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Image Analysis Using Biorthogonal Wavelet

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Abstract:
The main objective is to investigate the still image compression and de-noising of a gray scale image using wavelet theory at different decomposition and threshold levels. The "Image Analysis Using Biorthogonal Wavelet" is implemented in software using MATLAB Wavelet Toolbox and 2-D DWT technique. The experiments and simulation is carried out on .jpg format images. The scope of the work involves knowing the Biorthogonal wavelet on compression and denoising, image clarity, to find the effect of decomposition & threshold levels and energy retaining and lost. Therefore, the image recovery is good and clarity, but the percentage of compression and retaining the energy is different. In order to quantify the performance of the denoising, a random noise is added to the still image and given as input to the denoising algorithm, which produces an image close to the original image. The significant advantage of using wavelets for image processing can be used in applications in which fourier methods are not well suited, like progressive image reconstruction.

***Keywords**: Image Processing Toolbox(IPT), Graphical User Interfaces(GUIs), Joint production experts group(.JPG), Two-Dimensional Discrete Wavelet Transform, Wavelet Toolbox (WT), Biorthogonal Wavelet.*

1.Introduction

The main objective of this research is to investigate and provide a foundation for implementing wavelet-based image processing algorithms using modern software tools MATLAB. A complementary objective was to analyze still images using wavelets theory of Biorthogonal wavelet family. Following approach made it possible to present a simulation to maintain a focus on the software implementation aspects of image processing problems and solutions. Because it works in the MATLAB computing environment, the Wavelet Toolbox (WT) offers some significant advantages, not only in the breadth of its computational tools, but also because it is supported under most operating systems in use today and to enhance existing MATLAB [1], [2], [3]and Wavelet Toolbox.

The Wavelet transform analysis has emerged as a major new time-frequency decomposition tool for data analysis. The wavelet transform has been found to be particularly useful for analyzing signals which are transitory, discontinuous, noisy, and so on. Its ability to examine the signal in both time and frequency resolution is distinctive and enables myriads of possible applications that traditional signal analysis tools such as Fourier Transform cannot handle. It has now been applied to diverse realm of data analysis/process: climate analysis, financial indices analysis, signals denoising, characterization, feature extraction, data compression, and so on. Images contain large amounts of information that requires much storage space, large transmission bandwidths and long transmission times. Therefore it is advantageous to compress the image by storing only the essential information needed to reconstruct the image. An image can be thought of as a matrix of pixel (or intensity) values. In order to compress the image, redundancies must be exploited, for example, areas where there is little or no change between pixel values. Therefore images having large areas of uniform color will have large redundancies, and conversely images that have frequent and large changes in color will be less redundant and harder to compress.

Wavelet analysis can be used to divide the information of an image into approximation and detail subsignals [9]. The approximation subsignal shows the general trend of pixel values, and three detail subsignals show the vertical, horizontal and diagonal details or changes in the image. If these details are very small then they can be set to zero without significantly changing the image. The value below which details are considered small enough to be set to zero is known as the threshold. The greater the number of zeros the greater the compression that can be achieved. The amount of information retained by an image after compression and decompression is known as the energy retained, and this is proportional to the sum of the squares of the pixel values. If the energy retained is 100% then the compression is known as lossless, as the image can be reconstructed exactly. This occurs when the threshold value is set to zero, meaning that the detail has not been changed. If any values are changed then energy will be lost and this is known as lossy compression [13]. Ideally, during compression the number of zeros and the energy retention will be as high as possible. However, as more zeros are obtained more energy is lost, so a balance between the two needs to be found.

The objective was to review the compression, de-noising and decomposition & reconstruction property of wavelet by applying Biorthogonal wavelet [7] to analyze image data. This is followed by a review of a practical investigation into how compression and denoising can be achieved with wavelet. The purpose of the investigation was to find the effect of the decomposition & threshold level, knowing the efficiency of Biorthogonal wavelet on compression and denoising, image clarity, to find out energy retaining(image recovery) and lost. Therefore, the image used in the analysis is .jpg format.

2.Work Limitations

This work does not intend to develop a fully automatic object extraction system or algorithm. Adaptability of the research for still images with complex building is considered to be of secondary importance. Finally, do not intend for an in-depth look for all the routines of wavelet theory or segmentation. Therefore, mathematical proofs are not given thoroughly. More importantly, it remains on the application side of wavelet theory.

In fact, the decomposition results depends on the choice of analyzing wavelet i.e., its corresponding filter that are used. The choice of mother wavelet depends whether one needs to obtain better resolution in time or frequency. The design and proper choice of the wavelet function for diverse tasks comprises a considerable part of wavelet research.

3.Work Approach

In principle, the approach follows to know the Biorthogonal wavelet in image compression and denoising. The experiments are conducted on still images(.jpg format). Image analysis using Biorthogonal wavelet remains the implementation of 2D DWT for still gray images. The main framework of this research comprises a number of experiments such as image compression, to find the effect of the decomposition & threshold level, to find out energy retaining(image recovery) and lost, image denoising and image clarity.

4.Wavelets

To give a full overview of wavelet [7], [14] theory would require more than a single book, for the theory of wavelets, wavelet decomposition, & multiresolution analysis. This research will limit to the basics concept of wavelet analysis, which provides a basis for the application of wavelet.

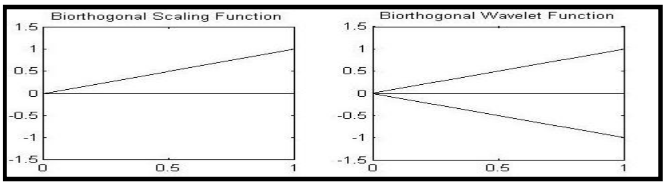
The wavelet multiresolution [9], [14], [16], [18] decomposition is one the most popular methods to cut up the signal into different frequency components. Multiresolution analysis allows us interpret an image as a sum of details that appear at different resolutions. Although wavelet theory was first introduced as a mathematical tool in the mid-1980s, it has been widely used in image processing, especially in compression. The wavelet analysis begins with a mathematical function, called Mother Wavelet or Wavelet Kernel. There is infinite number of possible wavelets and the best one depends on application, but all of them have some common mathematical characteristics. "Wave"lets are actually waveforms of effectively limited duration (which means they are short waves) and have an average value of zero. A short comparison with well-known Fourier analysis will give an idea about the concept of wavelet analysis. In Fourier analysis a signal is breaking into sine waves of different frequencies. In wavelet analysis the signal is breaking into scaled and translated (shifted) versions of the selected mother wavelet.

The theory of wavelets is difficult to understand without a strong mathematical background. Wavelets are mathematical functions that cut up data into different frequency components, and then study each component with a resolution matched to its scale. They have advantages over traditional Fourier methods in analyzing physical situations where the signal contains discontinuities and sharp spikes. Wavelets were developed independently in the fields of mathematics, quantum physics, electrical engineering, and seismic geology. Interchanges between these fields during the last ten years have led to many new wavelet applications[19] such as image compression, turbulence, human vision, radar, and earthquake prediction.

This study introduces wavelets of the digital signal processing field. However, it can be explained in an intuitive way that is understandable for the readers who are new to this subject. As an introduction to the wavelet, a simple example of the wavelet transform will be presented. Finally, the discrete wavelet transform (DWT) will be introduced as well as issues of its practical implementation for images.

5.Biorthogonal Wavelet

The oldest and simplest wavelet transform is based on the Haar scaling and wavelet functions. Any discussion of wavelets begins with Haar wavelet, the first and simplest. Haar wavelet [8] is discontinuous, and resembles a step function. It represents the same wavelet as Daubechies(db1) [14].



Figureure 1: Biorthogonal Wavelet

This family of Biorthogonal [14], [18] wavelets exhibits the property of linear phase, which is needed for signal and image reconstruction. By using two wavelets, one for decomposition (on the left side) and the other for reconstruction (on the right side) instead of the same single one, interesting properties are derived.

6.The Discrete Wavelet Transform

Dilations and translations of the “Mother function" or “analyzing wavelet" **Φ(x)**; define an orthogonal basis, our wavelet basis:

$$\Phi_{(s,l)}(x) = 2^{-s/2}\,\Phi(2^{-s}x - l) \qquad (1)$$

The variables **s** and **l** are integers that scale and dilate the mother function **Φ** to generate wavelets, such as a Daubechies wavelet family [14]. The scale index s indicates the wavelet's width, and the location index **l** gives its position. Notice that the mother functions are rescaled, or “dilated" by powers of two, and translated by integers. What makes wavelet bases especially interesting is the self-similarity caused by the scales and dilations. Once we know about the mother functions, we know everything about the basis.

To span our data domain at different resolutions, the analyzing wavelet is used in a scaling equation:

N-2

$W(x) = \sum(-1)_k c_k+1\Phi(2x+k)$ (2)

k= -1

where W(x) is the scaling function for the mother function Φ; and c_k are the wavelet coefficients. The wavelet coefficients must satisfy linear and quadratic constraints of the form

N-1 N-1

$\sum c_k=2, \quad \sum c_k c_k+2l=2\delta_{l,0}$ (3)

k=0 k=0

where δ is the delta function and l is the location index.

One of the most useful features of wavelets is the ease with which a scientist can choose the defining coefficients for a given wavelet system to be adapted for a given problem. In Daubechies' original paper, she developed specific families of wavelet systems that were very good for representing polynomial behavior. The Haar wavelet is even simpler, and it is often used for educational purposes.

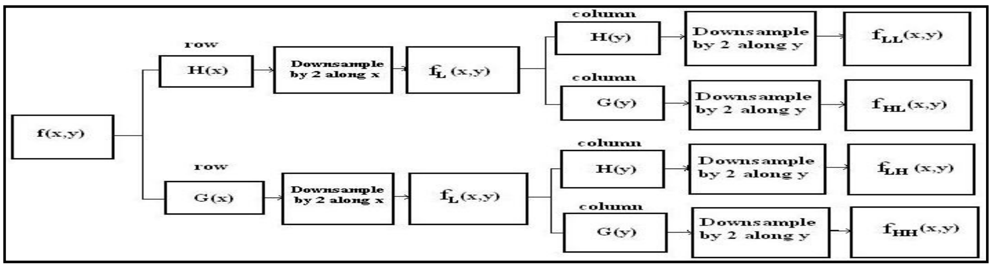
It is helpful to think of the coefficients **$\{c_0,\ldots\ldots,c_n\}$** as a filter. The filter or coefficients are placed in a transformation matrix, which is applied to a raw data vector. The coefficients are ordered using two dominant patterns, one that works as a smoothing filter (like a moving average), and one pattern that works to bring out the data's “detail" information. These two orders of the coefficients are called a Quadrature Mirror Filter(QMF) [9] pair in signal processing parlance. A more detailed description of the transformation matrix can be found elsewhere.

To complete our discussion of the DWT [7], [16], let's look at how the wavelet coefficient matrix is applied to the data vector. The matrix is applied in a hierarchical algorithm, sometimes called a pyramidal algorithm. The wavelet coefficients are arranged so that odd rows contain an ordering of wavelet coefficients that act as the smoothing filter, and the even rows contain an ordering of wavelet coefficient with different signs that act to bring out the data's detail. The matrix is first applied to the original, full-length vector. Then the vector is smoothed and decimated by half and the matrix is applied again. Then the smoothed, halved vector is smoothed, and halved again, and the matrix applied once more. This process continues until a trivial number of “smooth-smooth- smooth..." data remain. That is, each matrix application brings out a higher resolution of the data while at the same time smoothing the remaining data. The output of the DWT consists of the remaining "smooth (etc.)" components, and all of the accumulated "detail" components.

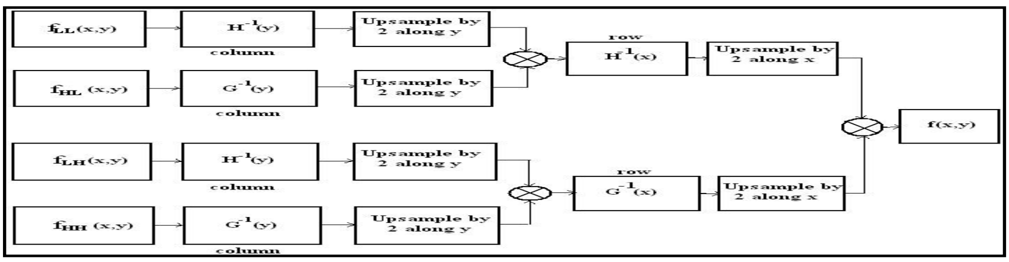
6.1.Two - Dimensional Discrete Wavelet Transform Decomposition

In the discrete wavelet transform, an image signal can be analyzed by passing it through an analysis filter bank followed by a decimation operation. This analysis filter bank, which consists of a low pass and a high pass filter at each decomposition stage, is commonly used in image compression. When a signal passes through these filters, it is split into two bands. The low pass filter, which corresponds to an averaging operation, extracts the coarse information of the signal. The high pass filter, which corresponds to a differencing operation, extracts the detail information of the signal. The output of the filtering operations is then decimated by two.

A two-dimensional transform (Figureure.2) can be accomplished by performing two separate one-dimensional transforms. First, the image is filtered along the x-dimension and decimated by two. Then, it is followed by filtering the sub-image along the y-dimension and decimated by two. Finally, we have split the image into four bands denoted by LL, HL, LH and HH after one-level decomposition (Figureure.4b). Further decompositions can be achieved by acting upon the LL subband successively and the resultant image is split into multiple bands as shown in Figureure.4c and Figureure.4d.



Figureure2: -D DWT



Figureure 3: D IDWT

In mathematical terms, the averaging operation or low pass filtering is the inner product between the signal and the scaling function (□) as shown in equation-4 whereas the differencing operation or high pass filtering is the inner product between the signal and the wavelet function (□) as shown in equation-5

Average coefficients.

$$C_j (k) = < f(t), \phi_{j,k} (t) > = \int f(t), \phi_{j,k} (t)\, dt \qquad (4)$$

Detail coefficients.

$$d_j (k) = < f(t), \psi_{j,k} (t) > = \int f(t), \psi_{j,k} (t)\, dt \qquad (5)$$

The scaling function or the low pass filter is defined as

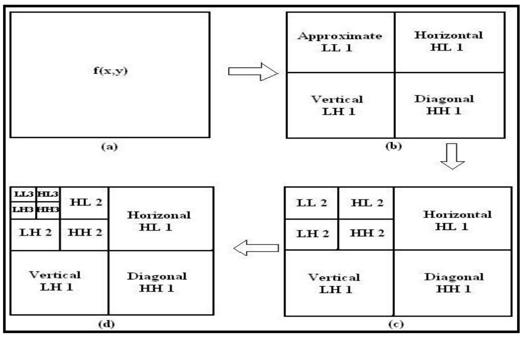
$$\phi_{j,k} (t) = 2^{j/2} \phi (2^j t - k) \qquad (6)$$

The wavelet function or the high pass filter is defined as

$$\psi_{j,k} (t) = 2^{j/2} \psi (2^j t - k) \qquad (7)$$

where **j** denotes the discrete scaling index, **k** denotes the discrete translation index.

The reconstruction of the image can be carried out by the following procedure. First, we will upsample by a factor of two on all the four subbands at the coarsest scale, and filter the subbands in each dimension. Then we sum the four filtered subbands to reach the low-low subband at the next finer scale. We repeat this process until the image is fully reconstructed shown in Figureure.3.



Figureure 4: D DWT Decomposition: a) Original image, b) One level decomposition, c) Two levels decomposition, d) Three levels decomposition

7.Algorithms For Image Analysis Using Wavelets

7.1.Algorithm For Decomposition

- Step 1: Start-Load the source image data from a file into an array.
- Step 2: Choose a Biorthogonal Wavelet.

- Step 3: Decompose-choose a level **N**, compute the wavelet decomposition
  of the signals at level **N**.
- Step 4: Compute the DWT of the data.
- Step 5: Read the 2-D decomposed image to a matrix.
- Step 6: Retrieve the low pass filter from the list based on the wavelet type.
- Step 7: Compute the high pass filter **i=1**.
- Step 8: **i >= 1**decomposed level, then if Yes goto step 10, otherwise if No go to step 9.
- Step 9: Perform 2-D decomposition on the image **i++** and goto to step 8.
- Step 10: Decomposed image.
- Step 11: End.

7.1.Algorithm For Reconstruction

- Step 1: Start-Load the source image data from a file into an array.
- Step 2: Choose a Biorthogonal Wavelet.
- Step 3: Decompose-choose a level N, compute the wavelet decomposition
  of the signals at level N.
- Step 4: Compute the DWT of the data.
- Step 5: Read the 2-D decomposed image to a matrix.
- Step 6: Retrieve the low pass filter from the list based on the wavelet type.
- Step 7: Compute the high pass filter i=decomp level.
- Step 8: i <= 1, then if Yes goto step 10, otherwise if No goto step 9.
- Step 9: Perform 2-D reconstruction on the image and goto to step 8.
- Step 10: Reconstruction image.
- Step 11: End.

8.Compression Procedure.

The compression procedure contains three steps:

- Decompose -Choose a wavelet, choose a level **N**. Compute the wavelet decomposition of the signals at level **N**.
- Threshold detail coefficients, for each level from 1 to **N**, a threshold is selected and hard thresholding is applied to the detail coefficients.
- Reconstruct -Compute wavelet reconstruction using the original approximation coefficients of level **N** and the modified detail coefficients of levels from 1 to **N**.

The difference of the de-noising procedure is found in step 2. There are two compression approaches available. The first consists of taking the wavelet expansion of the signal and keeping the largest absolute value coefficients. In this case, you can set a global threshold, a compression performance, or a relative square norm recovery performance. Thus, only a single parameter needs to be selected. The second approach consists of applying visually determined level-dependent thresholds.

8.1.Algorithm For Compression

- Step 1: Start-Load the source image data from a file into an array.
- Step 2: Choose a Biorthogonal Wavelet.
- Step 3: Decompose-choose a level **N**, compute the wavelet decomposition of signals at level **N.**
- Step 4: Threshold detail coefficients, for each level from **1** to **N**, a threshold is selected and hard thresholding is applied to the detail coefficients
- Step 5: Remove(set to zero) all coefficients whose value is below a threshold(this is the compression step).
- Step 6: Reconstruct, Compute wavelet reconstruction using the original approximation coefficients of level **N** and the modified detail coefficients of levels from **1** to **N.**
- Step 7: Compare the resulting reconstruction of the compressed image to the original image.
- Step 8: End.

8.2.De-Noising Procedure

The two-dimensional de-noising procedure has the same three steps and uses two-dimensional wavelet tools instead of one-dimensional ones.

The general de-noising procedure involves three steps. The basic version of the procedure follows the steps described below.

- Decompose - Choose a wavelet, choose a level **N**. Compute the wavelet decomposition of the signals at level **N**.
- Threshold detail coefficients, for each level from 1 to **N**, select a threshold and apply soft thresholding to the detail coefficients.
- Reconstruct - Compute wavelet reconstruction using the original approximation coefficients of level **N** and the modified detail coefficients of levels from 1 to **N**. Two points must be addressed: how to choose the threshold, and how to perform the thresholding.

8.3.Algorithm for Denoising

- Step 1: Start-Load the source image data from a file into an array.
- Step 2: Choose a Biorthogonal Wavelet.
- Step 3: Decompose-choose a level N, compute the wavelet decomposition of the signals at level N.
- Step 4: Add a random noise to the source image data.
- Step 5: Threshold detail coefficients, for each level from 1 to N, a threshold is selected and soft thresholding is applied to the detail coefficients.
- Step 6: Reconstruct, Compute wavelet reconstruction using the original approximation coefficients of level N and the modified detail coefficients of levels from 1 to N.
- Step 7: Compare the resulting reconstruction of the denoised image to the original image.
- Step 8: End.

9.**Experimental Result**

The Wavelet transformation is powerful because of its multi-resolution decomposition technique. This technique allows wavelets to decorrelate an image and concentrate the energy in a few coefficients. The most important reason why wavelet transformation is so powerful is its Multi-Resolution Analysis (MRA) [9] capability, which allows it to analyze signal at various scale and resolution. With the help of the simulated program, it is able to capture how wavelets transform a two-dimensional image. The results that were collected were values for percentage energy retained(image recovery) and percentage number of zeros. These values were calculated for a range of threshold values on all the images, decomposition levels [20]-[34] and, the energy retained describes the amount of image detail that has been kept, it is a measure of the quality of the image after compression. The number of zeros is a measure of compression. A greater percentage of zeros implies that higher compression rates can be obtained.

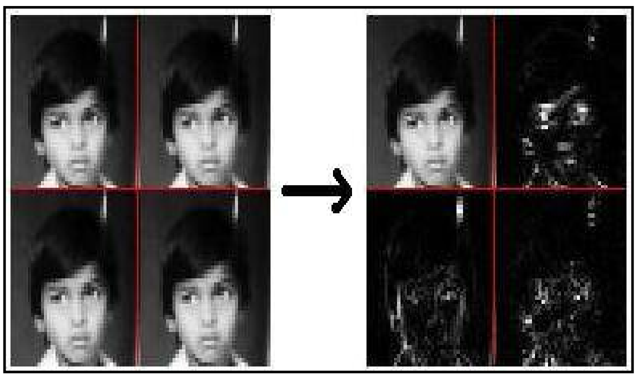
8.1.Decomposition Results

- Note: Experiments are conducted on Kumar gray image and results noted on this image only.

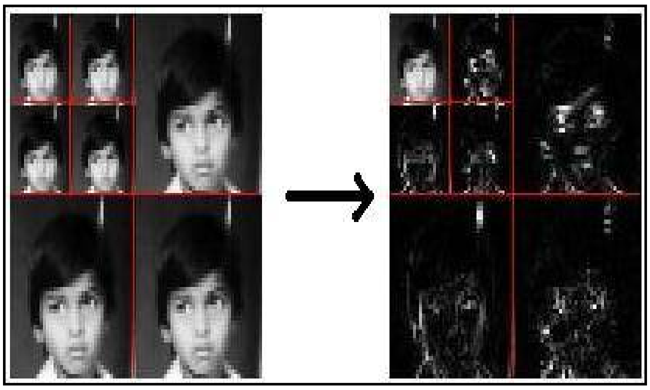
Image Used (grayscale)=kumar.jpg,

Image size=147 X 81

Figureure 5: Kumar Original Image

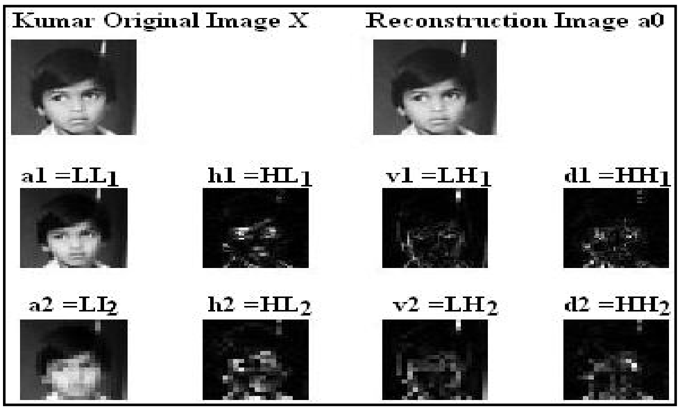


Figureure 6: 1^{st} level Decomposition



Figureure 7: 2nd level Decomposition

Figureure 8: Reconstructed Image



Figureure 9: Decomposition approximations

The decomposition [18] experiment is conducted using Biorthogonal, wavelet has two functions “wavelet” and “scaling function”. They are such that there are half the frequencies between them. They act like a low pass filter and a high pass filter, a typical decomposition scheme. The decomposition of the signal into different frequency bands is simply obtained by successive high pass and low pass filtering of the time domain signal.

This filter pair is called the analysis filter pair. First, the low pass filter is applied for each row of data, thereby getting the low frequency components of the row. But since the low pass filter is a half band filter, the output data contains frequencies only in the first half of the original frequency range. By Shannon's Sampling Theorem, they can be sub-sampled by two, so that the output data now contains only half the original number of samples. Now, the high pass filter is applied for the same row of data, and similarly the high pass components are separated.

This is a non-uniform band splitting method that decomposes the lower frequency part into narrower bands and the high-pass output at each level is left without any further decomposition. This procedure is done for all rows. Next, the filtering is done for each column of the intermediate data. The resulting two-dimensional array of coefficients contains four bands of data, each labeled as LL (low-low), HL (high-low), LH (low-high) and HH (high-high). The LL band can be decomposed once again in the same manner, thereby producing even more sub bands. This can be done up to any level, thereby resulting in a pyramidal decomposition as shown in Figureure.2 & 3, 7 & 8.

The LL band is decomposed thrice in Figureure.4. The compression ratios with wavelet based compression can be up to 300-to-1, depending on the number of iterations. The LL band at the highest level is most important, and the other 'detail' bands are of lesser importance, with the degree of importance decreasing from the top of the pyramid to the bands at the bottom. This can be done to any image Figureure.4., shows how it would work for an image at different levels. The Image is reconstructed Figureure.8., to retain as original image by IDWT(Figureure.3 & algorithm for reconstruction [6]).

8.2.Compression Result

The Wavelet work by looking at the values of neighboring pixels, and splitting those values into an approximation value and a detail value. If the pixel values are similar then the value of the detail is small. Thus an image with intensity values that only have small changes between pixel values is easier to compress with wavelets than those that have dramatic and irregular changes. This is because with these images the approximation signal will contain most of the energy (image recovery); the detail signals will have values close to zero and therefore not much energy. Thresholding the detail signals will therefore have little effect on the energy, but provide more zeros. So compression [17] can be obtained with little cost in energy loss. Thus if an image contains a high frequency of a certain intensity value, then this could help to provide a good compression rate, but it depends on where they are in the image. If they are all together then there will be an area of the same intensity value, and this means that the detail values will be zero. If they are randomly spread throughout the image, next to pixels of dissimilar intensities, then the fact that there was a high frequency of certain intensity will not be enough to provide good compression.

9.At Different Decomposition Levels

The decomposition level changes the proportion of detail coefficients in the decomposition. Decomposing a signal to a greater level provides extra detail that can be thresholded in order to obtain higher compression rates. However this also leads to energy lose. The best trade-off between energy loss and compression is provided by decomposing to higher levels. Decomposing to fewer levels mean provides better energy retention but not as great compression when threshold level is lower. When threshold level is higher provides better compression but more energy loss.

The type of wavelet affects the actual values of the coefficients and hence how many detail coefficients are zero or close to zero and therefore how much energy and zeros can be obtained. Wavelets that work well with an image redistribute as much energy as possible into the approximation subsignal, while giving a large proportion of the coefficient value to describe details. An image is a collection of intensity values and hence a collection of energy varying. The image has a huge effect on the compression and how well energy can be compacted into the approximation subsignal.

As shown in the Figureureures & table-1 the compression at different decomposition levels, it is clearly seen at higher decomposition levels having better energy retaining(image recovery) and compression is not excellent. At higher levels of decomposition the number of zeros decreasing and hence the compression rate is low. The experiments are conducted keeping threshold level constant and varying the decomposition levels.

At denoised compression the image retains same as original but differs in number of zeros. The Biorthogonal wavelet having good denoised compression rate then the other wavelets. Biorthogonal is the high-quality wavelet in denoised compression at different decomposition levels.

- Biorthogonal Wavelet Compression(Decomposition Level)

  Threshold (thr) = 20, Image Used (grayscale)=kumar.jpg,

  Image size=147 X 81

Sl. No.	Decom levels	Short Name (w)	Compressed Image (%)		Denoising Compressed Image (%)	
			Norm Rec	Nul Coeffs	Norm Rec	Nul Coeffs
1	One	bior3.9	99.93	74.03	100.00	50.26
2	Two	bior3.9	99.91	85.64	100.00	50.26
3	Three	bior3.9	99.94	87.03	100.00	50.26
4	Four	bior3.9	99.97	83.92	100.00	50.26
5	Five	bior3.9	99.99	80.73	100.00	50.26
6	Ten	bior3.9	100.00	65.52	100.00	50.26

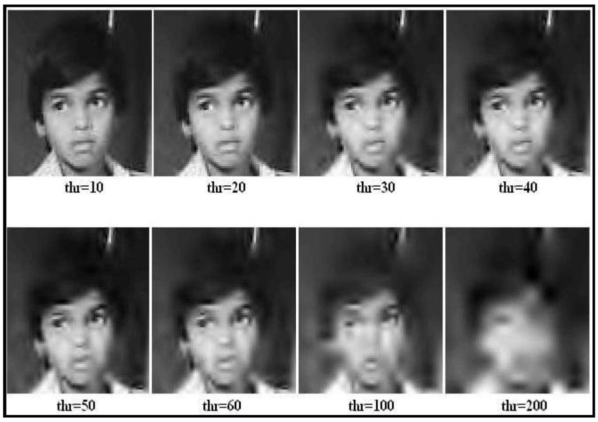
Table 1: Biorthogonal Wavelet Compression(Decomposition Level)

Figureure 10 : Birothogonal Wavelet Compression(Decomposition Level)

10.At Different Thresholds Levels

As shown in the Figureureures & table-1 the compression at different threshold levels, To change the energy retained(image recovery) and number of zeros values, a threshold value is changed. When threshold values are changed i.e. increased the energy lost but having good compression rate. The threshold is the number below which detail coefficients are set to zero. The higher the threshold value, the more zeros can be set, but the more energy is lost as shown in the Figureureures and tables. The Biorthogonal wavelet [20]-[34] having balance in energy retaining(image recovery) and number of zeros as threshold is changed and decomposition levels, hence the Biorthogonal is the best wavelet in compression as threshold increases and more efficient then the other wavelets.

- Biorthogonal Wavelet Compression(Threshold)
  Level (n)= 5, Image Used (grayscale)=kumar1.jpg,
  Image size=109 X 87, Wavelet Short name – 'bior6.8'



Figureure 11: Birothogonal Wavelet Compression(Threshold)

Sl. No.	Thresahold (thr)	Compressed Image (%)		Denoising Compressed Image(%)	
		Norm Rec	Nul Coeffs	Norm Rec	Nul Coeffs
1	10	100.00	77.13	99.95	80.39
2	20	99.99	84.07	99.95	80.39
3	30	99.98	87.33	99.95	80.39
4	40	99.97	89.18	99.95	80.39
5	50	99.95	90.55	99.95	80.39
6	60	99.94	91.31	99.95	80.39
7	100	99.87	93.71	99.95	80.39
8	200	99.64	95.92	99.95	80.39

Table 2: Biorthogonal CompressionWavelet (Threshold)

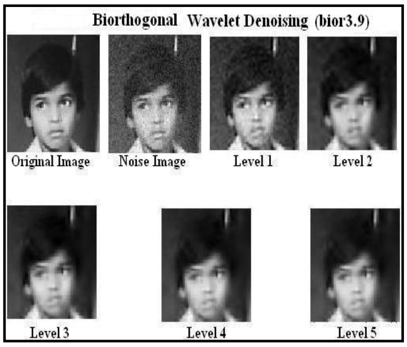
The graphical tools automatically provide an initial threshold based on balancing the amount of compression and retained energy. This threshold is a reasonable first approximation for most cases. However, in general to refine the threshold by trial and error so as to optimize the results to fit the particular analysis and design criteria.

The tools facilitate experimentation with different thresholds, and make it easy to alter the tradeoff between amount of compression and retained signal energy.

11.De-noising Result

Image Used (grayscale)=kumar.jpg, Image size=147 X 81

- Birothogonal Wavelet Denoising



Figureure 12: Birothogonal Wavelet Denoising

12.Conclusion And Future Scope

The major goal of this research is to provide practical ways of exploring compression, denoising and decomposition & reconstruction of DWT technique within the context of MATLAB. The main objective is to analyze still images using wavelets theory of Biorthogonal wavelet family. The experiments and simulation is carried out on .jpg format images.

The main framework of this project comprises a number of experiments such as compression at different decomposition & threshold levels, to find out energy retaining and lost, denoising, image clarity and knowing the efficiency of Biorthogonal wavelet. The project involved writing of results for a range of thresholds and decomposition levels. The experiments and simulations are performed using WT. Using of WT because the IPT does not include routines for computing or using wavelet transforms.

The study concentrated on the decomposition and reconstruction by DWT technique and the results that were collected were values for percentage energy retained and percentage number of zeros. These values were calculated for a range of threshold and decomposition values on all the images. The energy retained describes the amount of image detail that has been kept, it is a measure of the quality of the image after compression. The number of zeros is a measure of compression. A greater percentage of zeros implies that higher compression rates can be obtained.

The decomposition level changes the proportion of detail coefficients in the decomposition. Decomposing a signal to a greater level provides extra detail that can be thresholded in order to obtain higher compression rates. However this also leads to energy lose. The best trade-off between energy loss and compression is provided by decomposing to higher levels. Decomposing to fewer levels means provides better energy retention but not as great compression when threshold level is lower. When threshold level is higher provides better compression but more energy loss.

To change the energy retained and number of zeros values, a threshold value is changed. When threshold values are changed i.e. increased, energy lost but having good compression rate. The threshold is the number below which detail coefficients are set to zero. The higher the threshold value, the more zeros can be set, but the more energy is lost.

The wavelets are efficient in image processing but differ in compatibility of individuality of wavelet families. All the wavelets having good denoised compression image with clarity, but differ in energy retaining (image recovery) and (percentage) number of zeros. The denoising at lower level of decomposition having reasonable clarity but at the higher levels the image is not clear. It is found the Biorthogonal wavelet for compression at decomposition and thresholding is having good compression rate and denoising then the other wavelet families.

The wavelet transforms provide significant insight into both an image's spatial and frequency characteristics can be used in applications in which Fourier methods are not well suited, like progressive image reconstruction. In the course of this study, it is managed to develop a simulation that implements for the lossy compression, denoising and decomposition of the two-dimensional images. This simulation has achieved reasonable performance in general.

The wavelets theory is new advanced topic to go research in enormous field of different image formats and also very interesting. Hence, therefore wavelets theory can be implemented as applications [19] to provide better results in digital signal processing and digital image processing.

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