CHAPTER 1

INTRODUCTION

1.1 BACKGROUND

Digital images are the major methods of communication to transmit visual information in the modern era. They are used in applications ranging from photography, printing, medical and remote sensing. A major problem encountered in the use of digital image is the degradation of its quality due to noise. Noise corrupts the images at the time of their acquisition and transmission. Hence image denoising is necessary before it can be used for further applications. Image preprocessing is done to:

i. bring out specific features of an image
ii. highlight certain characteristics of an image
iii. get an output image more suitable than the original image for particular application

Image denoising is a process of manipulating the image data to produce a high quality image. The objective of denoising is the removal of noise present in images while keeping the important features unaltered.

Medical imaging and noise

Medical images such as MR, X-rays, US etc., are very useful tools for the diagnosis and study of various abnormalities present in the human body. US imaging is the most widely used medical diagnostic technique for clinical decision making, due to its non-invasiveness, portability, ability in making real time imaging for moving structures, low cost and safety.

Unfortunately, the quality of US images is limited due to the physical phenomena of the image acquisition process. The unwanted physical effects should be compensated via using efficient image processing tools. As a result, considerable efforts have been focussed in the field of ultrasound imaging in the past few decades (Michailovich & Tannenbaum 2006) towards the development of image processing techniques intended to fight the main rival of this imaging modality, speckle noise.

1.2 OVERVIEW OF ULTRASOUND IMAGING

Investigations have been started since 1950s to use ultrasound imaging for medical applications. Today ultrasonography is the most widely used modality in clinical applications including vascular imaging, abdomen, obstetrics and gynaecology, thyroid , cardiology and all the other parts of the body. Figure 1.1 illustrates the B-mode US imaging technique (Finn 2010).

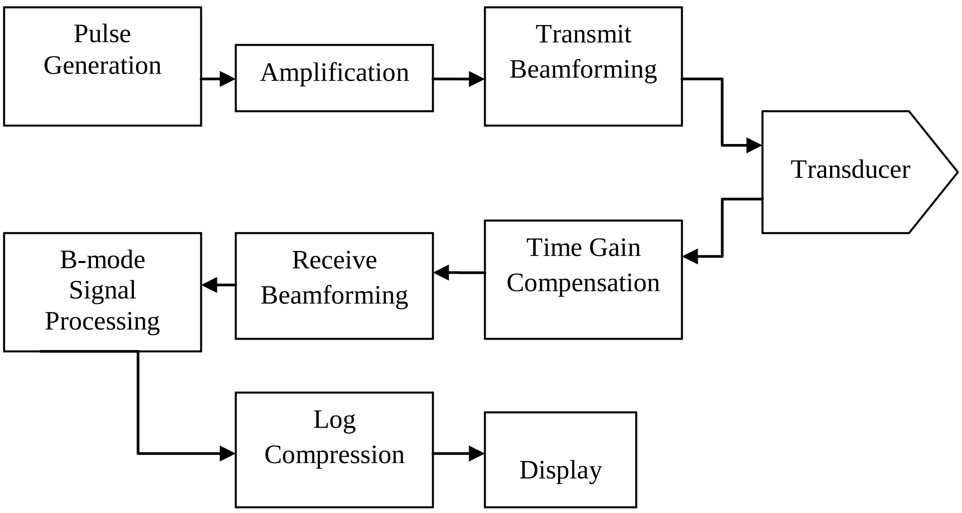


Figure 1.1 B-Mode US imaging system

Imaging in ultrasound scan is done by transmitting sound pulses into the body. These acoustic pulses incident on the tissues and a beam of sound pulses (echoes) are reflected back by the tissue interfaces. A receiver is used to detect the reflected echoes. The amplitude and phase characteristics of the received echo provide information regarding the interaction and also signify the nature of the media. The ultrasound images are generated from the amplitude of the reflected echo, whereas the moving targets are imaged using the frequency shifts. The various components of a practical ultrasound system (Finn 2010) and their functions are detailed below.

Pulsing System: The pulsing system is a mechanism which provides the electrical signals necessary to drive sound wave production. The active elements in the transducer which generate the acoustic pulses require precisely timed driving signals. These signals determine the centre frequency of the acoustic pulses, the pulse repetition frequency (i.e. the interval between pulses) and the spectral and amplitude properties of the pulses.

Transducer: In modern ultrasound systems, transducers contain active elements which are generally made from piezoelectric ceramic materials. These piezoelectric elements produce pressure (sound) waves when the polarity of an applied electric field changes. In the reverse situation, the elements are compressed as they are struck by returning sound waves. A measurable potential difference is then produced, which forms the basis of an ultrasound image.

Beamforming: Ultrasound systems generally perform beamforming in both transmit and receive directions. The sequence of active element excitation in transmission allows the steering and focusing of the beam.

Time gain Compensation: It is a process of amplifying the received signals from each transducer element for compensating the attenuation.

Signal Processing: The individual signals from the elements are then combined to form the composite received signal, generally using the delay and sum method. After the received signals have been acquired, a number of processing steps are applied to facilitate image display. The steps involved differ between imaging modes (e.g. B-mode, Doppler, etc.). For B-mode band-pass filtering is usually performed first to isolate the frequencies of interest, followed by a detection step. Detection refers to the process of extracting an amplitude image. This involves demodulation of the signals to baseband and envelope detection. The high frequency signals are known as Radio Frequency (RF) before demodulation and envelope detection. Finally, the dynamic range of the amplitude image is restricted to facilitate display. This is accomplished using log compression, as given in Equation (1.1).

$$Y = \alpha \log(X + 1) + \beta \tag{1.1}$$

where (X, Y, α, β) are respectively the amplitude image, log compressed image, selectable contrast and brightness parameters. Figure 1.2 shows an example of US echocardiographic image.

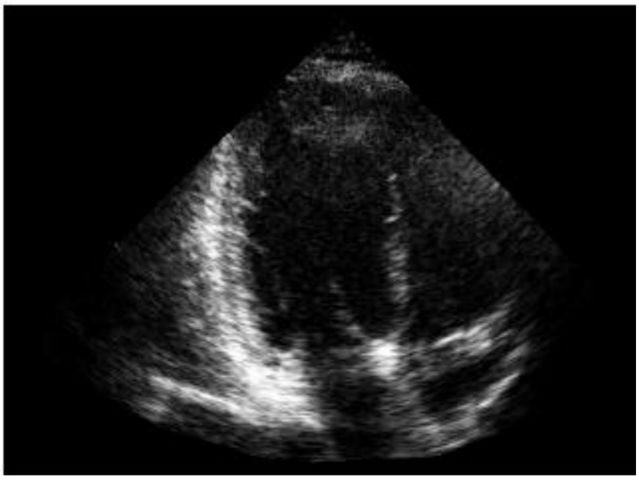
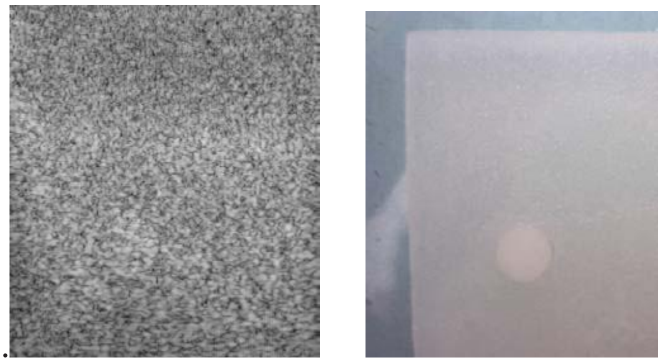


Figure 1.2 US Echocardiographic image

1.3 SPECKLE NOISE

Speckle is a granular artefact due to the coherent interferences of the reflected echoes, in a constructive and destructive manner, from the biological tissues that are much smaller than ultrasound wavelength. Burckhardt (1978) and Wagner et al (1983) investigated that speckle pattern is multiplicative in nature. Figure 1.3(a) shows an US image of a cylindrical phantom and Figure 1.3(b) is the image acquired using a digital camera. It can be seen that the cylindrical object is not very clear in the ultrasound image because of the speckle noise. Hence, noise filtering with advanced image processing techniques is indispensable after acquisition to alleviate the lack of SNR.



(a) (b)

Figure 1.3 (a) US image scanned from a cylinder phantom, (b) Phantom picture captured by a digital camera

1.3.1 Modeling of Speckle

Speckle noise is multiplicative and is generally of the form given as in Equation (1.2),

$$G(i,j) = F(i,j)\,N(i,j) + \xi(i,j) \tag{1.2}$$

where $G(i, j)$ denotes the noisy image, $F(i, j)$ is the original image and $N(i, j)$ is the speckle. $\xi(i, j)$ is additive noise component and can be neglected for speckle noise. The index (i, j) denotes the pixel location. As the RF is not an easily accessed output on commercial ultrasound equipments, limited attention has been paid on modelling its distribution. The simplest model is given by the Gaussian distribution (Bhuiyan 2007).

1.3.2 Effects of Speckle on US images

A number of specific negative effects of speckle and benefits of its removal in clinical ultrasonography as noted from Finn (2010) are

- speckle pattern can mask small grey level differences of the imaged medium, which can obscure tissue boundaries
- it reduces image contrast and
- it reduces the efficiency of further image processing steps such as edge detection and segmentation.

Thus, speckle in US images is seen to degrade its quality and hence is to be reduced without affecting important image features as discussed in literatures like Bao & Zhang (2003). The goal of speckle reduction is:

- to improve the human understanding of ultrasound images
- to make a clear ultrasound image with clear boundaries

1.4 DESPECKLING METHODS

Speckle reduction approaches can be broadly categorized into compounding and post-acquisition techniques as discussed by Finn (2010). Compounding approach is a process of combining several images of the same imaged region. The speckle pattern in each will be different, so that averaging of these images reduces the speckle noise and results in an enhanced output. Images taken from multiple scan directions are combined in spatial compounding. Temporal compounding (frame averaging) combines images taken through scans carried out at various time. Frequency compounding performs averaging of images taken at different ultrasound frequencies. The drawback of these approaches is that they suffer from dependence on motion or otherwise it can be seen that the images of fast moving regions seem to be smeared.

Post-acquisition methods perform filtering of speckle on the envelope detected images. These methods are a practical alternative to compounding approaches, as no particular mode of scanning is required or do not require RF data (which in most commercial systems is inaccessible to the user). In addition, it is reported through several simulation studies that post-acquisition filters show a better image quality improvement than compounding approaches. A large number of post-acquisition filtering techniques are seen in the literature.

This section discusses the various types of post acquisition speckle reduction filters. There are basically two types of post acquisition speckle reduction approaches seen in the literature, namely spatial domain approach and wavelet domain approach.

Spatial Domain Filtering

In spatial domain, a digital image is defined by spatial coordinates of its pixels. The spatial domain processes can be represented by the following Equation (1.3).

$$O(i, j) = T(f(i, j)) \tag{1.3}$$

where $f(i, j)$ is the input image, $O(i, j)$ is the output image and T is an operator defined over a local neighbourhood of pixel with the coordinates (i, j). This kind of filtering approach fails to amply preserve important image features like edges in the US image.

Wavelet Domain Filtering

Recently, wavelet transform has been efficiently used as a powerful tool for the removal of noise from digital images, after the pioneering research done by Donoho (1995). The multiscale bases of decompositions are selected for signal and image processing applications, as they simplify the statistics of many signals and images (Achim et al 2001 and Achim 2003). Wavelet based image denoising consists of three main steps:

- decomposition of the input data by forward wavelet transform
- shrinking the wavelet coefficients by selection of proper threshold and thresholding function
- applying inverse wavelet transform for reconstruction of noise free image.

Discrete Wavelet Transform (DWT)

DWT splits an input image of size $N \times N$, into four sub-images after one level of decomposition, each of size N/2 x N/2. The LL subband is called approximation subband and LH, HL and HH subbands are called detail sub-bands. The critically sampled DWT has been successfully applied to a wide range of image processing tasks. However, as analyzed by Hostalkova & Prochazka (2007) and others, its performance is limited because of the following problems.

- shift variance
- aliasing and
- lack of directional selectivity in higher dimensions

The problem of shift variance is perhaps due to the lack of redundancy, which in general, helps in estimating a signal from its noise corrupted version. The shift variance problem of the DWT is overcome by using Undecimated Discrete Wavelet Transform (UDWT) (Coifman & Donoho 1995). The advantage of UDWT is that the correlation that exists among the wavelet coefficients present in adjacent resolution scales (inter-scale) facilitates the detection of important image features.

Undecimated Discrete Wavelet Transform (UDWT)

Saeedi et al (2010) and Chen & Suter (2004) dealt with a simple approach to shift-invariance through the removal of down sampling in the forward wavelet transform and up sampling the reverse wavelet transform. The result is that there is no aliasing in the output sub-band signals. More accurately, the input image is transformed at each point and saves the three detail subbands (LH, HL and HH) and utilizes one low frequency subband (LL) for next level decomposition. The size of the subbands is maintained the same as the original image for all the levels of decomposition. Thus information about noise and signal of interest coefficients could be more precisely obtained than in the discrete wavelet transform based decompositions. Gyaourova et al (2002) stated that this transformation reported more accurate relation among the spatial and frequency information. One level decomposition and reconstruction of undecimated wavelet transform is shown in Figures 1.4 and 1.5 respectively. In Figures 1.4 & 1.5 h(k) represents low pass filtering and g(k) represents high pass filtering.

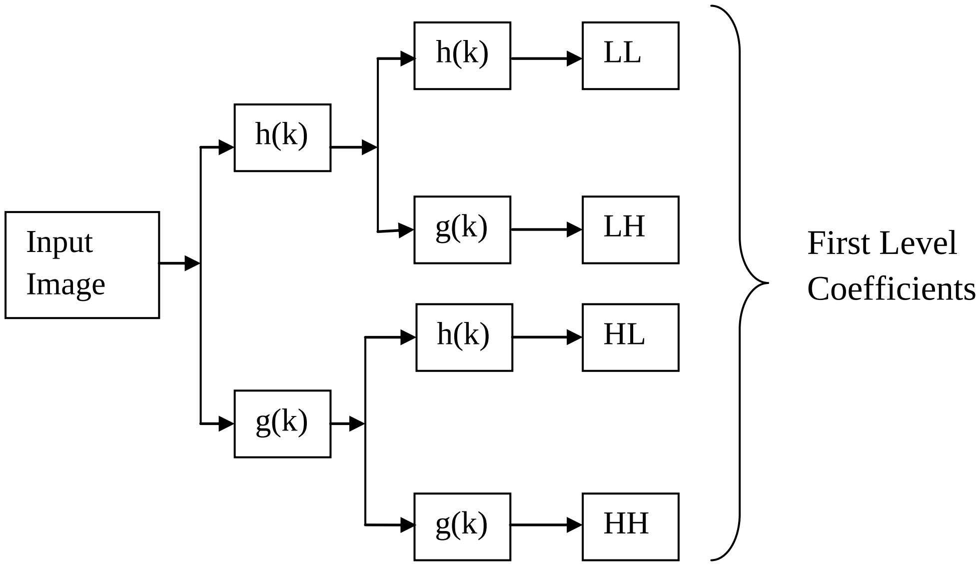


Figure 1.4 One level decomposition of UDWT

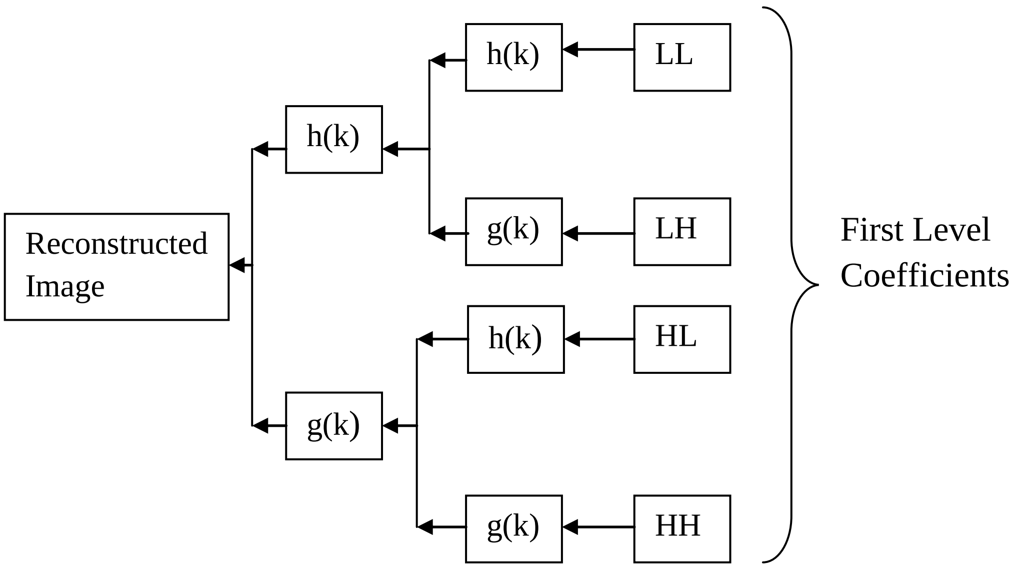


Figure 1.5 One level reconstruction of UDWT

Secondary Wavelet Properties

Wavelet coefficients at each level are correlated with the coefficients at the same level and also in the adjacent level. The type of dependency exhibited by the coefficients at the same level is called as intra scale dependency and with the coefficients in the adjacent level is called inter-scale dependency. Saeedi et al (2010) found that the statistical dependency of the wavelet coefficients is largely based on the following two properties of the wavelet transform:

1) Coefficients with larger magnitudes will persist across the scales, denoted as inter-scale dependencies.
2) If the magnitude of a coefficient is small (large), then some of its neighbourhood coefficients are likely to be small (large), named as intra-scale dependencies.

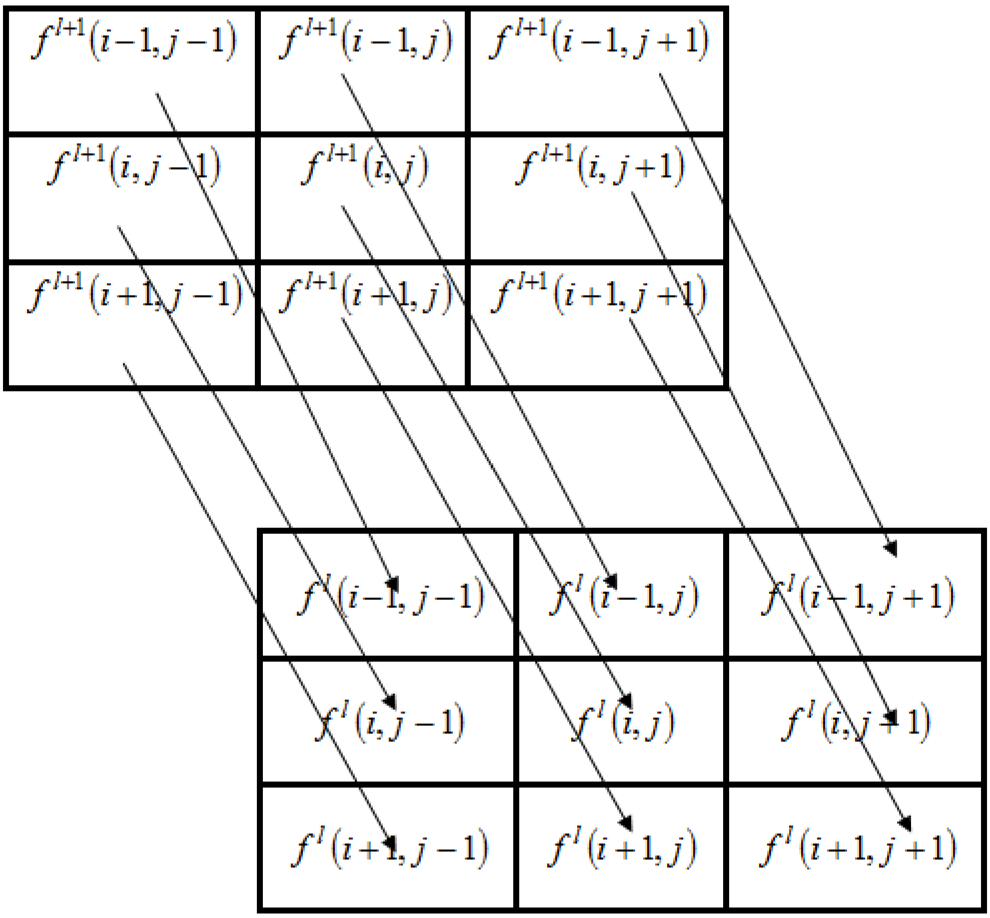


Figure 1.6 Inter-scale dependencies of the adjacent subband coefficients

Figure 1.6 shows the inter-scale relationship among the wavelet coefficients between the adjacent levels l and $l+1$. The arrows indicate the correlation of the adjacent scale coefficients at the corresponding pixel location. At positions of significant image details, the wavelet coefficients increase in magnitude across the scales and at positions of noise and their value tends to decrease as the resolution scale increases (Liu & Moulin, 2001).

1.5 TYPES OF THRESHOLDS

The following are the traditional thresholds defined in the literature and the wavelet shrinkage approach is named accordingly.

VisuShrink

VisuShrink is a wavelet thresholding scheme which makes use of the universal threshold proposed by Donoho & Johnstone (1995). The threshold is given by Equation (1.4) as,

$$T_V = \sqrt{\sigma^2 \log(P)} \tag{1.4}$$

where P is the number of pixels in the image. VisuShrink scheme does not focus on the minimization of mean squared error. This shrinkage technique removes only additive noise and not speckle noise. The denoised output provided by VisuShrink was a smoothed estimate.

SureShrink

Sure Shrink is a thresholding approach, which utilizes a sub band adaptive threshold. The threshold values for each of the detail subbands are calculated separately, based upon Stein's Unbiased Risk Estimator (SURE) proposed by Donoho & Johnstone (1995). It is a blend of SURE threshold and universal threshold. The SURE threshold is defined as in Equation (1.5).

$$T_{SURE} = \min\left(t, \sigma\sqrt{2\log(P)}\right) \tag{1.5}$$

where P is number of wavelet coefficients in the subband, t represents the value that minimizes SURE and σ is noise variance. The performance of SURE shrink in image denoising was good.

BayesShrink

Gao (1998) analyzed that in order to preserve more features in the reconstructed signal, it is desirable to have a data driven threshold selection method. Bayes Shrink (Chang et al 2000b) performs image denoising through wavelet soft thresholding, utilizing an adaptive data-driven threshold. The threshold is derived using Bayesian approach. The coefficients in each of the detail subbands are assumed to follow a generalized Gaussian distribution. The threshold for each of the detail subbands is estimated in such a way that it minimizes the Bayesian Risk. The formula for calculation of Bayes threshold is given in Equation (1.6).

$$T_B = \frac{\sigma^2}{\sigma_x} \tag{1.6}$$

where σ^2 is the noise variance and σ_x is the signal standard deviation. The reconstructed signal from Bayes Shrink is smoother and shows improved visual enhancement than SURE shrink.

1.6 THRESHOLDING FUNCTIONS

Thresholding function defines a rule, whether to retain the coefficients or to remove the coefficients based on a threshold. The two basic thresholding functions discussed in the literature to remove speckle noise are hard thresholding and soft thresholding functions.

Hard thresholding

Here, the magnitude of the wavelet coefficients is compared against a threshold T. Hard thresholding attempts to keep the wavelet coefficients whose magnitudes are above the threshold T. The coefficients whose magnitudes are less than the threshold are made zero. Hard thresholding function is shown in Figure 1.7 (b) and it is given by Equation (1.7) as,

$$\mathrm{ht}(w) = \begin{cases} 0 & |w| < T \\ w & |w| \geq T \end{cases} \tag{1.7}$$

where w is the wavelet coefficients and T is the threshold. In this approach, the denoised wavelet coefficients show discontinuity on threshold $+T$ and $-T$, resulting in Gibb's shock.

Soft thresholding

Soft thresholding (also called shrinkage) was introduced by Donoho (1995). Soft thresholding rule sets the value of the coefficients to zero, whose magnitudes are below the threshold. The coefficients whose magnitudes are bigger than the threshold are scaled with the threshold. They avoid spurious Gibb's oscillations, as the discontinuity that exists in hard thresholding is eradicated. The rule for soft thresholding is given by Equation (1.8).

$$\mathrm{st}(w) = \begin{cases} 0 & |w| \quad < T \\ \mathrm{sign}(w) & (|w| - T) \quad \geq T \end{cases} \tag{1.8}$$

where w is the image value. The graphical representation of soft thresholding function is shown in Figure 1.7(c).

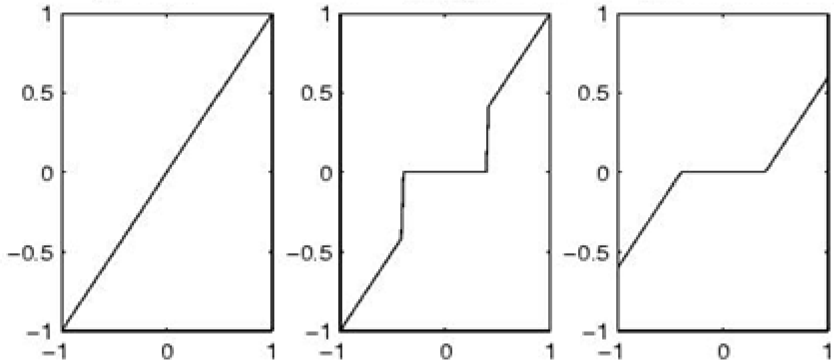


Figure 1.7 (a) Original (b) Hard thresholded (c) Soft thresholded signal signal signal

Figure 1.7(b) visualizes the discontinuity at the thresholds exhibited by the hard thresholding function. In the soft-thresholding method, there exists a fixed bias amid the denoised and original coefficients, when the processed coefficient is greater than the threshold as shown in Figure 1.7(c)(Gao & Bruce, 1997). The result is that the original features could not be maintained.

1.7 PERFORMANCE MEASURES

The performance metrics used in this research work for comparing the quantitative improvements are listed below:

Peak Signal to Noise Ratio (PSNR)

It is a measure which specifies the quality of an image using the power of the denoised and original images. Its unit is in decibels (dB). MSE is Mean Square Error which quantifies the amount of despeckling between original and despeckled images.

$$PSNR = 10\log_{10}\left(\frac{255^2}{MSE}\right)\ dB \tag{1.9}$$

$$MSE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}\left(X(i,j) - O(i,j)\right)^2 \tag{1.10}$$

where M and N are the row and column lengths of the image, X is an original image and O is the denoised image. A low value of MSE is required to get higher PSNR.

Structural Similarity Index Measure (SSIM)

This measure compares luminance, contrast and structure of the denoised and original images and is computed as in Equation (1.11). The value of SSIM should be closer to unity in order to have optimal measure of similarity.

$$SSIM(X,O) = \frac{(2\mu_X\mu_o + C_1)(2\sigma_{XO} + C_2)}{(\mu_X^2 + \mu_O^2 + C_1)(\sigma_X^2 + \sigma_O^2 + C_2)} \tag{1.11}$$

Where μ_X is the mean of X and μ_O is the mean of O; σ_X^2 represents the variance of X and σ_O^2 represents the variance of O; $2\sigma_{XO}$ is the covariance of X and O, $C_1 = (K_1L)^2$, $C_2 = (K_2L)^2$, $K_1 = 0.01$, $K_2 = 0.03$ and L is the dynamic range of pixels.

Equivalent Number of Looks (ENL)

It is the measurement of statistical fluctuations introduced by speckle. A large ENL value represents better quality performance of despeckled image.

$$\mathrm{ENL} = \frac{\mathrm{NMV}}{\mathrm{NSD}} \tag{1.12}$$

$$\mathrm{NSD} = \frac{1}{\mathrm{MN}}\,\mathrm{sqrt}\left(\sum_{i=1}^{M}\sum_{j=1}^{N}\left(X(i,j) - \mathrm{NMV}\right)\right) \tag{1.13}$$

$$\mathrm{NMV} = \frac{1}{\mathrm{MN}}\sum_{i=1}^{M}\sum_{j=1}^{N} X(i,j) \tag{1.14}$$

NSD is Noise Standard Deviation and NMV is the noise mean value.

Edge Preservation Index (EPI)

This measure determines the ability of a filter to preserve the edges. EPI is calculated as in Equation (1.15). The range lies between 0-1. The maximum value of 1 indicates a better edge preservation ability for a filter.

$$\mathrm{EPI} = \sum \frac{\left(\Delta X - \overline{\Delta X}\right)\left(\Delta O - \overline{\Delta O}\right)}{\sqrt{\sum\left(\Delta X - \overline{\Delta X}\right)^2\left(\Delta O - \overline{\Delta O}\right)^2}} \tag{1.15}$$

where ΔX and ΔO are obtained by high pass filtering of the images $X(i, j)$ and $O(i, j)$, with a Laplacian operator and $\overline{\Delta X}$ and $\overline{\Delta O}$ are the average values of ΔX and ΔO respectively.

1.8 PROBLEM FORMULATION AND PROPOSED METHODS

1.8.1 Problem Formulation

The rapid development of ultrasound imaging modality has provided an unprecedented way to diagnose illness in-vivo and non-invasively in the medical imaging field. However, with the introduction of speckle, the quality of the US image is degraded. This in turn reduces the accuracy of abnormality detection by the physician. Hence, post-processing of the data is considered as extremely significant in improving the quality of the images. The removal of noise present in images, with simultaneous preservation of important image features is still found to remain an essentially elusive and tricky problem in medical image processing.

Wavelets have been employed for image denoising since 1990 due to several advantages. The research direction of any wavelet based denoising algorithm is towards

- determination of new thresholds
- finding new thresholding functions and
- exploiting the correlation of the coefficients for noise removal

Selection of threshold is a crucial task in any image denoising algorithm. Several adaptive threshold determination techniques are being studied by the researchers to select an optimum threshold and are still being expanded. Most of the adaptive threshold determination techniques in the literature are computationally complex. The context selection and hence the estimation of the local statistics of the parameter for the threshold involve intensive mathematical calculation. Also, most of the techniques do not exploit the correlation of the coefficients in the estimation of the parameters for the threshold. Hence an efficient and low complex method is required for the estimation of local statistics of the coefficients. Several new thresholding functions have been reported in the literature to overcome the limitations of soft thresholding. The reduction of fixed bias between the original and the reconstructed coefficients is still boosting research interest. Also most of the thresholding functions developed so far modify the large magnitude coefficients (i. e. coefficients above a threshold). There are only few research papers that discuss the development of thresholding function for addressing the coefficients, below and around the threshold. The processing of low magnitude coefficients is very much essential to keep the fine details intact. Hence, the development of new thresholding functions in this direction is an essential task. Also, the existing thresholding schemes produce a smoothed image resulting in less edge preservation ability. Therefore there is a scope for improving the noise removal ability of the filter with simultaneous preservation of important image details.

1.8.2 Objectives of the Research

Owing to the above research interests, the thesis addresses approaches for improving the performance of speckle removal filters for ultrasound images, in the undecimated wavelet domain through,

- formulation of new thresholding functions
- low complex signal variance estimation approaches exploiting intra and inter-scale correlation
- improved adaptive threshold determination
- new fusion based algorithm

1.8.3 Methodology of the Research

Based on the above objectives the following methods are proposed to improve the performance of the speckle removal filters in the undecimated wavlet domain:

❖ Development of improved adaptive wavelet filter to address the coefficients above the threshold under three filter frameworks:

  - An Enhanced Adaptive Wavelet Filter (EAWF) with homogeneity based weighted variance estimate

- Shift Invariant Improved Adaptive Wavelet Filter[1] (SIIAWF[1]) with intra-scale measure based signal variance estimation

- Shift Invariant Improved Adaptive Wavelet Filter[2] (SIIAWF[2]) with a combined inter and intra-scale measure based signal variance estimation

❖ Development of an Inter-Scale Threshold based Wavelet Filter (ISTWF) with a new exponential thresholding function to address the small magnitude coefficients

❖ Development of a new Fusion based Wavelet Filter (FBWF) combing SIIAWF and ISTWF

1.9 ORGANISATION OF THE THESIS

The content of the chapters in this thesis is summarized as follows:

Chapter 2 presents the literature review of the speckle reduction approaches. Methods of traditional spatial domain speckle filters and DWT based methods are discussed here. The literatures examining the performance of UDWT based filters are also presented. The utilization of inter and intra-scale dependencies in a variety of ways by the researchers is summarized. Also, filters with simultaneous edge preservation are looked at. Studies contributing to several thresholding functions are discussed. Finally, fusion based denoising schemes are presented.

Chapter 3 focuses on the Enhanced Adpative Wavelet Filter (EAWF). It deals with a homogeneity measure based signal variance estimation exploiting inter-scale correlation of wavelet coefficients.

Chapter 4 proposes the development of Shift Invariant Improved Adaptive Wavelet Filter (SIIAWF) under two frameworks for shrinking the coefficients above threshold. In section 4.1, a shift invariant improved adaptive wavelet filter is delineated. It describes a new intra-scale measure based signal variance estimation technique for the determination of adaptive threshold. A new and improved adaptive thresholding function is proposed to improve the soft thresholding approach. In section 4.2, a hybrid intra and inter scale based improved adaptive wavelet filter with two stage filtering is explained. It utilizes a combined intra and inter scale measure based signal variance estimate for first stage thresholding and a near optimal thresholding for the second stage.

In Chapter 5, an Inter-scale Adaptive Threshold based Wavelet Filter (ISTWF) is mooted to modify the coefficients below the threshold. This chapter examines a new exponential thresholding function to reduce the low magnitude coefficients. An adaptive threshold exploiting the parent-child relationship of the coefficients is suggested to retain the fine details of the image.

In Chapter 6, a Fusion based Wavelet Filter (FBWF) is presented to achieve further reduction in noise with simultaneous preservation of edges and to improve the contrast. An inter scale and intra scale activity based fusion is advanced through a two stage fusion process. A new weighted entropy based activity measure is unfolded to improve the preservation of image details.

Chapter 7 presents the concluding remarks highlighting the contribution of the research work and provides some idea for future research.