WAVELET BASED THRESHOLDING APPROACH FOR IMAGE RESTORATION AND ENHANCEMENT

[1] KINITA B VANDARA, [2] DR.G.R.KULKARNI

[1] Research Scholar, Department of Electronics and Communication Engineering, Shri J.J.T.University, Vidyanagari, Jhunjhunu, Rajasthan
[2] Principal, Kalol Institute Of Technology And Research, Kalol – 382721 Gujarat

kinitawandra.er@gmail.com,grkulkarni29264@rediffmail.com

ABSTRACT *: In this paper, the methodology for image restoration and enhancement based on advanced time-frequency techniques is discussed. The noise component in image is removed by the multi-decomposition and different threshold technique is implemented. We present implementation of new proposed thresholding technique for denoising and enhancement of the medical images of Ultrasonography.*

1. Introduction

Generally, Most of the signals in Practice are Time-Domain signals in their raw design. That is, basically measurement of signal is a function of time. In other words, when we plot the signal one of the axes is time (independent variable), and the other (dependent variable) is usually the magnitude. When we plot time-domain signals, we obtain a time-magnitude representation of the signal. This representation is not always the best delegation of the signal for usually signal processing related applications. In many cases, the most illustrious information is hidden in the frequency content of the signal. The frequency Spectrum of a signal is basically the frequency components (spectral components) of that signal. The frequency spectrum of a signal shows what frequencies exist in the signal.

Today Fourier transforms (FT) are used in many different areas including all branches of engineering and mathematics. Although FT is perhaps the most popular conversion which is being used, it’s not the singular one. There are many other transforms that are used quite frequently by engineers and mathematicians. Hilbert transform, short-time FT (more about this later), Wigner distributions, the Radon Transform, and of course our featured transformation , the wavelet transform, constitute only a small portion of a huge list of transforms that are available at engineer's and mathematician's disposal. Every transformation technique has its own area of application, with advantages and disadvantages, and the wavelet transform (WT) is no exception.

For a better understanding of the need for the WT let's look at the FT more closely. FT (as well as WT) is a reversible transform, that is, it allows going back and forwarding between the unprocessed and processed (transformed) signals. However, only either of them is available at any specified time. That is, no frequency information is available in the time-domain signal, and no time information is available in the Fourier transformed signal.

When we will require both information time as well as frequency depends on the appropriate application and the features of the signal are given. We know that the FT gives the frequency information of the signal, which means that it tells us how much of each frequency exists in the signal, but it does not tell us when in time these frequency components exist. This information is not required when the signal in consideration is so-called stationary.

FT can be used for non-stationary signals, if we are only interested in what spectral components exist in the signal, but not interested positioning of them. However, if this information is needed, i.e., if we want to know, what spectral component occur at what time (interval) , then it is not intelligent to use Fourier transform.

When the time localization of the spectral components is needed, a transform giving the time frequency representation of the signal is needed. So the wavelet provides solution of this problem having time and frequency information both.

Wavelet analysis is an exciting new method for solving difficult problems in mathematics, physics, and engineering, with modern applications as diverse as wave propagation, data compression, signal processing, image processing, pattern recognition, computer graphics, the detection of aircraft and submarines and other medical image technology. Wavelets allow complex information such as music, speech, images and patterns to be decomposed into elementary forms at different positions and scales and subsequently reconstructed with high precision. Signal transmission is based on transmission of a series of numbers. The series representation of a function is important in all types of signal transmission. The wavelet representation of a function is a new technique. Wavelet transform of a function is the improved version of Fourier transform. Fourier transform is a powerful tool for analyzing the components of a stationary signal. But it is failed for analyzing the non stationary signal where as wavelet transform allows the components of a non-stationary signal to be analyzed.

Today, there is almost no area of technical endeavour that is not impacted in several way by digital image processing. The discoveries of determining physical phenomena such as X-rays, ultrasound, radioactivity, magnetic resonance and the development of imaging instruments that harness them have provided some of the most effective diagnostic tools in medicine. The medical imaging community is now able to probe into the structure, function and pathology of the human body with a diversity of imaging systems. These systems are also used for planning treatment and surgery, as well as for imaging in biology

The improvement of a specific imaging modality system starts with the physiological understanding of the biological medium and its relationship to the targeted information to be obtained through imaging. Once such a relationship is determined, a method for obtaining the targeted information using a specific energy transformation process, often known as physics of imaging, is investigated. Once a method for imaging is established, proper instrumentation with energy source(s), detectors, and data acquisition systems are designed and integrated to physically build an imaging system for imaging patients to obtain target information in the context of a pathological investigation.

The influence and impact of digital images on modern society is tremendous, and image processing is now a critical component in science and technology. The rapid progress in computerized medical image reconstruction, and the associated developments in analysis methods and computer-aided diagnosis, has propelled medical imaging into one of the most important sub-fields in scientific imaging.

Any imaging system must be predicted on the excellence of the images it produces. For medical imaging systems the images must be diagnostically useful, that is capable of leading to the detection and identification of an abnormality and its interpretation so as to determine its cause, and obtained at an acceptable dose to the patient.

Medical imaging techniques are predominantly used in medical diagnosis and therapy. The success of this technique depends largely on the quality of images. Due to various factors, images do not have appropriate contrast and are often overridden by noise, making the interpretation of the images too difficult leading to incorrect diagnosis. Our research is related with enhancement of medical images and it will be useful in improving the quality of medical images thereby helping in correct diagnosis and treatment. This will be a very important and significant contribution to the medical profession.

An image is a spatial pattern of intensities. Fundamentally, the quality of a digital image depends on the size of the pixels, relative to the size of the image, and the number of available values of gray tone that are accessible to describe the intensity range between black and white: image quality is highest for small pixels and a large number of available gray tones.

In a general sense, medical imaging refers to the process involving specialized instrumentation and techniques to create images or relevant information about the internal biological structures and functions of the body. Medical imaging is sometimes categorized, in a wider sense, as a part of radiological sciences. This is particularly relevant because of its most common applications in diagnostic radiology. In clinical environment, medical images of a specific organ or part of the body are obtained for clinical examination for the diagnosis of a disease or pathology. However, medical imaging tests are also performed to obtain images and information to study anatomical and functional structures for research purposes with normal as well as pathological subjects. Such studies are very important to understand the characteristic behaviour of physiological processes in human body to understand and detect the onset of pathology. Such an understanding is extremely important for early diagnosis as well as developing a knowledge base to study the progression of a disease associated with the physiological processes that deviate from their normal counterparts.

The significance of medical imaging paradigm is its direct impact on the healthcare through diagnosis, treatment evaluation, intervention and prognosis of a specific disease. This information has to be interpreted in a timely and accurate manner to benefit health care. The examination is qualitative in some cases, quantitative in others; some images need to be registered with each other or with templates, many must be compressed and archived. To assist visual interpretation of medical images, the international imaging community has developed numerous automated techniques which have their merits, limitations, and realm of application. This dissertation presents the development of concepts and digital techniques for processing and analyzing medical images after they have been generated or digitized.

2. Background and Motivation

Natural science is the search for “truth” about the natural world. In this definition, truth is defined by principles and laws that have evolved from observations and measurements about the natural world. The observations and measurements are reproducible through procedures that follow universal rules of scientific experimentation. They reveal properties of objects and processes in the natural world that are assumed to exist independently of the measurement technique and of our sensory perceptions of the natural world. The mission of science is to use observations and measurements to characterize the static and dynamic properties of objects, preferably in quantitative terms, and to integrate these properties into principles and, ultimately, laws and theories that provide a logical framework for understanding the world and our place in it .

As a part of natural science, human medicine is the quest for understanding one particular object, the human body, and its structure and function under all conditions of health, illness, and injury. This quest has yielded models of human health and illness that are immensely useful in preventing disease and disability, detecting and diagnosing illness and injury, and designing therapies to alleviate pain and suffering and to restore the body to a state of wellness or, at least, structural and functional capacity. The success of these efforts depends on our depth of understanding of the human body and the delineation of ways to intervene successfully in the progression of disease and the effects of injuries.

Progress toward these objectives has been so remarkable that the average life span of humans in developed countries is almost twice its expected value a century ago. Greater understanding has occurred at all levels, from the atomic through molecular, cellular, and tissue to the whole body, and includes social and lifestyle influences on disease patterns. At present a massive research effort is focused on acquiring knowledge about genetic coding (the Human Genome Project) and about the role of genetic coding in human health and disease. This effort is progressing at an astounding rate, and it causes many medical scientists to believe that genetics, computational biology (mathematical modelling of biological systems), and bioinformatics (mathematical modelling of biological information, including genetic information) are the major research frontiers of medical science for the next decade or longer.

The human body is an incredibly complex system. Acquiring data about its static and dynamic properties results in massive amounts of information. One of the major challenges to researchers and clinicians is the question of how to acquire, process, and display vast quantities of information about the body so that the information can be assimilated, interpreted, and utilized to yield more useful diagnostic methods and therapeutic procedures. In many cases, the presentation of information as images is the most efficient approach to addressing this challenge. As humans we understand this efficiency; from our earliest years we rely more heavily on sight than on any other perceptual skill in relating to the world around us. Physicians increasingly rely as well on images to understand the human body and intervene in the processes of human disease and harm. The use of images to manage and interpret information about biological and medical processes is certain to continue its expansion, not only in clinical medicine but also in the biomedical research enterprise that supports it.

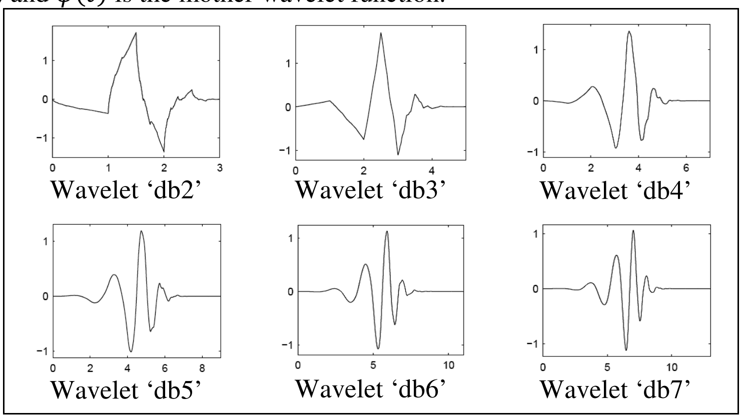
3. Wavelet Transform

Over the past about 15 years, wavelet theory has become one of the emerging and fast-evolving numerical and signal processing tools for its lot of different dignity. The novel concept of wavelet is first put forward by Morlet in 1984. In 1985, Meyer constructed an orthogonal wavelet base with very good time and frequency localization properties. Subsequently, the idea of multi-resolution analysis (MRA) made it easy to construct other orthogonal wavelet bases. The multi-resolution analysis (MRA) led to the famous fast wavelet transform - a simple and recursive filtering algorithm to compute the wavelet decomposition of the signal from its finest scale approximation. Before long, Daubechies constructed orthogonal wavelet bases compactly supported in a simple but ingenious way. In addition, Daubechies has done much research on wavelet frames that allow more liberty in the choice of the basis wavelet functions at a little expense of some redundancy. Daubechies, along with Mallat, are therefore credited with the development of the wavelet from continuous to discrete signal analysis.

A wavelet basis is a set of linearly independent functions constructed from a single mother wavelet with dilation and translation, i.e.

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right) \qquad \ldots 1$$

where a is the scale parameter (also known as dilation parameter) and t is the shift parameter (also called translation parameter) and $\psi(t)$ is the mother wavelet function.



Wavelet 'db2' Wavelet 'db3' Wavelet 'db4' Wavelet 'db5' Wavelet 'db6' Wavelet 'db7'

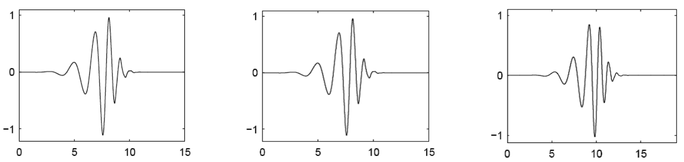


Figure 1 Daubechies wavelet family

When given signal $x(t)$ is translated, the translation 'b'describes the time localization of wavelet, while the dilation $a(a > o)$, determines the width or scale of the wavelet function $\psi_{a,b}(t)$.
A wavelet is any function that integrates to zero and its square is integrable, i.e.

$$\int_{-\infty}^{\infty} \psi(t)\, dt = 0\,, \qquad \ldots 2$$

$$\int_{-\infty}^{\infty} \psi^2(t)\, dt < \infty\,. \qquad \ldots 3$$

There are many different types of wavelet and their families such as Haar, Daubechies, Biorthogonal, Coiflets, Symlets, Mexican Hat, Meyer and Morlet. Ingrid Daubechies, one of the brightest stars in the world of wavelet research, invented what are called compactly supported ortho-normal wavelets - thus making discrete wavelet analysis practical. The names of the Daubechies family wavelets are written dbN, where N is the order, and db the "last name" of the wavelet. The db1 wavelet is the same as Haar wavelet. The wavelet functions psi of the next nine members of the family is given in Figure 1 which is an example of Daubechies wavelet family.

3.1Continuous Wavelet Transform

From Equation 1, a continuous wavelet transform (CWT) for a given input signal $x(t)$ is defined as

$$W_{(a,b)} = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t)\, \psi^* \left(\frac{t-b}{a}\right) dt \qquad \ldots 4$$

Where $\psi^*(t)$ is complex conjugate of analyzing wavelet $\psi(t)$, which $1/\sqrt{a}$ is the scaled and shifted versions of a so-called ''mother wavelet'' function.
The wavelet coefficient $\psi_{(a,b)}$ measures the similarity between the signals $x(t)$ and the analyzing wavelet $\psi(t)$ at different scales as defined by the parameter a, and different time positions as defined by the parameter b. The scaling operation performs the stretching and compressing operations on the mother wavelet function, which in turn can be used to represent the signal to be analyzed in a different frequency range. On the other hand, the time shifting operation shifts the mother wavelet along the time axis. The shifted version is used to catch the time information of the signal to be analyzed. Therefore, a family of scaled and shifted wavelets can be created by varying the scaling a and the shifting b parameters, which serve as the base to form a family of wavelets to analyze the captured signals. The factor $1/\sqrt{a}$ is used to ensure that the energy of the scaled and shifted versions is the same as the mother wavelet. The inverse CWT is given by

$$x(t) = \frac{1}{c_\psi} \int_0^{\infty} \int_{-\infty}^{\infty} W_{(a,t)} \frac{1}{\sqrt{a}} \psi \left(\frac{t-b}{a}\right) dt\, \frac{da}{a^2} \qquad \ldots 5$$

Where the constant $c_\psi$is equal to $\int_0^{\infty} \frac{|\psi(t)|^2}{t} dt$ …6

3.2 Discrete Wavelet Transform

In the discrete wavelet formalism (DWT), the scale a and the time b are discretized as following:

$$a = a_0^m \text{ And } b = n a_0^m b_0 \qquad \ldots 7$$

Where m and n are integers. The continuous wavelet function $\psi_{a,b}(t)$ in Equation 1 become the discrete wavelets given by

$$\psi_{m,n}(t) = a_0^{-m/2} \psi(a_0^{-m} t - n b_0) \qquad \ldots 8$$

The discretization of the scale parameter and time parameter leads to the discrete wavelet transform, defined as

$$W_x(m,n;\psi) = a_0^{-m/2} \int x(t) \psi^*(a_0^{-m} t - n b_0)\, dt \qquad \ldots 9$$

The discretization process partially depends upon the algorithm chosen to perform the transformation. To implement DWT for digital computation, there is an efficient DWT algorithm that uses the method of multi-resolution analysis (MRA). The idea of MRA is to decompose signal with a two-channel filter bank and a down-sampling process recursively. Figure 2 is a schematic diagram of a tow-channel filter bank where G represents a high-pass filter (or wavelet) filter and H is a low-pass (or scaling) filter.

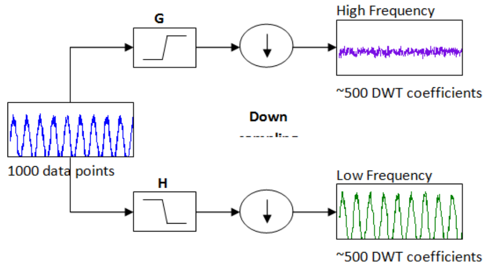


Figure 2 Schematic diagram of a two-channel filter bank for DWT

The first stage of MRA uses G to compute the first detail coefficients (cD) of the signal and uses H to obtain the first approximation coefficients (cA). The down-sampling process (↓) keeps the total number of coefficients equal to the total length of the original signal. The procedure of the basic step can be repeated on the approximation vector cA and successively on every new approximation vector cAj. Each vector cAj includes approximately $N/2^j$ coefficients, where N is the length of signal, and provides information about a frequency band $[0, Fs/2^{j+1}]$, where Fs is the sampling frequency. The DWT can be used to analyze, or decompose, signals and images. The down-sampling of the signal components performed during the decomposition phase introduces a distortion called aliasing. It turns out that by carefully choosing filters for the decomposition and reconstruction phases that are closely related (but not identical), it can 'terminate' the effects of aliasing. This process is therefore known as decomposition or analysis. The other half of the process is how those components can be assembled back into the original signal without loss of information. This process is called reconstruction, or synthesis. The mathematical manipulations that effects synthesis is called the inverse discrete wavelet transform (IDWT). It is also possible to reconstruct the approximations and information themselves from their coefficient vectors. Figure 3 shows Schematic diagram of Decomposition and Reconstruction of the DWT. The reconstructed information and approximations are true constituents of the original signal.

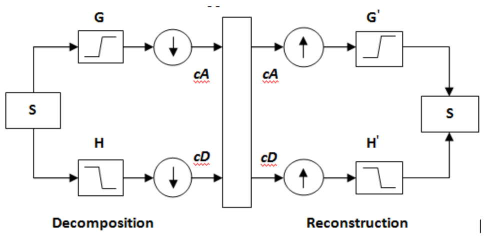


Figure 3 Schematic diagram of decomposition and reconstruction of the DWT

3.3 Wavelet Packet Transformation

The wavelet packet method is a generalization of wavelet decomposition that offers more affluent range of possibilities for signal analysis. In wavelet analysis, a signal is split into an a likeness and a information. The approximation is then itself split into a second-level approximation and information, and the process is repeated. For a machinery monitoring and diagnostics problem, this representation is not effective for feature extraction because of presence of many fault indicating components in a specific high frequency range. For j-level decomposition, there are j+1 possible ways to decompose or encode the signal. This leads to an instinctive thought to apply the same iterative decomposition on both the detail and the approximation sub-bands at each level. This method of decomposition is defined as the discrete wavelet packet transforms (DWPT). The result of the DWPT gives us sub-bands with even bandwidth at the same scale which allows having more flexibility to select the most informative packets with better resolution in the higher-frequency region. Each sub-band is a square integral modulated waveform, well localized in both position and frequency and is called the wavelet packet. In wavelet packet analysis, the details as well as the approximations can be split. This yields more than 2^{2j-1}different traditions to encode the signal. Figure 4 is a schematic of the wavelet packet decomposition hierarchy.

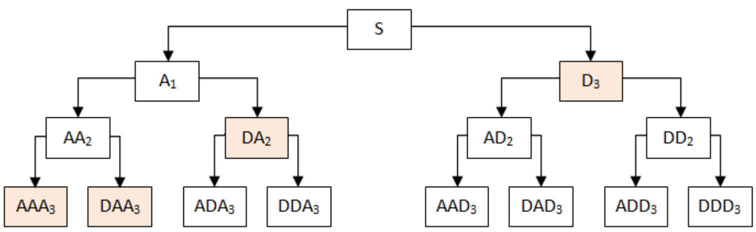


Figure 4 Tree structure of a sequence ordered wavelet packets

For instance, wavelet packet analysis allows the signal S to be represented as $AAA_3+DAA_3+DA_2+D_3$. This is an example of a representation that is not possible with ordinary wavelet analysis, where a 3-level wavelet packet transform produces a total of eight sub-bands, with each sub-band covering one eighth of the signal frequency spectrum. The enhanced signal decomposition capability makes WPT an attractive tool for detecting and differentiating transient elements with high frequency characteristics. The discrete wavelet transform may be initiated to overcome the redundancy problems linked with the Continuous wavelet transform.

Wavelet Packet Transform can be viewed as a cascade band pass filter with a varying bandwidth. Therefore it can be used to as a series of filters to acquire resonance responses that contain the maximum fault information. It is implemented through a combination of filters and down-sampling operations. These filters play a key role in the discrete wavelet algorithm and can be classed as hi-pass and low-pass decomposition filters as well as hi-pass and low-pass reconstruction filters. In Figure 2, H represents a half band high pass filter whose coefficients are determined based on the wavelet coefficients and G represents a half band low-pass filter whose coefficients are determined based on the scaling function. Filters of different cut off frequencies are used to analyze the signal at different scales. The signal is passed through a series of high-pass filters to analyze the high frequencies and produce the detail coefficients. Similarly, low-pass filters are used to analyze the low frequencies and thus producing the approximate coefficients. Filtering operations change the resolution and the scale is changed by up-sampling for reconstruction operations and down-sampling for decomposition operations. Sub-sampling a signal corresponds to reducing the sampling rate, or removing some of the samples of the signal. Sub-sampling by a factor n reduces the number of samples in the signal n times. Up-sampling a signal corresponds to increasing the sampling rate of a signal by addition new samples to the signal. Up-sampling a signal by a factor of n increases the number of samples in the signal by a factor of n.

After passing the signal through a half-band low-pass filter, its bandwidth is effectively halved. The signal now has a highest frequency of $\pi /2$ radians instead of π radians. By discarding every other sample, will subsample the signal by two, and the signal length will be halved. The low-pass filtering removes the high frequency information, but leaves the size unchanged. The sub-sampling processes change the size. The above procedure is repetitive for further decomposition. At every level, the filtering and sub-sampling will result in half the number of samples and half the frequency band spanned. The result of the DWPT can be called time-frequency decomposition since each DWPT coefficients can be localized to a particular band of frequencies and a particular interval of time.

The wavelet transform provides an appropriate basis for image handling because of its beneficial features. The main benefits of the wavelet transform are:

- The ability to compact most of the signal's energy into a few transformation coefficients, which is called energy compaction.
- The ability to capture and represent effectively low frequency components (such as image backgrounds) as well as high frequency transients (such as image edges).
- The variable resolution decomposition with almost uncorrelated coefficients.
- The ability of a progressive transmission, which facilitates the reception of an image at different qualities.

In that sense, the existence of small coefficients is more likely to be due to the noise contamination, whereas the large coefficients contain significant image details. Hence, the small magnitude coefficients may be threshold without affecting the large ones and therefore the quality of the image. The thresholding techniques are simple non-linear techniques that eliminate all the sub band coefficients that their magnitude is under a certain threshold. The remaining coefficients remain either unaffected, which is called hard-thresholding or modified, which is called soft thresholding. The soft thresholding techniques eliminate the coefficients with magnitude less than the pre-specified threshold and shrink the rest of them. The reconstruction of the "clean" image, after the thresholding process, is performed with the inverse wavelet transform. The quality of the reconstructed image, which will contain some noise and may be distorted, is measured either subjectively by an optical evaluation or objectively by the PSNR.

The signal S is passed through two complementary filters and emerges as two signals, approximation and Details. This is called decomposition or analysis. The components can be accumulating back into the original signal without loss of information. This process is therefore identified as reconstruction or synthesis. The mathematical manipulation, which implies analysis and synthesis, is called discrete wavelet transform and inverse discrete wavelet transform.

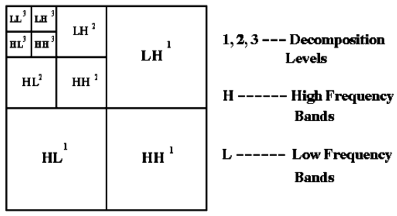


Figure 5 2D-DWT with 3-Level Decomposition

An image can be decomposed into a sequence of different spatial resolution images using DWT. In case of a 2D image, an N level decomposition can be performed resulting in 3N+1 different frequency bands namely, LL, LH, HL and HH as shown in figure 4. These are also known by other names, the sub-bands may be respectively called a1 or the first average image, h1 called horizontal fluctuation, v1 called vertical fluctuation and d1 called the first diagonal fluctuation. The sub-image a1 is formed by computing the trends along rows of the image followed by computing trends along its columns. In the same manner, fluctuations are also created by computing trends along rows followed by trends along columns. The next level of wavelet transform is applied to the low frequency sub band image LL only. The Gaussian noise will nearly be averaged out in low frequency wavelet coefficients. Therefore, only the wavelet coefficients in the high frequency levels need to be threshold.

4. Wavelet Based Restoration Techniques

Image restoration algorithm attempts to remove this noise from the image. Ideally, the resulting restored image will not contain any noise or added artefacts. Restoration of natural images corrupted by noise using wavelet techniques is very effective because of its ability to capture the energy of a signal in few energy transform values. The methodology of the discrete wavelet transform based image restoration has the following three steps

- Transform the noisy image into orthogonal domain by discrete 2-D wavelet transform.
- Apply Thresholding criteria to the noisy detail coefficients of the wavelet transform.
- Perform inverse discrete wavelet transform to obtain the Restored image.

The flow diagram for wavelet based restoration techniques is shown below. It includes three steps for Ultrasound image Restoration.

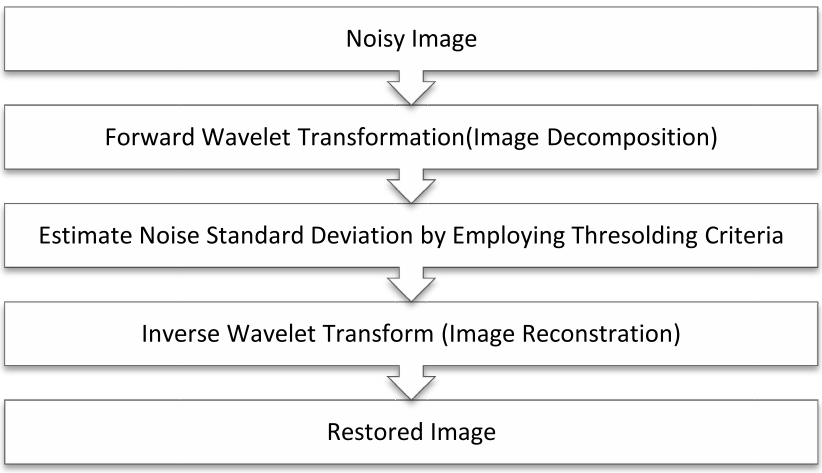


Figure 6 Flow Chart for Wavelet based Image Restoration

The thresholding step comprises of two subtasks, (i) threshold technique selection and (ii) applying using a threshold operator. Two threshold operators used during de-noising are soft thresholding and hard thresholding. Soft thresholding has major advantages over hard thresholding. Soft thresholding reduces the abrupt sharp changes and provides an image whose quality is not affected. Due to these advantages, soft thresholding is more frequently used. Once the thresholding operator has been defined, the next step is to deal with the difficulty of selecting the corresponding threshold.

The selection of threshold is the most important step in any WSD model. Careful selection is needed because a small threshold will produce an image which is still noisy, while a large threshold destroys details and produces blurs and artefacts. Two types of thresholding techniques namely, Universal Thresholding (UT) and Sub band Adaptive Thresholding (SAT) exist. Based on this, three shrinkage techniques used are Visushrink, Sureshrink and Bayesshrink. VisuShrink uses a universal threshold, while Sure Shrink uses a combination of Universal Threshold and SURE Threshold, which is derived from Stein's Unbiased Risk Estimator. Bayes Shrink performs soft thresholding, with the data-driven, sub band dependent threshold. The threshold is driven in a

Bayesian framework, with a Generalized Gaussian Distribution (GGD) for the wavelet coefficients in each detail sub band. Out of the three, Bayesshrink is effective in Denoising problem domain than VisuShrink and Sure Shrink.

4.1Restoration Using Thresholding Techniques

The selection of threshold value plays an important role in image denoising. The large value of threshold over smoothes the image and the fine detail of image will be removed and the smaller value of threshold will retain the noisy co efficient.

i. Soft Thresholding

A "Shrink or kill" method is of Soft Thresholding. The soft threshold makes the model which is smaller than the threshold of the wavelet coefficients replaced by zero and shrinks coefficients above the threshold in absolute value. The soft threshold operator is defined as:

$$y = sign(x)(|x| - T) \qquad \text{... 10}$$

ii. Hard Thresholding

Hard threshold is a "keep or kill" method and is more naturally pleasing. The hard threshold retains the model whose value is greater than the threshold of wavelet coefficients, and makes the model whose value is smaller than the threshold. The hard threshold operator is defined as:

$$y = x \text{ if } |x| > T$$
$$y = 0 \text{ if } |x| < T \qquad \text{... 11}$$

iii. Bayesshrink Thresholding

In Bayesshrink, the threshold for each sub band assuming a Generalized Gaussian distribution (GGD). The GGD is given by

$$GG_{\sigma_X, \beta(x)} = C(\sigma_X, \beta)\exp - \left[\alpha(\sigma_X, \beta)|x|\right]^{\beta} \qquad \text{... 12}$$

$$-\infty < x < \infty, \beta > 0$$

$$\alpha(\sigma_X, \beta) = \sigma_X^{-1}\left[\frac{\Gamma(3/\beta)}{\Gamma(1/\beta)}\right]^{1/2} \qquad \text{... 13}$$

and

$$C(\sigma_X, \beta) = \frac{\beta\alpha(\sigma_X, \beta)}{2\Gamma\left(\frac{1}{\beta}\right)} \qquad \text{... 14}$$

$$\Gamma(t) = \int_0^{\infty} e^{-u}u^{t-1}du \qquad \text{... 15}$$

The parameter σ_X is the standard deviation and β is the shape parameter it has been observed that with a shape parameter ranging from 0.5 to 1, the distribution of coefficients into a sub band for a large set of natural images. Assuming such a distribution for the wavelet coefficients, we empirically estimate β and σ_X for each sub band and try to find the threshold T which minimizes the Bayesian Risk, i.e., the expected value of the mean square error.

$$\tau(T) = E(\hat{X} - X)^2 = E_X E_{Y/X} ((\hat{X} - X)^2 \qquad \text{... 16}$$

Where $\hat{X} = \eta T(Y), Y/X \backsim N(x, \sigma^2)$ and $X \backsim G\,G_{x,\beta}$, the optimal threshold T^* is given by

$$T^*(\sigma_x, \beta) = \arg\min_T \tau(T) \qquad \text{... 17}$$

This is a function of the parameters σ_x and β. Since there is no closed form solution for T^* to find its value numerical calculation is used.

It is observed that the threshold value set by

$$T_B(\sigma_X) = \frac{\sigma^2}{\sigma_X} \qquad \text{... 18}$$

is closed to T^*. The estimated threshold is not only nearly optimal but also has an intuitive appeal. The normalized threshold T_B / σ is inversely proportional to σ, the standard deviation of X and Proportional to σ_x the noise standard deviation. When $\sigma/\sigma_X \ll 1$ the signal is much stronger than the noise, T_b / σ is chosen to be small in order to preserve most of the signal and remove some of the noise; when $\sigma/\sigma_X \gg 1$ the noise dominates and the normalized threshold is chosen to be large to remove the noise which has overwhelmed the signal. Thus, this threshold choice adapts to both the signal and the noise characteristics as reflected in the parameters σ and σ_X.

5. Results of Thresholding technique for Restoration

As a part of restoration process, all the Thresholding techniques are applied on the different USG images of Ultrasonography. The resultant images and measurement of quality assessment parameter are given below.

Noisy Image

Hard Thresholding

Soft Thresholding

Bayes Shrink Thresholding

Figure 7 Results of Thresolding technique for USG Kidney Image

TABLE 1 RESULTS OF QUALITY ASSESSMENT PARAMETER FOR USG KIDNEY IMAGE

SR. NO	Threshold Technique	MSE	PSNR	COC
1	Noisy Image	184.0564	24813	0.9897
2	Hard Thresholding	293.2762	23.4580	0.9910
3	Soft Thresholding	349.0799	22.7016	0.9884
4	Bayes Shrink Thresholding	23.1997	34.4760	0.9930

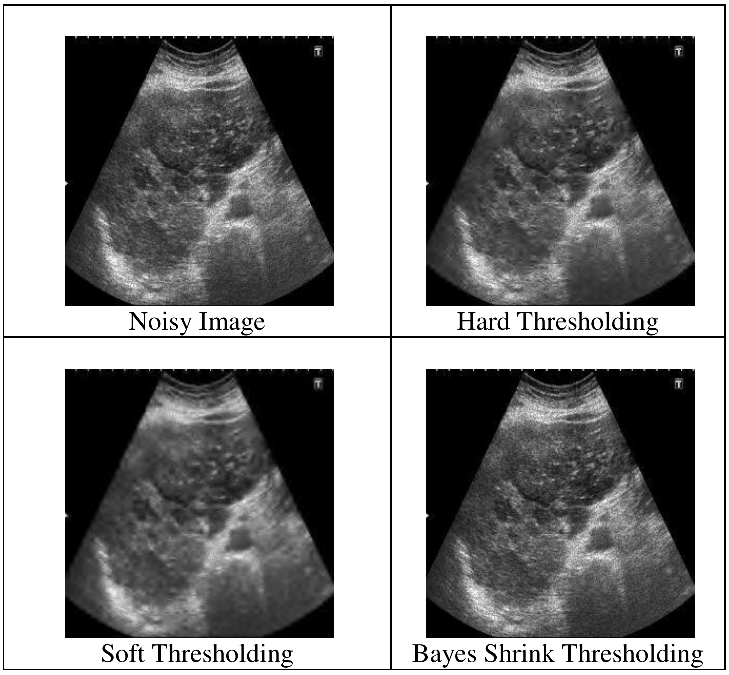


Figure 8 Results of Thresolding technique for USG Brest Metz Image

TABLE 2 RESULTS OF QUALITY ASSESSMENT PARAMETER FOR USG BREST METZ IMAGE

SR. NO	Threshold Technique	MSE	PSNR	COC
1	Noisy Image	139.5388	26.6839	0.9891
2	Soft Thresholding	163548	29466	0.9930
3	Hard Thresholding	99.7803	28.1404	0.9910
4	Bayes Shrink Thresholding	1.0267	48.0165	0.9900

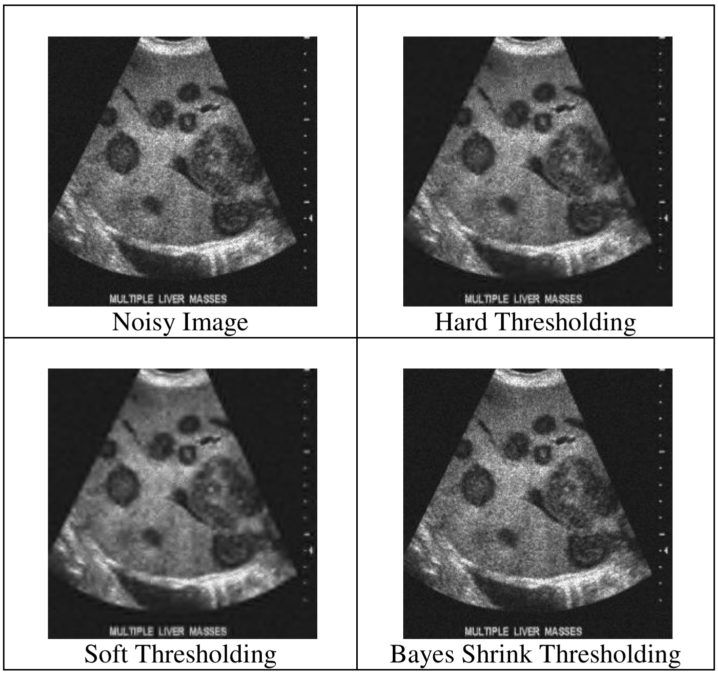


Figure 9 Results of Thresolding technique for USG Focal Liver Image

TABLE 3 RESULTS OF QUALITY ASSESSMENT PARAMETER FOR USG FOCAL LIVER IMAGE

SR. NO	Threshold Technique	MSE	PSNR	COC
1	Noisy Image	144.4791	26.5328	0.9896
2	Soft Thresholding	141.7512	26.6155	0.9945
3	Hard Thresholding	76.6510	29.2856	0.9916
4	Bayes Shrink Thresholding	0.4196	51.9027	0.9901

Conclusion

All these methods are based on the application of wavelet transforms after performing the experiment for our ultrasound image, experiment results are evaluated on visual and performance parameter. This is due to the fact that the threshold does not depend on the content of the image; rather it depends on the size of image. While comparing the three alternatives to calculate threshold, the performance of BayesShrink in terms of image quality and smoothness, is better when compared to others techniques.. Better performance can be achieved in BayesShrink thresholding and also the highest PSNR and COC is obtained for Second level of DWT decomposition. Among the DWT used, db4 wavelets performed better.

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