=0}^{N-1} f(x)e^{-\frac{j2\pi x\omega}{N}}$$

2D DCT is defined using the separability property as 1D transform on the rows and on the columns, applied separately One of the advantages of DCT is the fact that it is a real transform, whereas DFT is complex. This implies lower

$$F(u,v) = \mathbf{D}_Y\{\mathbf{D}_X\{f(x,y)\}\}$$

computational complexity, which is sometimes important for real-time applications. DCT is used in some lossy compression algorithms, including JPEG. (The JPEG standard codec is more complicated, for it includes a quantizer for DCT coefficients and DPCM statistical prediction scheme. The output of the codec is the prediction error, which is encoded using some lossless entropy code.)

In the transform image, DC is the matrix element (1,1), corresponding to transform value X(0,0). High spatial X and Y frequencies correspond to high column and row indexes, respectively.

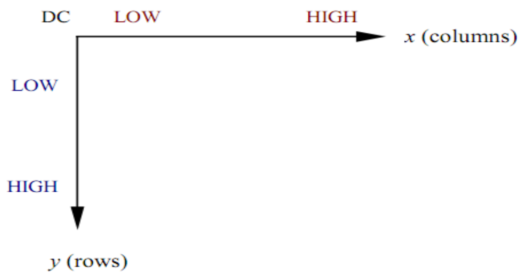


Figure 5: DCT image. Red labels denote horizontal spatial frequencies, blue label denote vertical frequencies.

According to the DCT properties, a DC is transformed to discrete delta-function at zero frequency. Hence, the transform image contains only the DC component. This can be seen in the transform image. The DC value is a sum over the whole image. The majority of the DCT energy is concentrated on low frequencies. The reason is the fact that natural images possess mostly low-frequency features and high-frequency features (edges) are rarely encountered. The advantages of DCT compression are based on the fact that most natural images have sparse edges. Hence, most blocks contain primarily low frequencies, and can be represented by a small number of coefficients without significant precision loss. Edges are problematic since are associated with high spatial frequency. Consequently, the DCT at blocks where the edges pass has high-amplitude coefficients at high frequencies, which cannot be removed without significant distortion. This effect was seen on the coin image, where small number of coefficients resulted in very significant distortion of the edges.

a)

b)

Figure 6: a) Original Image Of Cameramen

a) Reconstructed Image after applying 8 x 8 block subset using DCT

Blocking Artifacts : A distortion that appears in compressed image as abnormally large pixel blocks. Also called "macro blocking," it occurs when the encoder cannot keep up with the allocated bandwidth. Image uses lossy compression, and the higher the compression rate, the more content is removed. At decompression, the output of certain decoded blocks makes surrounding pixels appear averaged together and look like larger blocks. Image compression using DCT and older techniques show this blocking effect due to fixed size window as in figure 8, however, this problem is removed with the help of wavelet based image compression.

D. DISCRETE WAVELET TRANSFORM

The discrete wavelet transform (DWT) is a mathematical tool that has aroused great interest in the field of image processing due to its nice features. Some of these characteristics are:
1) it allows image multi resolution representation in a natural way because more wavelet subbands are used to progressively enlarge the low frequency subbands;
2) it supports wavelet coefficients analysis in both space and frequency domains, thus the interpretation of the coefficients is not constrained to its frequency behavior and we can perform better analysis for image vision and segmentation; and
3) For natural images, the DWT achieves high compactness of energy in the lower frequency sub bands, which is extremely useful in applications such as image compression. The introduction of the DWT made it possible to improve some specific applications of image processing by replacing the existing tools with this new mathematical transform. The JPEG 2000 standard [1] proposes a wavelet transform stage since it offers better rate/distortion (R/D) performance than the traditional discrete cosine transform (DCT).

TIME ISSUES IN DWT

Due to the rate-change operators in the filter bank, the discrete WT is not time-invariant but actually very sensitive to the alignment of the signal in time. To address the time-varying problem of wavelet transforms, Mallat and Zhong proposed a new algorithm for wavelet representation of a signal, which is invariant to time shifts. According to this algorithm, which is called a TI-DWT, only the scale parameter is sampled along the dyadic sequence 2^j (j∈Z) and the wavelet transform is calculated for each point in time.

E. FAST WAVELET TRANSFORM

In 1988, Mallat produced a fast wavelet decomposition and reconstruction algorithm [Mal89]. The Mallat algorithm for discrete wavelet transform (DWT) is, in fact, a classical scheme in the signal processing community, known as a two-channel subband coder using conjugate quadrature filters or quadrature mirror filters (QMFs).

- The decomposition algorithm starts with signal *s*, next calculates the coordinates of A_1 and D_1, and then those of A_2 and D_2, and so on.
- The reconstruction algorithm called the inverse discrete wavelet transform (IDWT) starts from the coordinates of A_J and D_J, next calculates the coordinates of A_{J-1}, and then using the coordinates of A_{J-1} and D_{J-1} calculates those of A_{J-2}, and so on.

In order to understand the multiresolution analysis concept based on Mallat's algorithm it is very useful to represent the wavelet transform as a pyramid, as shown in figure 12. The basis of the pyramid is the original image, with C columns and R rows.

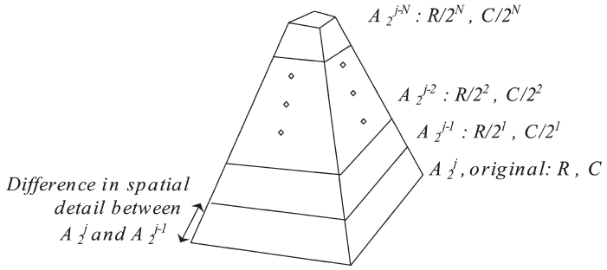
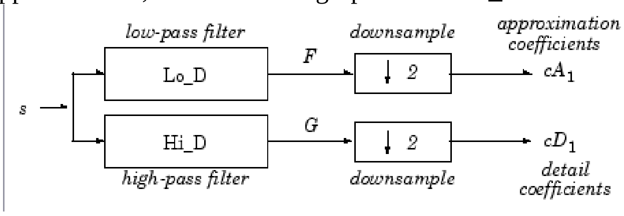


Figure 1: Pyramidal representation of Mallat's wavelet decomposition algorithm.

Given a signal s of length N, the DWT consists of $\log_2 N$ stages at most. Starting from s, the first step produces two sets of coefficients: approximation coefficients cA_1, and detail coefficients cD_1. These vectors are obtained by convolving s with the low-pass filter Lo_D for approximation, and with the high-pass filter Hi_D for detail, followed by dyadic decimation.



The length of each filter is equal to $2n$. If N = length (s), the signals F and G are of length $N + 2n - 1$, and then the coefficients cA_1 and cD_1 are of length

$$\text{floor}\left(\frac{(N-1)}{2}+n\right)$$

The next step splits the approximation coefficients cA_1 in two parts using the same scheme, replacing s by cA_1 and producing cA_2 and cD_2, and so on.

Classically, the DWT is defined for sequences with length of some power of 2, and different ways of extending samples of other sizes are needed. Methods for extending the signal include zero-padding, smooth padding, periodic extension, andboundary value replication (symmetrization). The basic algorithm for the DWT is not limited to dyadic length and is based on a simple scheme: convolution and downsampling [13] . As usual, when a convolution is performed on finite-length signals, border distortions arise. To Remove these border effects , Fast Wavelet Transform was introduced. This algorithm is a method for the extension of a given finite-length signal [16].

IV. Proposed Methodology For Image Compression Using Wavelets And Fast Wavelet Transform

Wavelet analysis represents the next logical step: a windowing technique with variable-sized regions. Wavelet analysis allows the use of long time intervals where we want more precise low-frequency information, and shorter regions where we want high-frequency information.

Figure 7: Wavelet Transform on a signal

Wavelet Transform in contrast with the time-based (eg. DFT), frequency-based (eg. FFT), and STFT (eg. DCT) views of a signal:

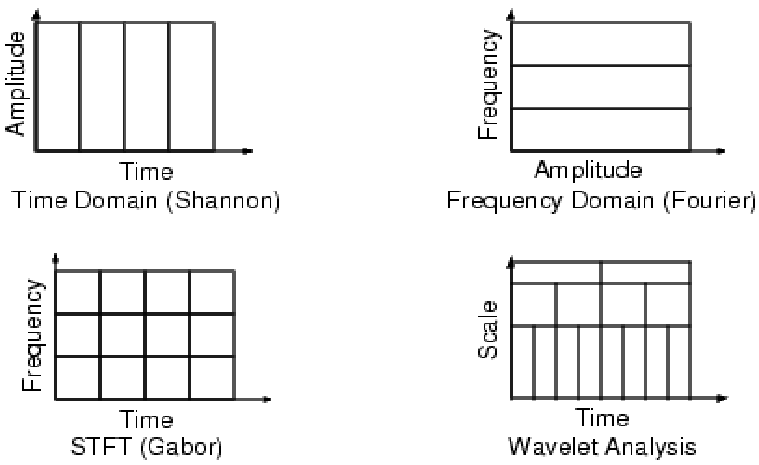


Figure 8: Comparision of Various Trasform Techniques

The decomposition process can be iterated, with successive approximations being decomposed in turn, so that one signal is broken down into many lower resolution components. This is called the wavelet decomposition tree.

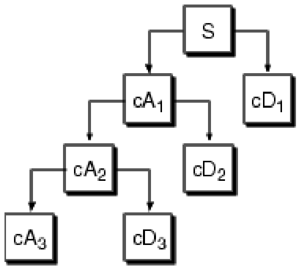


Figure 7: Multilevel Decomposition

V. Advantages Of Image Compression

i) It reduces the data storage requirements
ii) The audience can experience rich-quality signals for audio-visual data representation
iii) Data security can also be greatly enhanced by encrypting the decoding parameters and transmitting them separately from the compressed database files to restrict access of proprietary information
iv)The rate of input-output operations in a computing device can be greatly increased due to shorter representation of data
v) Data Compression obviously reduces the cost of backup and recovery of data in computer systems by storing the backup of large database files in compressed form

VI. Future Scope And Conclusion

Lifting schema of DWT has been recognized as a faster approach

- The basic principle is to factorize the polyphase matrix of a wavelet filter into a sequence of alternating upper and lower triangular matrices and a diagonal matrix .
- This leads to the wavelet implementation by means of banded-matrix multiplications

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